

Dipartimento di Informatica, Bioingegneria,
Robotica ed Ingegneria dei Sistemi

**GNSS Positioning with Low Cost Devices:
Perspectives for Human Movement Analysis**

by

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Robotica ed Ingegneria dei Sistemi

**Ph.D. Thesis in Computer Science and Systems Engineering
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Abstract

Outdoor quantitative analysis of human movement is constrained by the technologies currently available. Marker-based optical motion capture is laboratory-bound. Inertial measurement units are wearable but lack an absolute spatial reference and suffer from integration drift. Markerless video-based systems introduce camera geometry biases and operational constraints. None of these approaches simultaneously satisfies the requirements of outdoor, infrastructure-light, deployable motion capture.

This thesis investigates whether wearable Global Navigation Satellite System (GNSS) receivers, combined with inertial sensing and a portable reference station, can bridge that gap. A conceptual framework identifies three functional roles for GNSS in human motion analysis and operationalises them into three integration architectures of increasing scope. The thesis validates this framework through three experimental contributions of correspondingly increasing complexity, with Architecture 2 tested rigorously, Architecture 1 evaluated incidentally through a single reference receiver, and Architecture 3 demonstrated as a proof of concept.

A foot-mounted GNSS/IMU device achieved centimetre-level horizontal foot-trajectory accuracy at slow and normal walking speeds in a single-subject proof-of-concept study, and characterised the mechanism by which impulsive foot accelerations degrade carrier-phase tracking. A nine-subject outdoor campaign with a portable base station confirmed the degradation mechanism across subjects and yielded internally consistent stride parameters ($r = 0.997$ against a torso-derived walking speed reference), reflecting the near-identity relationship between stride length, cadence, and speed. A proof-of-concept multi-segment kinematic reconstruction with three GNSS/IMU devices and an OpenSim biomechanical model reproduced hip-flexion timing against a drone-based markerless reference (Pearson correlations between $r = 0.752$ and $r = 0.926$), with amplitude accuracy characterised separately through range-of-motion ratios.

The thesis establishes the conceptual, methodological, experimental, and software foundations for outdoor GNSS-aided human motion capture, with an operating envelope appropriate for further development towards clinical rehabilitation assessment.

To wit, stubbornness, and brighter future.

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List of Abbreviations

BASEC Business Administration System for Ethics Committees

CN0 Carrier-to-Noise density ratio

DC Deeply-Coupled (integration)

DGNSS Differential Global Navigation Satellite System

DOF Degrees of Freedom

DOP Dilution of Precision

ECEF Earth-Centered, Earth-Fixed (reference frame)

EKF Extended Kalman Filter

ENU East-North-Up (reference frame)

EUREF European Reference Frame

GLRT Generalised Likelihood Ratio Test

GNSS Global Navigation Satellite System

HAS High Accuracy Service (Galileo)

IGS International GNSS Service

IK Inverse Kinematics

IMU Inertial Measurement Unit

INS Inertial Navigation System

LC Loosely-Coupled (integration)

LLUI Lake Lucerne Institute

MEMS Micro-Electro-Mechanical Systems

MoCap Motion Capture

NMEA National Marine Electronics Association

PCA Principal Component Analysis

PLL Phase Lock Loop

PPK Post-Processing Kinematic

PPP Precise Point Positioning

RINEX Receiver Independent Exchange Format

RMSE Root Mean Square Error

ROM Range of Motion

RTK Real-Time Kinematic

RTS Rauch-Tung-Striebel (smoothing algorithm)

SD Standard Deviation

SHOE Stance Hypothesis Optimal dEtector

SI Symmetry Index

SNR Signal-to-Noise Ratio

TC Tightly-Coupled (integration)

VRS Virtual Reference Station

WGS84 World Geodetic System 1984

WMM World Magnetic Model

ZUPT Zero Velocity Update

Chapter 1

Introduction

1.1 Motivation and Problem Statement

Human motion capture — the reconstruction of body movement from sensor data — is significant for a broad range of scientific and clinical disciplines. In biomechanical research, it provides the quantitative basis for understanding how the body performs physical tasks. In rehabilitation, it enables objective assessment of movement disorders and longitudinal tracking of recovery [3, 4]. In sports science, it informs training decisions and technique optimization. Each of these domains has its own requirements in terms of measurement accuracy, system portability, and ease of deployment in real-world conditions [5].

Despite decades of development, no existing motion capture technology satisfies all of these requirements simultaneously. Optical marker-based systems, widely regarded as the gold standard for measurement precision, are confined to instrumented laboratory spaces and bounded capture volumes. Inertial-based systems offer portability and freedom from external infrastructure, but accumulate orientation and position errors over time, limiting their reliability for extended recordings. Markerless video-based approaches reduce the instrumentation burden but remain sensitive to occlusion, lighting conditions, and camera field of view.

The result is a persistent trade-off: systems that are accurate tend to be confined to the laboratory, while systems that can operate outdoors tend to be less precise. This trade-off has direct consequences for the validity of the data collected. It is well established, for instance, that gait characteristics measured on a treadmill do not faithfully represent overground locomotion, particularly over extended durations [6]. Yet for activities like long distance running or medical rehabilitation assessment, outdoor measurement is precisely what is needed. Outdoor and nature-based rehabilitation programmes are increasingly adopted in neurorehabilitation practice, with clinical evidence supporting their use in stroke and acquired brain injury recovery [7, 8], and the need for objective gait assessment within these real-world rehabilitation contexts has been explicitly

identified [9]. More broadly, gait characteristics measured in neurological patient populations under free-living conditions differ substantially from those captured in controlled clinical settings [10], and large-scale efforts to validate digital mobility outcomes in real-world conditions confirm that laboratory-based assessments cannot substitute for outdoor measurement [11, 12]. What can currently be measured outdoors, however, is narrower than what these motivating studies characterise: existing wearable systems can report aggregate spatiotemporal statistics but cannot yet resolve fine-grained stride-to-stride variability at the noise floor required to serve as a biomarker. No current system provides outdoor gait assessment at both the spatial resolution and the deployability that clinical rehabilitation contexts demand.

This thesis is motivated by the question of whether this gap can be narrowed. Global navigation satellite systems (GNSS) have become capable of centimeter-level outdoor positioning, through carrier-phase and differential processing techniques that are introduced in detail in Chapter 3, and offer a physically grounded absolute position reference that is available without laboratory infrastructure. Combined with inertial sensing, such a system could in principle provide the spatial grounding that inertial-only approaches lack, while retaining the portability that optical systems cannot offer. Whether this is achievable in practice — and under what conditions, with what accuracy, and at what level of biomechanical detail — is the central question this thesis addresses. Chapter 2 reviews the state of the art in human motion capture, and Chapter 3 introduces the principles of GNSS positioning and its prior applications to human movement analysis. The open problems these chapters reveal, enumerated in Section 3.2.5, motivate the research question and contributions presented below.

1.2 Research Question

The central research question this thesis addresses is the following:

Can wearable GNSS receivers, combined with inertial sensing and a portable base station, bridge the gap between laboratory-grade optical motion capture and fully wearable IMU-only systems, enabling sufficiently accurate outdoor human movement reconstruction for applications in unconstrained environments?

1.3 Research Objectives

Four specific objectives structure the work presented in this thesis, each corresponding to a dedicated experimental or conceptual chapter.

1. Define a principled conceptual framework for integrating GNSS positioning into human

motion capture, mapping out the levels at which GNSS can contribute biomechanically meaningful information and identifying the configurations worth pursuing experimentally.

2. Demonstrate that wearable GNSS combined with inertial sensing can produce spatiotemporal gait parameters in unconstrained outdoor conditions, and identify the conditions under which the approach holds.
3. Establish that the approach generalises across multiple subjects in a deployable field setting, and assess its outputs against an independent measurement reference.
4. Extend the framework from spatiotemporal gait analysis to multi-segment kinematic reconstruction, demonstrating that wearable GNSS positions and IMU orientations together can drive a musculoskeletal model in a globally referenced frame.

1.4 Thesis Contributions

The work presented in this thesis advances the state of the art through the following contributions, organized by type.

1.4.1 Conceptual Contributions

- A taxonomy of three GNSS+IMU integration architectures for outdoor human motion capture is proposed and formalized. The three architectures span the design space from a single receiver providing global body translation, through per-segment receivers enabling foot trajectory reconstruction and drift correction, to a multi-receiver configuration in which GNSS positions serve as pseudo-markers for model-based multi-segment inverse kinematics. This framework provides a structured basis for future research in this area.

1.4.2 Methodological Contributions

- A loosely-coupled GNSS/INS Kalman filter incorporating zero-velocity updates is developed for foot trajectory reconstruction in a geodetic reference frame, with covariance-based reliability estimation per solution point.
- The effect of human body dynamics on wearable GNSS signal quality is characterized, with impulsive foot accelerations at heel strike and toe-off identified as the dominant driver of carrier-phase disruption and cycle slip occurrence in foot-mounted receivers, in combination with adverse antenna geometry and ground-proximity multipath specific to foot mounting.

- A multi-segment inverse kinematics formulation is proposed in which GNSS receiver positions serve as pseudo-markers and IMU orientations provide segment constraints, offering absolute spatial grounding unavailable in IMU-only systems.

1.4.3 Experimental Contributions

- A proof-of-concept outdoor validation dataset is collected with a single subject across multiple walking speeds at a controlled outdoor location, including surveyed trajectory ground truth and metronome-paced cadence reference.
- A multi-subject outdoor experimental dataset is collected at a stadium in Switzerland using a portable base station and drone-based markerless motion capture as independent ground truth, demonstrating the deployability of the system in realistic field conditions.

1.4.4 Software Contributions

- An automated cloud-based processing pipeline is developed, covering the full processing chain from raw GNSS and IMU observations to spatiotemporal gait parameters and IK-derived pose estimates. The pipeline enables systematic reprocessing of multi-device recordings and supports the reproducibility of the experimental results presented in this thesis.

1.5 Thesis Overview

The remainder of this thesis is organized as follows. Chapter 2 reviews the state of the art in human motion capture, covering marker-based optical, inertial, and markerless optical systems, and identifies the outdoor measurement limitations that motivate the present work. Chapter 3 introduces the principles of GNSS positioning and reviews prior applications of GNSS to human movement analysis, concluding with a detailed statement of the open problems that this thesis addresses. Chapter 4 introduces the conceptual framework and proposes the three GNSS+IMU integration architectures. Chapter 5 presents the implementation and proof-of-concept validation of the foot trajectory reconstruction approach. Chapter 6 describes the multi-subject outdoor validation campaign and its results. Chapter 7 extends the framework to multi-segment kinematics and presents the automated processing pipeline. Chapter 8 synthesizes the findings across all experimental chapters, discusses the system’s position relative to existing approaches, consolidates limitations, and proposes directions for future work.

Chapter 2

Human Motion Capture

This chapter reviews the principal technologies used for quantitative human motion capture (commonly abbreviated as MoCap). Section 2.1 formulates motion capture as a state estimation problem and establishes the formal notation used throughout the thesis. Sections 2.2, 2.3, and 2.4 review the three main technological families: marker-based optical, inertial, and markerless optical systems. Section 2.5 compares them along the dimensions of accuracy and portability, and identifies the limitations that motivate the integration of GNSS into outdoor motion capture pipelines.

2.1 The Motion Capture Problem

At its core, motion capture is a state estimation problem. The objective is to reconstruct the time-varying configuration of a moving mechanical system from measurements that might be partial, noisy, and indirect. In the human motion capture case, the system of interest is the human body, though the same formal framework applies to animals, robots, or any articulated structure whose movement one wishes to quantify.

The human body is most commonly modeled, at an appropriate level of abstraction, as a kinematic chain of N interconnected rigid segments (the limb segments, trunk, and head) each characterized by its position and orientation in a global reference frame. The quantity that motion capture seeks to reconstruct is therefore the full set of segment poses over time, which can be written compactly as

$$\mathbf{x}(t) = \{\mathbf{p}_i(t), \mathbf{R}_i(t)\}_{i=1}^N, \quad (2.1)$$

where $\mathbf{p}_i(t) \in \mathbb{R}^3$ is the position of the i -th segment and $\mathbf{R}_i(t) \in SO(3)$ its orientation. The special orthogonal group $SO(3)$ is the group of rotations in three-dimensional space; its elements admit several equivalent concrete representations, including 3×3 orthogonal matrices with unit

determinant, unit quaternions, and Euler angles. The choice between them is one of numerical, computational, and notational convenience, and the quaternion form is adopted in the discussion of inertial sensor integration in Section 2.3. This state, in principle, fully describes the configuration of the body at any instant. Depending on the application, the state may be augmented with velocities and angular rates, or reduced to a smaller set of joint angles by exploiting the kinematic relationships between connected segments.

No sensing modality measures $\mathbf{x}(t)$ directly. Instead, sensors provide observations that are related to the state through a measurement model, and $\mathbf{x}(t)$ must be recovered from these observations in the presence of noise, ambiguity, and missing data. Different technologies differ precisely in what they observe and how that observation relates to the underlying state. Optical systems measure the positions of markers or anatomical landmarks within a camera-covered volume. Inertial sensors measure local accelerations and angular velocities at the point of attachment. Markerless video systems detect image-space keypoints that correspond, through geometric projection, to body joint positions. Each of these measurement types provides complementary but incomplete information: optical measurements are spatially precise but bounded by the capture volume; inertial measurements are continuous and portable but accumulate errors when integrated over time; image-based measurements are non-invasive but depend heavily on camera coverage, viewing conditions, and underlying computer vision and machine learning algorithms.

The reconstruction problem is further structured by physical constraints. The segments of the body are not independent; they are connected at joints with limited degrees of freedom, subject to anatomical range-of-motion limits, and, during locomotion, interact with the environment through contact conditions such as foot strike and toe-off. These constraints reduce the space of physically admissible states and must be incorporated, explicitly or implicitly, into any reconstruction approach. It is the combination of noisy and partial observations with a constrained, high-dimensional state space that makes motion capture a non-trivial estimation problem, and that drives the diversity of technical approaches developed to address it.

The following sections review the three main technological families — marker-based optical, inertial-based, and markerless optical — each of which represents a different choice of sensing modality and, consequently, a different set of trade-offs in terms of accuracy, portability, and applicability to outdoor environments.

2.2 Marker-Based Optical Motion Capture

Marker-based optical motion capture is historically one of the earliest and most established technologies for quantitative human movement analysis. Its origins can be traced back to early photogrammetric techniques and multi-camera film-based motion analysis systems developed in the second half of the twentieth century for biomechanical and clinical research. With the advent of digital cameras, infrared illumination, and real-time processing algorithms in the 1990s

and early 2000s, optical motion capture evolved into a highly accurate and reliable laboratory technology. Over time, it became widely regarded as the gold standard for kinematic analysis in biomechanics and related disciplines [13, 14].

In a marker-based optical system, retroreflective markers are attached to specific anatomical landmarks of the subject. A set of synchronized cameras, typically operating in the infrared spectrum, illuminates the capture volume and detects the reflected light from the markers. By triangulating the two-dimensional observations from multiple camera views, the three-dimensional position of each marker can be reconstructed. Let $\mathbf{m}_j(t) \in \mathbb{R}^3$

denote the reconstructed position of the j -th marker at time t . The marker positions are obtained by solving a triangulation problem of the form

$$\mathbf{m}_j(t) = \text{Triangulate}(\{\mathbf{u}_{j,k}(t)\}_{k=1}^K), \quad (2.2)$$

where $\mathbf{u}_{j,k}(t)$ represents the two-dimensional image coordinates of the j -th marker in the k -th camera, and K is the number of cameras observing the marker.

Triangulation is the standard multi-view geometry procedure for recovering a three-dimensional point from its two-dimensional projections in two or more cameras with known intrinsic and extrinsic calibration. Each two-dimensional detection $\mathbf{u}_{j,k}$ defines a ray in three-dimensional space passing through the camera center, and the three-dimensional position $\mathbf{m}_j$ is recovered as the point that minimizes the total reprojection error across all observing cameras. With $K \geq 2$ cameras the problem is overdetermined and solved by least-squares, which also provides an uncertainty estimate per marker. A detailed treatment is given in [15].

Once marker trajectories are reconstructed, a biomechanical model is used to estimate segment poses and joint angles. This is typically achieved through rigid body pose estimation, in which the pose of each segment, that is, the position $\mathbf{p}_i(t)$ and orientation $\mathbf{R}_i(t)$ introduced in Section 2.1, is estimated by minimizing the distance between measured marker positions and their corresponding positions predicted by the segment model. Formally, for a given segment i , the pose parameters $(\mathbf{p}_i, \mathbf{R}_i)$ can be estimated by solving

$$\min_{\mathbf{p}_i, \mathbf{R}_i} \sum_{j \in \mathcal{S}_i} \|\mathbf{m}_j(t) - (\mathbf{p}_i(t) + \mathbf{R}_i(t)\mathbf{r}_j^i)\|^2, \quad (2.3)$$

where $\mathcal{S}_i$ denotes the set of markers attached to segment i , and $\mathbf{r}_j^i$ is a position vector of the marker j in the frame of segment i .

Among the most prominent commercial providers of marker-based optical motion capture systems are Vicon and OptiTrack, which are found in the majority of dedicated motion capture laboratories worldwide. Both companies rely on multi-camera infrared tracking architectures and provide proprietary calibration, reconstruction, and biomechanical modeling software.

Marker-based optical systems are capable of achieving sub-millimeter spatial accuracy under controlled laboratory conditions [16]. High sampling frequencies, often exceeding 100 Hz, allow

detailed reconstruction of rapid movements. However, this level of performance requires careful calibration of the camera network, controlled lighting conditions, and an unobstructed capture volume.

Despite their high precision, these systems present several limitations. First, they require a dedicated laboratory space equipped with a calibrated multi-camera setup, which significantly limits portability. Second, marker placement on anatomical landmarks introduces preparation time and is subject to soft tissue artifacts: since markers are attached to the skin and not directly to the underlying bone, skin deformation and muscle movement during dynamic tasks cause the markers to shift relative to the skeletal segment they are meant to represent, introducing errors [17, 18]. Third, marker occlusions can occur when markers are temporarily hidden from multiple cameras, resulting in gaps in the reconstructed trajectories.

Consequently, while marker-based optical motion capture remains the reference technology for high-precision laboratory analysis, its limited portability and environmental constraints restrict its applicability in large-scale outdoor scenarios and long-duration recordings. These limitations motivate the exploration of alternative or complementary sensing modalities capable of extending motion analysis beyond controlled laboratory environments.

2.3 Inertial-Based Motion Capture

Inertial-based motion capture systems rely on wearable inertial measurement units (IMUs) to estimate the motion of body segments. Unlike optical systems, inertial approaches do not require external cameras or a dedicated capture volume, making them inherently portable and suitable for field measurements. The rapid development of microelectromechanical systems (MEMS) technology over the past two decades has enabled the widespread adoption of compact, low-cost IMUs in biomechanics, rehabilitation, sports science, and wearable computing [19].

An IMU typically consists of a tri-axial accelerometer and a tri-axial gyroscope, and in some cases a tri-axial magnetometer. The accelerometer measures specific force $\mathbf{f}(t)$, which is the kinematic acceleration vector of the device minus the vector of acceleration due to gravity. Accelerometers cannot sense gravity directly: they respond to the support force acting on the internal proof mass, which is equal to the difference between the device's true acceleration and gravitational acceleration. The gyroscope measures angular velocity $\boldsymbol{\omega}(t)$. Both quantities are expressed in the sensor frame. When attached to a body segment, the IMU provides local kinematic information that can be used to estimate the segment orientation and, indirectly, its position.

The orientation of a segment is an element of $SO(3)$, the group of rotations introduced in Section 2.1. The two representations most commonly used in IMU-based motion capture are the rotation matrix $\mathbf{R}(t)$ and the unit quaternion $\mathbf{q}(t)$ [20]; in the kinematic equation that follows,

the quaternion form is adopted for its numerical robustness under integration of the gyroscope signal. The temporal evolution of orientation is governed by the measured angular velocity. In quaternion form, the kinematic equation can be written as

$$\dot{\mathbf{q}}(t) = \frac{1}{2} \Omega(\boldsymbol{\omega}(t)) \mathbf{q}(t), \quad (2.4)$$

where $\Omega(\boldsymbol{\omega})$ is the quaternion multiplication matrix constructed from the angular velocity vector. By integrating this equation over time, the segment orientation can be estimated.

In principle, position can also be recovered from inertial measurements through double integration of the specific force, after compensating for gravity and transforming into a global reference frame:

$$\mathbf{a}(t) = \mathbf{R}(t)\mathbf{f}(t) + \mathbf{g}, \quad (2.5)$$

$$\mathbf{v}(t) = \int \mathbf{a}(t) dt, \quad \mathbf{p}(t) = \int \mathbf{v}(t) dt, \quad (2.6)$$

where $\mathbf{g}$ denotes the gravity vector expressed in the global frame. In practice, however, this approach is not viable for general motion capture: the double integration amplifies even small sensor errors into rapidly growing position drift, making standalone inertial positioning unreliable beyond very short time intervals. As a result, commercial inertial MoCap systems are almost exclusively used to estimate segment orientations and joint angles, and not absolute positions.

The fundamental reason for this limitation lies in the error characteristics of inertial sensors. Gyroscope and accelerometer measurements can be modeled as

$$\boldsymbol{\omega}_m(t) = \boldsymbol{\omega}(t) + \mathbf{b}_\omega(t) + \mathbf{n}_\omega(t), \quad (2.7)$$

$$\mathbf{f}_m(t) = \mathbf{f}(t) + \mathbf{b}_f(t) + \mathbf{n}_f(t), \quad (2.8)$$

where $\mathbf{b}_\omega(t)$ and $\mathbf{b}_f(t)$ are slowly varying sensor biases, and $\mathbf{n}_\omega(t)$ and $\mathbf{n}_f(t)$ represent measurement noise. Even small biases, when integrated over time, lead to a progressive accumulation of error in the estimated orientation, velocity, and position. This phenomenon, known as *drift*, is the principal limitation of inertial-only motion capture: gyroscope biases accumulate into orientation errors, while accelerometer biases compound into velocity and position errors. The unbounded growth of drift over time means that inertial navigation cannot maintain absolute accuracy without external corrections or measurement constraints.

To mitigate orientation drift, various correction strategies are employed. Accelerometers provide a static reference for roll and pitch through the direction of the gravity vector, and are commonly fused with gyroscope data through complementary or Kalman-based filters [21, 22], as well as gradient descent optimization-based approaches, such as Madgwick filter [23, 24]. Magnetometers can additionally provide heading information to correct yaw drift, although they are sensitive to local magnetic disturbances from electronic equipment and metallic structures, which limits

their reliability in many practical environments. In gait analysis specifically, zero-velocity updates (ZUPT) exploit the known stance phases of the gait cycle to constrain velocity estimates and partially mitigate positional drift [25].

Commercial inertial motion capture systems typically consist of multiple synchronized IMUs placed on major body segments. Xsens is among the most widely adopted providers in this field [26], offering full-body wearable systems used extensively in biomechanics, clinical gait analysis, and animation. These systems provide real-time estimation of segment orientations and joint angles through proprietary sensor fusion algorithms, and have become a common reference benchmark in academic research.

The main advantages of inertial motion capture are its portability, relative independence from external infrastructure, and ability to operate over large areas and extended durations. These properties make it the only established technology currently capable of recording human movement in unconstrained outdoor environments. Some commercial systems retain practical constraints on the recording volume: the Xsens MTw Awinda, for instance, requires a 2.4 GHz radio link to a base station for synchronization and data streaming, which limits the usable area unless the base station follows the subject. Systems with on-body data storage, such as Xsens MVN Link in standalone configuration, are not subject to this limitation.

Moreover, inertial systems provide only relative motion with respect to an arbitrarily defined initial configuration; they do not yield an absolute position in a global coordinate frame. Combined with the accumulation of orientation drift over time, this means that while joint angle estimation can be robust over moderate recording intervals [27], global trajectory reconstruction remains beyond the reach of inertial-only approaches.

For these reasons, inertial motion capture represents a powerful but fundamentally incomplete solution to the outdoor motion capture problem. Its strengths in portability and flexibility make it the natural starting point for field applications, yet its inability to provide an absolute position reference in a global coordinate frame motivates its integration with complementary technologies — most notably, satellite-based positioning — as explored in this thesis.

2.4 Markerless Optical Motion Capture

Markerless optical motion capture systems aim to reconstruct human movement without the use of physical markers attached to the body. Instead, it relies on computer vision algorithms applied to video recordings to detect and track anatomical landmarks directly from the image data. Advances in digital imaging, computational power, and, more recently, deep learning have significantly accelerated the development and adoption of markerless approaches.

Early markerless systems were based primarily on model-based tracking and feature detection techniques, requiring carefully controlled environments and simplified backgrounds [28, 29]. In

recent years, however, convolutional neural networks and large annotated datasets have enabled robust human pose estimation from monocular or multi-camera video streams [30, 31, 32]. Two main paradigms have emerged within this body of work. The first detects two-dimensional keypoints in image space and then reconstructs three-dimensional joint positions, either through triangulation across multiple calibrated views, as in the marker-based case described in Section 2.2, or through model-based pose lifting from a single view. Pose2Sim [33, 34] is a representative end-to-end implementation of this approach, combining 2D keypoint detection with multi-view triangulation and a biomechanical model. The second paradigm bypasses the intermediate two-dimensional representation and predicts three-dimensional joint positions or parametric body model parameters directly from image data; representative approaches include direct regression methods such as VNect [35], parametric mesh recovery networks [36], and more recent transformer-based architectures that incorporate temporal context [37].

The principal advantage of markerless motion capture over marker-based systems lies in its reduced intrusiveness. Since no markers or wearable sensors are required, subject preparation time is significantly reduced and natural movement is less likely to be disrupted. More significantly, monocular approaches, in which a single camera is used alongside a parametric body model to reconstruct three-dimensional pose, offer a step toward genuine portability, since a single camera can in principle be moved or repositioned to follow the subject. Systems such as OpenCap [38], which reconstructs joint kinematics from smartphone video and a musculoskeletal model, illustrate the trajectory of this line of work in biomechanics, though they still only support static camera conditions.

This has motivated a growing body of work in which cameras are mounted on aerial drones, extending the capture area beyond any fixed installation. Early demonstrations established the concept of fully autonomous outdoor markerless capture using multiple cooperating drones, with the diversity of viewpoints provided by simultaneously airborne RGB cameras enabling three-dimensional pose reconstruction in unconstrained settings [39]. Subsequent systems have refined this multi-UAV configuration and reported joint position accuracy benchmarked against commercial reference systems [40], and a recent systematic review by Teh et al. [41] consolidates the state of the field across 34 published studies. Drone-based markerless capture remains technically demanding: accurate pose reconstruction with respect to a fixed frame requires precise knowledge of each camera’s position and orientation throughout the recording, and the synchronization of aerial platform dynamics with biomechanical estimation introduces substantial engineering challenges. To the best of the author’s knowledge, no drone-based system has yet been adopted for routine clinical biomechanical use, although the approach is increasingly explored as an experimental reference for outdoor motion analysis, including in the multi-subject validation campaign presented in Chapter 6 of this thesis.

However, markerless systems remain sensitive to several factors that limit their reliability, including lighting conditions, background complexity, camera placement, occlusions, and the representativeness of the training datasets used in deep learning models [42]. The accuracy of joint

center estimation is typically lower than that achieved by marker-based optical systems, with reported joint position errors on the order of 10–30 mm RMS for multi-camera markerless against marker-based reference [43], and substantially larger for monocular configurations. Soft tissue deformation and clothing introduce additional uncertainties in keypoint detection, and unlike marker-based systems, there is no direct physical correspondence between detected keypoints and underlying skeletal landmarks.

In summary, markerless optical motion capture is a rapidly advancing technology that substantially reduces experimental complexity compared to marker-based systems. Nevertheless, it does not yet consistently achieve the precision and robustness of traditional marker-based approaches in controlled biomechanical analysis, and its deployment in large-scale outdoor environments remains constrained by the same fundamental dependency on camera coverage that limits optical systems more broadly. As such, it extends the accuracy-portability trade-off in a useful direction, but does not completely resolve it.

A distinct branch of markerless optical motion capture exists at the opposite end of the infrastructure spectrum. Large-scale tracking systems deployed in professional sports stadiums, such as Hawk-Eye and TRACAB, use arrays of synchronized high-definition cameras, on the order of thirty units mounted at fixed positions in the venue, to track all players and the ball continuously throughout a match. These systems operate at frame rates of approximately 25 Hz and provide player position accuracy at the decimeter level over the entire field area [44]. Their performance demonstrates the scalability of markerless optical tracking to large outdoor scenarios, but only at the cost of substantial fixed infrastructure investment. The wearable, infrastructure-light motion capture configurations considered in this thesis do not target this application domain.

2.5 Comparative Summary and Outdoor Limitations

The three technologies reviewed in the preceding sections, namely marker-based optical, inertial, and markerless optical motion capture, each represent a well-developed and practically validated approach to human movement analysis. Yet when evaluated against the requirements of outdoor, unconstrained motion capture, none of them provides a fully satisfactory solution, and their respective failure modes are largely complementary. Figure 2.1 summarises this comparison, identifying for each technology family its principal strengths and the limitations that constrain its applicability.

Marker-based optical systems offer the highest spatial accuracy, routinely achieving sub-millimeter precision under laboratory conditions, but they are fundamentally tied to a bounded, instrumented capture volume. The required infrastructure, such as a calibrated multi-camera network, controlled lighting, and a static setup, makes routine outdoor deployment practically infeasible. While temporary outdoor installations have been demonstrated in experimental contexts, they remain exceptional and are unsuitable for recordings involving large-scale or long-distance

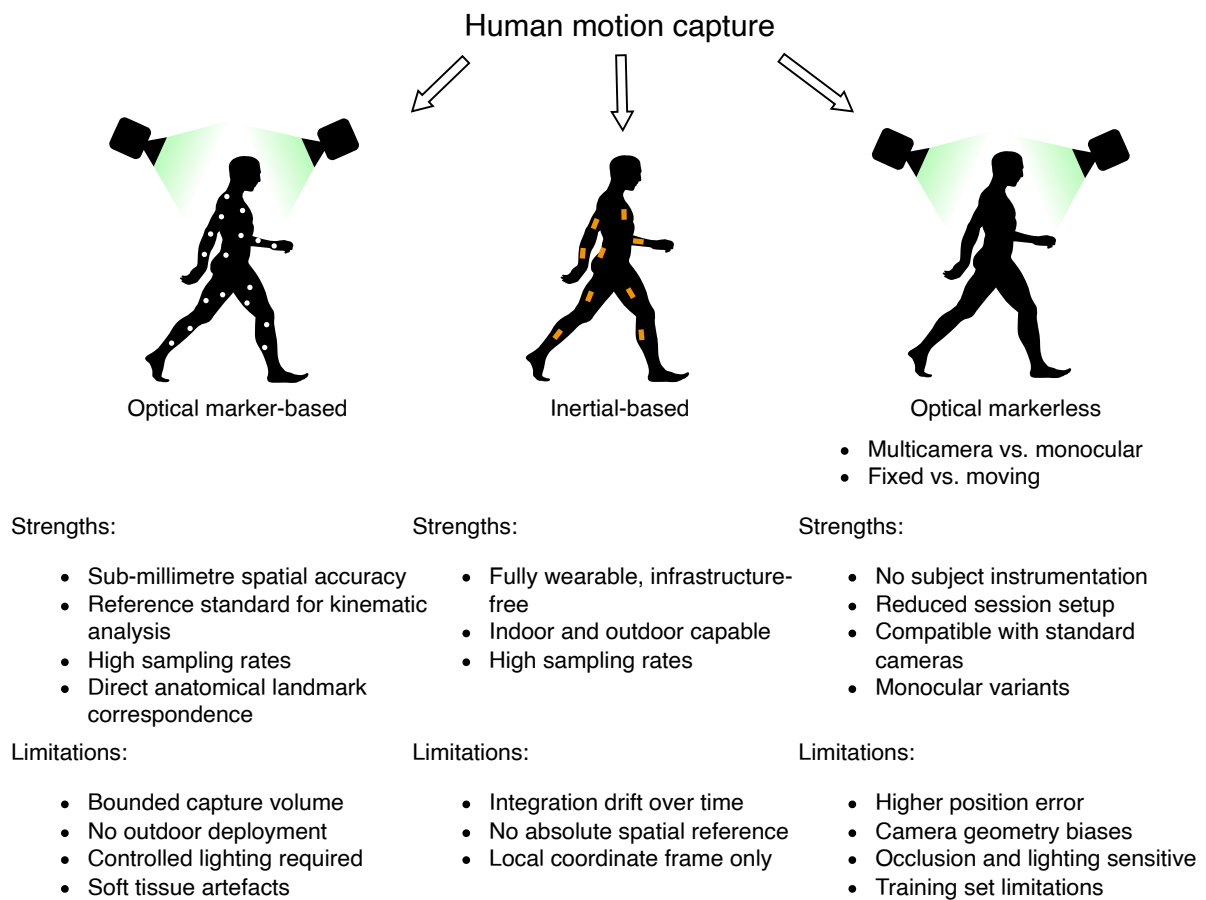


Figure 2.1: The three principal families of human motion capture technologies, with their respective strengths and limitations.

Table 2.1: Comparison of human motion capture technology families along dimensions relevant to outdoor deployment. Numerical values are representative; system-specific performance varies. The bottom row indicates the target characteristics of the GNSS+IMU framework proposed in this thesis.

Technology	Spatial accuracy	Sampling rate		Outdoor capability	capa-	Subject preparation
Marker-based MoCap	Sub-millimeter, laboratory conditions	100–1000 Hz typical		Very limited (bounded volume, controlled lighting required)		High (per-subject marker placement)
Inertial MoCap	No absolute position; joint angle errors of a few degrees; drift	60–240 Hz typical		High (some systems bounded by data-link range)		Moderate (segment-mounted sensors plus calibration pose)
Markerless MoCap	10–30 mm joint position RMS (multi-camera); monocular substantially less accurate	25–120 Hz typical		Limited (lighting, occlusion, camera coverage)		None
GNSS + IMU (target)	Centimeter-level absolute position at receiver locations, IMU-derived joint angles, drift corrected	10 Hz GNSS, 100–200 Hz IMU		High (primary design target)		Moderate (per-segment device placement)

movement.

Inertial systems occupy the opposite corner of this trade-off: they can be fully portable, wearable, and infrastructure-free, but they provide only relative motion with respect to an arbitrary initial configuration and accumulate orientation errors over time. Critically, they offer no absolute position reference in a global coordinate frame, which makes global trajectory reconstruction unreliable for extended recordings. Markerless systems reduce the instrumentation burden considerably and, in their monocular form, approach genuine portability; yet they remain constrained by camera coverage, sensitive to environmental conditions, and not yet sufficiently accurate or robust for validated biomechanical analysis in uncontrolled outdoor settings.

The requirements that outdoor motion capture must satisfy can be stated precisely: the system must operate without fixed laboratory infrastructure, provide absolute spatial reference over an unbounded area, maintain accuracy over extended recording durations, and be deployable by a small team without extensive setup time. No combination of the technologies reviewed above currently meets all of these requirements. The gap reflects fundamental observability limitations inherent to each sensing modality when used in isolation.

It is this gap that motivates the present work. Global navigation satellite systems, which have become capable of centimeter-level positioning through carrier-phase techniques, usage of differential corrections, and other modern approaches, offer an absolute position reference that is available outdoors without laboratory infrastructure. Chapter 3 introduces the technical foundations of GNSS positioning and reviews prior attempts to apply it to human motion analysis, before the research gap is formally stated in Section 3.2.5 and addressed by the conceptual framework of Chapter 4.

Chapter 3

GNSS Technology and Applications to Human Motion Analysis

This chapter introduces the technical foundations of GNSS positioning and reviews prior applications of GNSS to human movement analysis. Section 3.1 describes the GNSS system architecture, the principal signal observables, the main positioning techniques and their accuracy levels, and the error sources affecting wearable receiver use. Section 3.2 surveys the existing literature on GNSS-based human motion analysis, organised by progressive levels of measurement precision and biomechanical detail, and concludes with a statement of the open problems in Section 3.2.5 that together define the research gap addressed by this thesis.

3.1 Overview of GNSS Technology

3.1.1 GNSS Architecture and Positioning Principle

GNSS (Global Navigation Satellite System) refers to the family of systems that currently represent the dominant technology in the fields of geodesy, surveying, and navigation. The fundamental principle of GNSS is to determine the position of a point in space based on the reception of signals transmitted by dedicated constellations of medium Earth orbit satellites. Four GNSS constellations are currently operational and globally available: GPS, operated by the United States; GLONASS, operated by Russia; BeiDou, operated by China; and Galileo, operated by the European Union [45, 46].

A GNSS is traditionally described as comprising three main segments. The space segment consists of the satellite constellation, which continuously transmits precisely time-stamped navigation signals containing orbital parameters and clock information. The control segment comprises

a global network of ground monitoring stations, master control facilities, and uplink antennas, responsible for tracking satellite orbits, estimating clock corrections, maintaining system integrity, and uploading updated navigation messages to the satellites. The user segment includes all GNSS receivers and associated processing algorithms that utilize the transmitted signals to estimate position, velocity, and time.

The basic positioning principle underlying all GNSS is multilateration; that is, the determination of an unknown position from measured distances (ranges) to a set of reference points at known locations. In GNSS, these distances are derived from the time of flight of signals traveling from each satellite to the receiver, multiplied by the speed of light. Since these distance estimates are corrupted by receiver clock errors and various other error sources, they are referred to as pseudoranges. Solving for the receiver's three-dimensional position requires simultaneously estimating a fourth unknown: the receiver clock bias, which is why a minimum of four satellites must be visible at any given epoch for a complete solution. The satellite positions at the time of transmission are computed from ephemeris parameters broadcast within the navigation message, allowing the receiver to set up and solve the multilateration problem autonomously.

3.1.2 GNSS Signal Observables

GNSS receivers estimate position, velocity, and time by processing three fundamental observables derived from the transmitted satellite signals: the code pseudorange, the carrier phase, and the Doppler frequency shift. Each provides complementary information about the receiver-satellite geometry, with different accuracy levels and error characteristics.

The code pseudorange is the most basic observable. It is obtained by correlating a locally generated replica of the satellite's pseudorandom noise (PRN) code with the received signal and measuring the time delay required to achieve maximum correlation. This delay, multiplied by the speed of light, yields an apparent distance between satellite and receiver. Code-based positioning is robust, unambiguous, and available from any standard GNSS receiver, but its accuracy is inherently limited to the meter level due to code tracking noise and residual propagation errors.

The carrier phase observable exploits the phase of the high-frequency carrier signal on which the navigation code is modulated. Since GNSS carrier wavelengths are on the order of centimeters (approximately 19 cm for the GPS L1 frequency), phase measurements are far more precise than code pseudoranges, and carrier-phase-based solutions can achieve centimeter-level accuracy once certain conditions are met. The fundamental challenge is that the carrier phase measurement is ambiguous: the receiver can only observe the fractional part of the phase, while the integer number of full wavelengths elapsed since signal acquisition, known as the integer ambiguity, is initially unknown. Resolving this ambiguity is the key computational step in high-precision positioning techniques such as Real-Time Kinematic (RTK) and Post-Processing Kinematic (PPK), which are central to the approach developed in this thesis [47].

The Doppler observable is derived from the frequency shift of the received carrier signal caused by the relative motion between satellite and receiver. It provides a direct estimate of the line-of-sight range rate and can therefore be used to determine receiver velocity without numerically differentiating position estimates. Doppler-based velocity estimates are typically less noisy than position-derived velocities and are particularly valuable in dynamic applications where short-term kinematic consistency is important.

Modern GNSS receivers track signals from multiple constellations and on multiple frequency bands simultaneously, improving robustness, redundancy, and the speed of ambiguity resolution. The combination of code, carrier phase, and Doppler observables across several constellations forms the foundation for all positioning and velocity estimation algorithms discussed in the following subsection.

The design of the GNSS antenna substantially affects positioning quality. Ground-plane size, gain pattern symmetry, and phase-center stability determine multipath rejection and the consistency of carrier-phase measurements. The most common antenna types in GNSS hardware are patch antennas, which are compact and inexpensive and dominate consumer-grade devices; helix antennas, which offer wider, azimuthally symmetric gain patterns suitable for body-worn applications; and choke-ring antennas, which provide excellent multipath rejection at the cost of size and weight, and are typical of permanent reference stations. Geodetic survey-grade antennas combine multi-frequency support with stable phase centers but are not compatible with wearable use. The wearable system developed in this thesis uses a helix antenna, described in Section 5.2.1.

There are multiple data formats commonly accepted for usage in GNSS, varying by application context, apart from numerous proprietary formats used by hardware manufacturers. For real-time navigation, NMEA 0183 [48] is widely used. That is a sentence-based ASCII protocol in which each sentence encodes a specific subset of derived information: e.g., \$GPGGA provides the position fix and the number of satellites used, \$GPRMC includes the minimum sentence with position, velocity, and time, and \$GPVTG provides track over ground and ground speed. For post-processing applications, the receivers can also output raw observables: code pseudoranges, carrier phases, Doppler shifts, signal-to-noise ratios. The de facto standard for that is the Receiver Independent Exchange Format (RINEX) [49], a text format maintained by the International GNSS Service.

3.1.3 Positioning Techniques and Accuracy Levels

GNSS positioning techniques span a wide range of accuracy levels, from several meters down to the centimeter level, depending on the observables used, the availability of external corrections, and the sophistication of the processing algorithms. This subsection reviews the main approaches in order of increasing precision.

Standalone positioning relies solely on code pseudorange measurements received by the user without any external corrections. This approach is widely available, simple to implement, and sufficient for general navigation purposes, but it is limited by atmospheric delays, satellite clock errors, multipath, and receiver noise. Typical positioning accuracy is on the order of several meters, which is inadequate for biomechanical motion analysis.

Differential GNSS (DGNSS) improves on standalone positioning by introducing one or more fixed reference receivers at known locations. These reference stations compute corrections for common error sources, including satellite clock offsets and atmospheric delays, and transmit them to the user processor. Since many error sources are spatially correlated over short baselines, the corrections are highly effective when the reference station is located close to the user. In its standard form, DGNSS relies on code observables and achieves sub-meter accuracy, making it suitable for applications requiring moderate precision but insufficient for detailed kinematic analysis.

Real-Time Kinematic (RTK) positioning extends the differential approach to carrier phase observables, enabling centimeter-level accuracy by resolving the integer ambiguity [50]. A local reference station transmits raw observations or corrections to the moving receiver (rover) in real time, allowing the rover to form differential carrier phase measurements and resolve the integer ambiguities on-the-fly. RTK is widely used in surveying, navigation, and robotics, and provides results in real time, which is advantageous when immediate feedback is required. Its main practical constraint is the need for a continuous real-time data link between the reference station and the rover, which is usually achieved by means of specialized services.

Precise Point Positioning (PPP) takes a different approach by dispensing with a local reference station entirely. Instead, it relies on precise satellite orbit and clock products disseminated by global networks, allowing a single receiver to achieve decimeter- to centimeter-level accuracy anywhere in the world [51]. PPP does not require nearby infrastructure, but it typically demands longer convergence times for ambiguity resolution and is therefore less suited to short kinematic recordings. It is more widespread in long-time surveying and continuous monitoring.

Post-Processing Kinematic (PPK) positioning combines the accuracy of RTK with greater operational flexibility. Like RTK, it uses carrier phase observations from both a reference station and a rover, but the processing is performed not in real time but after data collection. This removes the requirement for a live data link during the recording, which is a significant practical advantage in field conditions where reliable communication may not be available. Furthermore, PPK allows the use of more sophisticated processing strategies — including forward-backward smoothing and the integration of precise orbit and clock products — that are not feasible in real time, often resulting in higher fix rates and more reliable ambiguity resolution than RTK under the same observation conditions. For these reasons, PPK is the technique adopted in this thesis for processing wearable GNSS data collected during outdoor motion capture experiments.

A complementary architecture for high-accuracy GNSS has emerged through satellite-based cor-

rection services, in which the precise orbit and clock products that drive PPP are broadcast directly through the satellite signals themselves rather than retrieved from internet sources or fixed reference stations. The Galileo High Accuracy Service (HAS) [52], declared operational in 2023, transmits PPP-style corrections through the Galileo E6-B signal and is available worldwide free of charge, targeting horizontal positioning accuracy on the order of 20 cm in near-real-time without a local reference station or internet connection¹. Equivalent concepts are deployed by other constellations, including the Japanese QZSS Centimeter Level Augmentation Service (CLAS), alongside a number of commercial offerings. These services represent a significant operational simplification compared with fixed-base-station architectures, although their convergence times remain longer than RTK and centimetre-level accuracy is typically reached only after several minutes of stable tracking. For the highly local experimental setups considered in this thesis, where the rover is at most a few tens of meters from the base station, a local PPK pipeline is retained for its faster convergence and higher fix rates under dynamic conditions.

Open-source software has been instrumental in making high-precision GNSS accessible outside the geodetic and surveying communities. The de facto reference implementation for both RTK and PPK is RTKLIB [53], an open-source library developed by T. Takasu that supports a wide range of receiver formats and positioning modes; it is the processing engine used throughout this thesis. The BKG Ntrip Client (BNC) and gLAB are widely used for real-time correction streaming and educational PPP processing respectively, and several institutional services such as the Canadian Spatial Reference System CSRS-PPP and the Australian AUSPOS provide free online PPP processing. A significant advantage of RTKLIB is its parameter flexibility, cross-platform availability, and command line interface, which allows for easier automation, pipeline integration, and scalability than GUI-based applications.

3.1.4 Error Sources and Signal Degradation

GNSS measurements are affected by several error sources that degrade positioning accuracy to varying degrees depending on the environment, receiver quality, and processing strategy. Understanding these error sources is essential for interpreting GNSS data in any kinematic application, and particularly so in the wearable receiver scenario considered in this thesis.

The ionospheric delay is one of the largest contributors to pseudorange and carrier phase errors. As GNSS signals traverse the ionosphere (the charged upper layer of the atmosphere), their propagation speed is altered, introducing a path-length error that can reach several meters if uncorrected. The magnitude of this delay is frequency-dependent, which allows dual-frequency receivers to estimate and largely remove it through linear combinations of measurements on two frequencies. For single-frequency receivers, ionospheric models or differential corrections from a nearby reference station are used instead [54, 55].

¹<https://www.gsc-europa.eu/galileo/services/galileo-high-accuracy-service-has>

Table 3.1: Comparison of high-precision GNSS positioning techniques along the dimensions relevant to wearable kinematic applications. Accuracy figures refer to ambiguity-resolved (fixed) carrier-phase solutions under favourable conditions; float solutions are typically an order of magnitude less accurate. Vertical accuracy is generally $1.5\text{--}2\times$ worse than horizontal for all three techniques.

Technique	Horizontal accuracy (fixed)	Time to first fix	Infrastructure and baseline	Robustness and applications
RTK	1–5 cm	Seconds under good sky conditions; tens of seconds for cold start	Local base station or network RTK, live data link; baseline up to $\sim 10\text{--}30$ km before atmospheric decorrelation degrades fixing	Fast re-acquisition after signal interruption; machine guidance, surveying, autonomous vehicles, real-time UAV photogrammetry
PPP	dm in real-time without ambiguity resolution; cm with PPP-AR or after offline processing	15–30 min (classical); 5–10 min with PPP-AR or HAS	Global precise orbit and clock products (internet or satellite-broadcast such as Galileo HAS); no baseline constraint	Sensitive to interruptions through long re-convergence; marine and agricultural applications, scientific monitoring, infrastructure-light deployments
PPK	1–5 cm	Same as RTK at the start of a session; convergence effectively shortened by forward-backward smoothing	Local base station, raw observations logged at both ends; same baseline limit as RTK	Forward-backward smoothing improves fix rates at session boundaries and in dynamic conditions; field surveying, photogrammetry, scientific data collection

The tropospheric delay arises from signal propagation through the lower atmosphere, where variations in temperature, pressure, and humidity alter the effective propagation speed. Unlike the ionospheric delay, the tropospheric effect is largely frequency-independent and therefore cannot be removed by dual-frequency combinations. It is typically modeled using empirical formulas based on standard atmospheric profiles, with residual errors on the order of a few centimeters under normal conditions [56].

Multipath errors occur when GNSS signals reach the receiver antenna via reflections off nearby surfaces — such as the ground, buildings, or vehicles — in addition to the direct line-of-sight path. The superposition of the direct and reflected signals distorts both code and carrier phase measurements, introducing errors that are difficult to model or predict. Multipath is particularly problematic in urban environments and near large reflective surfaces, and it represents one of the error sources least amenable to correction through differential processing.

The satellite geometry, quantified by the Dilution of Precision (DOP), describes how the spatial distribution of visible satellites amplifies measurement errors into position uncertainty. A well-distributed constellation spanning a wide range of elevations and azimuths yields a low DOP and therefore a favorable mapping from range errors to position errors. Conversely, a clustered or poorly distributed constellation amplifies the effect of all other error sources.

Signal blockage occurs when the line of sight between the receiver antenna and one or more satellites is obstructed, leading to a reduction in the number of tracked satellites and, in severe cases, to complete loss of positioning. In urban environments, buildings and vegetation are the primary sources of blockage. In the wearable receiver scenario, one might expect the human body itself to cause significant obstruction, particularly for receivers placed low on the body. However, experimental evidence gathered in the course of this work suggests that satellite visibility remains surprisingly good even for foot-mounted receivers during walking, and that body occlusion is not the dominant source of signal degradation in this configuration.

Instead, the primary hypothesis advanced in this thesis is that signal quality degradation in foot-mounted receivers is driven by the mechanical dynamics of the gait cycle itself. The impulsive accelerations associated with foot strike and toe-off are suspected to momentarily disrupt the receiver's phase lock loops, causing cycle slips and introducing noise into the carrier phase observable during and immediately after these events. This hypothesis is consistent with the speed-dependent degradation observed experimentally: faster walking produces more intense foot strikes and toe-offs, which proportionally worsen the effect. This is examined in detail in Chapter 5.

Table 3.2: Principal GNSS range-domain error sources, their typical uncorrected magnitudes, and the standard mitigation strategies. Magnitudes vary with environment, receiver quality, and observation geometry; the values shown are representative. Position-domain error is approximately equal to the combined range error multiplied by the corresponding Dilution of Precision (DOP) factor.

Error source	Typical magnitude (uncorrected)	Primary dependence	Mitigation strategies
Satellite clock	1–2 m	Time, satellite-specific	Precise clock products (IGS); SBAS or HAS-style satellite-broadcast corrections; differential processing
Satellite ephemeris	0.5–2 m (broadcast); ~ 5 cm with precise products	Time, satellite-specific	Precise orbit products; differential processing
Ionospheric delay	1–30 m at zenith (solar activity dependent); growing at lower elevations	Frequency ($\propto 1/f^2$)	Dual-frequency ionosphere-free combination; Klobuchar (GPS) and NeQuick (Galileo) models for single-frequency users; differential processing over short baselines
Tropospheric delay	2–3 m at zenith; growing at lower elevations	Non-dispersive (cannot be removed by dual-frequency)	Saastamoinen and Hopfield models; differential processing over short baselines; estimation as part of PPP
Multipath	0 to several m (code); up to $\lambda/4$ (~ 5 cm at L1) on carrier	Reflector geometry, antenna pattern, siting	Choke-ring or helical antennas with ground plane; siting away from reflectors; receiver-side narrow-correlator and multipath-estimation algorithms
Carrier-phase cycle slips	Discontinuity of integer wavelengths in the carrier observable	Receiver dynamics, signal strength, antenna obstruction	Multi-frequency consistency checks; phase-rate prediction; explicit cycle-slip detection in processing software; treatment as a new ambiguity if repair fails
Receiver noise and biases	cm to m (code); mm-level (carrier)	Receiver design, signal strength	Higher-quality receivers; carrier-smoothed code; bias estimation as part of the positioning solution

3.2 GNSS Applied to Human Motion Analysis

The preceding sections have established two parallel bodies of knowledge: on one hand, the capabilities and limitations of existing motion capture technologies; on the other, the principles and accuracy levels of modern GNSS positioning. The present section examines the intersection of these two domains — the application of GNSS receivers to the analysis of human movement — tracing a progression from coarse athlete tracking through high-precision gait parameter estimation and into the integration of GNSS with inertial sensing at the level of individual body segments. This progression reveals both the promise of satellite-based sensing for outdoor biomechanical analysis and the specific gaps that the present thesis addresses.

3.2.1 Sports Performance Tracking: Single-Point GNSS

The earliest and most widespread application of GNSS to human movement is athlete tracking in team and endurance sports. From the early 2000s onward, wearable GPS receivers began to be adopted by practitioners seeking to quantify the physical demands of training and competition through metrics such as total distance covered and speed and acceleration profiles [57, 58, 59]. The appeal was straightforward: GPS offered a means to collect movement data in unconstrained field conditions, without camera coverage or fixed infrastructure, in environments ranging from football pitches and athletics tracks to cross-country ski courses and surf breaks [60, 61, 62, 63, 64, 65].

The majority of commercial systems in this domain rely on standalone code-based positioning, yielding meter-level accuracy. Research applications have also employed differential code GPS, which reduces common-mode errors through a fixed reference station but still struggles to achieve sub-meter accuracy [59, 60]. In most cases, the receiver is mounted at the upper back or integrated into a garment, providing a single trajectory estimate for the athlete as a whole. When operating at the meter level of precision, these approaches are insufficient for biomechanical analysis of individual strides or body segments: the accuracy and sampling rate required to resolve foot contact events, step length variability, or segment trajectories lie well below what code-based positioning can consistently provide, no matter, standalone or differential. Validation studies of commercial units have documented how positional and speed errors increase with movement speed and change of direction, and that the reliability of derived metrics depends critically on the reference method used for assessment [66, 67, 68].

Despite these precision limitations, the sports tracking literature establishes an important proof of concept: wearable GNSS hardware can be reliably operated on a moving human body across a wide range of activities and environments. Receiver miniaturisation had already proceeded far enough by the mid-2000s to make body-worn GPS units practical for field deployment, and their adoption across team sports, endurance athletics, and action sports has since become rou-

tine [69, 70, 19]. The fact that a GNSS receiver mounted on a human body continues to track satellites reliably during vigorous movement is a prerequisite for all subsequent work seeking higher accuracy from the same class of wearable hardware.

3.2.2 High-Precision Single-Receiver GNSS for Gait Parameter Estimation

A qualitatively different approach was pioneered by Terrier and collaborators in the early 2000s [71, 72, 73]. They were the first to apply differential carrier-phase GPS instead of stand-alone code-based positioning to track a single antenna mounted on a walking subject in an outdoor athletic setting. Using a fixed base station and a professional-grade receiver, they achieved centimeter-level 3D positioning at 5 Hz and demonstrated that fundamental gait parameters — step duration, step frequency, vertical displacement of the trunk per stride, and intrastride speed variation — could be extracted directly from the resulting trajectories [71]. It is worth noting the hardware context explicitly: the processing equipment of that era required a backpack weighing approximately 4 kg, and the GNSS antenna was a professional survey-grade unit of approximately 15 cm in diameter, placed right on the head of the subject. While the scientific contribution was relevant and substantial, the system was clearly not compatible with unobtrusive wearability, and the complexity of deployment effectively limited this line of research to controlled experimental settings.

Subsequent work by the same group extended the approach to the analysis of gait variability over extended walks. By tracking step length, cadence, and walk ratio across several hundred consecutive strides in unconstrained outdoor conditions, they showed that stride-by-stride variability follows consistent patterns that are difficult or impossible to observe in short treadmill sessions or over the bounded walkways typical of optical gait laboratories [72]. A dedicated review consolidated this body of work and identified GPS-based gait analysis as a promising tool for monitoring long-range temporal correlations in stride parameters, patterns associated with neurodegenerative disease and ageing. At the same time, they acknowledged that the hardware complexity and cost of the time remained significant barriers to broader adoption [73].

More recent work has revisited the single-receiver approach using lighter and more accessible hardware. Abraham et al. evaluated the reliability of a low-cost GPS data logger for quantifying outdoor walking distances in healthy subjects and found acceptable inter- and intra-unit variability for health and clinical monitoring purposes [74]. Boronat et al. assessed the suitability of GPS-derived gait speed for physical frailty assessment in elderly populations, demonstrating that even consumer-grade single-point positioning retains sufficient consistency for coarse functional mobility classification [75]. These contributions confirm a translational interest in GNSS-based gait monitoring in clinical populations, though they remain limited to whole-body displacement metrics without any segment-level resolution.

The fundamental architectural constraint of all single-receiver approaches, regardless of accuracy level, is that a single antenna positioned anywhere on the body yields only the trajectory of that one point. It provides no information about the relative motion of individual limbs, cannot resolve their trajectories, and cannot reliably detect gait events such as heel strike or toe-off from position data alone. Deriving spatiotemporal parameters from a trunk- or head-mounted antenna requires biomechanical modelling assumptions that introduce uncertainty and are insensitive to the asymmetries and segment-level deviations that characterise many pathological gait patterns. Bridging this limitation requires either distributing multiple receivers across body segments, or fusing GNSS with inertial sensing. These directions are explored in the following subsections.

3.2.3 GNSS and IMU Integration for Outdoor Segment-Level Kinematics

The single-receiver approaches reviewed in the preceding subsection are limited to whole-body displacement. Recovering segment-level kinematic information, such as individual limb trajectories, foot contact events, or joint angles, requires combining GNSS positioning with inertial sensing, so that the absolute position reference provided by GNSS can be fused with the local kinematic detail provided by IMUs. This combination has been explored in a small but substantive body of work, primarily in the context of outdoor sports biomechanics.

An early and direct demonstration of this fusion for gait analysis was provided by Tan et al., who proposed a Kalman-filter-based complementary fusion scheme integrating a wearable GPS receiver with an IMU to measure stride parameters during running [76]. The GPS component provided absolute velocity and position over long time scales, correcting for inertial drift, while the IMU captured the higher-frequency dynamics of individual strides. The resulting system achieved standard deviations of 0.15 m/s for horizontal speed and 0.08 Hz for stride frequency across a speed range of 3–10 m/s. That is a meaningful result obtained from a low-cost unit weighing 28 g, already substantially more compact than the systems used in the Terrier series.

The most extensive development of outdoor GNSS+IMU integration for segment-level kinematics has taken place in alpine skiing biomechanics. Supej combined a single RTK-GNSS receiver providing a reference trajectory for the skier's whole-body position with a full-body inertial motion capture suit to reconstruct segment orientations and joint angles throughout an entire slalom race [77]. The GNSS trajectory anchored the global position of the inertial system, preventing the unbounded drift that would otherwise accumulate over a race duration of several minutes. Orientation accuracy was found to depend on the frequency of the movement, with errors increasing for higher-frequency oscillations. The authors have also observed the effect of horizontal positioning being about twice more precise than the vertical positioning, which is well-known and inevitable in GNSS, due to the specifics of the satellite configuration geometry. Gilgien et al. further developed the single-receiver approach, proposing a method to estimate the centre-of-mass trajectory in alpine skiing by combining the GNSS antenna position with terrain data and IMU-measured accelerations [78]. This approach dispensed with a full IMU suit in favour of a

simpler sensor configuration, achieving centre-of-mass position accuracy of approximately 9 cm against a video-based reference system. Still, the whole weight of the GNSS equipment in the experiments reached 1 kg. Fasel et al. subsequently extended this line of work to a more complete 3D body and centre-of-mass kinematic reconstruction using differential GNSS and multiple inertial sensors, validating the system against stereo photogrammetry and achieving centre-of-mass position accuracy and precision of 8 cm and 4 cm respectively [79].

These skiing studies share a common architectural feature: a single GNSS receiver is used to provide absolute global translation for the whole body, while inertial sensors carry the segment-level kinematic detail. This corresponds closely to what the present thesis formalises as Architecture 1 (Section 4). The approach has proven effective for high-dynamic outdoor sports, where the large displacements of skiing make GNSS the natural anchor for absolute positioning. Importantly, however, all three skiing studies used professional-grade differential GNSS receivers of the kind that were, at the time, incompatible with practical wearability in a clinical or everyday context.

A parallel line of work, originating from the geodetic engineering community rather than sports biomechanics, approached the same combination of GPS and inertial sensing from the perspective of pedestrian navigation and lower-limb kinematics. Kwakkel and collaborators at the University of Calgary attached multiple MEMS IMUs to the lower limbs of a single subject and fused them with a GPS receiver to reconstruct foot and ankle rotations and lower-limb trajectories during walking and running, including an experiment conducted during the Las Vegas Marathon, tracking kinematic changes over the full 42 km distance [80, 81]. The ZUPT-based INS mechanisation developed in this work, exploiting the brief stance phase of each gait cycle to reset velocity errors, is a direct conceptual predecessor of the integration approach developed in Chapter 5 of this thesis. The Kwakkel work remains, to the author’s knowledge, the earliest documented attempt to combine GPS/INS with the explicit goal of reconstructing lower-limb segment kinematics during human locomotion. It is worth noting that during the experiments at the marathon the foot-worn IMUs suffered damage and stopped logging, and the data eventually was not recovered. This, once again, underlines the technical challenges of using imperfect prototype devices in a real movement environment.

Alsén proposed a more general framework for GNSS-aided inertial body motion capture, exploring how GNSS position and velocity measurements could be incorporated into a multi-IMU body model to correct orientation drift and provide absolute position grounding [82]. While the work remained largely conceptual and was validated only in limited experimental conditions, it explicitly articulated the architecture that subsequent systems, including the present thesis, seek to realise.

More recently, Kim et al. developed a loosely-coupled GNSS/IMU integration filter for a wearable electronic performance and tracking system targeting football players [83]. Although this system integrates GNSS and IMU data through an extended Kalman filter, it operates at the body level, providing improved whole-body position and velocity estimates rather than per-segment kinematic reconstruction.

Taken together, the studies reviewed in this subsection demonstrate that GNSS+IMU integration can yield segment-level kinematic information in outdoor conditions, and that the combination is technically sound across a range of hardware configurations and movement contexts.

3.2.4 Foot-Mounted GNSS/INS Systems for Pedestrian Navigation

A parallel research thread, largely independent of the biomechanics literature reviewed above, has developed foot-mounted inertial navigation systems for pedestrian localisation. Although the primary goal of their work is not biomechanical analysis but accurate position tracking over extended distances, and indoor-outdoor seamless positioning (for applications such as emergency and military localisation in GNSS-denied environments), it has produced directly relevant results on the technical feasibility of foot-mounted GNSS/INS integration and on the algorithmic approaches required to make it work.

The foundation of foot-mounted inertial navigation is the zero-velocity update (ZUPT): during the stance phase of each gait cycle, the foot is momentarily stationary, and this known constraint can be applied as a measurement update in a Kalman filter to reset velocity errors and bound the growth of positional drift. The effectiveness of ZUPT is critically dependent on the accuracy of stance phase detection, which is typically performed by a threshold-based detector operating on the inertial sensor signals. Skog et al. conducted a systematic evaluation of four zero-velocity detectors for foot-mounted navigation systems, including the generalised likelihood ratio test detector known as SHOE, and demonstrated that gyroscope-based detectors consistently outperform accelerometer-based ones for forward levelled walking [84, 85]. The SHOE detector established in this work has become a common reference for stance phase detection in the pedestrian navigation community, and is the detector adopted in Chapter 5 of this thesis. Nilsson et al. subsequently developed an open-source wireless foot-mounted inertial navigation module providing a standardised hardware and software platform that significantly lowered the barrier to entry for research in this area [86]. Wahlström and Skog provide a comprehensive review of fifteen years of progress in zero-velocity-based foot-mounted navigation, covering the evolution of detectors, error models, and system architectures [87].

GNSS has been incorporated into foot-mounted navigation systems primarily to address the heading drift that ZUPT alone cannot fully control, and to provide absolute positioning in outdoor environments. Stirling et al. were among the first to propose a shoe-mounted navigation system that combined inertial sensors with GPS, using the foot-mounted configuration to enable precise stance phase detection and stride segmentation, and GPS to provide heading reference and absolute position anchoring in outdoor conditions [88]. Godha and Lachapelle developed this direction further, designing a system based on a low-cost MEMS IMU and a high-sensitivity GPS receiver that maintained positioning continuity in GPS-degraded environments through ZUPT-aided INS bridging, and demonstrated its performance for pedestrian navigation over mixed indoor and outdoor routes [89]. Hide et al. specifically investigated the integration

of a foot-mounted IMU with a co-located GNSS antenna: a configuration in which both sensors experience the same dynamics and the lever arm between them is negligible. They showed that tightly-coupled carrier-phase integration with this geometry could maintain centimeter-level accuracy even when the sky view was significantly compromised by the low antenna elevation [90]. This finding is directly relevant to the present thesis, as it establishes that useful carrier-phase observations can be obtained from a foot-mounted antenna despite the challenging sky visibility that the configuration implies.

Rantakokko et al. extended the GNSS/foot-INS concept to a dual foot-mounted configuration, fusing the GNSS data with INS to improve heading observability and positioning robustness in dense urban and indoor environments for safety-critical first-responder applications [91]. Le Scornec et al. presented the PERSY system, a foot-mounted reference navigation system combining tightly-coupled differential GNSS carrier-phase measurements with inertial and magnetic data, achieving a mean positioning error of 0.22% of travelled distance over a 1.4 km walking route with four subjects [92]. PERSY is notable in that it was designed specifically as a high-accuracy reference system for evaluating other pedestrian navigation solutions — its carrier-phase integration architecture is technically the closest published predecessor to the GNSS/INS integration approach developed in Chapter 5 of this thesis. Still, it is important that the antenna was head-mounted and, therefore, not subject to abrupt foot dynamics.

A consistent characteristic of all systems in this literature is that optimisation targets are navigational: position accuracy over distance, heading consistency, and robustness to signal outages. The output of these systems is a position and heading trajectory for the pedestrian, not a biomechanical description of the gait cycle. Gait events such as heel strike and toe-off are detected only as they define the ZUPT window, not as biomechanical quantities of interest. Spatiotemporal gait parameters, such as step length, stride length, cadence, step width, are not extracted or validated against independent biomechanical reference systems. The question of how GNSS signal quality at a foot-mounted receiver varies as a function of walking speed and gait dynamics has not been investigated in this literature. These are precisely the contributions that the present thesis adds to the technical foundation established by the pedestrian navigation community.

3.2.5 Summary of Open Problems

The review presented in the preceding subsections traces a coherent progression in the application of GNSS to human movement analysis, from coarse whole-body tracking in sports through centimeter-level gait parameter estimation from a single torso-mounted receiver, and into the first combinations of GNSS and inertial sensing at the level of individual body segments. At each stage, the work reviewed advances the field in a meaningful direction while also revealing the boundaries of what has and has not been demonstrated. The following open problems emerge from this review and define the specific gap that the present thesis addresses.

Segment-level GNSS+IMU integration has not been validated for gait analysis. The systems reviewed in Section 3.2.3, primarily developed for alpine skiing and marathon running, demonstrate that GNSS and inertial sensing can be combined to recover segment-level kinematic information in outdoor conditions. However, none of these systems were validated against an independent biomechanical ground truth for spatiotemporal gait parameters. Their outputs have not been assessed for the clinically relevant parameters — step length, stride length, step width, cadence, gait symmetry — that define the standard outcome measures of gait analysis. This validation gap means that the applicability of GNSS+IMU integration to clinical gait assessment remains an open question.

The foot-mounted GNSS/INS architecture has not been applied to biomechanical gait analysis. The pedestrian navigation systems reviewed in Section 3.2.4 operate the closest hardware configuration to the present thesis: body-mounted receiver, ZUPT-aided INS, carrier-phase GNSS correction; but their design objectives are navigational. Gait events are not evaluated as biomechanical quantities of interest, they are merely used as ZUPT triggers. No study in this literature has extracted or validated spatiotemporal gait parameters from foot-mounted GNSS/INS against an independent reference, characterised foot trajectory reconstruction accuracy, or assessed the system’s suitability for clinical walking-speed analysis.

The effect of foot-mounted receiver dynamics on carrier-phase signal quality has not been characterised. The work of Voutsis established that pedestrian motion can induce cycle slips in GNSS carrier-phase tracking loops through impulsive dynamics [93, 94]. However, this was demonstrated for receivers placed at conventional body locations — torso, arm, hand. The foot-mounted configuration subjects the receiver to a qualitatively different and more severe dynamic regime: the impulsive accelerations of heel strike and toe-off at the distal end of the kinematic chain are substantially larger than those experienced at the torso, and their interaction with carrier-phase lock loops at different walking speeds has not been experimentally characterised. Understanding this interaction is essential for designing a reliable foot-mounted GNSS/INS integration approach.

No system occupies the gap between IMU-only and laboratory optical motion capture for outdoor gait analysis. As established in Section 2.5, IMU-only systems provide relative motion without absolute spatial reference, and optical systems are confined to laboratory infrastructure. The single-receiver GNSS approaches of Section 3.2.2 provide absolute outdoor positioning but no segment-level detail. The GNSS+IMU and foot-mounted GNSS/INS systems of Sections 3.2.3 and 3.2.4 have the architectural potential to fill this gap but have not been validated in a clinical gait analysis context with independent ground truth. A hardware and algorithmic framework that combines per-segment GNSS positioning with IMU orientation sensing, validated for spatiotemporal gait parameter extraction at walking speeds against independent biomechanical reference, does not currently exist in the literature. It is precisely this framework that the present thesis proposes and evaluates.

The hardware constraints that limited earlier high-precision work have since been resolved.

A final observation that motivates the timing of this work: the technical barriers that prevented the Terrier series, the Kwakkel thesis, and the Hide integration study from achieving practical wearability were primarily hardware barriers. The receivers and antennas of those eras were incompatible with foot-mounted or multi-segment deployment in realistic field conditions. The current generation of miniature dual-frequency receivers removes these constraints, weighing under 20 g and achieving RTK-level accuracy in form factors compatible with wearable integration [95]. The algorithms proposed by prior work were sound; the limiting factor was hardware immaturity that no longer applies. This convergence of technical feasibility and unaddressed scientific need defines the context from which the present thesis originates.

Chapter 4

Conceptual Framework: Integrating GNSS into Motion Analysis

4.1 Introduction and Motivation

As established in previous chapters, a persistent and practically significant gap exists in the current landscape of human motion capture technologies. The three main sensing families: marker-based optical, inertial-based, and markerless optical, each represent a separate approach to movement analysis, some of which are well-validated, yet their respective failure modes are largely complementary. Marker-based optical systems achieve sub-millimeter accuracy under laboratory conditions but are fundamentally confined to bounded, instrumented capture volumes and cannot be routinely deployed outdoors. Inertial systems are fully portable and infrastructure-free, but provide only relative motion with respect to an arbitrary initial configuration: without an absolute position reference, global trajectory reconstruction remains unreliable over extended recordings, and orientation drift (particularly in yaw) accumulates progressively over time. Markerless optical approaches reduce the instrumentation burden and, in their monocular form, approach genuine portability, yet they remain sensitive to occlusion, lighting conditions, and camera coverage, and do not yet achieve the precision required for validated biomechanical analysis in uncontrolled outdoor settings. The result is that no existing technology currently satisfies the simultaneous requirements of accuracy, portability, and infrastructure independence that outdoor motion capture demands.

This chapter theoretically examines the extent to which Global Navigation Satellite Systems can contribute to closing this gap. Modern multi-constellation, multi-frequency GNSS receivers, operating in conjunction with a reference station and carrier-phase post-processing techniques, are capable of centimeter-level absolute positioning in outdoor environments without fixed laboratory infrastructure. The update rate of GNSS and its sensitivity to body dynamics preclude its use

as a standalone motion capture technology. This chapter focuses on the specific roles in which GNSS can augment existing portable systems, and operationalizes them into three concrete integration architectures of increasing complexity and biomechanical scope.

The chapter is organized as follows. Section 4.2 identifies the conceptual roles that GNSS can play in human movement analysis pipelines. Section 4.3 discusses the practical considerations that govern the use of GNSS in wearable configurations, including achievable accuracy, hardware constraints, and signal degradation mechanisms relevant to body-mounted receivers. Section 4.4 presents the three proposed integration architectures, each addressing a different level of system complexity and biomechanical detail. Section 4.5 provides a comparative analysis of the architectures across key design dimensions. The chapter closes in Section 4.6 by defining the scope of the contributions pursued in this thesis and summarizing the conceptual framework that the subsequent experimental chapters build upon.

4.2 Roles of GNSS in Human Movement Analysis

Before introducing specific integration architectures, it is useful to identify the distinct functional roles that GNSS can play within a human movement analysis pipeline. A role, in the sense used here, refers to a specific observational contribution that GNSS provides and that is not readily available from existing portable sensing modalities, namely, inertial and markerless optical systems. This distinction is important: the roles described in this section should be treated as conceptual primitives that motivate and inform the architectures proposed in Section 4.4, each of which operationalizes one or more of these roles into a concrete hardware and algorithmic configuration. Identifying the roles separately allows the contribution of GNSS to be understood independently of any particular implementation choice, and provides a principled basis for evaluating the trade-offs between architectures.

4.2.1 Global Translational Referencing

A fundamental limitation shared by all portable motion capture technologies is that they operate within a locally defined coordinate frame whose origin and orientation are determined by the measurement setup rather than by any fixed external reference. In marker-based optical systems, this frame is established through laboratory calibration and is bounded by the instrumented capture volume. In inertial systems, the reference frame is implicitly defined by the sensor orientation at initialization time, an arbitrary and session-specific choice that is furthermore subject to progressive drift over the course of a recording. In markerless optical systems, and particularly in monocular configurations, pose is typically estimated relative to the camera frame, which may itself be moving. The consequence in all cases is the same: the reconstructed motion cannot be expressed in a common, absolute spatial reference, which precludes direct comparison

across sessions, subjects, or recording locations, and limits the spatial extent of the capture area to whatever the local setup can cover.

GNSS operates on an entirely different spatial basis. Satellite orbits are defined in the Earth-Centered, Earth-Fixed (ECEF) frame, a Cartesian coordinate system whose origin coincides with the Earth's center of mass and whose axes are fixed with respect to the terrestrial surface. Positioning solutions computed from GNSS observables are naturally expressed in this frame, or equivalently in geodetic coordinates (latitude, longitude, ellipsoidal height) defined on the WGS84 reference ellipsoid. For practical motion analysis applications, it is convenient to project these solutions into a local navigation frame: typically the East-North-Up (ENU) frame, a Cartesian system tangent to the ellipsoid at a chosen reference point, which aligns coordinate axes with intuitive directions and is well-suited to the scales involved in human movement recording. Crucially, this reference is defined by the Earth itself, not by the measurement setup: any two recordings made with GNSS receivers, regardless of when or where they were conducted, share a common absolute spatial reference, making cross-session and cross-subject comparison straightforward and removing any constraint on the spatial extent of the recording area beyond the requirement for adequate satellite visibility.

In the context of human motion capture, this property can be exploited by using a GNSS receiver mounted on the body as a global anchor: a single point whose absolute trajectory in the ENU frame is known, and to which the relative motion estimated by other sensors can be spatially referenced. The result is a motion capture pipeline that is no longer confined to a laboratory volume and whose output is expressed in a coordinate frame with direct physical meaning, for example, enabling among other applications the longitudinal tracking of a patient's gait over successive clinical assessments conducted in different locations.

4.2.2 Inertial Drift Mitigation

The accumulation of sensor errors through numerical integration is a fundamental limitation of inertial navigation, and its consequences differ depending on the quantity being estimated. Orientation estimation relies on the integration of gyroscope measurements, and is therefore affected by gyroscope bias and noise accumulating at a rate proportional to time. Position estimation, by contrast, requires double integration of accelerometer measurements, which causes errors to grow at a rate proportional to the square of time. This difference in integration order means that orientation drift, while inevitable, is substantially slower to accumulate than positional drift, which is why inertial-based motion capture systems typically forgo absolute position estimation entirely and focus instead on segment orientation and relative kinematics.

Even orientation estimation, however, is not free of long-term drift. Practical mitigation strategies exploit physical references embedded in the sensor measurements: the direction of the gravity vector, as measured by the accelerometer during quasi-static phases, provides a reli-

able correction for roll and pitch errors in Kalman filter-based approaches. Heading, or yaw, is considerably more difficult to correct in this way, since it corresponds to rotation about the gravity axis and is therefore not observable from accelerometers alone. Magnetometers are commonly used to provide a heading reference, but their reliability may be compromised by magnetic disturbances from electronic equipment, metallic structures, and ferromagnetic surfaces: those conditions that are frequently encountered in both indoor and outdoor environments. The result is that yaw drift remains the most persistent and least tractable error source in standalone inertial motion capture.

In navigation applications, including robotics, autonomous vehicles, and precision agriculture, this class of problems is routinely addressed through GNSS/INS integration (INS stands for Inertial Navigation System). The principle is straightforward: GNSS provides absolute position and, through differentiation or Doppler measurement, velocity estimates that are drift-free over time, while the inertial system provides high-rate, continuous kinematic data between GNSS updates. When fused in a Kalman filter framework, the two modalities are complementary: GNSS corrects the long-term drift of the inertial solution, while the inertial system bridges the gaps between GNSS epochs and smooths the lower-rate satellite observations. Crucially, a sequence of GNSS position fixes carries implicit heading information, since the direction of travel can be inferred from consecutive positions. This makes GNSS-based fusion effective for yaw correction even in magnetically disturbed environments where magnetometers fail.

The same principle can be transposed to wearable motion capture. A GNSS antenna mounted rigidly on a body segment, moving together with the IMU attached to the same segment, provides the same type of absolute position and velocity observations that correct inertial drift in navigation systems. Applied to a wearable configuration, this approach can improve both the long-term consistency of orientation estimates and the reliability of any positional reconstruction attempted from inertial data. A practical consequence of this reasoning, however, is that drift correction is local to the segment carrying the receiver: since each body segment moves independently, full-body drift correction would in principle require one GNSS receiver per segment. The implications of this constraint for system design are examined in the architecture discussion of Section 4.4.

4.2.3 Spatial Grounding for Mobile Vision-Based Systems

Monocular markerless motion capture represents perhaps the most practically accessible form of movement analysis: it requires only a single camera, imposes no instrumentation on the subject, making the technique completely non-invasive, and can in principle be operated without technical expertise or dedicated laboratory space. These properties make it an attractive candidate for clinical and sports applications where setup simplicity is paramount. However, as noted in Section 2.4, monocular systems typically reconstruct human pose relative to the camera coordinate frame, or alternatively relative to a body-centered frame anchored to a detected base segment —

an approach analogous in its limitations to inertial-only systems. In either case, the reconstructed motion lacks absolute spatial grounding: it cannot be expressed in a fixed global reference frame, which limits its utility for locomotion analysis over extended distances and precludes meaningful cross-session comparison.

A GNSS receiver co-located with the camera could partially address this limitation. By providing the camera's absolute position in a globally referenced frame at each recording epoch, GNSS makes it possible to transform the camera-relative pose estimates into a fixed coordinate system, recovering the subject's global trajectory in addition to relative joint kinematics. It should be noted, however, that position alone is insufficient to fully define the camera's spatial transform: the camera's orientation must also be known, requiring either a co-mounted IMU or an alternative attitude estimation strategy. A particularly compelling realization of this concept is the use of an aerial drone equipped with a precise GNSS receiver as a mobile camera platform, which would allow the recording area to follow the subject over arbitrary distances while maintaining spatial referencing in a global frame.

Despite its conceptual appeal, this role of GNSS is outside the scope of the present thesis. It is mentioned here for completeness, as it represents a distinct and practically relevant integration paradigm, and is revisited briefly in the context of future work in Section 8.5. The remainder of this chapter focuses on integration architectures in which GNSS receivers are mounted directly on the body.

4.3 GNSS/INS Integration Considerations for Wearable Use

4.3.1 Receiver and Antenna Characteristics in Body-Worn Configurations

The technical foundations of GNSS positioning: signal observables, positioning techniques, and achievable accuracy levels, are reviewed in Chapter 3. The conclusion relevant to the present chapter is that carrier-phase post-processing techniques, operating in differential mode with respect to a reference station, are capable of centimeter-level absolute positioning in open outdoor environments, and that this accuracy level is the baseline assumed in the integration architectures proposed in Section 4.4. The present section focuses instead on the practical constraints that arise specifically from deploying GNSS receivers in a wearable, body-mounted configuration, as these constraints directly shape the design choices made in each architecture.

The first constraint concerns update rate. Commercial GNSS receivers typically operate at output rates between 1 and 20 Hz, with most wearable-grade units limited to 10 Hz under standard configurations. This is insufficient to resolve the biomechanically relevant features of human movement directly from GNSS alone: gait events such as foot strike and toe-off, rapid joint angle changes, and high-frequency oscillations of distal segments all occur at frequencies that exceed

what GNSS can capture. As a standalone kinematic sensor, a body-mounted GNSS receiver cannot provide the temporal resolution required for detailed motion analysis. This limitation is fundamental, and it is precisely what motivates the fusion with inertial sensors operating at rates of 100 Hz or higher: the IMU provides the high-rate kinematic detail that GNSS cannot, while GNSS provides the absolute spatial reference that the IMU lacks. In this sense, the update rate constraint is merely a design premise that defines the complementary roles of the two sensing modalities.

The second constraint concerns hardware form factor. Achieving centimeter-level positioning accuracy requires multi-frequency receivers capable of tracking signals from multiple constellations simultaneously, paired with antennas of sufficient ground plane area to limit multipath and maintain phase center stability. While the miniaturization of GNSS hardware has advanced considerably in recent years, wearable-grade multi-frequency receivers and their associated antennas remain significantly bulkier and more power-consuming than the MEMS IMUs with which they are to be integrated. This has direct consequences for system design: the added weight and volume of each receiver unit constrain the number of simultaneous receivers that can be mounted on the body without meaningfully affecting natural movement, and the power requirements necessitate battery capacity that further increases the wearable payload. These considerations impose a practical upper bound on the number of body segments that can be simultaneously instrumented, and therefore on the biomechanical detail achievable by any given architecture.

For concrete reference, the multi-frequency GNSS receiver and antenna used in the experimental work of this thesis (a u-blox ZED-F9P [96] paired with a Harxon HX-CH7018A helical antenna [97]) together draw approximately 435 mW during tracking and weigh approximately 10 g, against 0.6 g and 150 mW for a typical wearable-grade IMU such as the Xsens MTi-7 [98] co-located with them. This per-channel disparity, on the order of $15\times$ in mass and $3\times$ in power, scales linearly with the number of body-mounted receivers and constitutes the dominant practical bound on the achievable density of segment-level GNSS instrumentation.

The third constraint concerns signal quality under dynamic conditions. GNSS receivers and antennas are sensitive to a range of environmental and dynamic factors that affect the reliability of carrier-phase observations. Direct satellite visibility, multipath reflections from nearby surfaces, and the geometry of the visible satellite constellation all influence positioning accuracy in ways that are well understood in static and slowly moving applications. In body-mounted configurations, however, an additional source of degradation arises from the mechanical dynamics of the moving platform itself. The accelerations and vibrations associated with human locomotion are suspected to disturb the receiver's phase-lock loops, causing cycle slips and momentary loss of carrier-phase continuity. This hypothesis is consistent with the empirically observed degradation of GNSS signal quality at higher walking speeds, where foot strike dynamics are more intense, and is examined in detail in Chapter 5.

A fourth consideration concerns the choice between real-time and post-processing approaches. Real-time kinematic techniques such as RTK are well-established in robotics and autonomous

navigation, where immediate positional feedback is operationally necessary. Motion capture, however, does not generally require real-time output: the biomechanical analysis is typically performed after the recording session, and the subject does not need positional feedback during movement. This operational characteristic makes post-processing kinematic (PPK) techniques particularly well-suited to the wearable motion capture context. PPK removes the requirement for a live data link between the reference station and the rover during recording, which simplifies the hardware setup and eliminates a potential source of data loss in field conditions. More importantly, post-processing enables forward-backward smoothing of the positioning solution, which improves the consistency of the trajectory estimate throughout the recording and significantly increases ambiguity fix rates at the beginning and end of sessions where real-time methods often struggle. The use of PPK as the preferred processing strategy is adopted consistently across the architectures presented in this thesis, and its practical implications are discussed further in Chapter 5.

4.3.2 GNSS/INS Coupling Strategies

The integration of GNSS positioning with inertial navigation can be realized at different levels of algorithmic coupling, each representing a different trade-off between implementation complexity, achievable performance, and robustness to signal degradation. Three main coupling strategies are recognized in the literature: loosely-coupled (LC), tightly-coupled (TC), and deeply-coupled (DC) integration. The latter is also sometimes referred to as ultra-tightly-coupled (UTC). Understanding the distinctions between these strategies is important for contextualizing the design choices made in the architectures proposed in this chapter, and for understanding why the loosely-coupled approach is the natural choice for a research prototype operating in the wearable motion capture domain.

In loosely-coupled integration, the GNSS processing module and the inertial navigation system operate as independent processing modules. The GNSS processor computes its own position and velocity solution from the raw satellite observables, and these computed quantities are then passed as measurements to a Kalman filter that fuses them with the IMU-derived state estimates. The two subsystems are therefore interfaced at the level of navigation outputs, which means that any existing GNSS post-processing software (such as RTKLIB, which is used in this thesis) can be used without modification to produce the GNSS position and velocity inputs, while the IMU fusion is implemented separately as an independent component. This modularity is a significant practical advantage in a research context, as it allows established and validated software tools to be used for each subsystem independently. The principal limitation of LC integration is that it requires the GNSS processor to produce a valid position and velocity solution, which in turn requires a minimum number of satellites: at least four for a three-dimensional solution, as stated in section 3.1 . In degraded signal conditions where fewer satellites are available, the GNSS module fails to produce a solution and the Kalman filter must propagate on inertial data alone

until satellite availability recovers.

Tightly-coupled integration bypasses this limitation by fusing IMU data with the GNSS system at the level of raw observables (code pseudoranges and carrier phase measurements) rather than computed positions and velocities. The IMU predictions are incorporated directly into the GNSS positioning algorithm, allowing a combined solution to be maintained even when the number of visible satellites falls below the threshold required for a standalone GNSS solution. This makes TC integration substantially more robust than LC in degraded signal environments, such as urban canyons, areas with partial sky obstruction, or the dynamic conditions encountered in body-mounted receiver configurations. However, the tighter coupling comes at the cost of implementation complexity: the IMU and GNSS processing can no longer be treated as independent modules, and modifications to the core GNSS positioning algorithm are required. This places TC integration beyond the reach of standard off-the-shelf post-processing software and demands a more deeply integrated software architecture.

Deeply-coupled integration takes this a step further by incorporating IMU data at the level of the receiver's signal tracking loops, feeding inertial predictions into the phase-lock and delay-lock loops that track the satellite carrier and code signals [99]. This allows the receiver to maintain lock on satellite signals under conditions of high dynamics or weak signal strength that would cause a standard receiver to lose track entirely, and can significantly improve signal reacquisition after temporary obstructions. DC integration is implemented at the hardware and firmware level of the GNSS receiver itself, and is therefore the exclusive domain of the receiver manufacturer. It is not accessible as an integration strategy for external researchers working with standard commercial receivers, and is mentioned here for completeness, hoping that further development in the field of GNSS hardware would enable their usage for a wider audience.

For the purposes of this thesis, loosely-coupled integration is adopted as the coupling strategy for all three proposed architectures. This choice is motivated primarily by practical considerations: LC integration is the only coupling level that can be implemented using independent, off-the-shelf software components for the GNSS and IMU processing subsystems, which is both feasible and appropriate for a research prototype. In degraded signal conditions, which, as discussed in Section 4.3, are encountered in body-mounted receiver configurations, particularly at higher walking speeds, the LC approach is more susceptible to solution gaps than TC would be. However, for the walking-speed conditions under which the system is validated in this thesis, the GNSS signal quality is generally sufficient to maintain a valid LC solution, and the modularity advantages of the loosely-coupled approach outweigh its robustness limitations in this context.

In practical terms, RTKLIB itself provides a complete differential carrier-phase positioning algorithm through its `rx3rtkp` module, which produces position and velocity outputs that can be consumed directly by a loosely-coupled integration scheme. Tightly-coupled integration would require building an algorithm at the level of raw GNSS observables. While in principle such an extension could be built on top of RTKLIB's existing observation-processing routines, the implementation effort substantially exceeds that of using RTKLIB outputs in a loosely-coupled

configuration, which is part of the rationale for adopting the LC approach in this thesis.

4.4 Proposed Integration Architectures

The roles identified in Section 4.2 and the practical constraints discussed in Section 4.3 together define the design space for integrating GNSS into portable motion capture pipelines. The present section proposes three concrete integration architectures that operationalize these roles into specific hardware configurations and processing workflows. The architectures are ordered by increasing complexity and biomechanical scope: from a minimal single-receiver configuration providing global body translation, through a per-segment configuration enabling foot trajectory reconstruction and inertial drift correction, to a multi-receiver configuration supporting full-body kinematic reconstruction. Each architecture represents a distinct point in the trade-off space between system complexity, hardware cost, and achievable biomechanical detail, and each is grounded in the capabilities and constraints of current wearable GNSS hardware as discussed in the preceding section.

The three architectures are summarised in Figure 4.1, which identifies for each its sensor configuration, processing approach, and primary output. The remainder of this section describes each in turn.

4.4.1 Architecture 1: Single Receiver for Global Body Translation

Inertial motion capture systems, as discussed in Section 2.3, provide reliable estimates of segment orientations and joint angles over moderate recording durations. When multiple IMUs are attached to the major body segments and their data is fused through a biomechanical model, the resulting joint estimates are sufficiently accurate for a broad range of clinical and research applications. The fundamental limitation of such systems, however, is in their inability to express this relative motion in a fixed globally referenced coordinate frame. The position of the body as a whole — its translation through space with respect to a fixed external reference — is not observable from inertial sensing alone, and any positional estimate derived purely from inertial integration degrades rapidly due to the error accumulation mechanisms discussed in Section 4.2.2. The consequence is that while segment orientations and joint angles can be reconstructed with reasonable fidelity, the global trajectory of the body remains unknown, and the reconstructed motion is anchored to an arbitrary initial position that carries no physical meaning.

The simplest architectural response to this limitation is to introduce a single GNSS receiver with antenna mounted on the body at a location that provides stable satellite visibility throughout the recording. The torso, and in particular the upper back or sternum region, is the natural candidate for this placement: it maintains a largely unobstructed view of the sky during typical

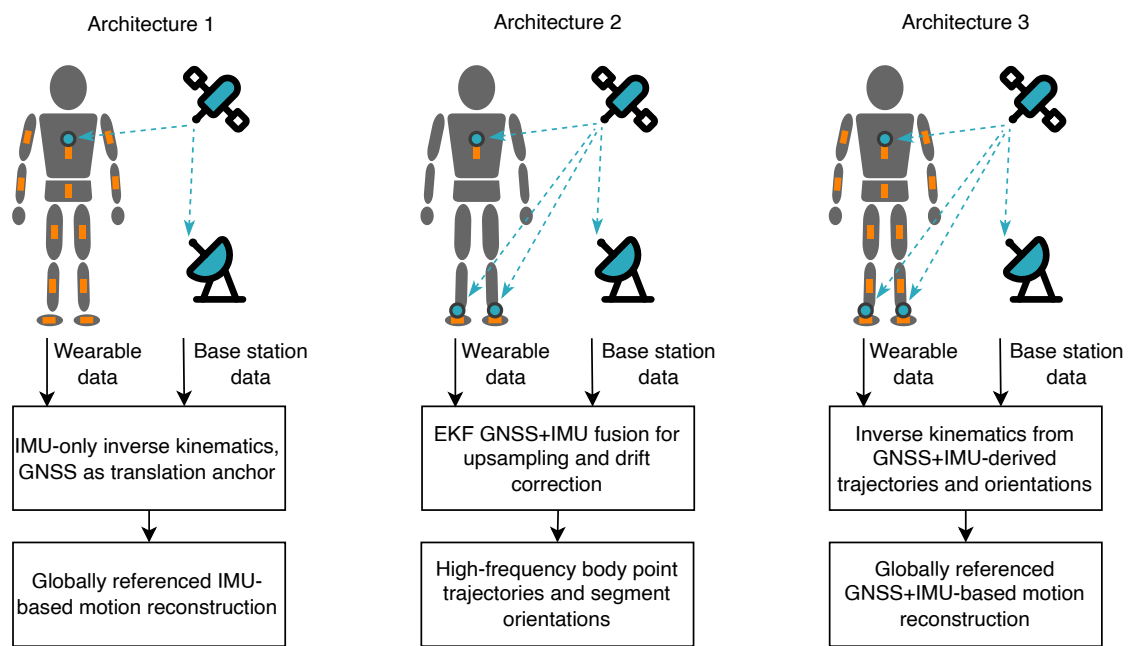


Figure 4.1: The three proposed GNSS/IMU integration architectures, of increasing complexity and biomechanical scope. Each architecture is characterised by its sensor configuration, processing approach, and primary output.

locomotion, is not subject to the rapid and impulsive dynamics of distal segments such as the feet, and its trajectory is biomechanically meaningful as a proxy for the overall displacement of the body’s center of mass. A receiver placed at this location provides, through carrier-phase post-processing techniques, a centimeter-level estimate of the body’s global trajectory in the ENU frame, which can be used as a translational anchor for the inertial motion capture pipeline. The IMUs continue to provide all segment orientation and joint angle information, while the GNSS receiver contributes the single missing observable: the absolute position of a reference point on the body in a globally defined coordinate frame.

The output of this architecture is a full-body motion capture recording in which segment orientations and joint angles are derived from the inertial system, and the global translation of the body is provided by the GNSS receiver. The result is spatially referenced motion data that can be compared across sessions, subjects, and locations — a capability that IMU-only systems fundamentally cannot offer. This concept has been recognized in the commercial domain: the Xsens MVN Link system includes an optional GNSS positional aiding feature, described in the manufacturer’s documentation as providing global position reference for outdoor recordings [100].

However, the precision claims stated in the Xsens documentation are consistent with a code-based positioning solution, which is limited to meter-level accuracy under favorable conditions. No carrier-phase or differential processing is described, and no independent peer-reviewed validation of this feature has been reported in the literature to the author’s knowledge. The architecture as implemented in the commercial product therefore operates at a precision level that might be insufficient for biomechanical trajectory reconstruction, and the potential of carrier-phase GNSS in this role remains unexplored.

The primary limitation of Architecture 1 is that the absolute positioning information is confined to a single point on the body. Segment orientations are still estimated entirely from inertial sensing and remain subject to the drift mechanisms described in Section 4.2.2, particularly yaw drift over extended recordings. More importantly, no per-segment absolute position is available: step lengths and widths, and other spatially grounded gait parameters cannot be derived from the GNSS measurement alone. These limitations motivate the extension to Architecture 2, in which a GNSS receiver is associated with more instrumented body segments, enabling both per-segment drift correction and the reconstruction of absolute segment trajectories.

4.4.2 Architecture 2: Per-Segment Receivers for Drift Correction and Trajectory Reconstruction

Architecture 1 establishes the principle of using a single GNSS receiver as a global translational anchor for an inertial motion capture pipeline. While this resolves the absence of absolute spatial reference at the body level, it leaves the segment-level inertial estimates uncorrected: joint angles and segment orientations remain subject to drift, and no absolute trajectory information

is available for individual body segments. Architecture 2 addresses both of these limitations by co-locating one or more GNSS receivers and antennas with selected IMUs on segments of interest, enabling a qualitatively different mode of integration in which GNSS and inertial sensing operate together at the segment level rather than at the level of the body as a whole.

The key architectural insight is that a GNSS antenna rigidly attached to the same segment as an IMU shares the segment's motion exactly, and can therefore serve two complementary functions simultaneously. First, the absolute position and velocity estimates provided by the receiver can be fused with the IMU data in a Kalman filter framework to correct inertial drift directly at the segment level — including, crucially, yaw drift, which is not observable from accelerometers alone and is poorly corrected by magnetometers in magnetically disturbed environments. Second, the receiver provides an absolute trajectory estimate for the segment it is mounted on, expressed in the ENU frame, which is not derivable from inertial sensing alone. These two functions (drift correction and trajectory reconstruction) are not independent: the same GNSS observations that correct the inertial solution also constitute the trajectory estimate, and the inertial system in turn provides high-rate kinematic continuity between GNSS epochs and smooths the lower-rate satellite observations.

The number and placement of receivers in this architecture is a configuration choice determined by the application and the segments of biomechanical interest. A configuration with receivers on both feet, for instance, enables the reconstruction of absolute foot trajectories in a geodetic reference frame, from which spatiotemporal gait parameters — step length, stride length, step width, cadence — can be derived directly without recourse to any additional ground truth or laboratory infrastructure. This is a capability that neither IMU-only systems nor Architecture 1 can provide, and it is the configuration explored in the experimental chapters of this thesis. Other configurations, such as a single receiver on one foot combined with a torso receiver, are equally conceivable depending on the specific parameters of interest.

An important complementary mechanism in this for foot-mounted receivers is the use of zero-velocity updates during the stance phases of the gait cycle. When a foot is in contact with the ground, its velocity is known to be zero, and this constraint can be incorporated as an additional measurement in the Kalman filter to partially suppress inertial drift during the intervals between GNSS corrections. ZUPT and GNSS corrections are thus complementary: ZUPT constrains the solution during stance, while GNSS provides absolute position corrections during and after swing, together producing a more accurate and consistent trajectory estimate than either mechanism alone.

The principal limitation of Architecture 2 relative to Architecture 1 is hardware complexity: each additional receiver increases the wearable payload in terms of weight, volume, and power consumption, as discussed in Section 4.3. Furthermore, while foot-mounted receivers provide excellent segment-level trajectory information for gait analysis, they do not by themselves enable full-body kinematic reconstruction: joint angles above the instrumented segments are still estimated from IMUs alone, and the relationship between segment trajectories and full-body

pose requires additional modeling assumptions. These limitations motivate Architecture 3, in which multiple high-precision receivers are used to reconstruct the full-body configuration directly through inverse kinematics.

4.4.3 Architecture 3: GNSS Receivers as Virtual Markers for Kinematic Reconstruction

Architectures 1 and 2 both treat GNSS as a corrective or augmentative input to an inertial motion capture pipeline: the inertial system remains the primary kinematic instrument, and GNSS contributes absolute positional information that the inertial system cannot provide on its own. Architecture 3 represents a conceptual departure from this paradigm by proposing treating the GNSS receivers themselves as the primary positional instruments, in a role directly analogous to the retroreflective markers of optical motion capture systems. The absolute positions of body-mounted receivers, reconstructed through carrier-phase post-processing at centimeter-level accuracy, serve as known-location constraints in an inverse kinematics solver, while IMU-derived orientations provide the complementary rotational information needed to fully constrain the pose estimation problem. The result is a kinematic reconstruction pipeline that borrows the structural logic of optical motion capture (position-constrained inverse kinematics) while operating entirely from wearable sensors without any fixed laboratory infrastructure or bounded capture volume.

The analogy with optical markers is instructive but should be understood with precision. In a marker-based optical system, the three-dimensional positions of physical markers are reconstructed by triangulation within a calibrated camera volume, and these positions are subsequently used to estimate segment poses through a rigid body fitting procedure. In Architecture 3, the GNSS receivers replace the markers as the source of three-dimensional positional observations, with the critical difference that their positions are determined through satellite ranging, and are therefore not subject to occlusion, lighting conditions, or capture volume constraints, nonetheless having their own limitations. The receivers with antennas can be mounted on any subset of body segments of interest — lower limbs, upper limbs, or any combination thereof. The architecture is therefore not necessarily a full-body system: its scope is determined entirely by the placement of receivers and the configuration of the biomechanical model used in the inverse kinematics solver.

The complementary role of IMU orientations is essential to the feasibility of this architecture. GNSS positioning provides the absolute position of each receiver in the ENU frame, but it carries no direct information about the orientation of the segment on which the receiver is mounted. Segment orientations, which are needed to fully define the pose of each rigid body and to resolve the inverse kinematics problem, are supplied by the IMUs co-located with the antennas. This combination — GNSS positions as virtual markers, IMU orientations as segment constraints — produces a kinematic input set that is more informative than either modality alone, and more constrained than IMU-only inverse kinematics, which lacks any absolute positional grounding. The absolute spatial grounding provided by GNSS is particularly significant in this context: it means

that the reconstructed joint angles and segment trajectories are expressed in a globally referenced frame, a property that IMU-only systems cannot achieve regardless of the sophistication of their sensor fusion algorithms.

Architecture 3 is the most demanding of the three proposed configurations in terms of hardware complexity, synchronization requirements, and sensitivity to signal degradation. Each additional receiver increases the wearable payload and introduces an additional channel of GNSS data that must be time-synchronized with the corresponding IMU and post-processed to centimeter-level accuracy. The inverse kinematics solver must furthermore be capable of handling the combined positional and orientational constraints in a consistent and numerically stable manner. These demands place Architecture 3 at the frontier of what current wearable GNSS hardware can reliably support, and its practical implementation requires careful attention to the signal quality considerations discussed in Section 4.3. The experimental realization of this architecture, and an assessment of its achievable accuracy under realistic outdoor conditions, are presented in Chapter 7.

4.5 Comparative Analysis of Architectures

The three architectures proposed in Section 4.4 span a wide range of system complexity and biomechanical capability. The progression from Architecture 1 to Architecture 3 reflects a monotonic increase in both hardware complexity and biomechanical output richness, and these two dimensions are not independent. The additional receivers introduced in Architectures 2 and 3 extend the positional observability of the system to more body segments, and it is precisely this extension that enables the additional biomechanical capabilities. The hardware constraints discussed in Section 4.3 — receiver size, weight, power consumption, and signal quality under dynamic conditions — impose a practical cost on each additional receiver, which means that the choice of architecture is always a trade-off between the richness of the biomechanical output and the feasibility of the wearable deployment.

It is important to recognize, however, that the transitions between architectures are qualitative. The step from Architecture 1 to Architecture 2 is a shift from global body anchoring to segment-level absolute positioning, which unlocks a class of biomechanical measurements that are entirely inaccessible to Architecture 1 regardless of the precision of its single receiver. For example, a foot-mounted receiver would provide a direct observability of foot trajectories, step lengths, stride lengths, step widths. Similarly, the step from Architecture 2 to Architecture 3 is a shift in the functional role of GNSS within the pipeline: from a corrective input to an inertial system, to a primary positional instrument in an inverse kinematics solver. Each architecture therefore represents a distinct biomechanical capability level.

The scope of the present thesis is defined by Architectures 2 and 3, with an important asymmetry in how each is evaluated. Architecture 1, while conceptually valid and practically straightfor-

ward, has been partially addressed in the commercial domain, albeit at code-based positioning precision that falls well short of the centimeter-level accuracy achievable through carrier-phase post-processing techniques. The contribution of Architecture 1 at carrier-phase precision levels, while not without interest, is less compelling as a research contribution than Architectures 2 and 3, neither of which has been explored at this level of positioning accuracy in the existing literature. Architecture 1 is therefore not the subject of a dedicated experimental study in this thesis, though its premise is incidentally supported by the torso-receiver behaviour observed in the multi-device campaigns of Chapters 6 and 7. Architecture 2 is implemented and rigorously validated in Chapters 5 and 6, where its ability to reconstruct absolute foot trajectories and derive spatiotemporal parameters is demonstrated under realistic outdoor conditions, together with the operating envelope within which the parameters hold. Architecture 3 is presented as a proof of concept in Chapter 7, where GNSS receiver positions are used as virtual markers in an inverse kinematics solver, combined with IMU-derived orientations, to reconstruct body segment kinematics in a globally referenced frame; the three-device configuration used in that chapter demonstrates the pipeline’s feasibility without yet delivering a fully constrained kinematic validation.

4.6 Conclusion

This chapter has proposed a conceptual framework for integrating GNSS technology into portable human motion capture pipelines. The framework is organized at two levels. The first level identifies three distinct functional roles that GNSS can play in outdoor motion analysis: global translational referencing, inertial drift mitigation, and spatial grounding for mobile vision-based systems, each corresponding to an observational capability that is unavailable from inertial or markerless sensing alone. The second level operationalizes these roles into three concrete integration architectures of increasing complexity and biomechanical scope, ranging from a single receiver providing global body translation to a multi-receiver configuration in which GNSS positions serve as virtual markers in an inverse kinematics solver.

The three architectures represent qualitatively distinct capabilities. Architecture 1 extends inertial motion capture to a globally referenced coordinate frame but leaves segment-level estimation entirely to the inertial system. Architecture 2 introduces absolute positioning at the segment level, enabling the reconstruction of body part trajectories and the derivation of parameters that are inaccessible to any inertial-only approach. Architecture 3 reframes the role of GNSS entirely, treating receivers as primary positional instruments in a kinematic reconstruction pipeline and enabling motion capture in a globally referenced frame.

The experimental contributions of this thesis are grounded in Architectures 2 and 3, which represent genuinely unexplored territory at carrier-phase positioning precision, and are evaluated at asymmetric levels of depth. Architecture 2 is characterised through two experimental cam-

paings that establish its operating envelope and the mechanisms limiting it. Architecture 3 is presented as a proof of concept whose principal purpose is to demonstrate the general viability of the pipeline. Architecture 1 is not the subject of a dedicated experimental study, though its premise is incidentally supported by the torso-receiver behaviour observed throughout the multi-device campaigns; while conceptually straightforward and partially realized in commercial products, to the author’s knowledge, it has not seen any adoption in the peer-reviewed literature at carrier-phase precision despite its availability. One plausible contributing factor is the technical complexity of advanced GNSS data processing, which requires expertise in geodesy and satellite navigation that falls outside the typical background of biomechanics and rehabilitation researchers. This barrier to adoption is not unique to Architecture 1, it applies to all three architectures, and that motivates both the methodological care taken in the experimental chapters of this thesis and the automated processing pipeline presented in Chapter 7, which is designed in part to lower this barrier for future users.

It is hoped that the conceptual framework presented in this chapter: the taxonomy of roles and the three integration architectures, will serve as a useful reference for researchers working at the intersection of GNSS positioning and human motion analysis. The design space defined here is not exhausted by the configurations explored in this thesis: different receiver placements, body segment selections, and processing strategies are all conceivable within the same architectural logic, and it is intended that the framework provides a structured basis for future work in this area. The experimental validation of Architectures 2 and 3 begins in Chapter 5, where the implementation of per-segment GNSS/IMU integration is described and its performance characterized under controlled outdoor conditions.

Chapter 5

Foot Trajectory Reconstruction and Spatiotemporal Gait Parameter Estimation

5.1 Introduction and Motivation

GNSS receivers co-located with inertial measurement units on segments of biomechanical interest enable, in principle, the reconstruction of absolute segment trajectories in a globally referenced frame, with simultaneous correction of inertial drift at the segment level¹. The present chapter investigates whether these capabilities are realizable in practice.

The specific question addressed here is whether a body-mounted GNSS/IMU device can reconstruct the trajectory of a foot during walking with sufficient accuracy to derive spatiotemporal gait parameters. Foot trajectory reconstruction represents a concrete and accessible first target: the motion is repetitive and well-structured, and the output parameters of interest, namely step length, step width, and stride length, are directly interpretable in a clinical and biomechanical context. Demonstrating feasibility at this level is a necessary precondition for the more demanding extensions pursued in Chapters 6 and 7.

To address this question, three elements are brought together. The first is a wearable prototype device developed within the REMOT project, which concluded in 2023, integrating a dual-frequency GNSS receiver and an IMU in a single wearable casing. The second is a loosely-coupled GNSS/INS integration algorithm augmented with zero-velocity updates, adapted from the pedestrian navigation literature and applied here to foot trajectory reconstruction. The third is a controlled outdoor walking experiment with a single subject at three walking speeds, providing a dataset against which the system's outputs can be assessed.

¹This configuration is formalized within the broader integration framework of this thesis as Architecture 2 (Chapter 4).

This investigation is constituted as a proof of concept: a single subject walking under three different cadence conditions, intended to validate jointly the physical setup, the data processing pipeline, and the algorithmic approach. The aim at this stage is to establish whether the approach is technically feasible. Characterization across populations, longer trajectories, and clinical contexts is out of scope of this chapter, and is addressed in the subsequent chapters.

The chapter is organized as follows. Section 5.2 describes the wearable hardware, the integration algorithm, and the experimental setup. Section 5.3 presents the results. Section 5.4 discusses the findings and states the limitations that motivate the subsequent chapters. Section 5.5 concludes the chapter.

5.2 Materials and Methods

5.2.1 Hardware: the REMOT Device

The experiments presented in this chapter were conducted using the REMOT device, a wearable GNSS/IMU unit developed by Stonex s.r.l. within the REMOT project as a purpose-built platform for outdoor human motion analysis. The device integrates a u-blox ZED-F9P dual-frequency GNSS receiver [96], a Harxon HX-CH7018A helical antenna [97], an Xsens MTi-7 IMU [98], an STM32 microcontroller for data acquisition, a microSD card for local data storage, and a Li-Po battery, all enclosed in a single housing measuring $5 \times 5 \times 6.5$ cm and weighing 75 g. For the experiments, the GNSS receiver is set up to operate at 10 Hz and the IMU at 100 Hz, with time synchronization between the two achieved through the GNSS receiver's time signal, providing a common temporal reference for all recorded data.

The design of the device was guided by two principal requirements: wearability and signal quality. Wearability is a non-trivial constraint in this application. The early high-precision GNSS experiments reviewed in Chapter 3, notably the work of Terrier et al. [71, 72, 73] and the systems used in alpine skiing biomechanics [77, 90], relied on professional-grade receivers and antennas whose combined weight and volume were incompatible with natural human movement. Achieving anatomically credible centimeter-level positioning with a foot-mounted device requires that the sensor does not significantly alter the natural kinematics of the movement being measured. At 75 g, the REMOT device is light enough to be worn on the foot without introducing visible gait modification, as verified through video review of the walking trials. The GoPro-style mounting system allows the device to be attached to different body locations (feet, head, or other segments) using interchangeable straps and clamps, providing flexibility for multi-segment configurations.

Signal quality is the second critical requirement. A foot-mounted receiver operates under challenging acquisition conditions: the antenna is close to the ground, subject to impulsive dynamics at heel strike and toe-off, and periodically oriented away from the sky throughout gait phases.

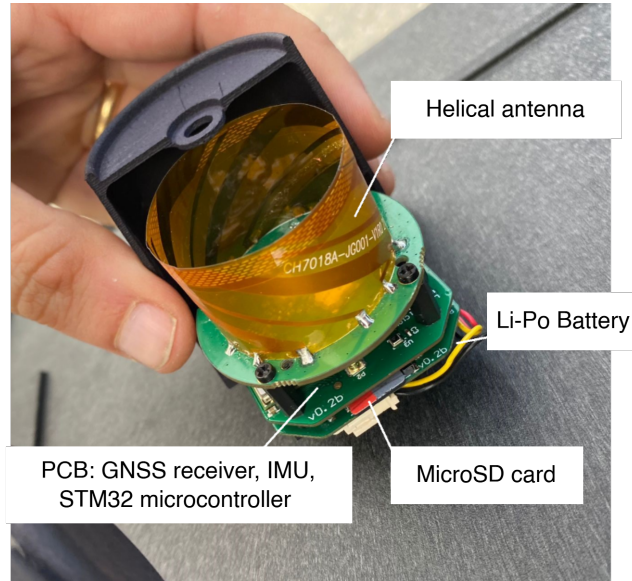


Figure 5.1: The REMOT device shown with the casing opened, exposing its integrated components.

These conditions motivate the use of a helical antenna, whose azimuthally symmetric gain pattern and relatively compact form factor make it better suited to body-worn configurations than the large ground-plane patch antennas typical of geodetic equipment. The ZED-F9P receiver supports simultaneous multi-constellation, dual-frequency tracking, which increases the number of available observations and improves the robustness of carrier-phase ambiguity resolution. Both properties are particularly valuable when individual satellite signals are intermittently degraded by the foot dynamics discussed in Section 5.3.

A further consequence of integrating the antenna and IMU within the same rigid housing is the reduction of the lever arm between the GNSS antenna phase center and the IMU origin to approximately 2 cm. This is significant for the integration algorithm: when the antenna and IMU are mounted on different body segments or at distant locations, the lever arm correction requires precise knowledge of the device orientation and introduces additional uncertainty into the position estimate referred to the IMU origin. At 2 cm, this correction becomes practically negligible, though it is nonetheless accounted for in the integration algorithm described in Section 5.2.2. This property is what makes segment-level trajectory reconstruction possible: the GNSS position estimate refers directly to the IMU location, avoiding the lever-arm uncertainty that would arise from a distant or variably oriented antenna.

5.2.2 ZUPT-Aided Loosely-Coupled GNSS/INS Integration

5.2.2.1 State Vector and Process Model

The integration algorithm is formulated as an extended Kalman filter (EKF) operating in the local East-North-Up (ENU) frame, with origin at the antenna phase center of the base GNSS station. The state vector is defined as

$$\mathbf{x} = \begin{bmatrix} \mathbf{p} \\ \mathbf{v} \\ \mathbf{q} \\ \mathbf{b}_g \end{bmatrix} \in \mathbb{R}^{13}, \quad (5.1)$$

where $\mathbf{p} \in \mathbb{R}^3$ is the position of the IMU origin in the ENU frame, $\mathbf{v} \in \mathbb{R}^3$ is the velocity in the ENU frame, $\mathbf{q} \in \mathbb{R}^4$ is the unit quaternion representing the rotation from the IMU frame to the ENU frame, and $\mathbf{b}_g \in \mathbb{R}^3$ is the gyroscope bias.

The process model implements standard INS mechanization equations [101]. At each IMU epoch, the state is propagated forward in time by integrating the inertial measurements. Denoting the gyroscope measurement as $\boldsymbol{\omega}_m$ and the accelerometer specific force as $\mathbf{f}_m$, the discrete-time propagation equations are

$$\mathbf{p}_{k+1} = \mathbf{p}_k + \mathbf{v}_k \Delta t, \quad (5.2)$$

$$\mathbf{v}_{k+1} = \mathbf{v}_k + (R(\mathbf{q}_k) \mathbf{f}_m + \mathbf{g}) \Delta t, \quad (5.3)$$

$$\mathbf{q}_{k+1} = \mathbf{q}_k + \frac{1}{2} \boldsymbol{\Omega}(\boldsymbol{\omega}_m + \mathbf{b}_{g,k}) \mathbf{q}_k \Delta t, \quad (5.4)$$

$$\mathbf{b}_{g,k+1} = \mathbf{b}_{g,k}, \quad (5.5)$$

where $R(\mathbf{q}) \in SO(3)$ is the rotation matrix from the IMU frame to the ENU frame corresponding to quaternion $\mathbf{q}$, $\mathbf{g} = [0, 0, -9.81]^T$ m/s² is the gravity vector in the ENU frame, $\boldsymbol{\Omega}(\boldsymbol{\omega})$ is the quaternion multiplication matrix constructed from the angular velocity vector, and Δt is the IMU sampling interval. The quaternion is renormalized after each propagation step to prevent numerical drift. The gyroscope bias is modeled as constant between measurement updates. The covariance is propagated through the Jacobian of the process model, computed analytically, and the process noise covariance is constructed via a noise influence matrix [101].

5.2.2.2 Zero-Velocity Detection

During the mid-stance phase of each gait cycle, the foot is momentarily stationary, and this known constraint can be exploited as a pseudo-measurement to bound the growth of inertial drift between GNSS updates. Detecting these zero-velocity intervals reliably is therefore a prerequisite for the integration algorithm. The detector used here is the Stance Hypothesis Optimal

dEctor (SHOE), introduced by Skog et al. [84], which formulates zero-velocity detection as a generalized likelihood ratio test (GLRT) on a sliding window of IMU measurements. The GLRT framing tests the null hypothesis H_0 that the foot is stationary throughout the window against the alternative H_1 that the foot is in motion, based on a single test statistic computed from the gyroscope and accelerometer measurements within the window.

For a window of W samples starting at sample k , the GLRT test statistic is computed as

$$T_k = \frac{1}{W} \sum_{j=k}^{k+W-1} \left(\frac{\|\boldsymbol{\omega}_j\|^2}{\sigma_g^2} + \frac{\|\mathbf{f}_j - g \hat{\mathbf{y}}_a\|^2}{\sigma_a^2} \right), \quad (5.6)$$

where $\boldsymbol{\omega}_j$ and $\mathbf{f}_j$ are the gyroscope and accelerometer measurements at sample j , $\hat{\mathbf{y}}_a = \bar{\mathbf{f}}/\|\bar{\mathbf{f}}\|$ is the unit vector in the direction of the mean accelerometer output over the window, $g = 9.81 \text{ m/s}^2$, and σ_g and σ_a are the gyroscope and accelerometer noise standard deviations respectively. The use of a sliding window of W samples averages out high-frequency noise in the IMU measurements: σ_g and σ_a enter the test statistic as the per-sample normalization, so the test is calibrated against the known sensor noise level, and the window length W controls the trade-off between noise suppression and temporal resolution of stance phase detection.

The statistic T_k is large when the gyroscope output is significant or when the accelerometer output deviates from a pure gravity vector, both of which indicate motion. A zero-velocity condition is declared at sample $k + W/2$ when $T_k < \gamma$, where γ is a manually tuned threshold. Under the GLRT framing introduced above, this corresponds to failing to accept H_0 when the evidence for motion falls below the chosen threshold.

The detector is applied with a window size of $W = 10$ samples, gyroscope noise standard deviation $\sigma_g = 0.1 \cdot \pi/180 \text{ rad/s}$, accelerometer noise standard deviation $\sigma_a = 0.01 \text{ m/s}^2$, and threshold $\gamma = 5 \times 10^5$. The window is centered on each sample by padding the output with zeros at both ends, so that the zero-velocity label is associated with the central sample of each window.

5.2.2.3 Measurement Updates: GNSS, ZUPT, and Magnetometer

The EKF incorporates three distinct sources of external measurement, each correcting a different aspect of the inertial solution: GNSS positions and velocities providing absolute spatial grounding, zero-velocity pseudo-measurements bounding drift during stance phases, and magnetometer readings providing continuous heading correction.

GNSS Position and Velocity. When a PPK solution is available at the current epoch, the baseline vector $\mathbf{p}_{GNSS} \in \mathbb{R}^3$ (the relative position of the rover antenna phase center with respect to the base station, expressed in the ENU frame) is used as a position measurement. Since the GNSS antenna phase center does not coincide with the IMU origin, a lever arm correction is applied

inside the filter: the predicted measurement is computed as

$$\hat{\mathbf{z}}_{pos} = \mathbf{p} + R(\mathbf{q}) \mathbf{l}, \quad (5.7)$$

where $\mathbf{l} \in \mathbb{R}^3$ is the lever arm vector from the IMU origin to the antenna phase center expressed in the IMU frame, and $R(\mathbf{q})$ rotates it into the ENU frame using the current orientation estimate. At approximately 2 cm, this correction is small but is nonetheless applied for consistency. The measurement noise covariance for the position update is taken directly from the position standard deviations exported by RTKLIB at each epoch, reflecting the solution quality at that specific instant.

When ZUPT is not active, the GNSS velocity estimate $\mathbf{v}_{GNSS}$ is additionally used as a velocity measurement, with the predicted measurement $\hat{\mathbf{z}}_{vel} = \mathbf{v}$ and noise covariance again taken from the RTKLIB output.

Zero-Velocity Update. When a zero-velocity condition is detected by the SHOE detector, a ZUPT pseudo-measurement is applied:

$$\mathbf{z}_{vel} = \mathbf{0}_3, \quad (5.8)$$

with predicted measurement $\hat{\mathbf{z}}_{vel} = \mathbf{v}$ and measurement noise covariance $\sigma_{zupt}^2 \mathbf{I}_3$, where σ_{zupt} is a manually tuned parameter reflecting the confidence in the zero-velocity assumption. The resulting innovation $-\mathbf{v}$ drives the velocity estimate toward zero. When a GNSS position update and a ZUPT update coincide at the same epoch, both are applied simultaneously: the position is corrected by the GNSS measurement while the velocity is reset to zero. The ZUPT measurement takes precedence over the GNSS velocity estimate at coincident epochs.

Magnetometer. A magnetometer-based heading correction is applied at every IMU epoch, regardless of GNSS availability or ZUPT status. The predicted measurement is the normalized reference magnetic field vector $\mathbf{m}_{ref}$ rotated from the ENU frame into the current IMU frame:

$$\hat{\mathbf{z}}_{mag} = R(\mathbf{q})^T \mathbf{m}_{ref}, \quad (5.9)$$

and the actual measurement is the normalized magnetometer reading $\hat{\mathbf{m}} = \mathbf{m}/\|\mathbf{m}\|$. The reference vector $\mathbf{m}_{ref}$ is obtained from the World Magnetic Model (WMM), evaluated at the initial receiver position and the date of the recording using the `pygeomag` library. The WMM output, provided in the North-East-Down convention, is converted to the ENU frame by reordering its components and negating the vertical component. The measurement noise covariance is set to $\sigma_{mag}^2 \mathbf{I}_3$, where σ_{mag} is a manually tuned parameter.

5.2.2.4 Measurement Scheduling and Update Logic

At each IMU epoch, the filter determines which combination of measurements is available and applies the corresponding update. The logic is governed by two conditions: whether a PPK

solution from RTKLIB is available at the current epoch, and whether the SHOE detector has declared a zero-velocity condition. GNSS availability is determined by timestamp matching: a PPK solution is considered coincident with the current IMU epoch if the absolute time difference between the two is less than 5 ms. The four resulting update cases are summarized in Table 5.1.

Table 5.1: Measurement update cases as a function of GNSS availability and zero-velocity detection.

GNSS available	ZUPT active	Measurement vector $\mathbf{z}$	Velocity source
Yes	Yes	$[\mathbf{p}_{GNSS}, \mathbf{0}_3, \hat{\mathbf{m}}]$	ZUPT
Yes	No	$[\mathbf{p}_{GNSS}, \mathbf{v}_{GNSS}, \hat{\mathbf{m}}]$	GNSS
No	Yes	$[\mathbf{0}_3, \hat{\mathbf{m}}]$	ZUPT
No	No	$[\hat{\mathbf{m}}]$	—

In all four cases the normalized magnetometer reading $\hat{\mathbf{m}}$ is included as a measurement, providing continuous heading correction regardless of GNSS availability or gait phase. When neither GNSS nor ZUPT is active, a condition that occurs during the swing phase in the absence of a valid PPK solution, the filter propagates on inertial measurements alone, with only the magnetometer constraining the orientation estimate.

The full per-epoch update logic is summarized in Algorithm 1. All per-epoch operations consist of fixed-size matrix operations on a 13-dimensional state, and their computational cost is independent of recording duration. The algorithm is therefore time-deterministic, with constant work per epoch, and is amenable to real-time implementation on embedded hardware such as a Raspberry Pi or comparable platform, although such implementation is not pursued in this thesis.

5.2.2.5 RTS Smoothing

The forward EKF pass described in the preceding subsections produces state estimates conditioned on all measurements up to and including the current epoch. While this is sufficient for real-time applications, it does not make use of future measurements when estimating the state at any given instant. In a post-processing context, where the full recording is available before any output is produced, a backward smoothing pass can be applied to incorporate information from the entire trajectory into each state estimate, typically resulting in a smoother and more accurate solution.

The Rauch-Tung-Striebel (RTS) smoother [102] is applied here as a single backward pass over the full recording after the forward EKF pass is complete. Starting from the final forward estimate, the smoother iterates backward through the sequence of stored forward means and covariances, computing smoothed estimates for all state variables (position, velocity, quaternion, and gyroscope bias) at each epoch. The smoothed estimates are conditioned on the full set of measurements from the entire recording. The practical effect is a reduction in trajectory noise,

Algorithm 1 ZUPT-Aided Loosely-Coupled GNSS/INS Integration

```
1: Initialize state  $\mathbf{x}_0$  and covariance  $\mathbf{P}_0$ 
2: for each IMU epoch  $k$  do
3:   Predict state  $\mathbf{x}_k$  via INS mechanization from  $(\boldsymbol{\omega}_m, \mathbf{f}_m, \Delta t)$ 
4:   Predict covariance  $\mathbf{P}_k$  through the process model Jacobian
5:   Renormalize quaternion  $\mathbf{q}_k$ 
6:   Compute SHOE test statistic  $T_k$  over the IMU window centered at  $k$ 
7:    $\text{zupt} \leftarrow (T_k < \gamma)$ 
8:    $\text{gnss} \leftarrow$  PPK solution available within  $\pm 5$  ms of epoch  $k$ 
9:   if  $\text{gnss}$  and  $\text{zupt}$  then
10:    Apply position update from  $\mathbf{p}_{GNSS}$ 
11:    Apply velocity update to  $\mathbf{0}_3$  (ZUPT)
12:   else if  $\text{gnss}$  and not  $\text{zupt}$  then
13:    Apply position update from  $\mathbf{p}_{GNSS}$ 
14:    Apply velocity update from  $\mathbf{v}_{GNSS}$ 
15:   else if  $\text{zupt}$  and not  $\text{gnss}$  then
16:    Apply velocity update to  $\mathbf{0}_3$  (ZUPT)
17:   end if
18:   Apply magnetometer heading update with  $\hat{\mathbf{m}} = \mathbf{m}/\|\mathbf{m}\|$ 
19:   Store forward mean  $\mathbf{x}_k$  and covariance  $\mathbf{P}_k$ 
20: end for
21: Apply RTS smoother backward pass over the stored sequence
22: return Smoothed state trajectory  $\{\mathbf{x}_k^s\}$ 
```

removal of estimate discontinuities (jumps), and a more consistent reconstruction of foot position during the swing phase, where GNSS updates may be sparse or absent and the forward filter relies primarily on inertial propagation. The improvement introduced by RTS smoothing relative to the forward-only solution is illustrated in Section 5.3.

Beyond the EKF and RTS smoother approach adopted here, alternative orientation estimators based on gradient-descent optimization over gyroscope and accelerometer signals are widely used in inertial motion analysis. The Madgwick filter [23, 24] is among the most prominent of these: it provides a robust orientation estimate at low computational cost, although it is deterministic and does not propagate a state covariance. In the present chapter, the Madgwick filter is used in an auxiliary preprocessing role for the acceleration analysis presented in Section 5.3.1, where the gravity component is subtracted from the raw accelerometer signal to compute the linear acceleration magnitude used in the comparison between head and foot dynamics.

5.2.3 Experimental Setup

5.2.3.1 Testing Environment

The experiments were conducted at the Giardini Govi, a public park located along the seafront in Genoa, Italy. The site was selected for its favorable GNSS acquisition conditions: the open coastal setting provides unobstructed sky visibility in all directions, with no tall buildings or dense vegetation in the immediate surroundings that could cause signal blockage or multipath. These conditions were considered important for a proof-of-concept experiment, where the goal was to assess the fundamental feasibility of the approach in the absence of environmental confounders.

Differential GNSS processing requires a reference base station at a known position. For this purpose, a professional-grade GNSS base station permanently installed on the roof of Gter s.r.l., a geomatics company co-funding this PhD project, was used. The straight-line distance between the base station and the recording site is approximately 1.5 km, which is well within the baseline length over which carrier-phase differential corrections remain highly effective.

5.2.3.2 Ground Truth Definition

Obtaining a reliable ground truth for foot trajectories in an outdoor environment presents a fundamental challenge. Laboratory-grade optical motion capture systems, which would provide the most accurate reference, are confined to bounded instrumented volumes and could not be deployed over the length of a walking path. No portable alternative capable of providing continuous foot trajectory ground truth with centimeter-level accuracy was available for this experiment.

Given these constraints, an indirect ground truth strategy was adopted. A straight walking path

was defined on the ground surface, and a series of duct tape stripes were placed at regular intervals of 70 cm along its length, defining the target foot contact points. The subject was instructed to step on the stripes during each walking trial, so that the expected step length between consecutive contact points of alternating feet, and stride length between consecutive contact points of the same foot, were both determined by the stripe spacing. This approach allows the derived spatio-temporal gait parameters to be assessed against a known reference, but it does not provide a ground truth for the continuous foot trajectory between contact points.

It should be noted that the accuracy of this reference depends on how precisely the subject steps on each stripe, a requirement that becomes increasingly difficult to satisfy at higher walking speeds. The ground truth should therefore be understood as an approximate reference, particularly for the faster walking conditions.

5.2.3.3 Experimental Protocol

Three REMOT devices were used simultaneously: one mounted on the left foot, one on the right foot, and one on the head. The foot-mounted devices are the primary instruments for trajectory reconstruction and gait parameter estimation. The head-mounted device serves a secondary purpose: since the head undergoes significantly lower dynamic accelerations than the feet during walking, comparing the GNSS signal and solution quality between the head and foot receivers provides a direct illustration of the effect of foot dynamics on carrier-phase acquisition, with the head receiver acting as an on-body reference under more favorable conditions. The wearable configuration and the marker-defined walking path are shown in Figure 5.2.

Five recording sequences were collected, each comprising three walking trials at speeds of 60, 90, and 120 steps per minute, corresponding to slow, normal, and fast walking respectively. The walking speed was regulated by the subject using a handheld metronome smartphone application. All sequences were recorded along the same straight path defined by the duct tape markers. Results are presented for a single representative recording, selected on the basis of GNSS solution quality, with the remaining sequences serving as supporting evidence for the consistency of the observations.

5.3 Results

5.3.1 Raw GNSS Observation Quality Across Walking Speeds

A key hypothesis underlying the use of foot-mounted GNSS receivers for motion capture is that the mechanical dynamics of the gait cycle adversely affect carrier-phase signal acquisition. To investigate this, the raw GNSS observation quality of the foot-mounted receiver is analysed

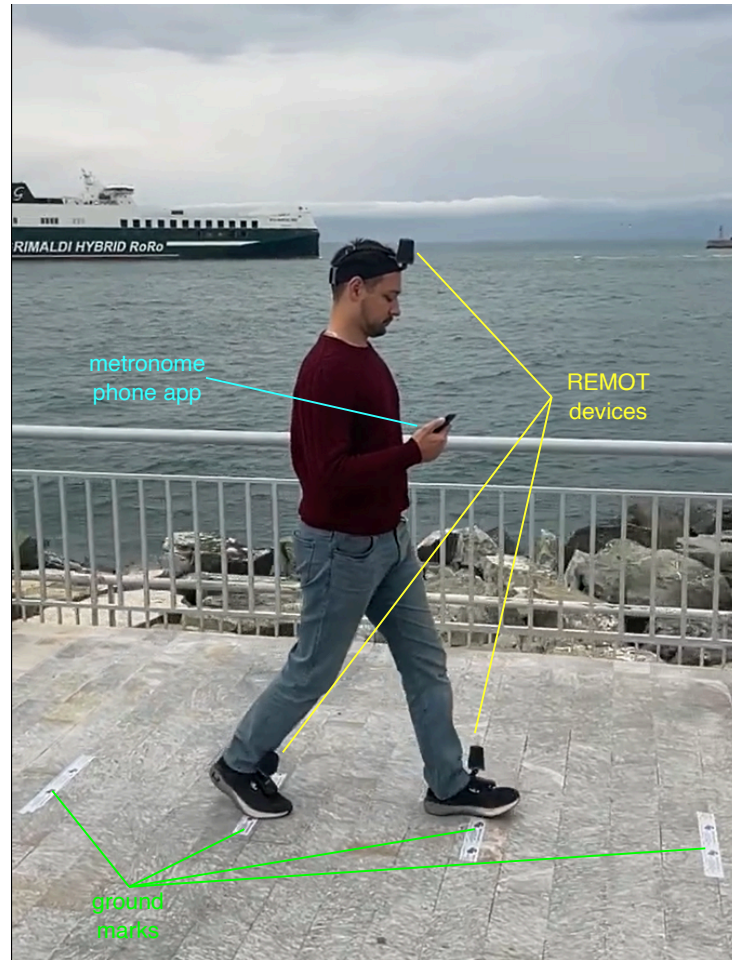


Figure 5.2: Experimental setup: subject walking along the ground-mark-defined path with REMOT devices mounted on the head and both feet. Duct-tape stripes spaced 70 cm apart define the target foot-contact points used as a discrete spatial reference.

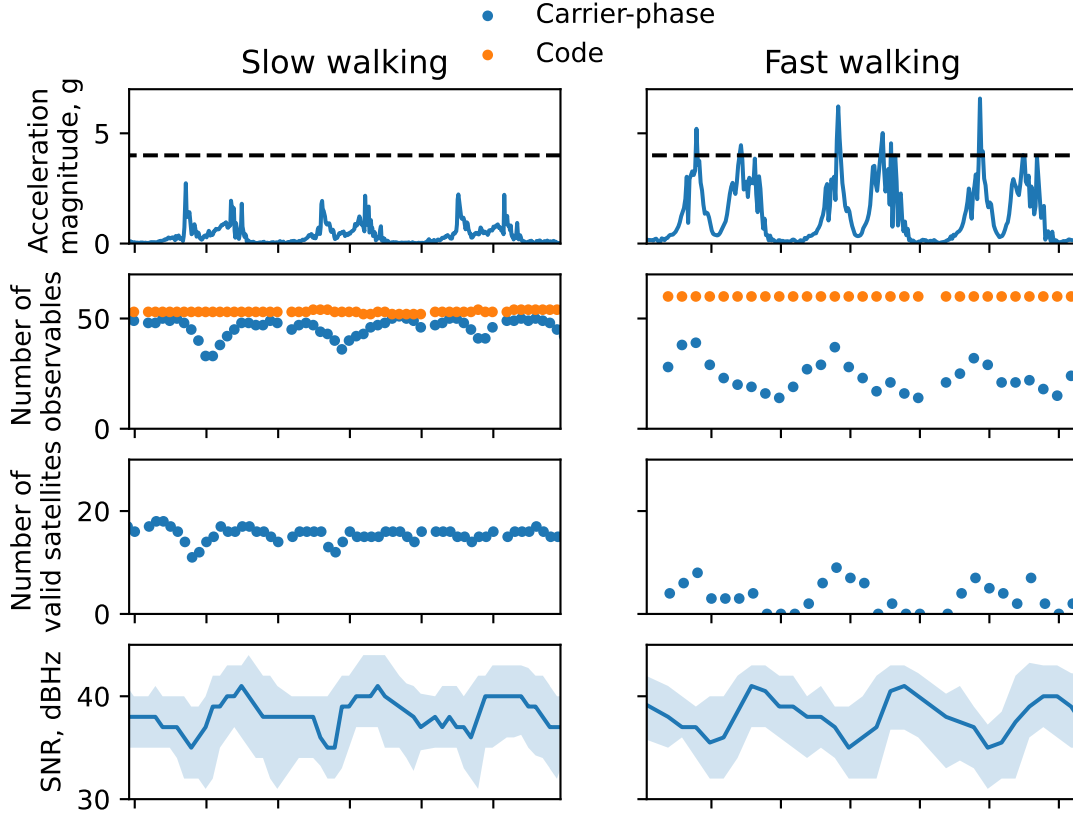


Figure 5.3: Raw GNSS observation quality for the foot-mounted receiver at slow (60 steps/min, left column) and fast (120 steps/min, right column) walking speeds. From top to bottom: acceleration magnitude with the 4 g receiver dynamic limit indicated by the dashed line; number of carrier-phase and code observables in the RINEX file; number of valid satellites in the RTK-LIB PPK solution, defined as satellites with valid carrier-phase observations used for ambiguity resolution; median SNR with interquartile range computed across all tracked carrier-phase observables.

across walking speeds and compared against the head-mounted receiver, which experiences substantially lower accelerations during locomotion and therefore serves as an on-body reference under more favourable dynamic conditions. The following analysis characterises the relationship between foot acceleration, carrier-phase observable count, and the quality of the resulting PPK solution, providing an empirical basis for understanding the speed-dependent degradation of trajectory reconstruction accuracy observed in Section 5.3.3.

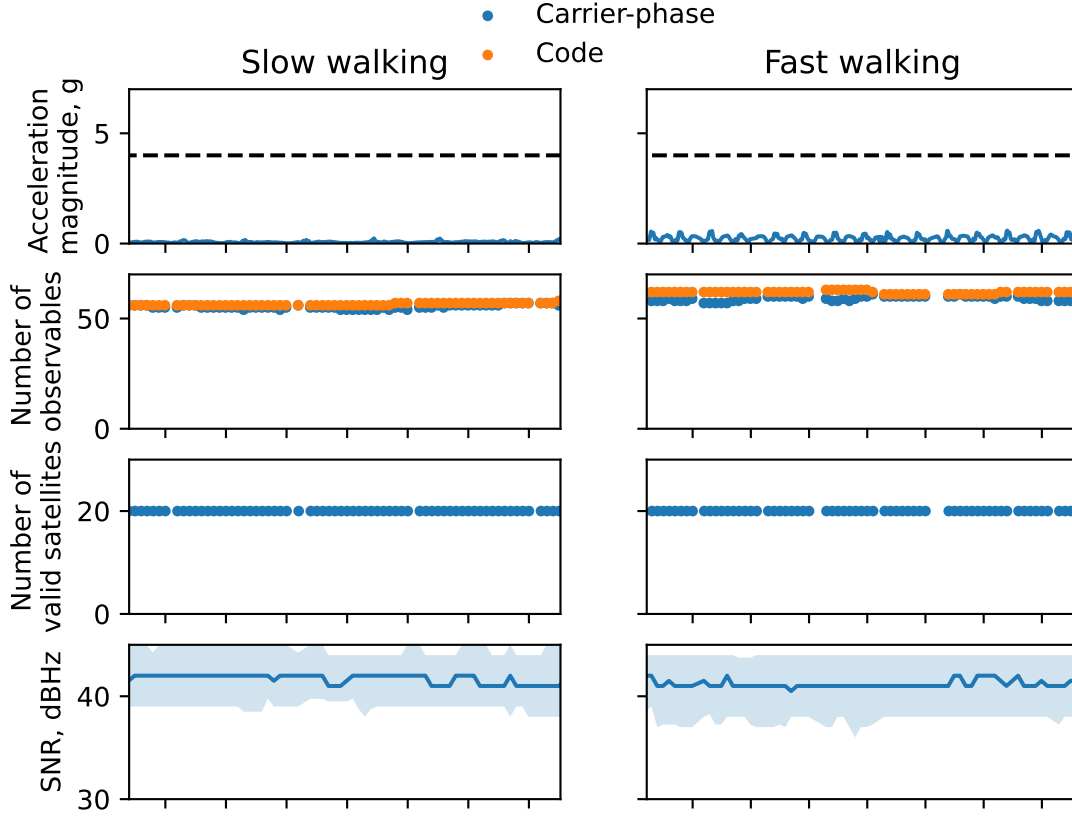


Figure 5.4: Raw GNSS observation quality for the head-mounted receiver at slow (60 steps/min, left column) and fast (120 steps/min, right column) walking speeds, recorded simultaneously with the foot-mounted data shown in Figure 5.3. Panel layout is identical. The head receiver experiences negligible dynamic accelerations at both speeds, and its carrier-phase observable count, valid satellite count, and SNR remain stable and largely unaffected by walking speed, in contrast to the foot-mounted receiver.

The acceleration magnitude is computed from the IMU specific force after subtracting the gravity component, which is estimated using a Madgwick filter applied to the raw IMU data as a preprocessing step, as discussed in Section 5.2.2.5.

The number of observables refers to the count of code and carrier-phase measurements present in the RINEX file at each epoch: since the ZED-F9P tracks signals on two frequency bands, each satellite contributes up to two code observables and two carrier-phase observables, so the maximum observable count is approximately twice the number of tracked satellites. The number

of valid satellites refers to the satellites whose carrier-phase observations are used by RTKLIB for ambiguity resolution in the PPK solution; when this count falls below four, an independent three-dimensional carrier-phase solution cannot be formed and RTKLIB falls back to a code-only positioning solution.

The acceleration profile of the foot exhibits a characteristic double-peak structure within each stride, reflecting the two principal dynamic events of the gait cycle: the first peak corresponds to toe-off, when the foot accelerates abruptly from its stationary stance position into the swing phase, and the second to heel strike, when the swinging foot decelerates abruptly upon ground contact. Both events are present at all walking speeds, though their magnitude increases substantially with speed.

Figure 5.3 shows the foot-mounted receiver data. At slow walking (60 steps/min), acceleration remains largely below the 4 g receiver dynamic limit. The carrier-phase observable count remains relatively stable, the number of valid satellites is consistently between 10 and 20, and the mean SNR is stable with moderate interquartile spread. The code observable count remains nearly constant throughout, confirming that code tracking is robust to the foot dynamics at slow walking speeds and that the degradation is specific to the carrier-phase observables. At fast walking (120 steps/min), the acceleration repeatedly and substantially exceeds the 4 g limit during both toe-off and heel-strike events, with peaks reaching approximately 6 g. The carrier-phase observable count drops sharply in direct correspondence with each acceleration peak, while the code observable count remains unaffected. Although partial recovery occurs during each stance phase, the interval between successive acceleration peaks is insufficient for full reacquisition, and the number of valid satellites consequently falls to zero at multiple epochs, indicating that only a code-based position estimate is available at those instants. Notably, the mean SNR of the surviving carrier-phase observables does not decrease during these episodes. On the contrary, it tends to increase slightly when the observable count is lowest. This counterintuitive behaviour is consistent with selective signal loss: the impulsive dynamics preferentially disrupt the tracking of weaker signals, leaving a reduced subset of stronger observations that is nonetheless insufficient to support reliable integer ambiguity resolution. The consequence is a positioning solution that is intermittent and geometrically underdetermined, despite the apparently adequate quality of the surviving individual signals.

Figure 5.4 shows the simultaneously recorded head-mounted receiver data. The head acceleration remains well below the 4 g limit at both walking speeds, reflecting the substantially lower dynamic environment experienced by a receiver mounted high on the body. Correspondingly, the carrier-phase observable count, valid satellite count, and SNR are stable and largely identical between slow and fast walking conditions. This contrast with the foot-mounted receiver confirms that the signal degradation observed in Figure 5.3 is a consequence of the foot dynamic environment specifically, unrelated to the recording conditions such as sky visibility or satellite geometry.

5.3.2 PPK Solution Quality Across Walking Speeds

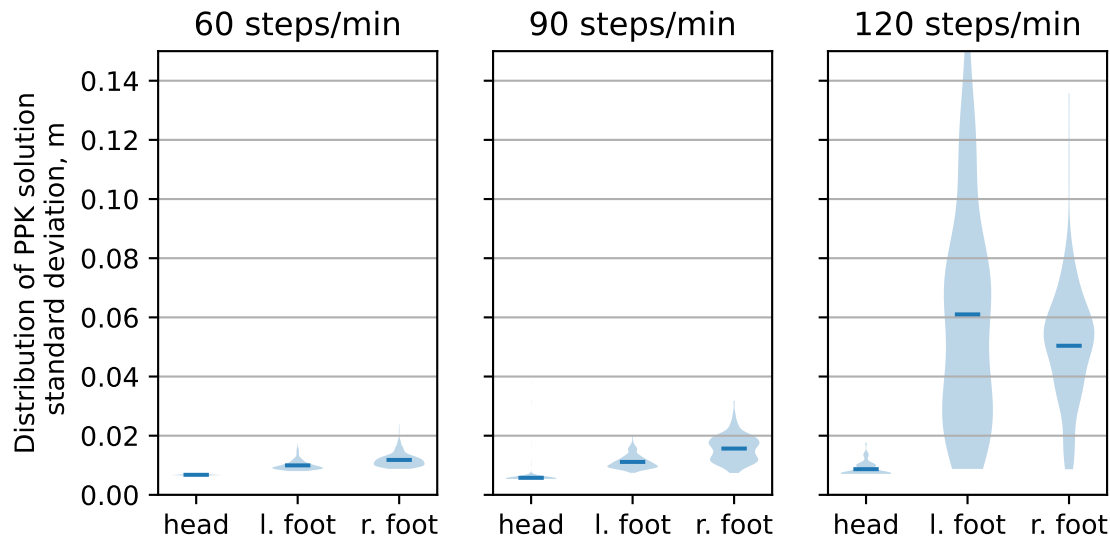


Figure 5.5: Distribution of the RTKLIB PPK position standard deviation for the head, left foot, and right foot receivers across three walking speeds, for a representative recording. The quantity plotted is the square root of the trace of the position covariance matrix exported by RTKLIB at each epoch. The dark blue horizontal bars indicate the mean. Note that RTKLIB-reported standard deviations tend to be optimistic and should be interpreted as relative indicators of solution quality. They should not be treated as absolute uncertainty estimates.

Figure 5.5 shows the distribution of the PPK position standard deviation, computed as the square root of the trace of the covariance matrix exported by RTKLIB, for all three receivers across the three walking speeds, with the static portions of each recording excluded. It should be noted that RTKLIB-reported covariances are known to be optimistic: in practice, position outliers of several tens of centimeters or more can occur while the reported standard deviation remains on the order of 10–20 cm, so these values are best interpreted as relative indicators of solution quality.

With this caveat in mind, the figure reveals a clear speed-dependent pattern. The head receiver maintains a tight distribution across all speeds, with mean standard deviation around 0.01 m, reflecting the stable dynamic environment experienced at that body location regardless of walking pace. The foot receivers show a different pattern: at 60 steps/min their distributions are compact and low, broadly comparable to the head; at 90 steps/min they broaden noticeably; and at 120 steps/min they spread substantially, with upper tails extending well beyond 0.10 m. This progression mirrors the carrier-phase observable loss documented in Section 5.3.1: as impulsive accelerations cause selective dropout of phase-locked satellites, the remaining constellation

becomes geometrically impoverished, ambiguity resolution degrades, and the reported solution uncertainty grows accordingly. The left and right foot receivers behave consistently with each other across all speeds, pointing to the shared foot dynamic environment as the primary driver and not to any device-specific factor, though minor differences in acquisition quality between the two units were occasionally observed. Trial-to-trial variability across the four recorded sequences was present, but the speed-dependent trend shown here is qualitatively consistent across recordings.

5.3.3 Foot Trajectory Reconstruction

Figure 5.6 shows the EKF-smoothed trajectories of the left foot, right foot, and head receivers for a representative slow walking sequence. In the ground plot, all three trajectories follow a straight line, consistent with the controlled walking path. The foot trajectories exhibit a characteristic sharp pattern at contact points, reflecting the abrupt change in horizontal velocity direction between heel strike and toe-off. The head trajectory shows a subtle lateral oscillation, with the head moving slightly toward the stance foot at each step, which is consistent with normal human walking mechanics. In the horizontal time series, the foot trajectories exhibit a staircase pattern in which stance intervals, where the foot is stationary, alternate with swing intervals, where the foot advances to the next contact point. The two feet alternate in this pattern, as expected. The head trajectory, by contrast, advances gradually and nearly linearly, reflecting the approximately constant forward velocity of the head during straight-line walking. The vertical component shows the two feet at approximately the same height and the head consistently above them, as expected. In the zoomed view, however, a constant vertical offset of approximately 5 cm between the two foot trajectories is apparent. This discrepancy likely reflects the accumulation of independent estimation errors in the two separate EKF pipelines, and not a true difference in foot height. It should also be noted that the GNSS antenna phase center is located approximately 10 cm above the geometric center of the foot, so the trajectories shown represent the motion of the device and not of the foot contact point itself.

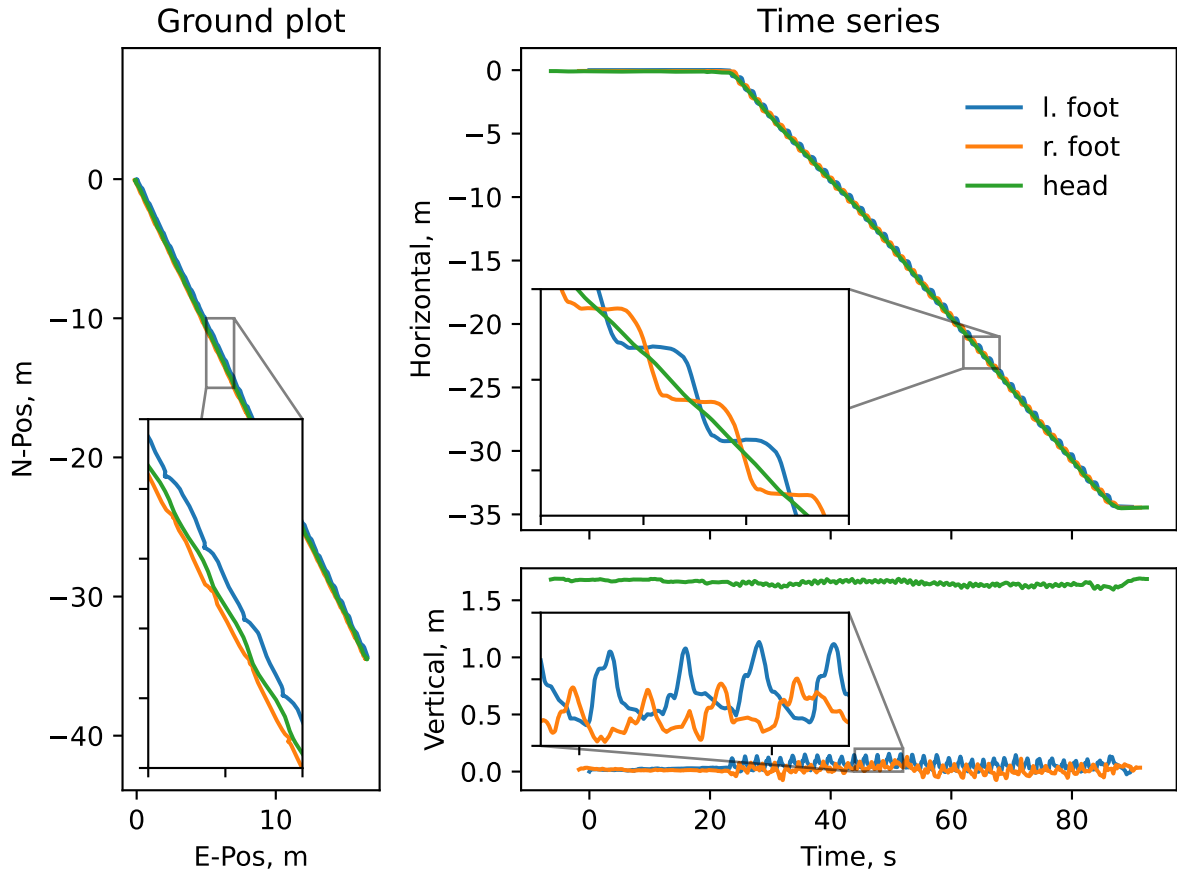


Figure 5.6: EKF-smoothed trajectories of the left foot, right foot, and head receivers for a representative slow walking sequence (60 steps/min). Left: ground plot in the East-North plane. Right: horizontal (along-track) and vertical position time series. Insets show zoomed views of selected portions of each panel.

Figure 5.7 shows the EKF position and velocity estimates for the left foot alongside the raw GNSS PPK corrections, for the same recording. The EKF position closely follows the GNSS points in the horizontal components, where the PPK solution is most reliable. In the vertical component, the EKF-estimated standard deviation, shown as a shaded envelope, is visible at the scale of the plot, reflecting the higher uncertainty of GNSS positioning in the vertical direction, which is regular for GNSS. A characteristic pattern is visible in the vertical component: the uncertainty envelope grows in the absence of GNSS corrections and contracts when a new correction becomes available, consistent with the filter's alternation between inertial propagation and GNSS update phases. In the velocity panels, the effect of zero-velocity updates is clearly evident: while the velocity estimates generally follow the GNSS-derived velocities during swing phases, they are periodically and abruptly reset to zero at detected stance phases, regardless of any GNSS velocity estimate available at those instants.

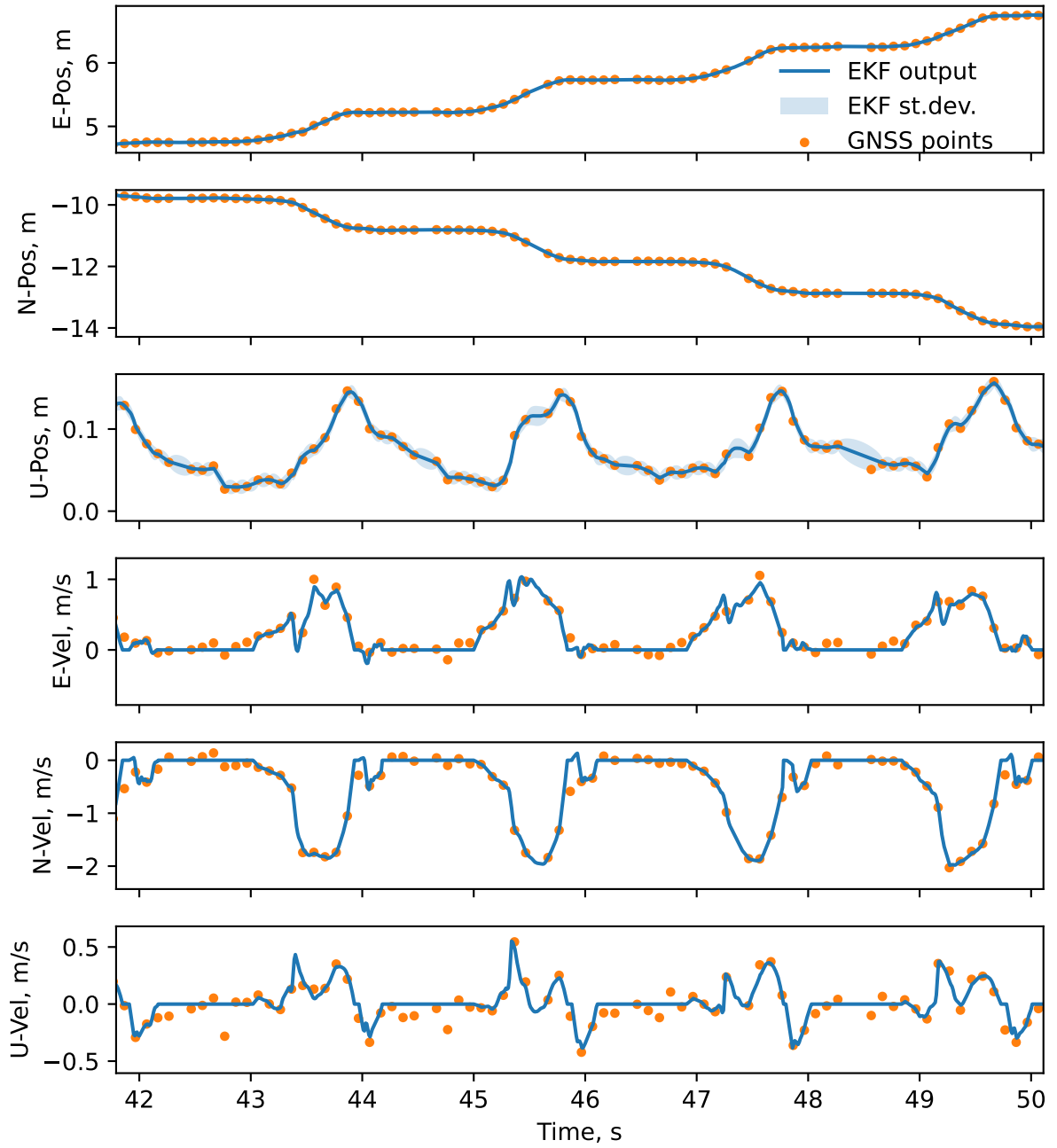


Figure 5.7: EKF position and velocity estimates for the left foot receiver during a representative slow walking sequence, shown alongside the raw GNSS PPK corrections. The shaded region represents the EKF-estimated position standard deviation. GNSS PPK points are shown as orange dots.

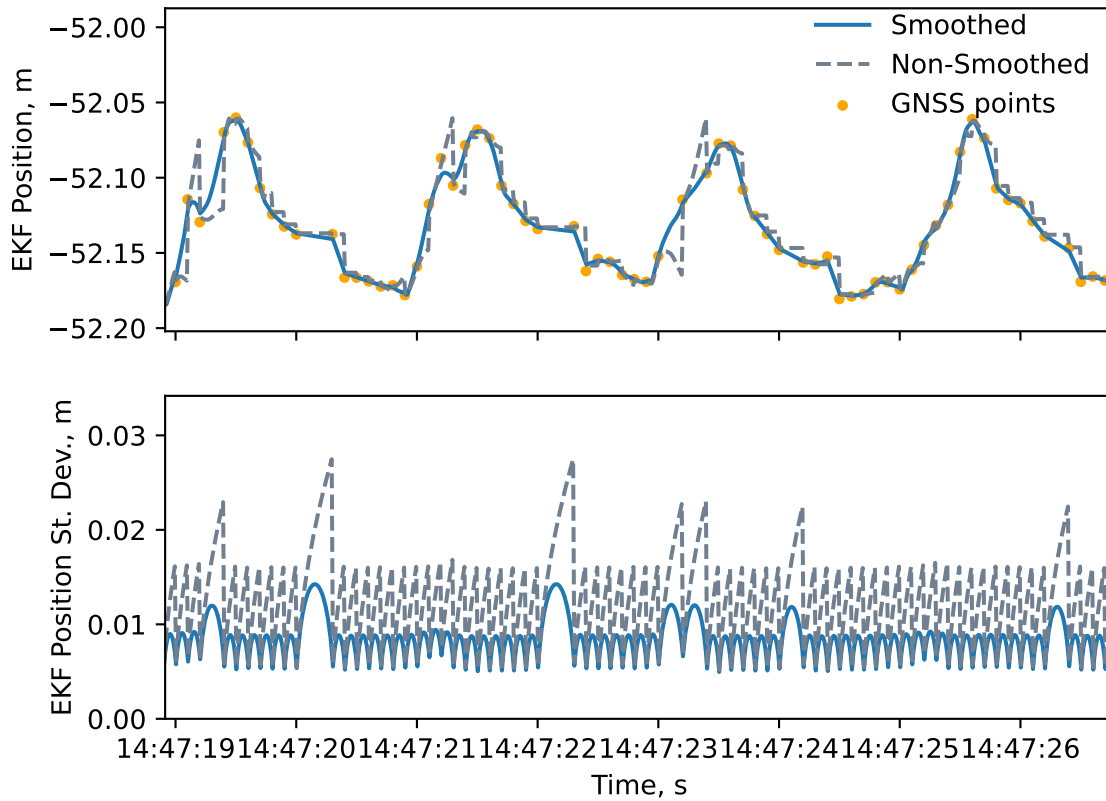


Figure 5.8: Comparison of the smoothed and non-smoothed EKF vertical position estimate and associated standard deviation for a representative excerpt of a slow walking sequence. Top: vertical position component with raw GNSS PPK points. Bottom: position standard deviation. The non-smoothed solution exhibits a sawtooth pattern in the standard deviation, growing between GNSS corrections and collapsing at each update. The smoothed solution produces a symmetric arc-shaped uncertainty envelope between consecutive corrections, reflecting the use of both past and future measurements.

Figure 5.8 illustrates the effect of RTS smoothing on the vertical position component and its associated standard deviation. The non-smoothed forward EKF solution exhibits discontinuous jumps at GNSS correction epochs where the incoming position estimate differs substantially from the predicted value, and the standard deviation follows a sawtooth pattern, growing rapidly during inertial propagation between corrections and collapsing at each GNSS update. The smoothed solution eliminates these discontinuities: by incorporating future measurements in a backward pass, the trajectory between consecutive corrections is interpolated consistently, and

the standard deviation profile becomes symmetric between corrections, forming an arc-shaped envelope with maximum uncertainty at the midpoint between two GNSS epochs and minimum uncertainty at the correction points themselves. This behaviour is the expected theoretical property of the RTS smoother and confirms that the backward pass is functioning correctly.

5.3.4 Spatiotemporal Gait Parameters

Spatiotemporal gait parameters are derived from ground points, the estimated positions of the foot at the instants of ground contact, extracted from the reconstructed trajectory using the zero-velocity intervals detected by the SHOE algorithm. Stride length is defined as the horizontal distance between two consecutive ground points of the same foot. Step length is the projection of the vector between consecutive ground points of alternating feet onto the walking direction, and step width is the component of the same vector perpendicular to the walking direction. For a straight-line walking path, the walking direction is determined directly from the overall trajectory, making these projections unambiguous. A more detailed description of the ground point extraction and parameter computation procedures is provided in Chapter 6.

Figure 5.9 shows the distribution of stride length, step length, and step width across the three walking speeds for a representative recording. In addition, the mean cadence estimated from gait event detection was 59.7, 89.2, and 119.9 steps/min for the slow, normal, and fast walking conditions respectively, compared to the metronome reference values of 60, 90, and 120 steps/min, a close agreement that validates the gait segmentation across all speeds.

Stride length estimates are consistent across speeds and close to the 140 cm reference, with the bulk of the distribution concentrated near the expected value at all three speeds. Stride length is computed within a single foot's trajectory and is therefore internally consistent. Step length, which requires combining position estimates from the two separately processed foot trajectories, shows greater asymmetry between the left and right foot: systematic offsets between the two independent solutions, of the kind observed in the vertical trajectory component in Section 5.3.3, propagate into the step length estimates and produce left-right differences that are unlikely to reflect true biomechanical asymmetry. Near-zero step length outliers are present at all speeds and are attributable to false gait event detections, not to solution errors: a spurious detection within a single stance phase produces two consecutive contact points at approximately the same location.

The variability of all three parameters increases slightly with walking speed, consistent with the degradation of GNSS solution quality documented in Sections 5.3.1 and 5.3.2. However, it is not possible to disentangle estimation error from natural gait variability in these results, since no independent kinematic ground truth for the foot trajectories is available. The reference values provided by the marker spacing validate only the mean step and stride length, not their variability.

Step width estimates are in the range of approximately 5 to 20 cm across all speeds, which is

broadly consistent with expected values for normal walking. No external reference is available for step width validation, and its distribution does not show a clear speed-dependent trend. The variability of step width estimates appears to be more sensitive to the quality of the GNSS solution for a given recording than to walking speed per se, consistent with the trial-to-trial variability in solution quality observed in Section 5.3.2.

5.4 Discussion

5.4.1 The Speed-Degradation Chain: From Raw Observation Loss to Trajectory Error

The results presented in the preceding section establish a coherent causal chain linking walking speed to trajectory reconstruction accuracy. At the observation level, increasing walking speed produces larger and more frequent acceleration peaks at toe-off and heel strike, which exceed the receiver’s specified dynamic limit and cause selective dropout of carrier-phase observations. At the solution level, this dropout reduces the number of satellites available for ambiguity resolution, degrading the PPK solution quality and increasing the frequency of code-only epochs. At the trajectory level, the resulting sparse and less reliable GNSS corrections reduce the effectiveness of the loosely-coupled integration, leading to larger position uncertainty and occasional trajectory deviations.

This chain was consistently observed in the representative recording presented here and is qualitatively reproducible across multiple recordings. It should be noted, however, that individual recordings did not always reflect the trend cleanly. On several occasions, the head receiver experienced abrupt and temporary loss of carrier-phase observables unrelated to walking dynamics, attributed to hardware resets caused by suboptimal device configuration during those sessions. These episodes are a consequence of prototype hardware immaturity and not of any fundamental limitation of the sensing approach, and they introduced trial-to-trial variability that partially obscured the speed-dependent trend in aggregate statistics. A production-grade implementation with more reliable hardware would be expected to exhibit the trend more consistently across recordings.

The counterintuitive increase in mean SNR during episodes of carrier-phase dropout deserves emphasis. Instead of a uniform degradation of all signals, the impulsive foot dynamics cause selective loss of the weakest observations, leaving a geometrically impoverished but individually higher-quality subset. This distinction has practical implications: it suggests that the primary failure mode is not signal attenuation but geometric diversity loss, and that strategies aimed at improving constellation geometry, such as multi-constellation tracking or antenna design optimized for low-elevation satellites, may be more effective than strategies aimed purely at signal amplification.

5.4.2 Trajectory and Derived Parameters Accuracy

The central result of this chapter is that centimeter-level horizontal positioning accuracy is achievable at slow and normal walking speeds under favorable sky visibility conditions, with vertical positioning being inherently less precise due to the one-sided distribution of satellites above the horizon. The GNSS/INS integration produces smooth, physically consistent trajectories whose horizontal components closely follow the PPK corrections, and whose spatial parameters, stride length and step length, are in close agreement with the reference values derived from the marker spacing. The RTS smoother eliminates the discontinuities inherent to the forward EKF solution and produces uncertainty estimates that are symmetric and physically interpretable, confirming that the full processing pipeline is functioning as intended.

It is important to be precise about what this result does and does not demonstrate. The validation is indirect: no continuous ground truth for the foot trajectory was available, and the marker-based reference validates only the mean step and stride length, not the trajectory itself or its variability. The separation of estimation error from natural gait variability in the parameter distributions is therefore not possible from these data alone. What can be concluded is that the system produces results that are internally consistent, physically plausible, and in agreement with the available reference values, which is the appropriate standard for a proof-of-concept validation at this stage.

The vertical component warrants specific comment. GNSS positioning is inherently less precise in the vertical direction due to the one-sided distribution of satellites above the horizon, and this limitation is visible in the larger uncertainty envelopes and the systematic offset observed between the two foot trajectories. The approximately 5 cm vertical offset between the left and right foot EKF solutions is an artifact of independent estimation, and it serves as a practical indicator of the residual error of the current implementation.

5.4.3 Limitations

Several limitations of the work presented in this chapter should be acknowledged explicitly, as they directly motivate the experimental extensions pursued in the subsequent chapters. Consistent with the proof-of-concept framing introduced in Section 5.1, these limitations define the boundaries of what the chapter validates and what it leaves open.

The most significant limitation is that all recordings were made with a single subject (the author). While this is appropriate for a proof-of-concept study focused on establishing technical feasibility, it means that the results cannot be generalised to other individuals with different gait patterns, body dimensions, or footwear. The generalisability of the approach across subjects is the primary question addressed in Chapter 6.

The recordings were short, covering a fixed straight-line path of approximately 30 steps per foot per trial. Performance over longer distances and more varied trajectories, including turns,

changes of surface, and extended durations, remains uncharacterised. Longer recordings would also provide a more statistically robust basis for assessing parameter variability.

The base station used for differential processing was a fixed professional-grade installation at a known location, 1.5 km from the recording site. While this baseline length is well within the effective range of carrier-phase differential corrections, the reliance on a fixed infrastructure station means that the system as validated here is not fully infrastructure-free. The use of a portable base station deployed on-site is demonstrated in Chapter 6.

Finally, the ground truth available for this experiment, namely the duct tape markers at 70 cm intervals, provides only an approximate reference for step and stride length, and no reference at all for the continuous foot trajectory or its variability. An independent and continuous ground truth source is needed to rigorously characterise trajectory accuracy, step width estimation, and the separation of estimation error from gait variability. This is addressed in Chapter 6 through the use of drone-based markerless motion capture as an independent reference.

5.5 Conclusion

This chapter has presented a proof-of-concept experimental investigation of foot-mounted GNSS/IMU integration², in which a GNSS receiver co-located with an IMU on a foot-mounted device is used to reconstruct absolute foot trajectories and derive spatiotemporal gait parameters in an outdoor environment. The central finding is that centimeter-level horizontal positioning accuracy is achievable at slow and normal walking speeds under favorable sky visibility conditions, and that the GNSS/INS loosely-coupled integration with ZUPT and RTS smoothing produces physically consistent and interpretable trajectory estimates.

A secondary but equally important finding concerns the mechanism by which walking speed limits system performance. The impulsive accelerations at toe-off and heel strike repeatedly exceed the receiver's specified dynamic limit, causing selective dropout of carrier-phase observations and reducing the geometric diversity of the satellite constellation available for ambiguity resolution. This degradation propagates through the processing chain from raw observations to PPK solution quality to trajectory accuracy, and was characterised empirically through a comparison between the foot-mounted and head-mounted receivers operating simultaneously under identical sky conditions.

The spatiotemporal gait parameters derived from the reconstructed trajectories, stride length, step length, step width, and cadence, are in close agreement with the reference values available from the marker-based ground truth and the metronome pacing, validating the gait segmentation and the trajectory-based parameter extraction pipeline. The limitations of this validation are acknowledged: a single subject, short recordings, a fixed infrastructure base station, and no con-

²This configuration corresponds to the per-segment integration scheme formalized as Architecture 2 in Chapter 4.

tinuous ground truth for the foot trajectory. Each of these limitations defines a specific direction for the experimental work presented in the following chapters. Chapter 6 addresses generalisability through a multi-subject outdoor validation campaign with a portable base station and an independent markerless motion capture alternative, while Chapter 7 extends the framework to multi-segment kinematic reconstruction using multiple body-mounted receivers.

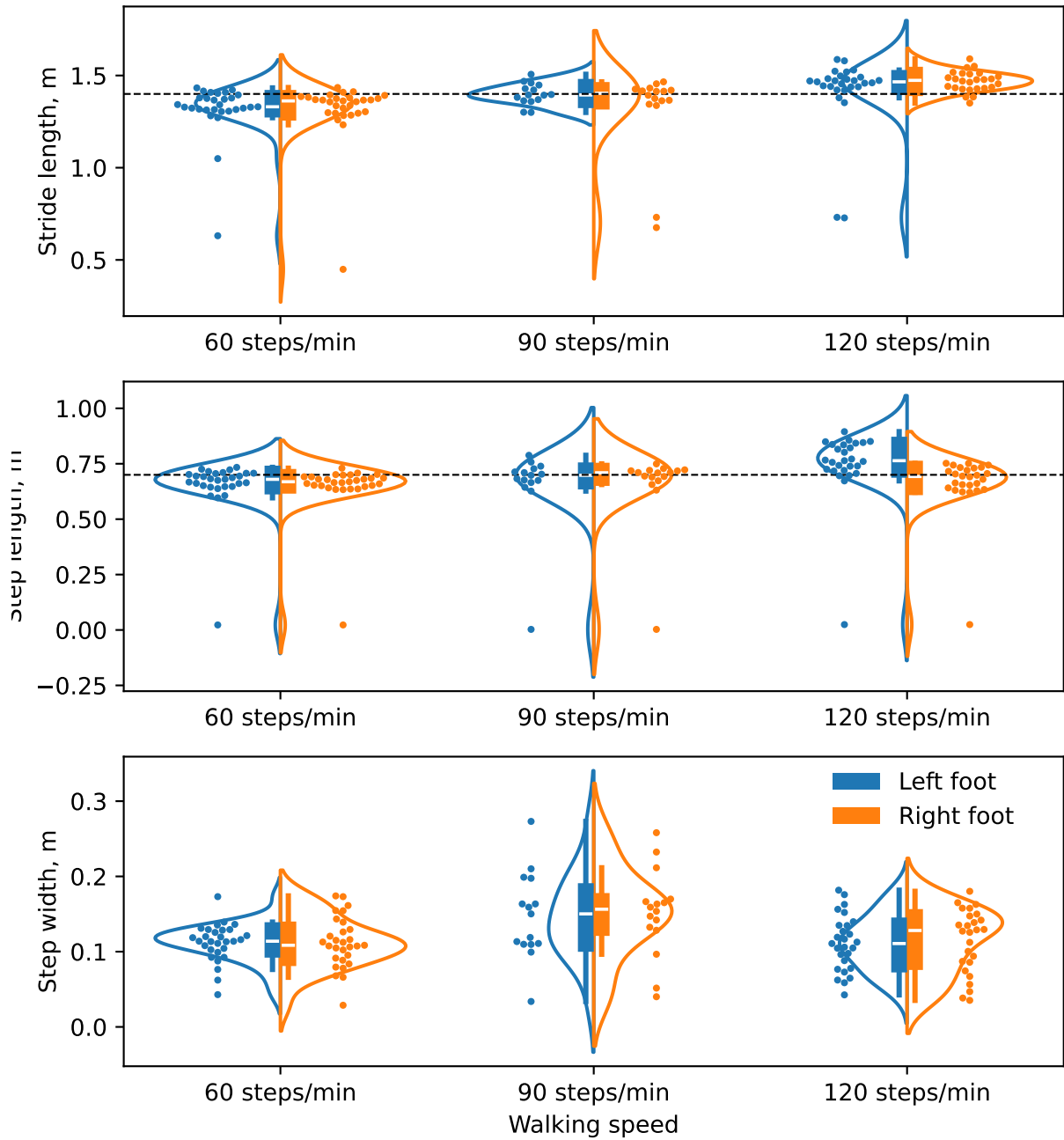


Figure 5.9: Stride length, step length, and step width estimated from the GNSS/INS foot trajectories across three walking speeds, shown separately for the left and right foot. Dashed horizontal lines indicate the reference values of 1.40 m and 0.70 m for stride and step length respectively, derived from the 70 cm marker spacing. Individual stride and step estimates are shown as swarm points overlaid on split violin plots. No reference value is available for step width.

Chapter 6

Multi-Subject Experimental Validation with Markerless Motion Capture

6.1 Introduction and Motivation

6.1.1 Limitations of the Previous Validation

The proof-of-concept investigation presented in Chapter 5 established that the foot-mounted GNSS/INS integration approach¹ can reconstruct foot trajectories and derive spatiotemporal gait parameters in an outdoor environment, with results that are internally consistent and in close agreement with the available reference values at slow and normal walking speeds. However, the scope of that validation was deliberately narrow, and four limitations were acknowledged explicitly as motivating directions for further work.

First, all recordings were collected from a single subject (the author) under controlled conditions on a straight, short path. Whether the approach generalises to other individuals, with different body dimensions, gait patterns, and footwear, was left as an open question. Second, the recordings were short, covering approximately 30 steps per foot per trial, which is insufficient to characterise parameter variability across a representative gait sample or to assess performance over longer distances. Third, the base station used for differential GNSS processing was a fixed, professional-grade installation located approximately 1.5 km from the recording site. This is a practical convenience that is not representative of a fully deployable field setup. Fourth, and most critically, no independent ground truth was available for the foot trajectories or the derived spatial parameters: the duct tape markers provided only an approximate reference for mean step and

¹This configuration is formalized within the broader integration framework of this thesis as Architecture 2 (Chapter 4).

stride length, leaving the separation of estimation error from natural gait variability unresolved, and providing no reference for step width or trajectory shape.

Each of these limitations is directly addressed in the present chapter.

6.1.2 Chapter Objectives and Contributions

This chapter presents a multi-subject outdoor validation campaign designed to evaluate the generalisability of the GNSS-based gait parameter estimation pipeline and to provide a first external comparison of its outputs against an independent measurement system. The campaign was conducted during a foreign research visit at the Lake Lucerne Institute (LLUI), Vitznau, Switzerland, which is a mandatory component of the PhD programme under which this thesis is developed. The recordings involved nine subjects walking at three self-paced speed conditions, at an outdoor stadium. A portable GNSS base station was deployed on-site, demonstrating that the system can operate without external fixed infrastructure. Simultaneous video recordings from an aerial drone were processed through a markerless motion capture pipeline to provide an independent estimate of spatiotemporal gait parameters for comparison.

Four specific objectives structure the chapter. The first is to characterise the GNSS signal quality and its speed dependence across multiple subjects and a new outdoor environment, extending and consolidating the single-subject observations of Chapter 5. The second is to assess the consistency and physiological plausibility of GNSS-derived gait parameters, namely stride length, step length, step width, and cadence, across subjects and speed conditions. The third is to evaluate the internal consistency of the GNSS pipeline through an independent cross-check of stride length and cadence against torso-derived walking speed. The fourth is to compare GNSS-derived parameters against those obtained from the markerless pipeline, with explicit attention to the methodological differences between the two approaches that bear on the interpretation of any observed discrepancies.

The intended application context throughout is clinical rehabilitation, where outdoor gait assessment at naturalistic walking speeds would substantially improve the ecological validity of outcome measures currently confined to laboratory settings. The findings of this chapter are evaluated with explicit reference to the typical walking speeds and operating conditions of rehabilitation gait assessment.

The chapter is organised as follows. Section 6.2 presents the materials and methods, covering the experimental design, the wearable and base station hardware, the aerial drone for independent evaluation, and the data processing pipelines for both GNSS and markerless components. Section 6.3 presents the results. Section 6.4 discusses the findings in the context of the thesis objectives, and Section 6.5 summarises the chapter’s contributions and motivates the extension to multi-segment kinematic reconstruction in Chapter 7.

6.2 Materials and Methods

6.2.1 Experimental Design

6.2.1.1 Field Site and Rationale

The experiments were conducted at the Luterbach public stadium in Küssnacht am Rigi, Switzerland. The site was selected for two principal reasons. First, the stadium provides a large flat surface with largely unobstructed sky visibility: the surrounding terrain is open, and the only nearby structure is a relatively low grandstand pavilion, in contrast to the steep slopes of the Rigi mountain that characterise the immediate surroundings of Vitznau, where the Lake Lucerne Institute hosting this research period is located. Second, as a community facility, the stadium was freely accessible without registration or advance booking, an important practical consideration given the logistic constraints of a six-month research visit. The straight walking path used for data collection was approximately 80 m in length, defined by the existing field markings.

6.2.1.2 Subjects

Nine healthy volunteers participated in the study, comprising five males and four females, with a mean age of 24.6 years ($SD = 1.9$), mean height of 175.8 cm ($SD = 6.8$), and mean weight of 66.7 kg ($SD = 14.9$). None of the participants reported diagnosed gait impairments or musculoskeletal conditions affecting locomotion. The participants were recruited from the staff, interns, and PhD students of the Lake Lucerne Institute. All participants provided informed consent prior to data collection.

The study was submitted for ethical review to the Ethics Commission of Northwestern and Central Switzerland (Ethikkommission Nordwest- und Zentralschweiz, EKNZ; BASEC-ID Req-2025-00661, submitted on 13 May 2025). On 5 June 2025, the commission issued a formal jurisdiction determination (*Zuständigkeitsabklärung*) stating that the project does not fall within the scope of the Swiss Federal Human Research Act (HFG, Art. 2) and that ethics committee approval was therefore not required. All data protection requirements specified by the commission were observed during the study.

6.2.1.3 Hardware: Wearable GNSS/IMU Devices

The wearable sensing units used in this campaign are the same REMOT devices described in Section 5.2.1, with no changes to hardware configuration or acquisition settings. Three devices were worn simultaneously by each participant: one mounted on the chest via a GoPro-compatible harness, and one on each foot via GoPro shoe mounts. The chest placement was preferred over

the head-mounted configuration used in Chapter 5 for the reference receiver: the torso exhibits more constrained and predictable movement than the head, which can rotate freely and independently of the walking direction, making it a more stable platform for the reference trajectory and solution quality assessment.

6.2.1.4 Portable Base Station

Post-processing kinematic positioning requires a reference GNSS receiver at a known location in the vicinity of the recording site. The professional base station used in Chapter 5, located approximately 1.5 km from the Genoa recording site, was not available for this campaign. The nearest freely accessible reference station, the Zimmerwald EUREF Permanent Network station, is located approximately 70 km from the Küssnacht site, a baseline length that substantially exceeds the effective range for centimetre-level carrier-phase differential processing. Preliminary tests confirmed that this baseline produced inadequate positioning quality even for a static receiver. A portable base station was therefore designed and assembled for this campaign, consisting of a u-blox ZED-F9P dual-frequency receiver, a ceramic patch GNSS antenna, a battery, and a microSD card logger, enclosed in a compact housing. The unit was configured to record raw observations at 1 Hz. For each session, the base station was placed on the ground at one of the stadium’s field markings and left stationary throughout the recording.

6.2.1.5 Aerial Drone for Independent Evaluation

Simultaneous video recordings were collected using a DJI Flip drone operating in automatic subject-following mode, flying at a fixed altitude behind the participant to maintain a consistent posterior view throughout each trial. This footage was subsequently processed through the markerless motion capture pipeline described in Section 6.2.2.4 to provide an independent estimate of spatiotemporal gait parameters for comparison with the GNSS-derived results.

The possibility of using the drone’s own GNSS receiver to provide an absolute spatial reference for the markerless pose estimates was considered, as this would have allowed direct comparison of segment trajectories in a globally referenced frame. Two obstacles prevented this. First, the DJI Flip platform does not expose raw GNSS observables to the user, making post-processed kinematic positioning of the drone unfeasible without reverse engineering and hardware modifications that were not possible within the available time and resources. Second, the drone’s camera is mounted on a gimbal that adjusts its orientation automatically and does not report it to the user; without knowledge of the gimbal orientation at each frame, the transformation from the camera frame to a navigation frame cannot be completed, even if the drone position were known. Absolute spatial referencing of the markerless estimates therefore remains a direction for future work, contingent on a platform that provides both raw GNSS observables and orientation telemetry.

A safety operator monitored all flights and remained ready to override to manual control at any time. Participants reported discomfort and a degree of insecurity from being followed at close range by the drone, and several incidents were recorded in which the platform temporarily lost tracking of the subject, subsequently reacquired and accelerated toward them before stopping safely. These observations are relevant to the broader adoption of drone-based motion capture in outdoor settings: flight regulations, subject safety and comfort are practical constraints that any such system must address before clinical or large-scale deployment can be considered.

6.2.2 Data Processing

6.2.2.1 GNSS Post-Processing

Raw GNSS observations from all wearable receivers and the portable base station were post-processed using the PPK approach described in Section 5.2.2, with RTKLIB as the processing software and the same configuration as in Chapter 5. The principal difference with respect to the tests performed in the previous chapter is the use of the portable base station described in Section 6.2.1.4 in place of the fixed professional installation used in Genoa. The baseline between the base station and the rover receivers was on the order of tens of metres throughout each session, substantially shorter than the 1.5 km baseline of the tests in Genoa, which is favourable for carrier-phase differential corrections.

A second difference concerns the walking speed reference. In Chapter 5, walking speed was regulated by a metronome and the three conditions corresponded to fixed cadence targets. In the present campaign, participants were instructed to walk at three self-paced speeds, namely slow, comfortable, and fast, without any external pacing reference. As a result, the absolute walking speeds varied substantially across subjects, with the slow condition of some participants overlapping with the comfortable condition of others. For all speed-dependent analyses in this chapter, walking speed is therefore treated as a continuous variable instead of a categorical label, and is estimated independently for each recording from the torso receiver output. Specifically, the velocity vectors provided by RTKLIB at each epoch are used to compute the mean velocity norm over all epochs where $\|\mathbf{v}\| > 0.5$ m/s, which excludes stationary periods at the start and end of each trial. As shown in Section 6.3, the torso receiver maintains near-perfect fix quality across all speed conditions, making it a reliable source for this estimate.

All gait parameters reported in Sections 6.3.3 through 6.3.5 are derived from the raw PPK trajectory, which constitutes the primary processing pipeline of this chapter. A loosely-coupled GNSS/IMU extended Kalman filter, identical to that described in Chapter 5, is additionally applied to the same dataset as a supplementary sensitivity check to assess the contribution of positioning noise to within-recording parameter variability. The results of this comparison are presented in Section 6.3.6.

6.2.2.2 Gait Segmentation

Midstance detection follows the same GLRT zero-velocity detection procedure applied to the foot IMU data as described in Section 5.2.2.2, with identical detector parameters. Each epoch labelled as a zero-velocity instant identifies a point within the stationary midstance phase of the gait cycle.

The stance boundary detection is extended relative to Chapter 5 to recover the full stance interval, including heel strike and toe-off events. This extension is motivated by two reasons. First, the ZUPT detector identifies only the stationary midstance phase, which is shorter than the full ground contact interval. Second, and more critically at higher walking speeds, the stationary midstance window may be brief enough to contain very few GNSS solution epochs at the 10 Hz receiver update rate, making a ground point estimate based on midstance alone unreliable. Extending the stance window to its full duration increases the number of available GNSS epochs per stance phase and therefore improves the robustness of the ground point estimate across all walking speeds.

For each contiguous block of zero-velocity epochs, the heel strike event is identified by searching backward from the start of the block to the nearest local maximum of the accelerometer norm $\|\mathbf{f}_m\|$, which corresponds to the impulsive acceleration at initial contact. The toe-off event is identified symmetrically by searching forward from the end of the block to the nearest local maximum of $\|\mathbf{f}_m\|$, corresponding to the push-off acceleration at terminal stance. The resulting stance interval $[\text{hs}, \text{to}]$ spans from the heel strike to the toe-off event and encompasses the full period of ground contact. Algorithm 2 summarises the procedure.

Algorithm 2 Stance interval extension from zero-velocity detections.

Require: Zero-velocity epoch labels $\{z_k\}$, accelerometer norm $\|\mathbf{f}_m\|$ over the recording

Ensure: Stance intervals $[\text{hs}, \text{to}]$ for the recording

- 1: Identify all contiguous blocks of zero-velocity epochs $[k_{\text{start}}, k_{\text{end}}]$ from $\{z_k\}$
 - 2: **for** each contiguous block $[k_{\text{start}}, k_{\text{end}}]$ **do**
 - 3: $\text{hs} \leftarrow$ nearest local maximum of $\|\mathbf{f}_m\|$ found by searching backward from k_{start}
 - 4: $\text{to} \leftarrow$ nearest local maximum of $\|\mathbf{f}_m\|$ found by searching forward from k_{end}
 - 5: Append candidate stance interval $[\text{hs}, \text{to}]$
 - 6: **end for**
 - 7: Discard candidate intervals shorter than 0.1 s
 - 8: Merge consecutive candidate intervals whose intervening swing-phase gap is shorter than 0.2 s
 - 9: **return** List of stance intervals
-

The nearest local maximum of $\|\mathbf{f}_m\|$ is not formally guaranteed to correspond to a gait event in all cases. In practice, the impulsive accelerations associated with heel strike and toe-off are the dominant peaks immediately adjacent to a stance phase, and the subsequent filtering rules act as

practical safeguards against the rare spurious detections that arise from secondary peaks during swing or from fragmented ZUPT detections within a single stance phase.

Two filtering rules are applied to the detected segments. Segments shorter than 0.1 s are discarded as spurious detections. If the gap between the toe-off of one segment and the heel strike of the next is shorter than 0.2 s, indicating an implausibly short swing phase, the two segments are merged into a single stance interval. This handles cases where the GLRT produces fragmented detections within a single stance phase. The 0.2 s threshold was verified by visual inspection of the detected events across the walking speeds tested in this campaign and was found to hold reliably; walking speeds outside this range might require proportional adjustment of the parameter.

6.2.2.3 Spatial Gait Parameter Extraction

Ground points are estimated from the trajectory epochs falling within each stance interval $[hs, to]$. A covariance-weighted fusion is applied to the available position estimates within each stance interval to prioritise higher-quality solution epochs. Denoting the position estimate and associated 3×3 covariance matrix at epoch i as $\mathbf{p}_i$ and $\mathbf{C}_i$ respectively, the fused ground point position and covariance are computed as

$$\mathbf{C}_{\text{gp}} = \left(\sum_i \mathbf{C}_i^{-1} \right)^{-1}, \quad (6.1)$$

$$\mathbf{p}_{\text{gp}} = \mathbf{C}_{\text{gp}} \sum_i \mathbf{C}_i^{-1} \mathbf{p}_i, \quad (6.2)$$

which is the maximum-likelihood position estimate under the assumption of independent Gaussian errors at each epoch. The resulting ground point covariance $\mathbf{C}_{\text{gp}}$ propagates the individual epoch uncertainties and provides a per-stance reliability estimate that can be used for downstream quality assessment. All subsequent parameter computations use only the horizontal East–North components of each ground point, discarding the vertical component for the same reasons as in Chapter 5.

The walking direction is estimated by fitting a straight line to the combined East and North coordinates of all ground points from both feet across the full recording. The slope of this regression defines the heading angle, from which a unit direction vector $\hat{\mathbf{p}}$ and its perpendicular $\hat{\mathbf{n}} = [-p_y, p_x]^T$ are derived.

Stride length is defined as the horizontal Euclidean distance between two consecutive ground points of the same foot. Step length and step width are computed from the displacement vector δ between consecutive ground points of alternating feet: step length is the projection $\delta \cdot \hat{\mathbf{p}}$ along the walking direction, and step width is the projection $\delta \cdot \hat{\mathbf{n}}$ perpendicular to it. Cadence is derived from the inter-stride intervals, defined as the time between consecutive heel strike events on the same side.

6.2.2.4 Markerless Motion Capture Pipeline

Drone video footage was processed through the monocular markerless biomechanics pipeline developed by Cotton et al. [30, 31], which fits a differentiable biomechanical model to video-extracted keypoints via end-to-end optimisation. The pipeline represents the movement trajectory as an implicit neural function mapping time to joint angles, which is optimised to minimise the reprojection error between predicted virtual marker positions and keypoints detected in the video frames, using GPU-accelerated forward kinematics in the MuJoCo physics simulator [103]. The output is a per-frame joint angle sequence compatible with the Rajagopal full-body musculoskeletal model in OpenSim [104]. The pelvis translations were excluded from the result, since they were not estimated with respect to a fixed frame. Subject-specific scaling was applied by multiplying all forward-kinematics-derived positions by the ratio of the subject’s measured height to the model’s reference height of 170 cm.

Heel strike events were detected from the knee flexion angle time series for each foot independently. The raw signal was first smoothed using a Savitzky–Golay filter to suppress pose estimation noise while preserving peak shape. Mid-swing peaks, namely the prominent flexion maxima occurring once per stride cycle and typically reaching 0.8–1.2 rad, were then identified using a peak-finding algorithm with a prominence threshold sufficient to reject the smaller loading-response flexion peaks. For each detected mid-swing peak, the algorithm scanned forward in time to locate the subsequent local minimum of the knee flexion signal, corresponding to terminal swing and initial contact, where the knee approaches full extension. The timestamp of this minimum was taken as the heel strike time. This two-step strategy, anchoring each search to the unambiguous mid-swing peak before locating the following extension minimum, avoids the ambiguity that arises from searching for extension minima directly, since two such minima occur per gait cycle: one at heel strike and one during terminal stance.

Spatial gait parameters were extracted from foot positions computed at each heel strike instant via forward kinematics. At each detected heel strike time, the joint angles were interpolated from the per-frame output and used to realise the model configuration in OpenSim, from which the three-dimensional position of the calcaneus body origin was retrieved in the ground frame. Only the horizontal plane components were retained for parameter computation. The walking direction unit vector was estimated within each trial as the mean of all inter-foot step vectors, defined as the vector from the trailing to the leading foot at each heel strike, which provides a robust sagittal direction estimate even in the presence of systematic lateral foot separation. Stride length was computed as the sum of two consecutive step lengths within a stride cycle, where each step length is the projection of the inter-foot displacement vector onto the walking direction. Step width is the projection of the right-to-left foot separation vector onto the direction perpendicular to walking. Cadence was derived from mean stride time.

It is important to note a methodological difference between the video and GNSS approaches that bears directly on the interpretation of any comparison between their outputs. In the markerless

pipeline, stride and step lengths are computed as differences between calcaneus positions at discrete heel-strike instants, that is, a single-frame forward kinematics snapshot. In the GNSS pipeline, the ground point representing each stance phase is a covariance-weighted average of all trajectory epochs spanning the full stance interval from heel strike to toe-off. These are fundamentally different quantities: the GNSS estimate integrates positional information over the entire period of ground contact, while the markerless estimate samples foot position at a single instant. The implications of this difference for the observed systematic offset between the two methods are discussed in Section 6.4.

6.3 Results

6.3.1 Dataset Overview

The campaign yielded a total of 27 possible recordings across nine subjects and three speed conditions. Not all recordings produced usable foot GNSS data. Subject s4 is entirely absent from the analysis: the foot-worn receivers powered off at the beginning of the session due to a prototype hardware failure, and it was not possible to repeat the recording with the same subject. Isolated failures of a similar nature affected fast-speed recordings of other subjects, resulting in one or both foot receivers producing no valid data for those trials. All remaining recordings where foot GNSS data exists are retained in the analysis regardless of solution quality, with the actual fix fractions informing the interpretation of the derived parameter. The per-trial data availability is summarised in Table 6.1, and the corresponding fix quality distributions are shown in Figure 6.1.

Table 6.1: Per-trial data availability for foot GNSS receivers. All trials marked as available are included in the analysis. s4 is absent at all speeds due to hardware failure; missing entries for other subjects reflect isolated device failures.

Subject	Slow	Normal	Fast
s1	Available	Available	Available
s2	Available	Available	Available
s3	Available	Available	No data
s4	No data	No data	No data
s5	Available	Available	One foot only
s6	Available	Available	Available
s7	Available	Available	Available
s8	Available	Available	Available
s9	Available	Available	One foot only

The torso receiver maintained near-perfect carrier-phase fix quality across all speed conditions,

achieving 100%, 95%, and 98% fixed epochs at slow, normal, and fast walking respectively. This is consistent with the Chapter 5 finding that a torso-mounted receiver experiences substantially lower dynamic accelerations than a foot-mounted one, and is therefore far less susceptible to the cycle slips and carrier-phase tracking failures that characterise foot receiver data at higher speeds. The torso receiver consequently serves two roles in this chapter: as a solution quality benchmark against which foot receiver performance is assessed, and as the source of the walking speed estimate used in all speed-dependent analyses.

Because walking speeds were self-paced without a common external reference, the condition labels slow, normal, and fast do not correspond to consistent absolute speeds across subjects. The walking speed assigned to each recording is therefore the mean velocity norm derived from the torso receiver output over all epochs where the velocity exceeded 0.5 m/s, which excludes stationary periods at the start and end of each trial. This continuous speed variable replaces the condition label in all subsequent analyses. The practical consequence of the self-paced design is visible in the data: some subjects walked at a pace during their slow condition that exceeded the normal-condition speed of others, which is reflected in the wide spread of fix quality within all artificial speed condition labels and motivates the continuous speed treatment adopted here.

6.3.2 GNSS Signal Quality

As shown in Figure 6.1, the fractions of fixed, float, and DGNSS solution epochs as a function of actual walking speed differ markedly across the three receiver locations. The torso and foot receivers present a stark contrast that persists across the full subject cohort and speed range.

The torso receiver maintains near-perfect carrier-phase fix at all speeds, with mean fixed fractions of 100%, 95%, and 98% at slow, normal, and fast walking respectively. Float and DGNSS epochs are rare and confined to brief transient episodes. This confirms, across nine subjects and a new outdoor environment, the Chapter 5 finding that a torso-mounted receiver is largely insulated from the foot dynamics responsible for carrier-phase degradation.

The foot receivers show a different trend. At slow walking speeds, fix quality is acceptable on average, though substantial inter-subject variability is visible in the scatter. As walking speed increases, both foot receivers degrade sharply: at normal speed, mean fixed fractions fall to approximately 28% and 25% for the left and right foot, with float solutions becoming dominant. At fast speed, carrier-phase lock is frequently lost entirely, with DGNSS epochs accounting for approximately 40% of the solution on both feet and fixed fractions falling below 25%. The transition from float to DGNSS with increasing speed reflects a progressive failure of carrier-phase tracking: at moderate speeds the receiver loses integer ambiguity resolution but retains phase observations, while at higher speeds the phase observables themselves are lost.

The degradation is not static across a recording. When the foot is stationary or moving slowly, during stance phases and at the start and end of trials, the receiver tends to reacquire carrier-

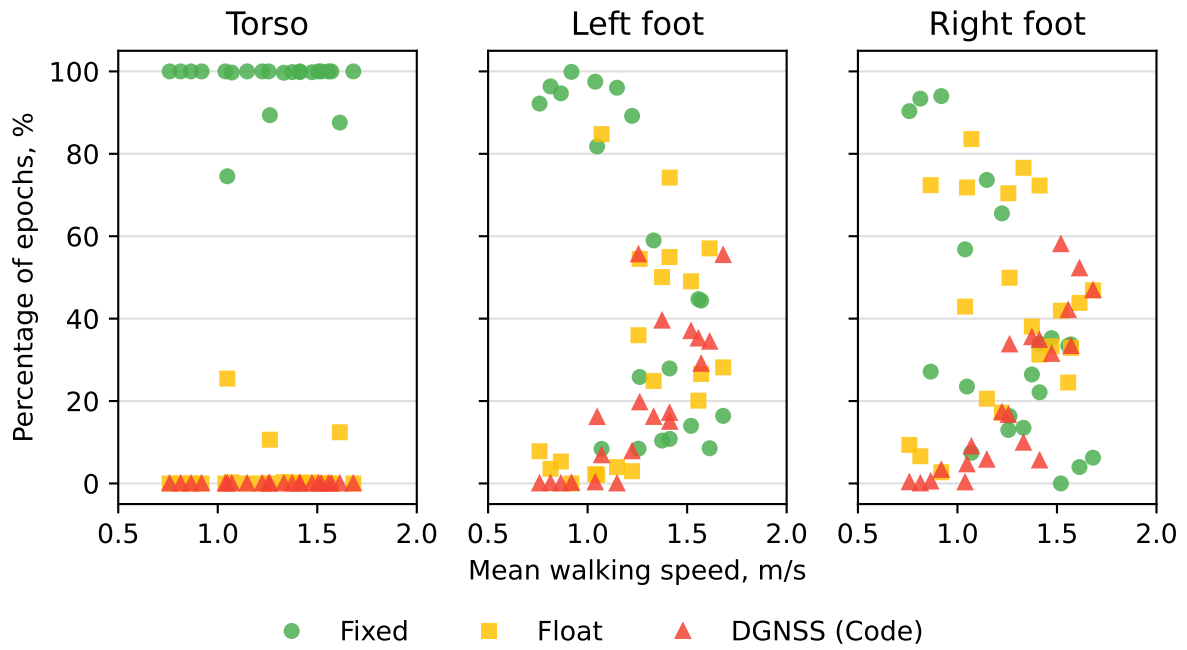


Figure 6.1: Fractions of fixed, float, and DGNSS solution epochs as a function of actual walking speed (torso-derived), shown separately for the torso (left), left foot (centre), and right foot (right) receivers. Each point represents one recording. The torso receiver maintains near-perfect fix across all speeds, while both foot receivers show progressive degradation with increasing speed, transitioning from predominantly fixed at slow walking to predominantly float and DGNSS at fast walking.

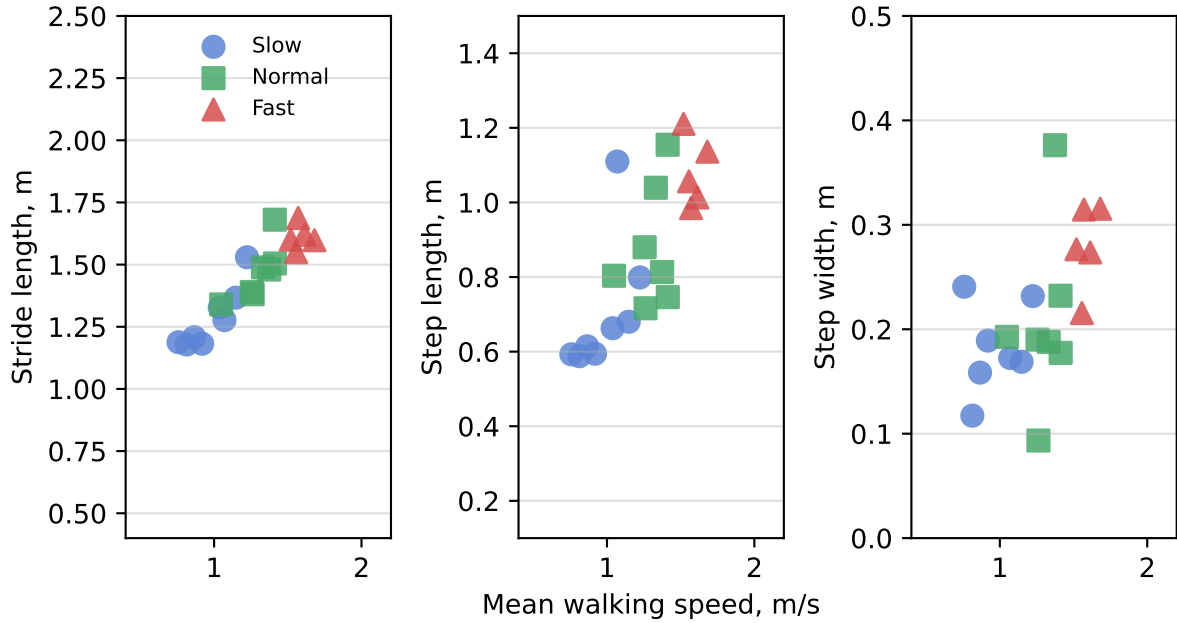


Figure 6.2: Per-recording mean stride length, step length, and step width as a function of actual walking speed, derived from the GNSS foot positioning pipeline. Each point represents one recording, coloured by speed condition. All three metrics increase monotonically with speed. Inter-subject variability in absolute values reflects differences in subject stature, as stride and step length scale with leg length.

phase lock, and the solution recovers toward fixed. At faster walking speeds, however, the interval between successive dynamic events at toe-off and heel strike is insufficient for consistent reacquisition, and the solution remains predominantly at float or DGNSS throughout the whole gait cycle. The full mechanistic account of this behaviour, including the role of impulsive foot accelerations in disrupting phase-lock loops, is provided in Chapter 5.

6.3.3 GNSS-Derived Gait Parameters

Figure 6.2 shows the per-recording mean stride length, step length, and step width as a function of actual walking speed for all subjects and conditions. All three metrics scale monotonically with speed, consistent with established gait physiology. The pooled means across subjects are 1.27, 1.47, and 1.61 m for stride length, 0.68, 0.85, and 1.07 m for step length, and 0.18, 0.18, and 0.28 m for step width at slow, normal, and fast walking respectively. These values reflect cohort averages across subjects of varying stature: since stride and step length scale with leg

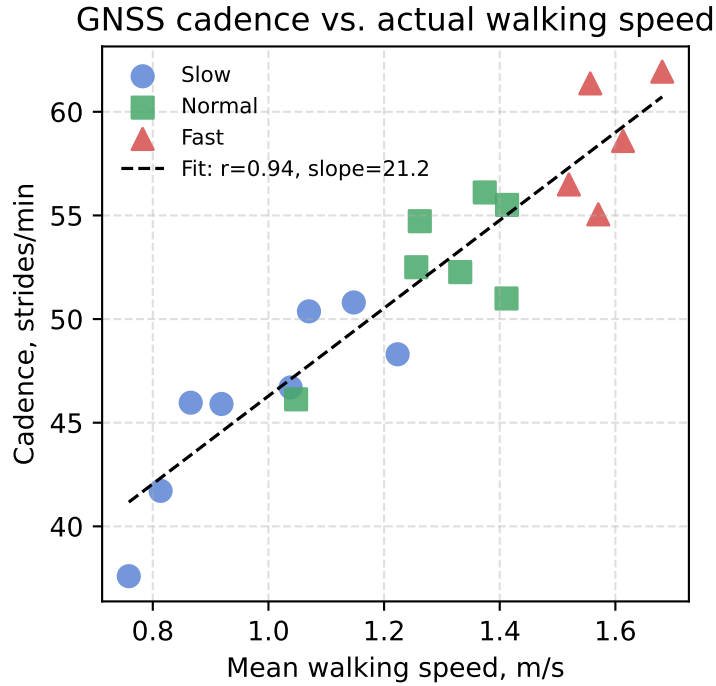


Figure 6.3: GNSS-derived cadence in strides/min as a function of actual walking speed, with linear fit ($r = 0.94$, slope = 21.2 strides/min per m/s). Each point represents one recording. Cadence increases approximately linearly across the full speed range.

length, inter-subject variability in absolute parameter values is expected and visible in the scatter. Cadence increases approximately linearly with speed (Figure 6.3), from a mean of 91 steps/min (equivalent to approximately 45 strides/min as shown in the figure) at slow to 117 steps/min at fast walking.

Figure 6.4 shows the within-recording standard deviation of each parameter as a function of walking speed. All three metrics show a positive correlation with speed ($r \approx 0.75$), with slopes of 0.39, 0.56, and 0.11 m per m/s for stride length, step length, and step width respectively. This growing variability should not be interpreted as increasing true biomechanical stride-to-stride variability with speed: it reflects the degradation of GNSS solution quality documented in Section 6.3.2, where higher walking speeds produce more frequent float and DGNS epochs, introducing noise into individual ground point estimates. In this regime, the per-recording mean is a more robust and meaningful quantity than the distribution of individual strides, as solution noise partially averages out across the strides of a recording.

Stride length shows lower within-recording variability than step length because it is derived entirely from a single foot's trajectory: consecutive ground points of the same foot share the same

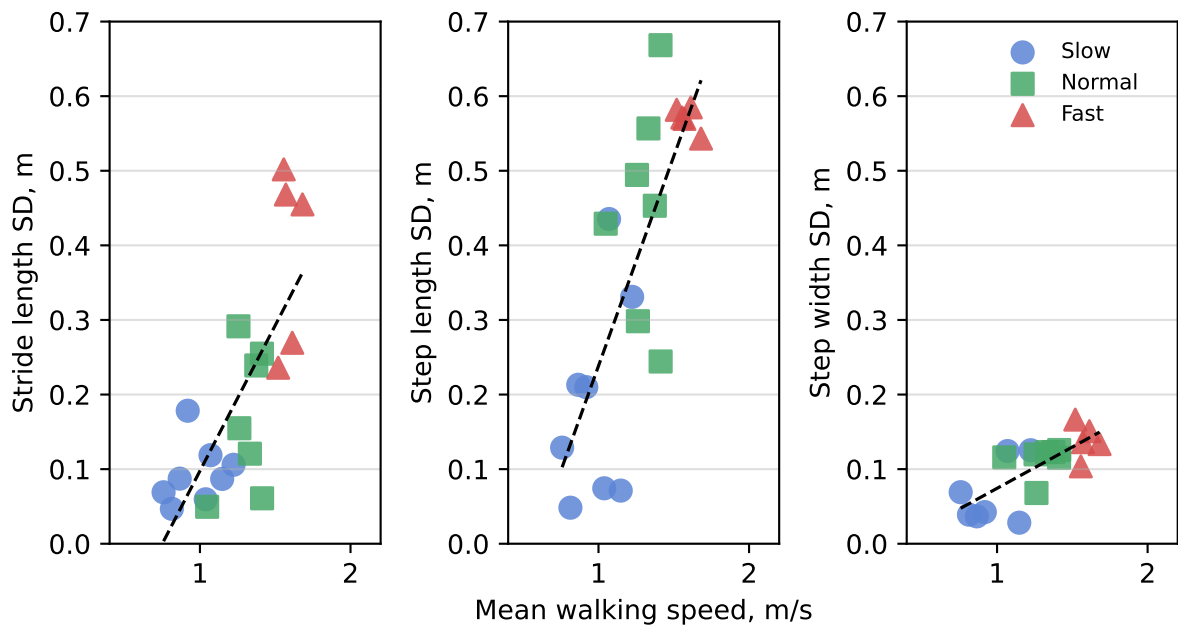


Figure 6.4: Within-recording standard deviation of stride length, step length, and step width as a function of actual walking speed, derived from the GNSS pipeline. Each point represents one recording. The positive correlation between SD and speed ($r \approx 0.75$ for all three metrics) reflects the degradation of GNSS fix quality at higher walking speeds rather than true biomechanical stride-to-stride variability.

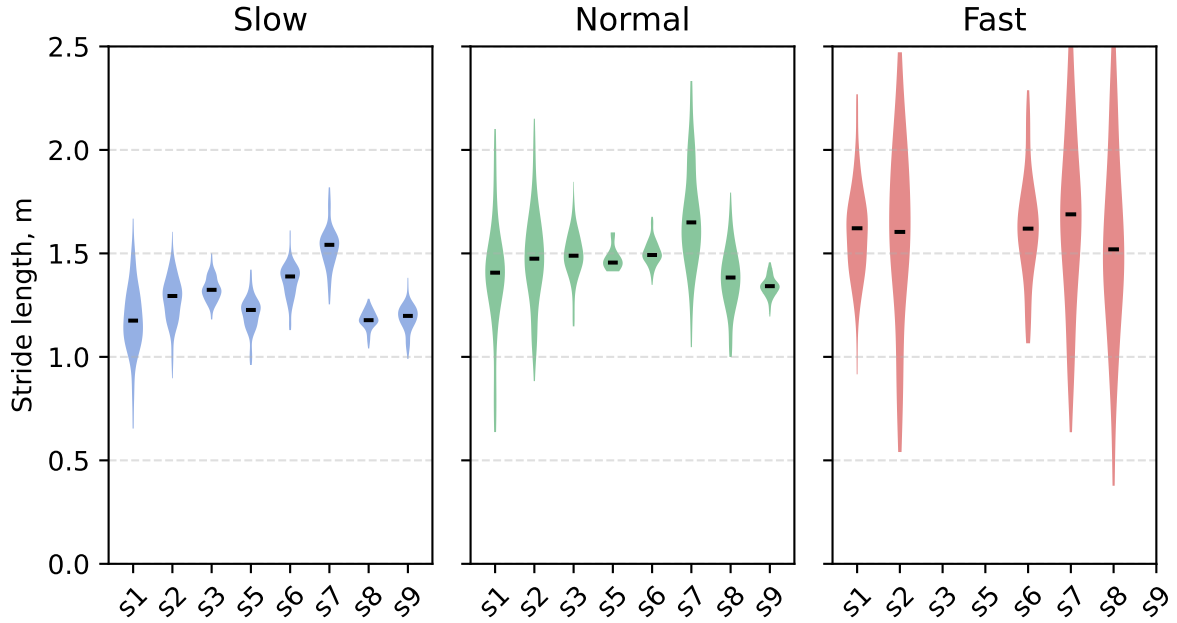


Figure 6.5: Per-recording mean stride length per subject for each speed condition. Inter-subject differences in absolute stride length reflect differences in stature and self-selected speed, while the spread across recordings within each subject and condition reflects the combined effect of true gait variability and GNSS solution noise.

solution characteristics, and their difference is less sensitive to absolute positioning errors. Step length and step width both combine ground points from two independently processed foot solutions, so their absolute positioning errors do not cancel and the resulting parameter estimates are more sensitive to inter-solution inconsistencies. Step width nonetheless shows a smaller absolute SD than step length, likely because GNSS positioning noise is lower in the lateral direction than along the sagittal walking axis, a consequence of the satellite geometry for a receiver moving primarily in the forward direction. Systematic left-right differences in mean step length are visible in some recordings, attributable to independent solution processing of the two foot receivers and not to true biomechanical asymmetry.

The per-subject stride length distributions are shown in Figure 6.5. The distributions confirm the speed-dependent scaling at the individual level and illustrate the inter-subject variability in absolute values. The spread of individual stride estimates within each subject and condition reflects the combined effect of true gait variability and GNSS solution noise, the latter becoming the dominant contributor at higher speeds as documented in Figure 6.4.

Figure 6.6 provides a self-consistency check by comparing the product of stride length and ca-

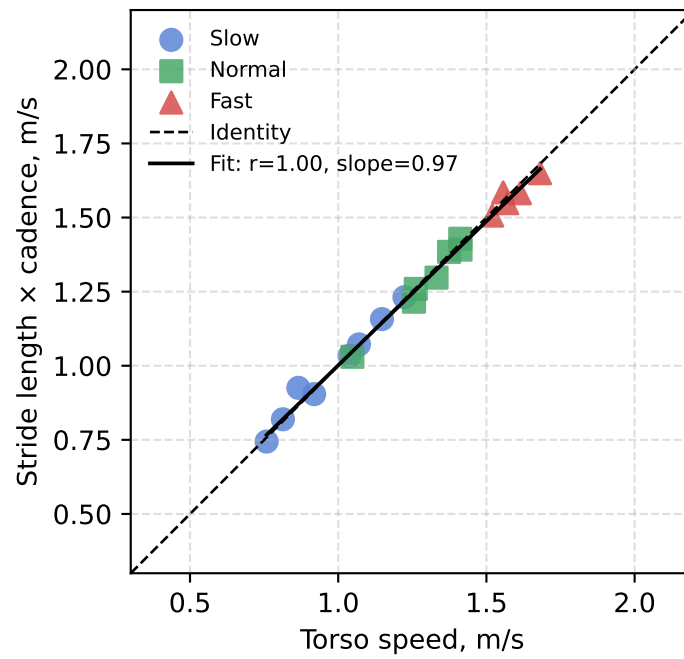


Figure 6.6: Internal consistency check for the GNSS gait pipeline: product of mean stride length and cadence plotted against torso-derived walking speed for each recording ($r = 0.997$, slope = 0.972). The relationship stride length $\times$ cadence $\approx$ walking speed is a near-identity, so the correlation evidences the mutual consistency of the two processing chains and the absence of gross error, not the absolute accuracy of stride length itself.

dence (in strides per second) against the independently derived torso walking speed for each recording. The two quantities agree with a Pearson correlation of $r = 0.997$ and a slope of 0.972 across all 19 matched recordings, spanning the full speed range from slow to fast walking. This comparison is a self-consistency check, not a validation of absolute accuracy: stride length multiplied by stride frequency equals walking speed by definition, so a high correlation between the two sides of this near-identity is expected whenever the foot and torso processing chains are internally coherent. What the result confirms is that the two independent processing chains, running on different receivers with different fix quality profiles, do not disagree at the level of gross error, and that the between-subject variance in walking speed is large enough to drive the correlation. It does not establish that the individual stride length estimates are quantitatively accurate: independent validation against a spatial reference would be required for that claim, and the limitations of the reference available in this campaign are addressed in Sections 6.3.5 and 6.4. The small slope shortfall of approximately 3% is consistent with minor timing offsets between the foot-event detection and the torso velocity estimate.

6.3.4 Markerless Video Gait Parameters

Figure 6.7 shows the per-recording mean markerless-derived stride length, step length, and step width as a function of actual walking speed. The pooled means across subjects are 0.93, 1.06, and 1.15 m for stride length, 0.47, 0.53, and 0.58 m for step length, and 0.08, 0.09, and 0.09 m for step width at slow, normal, and fast walking respectively. As with the GNSS-derived parameters, all three metrics scale with walking speed, confirming that the markerless pipeline correctly captures the qualitative speed-dependent trends in gait.

Figure 6.8 shows the within-recording standard deviation of the markerless-derived parameters as a function of walking speed. In contrast to the GNSS-derived variability shown in Figure 6.4, the markerless pipeline shows no meaningful speed dependence in within-recording SD: Pearson correlations with walking speed are $r = 0.11$, 0.07, and 0.17 for stride length, step length, and step width respectively. This absence of speed-dependent growth is consistent with the markerless pipeline’s uncertainty being driven primarily by pose estimation noise and camera geometry, and not by any mechanism that worsens with walking speed. The contrast between the two pipelines reinforces the interpretation that the speed-dependent SD increase observed in the GNSS results reflects a GNSS-specific degradation in solution quality, and not a genuine increase in biomechanical stride-to-stride variability at higher speeds.

Figure 6.9 shows the markerless cadence as a function of walking speed. The cadence-speed relationship closely mirrors that of the GNSS-derived cadence, as both ultimately reflect the timing of the same physical gait events.

The internal consistency of the markerless pipeline was assessed using the same stride length multiplied by cadence versus torso speed check applied to the GNSS results in Section 6.3.3.

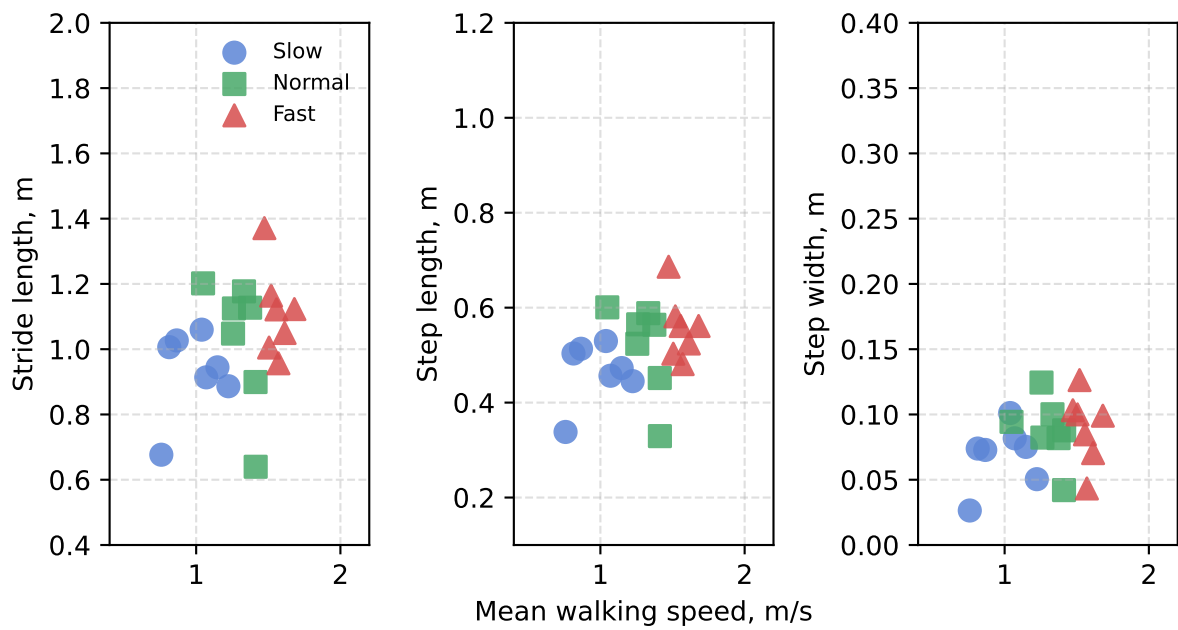


Figure 6.7: Per-recording mean markerless-derived stride length, step length, and step width as a function of actual walking speed. Each point represents one recording, coloured by speed condition. All three metrics increase monotonically with speed, consistent with the GNSS-derived trends shown in Figure 6.2, though with systematically smaller absolute values.

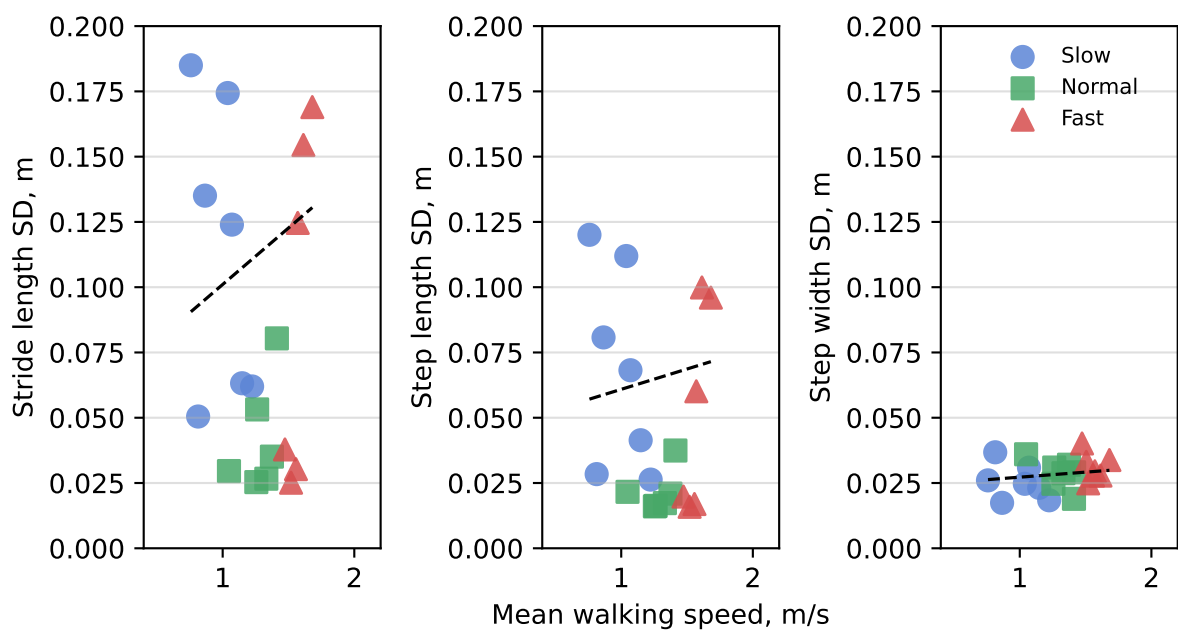


Figure 6.8: Within-recording standard deviation of markerless-derived stride length, step length, and step width as a function of actual walking speed. Each point represents one recording. For comparison with the GNSS-derived variability shown in Figure 6.4.

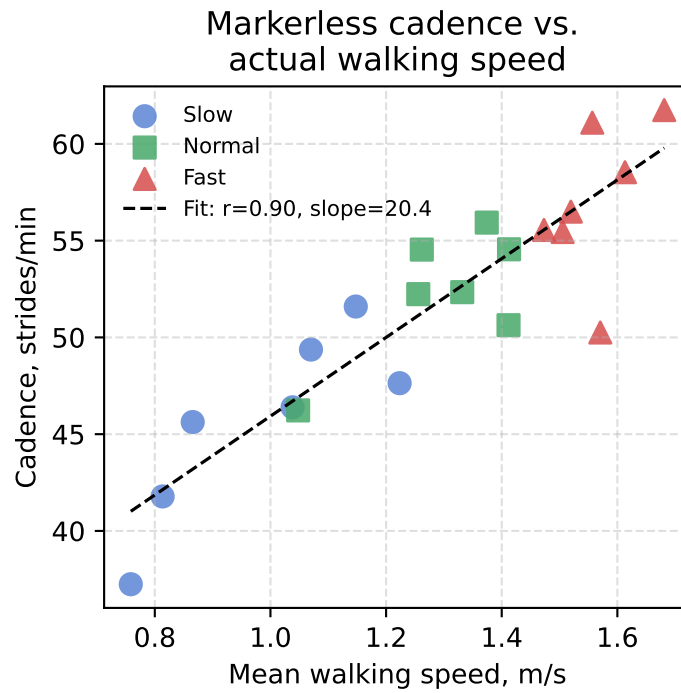


Figure 6.9: Markerless-derived cadence in strides/min as a function of actual walking speed, with linear fit ($r = 0.90$, slope = 20.4 strides/min per m/s). Each point represents one recording. The cadence-speed relationship closely mirrors that of the GNSS-derived cadence shown in Figure 6.3, as both are derived from the timing of the same physical gait events.

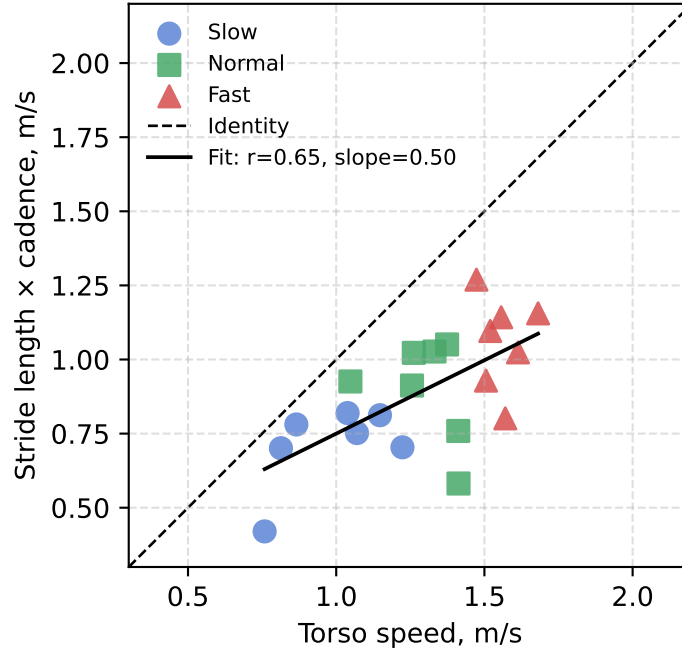


Figure 6.10: Internal consistency check for the markerless video gait pipeline: product of mean stride length and cadence plotted against torso-derived walking speed for each recording ($r = 0.647$, slope = 0.495). The weaker agreement compared to the GNSS pipeline (Figure 6.6) reflects lower internal consistency of the markerless pipeline, attributable to calcaneus landmark approximation, event timing uncertainty, and sagittal-plane foreshortening from the posterior drone camera.

The video pipeline yields $r = 0.647$ and a slope of 0.495 across approximately 18 matched recordings, substantially weaker than the GNSS result of $r = 0.997$. This comparison is fully independent: video stride length and cadence are derived from forward kinematics and knee-flexion-peak event detection, while the torso speed comes from the RTKLIB velocity output of a separate receiver. The weaker agreement indicates that the markerless pipeline is less internally self-consistent than the GNSS pipeline. Several factors likely contribute: approximation of the calcaneus landmark position within the scaled OpenSim model, timing uncertainty introduced by the knee-flexion-peak detection algorithm, and the posterior drone camera geometry, which limits the accuracy of sagittal-plane pose estimation.

The markerless-derived parameter values are systematically smaller than their GNSS counterparts across all metrics and speed conditions. Three methodological factors contribute to this offset. First, the posterior drone view causes foreshortening of the sagittal plane: forward displacement is partially projected out of the image, leading to underestimation of step and stride

lengths by the pose estimation algorithm. Second, the two pipelines locate different anatomical landmarks: the GNSS pipeline tracks the antenna phase center at the dorsal midfoot, while the markerless pipeline reports the calcaneus position from the OpenSim forward-kinematics model. Third, the two pipelines measure fundamentally different quantities: the markerless pipeline samples the calcaneus at discrete heel-strike instants via a single forward kinematics snapshot, while the GNSS pipeline averages foot position over the full stance interval. A detailed analysis of this systematic offset and its implications is presented in Section 6.3.5.

6.3.5 GNSS and Markerless Comparison

The agreement between the two pipelines is quantified using Bland–Altman analysis [105], a standard method for assessing agreement between two measurement techniques applied to the same quantity. The analysis plots the difference between paired measurements against their mean, with horizontal lines indicating the mean bias and the 95% limits of agreement (bias ± 1.96 SD of the differences). Unlike a simple correlation between the two methods, which can be inflated by between-subject variability when the absolute value of the measured quantity varies widely across subjects, the Bland–Altman analysis operates on the differences and is sensitive to systematic offsets and to the consistency of the disagreement.

Figure 6.11 shows per-recording mean GNSS-derived parameters plotted against their markerless counterparts for all three metrics, and Figure 6.12 presents the corresponding Bland–Altman analysis.

The scatter plot reveals no meaningful correlation between the two methods at the individual recording level: Pearson $r = 0.15$ for stride length ($p = 0.51$), $r = 0.29$ for step length ($p = 0.21$), and $r = -0.08$ for step width ($p = 0.74$). This absence of individual-level correspondence does not reflect a failure of either pipeline to capture gait trends. Both methods show clear speed-dependent increases in stride and step length when examined separately (Figures 6.2 and 6.7). The absence reflects the dominance of between-subject variability in absolute parameter values over the shared speed signal at this sample size: with $n = 20$ recordings across only three speed clusters and nine subjects of varying stature and self-selected pace, the between-subject differences in absolute stride length are large enough to obscure the correlation between methods at the recording level. The Bland–Altman analysis, which operates on the difference between matched pairs rather than their absolute values, is therefore the more informative comparison.

The pooled Bland–Altman results quantify the systematic offset between the two pipelines. For stride length, the mean bias is $+0.431$ m with limits of agreement from $+0.033$ to $+0.829$ m. For step length, the bias is $+0.360$ m with limits of agreement from -0.023 to $+0.743$ m. For step width, the bias is $+0.132$ m with limits of agreement from -0.031 to $+0.296$ m. The bias increases qualitatively with walking speed for all three metrics, a trend attributable to the systematic underestimation of the markerless pipeline: as true stride and step lengths increase

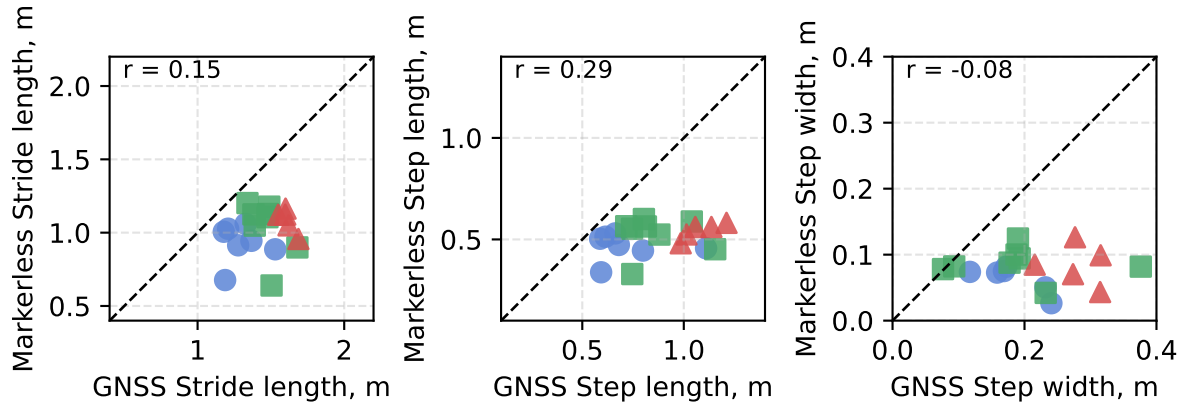


Figure 6.11: Per-recording mean GNSS-derived parameters plotted against their markerless counterparts for stride length, step length, and step width. The identity line is shown for reference. Points are coloured by speed condition. The absence of a meaningful correlation (stride length $r = 0.15$, step length $r = 0.29$, step width $r = -0.08$) reflects the dominance of between-subject variability over the shared speed-dependent signal at this sample size, rather than a failure of either pipeline to capture gait trends.

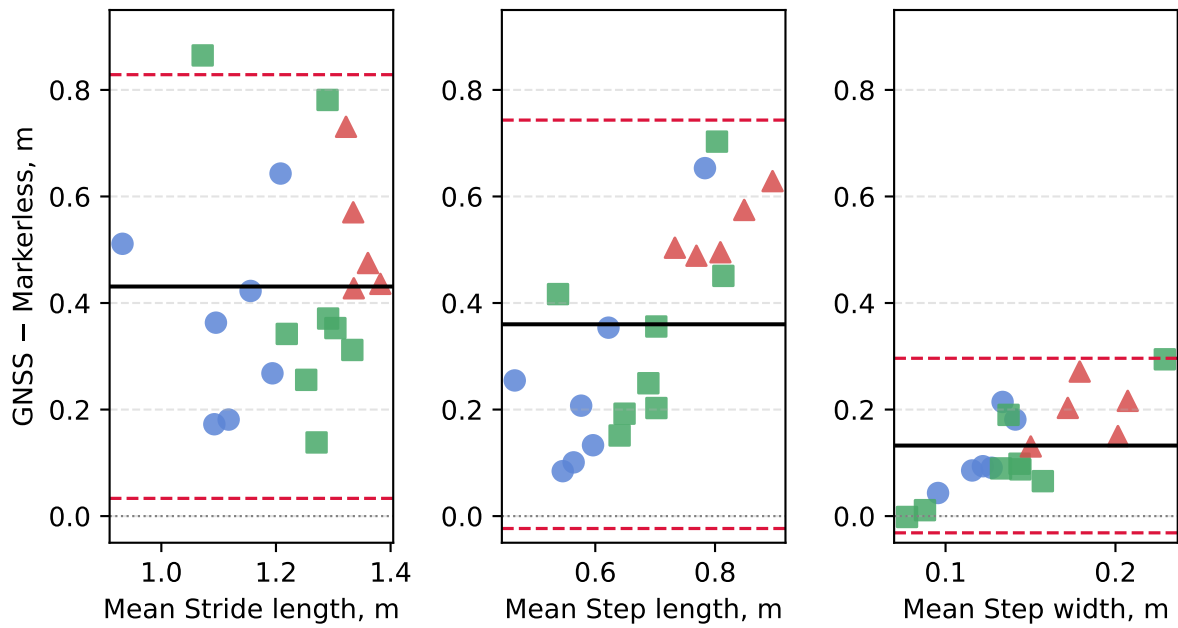


Figure 6.12: Bland–Altman plots showing the difference between GNSS-derived and markerless-derived parameters (GNSS – video) against their mean, for stride length, step length, and step width. The solid horizontal line indicates the mean bias; dashed lines indicate the 95% limits of agreement (± 1.96 SD). Points are coloured by speed condition. The systematic positive bias confirms that GNSS consistently yields larger values than the markerless pipeline for all three metrics.

with speed, the sagittal-plane foreshortening and reprojection errors cause the video pipeline to progressively underestimate the growing displacements, widening the gap with the GNSS estimates.

This interpretation is supported by the internal validation result (Section 6.3.3), which shows that GNSS-derived stride length and cadence are consistent with independently measured torso speed across the full speed range, suggesting that the GNSS mean estimates are closer to the true values than their markerless counterparts. The wide limits of agreement, particularly for stride and step length, indicate that the two methods are not interchangeable for individual-level measurements without an empirical calibration offset.

The step width result deserves particular attention. As a frontal-plane measurement, step width is directly visible from the posterior drone camera without sagittal foreshortening, placing it in a geometrically privileged position relative to the stride and step length metrics. Its bias of +0.132 m is approximately one third of the stride length bias of +0.431 m, and its limits of agreement are substantially narrower. This contrast between the frontal-plane metric and the sagittal-plane metrics is the clearest evidence in the dataset that camera perspective is a primary driver of the systematic offset: the one parameter that is mostly geometrically immune to posterior-view foreshortening is precisely the one that agrees best between the two systems.

The systematic offset between the two pipelines is methodological in origin and not a sensor error in either system. Three contributing factors are identified: the posterior camera geometry causing sagittal-plane foreshortening in the markerless estimates, differences in the body landmark used to represent foot position between the two pipelines, and differences in the heel-strike definition underlying each parameter extraction. The implications of each factor and their relative contributions are examined in detail in Section 6.4.

6.3.6 PPK and EKF Gait Parameter Comparison

The within-recording standard deviation of GNSS-derived gait parameters reported in Section 6.3.3 reflects a combination of true stride-to-stride gait variability and GNSS positioning noise. To assess the relative contribution of each, the loosely-coupled GNSS/IMU extended Kalman filter pipeline described in Chapter 5 was applied to the same dataset as a supplementary sensitivity check. By incorporating IMU dead-reckoning between GNSS epochs, the EKF produces smoother foot position estimates than the raw PPK trajectory, allowing the reduction in within-recording SD relative to PPK to be interpreted as an indicator of the positioning noise component.

Figure 6.13 shows the within-recording SD for EKF and PPK plotted against each other for all three metrics. The EKF reduces within-recording SD by approximately 20% across all metrics. The reduction is systematic and not noise-driven, as confirmed by the fit slopes (0.69, 0.74, and 0.88 for stride length, step length, and step width respectively) and the moderate-to-good correlations between PPK and EKF SDs ($r = 0.76, 0.77, \text{ and } 0.83$). Step width shows the smallest

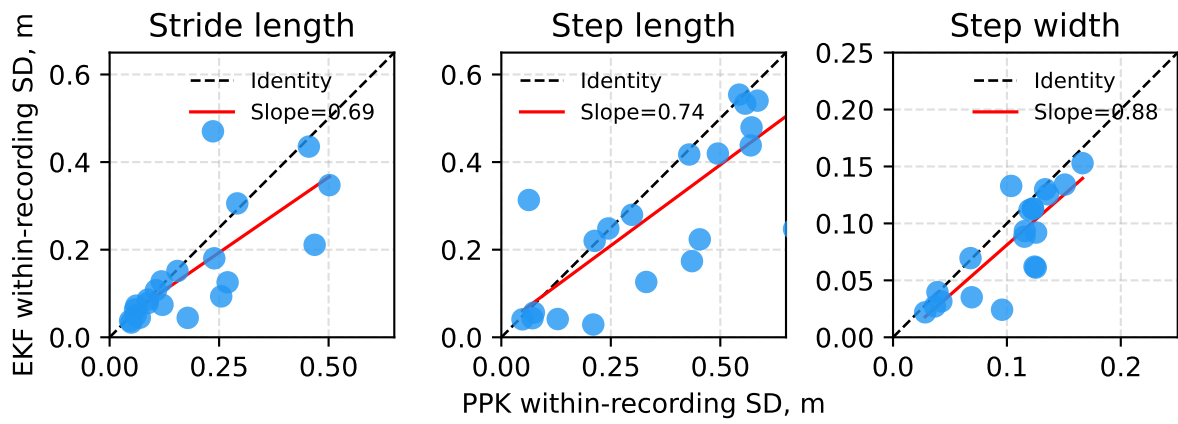


Figure 6.13: Within-recording standard deviation of stride length, step length, and step width: EKF versus PPK, for all matched recordings. Each point represents one recording. The identity line (dashed) and a linear fit through the origin (red) are shown. The fit slope below unity for all three metrics confirms a systematic reduction in within-recording variability when the EKF is used in place of the raw PPK trajectory.

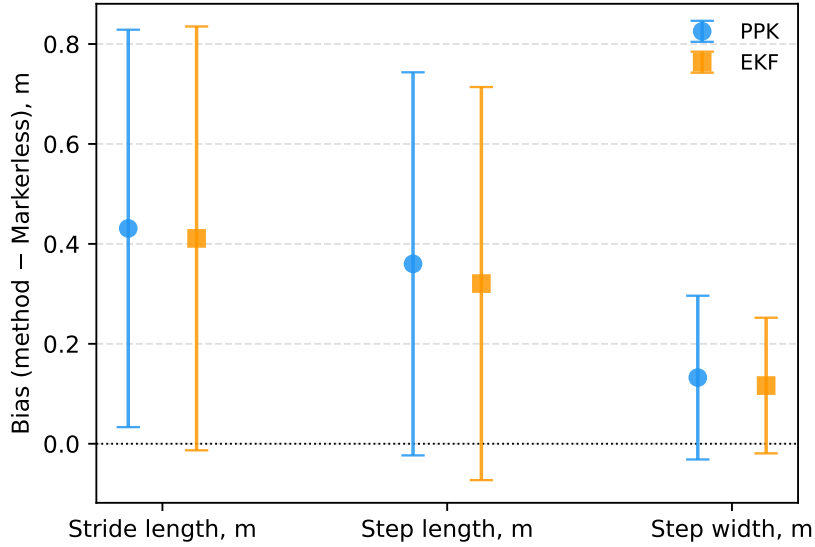


Figure 6.14: Comparison of Bland–Altman bias and 95% limits of agreement against the markerless pipeline for PPK and EKF, pooled across all speed conditions. Error bars indicate the limits of agreement (± 1.96 SD). The bias and limits of agreement are largely unchanged between the two GNSS pipelines, confirming that the systematic offset relative to the markerless pipeline is methodological in origin and is not resolved by EKF smoothing.

reduction, consistent with lateral positioning noise being lower than sagittal noise as discussed in Section 6.3.3. These results confirm that a meaningful fraction of the PPK within-recording SD reflects positioning noise rather than true gait variability, though a substantial component of variability remains even after EKF smoothing, likely reflecting both genuine stride-to-stride variation and remaining positioning error.

Figure 6.14 shows the Bland–Altman bias and limits of agreement against the markerless pipeline for both PPK and EKF, pooled across all speed conditions. The systematic offset is largely unchanged: stride length bias reduces from +0.440 to +0.411 m, step length from +0.372 to +0.321 m, and step width from +0.132 to +0.117 m. While a small reduction in bias is present across all metrics, it is not substantial, and the limits of agreement remain similarly wide for both pipelines. The EKF internal validation yields $r = 0.968$ compared to $r = 0.997$ for PPK, indicating that PPK retains superior internal consistency. Taken together, these results confirm that the systematic offset between the GNSS and markerless pipelines is methodological in origin, rooted in differences in body landmark definition, event detection, and camera geometry, and cannot be resolved by improvements to the GNSS positioning alone. The PPK pipeline is therefore retained as the primary analysis, with the EKF results serving as a sensitivity check confirming the robustness of the main findings.

6.4 Discussion

6.4.1 Speed-Dependent GNSS Degradation: Mechanism and Generalisability

The signal quality results presented in Section 6.3.2 confirm, across nine subjects and a new outdoor environment, the degradation mechanism characterised in Chapter 5: impulsive foot accelerations at toe-off and heel strike disrupt carrier-phase tracking in foot-mounted receivers, causing cycle slips and progressive loss of fixed solutions with increasing walking speed. The consistency of this pattern across subjects, despite substantial inter-subject variability in absolute fix quality at nominally the same speed condition, indicates that the mechanism is robust and not an artefact of the single-subject, controlled conditions of the earlier study. The inter-subject variability itself is explained by the self-paced design: subjects assigned to the same condition label walked at genuinely different speeds, and the continuous torso-derived speed variable reveals that fix quality degrades predictably with actual speed regardless of the condition label applied.

A further observation concerns the ecological validity of the speed range tested. In Chapter 5, the slow metronome condition was set at 60 steps/min, a pace so artificially slow that it has limited correspondence to any natural human walking, even in clinically slow populations. The self-paced slow condition in the present campaign produced walking speeds of approximately 0.8–1.0 m/s, corresponding to roughly 90 steps/min: a pace within the normal range of comfortable walking for healthy adults, and genuinely representative of the slow end of clinical rehabilitation walking. The validation in this chapter therefore covers a genuinely ecologically valid speed range, and the finding that fix quality is acceptable at these naturalistic slow speeds is directly relevant to the clinical rehabilitation context, where patients typically walk at or below comfortable speed.

6.4.2 Cross-Foot Trajectory Inconsistency and Bilateral Asymmetry

Step length and step width are computed from the horizontal displacement between consecutive ground points of the left and right foot, combining position estimates from two independently processed PPK solutions. Any systematic offset between the two receivers, arising from differences in satellite geometry, signal quality, or solution convergence, propagates directly into these parameters as apparent bilateral asymmetry. Stride length, computed within a single foot's trajectory, is largely immune to this effect, which explains the consistently lower within-recording SD observed for stride length relative to step length across all conditions.

To assess the extent of this cross-receiver inconsistency and its relationship to true gait asymmetry, a subset of recordings with both feet achieving above 50% fixed solution fraction was identified. This threshold restricted the analysis to five recordings, all at slow walking speed,

for subjects s3, s6, s7, s8, and s9. The bilateral asymmetry metrics, defined as the mean difference between left and right foot ground point estimates for step length and stride length, are summarised in Table 6.2.

Table 6.2: Bilateral gait asymmetry (left minus right foot mean value) for GNSS and markerless pipelines, restricted to recordings with both foot receivers achieving $>50\%$ fixed solution fraction. Positive values indicate the left side is larger.

Subject	LF fix	RF fix	Step asymmetry (m)		Stride asymmetry (m)	
			GNSS	Video	GNSS	Video
s3	97%	57%	+0.087	+0.186	-0.006	0.000
s6	96%	74%	-0.069	+0.014	-0.005	-0.001
s7	89%	66%	-0.114	+0.141	-0.032	-0.008
s8	96%	93%	-0.061	+0.021	+0.002	-0.001
s9	92%	90%	-0.045	+0.269	-0.009	+0.001

Several observations emerge from this table. First, stride length asymmetry is near-zero in both methods for all subjects ($\text{GNSS} \leq 0.032$ m, $\text{video} \leq 0.008$ m), consistent with the expectation that healthy young adults walk with minimal true stride asymmetry. The apparent Pearson correlation between GNSS and video stride asymmetry ($r = 0.85$) is not interpretable: both variables fluctuate around zero at the scale of measurement noise, and the correlation inverts to $r = -0.60$ when the threshold is relaxed to 30% fixed and n increases to seven, confirming its instability.

Second, step length asymmetry shows no meaningful agreement between the two methods ($r = 0.34$, $p = 0.58$). The disagreement is not merely quantitative: subject s7 shows GNSS step asymmetry of -0.114 m (right foot longer) while the video pipeline reports $+0.141$ m (left foot longer), indicating that the two methods do not agree even on which side is longer. This level of disagreement rules out any clinical interpretation of bilateral step asymmetry from either pipeline in this dataset.

Third, the video step asymmetry is positive for all five subjects, suggesting a systematic bias in the markerless pipeline rather than genuine gait asymmetry. This is consistent with a skeleton alignment or camera-angle artefact in the posterior-view FK reconstruction that systematically displaces one foot’s estimated position relative to the other.

The overall conclusion is that meaningful bilateral asymmetry assessment requires either substantially better bilateral fix quality sustained across a larger number of recordings, or a video pipeline that derives foot positions from absolute spatial displacement rather than snapshots anchored to a camera-relative pelvis frame. Neither condition is met in the current dataset, and asymmetry results should therefore not be interpreted clinically regardless of which pipeline is used. A clinical-grade reference for bilateral asymmetry, such as instrumented gait laboratory or pressure-plate data, was not available for this campaign, and the markerless pipeline cannot substitute for that purpose given its own bilateral biases documented above.

A separate methodological option for stabilising bilateral asymmetry estimation would be to impose biomechanical model constraints, for instance through a multi-segment musculoskeletal model with bilateral consistency assumptions linking the two foot trajectories. Such constraints could regularise the left-right foot estimates and reduce apparent asymmetry. They would, however, constitute assumptions imposed on the sensing observations and not measurements derived from them. Classical motion capture techniques, both marker-based optical and inertial, treat bilateral asymmetry as a clinically informative quantity to be measured directly, and the routine application of strong symmetry constraints would suppress the very signal of interest. The appropriate path forward for the wearable-sensor approach studied here is improving the underlying sensing through better bilateral fix quality, with model-based regularisation a separate methodological choice for applications where symmetry enforcement is acceptable.

6.4.3 Hardware Limitations and Prototype Maturity

Several of the data gaps documented in Section 6.3.1 are attributable to limitations of the prototype hardware and not to algorithmic failures. This should be interpreted accordingly. Three categories of hardware limitations were identified during the campaign.

The first concerns form factor and wearability. The REMOT device measures $5 \times 5 \times 6.5$ cm and weighs 75 g, which is sufficient for research use but remains larger and heavier than would be ideal for routine clinical deployment. The GoPro-style shoe mount, while practical and adjustable, adds additional bulk at the foot and positions the device on the dorsal surface of the shoe, which some participants found uncomfortable during extended walking. A flatter and lighter form factor would reduce both the physical profile and the potential for gait modification.

The second concerns battery management and operational reliability. The devices have an active battery life of approximately 30 to 60 minutes, which is sufficient for the recording sessions conducted here but limits their utility for longer assessments. More significantly, several devices experienced unexpected power-off events during recordings, which could not be attributed to battery depletion alone. The devices lack an adequate battery level indicator, making it difficult to verify charge status before deployment. The high power consumption of the dual-frequency GNSS receiver and antenna is a likely contributing factor, and improved battery management circuitry would be a straightforward engineering improvement in a production-grade implementation.

The third concerns mechanical robustness. The majority of unexpected shutdown events occurred during fast walking trials, where ground impact forces are substantially larger than at slow or normal speed. This pattern supports the hypothesis that the devices were switched off by mechanical shock at heel strike rather than by electrical failure, though this could not be confirmed directly. Shock-resistant enclosure design and hardware-level protection against transient power interruptions would be necessary to ensure reliable operation across the full speed range.

These limitations are characteristics of a research prototype operating outside its design envelope, and should not be conflated with fundamental limitations of the approach. A production-grade implementation addressing these three categories would be expected to yield substantially more complete datasets and more consistent performance across subjects and speed conditions.

6.4.4 Suitability for Rehabilitation-Speed Gait Analysis

The results of this chapter support a qualified positive assessment of the GNSS foot positioning pipeline for gait analysis at slow walking speeds. The internal validation result ($r = 0.997$, slope = 0.972) demonstrates that stride length and cadence derived from the foot receivers are mutually consistent and agree with the independently measured torso speed across the full speed range, including at the naturalistic slow speeds most relevant to rehabilitation assessment. Population-level mean gait parameters are physiologically plausible and scale monotonically with speed across subjects, and the signal quality analysis confirms that slow walking produces acceptable fix quality in most subjects.

An important qualification concerns the relationship between the foot-mounted GNSS approach and a simpler alternative: combining the high-quality torso receiver with IMU-based cadence detection to derive mean stride length as the ratio of torso speed to cadence. The internal validation result demonstrates that this simpler approach would reproduce the mean stride length and cadence values obtained by the foot pipeline with high fidelity, since the product of foot-derived stride length and cadence closely matches torso speed. For applications requiring only mean spatiotemporal parameters at the recording level, the torso-only approach is therefore a viable and substantially simpler alternative that avoids the fix quality limitations of foot-mounted receivers entirely.

The justification for foot-mounted GNSS lies in what the torso approach cannot provide: stride-by-stride spatial resolution, direct geometric observation of foot ground contact positions, step width estimation, and in principle bilateral asymmetry assessment. These capabilities are only realised, however, when bilateral fix quality is sufficient to produce reliable individual ground point estimates. As demonstrated in this chapter, this condition is met consistently only at slow walking speeds and only in a subset of subjects. At normal and fast speeds, individual stride estimates are corrupted by GNSS solution noise to a degree that makes per-stride analysis unreliable, and the mean parameters derived by both approaches converge. This produces a genuine tension in the value proposition of the foot-mounted approach as tested here: the parameters that the current implementation recovers robustly (mean stride length, cadence) are the same parameters the torso-only approach reproduces at lower hardware cost, while the parameters that would justify the additional foot instrumentation (per-stride step width, bilateral asymmetry, stride-to-stride variability) are those the fix quality does not yet support. The added value of foot-mounted GNSS is therefore conditional: it becomes real for a given application only once bilateral fix quality is sufficient to make individual ground point estimates trustworthy, which in the current

hardware generation is achieved consistently only at slow walking speeds and only in a subset of subjects. Extending the operating envelope through the hardware and algorithmic directions identified in Section 8.5 is what would turn the potential added value into a realised one; the current implementation demonstrates that the pipeline works within a well-characterised operating envelope, but not that the foot-mounted architecture is broadly preferable to the torso-only alternative for all rehabilitation gait analysis applications.

The system as currently implemented is therefore best characterised as a slow-speed gait analysis tool, with added value over simpler approaches when bilateral fix quality is adequate. This operating envelope is appropriate for the primary intended application domain of clinical rehabilitation assessment, where patients recovering from neurological conditions typically walk at or below comfortable speed. Extending this envelope to normal and fast walking speeds would require hardware improvements that reduce the susceptibility of foot-mounted receivers to dynamic accelerations. Two paths are open: receivers with wider carrier-phase tracking bandwidth, which is primarily a receiver design question; and deeply coupled GNSS/IMU integration that feeds inertial predictions into the receiver's tracking loops, an active area of development in the GNSS engineering community that represents a natural direction for future work.

6.4.5 Methodological Comparison with Markerless Motion Capture

The systematic offset between GNSS and markerless-derived gait parameters documented in Section 6.3.5 is the result of three methodological differences between the two pipelines, each of which contributes independently to the observed bias.

The first and most significant factor is the posterior camera geometry. The drone filmed subjects from directly behind, providing a frontal view of the body but a foreshortened view of the sagittal plane. Forward displacement, the primary component of both stride and step length, is partially projected out of the image in this configuration, causing the pose estimation algorithm to systematically underestimate sagittal-plane foot separation. The step width result provides the clearest evidence for this explanation: step width is a mediolateral measurement that is directly and fully visible from the posterior view without foreshortening, and its bias (+0.132 m) is approximately one third of the stride length bias (+0.431 m). The directional specificity of the bias, larger for sagittal-plane metrics and smaller for the frontal-plane metric, is consistent with camera perspective being the primary driver of the discrepancy.

The second factor is the difference in foot landmark definition. The GNSS pipeline estimates the position of the GNSS antenna phase center, located approximately at the dorsal midfoot, and uses this as the ground contact point after correcting for the stance-phase average position. The markerless pipeline locates the calcaneus body origin in the OpenSim forward kinematics model, which is a different anatomical point. The correspondence between these two landmarks depends on device placement, shoe geometry, and model scaling, and introduces a subject-specific offset

that contributes to the wide limits of agreement observed in the Bland–Altman analysis.

The third factor is the difference in heel-strike definition between the two pipelines. The GNSS ground point is a covariance-weighted average of foot positions across the full stance interval, from heel strike to toe-off as detected by the IMU acceleration peaks. The markerless pipeline samples the calcaneus position at the instant of heel strike, defined as the knee extension minimum following mid-swing flexion peak. These are fundamentally different quantities: the GNSS estimate integrates spatial information over the entire period of ground contact, while the markerless estimate is a single-frame snapshot at the moment of initial contact.

Taken together, these three factors explain why the two pipelines cannot be directly substituted for one another without an empirical calibration. Both correctly capture the direction and relative magnitude of speed-dependent gait changes, and both provide valid qualitative descriptions of walking behaviour across the speed range tested. For absolute spatial parameters, however, the methods are measuring related but not identical quantities, and the observed bias reflects this fundamental methodological difference.

The methodological differences also limit the value of directly combining the two pipelines at the parameter level: a weighted average of GNSS and markerless stride length, for instance, would inherit the biases of both methods without resolving either. A different mode of integration between body-mounted GNSS and video-based pose estimation is explored in Chapter 7, where GNSS receiver positions are used as virtual markers in a model-based multi-segment inverse kinematics formulation with IMU-derived segment orientations as additional constraints, and the markerless pipeline serves as a reference rather than a coupled measurement source. Independently of stride parameter estimation, the aerial drone platform also has uses beyond what is explored here: its viewpoint is well-suited to capturing whole-body trajectory (given the trajectory of the drone is obtained using methods like RTK), body segment orientations relative to the walking direction, and trunk rotations that are difficult to recover from wearable sensors alone. These extensions are not pursued in this chapter, which is focused on the multi-subject validation of GNSS-derived gait parameters.

6.5 Conclusion

This chapter has presented a multi-subject outdoor validation of the GNSS-based gait parameter estimation pipeline introduced in Chapter 5, extending the proof-of-concept single-subject results to nine subjects walking at self-paced speeds in a field setting, with a portable base station deployed on-site and an independent markerless motion capture reference derived from drone video. The central finding is that the GNSS foot positioning pipeline is internally consistent and produces physiologically plausible gait parameters at slow and naturalistic walking speeds. Internal consistency was demonstrated through the stride-length-times-cadence self-check ($r = 0.997$, slope = 0.972), which confirms coherence between two independent pro-

cessing chains without, by construction, validating absolute stride-length accuracy. The speed-dependent degradation mechanism characterised in Chapter 5 is confirmed across subjects and a new outdoor environment. Even the slowest self-paced speeds recorded in this campaign, approximately 0.8–1.0 m/s, corresponding to roughly 90 steps/min, exceed the artificially slow metronome condition of the earlier study and fall in a range that overlaps with self-selected walking speeds reported in some neurological rehabilitation populations. The extent to which these healthy self-paced speeds are mechanically representative of pathological slow gait, which involves distinct motor control patterns, remains outside the scope of this campaign. The comparison with the markerless pipeline reveals a large systematic offset for sagittal-plane metrics, attributable to posterior camera foreshortening, definitional differences in foot landmark and heel-strike timing, and the fundamental incompatibility of the two measurement quantities, and not to errors in either system.

The chapter’s limitations should be acknowledged alongside its contributions. Prototype hardware failures reduced the completeness of the dataset, and the operating envelope of the foot-mounted GNSS approach remains restricted to slow walking speeds in its current form, with normal and fast speeds producing insufficient fix quality for reliable per-stride estimates. No validation against a clinical gold-standard reference was performed, and the bilateral asymmetry analysis was inconclusive due to the small number of recordings with adequate bilateral fix quality. These limitations define the boundaries of the current system and point directly toward the hardware and methodological improvements needed for clinical deployment.

The natural next step from per-segment foot trajectory reconstruction, now explored and validated across two experimental campaigns, is its extension to multi-segment kinematic reconstruction². This extension uses the absolute positions of multiple body-mounted GNSS receivers as virtual markers in a model-based multi-segment inverse kinematics solver, combined with IMU-derived segment orientations as rotational constraints, generalising the per-segment approach of this chapter to the whole-body level. It is the subject of Chapter 7.

²Within the broader integration framework of this thesis, this corresponds to the progression from Architecture 2 (per-segment, implemented and validated in Chapter 5 and the present chapter) to Architecture 3 (multi-segment inverse kinematics, Chapter 7).

Chapter 7

Outdoor Multi-Segment Kinematic Reconstruction from Wearable GNSS/IMU Pseudo-Markers: A Proof of Concept

7.1 Introduction

This chapter presents a self-contained proof of concept. The relevant background is that Global Navigation Satellite Systems (GNSS) can provide absolute outdoor position estimates, inertial measurement units (IMUs) provide local orientation and high-frequency motion information, and musculoskeletal inverse kinematics can convert sparse sensor observations into anatomically constrained joint coordinates. The central question is whether these three components can be combined so that wearable sensors act as outdoor pseudo-markers for lower-limb kinematic reconstruction.¹

Quantitative movement analysis is central to biomechanics, rehabilitation, sports science and wearable health monitoring. Laboratory marker-based optical motion capture remains the reference technology for joint-level kinematics, but its use is restricted by a bounded capture volume, fixed camera infrastructure and substantial setup requirements. IMU-based systems are deployable in the field and can estimate segment orientations, but they do not provide a reliable absolute spatial reference over long outdoor recordings, and their translational estimates are affected by integration drift. Markerless video systems reduce the need for markers or wearables, yet their accuracy depends on camera placement, participant visibility, lighting, occlusion and calibration. These limitations motivate sensing strategies that retain the deployability of wearables while adding absolute spatial grounding.

¹This configuration is formalized within the broader integration framework of this thesis as Architecture 3 (Chapter 4).

High-precision GNSS is an attractive candidate for this role because carrier-phase processing can provide centimetre-level outdoor position estimates when satellite visibility and ambiguity resolution are favourable. Previous wearable applications have mainly used GNSS to estimate whole-body displacement, running speed, foot trajectories or spatiotemporal gait parameters. These outputs are valuable, but they remain positional or event-based descriptors. They do not directly provide the joint-angle time series required for comparison with conventional biomechanical analysis or for detailed assessment of lower-limb coordination. The next methodological step is therefore to use multiple body-worn GNSS/IMU devices as spatial constraints within a musculoskeletal inverse kinematics problem.

The approach evaluated here distributes wearable GNSS/IMU devices across body segments and treats their GNSS-derived positions as virtual markers expressed in a global metric frame, while the IMU-derived orientations provide rotational constraints for the same instrumented segments. These positional and orientational observations are supplied to an OpenSim inverse kinematics solver, which estimates the configuration of a musculoskeletal model that best satisfies all available constraints. In a dense configuration, one device per major segment could constrain most lower-limb degrees of freedom while retaining outdoor deployability. In the present proof-of-concept implementation, only three devices are available: one on the chest and one on each foot. This sparse layout is intentionally interpreted as a minimal configuration, still being far from a complete kinematic measurement system.

The primary outcome is hip flexion, because the relative position and orientation of the torso and foot devices provide information about the sagittal-plane relation between the trunk/pelvis region and the distal lower limb. Knee and ankle coordinates are reconstructed by the model but are not treated as validated outcomes, because no thigh or shank sensors are available to directly constrain the intermediate segments. The active reconstruction includes pelvis spatial coordinates, hip rotations, knee flexion and ankle flexion, but the lower-limb kinematic chain is only partially observed. The claim of this chapter is therefore deliberately narrow: the study tests whether spatially grounded GNSS pseudo-markers and IMU orientations can jointly drive a biomechanical solver in the field and reproduce the timing and phase of hip flexion during walking. It does not claim to approach complete lower-limb kinematic accuracy, clinical readiness or equivalence to laboratory optical motion capture.

Outdoor walking recordings collected in a stadium environment in Luterbach, Switzerland, were reprocessed using an automated two-stage pipeline combining GNSS post-processing, GNSS/IMU sensor fusion, musculoskeletal model scaling, sensor-to-segment calibration and inverse kinematics. The resulting hip-flexion time series were compared with joint angles obtained from a drone-based markerless video pipeline acquired during the same trials. The markerless system is used as an independent reference but not as a gold standard-level ground truth, because posterior monocular video can introduce camera-geometry biases, particularly for sagittal-plane range of motion. The primary endpoint is temporal agreement of hip flexion, with range-of-motion bias, RMSE, bilateral symmetry, GNSS fix quality and failure behaviour treated as secondary or

diagnostic outcomes.

7.2 Materials and Methods

7.2.1 Participants

The recordings used in this study are the Luterbach stadium dataset, collected across nine participants during outdoor walking trials with simultaneous wearable GNSS/IMU sensing and drone-based video recording. The present analysis used only recordings for which the chest device, both foot devices and markerless video reference were simultaneously available and time-alignable. Participants S1 through S5 were excluded from the inverse-kinematics analysis: S4 produced no usable foot data because all three foot-worn receivers powered off at the start of the recording session, as documented in Chapter 6; S3 and S5 had incomplete foot-device data at the analysed walking speed (one foot only); and S1, S2 produced bilateral foot GNSS data whose fix quality was insufficient to support stable inverse-kinematics convergence, with the resulting joint angle trajectories anatomically implausible across the recording. The remaining four participants (S6, S7, S8 and S9) provided usable recordings, although GNSS quality varied across devices and participants. For S7, only the first 42 s were retained, because the fixed GNSS solution was lost on both foot devices thereafter and the reconstructed signal diverged sharply from the markerless reference.

Per-participant inclusion status is summarised in Table 7.1.

Table 7.1: Participant inclusion in the inverse-kinematics analysis. Recording-level hardware failures for the broader campaign are documented in Chapter 6.

Participant	Included	Usable duration	Status / reason for exclusion
S1	No	–	Bilateral foot fix below IK convergence threshold
S2	No	–	Bilateral foot fix below IK convergence threshold
S3	No	–	Right-foot recording incomplete; bilateral IK not possible
S4	No	–	All foot devices powered off; no data (see Ch. 6)
S5	No	–	Right-foot recording incomplete; bilateral IK not possible
S6	Yes	~72 s	Right-foot GNSS degraded (56.1% fix)
S7	Yes (truncated)	42 s	Fix loss after 42 s; pre-failure segment used
S8	Yes	~140 s	Cleanest GNSS solution across all devices
S9	Yes	~138 s	High GNSS fix quality; markerless ROM asymmetry on left side

7.2.2 Experimental Apparatus

The wearable system consisted of three REMOT GNSS/IMU devices used simultaneously: one mounted on the chest with a GoPro-compatible harness and one mounted on each foot with GoPro shoe mounts. Each REMOT unit integrates a low-cost GNSS receiver and antenna, an IMU, onboard storage, battery and embedded electronics in a compact wearable package. The chest device provided a relatively stable sky view and supplied a torso-position constraint; the two foot devices supplied distal lower-limb position and orientation constraints. A local GNSS base station was installed at the recording site to support carrier-phase differential post-processing of the rover receivers.

The independent video reference was obtained with a drone-mounted camera recording the walking trials from a posterior aerial viewpoint. The markerless pipeline estimated body pose from the video sequence and exported joint angles, which were subsequently converted to the OpenSim coordinate conventions used by the wearable-sensor reconstruction. This video reference is independent of the GNSS/IMU pipeline, but it is not an absolute ground truth because posterior monocular viewing can introduce foreshortening and range-of-motion bias, and also does not reconstruct translation with respect to a fixed coordinate frame.

Kinematic reconstruction used the Rajagopal full-body musculoskeletal model [104], comprising 37 degrees of freedom spanning the lower limbs, pelvis, lumbar spine and upper extremities. For this sparse three-device reconstruction, the lumbar coordinates were locked to a neutral posture because no pelvis or lumbar sensor was available to constrain motion between the torso and pelvis. The upper-limb coordinates were excluded because no arm sensors were available and arm motion was outside the scope of the lower-limb analysis. The effective reconstruction therefore focused on pelvis and lower-limb coordinates, with hip flexion defined a priori as the primary interpretable output.

7.2.3 Task and Experimental Protocol

The recordings were collected during outdoor overground walking trials in a stadium environment in Luterbach, Switzerland. The site was selected to provide an open-sky GNSS environment while retaining enough spatial structure for drone-based video recording. Participants walked along the field while wearing the chest and bilateral foot devices, and the aerial drone recorded the movement from a posterior viewpoint. Only slow-speed trials yielded physiologically plausible inverse-kinematics outputs in the sparse three-device configuration; higher-speed recordings produced implausible body configurations under compromised GNSS conditions and are therefore used only as evidence of failure behaviour.

7.2.4 Data Analysis

7.2.4.1 Reconstruction Principle

The kinematic reconstruction pipeline treats the outputs of the GNSS/IMU sensing system as two complementary classes of constraint for a biomechanical inverse kinematics solver. GNSS-derived positions of each instrumented segment are supplied as virtual markers, three-dimensional positional observations expressed in a globally referenced metric frame, while IMU-derived orientations are converted into weighted coordinate references that constrain the rotational degrees of freedom of the corresponding model segments. This combined use of positional and orientational constraints within a single solver distinguishes the approach from both standard optical motion capture pipelines, which rely on marker positions alone, and from IMU-only systems, which provide orientational constraints without absolute spatial grounding. The solver used in this work is the `OpenSim InverseKinematicsSolver` [106], which natively supports both marker references and orientation sensor references as weighted inputs to the same assembly problem.

7.2.4.2 Inverse-Kinematics Solver

The `InverseKinematicsSolver` finds the set of model coordinates $\mathbf{q}$ that minimises the following weighted objective function:

$$J = \sum_i W_{m_i} (\mathbf{m}_i - \mathbf{m}_i^d)^T (\mathbf{m}_i - \mathbf{m}_i^d) + \sum_j W_{q_j} (q_j - q_j^d)^2 \quad (7.1)$$

where $\mathbf{m}_i$ and $\mathbf{m}_i^d$ are the model-predicted and observed positions of the i -th virtual marker (three-dimensional vectors); q_j and q_j^d are the model and desired values of the j -th generalised coordinate; and W_{m_i} and W_{q_j} are the corresponding scalar weights. The minimisation is subject to the hard kinematic constraints of the model:

$$\mathbf{c}_{\text{err}} = G(\mathbf{q}) - G_0 = \mathbf{0} \quad (7.2)$$

which enforce joint limits and model topology regardless of the data fit. IMU orientation observations enter the objective through the coordinate term: each observed segment orientation is converted into a set of desired coordinate values q_j^d for the degrees of freedom of the corresponding model segment, which are then weighted and minimised alongside the marker position errors. Per-marker and per-coordinate weights W_{m_i} and W_{q_j} are assigned based on the estimated reliability of each observation, as described in the automated processing pipeline below.

A practical consequence is that the IK output should be interpreted coordinate by coordinate. Hip flexion is the lower-limb coordinate most strongly modulated by the position and orientation

relationship between the chest and foot sensors, and is therefore the best-constrained joint coordinate in this sparse configuration. Knee and ankle coordinates, lying between the foot sensor and the proximal anchor with no directly instrumented intermediate segments, are not directly constrained by any sensor pair and are reconstructed only implicitly through the kinematic chain. They are computed by the solver but are not treated as validated outcomes.

7.2.4.3 Constraint Quality and Sensor Placement

The quality with which the solver can determine a given joint coordinate depends directly on the proximity and density of the available constraints in the kinematic chain. Joints whose parent and child segments are both instrumented are tightly constrained by both positional and orientational observations; joints located between two uninstrumented segments receive only indirect constraints propagated through the model topology, and are therefore poorly determined. In a sparse configuration, the solver will still produce a value for every coordinate in the model, but those values for poorly constrained joints reflect the weighted least-squares compromise of the assembly problem instead of a physically meaningful estimate. This property of the solver must be kept in mind when interpreting results from any configuration that does not provide dense coverage of the kinematic chain.

7.2.4.4 Scalability and Spatial Grounding

The framework scales naturally with the number of instrumented segments. As additional GNSS/IMU devices are placed on the body, more degrees of freedom become directly constrained, and the solver solution approaches the quality achievable with a dense optical marker set. At the upper end, a fully instrumented configuration with receivers on each major segment would constrain the complete kinematic chain in an outdoor, infrastructure-light setting, occupying the gap between laboratory optical motion capture, which is accurate but bounded by a capture volume, and fully wearable IMU-only systems, which are deployable but lack absolute spatial grounding. The minimal three-device configuration evaluated in this study is a consequence of the available prototype hardware, and the results presented here should be read as a lower bound on what the framework can achieve.

A complete IMU-based motion capture system, in which every body segment carries an IMU, can in principle constrain all rotational degrees of freedom of a biomechanical model. However, without absolute positional observations, the global position and translational trajectory of the body cannot be recovered, and segment lengths must be assumed instead of measured in situ. More critically for a sparse configuration such as the one evaluated here, the absence of positional constraints on intermediate segments leaves the corresponding joint coordinates underdetermined: the IK solver has no positional information to anchor the thigh or shank, and freely distributes residual errors across those degrees of freedom. GNSS-derived pseudo-markers

resolve this by providing metric-scale positional anchors at the instrumented segments, bounding the solution space even where orientational coverage is incomplete. This is the principal added value of the distributed pseudo-marker approach over a purely inertial approach in a sparse sensing scenario.

7.2.4.5 Orientation Estimation and Yaw Correction

Segment orientations were estimated using the extended Kalman filter used for GNSS/IMU sensor fusion, with RTS smoothing applied. For one device, which exhibited a two-regime yaw bias caused by the interaction between a faulty magnetometer and the GNSS velocity corrections applied during walking, the EKF quaternion output was replaced by the output of a Madgwick filter [23, 24], which produces a stable yaw estimate independent of GNSS velocity updates. For the remaining devices, the two estimators produced comparable orientation outputs. A PCA-based yaw alignment procedure was additionally applied to the affected device to correct residual misalignment between the sensor yaw reference and the walking direction: the principal component of the torso GNSS trajectory in the horizontal plane was used as a proxy for the walking direction, and the sensor frame was rotated accordingly. These corrections are pragmatic responses to a hardware limitation of the prototype devices and do not affect the processing of the remaining sensors.

7.2.4.6 Coordinate Frames, Synchronisation and Alignment

GNSS positions are first expressed in a local tangent frame (ENU), translated to the OpenSim ground frame, and assigned to virtual marker locations corresponding to the physical sensor mounts. IMU quaternions are converted from sensor-frame orientations to OpenSim segment-frame orientations using the neutral-pose calibration estimated by the IMU placement step. Markerless joint angles are mapped to the corresponding OpenSim coordinate signs and conventions before comparison.

Temporal alignment is performed once per trial by maximising the cross-correlation between the markerless and GNSS/IMU hip flexion signals over a plausible lag window. After this global alignment, no cycle-by-cycle time warping is applied. This distinction matters: the reported correlations therefore reflect preservation of gait timing and phase over the whole recording. The cross-correlation lag was computed within a window of ± 2 s for each trial and side. The selected lags fell within a narrow range across recordings, consistent with stable temporal alignment between the two systems; no trial failed alignment.

7.2.4.7 Automated Processing Pipeline

The multi-device, multi-participant dataset processed in this study involves a large number of interdependent processing steps spanning GNSS post-processing, sensor fusion, musculoskeletal model scaling, IMU calibration, and inverse kinematics. Each step exposes independent configuration parameters, such as GNSS processing settings, EKF tuning, IK solver weights, and model scaling mode, that must be maintained consistently across sessions to ensure reproducibility. Manual execution of this chain would be error-prone and difficult to audit. An automated pipeline was therefore developed to encapsulate the full processing sequence from raw sensor observations to joint angle trajectories, with all configuration stored explicitly in per-experiment files that travel alongside the data.

A further motivation is portability across computing environments. The pipeline is structured as two sequential processing stages, each encapsulated in an independent Docker container and orchestrated by a host-side Python script. Containerisation ensures that all dependencies of all software modules (the GNSS processing library, the EKF implementation, and the OpenSim installation) are fully specified and version-locked, so that the pipeline produces identical outputs regardless of the host operating system or software environment. This design also enforces a clean architectural separation between the sensor fusion stage and the biomechanical modelling stage, making each independently testable and replaceable.

The pipeline comprises two stages executed sequentially for each experimental session. The session data directory and a shared recording configuration file are mounted into each container in turn by the host orchestrator, which polls for Stage 1 output files before launching Stage 2, ensuring correct ordering without requiring inter-container communication.

Stage 1: Sensor Fusion. The first container transforms raw sensor observations into synchronised, calibrated time series of position and orientation for each instrumented segment. For GNSS-equipped devices, carrier-phase differential post-processing is applied to the raw observations to produce centimetre-level position estimates, which are subsequently fused with IMU readings by an Extended Kalman Filter with RTS backward smoother at 100 Hz. The full state covariance matrix is propagated throughout, providing per-epoch uncertainty estimates for both position and orientation. For IMU-only devices, a Madgwick filter is applied instead [24]. All data streams are synchronised to a common 100 Hz time grid by computing the temporal overlap interval across sensors and resampling through linear interpolation. An optional yaw correction step aligns the heading of each sensor to the principal axis of the torso GNSS trajectory. Stage 1 writes three output files: a `.trc` file encoding the GNSS-derived segment positions as virtual markers in the OpenSim convention; a `.sto` file encoding the quaternion orientation time series of all sensors; and a file containing the per-epoch EKF standard deviations for position and orientation components.

Stage 2: Biomechanical Modelling. The second container consumes the Stage 1 outputs and produces joint angle trajectories using OpenSim 4.5. The generic Rajagopal full-body muscu-

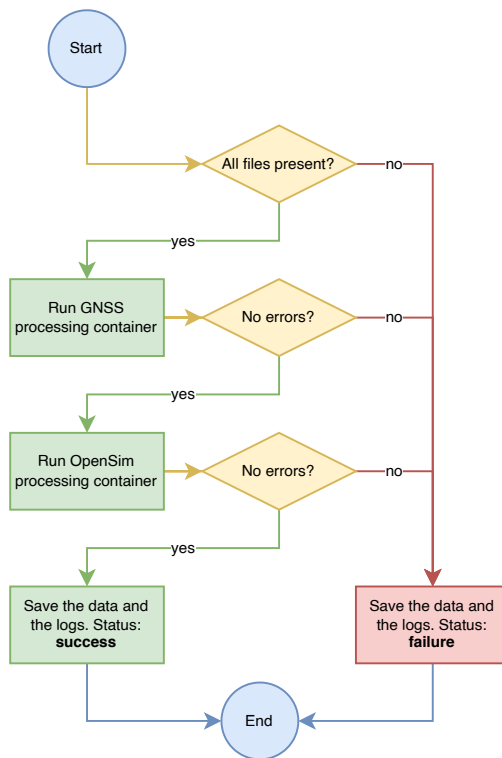


Figure 7.1: Host orchestration logic. The orchestrator verifies input file availability, launches the two processing containers sequentially, handles errors at each stage, and archives the data and logs together with a success or failure status.

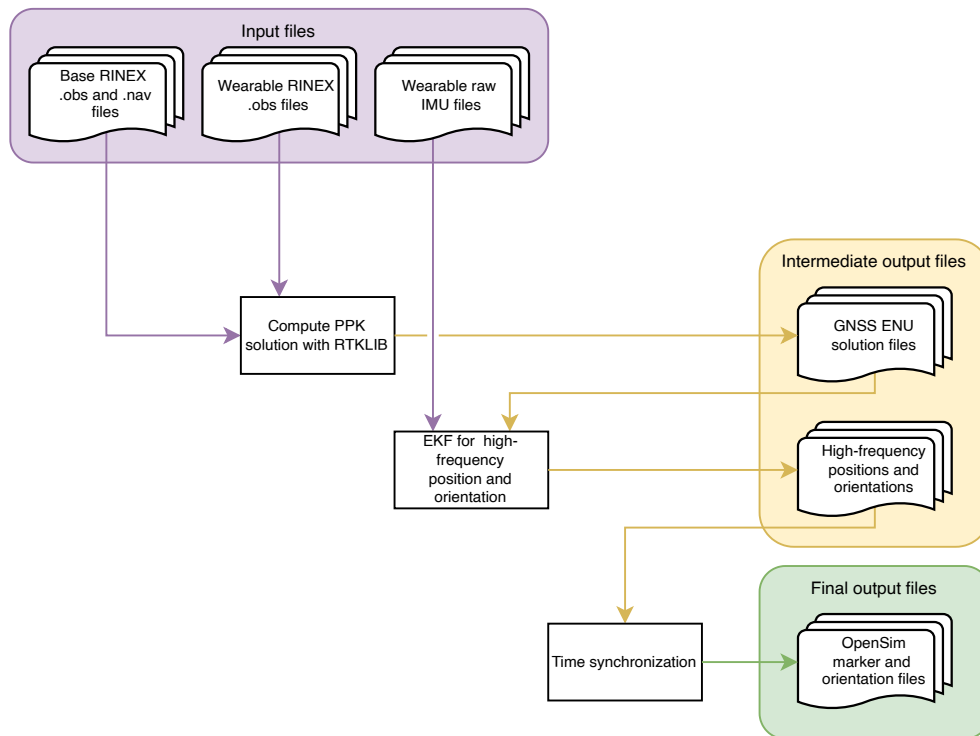


Figure 7.2: Stage 1 (Sensor Fusion container) data flow. Raw RINEX observations from the wearable devices, together with RINEX observation and navigation files from the base station, are post-processed by RTKLIB to produce ENU position solutions. These are fused with the IMU signals through an extended Kalman filter to produce high-frequency positions and orientations, which are then time-synchronised and exported as OpenSim-format marker and orientation files.

loskeletal model [104], comprising 37 degrees of freedom (lumbar rotations are locked, and the upper body is not instrumented, hence not making part of the IK problem), is first scaled to participant anthropometry. The scaling mode is height-based uniform scaling, in which a single isotropic scale factor is derived from the ratio of the participant’s height to the default model height and applied to all segments. The scaled model is then passed to the OpenSim IMUPlacer, which estimates the rotation offset between each physical sensor frame and the anatomical segment frame it is mounted on (sensor to segment alignment), using orientation data recorded during a brief neutral standing posture at the start of each trial, a standard requirement in IMU-based motion capture. Finally, joint angles are estimated at each epoch by the InverseKinematicsSolver, using the virtual marker positions and IMU orientations from Stage 1 as inputs.

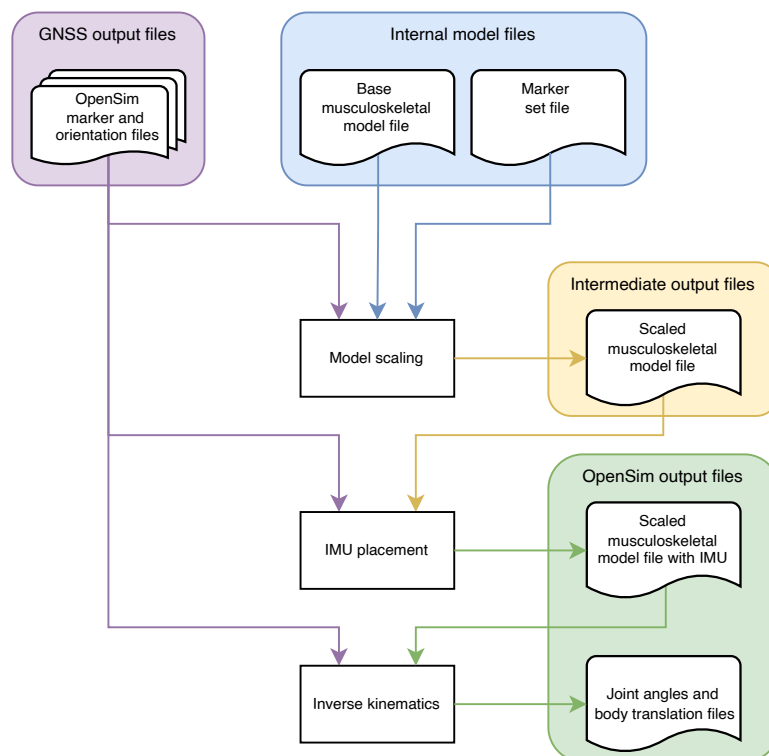


Figure 7.3: Stage 2 (Biomechanical Modelling container) data flow. The OpenSim-format marker and orientation files produced by Stage 1, together with the Rajagopal model file and a marker set definition, are processed sequentially through model scaling, IMU placement, and inverse kinematics, producing joint angle and body translation time series.

7.2.4.8 Per-Epoch Covariance-Derived Weights

The pipeline applies per-epoch covariance-derived weights to the IK solver: the solver weight for each virtual marker at epoch t is set inversely proportional to the positional variance reported by the EKF covariance:

$$w_i(t) = \frac{\sigma_{\text{ref}}^2}{\sum_j \sigma_{p_j}^2(t)} \quad (7.3)$$

where σ_{ref} is a reference standard deviation representing unit weight and $\sigma_{p_j}^2(t)$ are the position component variances at epoch t . Orientation weights are derived analogously from the quaternion component variances. For IMU-only devices, for which no EKF covariance is available (the Madgwick filter does not propagate a state covariance), a fixed neutral weight is assigned. All weights are clipped to a finite range to prevent numerical ill-conditioning. This scheme is a natural extension of the EKF covariance information into the downstream IK solver: epochs with degraded positioning quality, due to multipath, signal occlusion, or cycle slips, contribute proportionally less to the IK solution, allowing the orientation data to dominate when positional accuracy is low. The scheme requires no manual intervention and adapts continuously to the evolving signal environment throughout each trial. It is not claimed here as a separately validated contribution: a controlled ablation against fixed weights and orientation-only weighting on the same trials is identified as a direction for future work in Section 7.4.6.

7.2.5 Statistical Analysis

The primary analysis compared hip-flexion time series from the wearable GNSS/IMU inverse-kinematics pipeline with the corresponding markerless-reference time series. Time alignment was performed once per trial by maximising the cross-correlation between the two hip-flexion signals over a plausible lag window; after this global alignment, no stride-by-stride time warping was applied. This procedure preserves the ability to evaluate whether the wearable pipeline maintains gait-cycle timing over the whole recording instead of forcing local agreement at each stride.

The primary endpoint was the Pearson correlation coefficient r , interpreted narrowly as a measure of temporal and phase agreement between the two waveforms. The interpretive limits of this endpoint should be stated at the outset: hip flexion during walking is a quasi-periodic signal whose dominant spectral content is concentrated at the gait cycle frequency, and any two signals that share this frequency will exhibit high Pearson correlation regardless of whether their amplitudes match. A high r therefore establishes only that the pipeline reproduces the timing and phase of the gait cycle. Amplitude fidelity is the domain of the range-of-motion ratio and, secondarily, RMSE, which are treated as the more informative outcomes for the accuracy of the reconstruction. Additional secondary outcomes were mean offset, cycle-based hip-flexion range of motion (ROM), bilateral symmetry index, and GNSS fix-quality summaries for each device. Mean off-

sets between the two systems were subtracted before RMSE computation so that RMSE primarily reflected waveform mismatch and amplitude disagreement, and not arbitrary differences in coordinate zeroing. ROM was computed as the median cycle-based peak-to-trough angular excursion. With the number of usable participants limited to four, all numerical results are treated as descriptive proof-of-concept evidence. The wider question of inferential validation, including formal tests against a phase-randomised or cycle-shuffled null distribution to establish that observed correlations exceed what shared periodicity alone produces, is identified as a direction for future work in Section 7.4.6.

7.3 Results

This section reports the experimental findings obtained from the minimally instrumented three-device GNSS/IMU configuration. The results are presented first for a representative high-quality trial, then across all usable participants, and finally through diagnostic analyses of GNSS fix quality and failure behaviour.

Figure 7.4 shows a snapshot of the reconstructed motion for Participant 8, the participant with the cleanest GNSS solution quality across all three devices. The figure illustrates the qualitative output of the pipeline before the quantitative analysis that follows.

7.3.1 Representative Trial: Participant 8

Figure 7.5 shows the hip flexion reconstruction for Participant 8, the participant with the cleanest GNSS solution quality across all devices. The upper panel shows the full trial; the lower panel shows a 15-second detail window to illustrate cycle-level agreement. The GNSS/IMU pipeline and the markerless reference track each other closely in phase and rhythm throughout the recording, with a Pearson correlation of $r = 0.874$ for the right side and $r = 0.926$ for the left. The gait cycle structure, namely the flexion and extension phases and the timing of peak flexion, is consistently reproduced by the pipeline across the full trial duration.

Two systematic differences are visible. First, the pipeline signal exhibits a slowly fluctuating mean over timescales of tens of seconds, whereas the markerless signal maintains a nearly stationary baseline. This low-frequency fluctuation is not a monotonic drift but a stochastic variation driven by residual positional noise in the GNSS solution propagating into the underdetermined IK problem: with only three instrumented segments and sixteen active lower limb coordinates, the solver has insufficient constraints to prevent positional residuals from being absorbed into hip flexion. Second, the pipeline consistently produces a larger range of motion than the markerless reference: 78.2° versus 42.0° on the right and 75.9° versus 36.1° on the left. This overestimation has two contributing sources. The primary source is camera foreshortening in the markerless

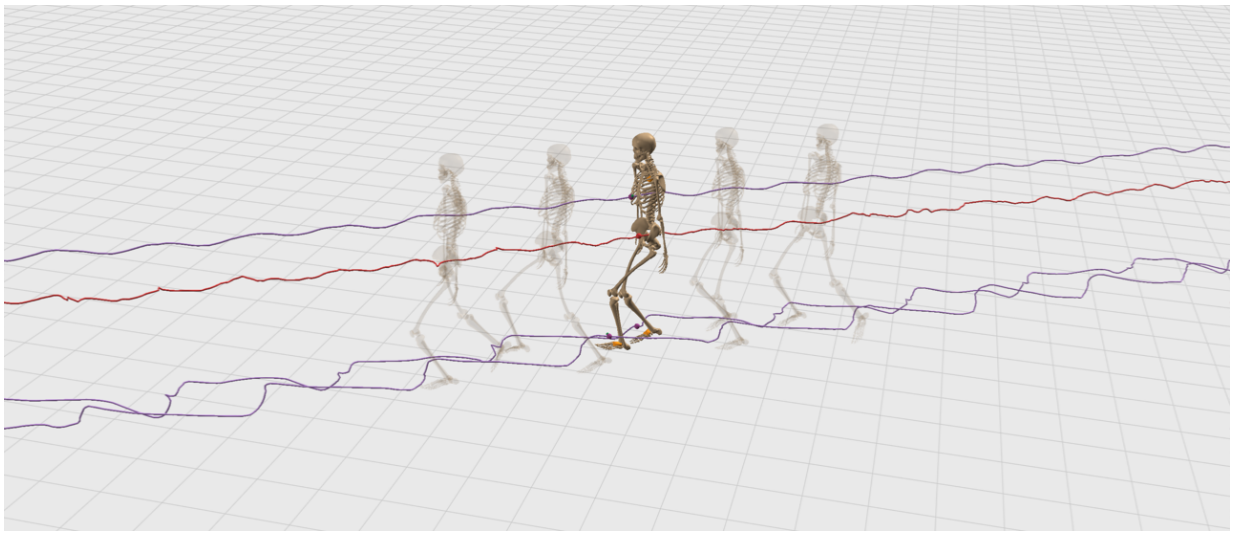


Figure 7.4: Reconstructed multi-segment motion of Participant 8 during outdoor walking. Transparent skeletal models show the OpenSim model configuration at sampled time instants along the walking path. Purple traces show the trajectories of the foot and torso devices, which are the GNSS-instrumented segments; the red trace shows the reconstructed pelvis trajectory. The motion is reconstructed in a globally referenced metric frame from the three-device GNSS/IMU configuration described in Section 7.2.2.

reference: the drone’s posterior monocular viewpoint compresses the apparent sagittal-plane excursion when the participant does not walk perfectly perpendicular to the camera axis, systematically underestimating hip flexion range of motion. This mechanism is consistent with the expected effect of posterior monocular viewing geometry on sagittal-plane motion under the same recording conditions. A secondary contribution comes from the locked lumbar joint in the musculoskeletal model: trunk motion that would physiologically distribute across lumbar and hip degrees of freedom is entirely absorbed into hip motion when the lumbar coordinates are fixed. A tertiary contribution comes from the underdetermined IK configuration, which under conditions of residual positional noise tends to distribute errors into the least-constrained degrees of freedom, further amplifying the apparent range of motion. The relative contribution of these sources cannot be fully separated without an absolute ground truth reference; all three are discussed in detail in the range-of-motion discussion.

Importantly, the degree of agreement observed here should not be evaluated against the standard of a fully instrumented system. With three sensors constraining the model, the lower limb kinematic chain is substantially underdetermined, and close agreement with any reference system is not guaranteed a priori. The phase coherence and cycle-level correspondence visible in Figure 7.5 therefore constitute a meaningful result in their own right, demonstrating that the GNSS/IMU pipeline captures the essential temporal structure of hip flexion during walking even in this minimal configuration.

7.3.2 Summary Across Participants

All quantitative comparisons are computed after subtracting the mean offset between systems over the analysed interval, so that RMSE reflects waveform mismatch and amplitude disagreement, and not arbitrary differences in coordinate zeroing. Pearson correlation is reported as the primary proof-of-concept endpoint because it measures preservation of gait timing and phase; RMSE and ROM ratio are reported as secondary bias-sensitive outcomes.

Figure 7.6 shows the hip flexion reconstruction for all four usable participants and both sides. In each panel, the pale traces show the raw signals and the bright dashed lines show 6-second moving averages, illustrating the low-frequency mean fluctuation of the GNSS/IMU signal relative to the stable markerless baseline. Table 7.2 summarises the quantitative agreement metrics.

ROM values reported here are median cycle-based peak-to-trough arcs of motion, equivalent to total hip angular excursion in the biomechanical convention, and should not be confused with peak hip flexion angle as reported in clinical goniometry literature, which is a different and smaller quantity. Pearson correlation values range from $r = 0.752$ to $r = 0.926$ across all participant-side combinations, indicating reliable capture of gait timing and phase throughout the dataset. The lowest value, Participant 9 left side ($r = 0.756$), is attributable to the anomalously small markerless ROM of 19.9 on that side, below the reference range of 39–50° for total

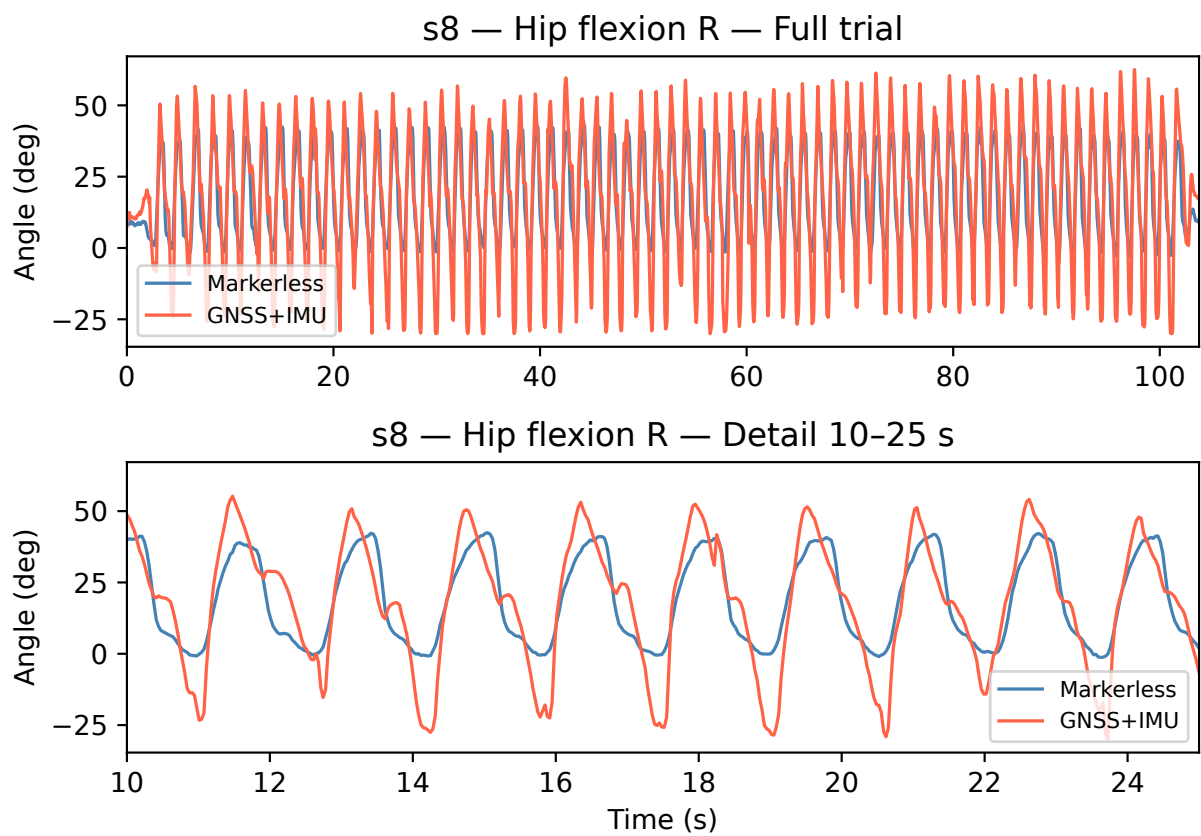


Figure 7.5: Hip flexion reconstruction for Participant 8 (right side). Upper panel: full trial. Lower panel: 15-second detail window. GNSS/IMU pipeline (orange) and markerless reference (blue).

Table 7.2: Hip flexion reconstruction metrics for all usable participants. ROM values are median cycle-based peak-to-trough arc of motion per gait cycle, equivalent to total hip angular excursion in the biomechanical convention, and distinct from the peak flexion angle reported in clinical goniometry literature. Reference range for total hip sagittal arc during walking in healthy adults: 39–50° [1, 2].

Participant	Side	Offset (°)	RMSE (°)	r	ROM _{video} (°)	ROM _{pipeline} (°)	Ratio
S6	R	0.3	18.3	0.752	49.4	72.3	1.46
S6	L	−12.2	21.1	0.898	32.4	82.6	2.55
S7*	R	7.7	11.2	0.832	32.0	53.7	1.68
S7*	L	2.3	8.8	0.923	28.9	61.7	2.14
S8	R	0.1	13.1	0.874	42.0	78.2	1.86
S8	L	2.0	13.7	0.926	36.1	75.9	2.10
S9	R	−8.7	20.2	0.894	33.4	84.0	2.51
S9	L	−11.6	21.7	0.756	19.9	61.7	3.09

*S7 truncated at 42 s due to GNSS fix loss; see the failure-case analysis.

hip sagittal arc during walking in healthy adults [1, 2], which reduces the signal-to-noise ratio for both systems simultaneously and makes reliable agreement difficult regardless of pipeline quality. Visual inspection of both the video and the pipeline output confirms that this participant exhibited genuinely reduced left-side hip flexion during this recording, and not a pipeline failure. RMSE values range from 8.8 to 21.7, reflecting amplitude differences between the two systems, and not phase errors; as noted in the representative-trial analysis, these are expected consequences of the underdetermined IK configuration and camera foreshortening in the markerless reference, and should not be interpreted as tracking failures.

The pipeline ROM values consistently exceed the markerless reference across all participants and sides (ratio always ≥ 1.46), and consistently exceed the reference range of 39–50° for total hip sagittal arc during walking in healthy adults [1, 2]. The markerless ROM values, by contrast, range from 19.9° to 49.4° across participants, spanning from below to within the reference range, consistent with a combination of genuinely slow walking speeds and systematic underestimation due to camera foreshortening. The ROM ratio is substantially higher for participants with compromised foot device GNSS quality, namely S6 left (2.55) and S7 left (2.14), compared to participants with clean foot GNSS such as S8 (1.86–2.10), confirming that IK noise amplification under poor GNSS conditions contributes to ROM overestimation beyond the foreshortening effect alone.

The bilateral symmetry of the hip flexion ROM provides an additional perspective on the reliability of the two systems. Table 7.3 reports the Symmetry Index (SI), defined as $SI = 2|ROM_R - ROM_L| / (ROM_R + ROM_L) \times 100\%$ [107], for both the markerless reference and the GNSS/IMU pipeline. For healthy adults performing straight walking, SI values close to zero

are expected. The markerless reference produces SI values of 41.4% and 50.6% for Participants 6 and 9 respectively, values that are physiologically implausible for healthy participants on a straight path, and indicative of pipeline artefacts and not true gait asymmetry. The GNSS/IMU pipeline shows better bilateral symmetry than the markerless reference for three of the four participants, with Participant 7 being the only case where the two systems show comparable and moderate asymmetry. These observations suggest that the markerless reference should not be treated as an unconditionally reliable standard, a point developed further in the range-of-motion discussion.

Table 7.3: Hip flexion ROM symmetry index (SI) for markerless and GNSS/IMU pipeline. Lower values indicate greater bilateral symmetry. The final column indicates which system shows greater bilateral symmetry.

Participant	SI — Markerless (%)	SI — GNSS/IMU (%)	More symmetric
S6	41.4	13.3	GNSS/IMU
S7	10.3	13.8	Markerless
S8	15.1	3.1	GNSS/IMU
S9	50.6	30.7	GNSS/IMU

7.3.3 GNSS Fix Quality and Reconstruction Variability

Table 7.4 reports the GNSS solution quality statistics for each device and participant. The torso receiver maintains a 100% fixed solution across all participants and recordings, consistent with the expected advantage of torso placement for sky visibility. Foot device quality is more variable: Participant 8 and Participant 9 show high fix rates on both feet ($\geq 91\%$), while Participants 6 and 7 show substantially degraded fix rates on the right foot (56.1% and 52.9% respectively), with a significant proportion of float and DGNSS epochs.

Despite the clear difference in foot GNSS quality between participants, fix quality alone does not explain the variability in reconstruction results. Participant 9, which has the cleanest foot GNSS of all participants, produces among the largest ROM ratios and RMSE values. This apparent contradiction reflects a fundamental characteristic of the present setup: the reconstruction is a demonstration of the architectural principle and not a claim of complete kinematic recovery. The active degrees of freedom in this reconstruction, namely pelvis spatial coordinates, bilateral hip flexion, abduction and rotation, knee flexion, and ankle flexion, are only partially constrained by the three available sensor locations. In a fully instrumented configuration, where every body segment carries a GNSS/IMU device, the problem would be overdetermined and GNSS positional observations would add redundancy to a well-constrained system. In the present minimal configuration, the solver operates with insufficient constraints to uniquely determine the full kinematic

Hip flexion: GNSS+IMU vs markerless

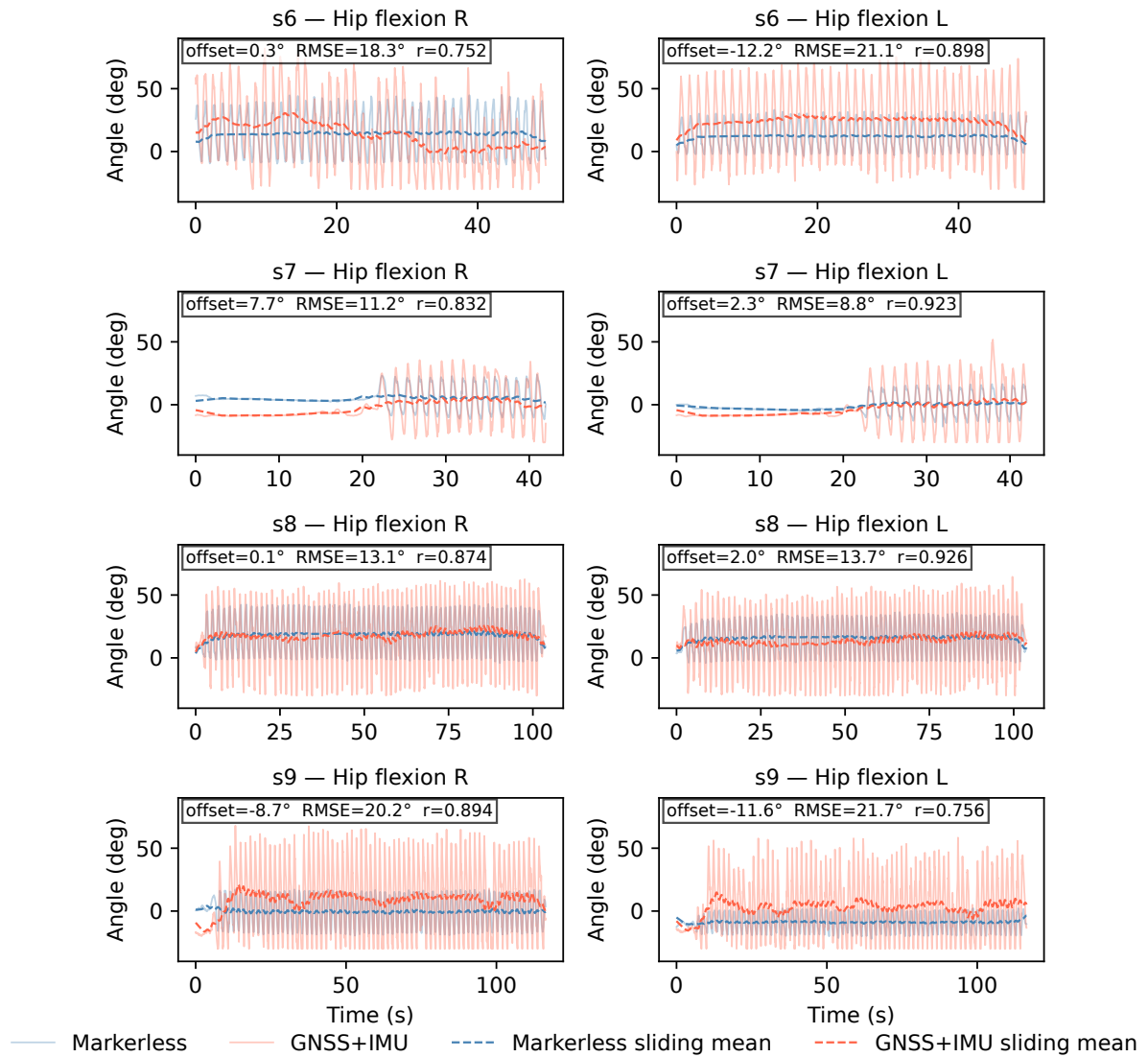


Figure 7.6: Hip flexion reconstruction for all usable participants, both sides. Orange: GNSS/IMU pipeline; blue: markerless reference. Pale traces: raw signals; bright dashed lines: 6-second moving averages. Metrics annotated per panel. Participant 7 truncated at 42 s.

Table 7.4: GNSS solution quality per device and participant. Fix: carrier-phase integer ambiguity resolved; Float: ambiguity not resolved; DGNSS: code-only differential solution.

Participant	Device	Fix (%)	Float (%)	DGNSS (%)	<i>n</i>
S6	Torso	100.0	0.0	0.0	721
S6	Left foot	95.6	4.4	0.0	731
S6	Right foot	56.1	37.6	6.3	729
S7	Torso	100.0	0.0	0.0	1000
S7	Left foot	76.9	11.6	11.6	1055
S7	Right foot	52.9	22.3	24.8	1100
S8	Torso	100.0	0.0	0.0	1403
S8	Left foot	95.2	4.7	0.1	1374
S8	Right foot	91.0	9.0	0.0	1391
S9	Torso	100.0	0.0	0.0	1376
S9	Left foot	97.5	2.4	0.1	1381
S9	Right foot	96.4	3.2	0.4	1389

state, and participant-specific factors such as body proportions, model scaling accuracy, magnetometer calibration quality, and the reliability of the markerless reference itself all contribute to result variability in ways that cannot be cleanly disentangled. GNSS fix quality remains a necessary condition for reliable reconstruction, as demonstrated by the degraded results for Participants 6 and 7 on the right foot, but it is not a sufficient one.

Fix percentage is a coarse summary of GNSS quality. The mechanism underlying its degradation, namely the impulsive foot accelerations at toe-off and heel strike that disrupt carrier-phase tracking on foot-mounted receivers, is characterised in detail in Chapter 5 for a single subject and confirmed across nine subjects in Chapter 6. A finer-grained diagnostic analysis at the level of individual gait events, including cycle slip rates, carrier-to-noise density, position covariances, and the temporal distribution of degraded epochs relative to heel strike and toe-off, would be needed to characterise the failure mode more precisely than fix percentage alone allows, and is identified as a direction for future work in Section 7.4.6.

7.3.4 Failure Case: Solution Degradation After GNSS Fix Loss

The full Participant 7 recording provides an unambiguous demonstration of the pipeline’s dependence on GNSS fix quality. As reported in Table 7.4, the right foot device maintains a fixed solution for only 52.9% of epochs, with substantial float and DGNSS fractions; the left foot device is similarly compromised at 76.9% fix. At approximately 42 s into the recording, the fixed

solution is lost on both foot devices simultaneously, and the pipeline output diverges sharply from the markerless reference, as shown in Figure 7.7. Prior to this point, the reconstruction is among the best observed across the dataset ($r = 0.832$ right, $r = 0.923$ left; RMSE 11.2 and 8.8 respectively), demonstrating that the pipeline is capable of reliable hip flexion estimation when the GNSS solution is stable. After fix loss, the GNSS/IMU signal becomes dominated by inertial mechanization with inaccurate GNSS corrections, producing large-amplitude, low-frequency excursions that bear no resemblance to the markerless reference. The transition is abrupt and clearly visible in both panels of Figure 7.7, confirming that GNSS fix quality is the critical dependency of the pipeline and that degradation is not gradual but occurs rapidly once the fixed solution is lost.

7.4 Discussion

This section interprets the results in relation to the proof-of-concept claim, identifies the mechanisms that most likely explain the observed agreement and biases, and defines the steps required to advance from feasibility demonstration to quantitative validation.

7.4.1 Interpretation and Implications

The empirical findings above support the feasibility of the distributed GNSS/IMU pseudo-marker approach, but they also delimit the current evidence. The system preserves hip-flexion timing under favourable GNSS conditions, while amplitude agreement remains affected by sparse instrumentation, model constraints, and reference-system uncertainty. The following subsections therefore distinguish between what the proof of concept demonstrates, what remains uncertain, and what must be improved before the method can be presented as a validated outdoor kinematic reconstruction system.

7.4.2 Gait Timing and Phase Agreement

The results presented in the summary results require careful interpretation, as the two primary metrics, namely Pearson correlation and RMSE, capture fundamentally different aspects of signal agreement. Correlation measures the degree to which two signals share the same temporal structure: their phase relationship, cycle timing, and the relative sequencing of flexion and extension events. RMSE, by contrast, is sensitive to both phase and amplitude differences, and in the present context is dominated by the latter. Interpreting these metrics jointly is therefore essential; a system that scores well on correlation but poorly on RMSE is not necessarily performing poorly. It may be accurately capturing the timing of movement while differing from the

s7 full recording: solution degradation after GNSS fix loss

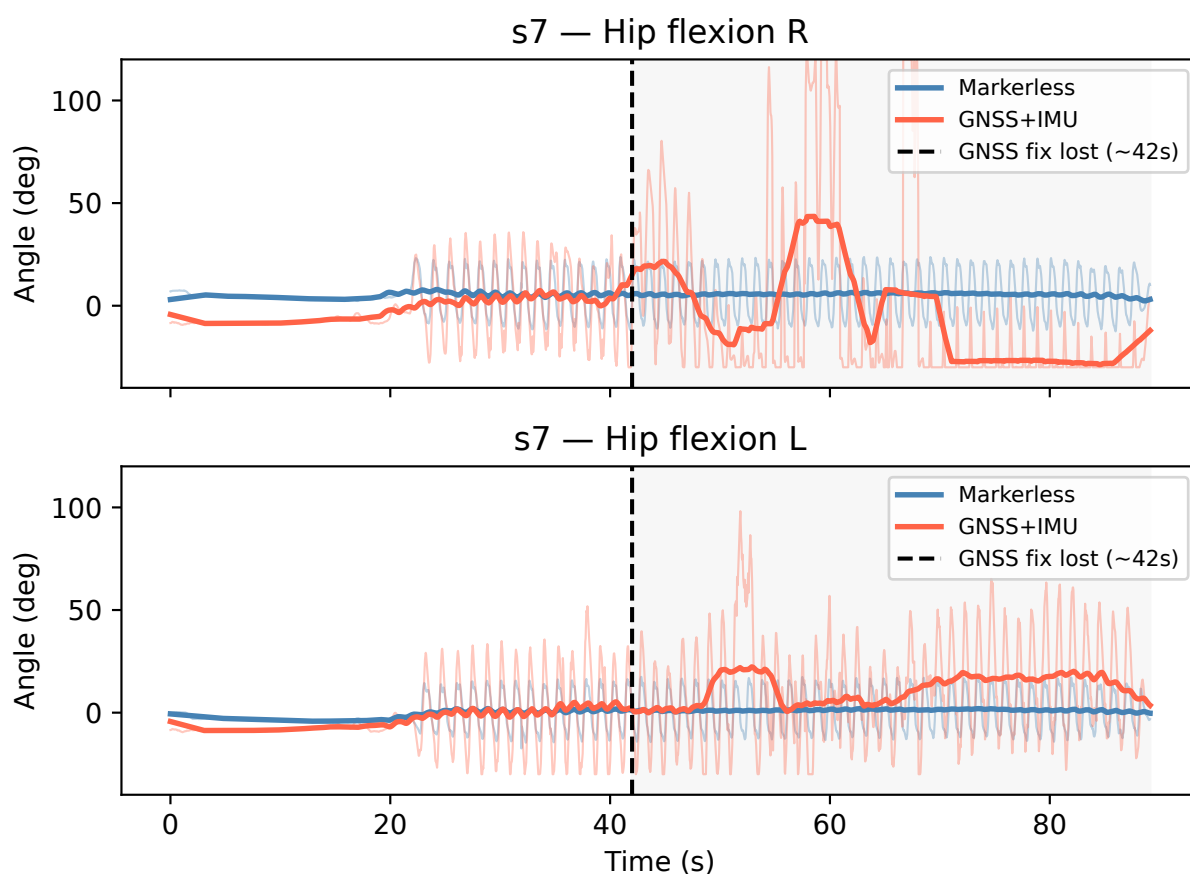


Figure 7.7: Hip flexion reconstruction for Participant 7, full recording. Orange: GNSS/IMU pipeline; blue: markerless reference. The vertical dashed line marks the point of GNSS fix loss at approximately 42 s. Prior to fix loss, agreement is close; after fix loss, the pipeline output diverges rapidly from the markerless reference.

reference in absolute amplitude, which is a distinct and separately interpretable phenomenon.

The safest interpretation is not that the method is already accurate, but that it is observably coupled to the same underlying gait cycle as the independent reference. The correlation results, ranging from $r = 0.752$ to $r = 0.926$ across all participant–side combinations, provide the phase-agreement half of this evidence: they demonstrate that the pipeline reliably reproduces the temporal structure of hip flexion during walking, including gait cycle rhythm, timing of peak flexion, and the alternating pattern of the two limbs. As noted in Section 7.2.5, this range of correlation values is high in absolute terms but should not be over-interpreted: two quasi-periodic signals sharing the gait cycle frequency correlate strongly whether or not their amplitudes agree, so a phase-randomised or cycle-shuffled baseline would be required to demonstrate that the observed values exceed what shared periodicity alone produces. What the correlation does establish, in the sparse-instrumentation configuration used here, is that no gross phase failure occurred, and that the pipeline does not decouple from the underlying gait cycle across trials lasting between 40 and 150 seconds. Amplitude fidelity is treated separately, and the ROM ratio and RMSE analyses in the following subsection provide the substantive evidence on that side.

The RMSE values, ranging from 8.8 to 21.7, should not be read as evidence of poor performance. Their magnitude is consistent across participants regardless of GNSS fix quality, including Participant 8 and Participant 9 where the GNSS solution is nearly perfect. This uniformity indicates that RMSE in this context reflects a structural disagreement between two systems with different and complementary biases, and not random noise or phase errors in the pipeline. The nature of this structural disagreement, and the evidence that it originates at least in part from the markerless reference and not from the GNSS/IMU pipeline, is examined in detail in the following subsection.

7.4.3 ROM Overestimation: Sources and Hierarchy

The consistent overestimation of hip flexion ROM by the GNSS/IMU pipeline relative to the markerless reference, visible across all participants and sides in Table 7.2, has three contributing mechanisms that can be ordered hierarchically based on the available evidence.

The primary mechanism is the locked lumbar joint in the musculoskeletal model. In physiological walking, sagittal trunk movement is distributed across both lumbar and hip degrees of freedom. With the lumbar coordinates fixed to a neutral posture, the IK solver has no lumbar degrees of freedom available to absorb trunk motion, and the full contribution of trunk dynamics is instead attributed to hip flexion. This effect is structural and operates regardless of sensor quality: it is present even in Participant 8 and Participant 9, where the GNSS solution is nearly perfect, and accounts for the baseline overestimation observed across the dataset. It is a direct and unavoidable consequence of the sparse instrumentation; a lumbar sensor would both constrain the lumbar degrees of freedom and allow the lumbar joint to be unlocked, removing this

source of bias entirely.

The secondary mechanism is camera foreshortening in the markerless reference. The drone's posterior monocular viewpoint compresses the apparent sagittal-plane excursion when the participant does not walk perfectly perpendicular to the camera axis, systematically underestimating hip flexion ROM. Three converging observations support this interpretation. First, the markerless ROM values span from below to within the reference range of 39–50° [1, 2] despite participants walking at slow speed, which would be expected to produce values at the lower end of that range and not below it. Second, the markerless reference produces physiologically implausible symmetry indices of 41.4% and 50.6% for Participants 6 and 9 respectively, indicating systematic measurement artefacts and not true gait asymmetry. Third, this pattern is consistent with the expected foreshortening effect of the same recording geometry on sagittal-plane displacement and joint excursion. Foreshortening therefore pushes the markerless reference below its true value, contributing to the observed ratio from below. We hypothesise that even a well-calibrated clinical IMU system would show elevated RMSE against this specific markerless reference for the same reason; this cannot be verified without an absolute ground truth, but the symmetry index evidence makes it plausible.

The tertiary mechanism is IK noise amplification under degraded GNSS conditions. When the GNSS fixed solution is intermittent or lost, positional noise propagates into the underdetermined IK problem and is partially absorbed into hip flexion, further inflating the pipeline ROM. This effect is visible in the correlation between foot device fix quality and ROM ratio: Participants 6 and 7, with right foot fix rates of 56.1% and 52.9% respectively, show substantially higher ratios than Participants 8 and 9, whose foot devices maintain fix rates above 91%. Critically, this mechanism is additive to the first two: the baseline overestimation from the locked lumbar and foreshortening effects is present regardless of GNSS quality, and GNSS degradation amplifies it further. Improving GNSS quality would therefore reduce but not eliminate the ROM overestimation, as the structural sources would remain until a lumbar sensor is added and the recording geometry is improved.

7.4.4 From Foot Trajectories to Joint-Angle Reconstruction

The results demonstrate that distributed GNSS/IMU pseudo-markers represent a qualitative extension beyond foot trajectory reconstruction. A foot-level GNSS/IMU configuration produces trajectories and derived spatiotemporal gait parameters, namely stride length, step length, step width, and cadence. These are clinically informative quantities, but they characterise only the distal extremities and provide no information about the movement of proximal joints. The distributed pseudo-marker approach, by contrast, produces joint angle time series for the lower limb kinematic chain, giving access to quantities such as hip flexion ROM, bilateral symmetry, and the temporal coordination of flexion and extension events across the gait cycle. These are the quantities most directly relevant to biomechanical assessment and rehabilitation monitoring, and

they are not accessible from foot trajectories alone.

The validation chain is also cleaner than a parameter-level comparison. Converting joint angles into stride length, cadence, or gait-event timings would introduce additional sources of discrepancy related to differing gait event definitions and parameter computation methods. Here, joint angle time series are compared directly, eliminating that intermediate step and producing a more interpretable validation. The correlation values of $r = 0.752\text{--}0.926$ observed here are a direct measure of waveform phase agreement for the reconstructed hip-flexion signal.

The distributed pseudo-marker approach occupies a distinct position on the accuracy–deployability spectrum. It aims at outputs associated with laboratory motion capture, namely joint angles and not only positional trajectories, while retaining the outdoor deployability and infrastructure independence of wearable GNSS/IMU sensing. The proof-of-concept results presented here demonstrate that this position is achievable in practice, even in a minimally instrumented configuration. Closing the remaining gap, in particular the ROM overestimation attributable to sparse instrumentation and the recording geometry of the markerless reference, is primarily a matter of adding sensors and refining the experimental setup, and not a fundamental limitation of the architecture itself.

Relative to drone-based markerless motion capture, the GNSS/IMU approach trades the need for favourable camera geometry and visual line of sight for the need for satellite visibility, wearable instrumentation, and reliable carrier-phase tracking. This trade-off is central to the intended use case: long-duration outdoor recordings in which fixed optical infrastructure is unavailable and camera-based coverage is difficult to maintain.

7.4.5 Limitations

Several limitations of the present proof of concept should be noted explicitly.

The most significant is the sparse instrumentation. With sensors on only three body locations, the active degrees of freedom of the lower limb kinematic chain are only partially constrained. Hip flexion is reliably determined by the relative positions and orientations of the chest and foot devices; other coordinates, including knee flexion and ankle flexion, receive only indirect constraints propagated through the model topology and should not be interpreted as reliable estimates. The locked lumbar joint, while necessary given the absence of a lumbar sensor, introduces a systematic upward bias in hip flexion amplitude as discussed above. The current chapter argues qualitatively that residuals in the underdetermined problem are absorbed by the least-constrained coordinate (hip flexion); a formal observability analysis of the sensor-to-coordinate sensitivity map would quantify which coordinates are recoverable at each instrumentation level and is a targeted extension identified in Section 7.4.6. Both issues would be directly addressed by adding sensors to the lumbar segment and the thighs, which would simultaneously unlock the lumbar joint and constrain the intermediate links of the kinematic chain.

A second limitation concerns magnetometer reliability. One device exhibited a faulty magnetometer that required a pragmatic yaw correction based on the principal axis of the GNSS trajectory, as described in the methods. While this correction produces a stable yaw estimate, residual orientation errors cannot be fully quantified and represent an uncontrolled source of error in the recordings where that device was worn.

Third, GNSS intermittency on foot-mounted devices remains a fundamental challenge of the approach. The S7 failure case illustrates that fix loss produces rapid and severe reconstruction degradation. While the adaptive weighting scheme of the pipeline mitigates the impact of intermittent degradation, it cannot compensate for complete fix loss, and the system's reliability in more challenging environments such as urban canyons, dense vegetation, or indoor-outdoor transitions, remains to be established.

Fourth, and most fundamentally, neither system used in this study provides an absolute ground truth for joint angles. The markerless pipeline carries systematic biases from camera foreshortening, and the GNSS/IMU pipeline carries biases from sparse instrumentation and the locked lumbar joint. The true reconstruction error of the pipeline cannot be determined from this comparison alone, and an independent validation against a laboratory optical motion capture system remains necessary to establish absolute accuracy.

Fifth, the number of usable recordings in this study is limited in part by the prototype maturity of the hardware. Data loss across the campaign is attributable to device shutdowns during recording sessions, which appear to combine mechanical-shock-induced power interruptions and battery management failures. The two mechanisms may be interrelated and cannot be cleanly separated from the available data. The magnetometer fault on one device, noted in the second limitation above, is a persistent device characteristic; recordings using that device remained usable through the PCA-based yaw correction described in the methods. GNSS fix loss is an acquisition issue caused by walking dynamics; it is addressed throughout the chapter via the adaptive weighting scheme. The shutdowns and battery-management issues are engineering limitations of the current prototype, and are expected to be resolved in more mature hardware iterations.

7.4.6 Directions for Improvement

The most impactful single improvement to the current reconstruction pipeline would be the addition of a lumbar IMU. As discussed in the range-of-motion discussion, the locked lumbar joint is the primary source of ROM overestimation in the current configuration. A lumbar sensor would both unlock that degree of freedom and provide an additional positional and orientational constraint on the pelvis–torso segment, directly addressing the dominant systematic bias in the present results.

More broadly, the framework would benefit from full instrumentation of the lower body kinematic chain: one device per segment, covering the pelvis, thighs, shins, and feet. In such a

configuration, the kinematic chain would be fully constrained by IMU orientations alone, and GNSS-derived positions would serve as redundant metric-scale anchors unlike the current setup. This is the configuration envisioned by a complete lower-body distributed-sensor implementation, and the scalability of the framework to this configuration is one of its principal advantages over purely inertial approaches, as discussed above.

The markerless pipeline used as a reference in this study has inherent limitations, namely monocular projection, camera foreshortening, and the absence of absolute spatial grounding, that cannot be resolved within the current experimental setup. These limitations make it an imperfect reference for validating joint angle reconstruction, particularly for sagittal-plane ROM. A rigorous absolute validation of the GNSS/IMU pipeline requires comparison against a calibrated multi-camera optical motion capture system, which remains the gold standard for joint angle measurement, or against a markerless system that has itself been validated against such a gold standard. Conducting this comparison in a controlled outdoor setting, where the GNSS/IMU system operates under realistic conditions while an optical reference is simultaneously available, is the logical next step toward establishing the absolute accuracy of the distributed GNSS/IMU pseudo-marker approach.

An observability analysis of the sparse-instrumentation configuration would substantively strengthen the interpretation of the present results. A synthetic sensitivity analysis, in which each virtual marker position and IMU orientation is perturbed within the same OpenSim model used here and the resulting change in each active coordinate is quantified, would produce a Jacobian-based sensor-to-coordinate map that identifies which coordinates are recoverable at the current three-device instrumentation level and which require additional sensors. Such an analysis would replace the qualitative argument in the limitations section with quantitative evidence, address the specific critique that hip flexion is the least-constrained sink for residuals, and provide a principled basis for prioritising sensor additions in future work.

On the hardware side, improved battery capacity and power management in future device iterations would increase the number of usable recordings per session, addressing the data scarcity that limits the present proof of concept to four participants.

7.5 Conclusions

This study presented a proof-of-concept implementation in which GNSS-derived positions and IMU-derived orientations from three wearable devices are combined as inputs to a biomechanical inverse kinematics solver to reconstruct lower limb joint angles in an outdoor setting. Outdoor stadium walking recordings from Luterbach, Switzerland, were reprocessed through an automated two-stage pipeline, and the resulting hip flexion time series were compared directly against joint angles from the drone-based markerless reference for four participants.

The primary finding is that the pipeline captures the timing and phase of hip flexion during walking, with Pearson correlation values of $r = 0.752\text{--}0.926$ across all usable participant–side combinations, interpreted narrowly as evidence of phase coherence rather than of amplitude accuracy given the near-tautological correlation between two signals sharing the gait cycle frequency. Amplitude fidelity was characterised separately through the ROM ratio, which showed consistent overestimation relative to the markerless reference (ratios between 1.46 and 3.09) attributed primarily to the locked lumbar joint in the sparse model configuration and secondarily to camera foreshortening in the reference system, with GNSS degradation as a tertiary modulating factor. The proof-of-concept therefore demonstrates methodological feasibility, namely that GNSS pseudo-markers and IMU orientation constraints can jointly drive a biomechanical IK solver to produce physiologically coherent joint angle estimates in an outdoor, infrastructure-light setting, and not complete or accurate kinematic reconstruction.

Taken together, the results show that GNSS-derived pseudo-markers can be used for more than global displacement estimation: when combined with IMU orientation constraints and a musculoskeletal model, they can support outdoor reconstruction of at least the timing and phase of lower-limb joint motion. The next step is primarily experimental strengthening: denser instrumentation, explicit observability analysis, adaptive-weighting ablation, and validation against a calibrated optical motion-capture reference are required before the approach can be claimed as an accurate clinical or biomechanical measurement system.

Chapter 8

Discussion and Conclusions

8.1 Summary of Contributions

The work presented in this thesis has followed a deliberate progression from conceptual foundation to experimental validation, with each chapter building on the findings and limitations of the preceding one. This section draws together the principal contribution of each stage before the synthesis that follows.

8.1.1 Conceptual Framework and Proposed Architectures

Chapter 4 established the theoretical basis for the thesis by identifying three distinct functional roles that GNSS can play in outdoor human motion analysis pipelines, namely global translational referencing, inertial drift mitigation, and spatial grounding for mobile vision-based systems, and operationalising these roles into three integration architectures of increasing complexity and biomechanical scope. The taxonomy provides a structured design space that situates the experimental contributions of this thesis and offers a reference framework for future work in this area. Architecture 1, which assigns a single receiver the role of providing a globally referenced translational anchor for an otherwise inertial system, was intentionally scoped out as a primary experimental objective, as its basic form is partially addressed by existing commercial solutions and its contribution at carrier-phase precision, while not without interest, was judged less novel than the segment-level and multi-receiver configurations of Architectures 2 and 3. As discussed in Sections 6.3 and 7.3, however, the multi-device experimental campaigns of this thesis incidentally demonstrate its premise: the torso-mounted receiver, operating on a dynamically stable segment, consistently achieved high carrier-phase fix rates and produced the globally referenced translational trajectory against which foot-level parameters were internally validated.

8.1.2 Foot Trajectory Reconstruction

Chapter 5 presented the first experimental investigation of Architecture 2, demonstrating that a foot-mounted GNSS/IMU device can reconstruct absolute foot trajectories and derive spatiotemporal gait parameters in an outdoor environment with centimetre-level horizontal accuracy at slow and normal walking speeds.

A secondary but equally important finding concerned the mechanism behind the observed speed-dependent performance loss. The impulsive accelerations at heel strike and toe-off repeatedly exceed the dynamic limits of the foot-mounted receiver, causing selective dropout of carrier-phase observables and reducing the geometric diversity of the available satellite constellations. This degradation propagates through the full processing chain, from raw signal quality to PPK solution to trajectory accuracy. Critically, this mechanism is specific to foot-mounted receivers: the simultaneously operating torso-mounted device, insulated from foot strike dynamics, maintained stable carrier-phase tracking across all speed conditions, which isolates foot dynamics as the source of the degradation.

The scope of the validation was deliberately narrow: a single subject, short recordings on a straight path, a fixed professional-grade base station, and no continuous independent ground truth for the foot trajectory. Each of these limitations defined a specific direction for the experimental work that followed.

8.1.3 Multi-Subject Outdoor Validation

Chapter 6 extended the proof-of-concept investigation to a multi-subject outdoor validation campaign, addressing the four limitations identified in Chapter 5 in a single experimental effort. Nine healthy subjects walked at three self-paced speed conditions at an outdoor stadium in Switzerland, with a portable base station deployed on-site and simultaneous drone video processed through a markerless motion capture pipeline as an independent reference. The campaign demonstrated that the system can operate without any fixed external infrastructure, a practically significant step toward genuine field deployability.

The speed-dependent degradation pattern characterised in Chapter 5 was confirmed across subjects and a new outdoor environment, consolidating it as a systematic property of foot-mounted GNSS. The internal consistency of the GNSS pipeline was demonstrated through a self-check of foot-derived stride length and cadence against the independently measured torso walking speed, yielding a high linear agreement ($r = 0.997$, slope = 0.972) across all subjects and speed conditions. This is a self-consistency check, not a validation of absolute accuracy: stride length multiplied by stride frequency equals walking speed by definition, so the correlation confirms the absence of gross error between two independent processing chains rather than the accuracy of stride length itself. The comparison with the markerless pipeline revealed a large system-

atic offset for sagittal-plane metrics, attributed to posterior camera foreshortening, differences in foot landmark definition, and fundamental incompatibility between the two measurement quantities. The offset reflects this methodological difference and is not a sensor error in either system. Both pipelines correctly captured the direction and relative magnitude of speed-dependent gait changes, confirming qualitative agreement despite the absolute offset.

The chapter’s limitations were acknowledged alongside its contributions. Prototype hardware failures reduced dataset completeness, the operating envelope remained restricted to slow walking speeds for reliable per-stride estimates, and no validation against a clinical gold-standard reference was performed. These boundaries, together with the restriction of Architecture 2 outputs to foot-level spatiotemporal parameters, motivated the extension to a sensor-fusion inverse kinematics approach combining GNSS-derived positions as pseudo-markers with IMU-derived orientations as segment constraints, presented in Chapter 7.

8.1.4 Multi-Segment Kinematic Reconstruction

Chapter 7 presented a proof-of-concept implementation of Architecture 3, extending the framework beyond foot-level spatiotemporal parameters toward joint angle reconstruction. Three wearable GNSS/IMU devices worn simultaneously on the chest and both feet provided GNSS-derived positions as pseudo-markers and IMU-derived orientations as segment constraints, which were jointly supplied to a biomechanical inverse kinematics solver. This combined use of positional and orientational constraints within a single solver distinguishes the approach from both standard optical motion capture pipelines, which rely on marker positions alone, and from IMU-only systems, which provide orientational constraints without absolute spatial grounding.

The primary finding was that the pipeline reliably captures the timing and phase of hip flexion during walking, with Pearson correlation values of $r = 0.752$ – 0.926 across all usable subject-side combinations when compared against the drone-based markerless reference. Consistent range-of-motion overestimation was observed across all subjects, attributed primarily to the locked lumbar joint imposed by the sparse three-device configuration, and secondarily to camera foreshortening in the markerless reference. The chapter is explicitly framed as a demonstration of architectural feasibility, not as a complete or fully accurate kinematic reconstruction, and the results should be interpreted accordingly.

The chapter also introduced an automated two-stage processing pipeline covering the full chain from raw GNSS and IMU observations to joint angle estimates. The pipeline enabled systematic reprocessing of the multi-device dataset and constitutes an independent software contribution that lowers the barrier to adoption of the proposed framework for future users. With Architecture 2 experimentally characterised across two campaigns and Architecture 3 demonstrated as a proof of concept, the experimental programme of this thesis is complete, and the ground is set for the thesis-level synthesis presented in the sections that follow.

8.2 Synthesis: Answering the Research Question

8.2.1 Direct Answer and Conditions of Validity

The experimental evidence presented in this thesis supports an affirmative answer to the research question, subject to a set of conditions that are worth stating explicitly. The GNSS/IMU integration framework proposed here can reconstruct outdoor human movement with centimetre-level accuracy and derive clinically relevant kinematic parameters, provided that three conditions are met: the recording environment offers adequate open-sky visibility, a portable base station is deployed in the vicinity of the recording site, and the movement speed remains within the envelope at which foot-mounted receivers can maintain stable carrier-phase tracking.

The third condition deserves particular attention. It reflects a fundamental finding about the relationship between receiver placement and body dynamics that goes beyond a simple speed threshold. The experimental campaigns of this thesis consistently demonstrated that GNSS receivers mounted on body segments with high movement dynamics (namely, the feet, which are subject to impulsive accelerations at heel strike and toe-off) are far more susceptible to carrier-phase disruption than receivers mounted on dynamically stable segments such as the torso. Beyond dynamics, foot mounting introduces two additional adverse factors: the antenna might be periodically oriented away from the sky during the swing phase, reducing the number of visible satellites, and its proximity to the ground increases multipath interference. This combination of dynamic, geometric, and environmental factors makes the foot a particularly challenging mounting location, and the asymmetry in signal quality between foot- and torso-mounted receivers observed throughout this thesis reflects all three simultaneously. These findings have direct implications for system design: the placement of a GNSS receiver on the human body is not a free choice, and segments with high kinematic variability and unfavourable antenna geometry impose a fundamental constraint on achievable signal quality that cannot be fully compensated by algorithmic means alone. Within the operating envelope defined by these conditions, the system produces results that are internally consistent, physiologically valid, and in agreement with independent reference measurements across multiple subjects and outdoor environments.

Architecture 3 extends the validated operating domain from spatiotemporal gait parameters to joint angle reconstruction, demonstrating that GNSS pseudo-markers and IMU orientation constraints can jointly drive a biomechanical inverse kinematics solver to produce physiologically coherent estimates in an outdoor setting. This result is explicitly a proof of concept: the sparse three-device configuration leaves the kinematic chain underdetermined, and the comparison against the markerless reference is complicated by the limitations of both systems. The contribution of Chapter 7 is therefore best understood as a demonstration that the architectural approach is viable, and that the path toward more complete kinematic reconstruction is one of incremental instrumentation and hardware refinement. No fundamental methodological revision is required.

8.2.2 Walking-Speed Scope as a Domain-Appropriate Constraint

The restriction of the system's reliable operating envelope to slow walking speeds is best understood as a scoping condition that overlaps meaningfully with the walking speeds relevant to the primary intended application domain. Clinical rehabilitation assessment, the domain that motivates this thesis, is concerned predominantly with patients recovering from neurological conditions such as stroke or acquired brain injury, who typically walk at or below comfortable speed. The naturalistic slow speeds recorded in Chapter 6, approximately 0.8–1.0 m/s corresponding to roughly 90 steps per minute, overlap with self-selected walking speeds reported in some patient populations, and the finding that carrier-phase ambiguity fix quality is acceptable at these speeds is directly relevant to the intended application domain. The extent to which these healthy slow speeds are mechanically representative of pathological slow gait, which involves distinct motor control patterns beyond a simple velocity reduction, remains an open question that the present campaign, conducted with healthy adults, cannot answer. Establishing this correspondence is part of the clinical validation work identified in Section 8.5.3.

It is furthermore important to distinguish between the speed constraint as a hardware limitation and as a fundamental architectural one. As discussed in Section 8.4.1, the degradation mechanism is rooted in the dynamic tracking capabilities of current foot-mounted GNSS receivers, and is therefore a property of the present hardware generation. The integration approach is compatible with hardware improvements that would extend the operating envelope, and advances in receiver tracking bandwidth or tighter GNSS/IMU coupling strategies represent credible paths in that direction, with the framework proposed in this thesis accommodating such improvements without architectural revision. It is also worth noting that the speed constraint applies specifically to receivers mounted on dynamically active segments: the torso-mounted receiver, insulated from foot strike dynamics, maintained stable carrier-phase tracking across all speed conditions tested in this thesis, confirming that the limitation applies specifically to placements on dynamically active segments.

8.2.3 The Thesis Contribution in Perspective

Taken together, the experimental chapters of this thesis demonstrate that GNSS-based outdoor human motion capture is not merely theoretically conceivable but practically realisable with current wearable hardware, portable infrastructure, and automated processing. The system has been deployed in genuine field conditions, operated by a single researcher without specialised geodetic infrastructure, and produced results that are internally consistent and have been compared against an independent reference across multiple subjects. This is a meaningful step beyond the conceptual and single-subject demonstrations that characterise much of the prior literature in this area.

At the same time, it is important to be precise about what has and has not been demonstrated.

The results of this thesis constitute a proof of feasibility and a characterisation of the operating envelope, with the understanding that they do not yet constitute a validated clinical tool. The hardware used throughout is a first-generation prototype, the datasets are limited in size, and the validation against independent ground truth is complicated by the methodological limitations of the markerless reference system. The contribution is therefore best understood as establishing the foundation (conceptual, methodological, experimental, and software) on which a deployable clinical or research system could be built. That system itself remains the subject of future work, with the directions required to advance from this foundation toward deployment identified in Section 8.5.

8.3 System Positioning Relative to Existing Approaches

The system proposed and tested in this thesis does not fit neatly into any of the existing categories of human motion capture technology reviewed in Chapter 2. Its position is best understood by situating it explicitly on the accuracy–deployability spectrum that runs from laboratory-grade optical motion capture at one end to fully wearable IMU-only systems at the other, and by comparing it against the markerless video-based approaches that also occupy an ambiguous position. The following subsections address each of these comparisons in turn, arguing that the proposed system occupies a niche that is not adequately served by any existing approach.

8.3.1 Versus Laboratory-Grade Optical Motion Capture

Laboratory-grade marker-based optical motion capture remains the gold standard for kinematic accuracy in biomechanics and clinical movement analysis. Its sub-millimetre precision and high temporal resolution set a benchmark that the system proposed here does not match, and that gap is directly acknowledged. The centimetre-level horizontal accuracy demonstrated in this thesis for foot trajectory reconstruction, and the proof-of-concept joint angle estimates of Architecture 3, cannot reach what a calibrated multi-camera optical system can deliver in a controlled environment. This is not a surprising finding: the comparison is between a wearable prototype operating outdoors and a purpose-built laboratory instrument, and the accuracy gap reflects the fundamental trade-off between precision and deployability that motivates this thesis in the first place.

What the proposed system offers in return is precisely what optical motion capture cannot provide: the ability to operate in unconstrained outdoor environments, over arbitrary distances, without fixed laboratory infrastructure, and with a wearable form factor. These are primary requirements for the application domains identified in Chapter 1: outdoor rehabilitation assessment, nature-based therapy monitoring, and free-living gait analysis in neurological patient populations, where optical motion capture is simply not deployable. The relevant comparison concerns

which system can provide valid and clinically useful measurements in the environments where those measurements are actually needed.

8.3.2 Versus IMU-Only Systems

Fully wearable IMU-only systems represent the closest existing alternative to the approach proposed in this thesis in terms of deployability and form factor. Their principal limitation is well established: without an absolute position reference, inertial integration accumulates errors over time, and the global position and translational trajectory of the body cannot be recovered. Orientation drift, particularly in yaw, compounds progressively over extended recordings, and the reconstructed motion is expressed in an arbitrary local frame whose relationship to any external reference is undefined. These are fundamental consequences of the absence of an absolute observational constraint.

GNSS addresses this limitation at two distinct levels, corresponding to the architectural distinction introduced in Chapter 4. At the first level, a single receiver placed on a stable body segment provides a globally referenced translational anchor for the entire system, expressing the body's trajectory in a metric coordinate frame that is consistent across sessions, subjects, and recording locations. This is consistent with the contribution of Architecture 1: the $r = 0.997$ agreement demonstrated in Chapter 6 between foot-derived stride parameters and the torso-derived walking speed reference provides indirect but meaningful evidence that a torso-mounted receiver produces a globally referenced translational trajectory sufficient for physiologically valid parameter extraction. At the second level, per-segment receivers provide local drift correction at each instrumented body part, bounding the inertial integration error not just for the whole body but for individual segments independently. This is the contribution of Architectures 2 and 3, and it unlocks capabilities (foot trajectory reconstruction, step width estimation, and absolute joint angle grounding) that are inaccessible to any IMU-only system regardless of the number of sensors or the sophistication of the fusion algorithm.

8.3.3 Versus Drone-Based Markerless Motion Capture

Drone-based markerless motion capture and the GNSS/IMU system proposed in this thesis share a common motivation: both aim to extend human motion analysis beyond the laboratory into spatially unconstrained outdoor environments. Beyond this shared starting point, however, their trade-off profiles are fundamentally different, and the choice between them depends on the specific requirements of the application.

The GNSS/IMU approach is wearable and therefore inherently invasive: sensors are attached to the subject's body, introducing additional mass and potential movement modification, however minimal at current device weights. In return, the system provides metric-scale absolute posi-

tioning, is insensitive to lighting conditions, requires no line of sight between the subject and any external equipment, and can in principle operate over arbitrary distances and durations. Its principal constraints are the speed-dependent signal quality limitation discussed throughout this thesis and the requirement for a portable base station in the vicinity of the recording site.

Drone-based markerless capture is non-invasive (the subject moves freely without any attached instrumentation) but introduces a different set of operational constraints. Flight permissions, battery endurance, wind and lighting sensitivity, and the need for a skilled operator all impose practical limits on deployment that are absent from the wearable approach. More fundamentally, monocular video from a single drone provides only a projected, perspective-distorted view of the subject, introducing systematic biases in sagittal-plane metrics that were demonstrated explicitly in Chapter 6. Extending markerless capture to multiple cameras would improve accuracy but at the cost of portability, pushing the system back to lower deployability and reintroducing many of the constraints that motivated the move outdoors in the first place.

The two approaches therefore occupy distinct positions on the accuracy–deployability spectrum, with different limiting factors and different suitable application contexts.

8.3.4 The Underserved Gap

The three comparisons presented in the preceding subsections converge on a consistent picture. Laboratory-grade optical motion capture achieves high accuracy but cannot systematically leave the laboratory. IMU-only systems are fully portable but lack absolute spatial grounding and are subject to progressive drift. Drone-based markerless motion capture avoids wearable instrumentation but introduces operational constraints and systematic measurement biases that limit its reliability for absolute spatial parameters. None of these approaches satisfies the simultaneous requirements of accuracy, portability, and infrastructure independence that outdoor human motion capture demands. The gap identified in Chapter 1 remains open.

The system proposed and tested in this thesis occupies precisely this gap. It is deployable in genuine outdoor field conditions with portable infrastructure, produces metric-scale absolute measurements that are internally consistent across sessions and subjects, and has been characterised across multiple subjects at the walking speeds most relevant to clinical rehabilitation practice. The evidence assembled here supports feasibility at the level of mean spatiotemporal parameters and hip-flexion phase reconstruction; establishing sufficiency for the individual-level, per-stride parameters of primary clinical interest, such as bilateral asymmetry, stride-to-stride variability, and step width, requires the operating envelope improvements and clinical-grade validation identified in Section 8.5. No existing commercial or research system currently combines the properties this thesis realises at carrier-phase GNSS precision, and it is in this specific sense that the contribution is novel.

8.4 Consolidated Limitations

The limitations of the individual experimental chapters have been acknowledged at the point where they arise; this section consolidates them into a unified view, distinguishing where possible between constraints that are fundamental to the approach and those that are specific to the current hardware generation.

8.4.1 Speed Constraints and Receiver Placement

The speed-dependent performance degradation observed consistently across both experimental campaigns is rooted in the dynamics of carrier-phase tracking in GNSS receivers. Carrier-phase measurements are obtained by tracking the phase of the incoming satellite signal using a phase-locked loop (PLL). The PLL has a finite tracking bandwidth: when the rate of change of the Doppler frequency shift, which is proportional to the receiver's acceleration along the line of sight to each satellite, exceeds what the loop can follow, tracking is lost and the carrier-phase observable is interrupted, producing a cycle slip. For a foot-mounted receiver, the impulsive accelerations at heel strike and toe-off repeatedly drive the Doppler rate beyond this threshold, causing selective and repeated carrier-phase dropouts at each step. The consequence is a reduction in the number of available carrier-phase observations, a loss of geometric diversity in the remaining satellite subset, and a degradation in the quality and fix rate of the PPK solution that propagates directly into trajectory accuracy.

This is a hardware limitation in the sense that it is determined by the tracking bandwidth of current commercial receivers, which are designed primarily for vehicular and geodetic applications without the dynamic profile of body-mounted human motion analysis. It is not a fundamental limitation of the GNSS/IMU integration architecture: receivers with wider PLL bandwidth, or deeply coupled GNSS/IMU integration in which inertial predictions are fed into the tracking loops to assist carrier-phase maintenance during high-dynamic episodes, would be expected to extend the operating envelope to higher speeds. As discussed in Section 8.2.2, the constraint is furthermore placement-specific: receivers mounted on more dynamically stable segments such as the torso are not subject to the same impulsive dynamics and maintained reliable carrier-phase tracking across all speed conditions tested in this thesis.

8.4.2 Hardware Maturity

A recurring theme across the experimental chapters is the impact of prototype hardware immaturity on dataset completeness and result reliability. Mid-recording device shutdowns documented in Chapters 6 and 7 are attributable to a combination of mechanical-shock-induced power interruptions and battery management failures, with the two mechanisms interrelated and not cleanly

separable from the available data. A persistent faulty magnetometer on one unit required a pragmatic yaw correction based on the principal axis of the GNSS trajectory throughout the affected recordings. These issues reduced the number of usable recordings, limited the Chapter 7 analysis to four subjects, and introduced uncontrolled sources of error whose magnitude cannot be fully quantified.

It is important to distinguish these from limitations of the integration architecture itself. The algorithmic framework (loosely-coupled GNSS/INS integration with ZUPT, RTS smoothing, and inverse kinematics with pseudo-marker and orientation constraints) is not affected by battery capacity or magnetometer reliability. These are engineering problems with straightforward solutions in a more mature hardware iteration: improved power management, higher-capacity batteries, and factory-calibrated magnetometers are all achievable within the same device form factor. The experimental results presented in this thesis should therefore be read as a lower bound on what the framework can deliver, obtained under the constraints of a first-generation prototype.

8.4.3 Satellite Visibility and Environmental Constraints

All experimental campaigns presented in this thesis were conducted in open outdoor environments specifically selected to maximise satellite visibility and minimise multipath interference. This was a deliberate methodological choice to characterise the system's performance under favourable GNSS conditions, but it means that performance in more challenging environments, such as urban canyons, dense woodland, or areas with significant built infrastructure, remains uncharacterised. Signal obstruction and multipath in such environments would be expected to reduce fix rates, increase positioning uncertainty, and in severe cases cause complete loss of carrier-phase observables, with direct consequences for trajectory accuracy and parameter reliability.

This is a genuine limitation of the current validation scope, but it is important to note that the system is not blind to such degradation. The PPK solution provides explicit quality indicators at each epoch (fix, float, or DGNSS status, together with covariance estimates that reflect the uncertainty of the positioning solution) which propagate through the integration pipeline and can be made available as reliability flags on the derived parameters. When signal conditions deteriorate, the system can detect and communicate this degradation, with the practical implication that the system's outputs carry intrinsic quality metadata that can inform downstream decisions, whether in automated processing pipelines or in clinical interpretation of results. This property distinguishes the system from IMU-only approaches where error accumulation is not directly observable.

8.4.4 Validation Scale

The experimental datasets collected in this thesis are appropriate for a proof-of-concept characterisation but insufficient to support stronger claims about generalisation or clinical reliability. The nine-subject campaign of Chapter 6 provides a meaningful first assessment of inter-subject variability and confirms that the speed-dependent degradation pattern is consistent across individuals, but it does not constitute a statistically powered validation across the range of body dimensions, gait patterns, ages, and pathological conditions encountered in clinical practice. The four-subject subset available for the Architecture 3 analysis of Chapter 7 is more limited still, and the conclusions drawn from it are correspondingly constrained to architectural feasibility, without quantitative accuracy characterisation. Bilateral asymmetry analysis, which requires adequate fix quality on both feet simultaneously, was inconclusive in Chapter 6 due to the small number of recordings meeting this criterion. Establishing the clinical utility of the system will require larger cohorts, including patient populations, and validation against a laboratory-grade optical motion capture reference, which remains the only ground truth capable of providing absolute joint angle accuracy without the methodological limitations of the markerless pipeline used here.

8.4.5 Base Station Requirement

Carrier-phase differential GNSS processing requires a reference receiver at a known location near the recording site. The portable base station demonstrated in Chapter 6 is a practical step forward compared to the fixed professional installation used in Chapter 5, showing that the system does not depend on permanent external infrastructure. However, the requirement itself does not disappear: the base station needs to be brought to the site, positioned, and left stationary for the duration of the recording. This adds a logistical step that is absent in fully wearable IMU-only systems, and the proposed system is therefore best described as infrastructure-light; full infrastructure independence is discussed as a future direction in Section 8.5.

8.5 Future Work

The directions identified here follow directly from the limitations consolidated in Section 8.4, and each corresponds to a specific gap in the current system whose resolution would constitute a meaningful advance.

8.5.1 Higher-Speed Movement and Tighter GNSS/IMU Coupling

Extending the system’s reliable operating envelope to normal and fast walking speeds, and ultimately to running and sport-specific movements, is the most impactful single direction for future work. As established in Section 8.4.1, the current degradation mechanism is rooted in the PLL tracking bandwidth of body-mounted receivers under impulsive dynamics. Two complementary approaches could address this. The first is hardware-level: receivers designed with wider carrier-phase tracking bandwidth would be more tolerant of the rapid Doppler rate changes induced by foot strike dynamics. The second is algorithmic: deeply coupled GNSS/IMU integration, in which inertial predictions are continuously fed into the receiver’s tracking loops to assist carrier-phase maintenance during high-dynamic episodes, represents an active area of development in the GNSS engineering community and is a natural evolution of the loosely-coupled architecture implemented in this thesis. Either approach, or a combination of both, would be expected to extend the operating envelope without requiring fundamental revision of the integration framework.

8.5.2 Production-Grade Hardware

Several of the limitations documented in this thesis, including mid-recording shutdowns, magnetometer faults, and unpredictable device behaviour, are consequences of prototype hardware immaturity and not of any fundamental constraint of the approach. A production-grade implementation of the same sensing configuration, with improved power management, higher-capacity batteries, and factory-calibrated inertial sensors, would directly address these issues and increase the number of usable recordings per session. Current trends in GNSS miniaturisation suggest that this is a realistic near-term prospect: dual-frequency, multi-constellation receivers in compact, low-power form factors are increasingly available at consumer-grade price points, and their integration into a purpose-built wearable platform for human motion analysis is a straightforward engineering task given the proof-of-concept demonstrated here. More reliable hardware would also enable larger experimental campaigns, addressing the validation scale limitation identified in Section 8.4.4.

8.5.3 Larger Validation Cohorts and Clinical Deployment

The datasets collected in this thesis are sufficient to demonstrate feasibility and characterise the operating envelope, but fall short of what is required to establish clinical utility. A natural next step is a larger validation study involving a more diverse subject pool, including older adults, patients recovering from neurological conditions, and individuals with gait impairments, conducted in outdoor environments representative of real rehabilitation practice. Such a study should include comparison against a laboratory-grade optical motion capture reference, which remains the

only ground truth capable of providing absolute joint angle accuracy without the methodological limitations of the markerless pipeline used here. This comparison, ideally conducted in a controlled outdoor setting where both systems operate simultaneously, would establish criterion validity for the GNSS/IMU pipeline.

Criterion validity is one component of the clinimetric evidence base that a clinical tool requires. A complete programme would additionally establish test-retest reliability through repeated measurements on the same subjects across sessions, quantified through the intraclass correlation coefficient and the standard error of measurement; determine the minimal detectable change for each target gait parameter, defining the threshold at which a measured difference exceeds measurement noise; benchmark the system's measurement error against the minimal clinically important differences established in the gait literature for each parameter, defining the threshold at which the system's precision would be sufficient to detect changes of clinical relevance; and evaluate responsiveness to longitudinal change in patient populations undergoing rehabilitation. The Bland–Altman analysis reported in Chapter 6 provides a first agreement estimate against an unvalidated reference, and is best understood as a preliminary step toward the criterion-validity element of this programme.

Undertaking such a programme is constrained by considerations that go beyond scientific design. Testing on patient populations requires the prototype to satisfy the safety, reliability, and characterisation standards typically expected of medical devices, and the ethics-committee approval needed to enrol vulnerable populations is contingent on demonstrating that the device meets those standards. The risk-benefit assessment applied to research with prototype wearables on patients is necessarily more stringent than for healthy volunteers [108, 109]: a device subject to mid-recording shutdowns, unpredictable behaviour, or uncharacterised sensor faults is unlikely to receive approval for clinical testing regardless of the scientific interest of the underlying question. The clinimetric programme sketched above therefore has a hardware-maturity prerequisite, and the sequencing is not a matter of preference: production-grade hardware precedes clinical enrolment, which precedes clinimetric characterisation, which precedes any claim of clinical utility. This ordering explains, in part, why the clinimetric properties absent from the present thesis are structurally deferred.

Beyond validation, the automated processing pipeline introduced in Chapter 7 provides a practical foundation for clinical deployment: its ability to process multi-device recordings systematically and without manual intervention is a prerequisite for any large-scale or routine clinical use of the system.

8.5.4 Architecture 1: A Lightweight Path to Spatial Grounding

As discussed in Section 8.1.1, Architecture 1 was intentionally scoped out as a primary experimental objective, but its premise is incidentally supported by the torso receiver results across both

experimental campaigns. A single carrier-phase receiver mounted on a stable body segment, with the torso being the most natural candidate as demonstrated here, consistently achieved high fix rates and produced a reliable globally referenced translational trajectory without any of the dynamic degradation observed at the feet. This is, in essence, Architecture 1 operating as intended, even if it was not designed as a standalone investigation.

The significance of this configuration should not be underestimated. In the context of an existing IMU-based motion capture system, a single additional GNSS receiver represents a minimal hardware addition, yet it introduces a qualitative change in what the system can provide: absolute spatial grounding in a globally referenced metric frame, cross-session and cross-subject comparability, and a reliable translational reference against which inertial drift can be partially bounded. These are capabilities that no amount of algorithmic sophistication can provide to an IMU-only system, and they come at the cost of a single wearable receiver and a portable base station. A dedicated investigation of Architecture 1 at carrier-phase precision, characterising its accuracy across environments, speeds, and body placements, would constitute a meaningful and practically accessible contribution. Furthermore, the use of virtual reference station services, which aggregate observations from networks of permanent stations to simulate a local reference receiver at an arbitrary point, could eliminate the base station requirement entirely for this configuration, making Architecture 1 a genuinely infrastructure-free option in areas with adequate network coverage.

8.5.5 GNSS Spatial Grounding for Mobile Vision-Based Systems

Section 4.2.3 of Chapter 4 identified a third role for GNSS in human movement analysis: providing spatial grounding for mobile vision-based systems. This role was introduced as a conceptual possibility but explicitly excluded from the experimental scope of this thesis, and it remains an open direction. The core idea is that a GNSS receiver co-located with a mobile camera (whether mounted on a drone, a body-worn unit, or a handheld device) could provide the absolute metric reference that monocular vision systems intrinsically lack. Monocular pose estimation recovers motion up to an unknown scale and in an arbitrary local frame; a GNSS position time series for the camera, combined with an estimate of camera orientation from an onboard IMU, would resolve both ambiguities simultaneously, enabling the reconstruction of human movement in a globally referenced metric frame from video alone, without any wearable instrumentation on the subject.

The limitations of the drone-based markerless pipeline used as a reference in this thesis (camera foreshortening, scale ambiguity, and the absence of absolute spatial grounding) are precisely the limitations that GNSS integration could address. A drone equipped with a carrier-phase GNSS receiver and a calibrated camera would, in principle, combine the non-invasive character of markerless capture with the metric grounding of the GNSS/IMU approach, occupying a distinct and practically attractive position on the accuracy–deployability spectrum. This direc-

tion connects the two methodological threads of this thesis, GNSS-based motion capture and drone-based markerless reference, into a unified future system, and represents a natural long-term extension of the framework proposed in Chapter 4.

8.6 Conclusions

This thesis set out to investigate whether wearable GNSS receivers, combined with inertial sensing and a portable base station, could bridge the gap between laboratory-grade optical motion capture and fully wearable IMU-only systems for outdoor human movement reconstruction. The answer provided by the experimental work presented here is affirmative, within a well-defined operating envelope: at slow walking speeds, in open-sky outdoor environments, and with receivers placed on dynamically stable body segments, the system produces metric-scale absolute measurements that are internally consistent, physiologically valid, and confirmed against independent references across multiple subjects. The conceptual framework proposed in Chapter 4 (the taxonomy of roles and three integration architectures) provides a structured design space that situates these results and defines the directions in which the system can be extended.

The contribution of this thesis is best understood as establishing a foundation for further advances in GNSS-aided outdoor motion capture. The experimental chapters have demonstrated, at proof-of-concept level, that foot trajectory reconstruction, spatiotemporal gait parameter estimation, and joint angle reconstruction from GNSS pseudo-markers and IMU orientations are all achievable in realistic outdoor conditions. The operating envelope overlaps with the walking speeds encountered in clinical rehabilitation practice, and the principal obstacles to a deployable clinical tool are threefold: hardware maturity, validation scale, and the establishment of the clinical evidence base (criterion validity, reliability, minimal detectable change, and responsiveness) that clinical adoption requires. The methodological framework is in place. The automated processing pipeline developed alongside the experimental work is a concrete step toward making the framework accessible beyond the research setting.

The gap identified in Chapter 1 between accurate and deployable motion capture systems has not been fully closed by this thesis, but the results presented here show it is not unbridgeable. The work presented here demonstrates that centimetre-level outdoor human motion capture with wearable hardware is achievable in practice within the constraints characterised throughout. What remains is to push those constraints back.

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