Replacing Force Plates with IMU-based SmartGlasses for Balance Assessment

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***Abstract*—Human balance is essential for everyday activities, from basic functions like standing and walking to more complex movements required in sports and work tasks. Optimal balance reduces the risk of falls, a major cause of injuries among the elderly and individuals with certain medical conditions. However, traditional force platforms can be prohibitively expensive for smaller clinics and individual practitioners, and patients with mobility issues may find it difficult to access locations equipped with such platforms. In light of these challenges, this work explores the effectiveness and versatility of using simpler hardware for pressure sensing. As an alternative to conventional force platforms, low-cost wearable sensors, such as Inertial Measurement Units (IMUs), have been explored. This research focuses on developing a simple yet effective balance evaluation system using smart-glasses embedded with an IMU sensor to replace traditional feet pressure sensing machines. Furthermore, we developed a custom dataset for the estimation of sway parameters by simultaneously collecting the IMU data and labels from the force platform for a set of 20 participants. We experimented with various Deep Learning (DL) models, leveraging the latest advancements in Machine Learning (ML), to estimate sway parameters such as sway path, sway area, and their ratio, typically measured by the gold standard force platform. When evaluated with appropriate performance criteria, the experimental results indicate that our proposed methodology performs robustly using only accelerometer data.**

***Index Terms*—force platform, balance assessment, smart-glasses, risk of fall, motor control, IMUs, machine learning.**

I. Introduction

Progress in Information and Communication Technology (ICT), coupled with the capabilities of Artificial intelligence (AI) and the widespread connectivity facilitated by the Internet of Things (IoT), is transforming the healthcare system, bringing transformative benefits that enhance patient care, streamline clinical operations, and foster innovative medical research. From the integration of telemedicine and electronic health records to the deployment of IoT devices for real-time health monitoring, ICT innovations are enabling healthcare providers to deliver more precise, personalized, and efficient care. These technologies enable seamless communication between patients and healthcare professionals, ensure the secure management of sensitive health data, and foster the development of data-driven insights for better health outcomes. As ICT continues to evolve, its potential to create a more responsive, accessible, and effective healthcare system becomes increasingly evident, promising a future where cutting-edge technology and healthcare excellence go hand in hand.

In this framework, load balancing estimation involves evaluating how a patient distributes his/her weight across the feet. This assessment helps identify imbalances or abnormalities in weight distribution, which can indicate underlying issues such as posture problems, gait abnormalities, or conditions affecting the musculoskeletal system. By analyzing this distribution, healthcare professionals can develop targeted treatment plans to improve balance, prevent injury, and enhance overall mobility and well-being. Human balance, or postural control, refers to the capacity to sustain stability and avoid falling while engaging in different tasks. The process entails intricate interplay among the neurological system, muscles, and sensory input [1], [2]. Several medical diseases, such as Parkinson's Disease (PD), stroke, and multiple sclerosis, are strongly correlated with balance impairments [3]. Therefore, assessing and analyzing balance is essential for recognizing an individual's posture stability and motor function [4].

Various instruments and technologies are employed to assess human posture control, spanning from basic clinical inspections to sophisticated computerized systems. Clinical examinations such as the Romberg Test [5], Timed Up and Go (TUG) Test [6], and Berg Balance Scale (BBS) [7] provide preliminary assessments of balance through simple tasks. Instrumented equipment, such as force plates, measure the distribution of forces across the feet to determine Center of Pressure (CoP) and sway parameters [8]. Traditional clinical evaluation provides quick, cost-effective, and easy balance assessments. However, subjectivity and inadequate data constrain them due to biases and variations in the outcomes. On the other hand, sensorized systems address such limitations by performing objective measurements, thus offering quantitative analysis and

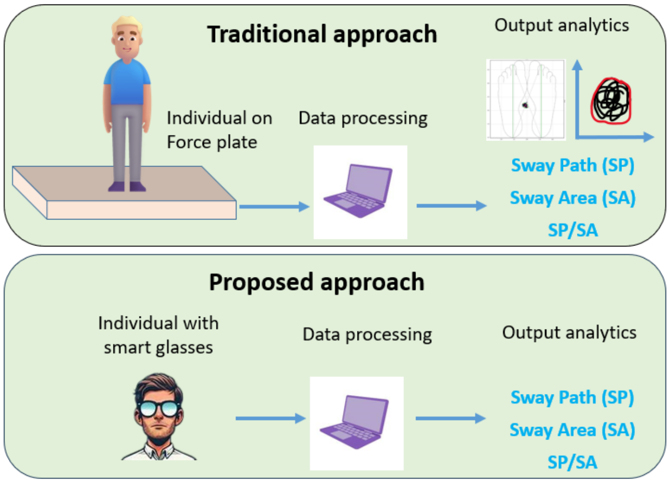

Fig. 1. Conceptual overview of the traditional (top) and the proposed (bottom) approaches.

providing deeper insights into balance and postural control.

Among traditional assessment techniques, the Romberg test for static postural activities has gained widespread adoption in clinical settings due to its simplicity and ease of use [8], [9]. Nevertheless, the high cost and unwieldy characteristics of force platform devices pose challenges to their wider adoption. As an alternative, wearable devices such as Inertial Measurement Unit (IMU) sensors provide a convenient, low-cost, and user-friendly way to continuously and real-time monitor static and dynamic motions, making them accessible to a broader range of users. Therefore, this research aims to conduct preliminary work to estimate sway parameters generated by a force platform using a single IMU sensor embedded in a pair of glasses, by leveraging its capability to collect accelerometer data.

Fig.1 illustrates the conventional and proposed approaches for estimating sway parameters in order to assess load balance. The traditional approach entails utilizing a force platform to quantify sway parameters. This platform collects measurements related to the force exerted by the pressure of the feet to infer the trajectory of the CoP, allowing for the analysis of postural sway and balance. The proposed approach instead leverages IMU sensors, which are small pieces of hardware embedded in a wearable device, able to collect motion data to calculate sway characteristics. This method offers greater adaptability and portability compared to a stationary and cumbersome instrument such as the force platform. In light of the above considerations, in the following, we highlight the main contributions of this preliminary research work:

- An innovative method is proposed to assess human load balance, which leverages a pair of smart-glasses equipped with a single IMU sensor to collect accelerometer data and foresee the same indicators produced by the considered force platform.
- A custom dataset is developed by collecting the data using smart-glasses and the force platform simultaneously, throughout three different tests: open eyes, closed eyes, and free.
- Various deep learning (DL) models are trained and tested on the custom-built dataset to predict the force platform-based generated sway parameters, Sway Path (SP), Sway Area (SA), and their ratio.
- The proposed approach is thoroughly assessed using real-world data from individuals, in order to showcase the efficacy and practicality of the approach.

The remainder of this paper is organized as follows: Section II surveys the State-of-the-Art on the considered research topic, Section III describes the problem in general, and Section IV provides the methodology used in this work, including the data collection process. Section V presents the results obtained employing the proposed solution. Finally, in Section VI conclusions are drawn, and a discussion on open challenges and future works is provided.

II. Background and Motivation

A. State of the Art

The best approach to preventing falls is to identify individuals at Risk of Fall (RoF) and determine the cause of the problem through a suitable diagnostic path. The most predictive factors for future falls include motor problems, sensory impairment, cognitive or mood impairment, and so on [8]. The Romberg test evaluates balance by targeting the visual, proprioceptive, and vestibular systems, which keep the body in alignment [10]. Combining this test with force platforms increases its diagnostic power [8]. Although force platforms facilitate balance disorder diagnosis, rehabilitation, and postural control research, there are portability issues, high costs, and user training and support demands. Alternatives include mobile devices like IMUs for balance and fall risk assessment.

Several authors have endeavored to deploy wearable devices for balance testing, such as [4], [10]–[13]. More precisely, authors have proposed using ML algorithms and IMUs in [4] to predict the Berg Balance. Further, in order to measure the RoF during the Romberg test on a posturograph, an IMU sensor was affixed to the back of the waist in [10]. Furthermore, multiple IMU sensors were implemented in [11] to evaluate the average velocity score of the CoP by extracting features from the raw data. Moreover, [12] estimated the Ground Reaction Force (GRF) and captured the motion characteristics of a human walking using two IMU sensors. Besides, [13] employed IMUs on the head, pelvis, and ankles to evaluate the instrumented Romberg test motion features of vestibular hypofunction patients versus healthy controls.

B. Quantities Definition

In this study, we chose to assess the human balance by estimating the sway parameters directly using only single IMU sensor data. The SP, SA, and their ratio SP/SA are the parameters to be estimated. The SP is the distance traveled by the CoP over a given time period while an individual is standing. A longer SP suggests increased postural instability since the individual is moving more to maintain balance.

Further, the SA is defined as the area enclosed by the CoP's trajectory. A larger value of SA indicates higher levels of postural instability. Furthermore, the ratio of the two reflects how effectively an individual maintains a stable state. A higher ratio indicates that the person is covering a greater distance relative to the area, which could indicate less efficient or irregular postural control.

III. Problem description

Force platforms are excellent tools for the Romberg test because of their accuracy and reliability, yet they have characteristics that limit their practical deployment. Force platforms are often large and cumbersome, which is a major drawback that prevents their use outside clinical or laboratory settings. Furthermore, there are issues related to usability because force platforms typically necessitate specialized knowledge and training for setup and operation. For these reasons, there is a growing need for qualified individuals to help with the test administration and result interpretation. A further obstacle to broad usage, especially in settings with limited resources, is the device's complexity and the requirement for substantial training. All of these factors make the Romberg test, which measures balance using force platforms, less convenient and accessible. Due to the above considerations, in this preliminary work, we propose a wearable system based on an IMU sensor to assess load balance to replace force platforms. A primary objective of the present study is to determine how the IMU sensor, and more specifically accelerometer data, can be used to determine the sway parameters, which are conventional indicators of the force plate-based balancing assessment.

It has been common practice to place wearable sensors in the lower back to measure postural stability due to its vicinity to the body's center of gravity [14]. On the other hand, tiny displacements caused by the wearer's motion make it difficult for the sensors to remain perfectly aligned during manual wear [15]. Furthermore, patients are bound to wear these wearables continuously. Therefore, in this study, we employ an IMU sensor integrated inside glasses as a prototype inspired from [16] that may be worn as regular eyeglasses or sunglasses.

IV. Methodology

In the instrumented Romberg test [8], the CoP is determined by measuring the GRF components on the force platform. This process is repeated at fixed time intervals according to a predefined sample frequency. A sequence of succeeding positions is thereafter used to represent the CoP path. By applying signal processing techniques to the CoP path, specific sway parameters are extracted, namely SP length, SA, and maximum sway displacement, alongside other statistical information.

In this research, we aim to estimate sway parameters, particularly focusing on the SP and SA at this preliminary stage, using only wearable IMU sensors. The IMU sensor embedded in the glasses acquires accelerometer measurement data at a sampling rate of 100Hz. This yields a $M \times 1$ observation vector $x(t) = [a_x(t)\ a_y(t)\ a_z(t)]^T$, containing accelerations a_i for each axis $i \in \{x, y, z\}$. Since we consider

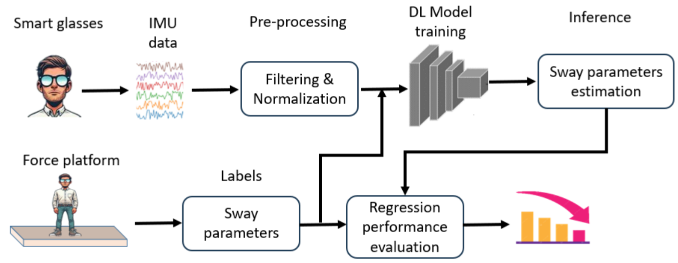

Fig. 2. Overall block diagram of the proposed system. DL: Deep Learning

only accelerometer signals, in this work $M = 3$, represents a 3-dimensional space. As a whole, the accelerometer data from IMU is represented as:

$$I_{\text{acc}} = \{(t, a_x(t), a_y(t), a_z(t)) \mid t \in [0, T]\} \quad (1)$$

Given a sequence of the aforementioned observations x over time t, our objective is to predict the sway parameters as generated by the force platform. In this context, the multivariate time series associated with head side movements at each time instant t can be characterized as:

$$y(t) = \mathcal{F}[x(t)] \quad (2)$$

where $y(t)$ represent the sway parameters based labels for the predefined stages of the Romberg test used for the data collection and $\mathcal{F}$ is a function expressing the correlation between the obtained IMU data and the consequent body movement at the head side. In this study, to obtain a reliable prediction based on the accelerometer data, the function $\mathcal{F}$ is approximated using DL algorithms. So considering the DL algorithm as a function $\mathcal{F}_\theta$, where θ represents the neural network's weights and biases. The model receives accelerometer data as input and returns an estimation of the SP and SA parameters:

$$\mathcal{SP}, \mathcal{SA} = \mathcal{F}_\theta(a_x(t), a_y(t), a_z(t)) \quad (3)$$

Fig. 2 shows the block diagram of the proposed system, which aims at estimating the sway parameters using the accelerometer data obtained from the IMU sensor by employing a DL model. The solution presented in this work involves the use of smart-glasses equipped with an embedded IMU sensor, which is utilized to collect raw motion signals. These signals undergo a pre-processing stage which includes low-pass filtering and data normalization. Additionally, different DL models are trained for the regression task, with the data being labeled using the Ground Truth (GT) obtained from a reference force platform. During the process of inference, the model's estimations are compared to the GT labels, and the regression errors are then generated to assess the performance.

A. Data Collection

To be in harmony with established procedures, we follow the guidelines of the instrumented Romberg test [8] for data collection. The experimental setup considered for the measurements is shown in Fig.4. During the test, data from the IMU sensor and force platform are collected simultaneously, while the individual is wearing the glasses and standing on the force plate. The IMU sensor is equipped on the left arm of the glasses. The x-axis points forward, the y-axis points

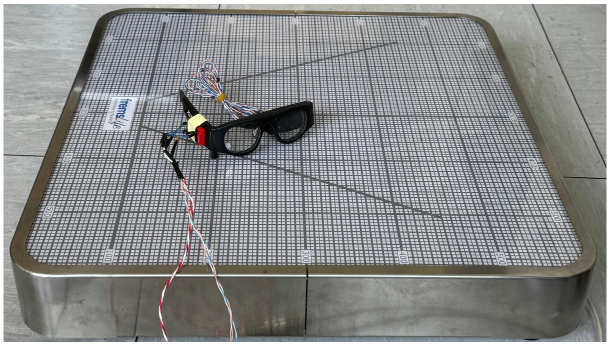

Fig. 3. Real images of force platform and smart-glasses.

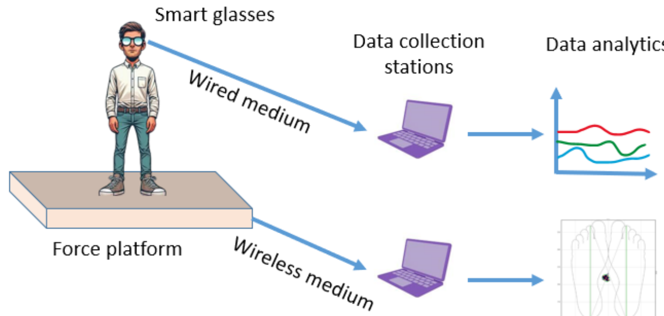

Fig. 4. Experimental setup to collect the data from the force platform and smart-glasses equipped with an IMU sensor.

downward, and the z-axis points away from the head, indicating the orientation of the IMU sensor. The signals obtained from the IMU sensor are sampled at a rate $fs = 100Hz$, and data can be sent to a desktop personal computer over a USB interface. Alternatively, the data can be saved on an SD card, allowing for downloading at a later time. The real pictures of smart-glasses and force platforms are shown in Fig.3.

Each participant received instructions to assume a relaxed standing position with both feet on the force platform aligned with specific references [8], standing as still as possible, and wearing the sensorized glasses [16]. The test was carried out in three subsequent stages: *i)* standing on the force plate with their feet together and eyes closed, *ii)* standing in the same position with eyes open, and *iii)* standing freely, assuming a custom posture with eyes open. By monitoring the pressures the feet apply, the force plate records precise information about the CoP's trajectory. A detailed quantitative evaluation of the person's postural control and balance assessment report is generated from the recorded and processed data, which comprises the parameters like SP, and SA, alongside other statistical information. The values of these parameters are recorded separately for the three stages.

The force platform is configured to gather the data for a duration of 40 seconds for each stage. Therefore, signals from the IMU sensor are also recorded for the same time duration. The data collection procedure included 20 participants, and each individual carried out the experiment once resulting in a total of 60 samples. These samples are used for training and testing purposes. Details of the participants are reported in Table I. Specifically, this work included 13 males and 7 females, aged between 27 and 38 years. The heights of the individuals ranged from 157 to 185 cm, while their weights varied between 55 and 85 kg. We considered healthy participants because the goal of the research at this preliminary stage is to correctly estimate the sway parameters measured by the force plate using only the IMU data.

B. Data Pre-Processing

The data is pre-processed once it is collected and the pre-processing stage consists of a low pass filter and zero mean normalization. The low pass filter has an 11-Hz cutoff frequency, and zero mean normalization is used to standardize data by subtracting the mean value of each feature from the dataset and dividing it by the standard deviation. This procedure ensures the data is centered around the origin, which improves performance and speeds up convergence in DL algorithms.

TABLE I
DETAILS OF THE PARTICIPANTS.

Parameter	value	Parameter	value
Number of participants	20	Age group	27-38
Male	13	Hieght (cm)	157 - 185
Female	7	Weight (kg)	55 - 85

C. Regression Models

The task of estimating the sway parameters from IMU data is the regression task. Keeping in view the nature of data, time series-based DL models have been implemented. More specifically, InceptionTime [17], RNN-FCN [18], XResNet1d [19], Transformer RNN [20], and ResNet [21] are implemented. In particular, an InceptionTime model is introduced in [17], which is an ensemble of deep CNN models that draw inspiration from the Inception-v4 architecture, specifically designed for Time Series Classification. Further, a method for classifying multivariate time series by using a squeeze-and-excitation block in [18]. This enhanced the performance of the models and needed minimum preprocessing. Transformer-based model for predicting multivariate time series is presented in [20] which employs time series segmentation into patches, resulting in a notable enhancement in long-term prediction precision and reduction in computational requirements. Moreover, in [21], a ResNet architecture is investigated for the task of time series classification. These models were mainly employed for the classification task in their original work. However, we modified them for the regression task in this study.

V. EXPERIMENTS AND RESULTS

The proposed approach is validated via various experiments and results are reported in this section. The trained model was subjected to five-fold cross-validation to circumvent overfitting and selection bias. The data of participants were randomly allocated across five groups. We used the Adam optimizer, which has a learning rate of 0.001. The training was carried out on NVIDIA GPU with an early stopping on validation losses

TABLE II
PERFORMANCE EVALUATION OF VARIOUS DL MODELS ON THE CUSTOM-BUILT DATASET FOR SWAY PARAMETER ESTIMATION.

Models	Sway Path (SP)			Sway Area (SA)			SP/SA		
	MAE	MSE	RMSE	MAE	MSE	RMSE	MAE	MSE	RMSE
InceptionTime [17]	0.09	0.01	0.11	0.11	0.03	0.16	0.63	2.32	0.97
RNN FCN [18]	0.08	0.01	0.1	0.11	0.02	0.12	0.19	0.17	0.26
XResNet1d [19]	0.07	0.01	0.1	0.1	0.016	0.13	0.27	0.24	0.31
TransformerRNN [20]	0.10	0.01	0.11	0.15	0.03	0.17	0.34	0.39	0.4
ResNet [21]	0.12	0.02	0.14	0.14	0.02	0.15	0.29	0.3	0.35

to avoid overfitting. Since the regression model is employed, metrics such as Mean Absolute Error (MAE), Mean Squared Error (MSE), and Root Mean Squared Error (RMSE) are used to assess the model's performance. The MAE is the average absolute difference between the actual and anticipated values while MSE is simply the average of the squared discrepancies between the actual and predicted values. Since the error is squared, MSE emphasizes major disparities in predictions by attributing greater weight to larger errors. The RMSE is calculated by the square root of the MSE and penalizes larger errors while providing a general idea of how accurate predictions are.

A. Discussion

Table II compares the performance of five different DL-based models on the customized dataset using MAE, MSE, and RMSE metrics for three sway parameters. In SP parameter prediction, the XResNet1d model has the lowest errors across all three metrics, whereas ResNet has the highest errors, indicating it is most uncertain. For the SA parameter, the XResNet1d model has minimal errors (MSE value of 0.016), indicating efficient performance, while the TransformerRNN model has significant errors, particularly for MAE and RMSE metrics. The RNN-FCN model performs best in all parameters and three error measures, proving the most efficient model with the lowest SP/SA ratio errors across all three metrics. Therefore, we applied k-fold cross-validation to the custom dataset using this model.

The performance of an RNN-FCN model in estimating the sway parameters using a 5-fold cross-validation approach is presented in Table III. Each fold has its own set of reported errors, and the table shows the summary of their means. Each sway parameter (SP, SA, and their ratio) has three error metrics (MAE, MSE, and RMSE). Because the system only has two outputs, SP and SA, to calculate SP/SA error metrics, we computed the ratio of their predictions and compared them to their respective GT values. The model outperforms the SA parameter in predicting the SP parameter across all three error metrics for all five folds, indicating reasonable predictions. It appears that there is more complexity in estimating the SA parameter since errors are marginally larger than SP. Error metrics for the SP/SA ratio, especially MSE, and RMSE, are the highest of all, indicating that predicting sway parameters is a challenging task and that there is potential for additional improvement, even though the results for the SA and SP parameters are promising.

To examine how well the RNN-FCN model predicted the sway parameters on the custom-built dataset, a box plot anal-

TABLE III
K-FOLD EVALUATION OF THE RNN-FCN MODEL ON THE CUSTOM-BUILT DATASET. RNN: RECURRENT NEURAL NETWORK, FCN: FULLY CONVOLUTIONAL NETWORK.

K-fold	Sway Path (SP)			Sway Area (SA)			SP/SA		
	MAE	MSE	RMSE	MAE	MSE	RMSE	MAE	MSE	RMSE
1	0.08	0.01	0.1	0.11	0.015	0.12	0.19	0.17	0.26
2	0.12	0.03	0.18	0.19	0.07	0.26	0.31	0.15	0.35
3	0.2	0.06	0.24	0.22	0.07	0.26	0.19	0.13	0.24
4	0.13	0.04	0.19	0.17	0.04	0.21	0.12	0.83	0.28
5	0.15	0.06	0.25	0.21	0.09	0.3	0.08	0.9	0.29
Mean	0.150	0.048	0.215	0.198	0.068	0.258	0.175	0.503	0.290

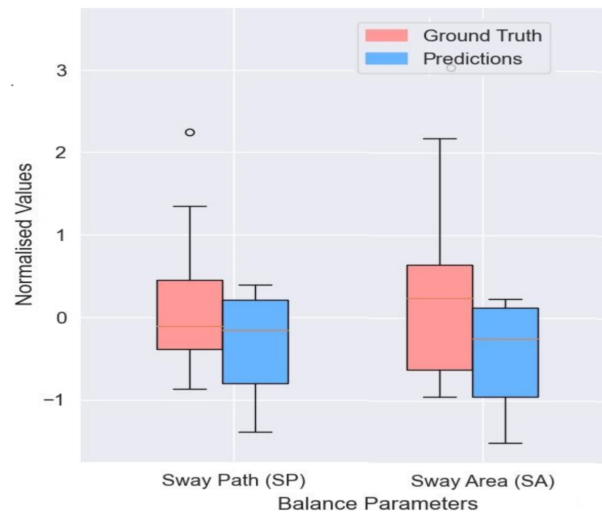

Fig. 5. Box plot analysis for the custom-built sway parameter estimation validation dataset.

ysis is carried out, shown in Fig. 5. It depicts the predictions of the RNN-FCN model for SP, and SA parameters on the validation dataset, compared to their respective GT values. Each parameter contains two boxes: predictions and GT values. The prediction value of boxes for parameters SP and SA have similar interquartile ranges corresponding to their GT box values. This means predicted data variability is equivalent to actual data variability. However, their median prediction values are lower compared to the GT values. Overall, the results in Table II, Table III, and in Fig. 5 show that the sway parameters of the force platform can be robustly predicted using only accelerometer data from the smart-glasses' IMU sensor. Despite some deviations in the prediction values from their respective GT values, the performance of sway parameter estimation can be significantly improved with increased data samples and more efficient DL models.

B. Limitations

As preliminary research into replacing force platforms with smart-glasses, a few limitations must be addressed in future work. First, the dataset is small with 60 samples only, which limits generalizability. To develop robust models and generate statistically relevant results, the dataset needs to be expanded. Second, only healthy participants were tested, which limits its clinical relevance. Using real patient data will help us understand the system's capabilities to diagnose and monitor balance disorders in a variety of populations. Third, the current study considered only three sway parameters. However, including more parameters may improve predictions and provide more insight into balance assessment. Lastly, the data from the force platform and smart-glasses were collected simultaneously but they were not synchronized at a fine-grained level, which may result in inaccuracies in recording exact information for larger datasets, rendering temporal connection between modalities erroneous. Thus, better synchronization is critical for increasing data accuracy and will be carried out in future work. Furthermore, when dealing with data sequences exceeding 40 seconds, various parameters need to be considered, such as modifying the model architecture to accommodate longer sequences, managing computational complexity, dividing the data into smaller segments, and expanding the model to accommodate consistent data patterns, among others.

VI. Conclusion and Future Work

In the proposed work, the preliminary study considers the feasibility of using smart-glasses embedded with an IMU sensor to estimate the sway parameters, which are measured by a force platform during the Romberg test. We aim to provide a low-cost, portable alternative to the traditional facilities. Our findings demonstrate that SP and SA are predictable via using accelerometer data from the IMU sensors, which shows that smart-glasses can be an effective tool for balance assessment. Moreover, several learning approaches are evaluated, where the RNN-FCN model shows a promising achievement in terms of regression error metrics. Future work will address the current limitations in several key areas. We plan to increase the number of participants to enhance the generalizability of the proposed model. Additionally, we intend to include participants with balance impairments, such as those affected by PD or stroke, to evaluate the model's efficiency in a clinical setting and its monitoring capabilities for various medical conditions. Moreover, limitations mentioned in Section V-B shall be dealt with in future work.

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