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Enhancing Occupational Back-Support Exoskeletons Versatility

by

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Hold fast to dreams
For if dreams die
Life is a broken-winged bird
That cannot fly.
Hold fast to dreams,
For when dreams go
Life is a barren field
Frozen with snow.

Langston Huges, Dreams

Se tu segui tua stella
non puoi fallire a glorioso porto

Dante, Inferno XV, 55-56

Declaration

I hereby declare that except where specific reference is made to the work of others, the contents of this dissertation are original and have not been submitted in whole or in part for consideration for any other degree or qualification in this, or any other University. This dissertation is my own work and contains nothing which is the outcome of work done in collaboration with others, except as specified in the text and Acknowledgements.

Tommaso Poliero
April 2021

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This thesis is the result of three and a half years of research carried out in the XoLab group of the Advanced Robotics department. My first thanks, therefore, goes to Jesús and Professor Caldwell for the incredible opportunity they have given me. A special thanks goes to Jesús. When I joined IIT in September 2016, as a master thesis student, the idea of doing a PhD seemed like a very difficult goal to achieve and full of pitfalls. However, thanks to Jesús' guidance and his teachings, I was able to complete my path.
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In queste righe non posso non citare Stefano e Gabriele. A Gabri il mio grazie per tutti i viaggi condivisi insieme. Viaggiando si creano ottime amicizie. Inizialmente io ero più un tipo da radio, tu uno a cui piace essere la radio; credo che abbiamo trovato un ottimo equilibrio e ti ringrazio per le innumerevoli discussioni che abbiamo avuto. A Daf, un grosso ringraziamento perchè con gli anni siamo passati dall'essere semplici compagni di corso ad amici veri. Condividere la casa con un amico come te è stata un'esperienza incredibile. Inoltre, abbiamo anche sfatato il mito che la tua presenza porti sempre pioggia. Certo, rimane un piccolo dubbio...ma nel complesso abbiamo fatto molti progressi, no?

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Tommaso Poliero

Abstract

In the 1970s, the scientific community began addressing the relationship between musculoskeletal disorders (MSDs) and work ergonomics. Since then, many studies have been published regarding this topic. Yet, 50 years later, MSDs are still cited as the most common work-related health problem, in the majority of the cases due to back pain. Workers performing manual material handling (MMH) activities (e.g., package loading and unloading in a warehouse or luggage handling in airports) are among the most exposed to risks and injuries. Several solutions have been proposed but, due to high implementation costs or lack of acceptability by the workers, MSD problem has not been solved.

Occupational back-support exoskeletons have been investigated for their ability to reduce muscle activation and, hence, mitigate the risk of injuries. Exoskeletons can be categorized as *soft* or *rigid*, if how the assistance is delivered to the user is taken into account, or as *active*, *passive* or *quasi-passive*, if, instead, focus is on the actuators that generate the assistance. Regardless of the categories, exoskeletons have been designed and tested, mostly, for static bending or lifting tasks. This is justified by the high risk of developing injuries associated with these tasks, but, on the other hand, does not address the complexity that *out-of-the-lab* environments might present. In this regard, an interesting study reported that if passive exoskeletons are used in non-lifting tasks, as walking, rather than helping they actually hinder and obstacle the wearers' movements. And, it is clear, that in industrial settings, workers do not lift for the whole duration of their schedule. Other relevant activities might be pushing, pulling or carrying. Indeed, the *International Standard ISO 11228* establishes ergonomic guidelines also for these activities, highlighting that they could yield risk of injuries. Therefore, designing exoskeletons that address also these activities might help promote the acceptability of these devices.

In this work, *exoskeleton versatility* is defined as the device ability to recognize which activity the user is performing and provide assistance accordingly. As an example, assisting with lifting could require the design of strategies that are not fit for carrying assistance. More in details, in the first part of this thesis, it is shown that considering spinal loading, carrying has an impact comparable to that of lifting. However, if lifting control strategies are used to assist with carrying, this produces gait impairments. The need of assisting with these two activities in different ways requires, first of all, a mean to recognize which task is taking place. This is addressed in the second part of the thesis. In particular, by using Support Vector Machines (SVM), it is shown that it is possible to build an automatic Human Activity Recognition (HAR) algorithm. Moreover, this algorithm can be embedded in the control architecture of XoTrunk, the back-support exoskeleton developed at our lab, enhancing

its versatility. The third and last part of this this work assesses the advantages of using a versatile exoskeleton, comparing its performance to state-of-the-art exoskeletons and control strategies. At the end of the work, it is described the impact that exoskeleton versatility had on field testing.

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Chapter 1

Introduction

In the 1970s, the scientific community began addressing the relationship between musculoskeletal disorders (MSDs) and work ergonomics. Since then, many studies have been published regarding this topic (Bernard and Putz-Anderson (1997), Cohen (1997), Silverstein and Clark (2004), Fujishiro et al. (2005), Hamberg-van Reenen et al. (2008), Tullar et al. (2010)). Yet, in the most recent EU-OSHA report by de Kok et al. (2019), MSDs are still cited as the most common work-related health problem in the EU. Indeed, 60% of workers still experience such disorders. In the majority of the cases the most affected body region is the lower-back. As an example, Figure 1.1 shows the impact of MSDs on the total occupational diseases registered in Italy in the years 2015-2019[1], whereas Figure 1.2 categorizes MSD according to the affected body region. MSDs affect not only the workers, but also the employers that, in turn, have to cope with absenteeism and productivity losses. To have an idea of the economic impact, in 2012, the total annual cost related to MSDs to the European Community represented 2% of the GDP, Bevan (2012).

Workers performing *manual material handling* (MMH) activities (e.g., package loading and unloading in a warehouse or luggage handling in airports) are among the most exposed to risks and injuries. Indeed, biomechanical models (Chaffin (1969), Toxiri et al. (2015), Koopman (2020)) describe how spinal muscles and passive tissues generate an extensor moment at the *L5-S1* disc that grows as trunk inclination and handled weight increase. Moreover, several studies underline how the activity of spinal muscles can be used for the estimation of the lumbar compression forces, Dolan and Adams (1993), Granata and Marras (1995), Davis et al. (1998). If these latter exceed specific biomechanical limits the risk of developing MSDs increases, Brinckmann et al. (1987), Moore and Garg (1995). MMH activities easily exceed these limits. Luckily, there are many solutions that can be adopted to mitigate the development of new MSDs.

Traditionally, a hierarchy of controls is applied to implement feasible and effective control solutions. The *National Institute for Occupational Safety and Health*[2] (NIOSH), ranks these solutions from the most to the least effective in an inverted pyramid (Figure 1.3). According to this ranking,

[1] https://dati.inail.it/opendata/
[2] https://www.cdc.gov/niosh/index.htm

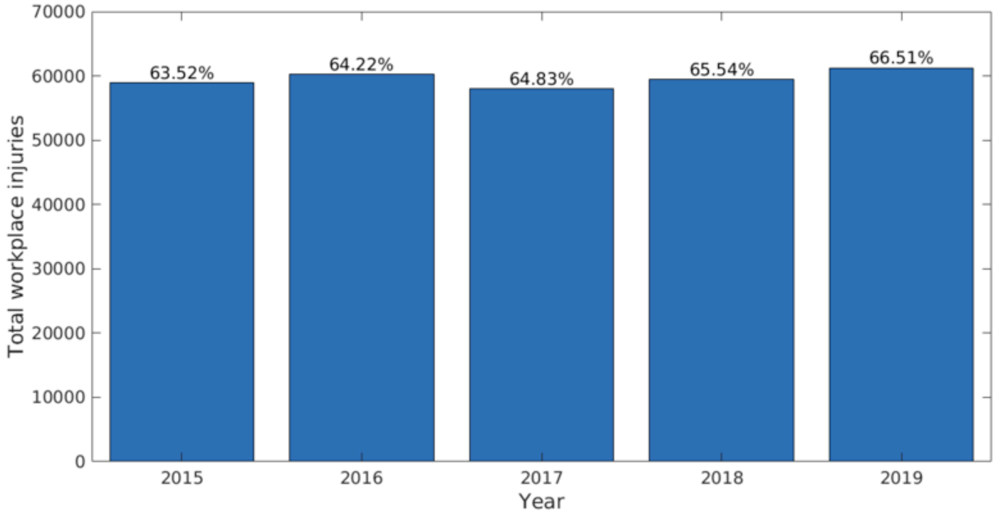


Figure 1.1 The graph shows the number of occupational diseases cases occurred in Italy in the years 2015 – 2019. The percentage of cases linked with MSDs is reported for each year on top of the bar.

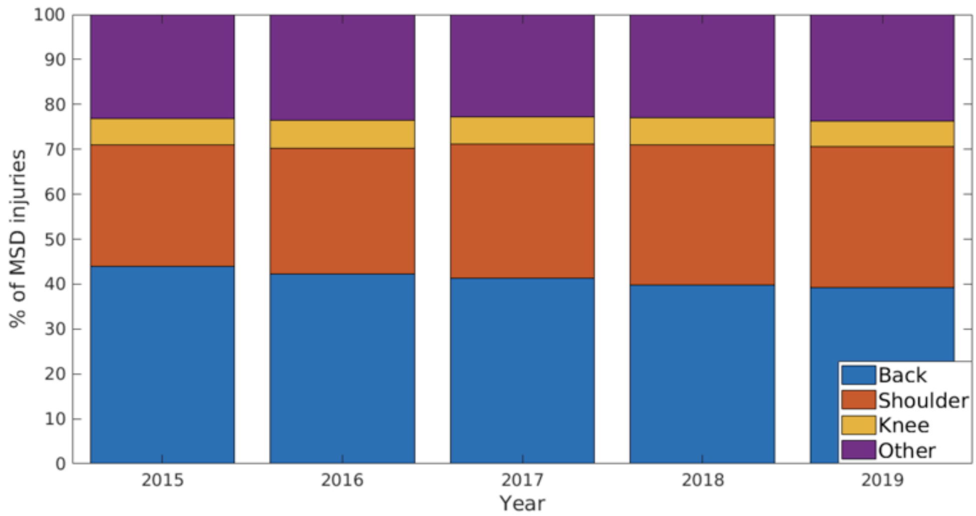


Figure 1.2 The graph shows which body parts are mostly affected by MSDs. Note that *back* and *shoulder* are the most commonly injured parts.

Elimination and Substitution controls are the most effective as they require to completely remove or replace the hazards. However, time and resources needed for these kind of implementation are serious drawbacks. The next level of the pyramid suggests to consider *Engineering controls*. This type of control isolates workers from the hazards or reduces its severity through physical design changes to the workstation. Some of the most applied changes can be found in the NIOSH Engineering Controls Datatabe[3]. Finally, changing the amount of time workers are exposed to a given risk or using *personal protective equipment* (PPE) appears to be the least effective solution.

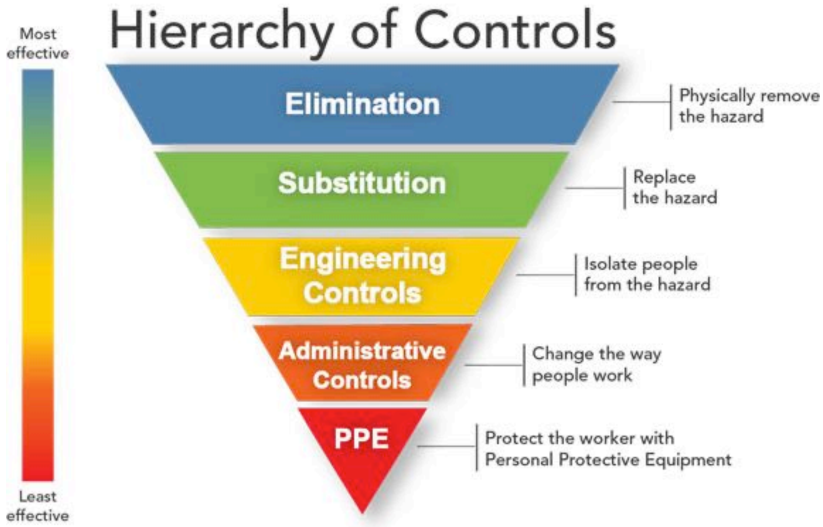


Figure 1.3 Hierarchy of controls for controlling occupational hazards.
Source: https://www.cdc.gov/niosh/

Despite the growing number of available solutions, the number of MSDs in the last years has not dropped (see Figure 1.1, for an example of the Italian trend). This might be caused not only by the high cost of some solutions but also to the lack of adoption of new tools by the users.

1.1 Motivation

Recent reviews on ergonomic interventions to reduce MSDs demonstrate that combining different controls appears to have the greatest effect in the reduction of work-related MSDs, Silverstein and Clark (2004), Goggins et al. (2008), Tullar et al. (2010). Therefore rather than following the standard hierarchical approach (see Figure 1.3), it is advisable to evaluate a given solution according to its capability of reducing/eliminating the level of exposure and reducing the time of exposure, see Figure 1.4. The former capability implies that a solution can *reduce strain and fatigue* for the worker, whereas the latter implies that it can have a positive impact on the *working performance*.

[3]https://www.cdc.gov/niosh/engcontrols/ecd/detail25.html

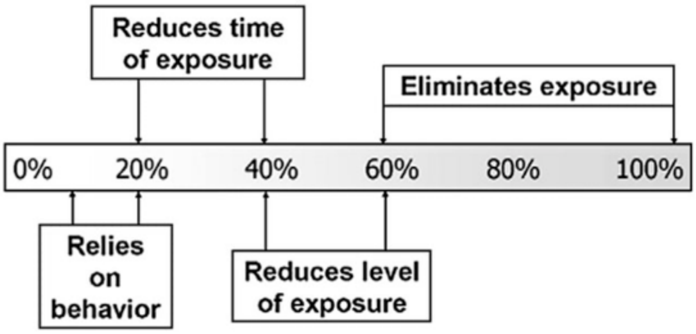


Figure 1.4]
Goggins' proposed relationship between level of control and estimates of effectiveness, Goggins et al. (2008).

In the framework of MMH, many practitioners (e.g., ergonomists, engineers, H&S managers and compensation authorities) have started evaluating *exoskeletons* as a possible novel solution for reducing MSDs. Indeed, exoskeletons are wearable devices that generate forces/torques at human joints to support the execution of physical activities. The forces/torques delivery is subject to control strategies that are designed specifically for the task being executed. When referring to devices that provide assistance at the *L5-S1* joint and that are meant to be used by industrial workers, exoskeletons are referred to as *occupational back-support* exoskeletons. More in particular, a 2016 review on occupational exoskeletons reported that their usage yields back-muscle activity reduction by up to 40% during repetitive lifting and static holding tasks, de Looze et al. (2016). As presented before, the primary consequence of muscle activity reduction is the de-compression of the lumbar spine. Such results are also confirmed by more recent reviews Theurel and Desbrosses (2019), Kermavnar et al. (2020). Therefore, the ability of these devices to reduce the physical loading on the lumbar spine suggests that they may present a possible novel solution to the mitigation of MSD related back-pain, reducing the level of exposure. However, there is still insufficient current knowledge to justify an unreserved adoption of this technology and the long-term effects on the working performance are still unclear, Theurel and Desbrosses (2019).

The belief that exoskeletons can truly make a positive impact in mitigating MSDs and the need for a deeper understanding on how this technology could be adopted by final users, were the main motivations for the start of a collaboration between the research group I'm part of (XoLab, Advanced Robotics, Istituto Italiano di Tecnologia) and INAIL, the Italian Workers' Compensation Authority). This collaboration also promoted the further development of Robo-Mate, the back-support exoskeleton presented in Toxiri et al. (2018a), into *XoTrunk*, Ortiz et al. (2018b), Sposito et al. (2020b), Di Natali et al. (2020b) (see Figure 1.5).

Figure 1.5 Example of XoTrunk usage during MMH activities at the Genova airport. Image published in Poliero et al. (2020a).

1.2 Problem Statement

Workers may find themselves performing many different activities in the same workplace. As an example, in logistics, it is possible to imagine a quite simple task where a worker *walks* to the shelf, *picks* the required object, *carries* it back to the cargo area and, eventually, *lowers* it in the appropriate container. A similar scenario can be pictured in other contexts where MMH is involved. In such conditions, the *International Standard ISO 11228* establishes ergonomic guidelines for lifting, carrying, pushing and pulling. As an example, the NIOSH engineering controls database[4] reports that considering the compensable cases of low back pain associated with MMH tasks, *lifting* has been implicated in 37 to 49 percent of the cases; *pushing*, 9 to 16 percent; *pulling*, 6 to 9 percent; and *carrying*, 5 to 8 percent. Even though the majority of the cases are linked with lifting activities, the remaining ones cannot be neglected when designing an exoskeleton meant to be used on field.

At this point, it is worthy anticipating that exoskeletons can be categorized according to their actuation principle into *passive*, *active* or *quasi-passive* devices. A passive device couples its wearer's movements to elements such as flexible beams or elastic bands (Näf et al. (2018), Lamers et al. (2017), Abdoli-e et al. (2006)) to store and then release energy. On the other hand, active devices have the ability to deliver additional energy to the user exploiting electrical motors or pneumatic actuators. Such active elements, rather than relying onto the users' movement, are powered by

[4] https://www.cdc.gov/niosh/engcontrols/ecd/detail25.html

batteries or external supplies. Finally, quasi-passive devices take advantage of active elements such as electro-magnetic clutches to decide when to engage the passive elements.
Given the strong bond between movement and assistance, in the past years, passive exoskletons have been optimized and evaluated specifically for lifting tasks. Moreover, the same approach was used for active devices as they have been evaluated predominanlty focusing on lifting assistance, Grazi et al. (2019).
Nevertheless, as introduced above, the analysis of the exoskeleton usage effects should not be limited to lifting tasks, but importantly should also tackle other activities. This extension would allow to capture the complexity of *out-of-the-lab* environments more reliably. As an example, an interesting study presented in Baltrusch et al. (2019) focuses on the capability of a commercial passive back-support exoskeleton not only to assist with lifting but also with walking. The study concludes that the passive exoskeleton is beneficial for the lifting task but restricts users' movements during walking. As expected, this is due to the initial design of the exoskeleton that addressed only lifting tasks.

Now, one of the reasons why an innovation fails to be accepted by workers is that, even though it proves to be effective in reducing the work burdens, it hinders or slows down their working routine. This could help explain why, despite the introduction of *industrial manipulators*, *cobots* and *Personal Protective Equipments* (PPEs), MSDs cases are not dropping, yet. Being wearable devices, exoskeletons are expected to better **match human versatility**. However, if an exoskeleton is helpful only in a subset of user activities and hindering the others, what are the expectations on the technology acceptance? Is it possible, and fair, to imagine workers wearing such devices the whole working shift? In order to match human versatility, exoskeletons themselves need to become *versatile*, meaning being able to recognize which activity the user is performing and provide assistance accordingly. By design, passive devices cannot provide the required flexibility, whereas active and quasi-passive exoskeletons are expected to be more versatile. As most of the studies have focused solely on lifting, there are still open questions on how current exoskeletons are expected to perform in non-lifting tasks, if each of these tasks requires specific control strategies and, if so, how to switch between strategies.

1.3 Approach and objectives

During my research activity I had the grateful and invaluable opportunity to visit many plants in several industrial sectors like logistics, chemistry, manufacturing and food. Each plant is a well-oiled ecosystem with its own routines and peculiar needs. It follows that in these scenarios, the introduction of changes is a thoroughly weighted decision, supported by positive impact both for the workers and the employers. These visits were an invaluable opportunity to let workers try *XoTrunk*, our back-support exoskeleton. End-users' precious feedback and, sometimes, having the chance of trying my hand at performing the MMH activities that are part of the workers' routines, have confirmed the potential of back-support exoskeletons in mitigating the burdens of MMH tasks. However, it also highlighted some current exoskeleton limitations that might interfere with this technology adoption.

The one I wanted to focus on in my research is the *lack of exoskeleton versatility*. Here *exoskeleton versatility* is defined as the ability of an exoskeleton to recognize which task the user is performing and, thus, trigger the appropriate control strategy. This recognition can rely on user input or be automatic, as preferable in MMH scenarios. In the literature, it is possible to find some works that addressed versatility but only emphasizing on lifting. However, as stated in Section 1.2, lifting should not be the only task under analysis.

To deal with the lack of exoskeleton versatility, the work presented in this thesis can be divided in three objectives:

O1 *Quantifying the need for back-support exoskeleton versatility*. Before addressing versatility, the focus was on the requirements: is versatility really necessary? Could a one-control-strategy-fits-all-tasks approach be sufficient? Answering these questions required the identification of other relevant tasks besides lifting. This *task identification* leveraged both on literature studies and on direct experience, gained during the plant visits. *Carrying* was identified as a significant task as it is more often combined with lifting tasks than pushing or pulling. Then, two assessments were conducted. The first on the impact that carrying, compared to lifting, has on spinal loading. The second on what assisting with carrying, relying on control strategies usually employed for lifting tasks, entails, Poliero et al. (2020a). This study, to the author's knowledge, was the first of its kind and, together with the former, underlined the need for back-support exoskeleton versatility.

O2 *Finding a solution to enhance back-support exoskeleton versatility*. Having assessed the need, the objective was, then, to highlight how, exploiting HAR algorithms it is possible to enhance exoskeletons versatility. HAR has a lot of applications in office, sports, industrial or entertainment scenarios, Bulling et al. (2014). Applying HAR algorithms to occupational back-support exoskeletons is not trivial as it requires the identification of tasks that are specific to the industrial scenario. Additionally, another challenge is the availability of partial information on the workers' state. Indeed, developing algorithms that require input from many sensors could drastically affect the device wearability. Consequently, this work aims at achieving satisfactory performance taking advantage of sensors already required for the exoskeleton control, Poliero et al. (2019a), Poliero et al. (2019b). The results discussed in these studies hold true for both active and quasi-passive exoskeletons.

O3 *Assessing the benefits of back-support exoskeleton versatility*. The final objective of this thesis was to assess whether the introduced improvements can have a positive impact compared to current state-of-the-art exoskeletons. Therefore, a final laboratory study was devised to show how, implementing HAR algorithms into *XoTrunk*, its performance changes. This is done by analysing both the device efficacy and its dynamic fit, namely how the exoskeleton and the wearer interact one with the other. Finally, trying to make a positive impact towards solving the problem of work-related MSDs, this thesis also aims at understanding the impact that exoskeleton versatility had for workers based on on-field trials. Preliminary findings showed that, thanks to its versatility, XoTrunk acceptance by workers increased. The results discussed in this chapter have been accepted for publication in the Petrae21 conference (Poliero et al. (2021a)) and have been submitted to the Wearable Technologies Journal (Poliero et al. (2021b)).

1.4 Thesis outline

The work presented hereafter has been sponsored by INAIL, the Italian Workers' Compensation Authority, in the framework of the National project "Sistemi Cibernetici Collaborativi- Esoscheletri". INAIL's interest in this project is to promote the development and adoption of technologies and solutions that are ought to have a beneficial impact for both workers and employers dealing with work-related musculoskeletal disorders (wMSDs). This introduction (Chapter 1) analysed how occupational back-support exoskeletons can represent a novel solution and why exoskeleton versatility is considered to be an important feature to promote their adoption among final users.

Chapter 2 presents the basic information required for addressing the topics discussed in this thesis, namely an analysis of the state-of-the-art for occupational back-support exoskeletons and HAR algorithms.

Chapter 3 is dedicated to *XoTrunk*, the occupational back-support exoskeleton developed by IIT and used as development platform in this work. Particular attention is on its three control levels (*high, middle and low*), Tucker et al. (2015). Even though the contributions of this PhD thesis are on the high level, also the remaining ones will be detailed for a better understanding of the exoskeleton working principle.

After these initial chapters, the work is divided into three parts, one for each objective of the thesis. Part I is on **the need for back-support exoskeleton versatility**. Currently, in many industrial scenarios, occupational back-support exoskeletons are proving to be a valid solution for mitigating the risk of low back pain and injuries when performing lifting tasks. Still, it appears that a widespread adoption of exoskeletons is not close, yet. A possible explanation could be that many studies have only evaluated the capability of these tools to solve specific problems, e.g., *reducing fatigue when lifting a box*. This approach appears to be well suited to laboratory simulations but hardly captures the variety and complexity of tasks that a worker has to perform during a shift. Therefore, Chapter 4 highlights that in the context of MMH, ergonomic risk is related not only to *lifting* activities, but can also be associated with other ones like *carrying*, *pushing* and *pulling*. This consideration is supported by well-established ergonomic guidelines like the *International Standard ISO 11228*. Moreover, leveraging on the opportunity to visit a number of Italian industrial plants during my research period, I could verify the importance that *carrying* has in these scenarios. Therefore, Chapter 4 also reports on a study conducted to investigate the impact that carrying has on *spinal loading*, compared to lifting. Results discussed in this chapter have been published in Poliero et al. (2020a).

Having assessed that ergonomic risk can also be associated with carrying activities, Chapter 5 introduces the reader to the concept of exoskeleton *versatility* and its need. This is done by reporting on the applicability of assisting carrying with control strategies designed for (symmetric) lifting. Indeed, this is the case of current occupational back-support exoskeletons that are thought and designed for assisting (symmetric) lifting only. The study conducted in our laboratory (Poliero et al. (2020a), Poliero et al. (2020b)) shows that if a user is performing carrying and the exoskeleton delivers an assistive profile designed for lifting, the exoskeleton effect is not ideal.

Part II is on **how to enhance back-support exoskeleton versatility**. This is done by relying onto HAR algorithms. In particular, in Chapter 6, two studies (Poliero et al. (2019a), Poliero et al. (2019b)) highlight how HAR techniques have been integrated into *XoTrunk*. It follows that the exoskeleton control strategy can be upgraded from the two-level one presented in Chapter 3 to a *three-level* one, enhancing the device versatility.

Finally, Part III is on **the effects and the impact** that a versatile exoskeleton can have for workers using it. In Chapter 7, the impact is assessed via a laboratory testing simulating the execution of a complex task scenario, as seen in industrial plant visits. Here an assessment of how occupational back-support exoskeleton versatility influences users' performance is reported. Also, in the final part of the chapter, as the big ambition of this work is to help improve exoskeleton adoption, the impact that the findings presented in this work have had for the workers using *XoTrunk* are presented.

Overall conclusions, a summary of the contribution of this thesis to the state-of-the-art and future challenges are addressed in Chapter 8.

Chapter 2

State of the art

Exoskeletons are wearable devices that generate forces/torques on one or multiple human joints to support the execution of physical activities, Toxiri et al. (2019). Reading this statement, it is easy to be tricked by the idea of associating exoskeletons with science-fiction devices that encompass the whole body, can assist with any kind of task and provide super human strength, as in movies like *Iron-man* or *Avatar*. Indeed, the early stages of exoskeleton development were driven by this idea and desire. Classical examples are represented by Nicholas Yagn's apparatus for facilitating walking, running and jumping (1890), by Neil J. Mizen's Man amplifier (1961) or by the General Electric Hardiman I prototype (1971), see Figure 2.1. However, these first prototypes have been considered not fit to be commercially released, as they were too bulky, not easy to wear or operate and expensive.

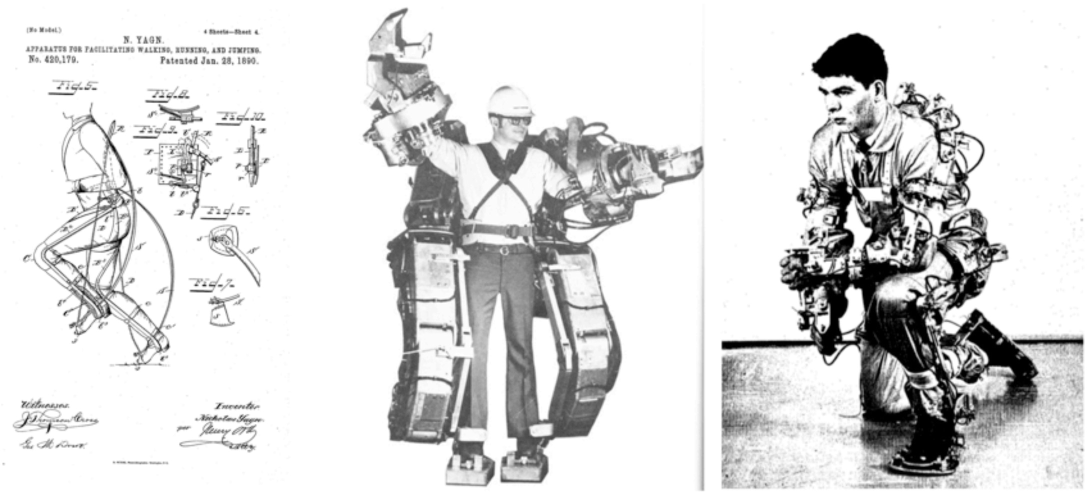


Figure 2.1 (left) Nicolas Yagn's apparatus for facilitating walking, running and jumping. Image credit: US420179A patent; (middle) Hardiman I prototype by General Electric. Image credit: cyberneticzoo.com; (right) Niel J. Mazen's "Man amplifier" in a Cornell Aeronautical Laboratory. Image from "Design and test of a full-scale, wearable, exoskeletal structure" - Niel J. Mizen

Taking advantage of the early mistakes, the recent exoskeleton development has focused on *specialization*, meaning that the devices are designed and tested focusing on single tasks or specific joints, as shown in Figure 2.2. Narrowing the scope for which these devices are built, allows for an easier understanding of the requirements and, also, easier usage and more slender designs. For some application fields, like rehabilitation, these features might not be so relevant, as the device is rarely meant to be used by the patient, autonomously. However, it is clear that in military applications, ease of use and a reduced footprint of the exoskeleton are of paramount importance. This new design approach and the desire of finding additional solutions to the improvement of working conditions in industrial scenarios, entailed that exoskeletons designed for occupational tasks have become available, Nussbaum et al. (2019). Occupational exoskeletons are categorized according to the assisted body region, as presented in Lee et al. (2012) and de Looze et al. (2016). Chapter 1 introduced that in this work, given the prevalence of MSDs affecting the back and the potential of occupational back-support exoskeletons to mitigate the exposure to injuries, attention would have been on this specific exoskeleton category. Therefore, this chapter, at first, introduces the working principle of occupational back-support exoskeletons and why they can mitigate MSDs onset (Section 2.1). Then, the most common actuation choices and control strategies are presented in Section 2.2. Section 2.3 describes how exoskeletons are evaluated and how, due to specialization, lifting and static bending tasks are the most considered. This is justified by the high impact that lifting can have on back-injuries, as discussed in Section 1.1. Specialization, especially from a mechanical point of view, has certainly paved the way towards occupational back-support exoskeleton adoption, but might have promoted the belief that only lifting tasks should be considered. However, rarely, a worker performs only this type of activity. Luckily, exoskeletons characterized by specific actuation choices can provide support also in other MMH tasks, exploiting what was defined as *exoskeleton versatility* (Section 1.3). Versatility requires that the device can recognize which activity the user is performing and, for such reason, Section 2.4 introduces the most common algorithms to perform recognition of human activities (HAR) and Section 2.4.3 how these algorithms are applied to exoskeletons. Finally, Section 2.5 summarizes the main take-home messages.

Figure 2.2 (left) Ottobock Paexo Thumb, the smallest exoskeleton in the world for transfering forces from the thumb to the entire hand. Image credit: Ottobock; (middle) Comau Mate, a shoulder exoskeleton for assisting the worker in overhead tasks. Image credit: Comau; (right) Roam Elevate, the exoskeleton supporting skiers' knees and quads during downhill skiing. Image credit: Roam robotics

2.1 The working principle

Back-support exoskeletons are assistive devices that are worn like backpacks, additionally anchored also to the thighs. By means of actuation elements, they generate forces/torques that contribute to the extension of the hips and the trunk, reducing the requirement for the resulting *L5-S1* joint extension moment. Several biomechanical models (Chaffin (1969), Reeves and Cholewicki (2003), Luo and Yu (2013), Toxiri et al. (2015) and Koopman (2020)) can be used to detail how the provided support results in a reduction of the *Erector Spinae* muscle activity and, consequently, a reduction of the lumbar intervertebral discs compression. This is a compelling result because, if the compression exceeds specific biomechanical limits — as in many MMH activities —, the risk of developing MSDs increases, Brinckmann et al. (1987), Moore and Garg (1995).
According to how the exoskeleton force is transmitted to the wearer, it is possible to classify them as *soft* or *rigid*, as depicted by Figure 2.3. Soft exoskeletons transmit forces that are parallel to the lumbar spine and, by design, these devices are relatively simple (see Figure 2.4 for an example). On the contrary, rigid exoskeletons take advantage of structural frames to transmit forces perpendicularly to the spine. In this way, the exoskeleton additional force does not contribute to the lumbar compression. Figure 2.4 also shows how, the inclusion of a rigid frame permits to select how trunk and hip extension should be achieved, namely pulling from the shoulders (common to many soft devices) or pushing on the chest, pushing on the thighs or pulling from them. Rigid exoskeletons also have to deal with a third force that is exerted perpendicularly to the spine, at the *L5-S1* level, and represents the exoskeleton reaction force (see Figure 2.3). To dissipate it, lumbar cushions and/or buttocks belts are generally used.

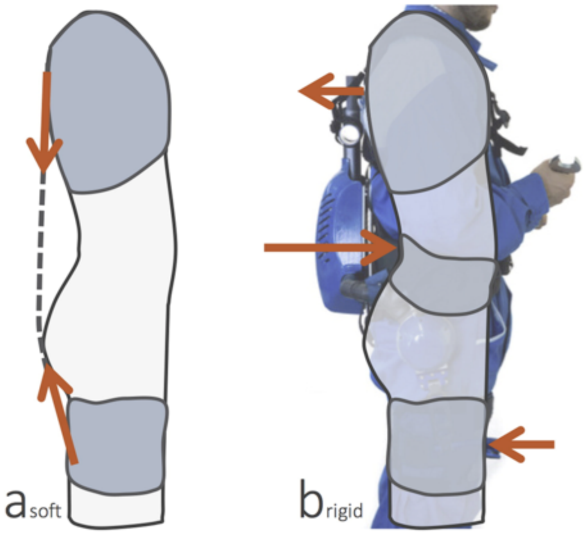


Figure 2.3 This schematic representation from Toxiri et al. (2019), represents by means of red arrows the exoskeleton forces and how they are applied on the user. In the soft case (a), forces are parallel to the lumbar spine, whereas in the rigid case (b), forces are perpendicular to the spine. Note that, in this second case, there is an additional force acting at the *L5-S1* level, representing the exoskeleton reaction force.

Figure 2.4 Representation of a soft and three rigid exoskeletons and some implementation details. From left to right: *(i)* Hunic SoftExo (image credit: Hunic), an example of soft exoskeleton where the trunk extension is supported pulling from the shoulders; *(ii)* Laevo v2.5 (image credit: Laevo), an example of rigid exoskeleton where the trunk extension is supported by pushing on the chest; *(iii)* Robo-Mate Trunk module (image credit: robomate.eu), an example of rigid exoskeleton that assists hip extension by pushing on the thighs; *(iv)* Atoun Model Y (image credit: Atoun), an example of rigid exoskeleton that supports hip extension by pulling from the thighs. Also note how Robo-Mate and Atoun present a lumbar cushion and a buttocks belt, respectively.

2.2 Actuation and control strategies

According to the actuator choice, an exoskeleton can be defined as *passive*, *active* or *quasi-passive*. In some works, this latter category is also referred to as *semi-active*, Tanaka et al. (2008), Jimenez-Fabian and Verlinden (2012), Manna and Dubey (2018), Voilqué et al. (2019).

A passive exoskeleton, as suggested by the name, relies on passive actuation elements — like gas/coil springs, flexible beams or elastic bands — to store and then release energy (Abdoli-e et al. (2006), Näf et al. (2018), Alemi et al. (2019)). A fundamental aspect of these devices is that in order to deliver support, they first need to absorb part of the wearer's energy (kinetic and potential). As a consequence, it is common practice to optimize the passive elements characteristics (like the elastic coefficient) in order to maximize, for a given movement, the exoskeleton output force/torque. As an example, in Harant et al. (2017) the study objective was to determine the proper spring torque-angle characteristic for a back-support exoskeleton supporting stoop-lifts of a 10 kg box. In Poliero et al. (2018), it was discussed how the optimization should also guarantee that the workers' usual behaviour, analysed as the power profile of the *L5-S1* joint, is not affected by the introduction of passive elements. Indeed, the choice of springs or elastics that are too rigid, might seriously impact the wearers' freedom of movement. It follows that passive exoskeletons cannot provide a great amount of support and, also, have little versatility as they cannot adapt to tasks differing from the ones for which they were optimized. In Toxiri et al. (2019), it was argued how the best application for such devices is to assist static bending tasks, as it permits full exploitation of the passive elements potential. However, listing the advantages of integrating passive actuation into the exoskeleton design, it is worth mentioning that it requires minimal or no frames at all, is very cheap, intuitive and does not involve any control strategy. These are the main reasons why, passive exoskeletons are dominating the market. Some examples of commercially available devices are shown in Figure 2.5.

In contrast to passive exoskeletons, active ones have the ability to deliver assistive forces/torques exploiting active elements such as electrical motors (Toxiri et al. (2015) and Yu et al. (2015)) or pneumatic actuators (Aida et al. (2009) and Inose et al. (2017)). Such active elements, rather than relying onto the users' movement, are powered by batteries or air reservoirs. Properly controlling the active actuators allows designers to tune the assistance being provided, according to specific task and user needs. Generally, as described in Tucker et al. (2015), the control strategy is hierarchically divided into three levels. The *high-level* is responsible for recognizing the activity carried out by the user. Once this information is available, it is input to the *mid-level* that defines the best suited assistive strategy for the recognized activity. Finally, the *low-level* ensures that the actuators properly deliver the desired torque/force set by the mid-level.

It is worth mentioning that out of the 11 active exoskeletons analysed in Toxiri et al. (2019), only 2 take advantage of the *high-level* to vary control strategy. In particular, APO, the research prototype presented in Chen et al. (2018), assists only if it recognizes the user is *lifting* a load, whereas activities

Figure 2.5 (Left) Innophys Muscle Suit Every. Image credit: Innophys. (Right, top) Hunic SoftExo. Image credit: Hunic. (Right, bottom) SuitX backX. Image credit: SuitX.

like *walking* or *lowering* are not addressed. Also the commercial exoskeleton ATOUN Model Y[1] implements control strategies for *walking*, *lifting* and *lowering*. The vast majority of back-support exoskeleton devices, however, only developed *mid-level* assistive strategies for lifting, neglecting the other tasks. These assistive strategies, generally, rely on kinematic variables like trunk inclination or acceleration to provide assistance accordingly, like as an example, in Luo and Yu (2013), Ko et al. (2018) and Lazzaroni et al. (2020). In Chen et al. (2018) the torque provision depends also on the hip angles. There are some strategies that exploit muscle activity to proportionally determine the assistance, as in Hara and Sankai (2010) and Tan et al. (2019), where the Lumbar Erector Spinae muscle surface electromiography (sEMG) is selected as the control input, or in Toxiri et al. (2018a) where the forearm muscle activity is used as an estimator of the back one.
The possibility of tuning the delivered support implies that active exoskeletons can provide more assistance than passive ones and are, potentially, also more versatile. However, integrating active actuators, the associated electronics and batteries yields exoskeletons that are bulkier, heavier and more difficult to control. In Toxiri et al. (2019), it was argued that the best application for these devices is to assist dynamic tasks like repetitive lifting. Even though lacking relevant adoption in industrial scenarios, there are several examples of active commercial exoskeletons, as shown in Figure 2.6.

Figure 2.6 (Left) GBS Cray X. Image credit: GBS. (Centre) Atoun Model Y. Image credit: Atoun. (Right) Cyberdyne HAL for labour support. Image credit:aviationpros.com

Finally, quasi-passive exoskeletons rely on passive elements that cannot produce any force until they are engaged. This idea has only recently been applied to back-support exoskeletons, like in Cevzar et al. (2018) and Jamšek et al. (2020), even though the idea was widely adopted in other types of exoskeletons (Endo et al. (2006), Dollar and Herr (2008), Manna and Dubey (2018) and Ortiz et al. (2018a)). The passive element engagement can be controlled by active elements like electro-magnetic clutches and motors, by switches manually triggered by the user, or by mechanical coupling with the

[1] https://atoun.co.jp/en/products/atoun-model-y/

user's motion. In this way, it is possible to combine the simplicity of passive elements with some degree of versatility, as the user has freedom to decide whether the passive elements should provide force, typically when *lifting*, or be dis-engaged, typically in other activities like *walking*. Commercial devices that exploit quasi-passive actuators are reported in Figure 2.7.

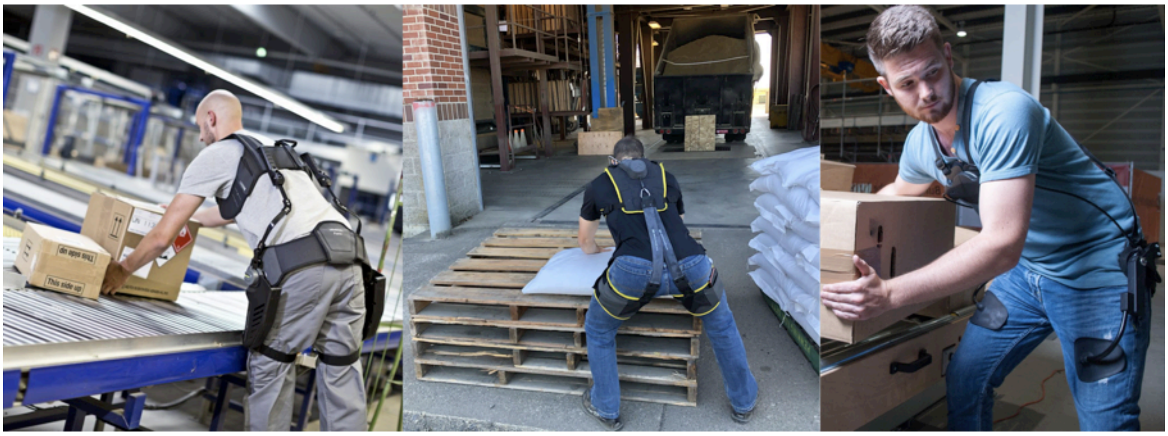


Figure 2.7 (Left) Ottobock Paexo Back. Image credit: Ottobock. (Centre) HeroWear Apex. Image credit: HeroWear. (Right) Laevo v2.5. Image credit: Laevo.

2.3 Evaluation

There are several reviews on occupational back-support exoskeletons that underline their huge potential. As an example, a 2016 review reported that their usage yielded back-muscle activity reductions by up to 40%, during repetitive lifting and static holding tasks (de Looze et al. (2016)). Such results are confirmed by a more recent investigation (Theurel and Desbrosses (2019)) that stresses the clear potential of exoskeletons in limiting muscular demand. However, this latter report also warns that there is insufficient current knowledge to justify an unreserved adoption of this technology. In this regard, a work by Grazi et al. (2019) presents an overview of the methodologies used in the literature to evaluate the potential of back-support exoskeletons. Indeed, the authors identify that to compare different prototypes and foster promotion, it would be important to define a common evaluation method among the many proposed. The analysis, however, focuses only on lifting activities.

The most spread practice in the evaluation of the exoskeleton effects is to measure via surface elctromyography (sEMG) the activity of the muscles responsible for back extension (like the Erector Spinae) and compare conditions with and without exoskeleton. Investigating, by means of sEMG analysis, the behaviour of muscles not directly affected by the exoskeleton (like the Rectus Abdominis or the Rectus Femoris) might also provide information on possible side effects, namely the increase of fatigue or muscle activity. In Pons (2008), the author describes several methods to perform sEMG analysis, dividing it into the domains of time and frequency. In time domain, standard procedures require to amplify the raw signals (common gains $K = 100, 1000, 10000$), filter out non relevant frequencies ($f < 20$ Hz and $f > 250$ Hz) and rectify the filtered output. Then, to express the muscle contraction level, it is possible to compute *(i)* the linear envelope and extract activation peaks (Toxiri et al. (2018a)), *(ii)* integrate the rectified signal (Lanotte et al. (2018)) or *(iii)* determine the root mean square value (Lotz et al. (2009)). Some works also use time domain approaches to evaluate the overall muscle activation and draw conclusions on fatigue, extracting the average value of the linear envelope (Lanotte et al. (2018)). Finally, based on the findings presented in Jonsson (1982), it is possible to substitute peak and average activation with the 90^{th} and the 50^{th} percentile of the muscle activity distribution.

On the other hand, frequency domain analysis focuses on metrics like mean and median frequencies of the signal spectrum. A shift of these metrics towards lower frequencies can be associated with increased muscle fatigue, as described in Payton and Burden (2017) and Pons (2008).

The possibility of choosing so many different metrics is one of the reasons why in Grazi et al. (2019) the authors suggest to identify a common evaluation method. Also, a very interesting analysis has been proposed in Lazzaroni (2020), where evaluation studies are summarized focusing on sEMG reduction, provided torques, considered metrics and actuators. The results are reported in Figure 2.8, where blue markers are used to indicate passive exoskeletons and red markers for active ones. The

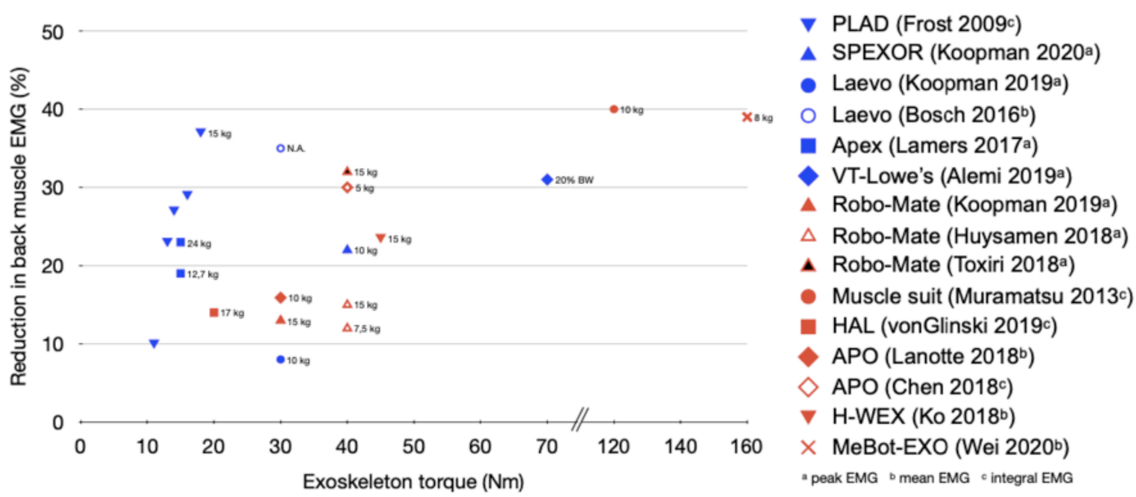


Figure 2.8 Image from Lazzaroni (2020). The chart reports on the y axis the percentage reduction in back muscle EMG, whereas the x axis describes the torque provided by the exoskeleton. Blue markers identify passive exoskeletons whereas active ones are represented by red markers. For each study evaluating exoskeleton performance during lifting, the information on the selected metric for EMG analysis ([a] peak EMG, [b] mean EMG and [c] integral EMG) is reported on the right. Indications on the lifted payload are detailed in the chart, as well.

analysis of this representation highlights two important aspects. The first is that high torques are

predominantly provided by means of active exoskeletons. The second is that, the same amount of muscle activity reduction can be obtained both using passive and active exoskeletons. As an example, the chart shows that PLAD (Frost et al. (2009)) and Robo-Mate (Toxiri et al. (2018a)) reduce the muscle activity by 30% when lifting 15 kg. Therefore, it appears that there is no clear evidence that active and, so, more versatile exoskeletons are better than passive ones. These latter have the additional advantage of being lighter, cheaper and simpler. Is this because these metrics only provide information on the *efficacy* (Singal et al. (2014)) of the device, namely its ability to reduce muscle activation under ideal and controlled circumstances (laboratory testing)? To better understand how a device might influence user acceptance, other relevant metrics are: *(i)* perceived comfort, fit and ease of use (Gillette and Stephenson (2019), Luger et al. (2019), Hensel and Keil (2019), Omoniyi et al. (2020), de Vries et al. (2020), Kermavnar et al. (2020)), generally investigated by means of subjective questionnaires like the Borg scale, the system usability scale (SUS), the NASA-TLX and ad-hoc surveys (Borg (1990), Jordan et al. (1996), Hara and Sankai (2010) and Moyon et al. (2019)); *(ii)* range of motion (RoM) and movement quality (Baltrusch et al. (2018), Koopman et al. (2019a), Marino (2019)), analysed by means of $3D$ joint kinematics and *(iii)* physiological parameters like heart rate or metabolic consumption that are indicators of global fatigue (Del Ferraro et al. (2020), Baltrusch et al. (2020), Wei et al. (2020)).
The inclusion of the above mentioned metrics and the analysis of the exoskeleton performance also in non-lifting tasks, would increase the dimensionality of the exoskeleton evaluation, providing additional tools to select the most appropriate device. Moreover, a multi-dimensional evaluation study is expected to underline the advantages of versatile exoskeletons. As an example, in Baltrusch et al. (2019) the passive exoskeleton Laevo is tested in lifting and walking. For the first task the results showed reduced metabolic consumption (-7%) and reduced back muscle activity (not significant, though); whereas during walking the exoskeleton proved to be hindering the users' motion, as metabolic cost increased by 12% and the muscle activity did not change significantly. In Chapter 7 of this work, a similar assessment is presented to evaluate the performance of an active exoskeleton and stress the potential of *exoskeleton versatility*.

2.4 HAR

The goal of Human Activity Recognition (HAR) is to provide information on the task performed by the user, Abowd et al. (1998). This piece of information is, then, used to achieve different objectives. Examples presented in De-La-Hoz-Franco et al. (2018) are behaviour monitoring (Alemdar et al. (2015)), fall or stress detection (Gjoreski et al. (2014), Gjoreski et al. (2015)), energy expenditure estimation (Altini et al. (2014)), ergonomic assessments (Malaisé et al. (2019)), or proactively assisting with the task (Leightley et al. (2013), Lin et al. (2015)). There are several application fields that can benefit from HAR employment, like industrial or office scenarios (Maurtua et al. (2007), Stiefmeier et al. (2008), Minnen et al. (2006a)), sports (Kunze et al. (2006), Ladha et al. (2013)), entertainment

(Gill et al. (2011)) and surveillance (Poppe (2010)). In the following, Section 2.4.1 presents a brief analysis of the single steps that compose what is defined as the Activity Recognition Chain (ARC), Bulling et al. (2014). These steps heavily rely on conventional Pattern Recognition (PR) methods. Section 2.4.2, on the contrary, briefly introduces how exploiting the advancements of Deep Learning (DL), it is possible to overcome some of the issues related to these conventional methods. Finally, how HAR techniques have been used in exoskeleton controls, with particular focus on occupational back-support devices is detailed in Section 2.4.3.

2.4.1 The Activity Recognition Chain (ARC)

The steps that compose an ARC are: *(i)* Sensing; *(ii)* Data Segmentation; *(iii)* Feature Extraction and Selection; *(iv)* Learning (composed by training and testing) and *(v)* Prediction.

(i) Sensing

To gather information on the human activity, several types of sensors can be used. According to the specific needs, the choice might be to instrument the environment where the action takes place or to directly instrument the user. Typical examples of sensors are microphones (Oliver et al. (2002)), cameras (Mitra and Acharya (2007)), 3*D* motion capture systems (Gill et al. (2011)) and IMUs (Bao and Intille (2004), Avci et al. (2010), Mannini and Sabatini (2010), Kwapisz et al. (2011)). Attaching sensors on the body has the advantage of allowing ubiquitous computation, but has to deal with problems like energy management (Anguita et al. (2013)) or sensor displacement (Banos et al. (2014b)).

(ii) Data Segmentation

Having chosen the sensing mode, the stream of data is segmented into sections of interest that are likely to contain specific gestures or activities (Bulling et al. (2014)). This operation can rely on sliding windows, the occurrence of specific events, energy-based methodologies, or take advantage of one sensor modality to segment data of other sensors. According to the former method, data is partitioned by means of a window that is moved over time series data. As the window size increases, so does the recognition delay, but the computational load decreases. It follows that defining the optimal window size is non trivial (Huynh and Schiele (2005), Banos et al. (2014a)). Understanding that different activities are performed with different intensities, is the idea upon which energy-based segmentation is built. Indeed, thresholds on the energy levels are used to segment the data series (Wilson and Bobick (2000), Guenterberg et al. (2009)). Multi-modal sensing can be used to segment data. As an example, to separate IMUs data into several segments, in Ashbrook and Starner (2003) and Lu et al. (2009), GPS or microphone data are used. Finally, in Bulling and Roggen (2011) the occurrence of specific events, like the eye blink, are used to partition the sensors' stream.

(iii) Feature Extraction and Selection

Extracting, from the segmented data, features that are discriminative for the considered activities is time-consuming and complex. A good feature is one that clearly separates the activities in the so-called *feature space*, namely the space onto which data is transformed after feature extraction. There are several types of features like *(a)* signal based: mostly statistical measures like mean, maximum, minimum value of the signal in a given segment (Bao and Intille (2004), Espinilla et al. (2018)); *(b)* body-model based: calculated matching measurements and a $3D$ model of the body (Zinnen et al. (2009), Blanke et al. (2010)); *(c)* multilevel based: exploiting data clustering and then statistic occurrence analysis (Huynh et al. (2008)). There are also methods that automatically generate features based on principal component analysis, deep-learning or ontologies (Plötz et al. (2011), Salguero et al. (2019)), see Section 2.4.2. When extracting features, the higher the dimensionality of the feature space, the more data is needed for model training and the more computational power is required. This is the so-called *curse of dimensionality*. Luckily there are several algorithms that automatically select the most relevant features (Kohavi et al. (1997), Peng et al. (2005), Somol et al. (2006)).

(iv) Learning

Data training consists in building an activity model that, given as input a set of features, outputs the predicted activity. This stage, is referred to as *supervised learning*, because the models are learnt from labelled data. Data labelling is done by means of ground truth tags, requiring that the performed activity is annotated in real-time or post-hoc, Bulling et al. (2012). Manual labelling can be partially mitigated by means of techniques like knowledge transfer or reinforcement learning, Zheng et al. (2009), van Kasteren et al. (2011), Blanke et al. (2010). There are two different approaches to learning: Knowledge Driven Approach (KDA) and Data Driven Approach (DDA), Salguero et al. (2019). The former incorporates prior domain knowledge into the activity model. This is done, for example, by means of ontologies (Chen and Nugent (2009)) or threshold-based classifiers (Coley et al. (2005)). It follows that as the complexity of the classification problem starts increasing, a DDA based on machine learning techniques might be preferred. These algorithms take advantage of different approaches like template-based similarities (Stiefmeier et al. (2007), Cottone et al. (2015)), probabilistic methods as Decision Trees, Hidden Markov Models and Naïve Bayesian classifiers (Liao et al. (2005), Tapia et al. (2007), Kose et al. (2012), Piyathilaka and Kodagoda (2013), San-Segundo et al. (2016)), and geometric approaches as Support Vector Machine (SVM) and Artificial Neural Networks (Anguita et al. (2012), Chen et al. (2017), Bourobou and Yoo (2015), Ronao and Cho (2016)). In terms of performance, generally evaluated by means of Confusion Matrices (CM), accuracy, recall, precision and F1-score, discriminative approaches have shown higher recognition performance, Bulling et al. (2014). In HAR, particular importance is also given to time-based evaluation that introduces concepts like fragmentation, merge, underfill and overfill (Ward et al. (2006), Minnen et al. (2006b) and Bulling et al. (2014)).

(v) Prediction

Eventually, once the model is learnt, it is ready for predicting the activity from un-seen data. There are, also, examples in the literature where the output of several classifier is fused in order to obtain more robust and accurate estimations (Polikar (2006), Banos et al. (2015), Chowdhury et al. (2017), Cumin et al. (2017)).

2.4.2 Deep learning: a new trend

The sequence of operations described above (sensing→data segmentation→feature extraction and selection →learning → prediction), heavily relies on conventional PR methods. However, as described in a recent review by Wang et al. (2019), exploiting DL can help improve performance of the algorithms. Indeed, PR models have proven to be extremely helpful in controlled environments where there are only a few labelled data or specific domain knowledge is available. Given the relative small amount of data and the strong knowledge of the events, those methods heavily rely on heuristic hand-crafted feature extraction. Even though, from one perspective, this allows for a better understanding and analysis of the trained models, on the other, the feature extraction could be limited by human domain knowledge (Bengio (2013)) and, hence, only shallow features can be learnt (Yang et al. (2015)). As a consequence, exploiting PR models, it is possible to recognize only primitive activities, such as walking or standing. However, the performance become quite unsatisfactory when it is required to discriminate between more complex activities, such as the type of grasping style. Indeed, in Hammerla et al. (2016), it was shown that as the activity complexity increases, automatic feature learning based on a DL approach can improve classification performance notably. In Wang et al. (2019), the authors present several models that can be used to perform deep learning. As an example, it is possible to cite the work by Vepakomma et al. (2015) and by Xu et al. (2019) on Deep Neural Networks (DNN), by Almaslukh et al. (2017) and by Prabono et al. (2020) on Autoencoders, by Jiang and Yin (2015) and by Lee et al. (2017) on Convolutional Neural Networks (CNN) and by Pienaar and Malekian (2019) and by Porta et al. (2021) on Recursive Neural Neworks (RNN). These two latter models (CNN and RNN), were designed for image recognition and speech processing, respectively. However, when applied to HAR, these models present interesting advantages. As an example, for CNN, local dependency and scale invariance imply that in a time series, as in an image matrix, nearby signals are probably correlated and models adapt to different paces or frequencies. RNN, on the other hand, allows information to persist so that it is not required to learn the activity, from scratch, at every new iteration. Another limitation of PR methods is that they require well-labelled data to train the model. On the contrary, DL models can take advantage of the unlabelled samples for model training, Hinton et al. (2006). Also, DL models have a structure that is more feasible to perform incremental learning, Wang et al. (2019).

2.4.3 HAR and Exoskeletons

It was shown at the beginning of the preceeding section, that there are a lot of applications for HAR. Narrowing the analysis to the exoskeletons field, it is not surprising that a literature search combining *HAR* and *exoskeletons* returns results predominantly for lower limb devices. Indeed, this might be correlated wih the fact that lower limb exoskeletons are being developed taking advantage of active actuators and with the objective of assisting Activities of Daily Living (ADL) like *walking*, *climbing stairs* or transitions like *stand-to-sit* and viceversa. For such reasons, given the variety of target tasks, it is possible to find many examples of control strategies that change assistance profile according to the activity, as reported in the reviews by Yan et al. (2015) and Labarrière et al. (2020).
At the beginning of this chapter, it was discussed how occupational back-support exoskeletons have been developed restricting their scope to a single task assistance, namely lifting. Therefore, adapting to different tasks was not an implicit design need. Interestingly, the commercially available Muscle Suit by Innophys[2] requires the user to manually operate a pump to decide when the exoskeleton has to provide assistance. While this workaround augments the user's control on the exoskeleton, the choice of relying on manual inputs is questionable, as it might impact with the object handling or increase the users' cognitive load. Applications of automatic HAR to occupational back-support exoskeletons, on the contrary, seems to be more marginal and limited to posture classification (Tran et al. (2019)) or lift-detection. In this latter case, regardless of the exoskeleton actuation (active or quasi-passive), only the lifting motion is assisted, whereas all the other tasks are not addressed. As an example, in Kawai et al. (2004), the authors built a 2*D* human model that comprises seven links (forearm, upper arm, upper back, lower back, thigh, shank and foot) and six revolute joints in between. Then, it was noted that in lifting and lowering motions, hip and knee joint torques reveal characteristic behaviours that can be exploited in the control of the cable-driven exoskeleton presented in Naruse et al. (2003) (see Figure 2.9). The idea is that, recognizing whether the user is lifting or lowering a load, the motor should pull or loosen the cable. As the torques are linked with muscle intensity, the authors used sEMG electrodes to measure the activation of the Vastus Lateralis, the Vastus Medialis and the Biceps Femoris. Then, an ANN was trained to automatically distinguish lifting or lowering of the load. However, in Chen et al. (2018), it is noted that, in industrial settings, this EMG-based approach might present drawbacks caused by the great variability of EMG signals — due to sweat, electrode displacements and changes in skin conductivity — and the need of using sensors that are not embedded in the exoskeletons. For such reason, the authors propose a two-level lift detection algorithm, that only uses information coming from embedded sensors, to control the active back-support APO exoskeleton (see Figure 2.9), developed at The BioRobotics Institute of Scuola Superiore Sant'Anna (Pontedera, Italy). APO is controlled alternating *Assistive Mode* (AM) and *Transparent Mode* (TM). In AM, the exoskeleton delivers torques to assist the movement, whereas in TM the exoskeleton provides the amount of torques sufficient to obtain zero-torque interaction between the user and the device itself. In particular, in the first level, hip joint angles are taken into

[2] https://innophys.jp

account for identifying possible lifting movements. If a possible lift is detected, the second-level — via trunk angle inclination — checks that the analysed movement is an actual lift and not a similar activity, like sitting or walking. The reported results underline the good classification performance obtained, as no lifting detection was missed, accuracy was greater than 97% and activity recognition was robust to different lifting speeds and styles. On the contrary, the rule-based algortithm required the manual setting of 8 different thresholds, raising a concern on how easily the algorithm can generalize to new tasks. With respect to the lifting style, in Chen et al. (2019), the authors introduce a real-time classification of different lifting techniques, namely squat, stoop, left-asymmetric and right-asymmetric. The idea is that proper knowledge on the lifting style is needed to provide the most appropriate assistive strategy. For this reason, 15 subjects were required to perform several lifting tasks while wearing the exoskeleton in TM control. Then, the classification of the lifting style was performed using a Quadratic Discriminant Analysis (QDA) based on hip angles and trunk inclination. Again, results were very interesting: accuracy $> 99.3\%$, onset recognition delay < 170ms. However, the authors recognize that an understanding of the algorithm in AM is needed to check whether the torque provision alters the lifting and, so, the classification. Furthermore, the test subjects were instructed to adopt very specific lifting techniques, but it is expected that in an industrial setting, workers might rely on hybrid techniques that combine elements of squat and stoop. Therefore, the robustness of the proposed algorithm in real working environments still has to be investigated.

There are also examples of HAR algorithms applied to quasi-passive devices, as for the SPEXOR exoskeleton, where the passive spring-based mechanism at the hips can be engaged or disengaged by means of a clutch, see Figure 2.9. In particular, in Jamšek et al. (2020), the classification estimation provided by Gaussian Mixture Models (GMM) is used to condition transitions between different states (walking, sitting, pre-lifting, squatting and lifting) of the control state machine. To train the algorithm, 7 subjects performed 20 repetitions of walking, sitting, squatting and lifting of a 3 kg box from the floor. All the movements were separated by the subjects returning to upright posture. The movements were done wearing the exoskeleton and with disengaged clutches (equivalent to the TM mode discussed above). The overall accuracy for providing support to the user was 86.72%, whereas precision and recall scored values of 83.15% and 97.46%, respectively. These results indicate that the proposed approach is a promising tool for the control of quasi-passive back-support exoskeletons. However, the online performance evaluation of the algorithm was not addressed and, so, it is not clear if possible kinematic changes, due to the exoskeleton action, might affect the obtained results.

Considering commercially available back-support exoskeletons, it is worth recalling the ATOUN Model Y, introduced in Section 2.2, that implements automatic switching between three different modes, namely *assist*, *brake* and *walk*. In assist mode the exoskeletons helps the user with lifting operations, in *brake* mode it helps the user with lowering operations and, eventually, in *walk* mode it removes assistance when walking in order not to hinder the movements (equivalent to TM mode). To offer even more versatility, the left and right motors are controlled independently. Unfortunately, there are no details on how the recognition is achieved.

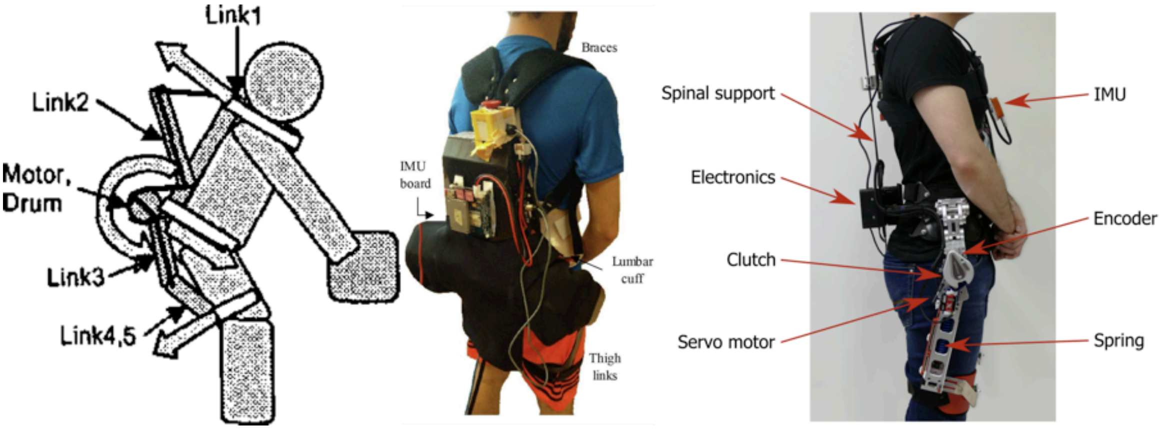


Figure 2.9 (Left) Schematic diagram of the proposed power assist mechanism in Naruse et al. (2003); (Centre) The APO exoskeleton presented in Chen et al. (2019); (Right) The SPEXOR exoskeleton described in Jamšek et al. (2020).

2.5 Conclusion

In this chapter it was presented how, initially, exoskeleton designs were aimed at assisting multiple joints and tasks. However, technical limitations suggested that a solution could be represented by *specialization*, namely designing and testing devices focusing on single tasks or specific joints. This shift in paradigm paved the way towards the development of occupational back-support exoskeletons, with the main objective of assisting with lifting tasks. Then, these devices were analysed and categorized according to how forces are transmitted, that is perpendicularly or in parallel to the spine; and how forces are generated, namely exploiting passive, quasi-passive or active actuation. Passive exoskeletons have the advantage of being ligthweight, intuitive to use and cheap. Even though they cannot be controlled, optimizing the passive characteristics of the actuators allows to maximize the assistance provided when a specific movement is done. However, the need of storing energy from the user movement implies that they cannot be successfully used in tasks differing from that meant at design stage. On the contrary, active exoskeletons can implement several control strategies according to the activity being performed. Interestingly, there are no examples of active devices supporting non-lifting tasks. It was, then, discussed how, in general, exoskeleton performance are evaluated only taking into consideration the device efficacy in lifting activities. This type of analysis neglects relevant metrics like perceived comfort, fit, ease of use, movement quality and metabolic consumption. The inclusion of the above mentioned metrics and the analysis of the exoskeleton performance, also in non-lifting tasks, would provide additional understanding on the most appropriate devices to be selected. In order to adapt to different tasks, exoskeleton controllers need to recognize the activity being carried out. For such reason, at first, details on the common ARC and DL steps were discussed and, afterwards, examples of back-support exoskeletons implementing HAR were presented. Final remarks of the chapter were on the need to perform an online evaluation of the HAR algorithms performance, as the exoskeleton action might affect the classification output. Overall, most of the research studies highlighted the need of detecting lifting movements, without interest in other activities like carrying, pushing or pulling. Nevertheless, these activities, as presented in Section 1.2, can also be associated with the risk of developing MSD and, therefore, should be addressed by versatile exoskeletons.

Chapter 3

XoTrunk

The contributions presented in this thesis can be generalized for most of the active devices and, some results can also be extended to quasi-passive exoskeletons. However, the original studies of this thesis are carried out on *XoTrunk*, that is used as development platform. Therefore, in this chapter, details on this particular exoskeleton are provided. XoTrunk is an improved version of the trunk exoskeleton Robo-Mate, developed by the Istituto Italiano di Tecnologia (Genova, Italy) and presented in Toxiri et al. (2015). The developments that turned Robo-Mate into XoTrunk were possible thanks to the collaboration with INAIL (Italian Workers' Compensation Authority) within the framework of the National project *Sistemi Cibernetici Collaborativi - Esoscheletro*. The main objectives of this new collaboration were described in Ortiz et al. (2018b). Figure 3.1 shows the two exoskeletons, while being used in relevant scenarios like warehouses or airports.

Adopting the same categories introduced in Chapter 2, XoTrunk can be defined as a rigid and active device. It has an overall weight of 6.5kg (including batteries) and it is worn like a backpack with additional attachments on the user's thighs. The rigid frame houses the anchoring point for the actuation units (one per side, at hip level, each including a brushless DC motor and reduction gear), the electronics and the lumbar cushion for improving comfort and dissipating the exoskeleton reaction force. The actuators are torque-controlled and, when commanded, they deliver assistance in the sagittal plane. Additional passive degrees of freedom allow unhindered movements outside the plane of interest. In particular, 3 passive degrees of freedom are introduced by a spherical joint, located between the shoulder attachments and the rigid frame, to permit trunk rotations in the frontal and transverse plane. Moreover, each link connecting the actuator with its respective thigh attachment offers 5 passive degrees of freedom for hip abduction, adduction, internal and external rotation. A more detailed analysis of how misalignments in the XoTrunk kinematic chain can negatively influence physical comfort and might compromise users' acceptance is presented in Sposito et al. (2020b). With respect to Robo-Mate, tangible differences are weight reduction (from 11 to 6.5 kg) and the exoskeleton action on the hips being provided by pulling the thighs, rather than pushing onto them. This choice was done in order to minimize the device encumbrance and increase its stability. Another additional feature of XoTrunk is its enhanced *versatility*, as it is able to recognize the activity

(a) Robo-Mate usage during warehouse pick and place operations.

(b) XoTrunk usage during the loading of an aircraft hold.

Figure 3.1 Images of the back-support exoskeletons Robo-Mate and XoTrunk developed at the Istituto Italiano di Tecnologia (IIT).

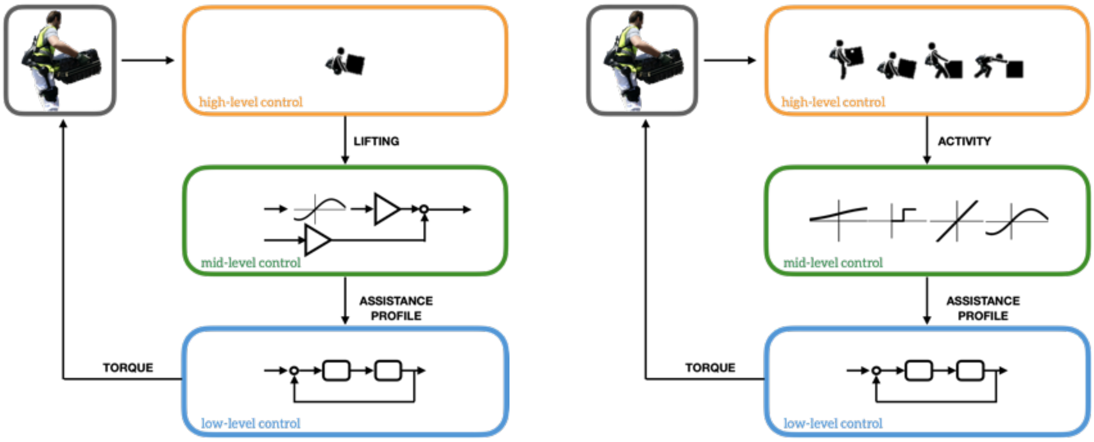
performed by the user and choose the best assistive strategy. Indeed, as previously introduced, the control of an exoskeleton can be divided into three levels. The low-level minimizes the desired torque (τ_{exo}) tracking error. More details about the implementation of this level, and about the actuators used to generate the torque can be found in Di Natali et al. (2020b). The middle level modulates the desired torque, relying on several inputs such as trunk inclination, trunk acceleration and myoelectric activity of the forearm (Toxiri et al. (2018a), Lazzaroni et al. (2020)). For the sake of simplicity, in the assessment studies presented hereafter, the trunk acceleration component is neglected. Therefore, the desired torque profile (τ_{exo}) is computed as in equation (3.1)

$$\begin{aligned} \tau_{exo}(t) = &+ sin(\theta(t))K_{IMU} \\ &+ \Sigma_{fa}(t)K_{EMG} \end{aligned} \tag{3.1}$$

where θ represents the trunk inclination with respect to the gravity acceleration direction, Σ_{fa} is the activation of the forearm muscles, acquired via the Myo gesture control armband (now available as CTRL-kit[1]), K_{INC} and K_{EMG} are proportional gains to scale the assistance. The torque profile is designed to be assisting with hips and trunk extension and does not distinguish between right or left actuator, meaning that the delivered profile is symmetrical.

The high-level, responsible for recognizing the activity that is performed by the user is omitted, as its development is among the contributions of this thesis and, therefore, will be detailed in the following chapters. At this stage, it is possible to assume that the exoskeleton control strategies are designed considering only lifting tasks, just like if the high-level could only recognize this latter activity, as represented in Figure 3.2a. The final objective is to introduce a HAR algorithm that can discriminate between relevant MMH tasks like lifting, pushing, pulling and carrying (Figure 3.2b).

[1] https://www.ctrl-labs.com/ctrl-kit/



(a) Two-level control (b) Three-level control

Figure 3.2 Schematic representation of (a) a non versatile controller that assumes the user is always performing lifting and (b) a versatile one that detects additional relevant MMH activities like carrying, pushing and pulling. Note how in (a) the mid-level control (green box) only implements one control strategy, whereas in (b) multiple control strategies are designed to assist the different activities.

Part I

On the need for back-support exoskeleton versatility

Chapter 4

Is there only lifting?

This chapter and the following one introduce the part of the thesis dedicated to understanding if there is an actual need for back-support exoskeleton versatility. Indeed, the analysis described in Chapter 2 and Chapter 3 underlined how this type of exoskeletons only focus on assisting with lifting tasks. Are there other relevant activities? Does it make sense to assist also with these ones?

In the context of MMH, workers may find themselves performing different activities. As an example, in logistics, it is possible to imagine a quite simple task where a worker *walks* to the shelf, *picks* the required object, *carries* it back to the cargo area and, eventually, *lowers* it in the appropriate container. In railways maintenance scenarios, to provide another example, a worker has to *walk* alongside the track to identify damaged parts and replace them. This operation requires the worker to *lift* and *carry* loads, but also to work in non-ergonomic *static postures*. Similar scenario can be pictured in other contexts where MMH is involved. In such conditions, the International Standard ISO 11228 establishes ergonomic guidelines not only for lifting but also carrying, pushing and pulling. Therefore, the analysis of the exoskeleton usage effects should not be limited to lifting tasks, but — to capture the complexity of *out-of-the-lab* environments more reliably — also tackle these latter ones. Taking advantage of the opportunity to visit a number of Italian industrial plants during my research period, *carrying* appeared to be very relevant in these scenarios. Therefore, in the study presented hereafter, the investigation focuses on this activity and, in particular, on *the impact that carrying has on lower-back loading* compared to lifting. Indeed, during lifting, spinal loading, which is closely associated with risk of injuries, is caused by the activation of deep back muscles – related to back extension – generating compression on lumbar discs. When a worker is carrying a load, back extensors activate to keep the trunk stable and straight, thus, this situation also presents risks to the user. In the following, details on how the experimental testing was devised are reported in Section 4.1. Section 4.2 presents the results that are then discussed in Section 4.3. Finally, Section 4.4 summarizes the main results. Most of the work presented hereafter, has been published in Poliero et al. (2020a).

4.1 Experimental testing

An experiment, approved by the Ethics Committee of Liguria [1], was carried out at the Istituto Italiano di Tecnologia (IIT, Genova, Italy). In the following, a detailed description of the task, data acquisition, data processing and outcome measures is reported.

4.1.1 Experimental set-up and protocol

Nine healthy male subjects ($N = 9$, 1.78 ± 0.04 m, 76.55 ± 8.22 kg, 31 ± 3.46 years old) were asked to wear sporting clothes and informed they would have to perform the following tasks:

- *Lifting*. The sequence of: standing upright, reaching for a box lying 0.30 m from the ground, grasping and lifting it, reaching upright posture again, then putting the box back down on the ground and returning to the upright posture. Each sequence was repeated three times at a self-selected speed and with a freestyle lifting technique, meaning no specific instructions on lifting motion were given, Burgess-Limerick (2003).

- *Carrying*. Straight level walking for 7.5m, while holding a box close to the trunk at a self-selected speed.

Each test subject lifted and carried the box (1.2 kg) housing three different payloads, namely 0, 7 and 15 kg. In the following, the different weights are referred to as *light* (*L*), *medium* (*M*) and *heavy* (*H*). The payload range was chosen in order to allow comparison with previous studies, like those presented in Toxiri et al. (2018a) and Lazzaroni et al. (2020). All the conditions were repeated three times for a total of 9 tests per subject, in randomized order. Table 4.1 summarizes the protocol and its independent variables.

Table 4.1 Overview of the testing protocol

Tasks	Lifting; Carrying
Condition	Free-body
Loads	Light 1.2 kg (*L*), Medium 8.2kg (*M*), Heavy 16.2kg (*H*)
Repetitions	3x

4.1.2 Data acquisition and data processing

To collect muscular activity data, the subjects were asked to wear surface EMG (sEMG) electrodes (BTS FREEEMG, BTS Bioengineering, Italy). These latter were placed, according to SENIAM

[1]protocol reference number: CER Liguria 001/2019

guidelines, to measure the bilateral activation of the muscles responsible for trunk extension, namely the Erector Spinae Longissimus Lumborum (LL) and the Erector Spinae Iliocostalis (IL). Back muscles were chosen based not only on their relevance when performing lifting activities but also on the number of studies that analyse them, in order to allow comparisons of findings across different protocols, Grazi et al. (2019). Figure 4.1 illustrates the locations of the chosen muscles. Prior to

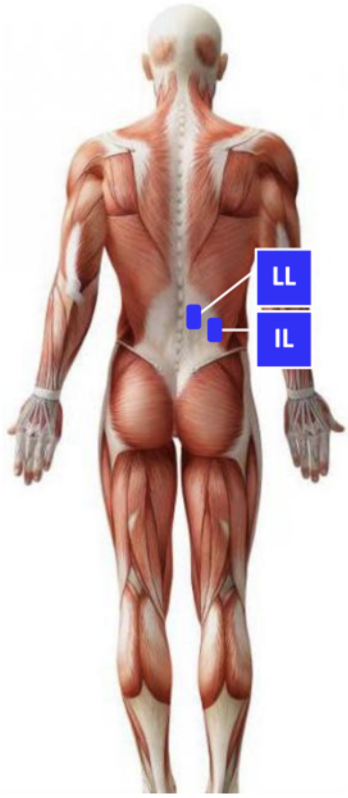


Figure 4.1 Schematic representation of electrodes placement. For greater clarity, only the right side electrodes are displayed. It is possible to identify the Erector Spinae Longissimus Lumborum (LL) and the Erector Spnae Iliocostalis (IL)

attaching the electrodes onto the skin, the site was cleaned with alcohol, as suggested in Stegeman and Hermens (2007). Muscular activity information was acquired at a sampling frequency of 1kHz. Extraction of metrics from the sEMG signals requires data post-processing. The common approach reported in Section 2.3, consists of filtering the amplified raw sEMG signals (BTS FREEEMG output), rectifying the output and, eventually, computing the linear envelope (low-pass frequency filter at 2.5 Hz, Potvin et al. (1996)). EMG data were normalized to maximum voluntary contractions (MVC), McGill (1991). Overall lumbar extensor activity (averaged IL and LL muscle activity, right and left side) was computed prior to performing deep-back muscles analysis as in Koopman et al. (2019b). Before data recording, MVC acquisition routines were performed for each subject, Halaki and Ginn (2012), Vera-Garcia et al. (2010).

4.1.3 Outcome metrics and analysis

Muscle fatigue may be experienced as symptoms or signs of reduced motor control such as localized discomfort or decreased strength. Generally, physical exertions can cause fatigue that lasts for just a few hours. If fatigue persists, it may cause tissue damage and yield MSDs, ACGIH (2008). In Jonsson (1982), the 50^{th} percentile/median of the muscle activity distribution (M) is selected to reflect how the muscle has been working during the whole recording period. Based on this reasoning, in this study, M was chosen to monitor the risk associated with repetitive/cumulative fatigue for the back muscles. Additionally, ergonomic guidelines for industry define the maximum allowed spinal compression. If this threshold is exceeded, traumatic damages in the inter-vertebral discs may result, Moore and Garg (1995). Biomechanical models can be used to show how this compressive force is directly linked to muscle activity, Chaffin (1969) and Toxiri et al. (2015). In Jonsson (1982), the 90^{th}percentile of muscle activity distribution (P) is indicated as being more informative than the maximum muscle activity. For such reasons, in this study, P was chosen to monitor the risk associated with traumatic damages in the inter-vertebral discs.

To report on the impact that carrying has on spinal loading compared to lifting, a simple comparison of lifting (control group) and carrying (test group) is presented, focusing on the analysis of M and P.

Statistical analysis

Standard one-way analysis of variance (ANOVA) with significance level set at $p < 0.05$ was meant to be adopted for the muscle activity analysis. However, due to large variability in inter-subject muscle activation signals (even after normalization with respect to the MVC), the choice was made to centre the analysis around intra-subject variability. Indeed, big data variability implies that standard statistical analysis would not be very informative. For this reason, ratios between the test and control conditions (specified in Section 4.1.3) were adopted as an alternative form of intra-subject normalization, prior to comparison with the results obtained by other subjects. In the following, ρ_i^x is defined as the ratio computed considering metric x (either M or P) in the control and test condition for a subject i.

$$\rho_i^x = \frac{X_i^{control}}{X_i^{test}} \tag{4.1}$$

The vector collecting ρ_i^x for all the nine healthy subjects is referred to as ρ^x. To deepen the analysis of ρ^x, and to better highlight trends in the data, the following values are taken into account for each ρ^x distribution:

- the median value (α);
- the inter-quartile range (iqr), defined as the difference between the 75^{th} and the 25^{th} percentile of the ρ^x distribution;

- the number of subjects for which $\rho_i^x < 1$ (γ)

Table 4.2 updates Table 4.1 including also the considered metrics.

Table 4.2 Overview of the testing protocol and the selected metrics.

Tasks	Lifting; Carrying
Conditions	Free-body
Loads	Light 1.2 kg (L), Medium 8.2kg (M), Heavy 16.2kg (H)
Repetitions	3x
Metrics	M, P
Statistical Analysis	for each ρ^x, α, iqr, and γ were analysed (x being any of the above metrics)

4.2 Results

Figure 4.2(A) and Figure 4.2(B) present the boxplots of the distribution of ρ^M and ρ^P when comparing the overall lumbar muscle activity during carrying and lifting activities.
Lower-back muscle activation are in the same order of magnitude, but generally lower during carrying compared to lifting, according to the reported measurements. This is true in all cases for ρ^P, whereas ρ^M shows a few subjects for which $\rho_i^M > 1$, meaning that the lumbar muscle median activation (50^{th} percentile) was higher in carrying than lifting. In the heavy load test, one of the subjects is considered an outlier (represented by a red cross). For light loads, considering both ρ^M and ρ^P, the median (α) is around 0.40, while this number increases up to 0.60 for heavier loads, showing an overall trend.
It is also possible to note that the 90^{th} percentile of trunk extensors activation shows a greater difference between carrying and lifting compared to the 50^{th} percentile. As a last remark, it is worth highlighting that γ is always quite close to $N = 9$, indicating a shared trend among all the subjects.

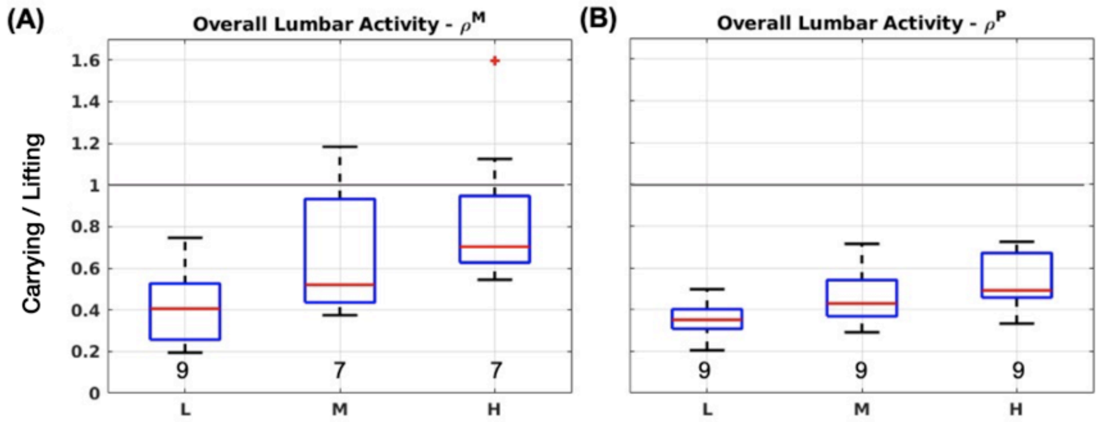


Figure 4.2 Representations for ρ^M and ρ^P considering the overall lumbar muscle activity performing lifting and carrying. **(A)** refers to the 50^{th} percentile of muscle activation (ρ^M); **(B)**, instead, refers to the 90^{th} percentile (ρ^P). L, M and H refer to the light, medium or heavy loading condition. A grey line identifies where $\rho = 1$ (i.e., where carrying and lifting are equivalent according to the selected metric). Numeric values at the bottom of each box report the value of γ.

4.3 Discussion

The assumption in this study was that spinal loading would be comparable between lifting and carrying. This supports and validates the assertion that an occupational back-support exoskeleton is needed/valuable in providing assistance, also, during carrying.

The results summarized in Figure 4.2 confirm that – from an ergonomic viewpoint - carrying activities can be associated with risk. Indeed, compared to lifting, muscle activity, although less during carrying, is in the same order of magnitude. In particular, as the handled payload increases, the differences between lifting and carrying are reduced and become less pronounced. This trend is particularly evident if the 50^{th} percentile of the muscle activity distribution is considered. Generally, this value can be associated with repetitive/cumulative fatigue, whereas the 90^{th} percentile is related to traumatic damages of the inter-vertebral discs. Despite traumatic damage is seen as more concerning, it is clear that damage can occur in both lifting and carrying and, thus, should be prevented/limited. The results found in Section 4.2 are consistent with the ISO 11228-1 standard that establishes ergonomic guidelines for performing both lifting and carrying, identifying the latter activity as equally worthy of attention. Therefore, it makes sense to try to assist also the carrying activities by means of an active occupational exoskeleton.

The results on the spinal loading during carrying compared to lifting also reported a macro-element that is worth a further discussion. In particular, the 90^{th} percentile of trunk extensors activation shows a greater difference between carrying and lifting compared to the median activation of the same muscles. This difference may be interpreted by taking into consideration what happens during the task executions. As far as the the 90^{th} percentile is concerned, when lifting the load there is a substantial increase in the muscle activation due to the upwards acceleration of the payload, against gravity. This event does not take place during carrying where, unlike the requirement in lifting, the back is never (or only marginally) bent. Hence, the payload dynamics in the sagittal plane are almost negligible. With respect to the median activation analysis, during lifting there are some phases of the movement in which the user has to compensate for only the body weight (when reaching for the load or when returning to the upright posture at the end of the movement.) During carrying, however, the load is always handled by the user who has to actively sustain it. As an example of what just discussed, Figure 4.3 reports the time plot of the overall lumbar muscle activity during one carrying step and during a lifting sequence for subject 1. Each plot is normalized with respect to the MVC.

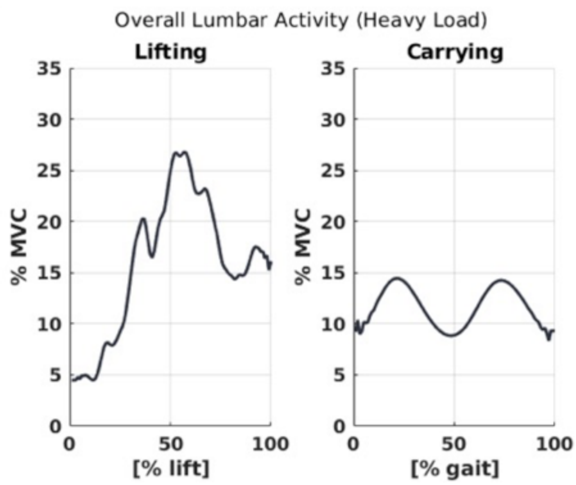


Figure 4.3 Carrying and lifting muscle activation profile over a single repetition (lift or step). The y axis represents the activation intensity with respect to the MVC value. It is possible to note that lifting presents both higher and lower peaks.

4.4 Conclusion

In the context of manual material handling and, more specifically regarding the ISO 11228-1 standard, carrying can have an impact on the spinal loading comparable to lifting. However, back-support exoskeletons are generally used only to assist lifting. In this study[2], an experimental campaign involving 9 users and three different payloads (1.2, 8.2 and 16.2 kg) was designed to assess the relevance of carrying compared to lifting. The findings indicate that the former activity, from an ergonomic viewpoint, is relevant because the corresponding spinal loading is comparable to lifting.
This result supports and validates the initial assertion that back-support exoskeleton should be used to provide assistance also with non-lifting tasks. Moreover, the findings appear to justify the need of building HAR algorithms that can discriminate lifting and carrying activities. However, an additional

[2]presented and published in Poliero et al. (2020a)

verification step is still needed, namely understanding if an exoskeleton supporting carrying, with the same assistive strategies designed for lifting, is beneficial or not. If not, this would further highlight the need of exoskeleton versatility. Chapter 5 presents a study that addresses this open point.

Chapter 5

Is exoskeleton versatility needed?

In the previous chapter, it was shown that ergonomic risk can also be associated with carrying activities. For such reason, this chapter investigates whether exoskeleton versatility is actually needed. This is done by reporting on the applicability of assisting carrying with control strategies designed for (symmetric) lifting. The study results were published in Poliero et al. (2020a) and Poliero et al. (2020b). To better understand the need of different controllers according to the task, it might be useful to report a consideration. To-date, the vast majority of available occupational back-support exoskeletons are designed and programmed to provide assistive torques that contribute *simultaneously* to the extension of the back and both hips, regardless of their actuation principles and control strategies. This assistance principle is derived from and replicates the typical movements observed during symmetric lifting activities. Indeed, in this situation, every time there is back flexion or back extension, there is also a corresponding flexion or extension of the hips, respectively. Therefore, the presented assistance principle seems appropriate. In Figure 5.1 a graphical representation of this principle is sketched. However, the soundness of applying this strategy in carrying activities has to be investigated. Indeed, the inclusion of gait shows a different situation with respect to symmetric lifting, see Figure 5.2. In particular, during carrying, contributing to back extension is appropriate, but simultaneously pushing both hips towards extension might interfere with their natural movement. More specifically, the support could be beneficial during hip extension (associated with the leg in stance phase), but may result in restriction of the hip flexion (forward swing, characteristic of the leg not in contact with the ground). Hence, to understand the need for different controllers according to the task, this chapter describes the effects on the users of assisting with carrying – adopting an assistance principle derived from observation of symmetric lifting activities. The effects will be assessed in terms of muscle activity, gait kinematics and subjective perceptions. In particular, details on how the experimental testing was devised are reported in Section 5.1. Results are, at first, described in Section 5.2 and, then, discussed in Section 5.3. As usual, Section 5.4 summarizes the main results. At the end of the study presentation, Section 5.5 answers the question that is central to the whole Part I: is there need for back-support exoskeleton versatility?

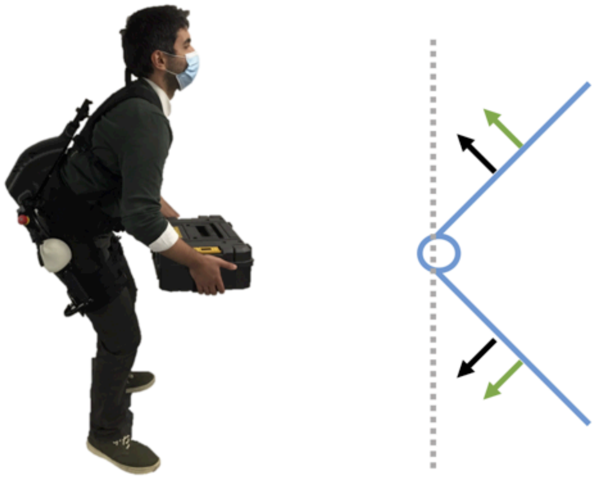


Figure 5.1 Schematic representation of what happens when a back-support exoskeleton assists the user lifting of a load. The green lines indicate that when back and hip extensors activate, they produce an extension of these body regions. Similarly, when the exoskeleton motors delivers an extension torque, they produces black assistive forces that are aligned with the muscles action. The same happens when lowering a load, as back and hip extensors and the exoskeleton activate for gravity compensation.

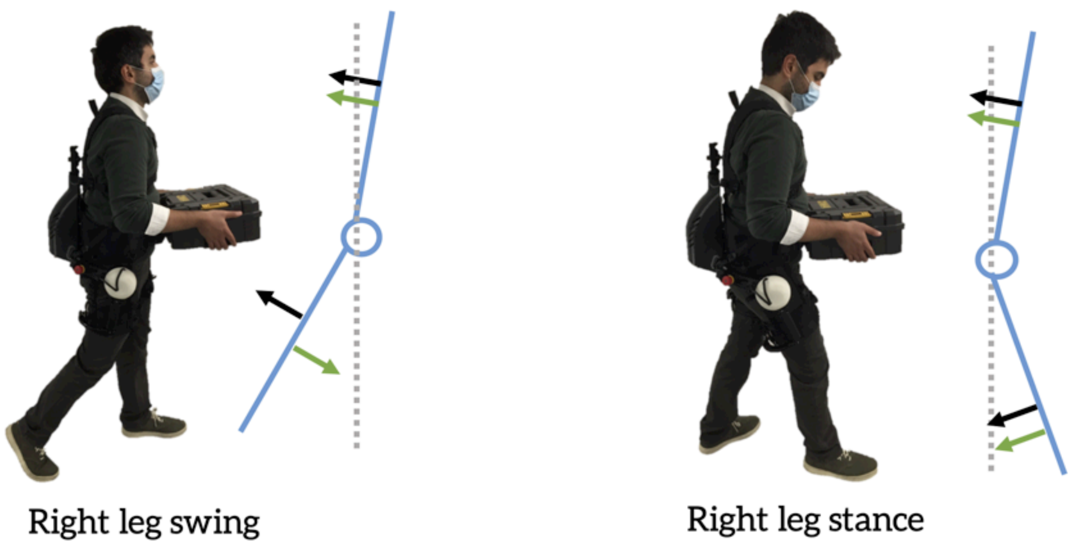


Figure 5.2 Schematic representation of what happens when a back-support exoskeleton assists the user during carrying. The green lines indicate that when back extensors activate, they produce an extension of these body regions. This action is always aligned with the exoskeleton action. What happens on the legs is that the movement is non-symmetrical. Therefore, if the exoskeleton always assists extension, it will interfere with the leg that is in swing phase.

5.1 Experimental testing

This experiment was conducted on the same pool of subjects presented in Chapter 4. The main differences are that, in this situation, only carrying was studied and that the XoTrunk exoskeleton was involved. Therefore, in the following, first it is detailed how, for the sake of this study, XoTrunk was controlled. Then, as in the previous chapter, a detailed description of the task, data acquisition, data processing and outcome measures is reported.

5.1.1 XoTrunk Control Mode

The versatility provided by XoTrunk electrical motors entails that it is possible to test and study different control strategies, as presented in Chapter 3. However, regardless of the selected control strategy, the motors always provided assistive torques that contribute simultaneously to the extension of the back and both hips. The backwards push on the back is the combination of the assistance provided by the left and right sides. The control strategy selected here was based on a constant extension torque provision. Indeed, for the sake of simplicity, during carrying the torso inclination can be neglected, whereas the forearm muscle activity can be assumed to be constant during load handling. Therefore the assistive profile delivered by the mid-level can be simplified to

$$\begin{aligned} \tau_{exo}(t) &= sin(\overset{\theta = 0}{\cancel{\theta(t)}})K_{IMU} + \overset{K_{CARRYING}}{\cancel{\Sigma_{fa}(t)K_{EMG}}} \\ &= K_{CARRYING} \end{aligned} \tag{5.1}$$

Such simplifications were introduced to facilitate the analysis of the effects that assistance during carrying has on the users. In the following, this control mode is referred to as the Exoskeleton On (*Exo-on*) condition. For each motor, $K_{CARRYING}$ was set to 10 Nm, resulting in an overall extensive torque of 20 Nm.

5.1.2 Experimental set-up and protocol

Nine healthy male subjects[1] (the same pool of Chapter 4, $N = 9$, 1.78 ± 0.04 m, 76.55 ± 8.22 kg, 31 ± 3.46 years old) were asked to wear sporting clothes and informed they would have to perform carrying, namely straight level walking for 7.5m, while holding a box close to the trunk at a self-selected speed. The carrying sequence were done varying the handled weight, i.e., 1.2 kg box housing 0, 7 or 15 kg payloads. In the following, the different weights are referred to as *light* (*L*), *medium* (*M*) and *heavy* (*H*). All the conditions were repeated three times for a total of 9 tests per subject. The task was performed not only varying the loads, but also the supplied assistance. In particular, two conditions were tested:

a) No Exoskeleton (*No-exo*): carrying without the exoskeleton;

[1] no female subjects were involved, because due to the COVID-19 related safety protocol, I could not test subjects not from our lab.

b) Exoskeleton On (*Exo-on*): carrying while wearing the exoskeleton in the *on-mode*. The exoskeleton provides an angle independent constant torque of 20 Nm to provide support for the extension of the back and of both hips (see Section 5.1.1).

Each assistance condition was repeated three times for a total of 18 tests per subject. The task execution order, the handled weights and the supplied assistance were randomized between subjects. At the end of the experimental protocol, the subjects were asked to fill in a simplified version of an RPE (Rate of Perceived Exertion) questionnaire to rate the differences between carrying in the *No-exo* and in the *Exo-On* condition, Huysamen et al. (2018). Table 5.1 summarizes the protocol and its independent variables.

Table 5.1 Overview of the testing protocol

Task	Carrying
Conditions	Without exoskeleton (*No-exo*); with exoskeleton (*Exo-on*)
Loads	Light 1.2 kg (*L*), Medium 8.2kg (*M*), Heavy 16.2kg (*H*)
Repetitions	3x

5.1.3 Data acquisition and data processing

Additionally to the back muscles analysed in the previous study (Chapter 4), to better understand the exoskeleton effects, also the subjects' right leg was instrumented to measure the activation of two muscles responsible for hip flexion and extension, i.e. the Rectus Femoris (RF) and the Semitendinosus (ST). The left leg was not instrumented as the exoskeleton action is the same on both legs. Figure 5.3 illustrates the locations of the chosen muscles. Skin conditioning and sEMG signals post-processing were analogous to what describe in Section 4.1.2.

To collect motion data, the subjects were also equipped with a 3D motion tracking system (MTw Awinda, Xsens, The Netherlands). 7 Xsens IMUs were attached to the feet, shanks, thighs and pelvis, in order to reconstruct lower limb kinematics and gait phase events. The Xsens software can reconstruct motion data at a 60Hz sampling frequency. Using IMU trackers and biomechanical models, the software also provides gait phase information that can be used to perform data segmentation (Di Natali et al. (2020a)). Two consecutive *heel strike* events generated by the same foot are used to identify the start and finish of the stride.

Before data recording, Xsens calibration and MVC acquisition routines were performed for each subject, Halaki and Ginn (2012), Vera-Garcia et al. (2010).

5.1.4 Outcome metrics and analysis

In the following, the metrics used for the assessment of the effects of assisting with carrying are reported, in addition to how the statistical analysis was performed. Table 5.2 summarizes what

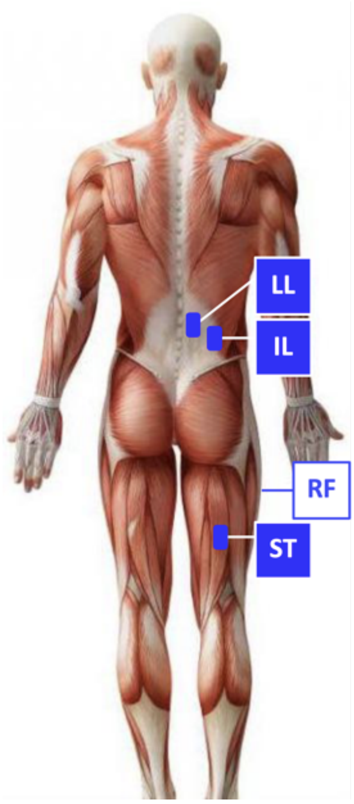


Figure 5.3 Schematic representation of electrodes placement. For greater clarity, only the right side electrodes are displayed. It is possible to identify the Erector Spinae Longissimus Lumborum (LL), the Erector Spnae Iliocostalis (IL), the Semitendinosus (ST) and the Rectus Femoris (RF). Note that this latter muscles is on the front side of the body.

presented hereafter. In the previous chapter, it was discussed how M and P (the 50^{th} and the 90^{th} percentile of the muscle activity distribution, respectively) can be assessed to monitor the risk associated with traumatic damages and cumulative fatigue. For the sake of consistency, these metrics were analysed also for the lower limb muscles, even though, in the particular case of P, there is no clear traumatic damage associated with those sites.

The gait kinematics analysis is focused on the hip and knee ranges of motion (RoM_h and RoM_k, respectively) that are defined as the difference between the 90^{th} and the 10^{th} percentile of the lower limb trajectories distribution during carrying. Since users were instructed to walk at a self-selected speed, an analysis on the average stride time ($\overline{\delta}$) per condition is conducted. $\overline{\delta}$ is defined as in eq. (5.2)

$$\overline{\delta} = \frac{1}{S-1}\sum_{k=1}^{S-1} H_{k+1} - H_k, \text{ for k =1,2,...,S-1} \tag{5.2}$$

where S represents the number of strides in a test and H is a vector collecting all the right heel strike time events.

Statistical analysis

Kinematic data were analysed applying a standard one-way analysis of variance (ANOVA) with significance level set at $p < 0.05$. Such analysis was performed for both hip and knee angles. Muscle activity, instead, was analysed comparing the ratios between the control condition (*No-exo*) and the test one (*Exo-on*) for a given metric (ρ^x).

Table 5.2 Overview of the testing protocol and the selected metrics.

Task	Carrying
Conditions	Without exoskeleton (*No-exo*); with exoskeleton (*Exo-on*)
Loads	Light 1.2 kg (L), Medium 8.2kg (M), Heavy 16.2kg (H)
Repetitions	3x
Metrics	M, P, RoM_h, RoM_k, $\overline{\delta}$
Statistical Analysis	for each ρ^x, α, iqr, and γ were analysed (x being any of the above metrics)

Subjective evaluation

The subjective evaluation forms, filled in by each subject at the end of the experimental protocol, allow a comparison to be made on whether or not the perceived effect is consistent with the objective data. Table 5.3 reports the asked questions for the investigated body regions:

◯ Shoulders

◯ Arms

◯ Back/Trunk

◯ Waist

◯ Right leg

◯ Left leg

Table 5.3 The simplified questionnaire that the subjects were required to fill-in

Q1	Where did you feel benefit from the exoskeleton usage compared to the free-body execution of the same task? (check all that apply)
Q2	Where did you feel hindrance or discomfort from the exoskeleton usage compared to the free-body execution of the same task? (check all that apply)
Q3	For each body region where you experienced some effect (either benefit or hindrance/discomfort), please briefly describe it

5.2 Results

In the following, the results concerning the effects of the assistance during carrying are split into muscle analysis and gait kinematics.

5.2.1 Effects of assistance during carrying - Muscle activation

Figure 5.4 reports the boxplot associated with ρ^M and ρ^P for the overall activation of the lumbar muscles when comparing carrying activities with and without the exoskeleton. Overall, the population distributions are around the unit value and the *iqr* range is quite large (up to 0.62). However, the *iqr* has a trend to reduce as the payload increases, both for mean and for peak. Indeed, the variability in the heavy load condition is about one third of that recorded for the lighter loads.
Light and heavy load tests display opposite behaviours, with the first (light load) belonging almost entirely to the $\rho^x > 1$ region (i.e., the exoskeleton produced an increase of the metrics) and the second (heavy load) to the $\rho^x < 1$ region (i.e., the exoskeleton produced a reduction of the metrics). This is more evident for ρ^M rather than ρ^P. An additional interesting observation is that for both metrics the lowest value is for the intermediate weight. For both ρ^M and ρ^P, γ indicates that the majority of the subjects experienced a reduction of muscle activation in the *Exo-on* condition, with respect to the control case. Moreover, as the payload increases, the value of γ increases as well. Figure 5.5 refers to the lower limb muscles activation analysis. Similarly to above, the distributions are centred around the unit value. The *iqr* still displays large variability (up to 0.71) and there is no longer a clearly narrowing trend as the payload increases. Indeed, in the case of the Rectus Femoris, the *iqr* is smaller for the intermediate loads than it is for heavier loading condition. Red crosses identify outliers in

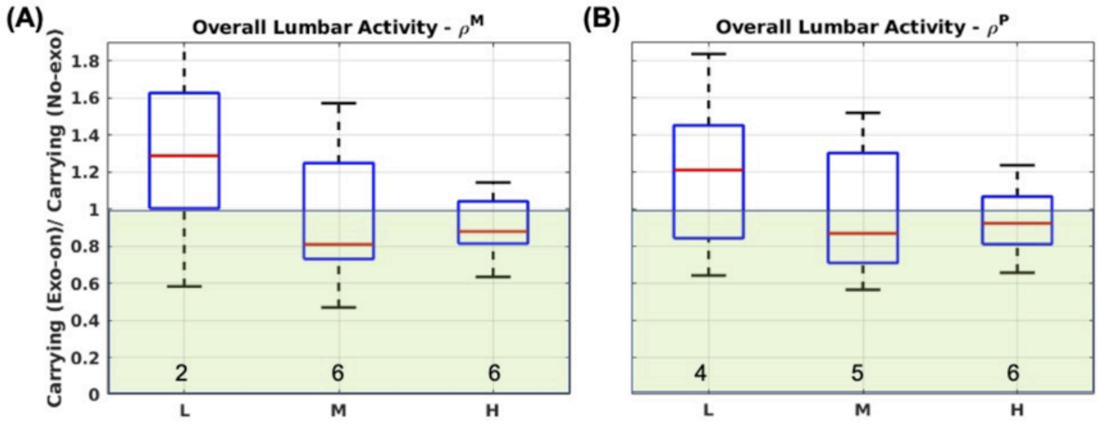


Figure 5.4 Representations for ρ^M and ρ^P considering the overall lumbar muscle activity performing carrying in the *No-exo* condition and in the *Exo-on* one.
(A) refers to the 50^{th} percentile of muscle activation (ρ^M) while **(B)** refers to the 90^{th} percentile (ρ^P). L, M and H refer to the light, medium or heavy loading condition. Green shaded areas identify the regions where $\rho_i^x < 1$ (i.e., the exoskeleton reduces the muscle activity).
Note that in **(A)** the top whisker for the light loading condition extends up to 2.3. Numeric values at the bottom of each box report the value of γ.

the Semitendinosus ρ^M, and in the Rectus Femoris and Semitendinosus ρ^P. Also in this case, it is possible to identify an increasing trend for γ as the payload increases.

Effects of assistance during carrying - Gait kinematics

How the RoM changed between the two conditions is reported in Figure 5.6, revealing a clear trend for both the hip and the knee joints. Indeed, for both hip and knee RoM it almost always holds that $\rho^{RoM_k} < 1$ and $\rho^{RoM_h} < 1$ (see also γ values). On average, the median values (α) are around 0.90 indicating that there is a reduction in the RoMs of about 10% due to the exoskeleton action. The *iqr* values are much lower than in the muscle analysis (maximum *iqr* is 0.12 with respect to 0.71).
Significance levels obtained comparing the *Exo-on* and the *No-exo* condition are reported in Table 5.4. Bold values indicate where significance was reached (p-value$<$ 0.05). In each condition, at least one joint had a significant RoM reduction between the test and control condition.
Moreover, by inspection of Figure 5.7, it is possible to see how the *Exo-on* condition yielded an increase of stride duration ($\overline{\delta}$), as all the distributions lie in the $\rho^{\overline{\delta}} > 1$ region. The trend indicates a median increase in cycle time duration of about 6%. Outliers can be identified in the light and medium load conditions. The values of γ indicate a clear effect for all the subjects.

Subjective perception

Finally, Figure 5.8 summarizes, for each body region under analysis, how many users reported a benefit or hindrance/discomfort when comparing the *Exo-on* and the *No-exo* conditions. No difference

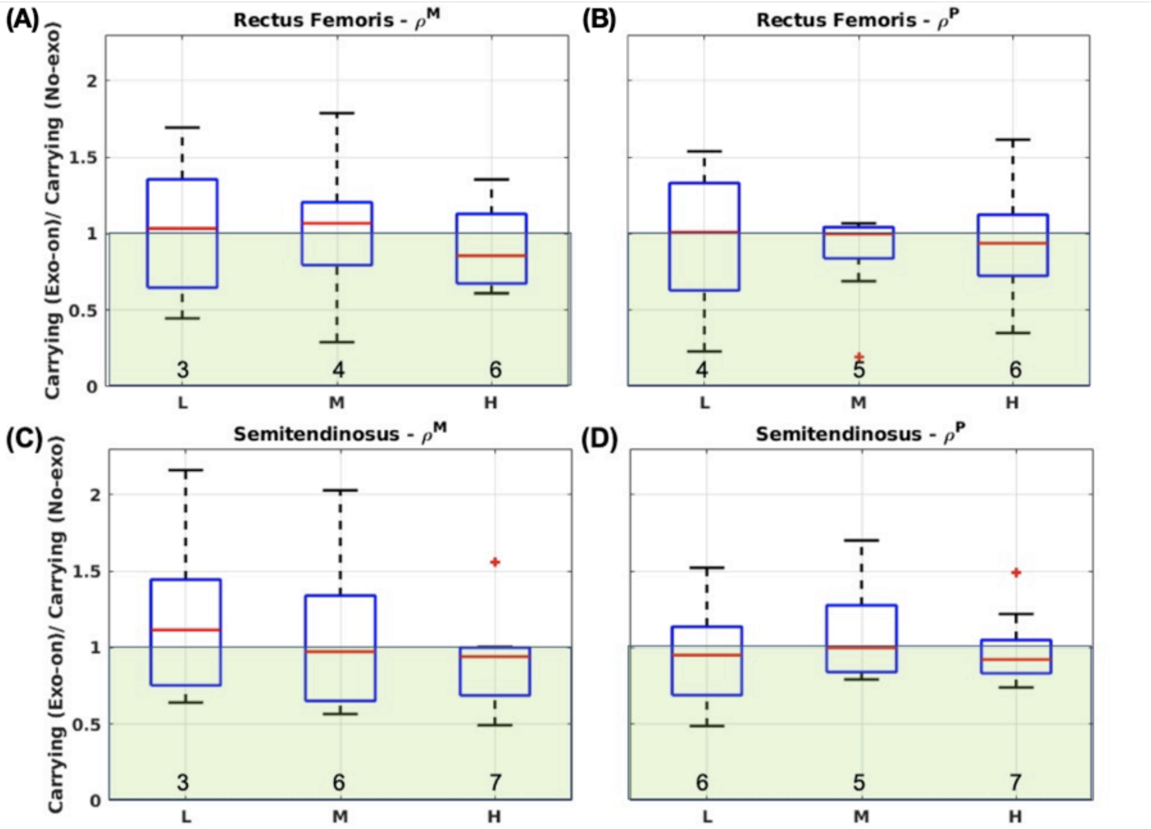


Figure 5.5
(A) Boxplot of ρ^M considering the Rectus Femoris activity performing carrying in *Exo-on* and *No-exo* condition.
(B) Boxplot of ρ^P considering the Rectus Femoris activity performing carrying in *Exo-on* and *No-exo* condition.
(C) Boxplot of ρ^M considering the Semitendinosus activity performing carrying in *Exo-on* and *No-exo* condition.
(D) Boxplot of ρ^P considering the Semitendinosus activity performing carrying in *Exo-on* and *No-exo* condition.
L, M and H refer to the light, medium or heavy loading condition. Green shaded areas identify the regions where $\rho_i^x < 1$ (i.e., the exoskeleton reduces the muscle activity). Numeric values at the bottom of each box report the value of γ.

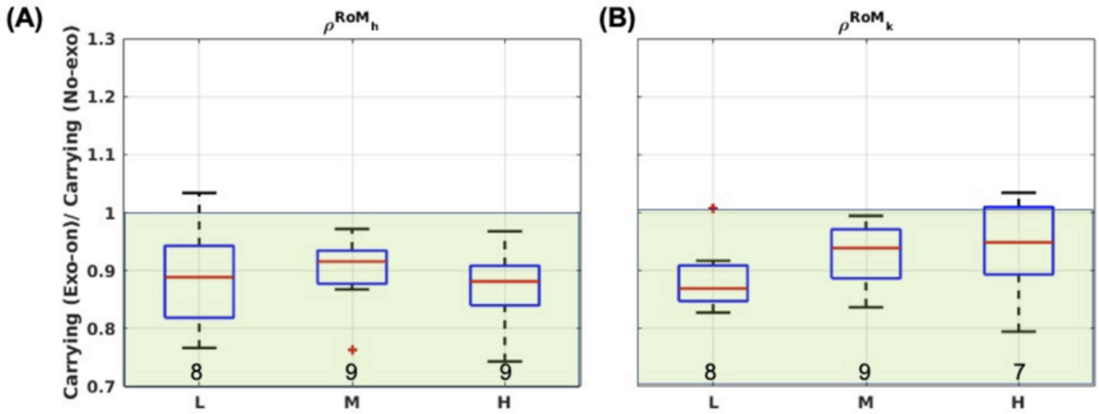


Figure 5.6 Boxplots representations for ρ^{RoM_h} and ρ^{RoM_k} considering carrying in *Exo-on* and *No-exo* condition. Two different joints are analysed: **(A)** Hip and **(B)** Knee.
L, M and H refer to the light, medium or heavy loading condition. Green shaded areas identify the regions where $\rho_i^x < 1$ (i.e., the exoskeleton reduces the RoMs). Numeric values at the bottom of each box report the value of γ.

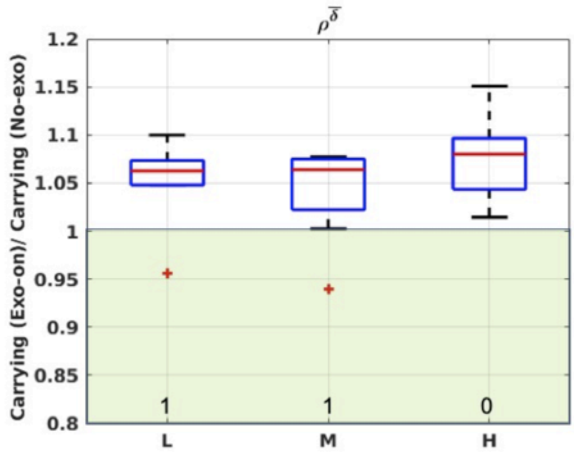


Figure 5.7 Boxplot representation for $\rho^{\overline{\delta}}$ considering carrying in *Exo-on* and *No-exo* condition.
L, M and H refer to the light, medium or heavy loading condition. Green shaded areas identify the regions where $\rho^{\overline{\delta}} < 1$ (i.e., the exoskeleton reduces the stride duration). Numeric values at the bottom of each box report the value of γ.

Table 5.4 Gait kinematics - Statistical significance for the considered loading conditions. The table reports the p-values obtained from the one-way ANOVA test. **Bold** values indicate where statistical significance was reached (p-value< 0.05).

	L	*M*	*H*
Hip	0.0534	0.0970	**0.0396**
Knee	**0.0040**	**0.0441**	0.1582

was reported between left and right leg, so, in Figure 5.8 the results are joined. Almost all the users reported benefit in the back/trunk region (8 out of 9) and discomfort in the legs (7 out of 9). No user reported perceived benefit in the legs whereas 1 subject felt hindrance also for the trunk region. It is also interesting to report that on the waist (where the exoskeleton is anchored) 3 users could feel a benefit from the exoskeleton usage and 1 experienced discomfort. Even though the exoskeleton is not assisting the arms, 2 subjects felt a benefit also in this body region. Consistently with the exoskeleton action, no user reported effects on the shoulder region. As the users were instructed to report benefit or hindrance only if actually perceived, for a given body region, the sum of hindrance and benefit does not have to be $N = 9$

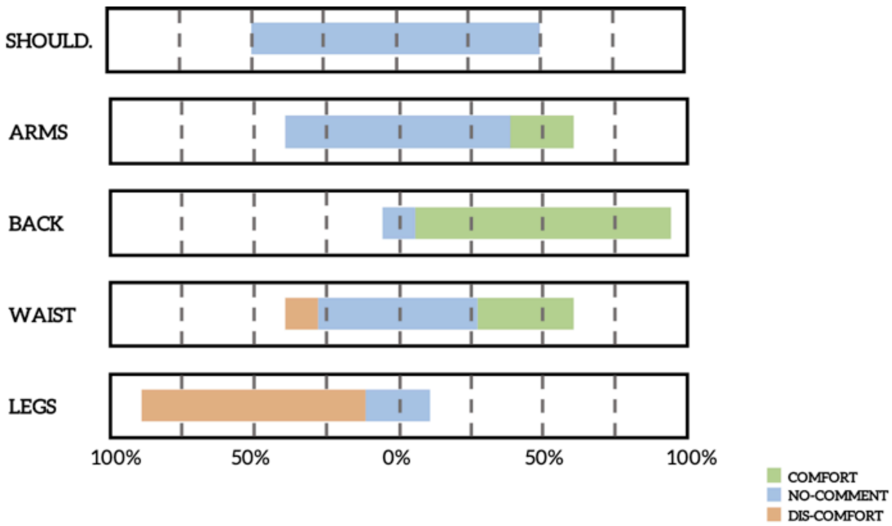


Figure 5.8 Graphical representation of the results obtained for each body-region under analysis. Green rectangles are used to indicate the percentage of users that reported a perceived comfort while executing the task with the exoskeleton; red rectangles are used for those who reported discomfort and blue indicate those that did not feel any difference between control and test condition. The sum is always 100100%

5.3 Discussion

In this study, it was tested if an exoskeleton providing constant extensive torques could be beneficial or not, during carrying activities. A control strategy of this type is a simplification of what happens if an exoskeleton, programmed to assist lifting, is also used during carrying. Here, the hypothesis was that this strategy would turn out to be sub-optimal, namely being beneficial for the back but hindering the lower limbs, particularly in the swing phase. The following discussion is separated according to the two body regions under analysis.

The lower back

The experimental results do not indicate a clear polarity on the data and, thus, it is not possible to confidently conclude that, with respect to the conditions of this study, the exoskeleton is providing a reduction in the activation and work intensity of the lower-back muscles. Nevertheless, it is worth highlighting how the data variability shows a general trend to reduce as the payload increases and that the heavy load condition has a much clearer trend towards the $\rho^M, \rho^P < 1$ region, i.e., where the exoskeleton has a benefit on the muscle activation. This suggests that conclusions drawn for this condition are more reliable than those drawn for lighter loads. In particular, for the heavier load condition, α values for ρ^M and ρ^P suggest that the exoskeleton effect is beneficial, reducing the overall lumbar activity by 12.08% and 7.99%, respectively. It is also important and encouraging that the exoskeleton is seen to have the greatest effect with the heaviest loading, as this is the circumstance that is most in need of assistance. Also, a comparison of objective and subjective data confirm the beneficial effect of the exoskeleton. Indeed, as outlined in Figure 5.8, 8 out of 9 users reported benefit on the back and only 1 out of 9 experienced discomfort or hindrance on the same body segment. On the other hand, a part from the light load condition, lower-back muscle analysis showed that, out of 9, 5 to 6 subjects (according to the analysed metric) had a reduction of muscle activation (see γ values in Figure 5.4). These values are not so far from those reported by the subjective evaluation forms. Therefore, the consistency between objective and subjective data suggest that, considering spinal loading, there is some evidence that the exoskeleton effect is somehow beneficial for most of the population. Contrary to the expectations, for the medium and high payload handling, the overall lumbar activity reduction is not in line with the potential of the device used in the assessment. In particular, in Toxiri et al. (2018a) the experiment showed significant back muscle activation reduction (around 30%), whereas a clear reduction was not obtained in this study, even though sound bio-mechanical models supported the hypothesis. This, along with the negative exoskeleton effect for the light load condition, suggests that there is room for improving the constant torque strategy used in this study.

One upgrade is to modulate the delivered torque according both to the handled payload and to the user's body mass. In particular, the analysis of both α and γ supports the need to modulate the assistance according to the handled payload. Indeed, considering the lightest loading condition, the exoskeleton does not clearly reduce spinal loading, as highlighted by α. On the other hand, as the handled weight increases, the exoskeleton assistance results in reductions of α values both for ρ^M and ρ^P ($\alpha < 1$). To this extent, it is interesting to note that, even if very slightly, the intermediate condition seems to be a minimum and might indicate that the amount of assistance provided is best around that payload range. Moreover, the number of subjects that show a benefit from the additional torque provided by the exoskeleton increased as the weight of the carried load increased (see Figure 5.4). For the light payload test, the muscle activity increase may be interpreted by subjects adopting abdominal and back-extensors co-contraction, stiffening the upper body to counteract the backwards push of the exoskeleton and to regain stability. Further experimentation could help clarifying this phenomenon and if modulating the torque according to the payload would, as expected, reduce it. Finally, the large variability in the results further suggests the possibility of modulating the delivered torque not only according to the payload, but also to the subjects' body-mass. Indeed, despite body-masses variability (76.55 ± 8.22 kg) the delivered torque was kept constant, and so, it is possible that subjects with different body mass experience and react differently to the same amount of assistance.

The lower limbs

The exoskeleton assistance on the lower limbs resulted in hindrance clearly affecting the gait kinematics of all the users. This hindrance is evident both as subjective perception of the users (7 out of 9 users felt hindered on the legs) and from the kinematic analysis. Indeed, hip and knee RoMs were reduced by up to 12%. Stride speed was also reduced, due to a corresponding increase in stride duration (between 6 and 8%). In addition, a study conducted on the effects of load carriage on energy cost of walking Abe et al. (2004), showed no significant differences in the energy cost associated with walking for values between the control condition (empty backpack) and the test one (backpack with a 6kg load). This suggests that the differences noted in this study are related more to the exoskeleton torque provision, rather than the exoskeleton weight itself (6.5kg). These elements suggest that simultaneously pushing both hips towards extension appears not to be the best assistive strategy.

Furthermore, even though the kinematic analysis and the subjective perceptions are clearly polarized, this does not happen in the muscle analysis. There may be two main reasons that explain this lack of a clear trend. The first reason being the non ideal choice of the muscles. Indeed, partially due to the exoskeleton fitting and partially due to the difficulty in assessing via sEMG the hip flexor activity, in the proposed protocol it was not possible to measure the muscle activity of the Iliopsoas (hip flexor) and of the Gluteus Maximus (hip extensor), Byrne et al. (2010). For these reasons, the activity of the Rectus Femoris and of the Semitendinosus were chosen as representative of hip flexion/extension muscle activation. Problems in assessing the proper flexors and extensor are reported also in Baltrusch et al. (2019), where muscle activity did not show any significant differences between conditions.

The second reason why no trend emerges in the selected muscles might be related to the changes in the gait trajectory, as reported above. Analysing both hip and knee joints, for each load condition, the exoskeleton assistance resulted in a reduced RoM. Indeed, almost all of the population lies in

the $\rho^{RoM_h}, \rho^{RoM_k} < 1$ region. It is interesting to note the little data variability (*iqr*), suggesting its reliability.
Moreover, the one-way ANOVA test, significance level = 0.05, conducted to compare the *Exo-on* and the *No-exo* condition, found statistically significant differences at least for one joint in all of the conditions (see Table 5.4). In the case of the hip joint, the RoM reduction is due both to smaller flexion angles, hindered by the constant torque, and to smaller extension angles, possibly due to a compensation for the unwanted/unexpected backwards push of the exoskeleton. Differences in the knee trajectory can be explained as a consequence of the hip changes. Delving a bit more into the kinematic analysis, Figure 5.7 shows that the *Exo-on* condition caused a speed reduction in the users walking speed: all the population, apart from an outlier, lies within the $\rho^{\overline{\delta}} > 1$ region. Therefore, reduced RoMs and slower stride durations show an evident hindrance confirming the initial expectations.

5.3.1 Limitations

In the designed testing protocol, MVC calibration was performed adopting a single posture. However, this procedure is more prone to variability in the MVC normalization as subjects might exhibit differences in the posture to obtain maximum muscle activity, McGill (1991). The large inter-subject variability did not allow to always apply standard statistical analysis such as the analysis of variance. For this reason, an intra-subject normalization between the control and test conditions was performed. As a consequence, the results are discussed taking into consideration trends. The proposed testing protocol was carried out in a lab setting. This might present substantial differences to the conditions found in a workplace where users may be required to walk on undulating or sloped surfaces in addition to level ground. Therefore these findings cannot be directly generalized to out-of-the-lab scenarios. Additionally, the indication to perform the carrying task at a self-selected speed might be a further simplification of actual working conditions. Indeed, for given tasks, the workers could be required to walk as fast as possible so as not to limit productivity. Also, the relatively short duration of the activities performed during the testing protocol does not allow to observe fatigue effects, nor the effects of prolonged exoskeleton usage. Additionally, in the *Exo-on* condition, the use of a constant torque may be an oversimplification, given the natural variability in sagittal plane torques that occur at the lumbar spine during gait. However, this choice was related to the desire of simplifying the understanding of the consequences of assisting carrying with the same control strategy derived from lifting. Finally, an additional *Exo-off* condition, in which the exoskeleton would be worn but turned off, could have highlighted interesting additional information. In this study, nevertheless, it was chosen to rely on the results found in Abe et al. (2004), that analyse the cost associated with walking and carrying loads in a backpack.

5.4 Conclusion

Back-support exoskeletons are generally used to assist lifting and, thus, mitigate the ergonomic risks associated with this activity. The applicability of these devices to other activities, such as carrying, is still an open issue.
This study investigated the effects of assisting carrying with an exoskeleton designed for supporting lifting tasks. Contrary to the expected outcome, the findings of the experimental campaign, described above, do not provide clear evidence on the efficacy of the analysed strategy in supporting the lower-back. However, the overall lumbar activity shows a promising trend when carrying heavy objects as for muscle activation is reduced by up to 12%. Large data variability invites caution when interpreting it. In agreement with the expectations, the strategy yielded hindrance for the lower limbs. This is supported by reductions in hip and knee RoMs (around 10%) and an increase of stride duration (between 6 and 8%). Due to changes in gait kinematics and difficulties in assessing the proper hip flexor and extensor, muscular analysis for the lower limbs did not provide significant findings.

5.5 On the need of back support exoskeleton versatility

As presented in Chapter 2, back-support exoskeleton controllers are designed predominantly for assisting with lifting activities that are frequently associated with MSDs onset. It follows that, even though control strategies can be expanded by including HAR algorithms, it is uncertain whether this additional level of control is actually needed. Therefore, to define which of the many activities that can be performed in industrial scenarios have to be recognized, it was proposed to *(*i) check the impact that a given activity has on spinal loading, compared to lifting and *(ii)* understand if task recognition can, and should, yield to specific modifications in the exoskeleton control. In Part I the chosen MMH activity was *carrying*. Now that data has been presented and discussed, there are more elements to debate on the need for recognizing carrying. The first consideration is that, from an ergonomic viewpoint *carrying* has an impact on spinal loading comparable to lifting. This is supported by an analysis on the 90^{th} and the 50^{th} percentile of the overall lumbar extensor intensity that is in the same order of magnitude for both activities. For passive exoskeletons, recognizing that carrying is being performed does not add any value, as these devices are not versatile due to design choices described in Section 2.2. On the contrary, quasi-passive devices can take advantage of task awareness. Indeed, by resorting to manual clutches, spring offsets and automatic engaging or disengaging of passive elements, they can mitigate the hindrance of their actuators during *walking*. Additionally, the study presented in this chapter, has shown that a constant extensive torque on the hips results in perceived hindrance of the gait. Quasi-passive devices, due to mechanical design limitations, cannot provide support differently from what just described. Therefore, to reduce/remove gait restrictions, these devices should disengage the passive elements and, so, discriminating between *carrying* or *walking* is not relevant. Active exoskeletons are more versatile and, hence, are able to exploit the functionality and flexibility of their actuators to create assistance profiles that can be tailored to the specific demands of the assistive task, like carrying in this case. Not all the active exoskeletons, however, have the same "*degree of versatility*". As an example, the H-WEX exoskeleton, described in Ko et al. (2018), cannot provide support differently from the approach presented in this chapter. This is due to the choice of using a single motor for the actuation. Indeed, even though the exoskeleton is more compact, efficient and lightweight, the single motor can only modulate the delivered amount of torque and cannot assist the legs independently, according to gait phase. Instead, as an example, the APO exoskeleton (Chen et al. (2018)), the ATOUN Model Y and XoTrunk have two motors, one on each side. This design choice can be exploited to develop new assistive strategies, more appropriate for carrying. Indeed, in the previous sections, it has been discussed how a better strategy could improve the efficacy of the exoskeleton for the back region and, additionally, reduce the hindrance in the lower limbs (as seen in the data analysis).

As control strategies for back-support exoskeletons start addressing tasks differing from lifting, the capability of recognizing which activity is being performed and, thus, triggering the appropriate controller, becomes a relevant feature, promoting active exoskeletons versatility. How to design HAR algorithms, specific for back-support exoskeletons, is addressed in Part II of this thesis.

Part II

How to enhance back-support exoskeleton versatility

Chapter 6

Integrating HAR into XoTrunk

Part II is on the implementation of HAR algorithms for back-support exoskeletons. In particular, in this chapter the results obtained in two studies (Poliero et al. (2019a) and Poliero et al. (2019b)) are presented. At first, an approach that exploits a minimal set of sensors, like in Chen et al. (2018), and classifies movements by means of SVM is presented. The rationale behind the choice of relying on HAR algorithms based on PR techniques (as described in Chapter 2) is justified by the need of discriminating between non-complex tasks (as described in the following sections). Moreover, SVM algorithms are based on a geometric approach that offers a better understanding of what the classification limits are. Taking advantage of machine learning algorithms avoids manually setting thresholds for rule-based algorithms like in Chen et al. (2018). Since back-support exoskeletons have many different architectures and actuations, it is not easy to find the same sensors on all the exoskeletons. Therefore, the idea was to considerer kinematic-based features that could be easily extracted by wearable IMUs sensors. Section 6.1 describes how kinematic data were collected to train the classifier, results are detailed in Section 6.2 and discussed in Section 6.3, with particular emphasis on how active or quasi-passive devices could take advantage of these results. Eventually, Section 6.4 wraps up the relevant findings of this first study.

Then, this chapter shows how, in Poliero et al. (2019b), the SVM classifier can be extended to perform online classification of the user activities, while wearing XoTrunk. In particular, Section 6.6 presents the experimental protocol, along with the metrics used in the assessment of the classifier performances. Section 6.7 summarizes the obtained results and introduces the discussions (Section 6.8). Finally, Section 6.9 resumes the content of this chapter answering how HAR algorithms can be integrated into exoskeletons to enhance their versatility.

6.1 Training a SVM classifier

Given the objective of training a classifier that exploits a minimum set of sensors, only knee and trunk kinematic variables were considered. The rationale behind this choice was that knee and trunk are the most informative joints for the classification of the desired tasks. Training and testing data was collected from 10 healthy subjects. These subjects were divided in two groups characterized by different protocols, with the aim of defining the most appropriate approach for the study under analysis. The following sections disclose more details about the considered tasks (Section 6.1.1), the experimental setup and protocol (Section 6.1.2 and Section 6.1.3), the kinematic data analysis and how the multi class classifier (6.1.4) was trained.

6.1.1 Task Analysis

Initially, the choice of using only kinematic variables and the objective of developing a classifier for both quasi-passive and active exoskeletons yield the selection of the *walking* activity rather than the *carrying* one. An extension to carrying is presented in the second study of this chapter. Additionally to walking, also *bending* and *standing* were addressed. In particular, the subjects were required to:

- *walk*. Subjects were asked to freely walk in a room, changing speed and direction as many times as desired. This is an activity where wrong assistive profiles yield movement constraints, as described in Chapter 5;
- *stand*. Subjects were required to assume a relaxed standing position, as in Figure 6.1(A). This was done in order to simulate a situation where the user is resting and, again, does not need assistance.
- *bend*. Subjects were required to perform a *bending-sequence*, i.e., the subsequent lifting and lowering of a box. The bending style was either freestyle, squatting (Figure 6.1(B)) or stooping (Figure 6.1(C)). A more formal definition of these styles is found in Burgess-Limerick (2003). Bending is a typical example of material handling where exoskeleton assistance is required.

6.1.2 Experimental Set-up

The experimental set-up consisted of a 4.10 kg box and the MTw Awinda 3D human motion wireless tracker (XSens, Enschede, The Netherlands). This system offers a sampling frequency of $60Hz$ and is constituted by 17 IMU trackers that are used to derive kinematic variables of the main human joints and links. The trackers were located according to the XSens protocol. No exoskeleton was involved in the data collection process being the goal the development of an exoskeleton-independent algorithm.

6.1.3 Experimental Protocol

The 10 subjects were divided in 2 sessions characterized by different protocols.

- *Session A*. Six subjects (28.33 ± 2.58 years old and 1.72 ± 0.05 m) were required to wear the XSens equipment. Then, 3 different trials were recorded. In the first one, the subjects were instructed to walk in the room for $10s$; in the second one, the task involved performing bending-sequences for $10s$ without any indication on the style (freestyle bending) and, in the

Figure 6.1 The figure reports pictures of the subject (A) standing in relaxed position (B) squatting and (C) stooping. With respect to squatting, this latter style entails a very pronounced trunk inclination and negligible knee flexion. Also, in (A), blue circles show the location of the XSens IMUs used to compute knee and trunk angles. The subject authorized the authors to use these photos.

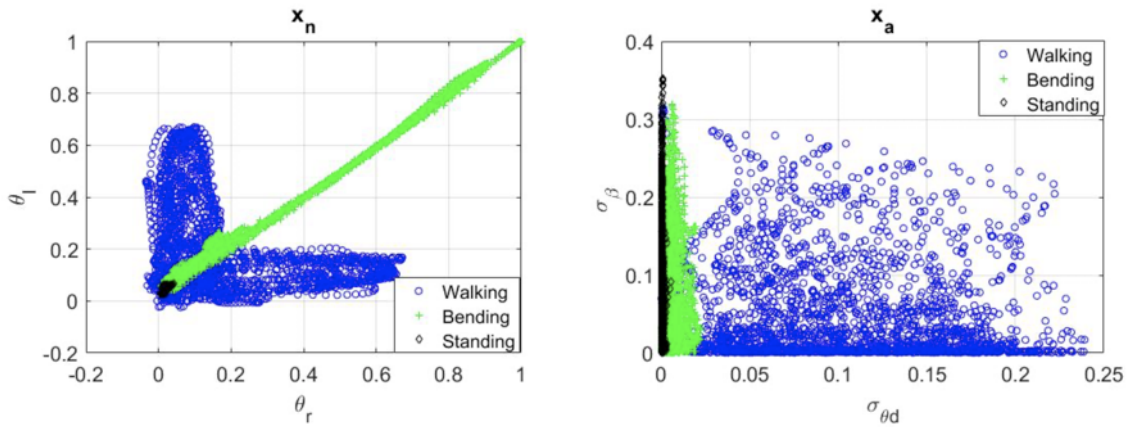
third one, the subjects had to perform the previous two trials successively. The first two records for each subject, were used for the classifier training, whereas the final one for testing on unseen data.

- *Session B*. Four subjects (28.75 ± 4.25 years old and 1.81 ± 0.01 m) were, again, required to wear the XSens equipment and carry out 3 different trials. In each trial, the subjects were required to perform 3 walking sequences and 3 bending-sequences, in random orders. This time, subjects were required to alternate specific bending techniques during the execution (squat, stoop or freestyle). Again, the first two trials were used for training, while the remaining one for testing.

The main difference between the two sessions is that, in session *B*, a standing phase was used to separate tasks and subjects were instructed to adopt a specific bending style. Separating walking from bending, introducing standing, seems to reproduce more closely the daily activities sequences and allows for more accurate data segmentation. On the other hand, in session *A*, standing was detected only when subjects took a rest between bending-sequences and, so, there is no stand-to-walk transition.

6.1.4 Kinematic Data Analysis and Multi Class Classifier

Only the information coming from 5 of the 17 IMUs was taken into account as displayed by the blue circles in Figure 6.1(A). Those IMUs are the trunk and the upper and lower legs ones. Again, the reason why only these joints were selected was to find a minimum set of variables. Choosing trackers on segments connected by the same joint (i.e., upper and lower legs) allows to easily compute the knee angle, as this can be found as the rotation of the lower leg with respect to the upper one. However, having selected only one tracker for the trunk, it was not possible to compute its inclination in a similar manner, but had to rely on the integration of the IMU signal. The first post-processing operation was to associate each data sample with a label representing the performed activity. This labelling was done thanks to the XSens software that offers a video reconstruction of the movements. Therefore, video-analysis was used to manually define the activity corresponding to each sample. In order to compare features with different orders of magnitude, all the data was normalized between $[-1,+1]$, dividing the data by its uniform norm $||x||_\infty$. Successively, given a dataset, properly post-processed, the following step was to define a set of features ($\vec{x}$) for training the classifier. As a first naïve approach all the normalized data was considered, i.e., $\vec{x}_n$ was defined as the set of features composed by left and right knee angles (θ_l, θ_r) and trunk 3D accelerations ($\ddot{\Theta}_x$,$\ddot{\Theta}_y$,$\ddot{\Theta}_z$). However, analysing Figure 6.2a, where only θ_l and θ_r are reported for sake of simplicity, it is clear that the feature-space does not clearly distinguish between walking (blue circles), bending (green crosses) and standing (black diamonds). Therefore, a new set of features ($\vec{x}_a$) was introduced. Those features were expected to be more informative and are reported in Figure 6.2b. In Figure 6.3a, it is evident that taking



(a) Distribution of θ_l and θ_r in $\vec{x}_n$ feature space (b) Distribution of σ_β and σ_{θ_d} in $\vec{x}_a$ feature space

Figure 6.2 2D feature space distribution of kinematic variables corresponding to walking (blue circles), bending (green crosses) and standing (black diamonds) measured in session *B*

into account the moving standard deviation, over a window of $w = 15$ samples, of the knee angles difference σ_{θ_d}, where $\theta_d = \theta_r - \theta_l$, it is easier to distinguish between different sequences. Indeed, during walking, σ_{θ_d} is much higher than during bending or standing. Figure 6.3b shows that the knee angle is strongly influenced by the bending style; the first bending-sequence — corresponding to stoop style — is characterized by a significantly different behaviour with respect to the second one (squat) and the third one (freestyle). As a consequence, a feature robust to changes in the bending technique was introduced. Figure 6.3c represents the moving standard deviation of the sum of right knee angle and trunk sagittal angle σ_β (where $\beta = \theta_r + \Theta_z$), again over a $w = 15$ samples window. By comparing Figure 6.3b and Figure 6.3c, σ_β looks more robust than the use of only knee angle. Indeed, while a squat bending mainly involves knee flexion/extension with very little trunk flexion/extension, in a stoop bending the consideration is reversed and, thus, the sum of knee and trunk angle compensates the change in style. As a comparison, Figure 6.3d represents only β. It is possible to see that also this feature is less sensitive to the bending style, but applying the moving standard deviation gives even better results. As a final remark, considering Figure 6.3b, it is evident that the subject did not separate each sequence with standing. Nevertheless, this was considered as a valid trial since it might be possible that the user in actual applications starts walking right after a bending-sequence or vice-versa. The features selected are reported in eq (6.1).

$$\begin{cases} \vec{x}_n = [\theta_l, \theta_r, \ddot{\Theta}_x, \ddot{\Theta}_y, \ddot{\Theta}_z] \\ \vec{x}_a = [\sigma_{\theta_d}, \sigma_\beta, \ddot{\Theta}_x, \ddot{\Theta}_y, \ddot{\Theta}_z] \end{cases} \tag{6.1}$$

Based on these features, two *multiclass Support Vector Machines* (mcSVMs) were trained. To describe the classifiers, the following notation is adopted:

$$svm(x|y)_j \tag{6.2}$$

where x and y refer to the testing and training session, respectively. Subscript j can be either n if the naïve approach is considered or a taking into account the second set of features, $\vec{x}_a$. The dataset dimension for session B was 46496 samples, while 10713 samples constituted session A dataset. Since *SVM*s are originally designed for binary classification, to train multi-class classifiers, the One-vs-One (*OVO*) approach was chosen. This trains $0.5K(K-1)$ classifiers, where K corresponds to the number of considered classes, i.e. 3. Applying a kernel function ϕ it is possible to map training vectors data into a higher dimensional space where the *SVM* optimization algorithm finds a linear feature-separating hyperplane with maximal margin. Therefore the function defined in eq (6.3)

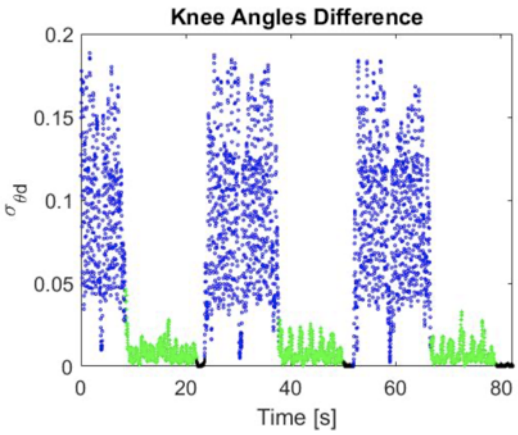
$$K(x_i, x_j) \equiv \phi(x_i)'\phi(x_j) \tag{6.3}$$

is called kernel function. In this analysis the adopted ϕ is the Radial Basis Function (*RBF*) and, hence, the previous equation becomes as in eq. (6.4). For this study, as a general convention, γ was set to

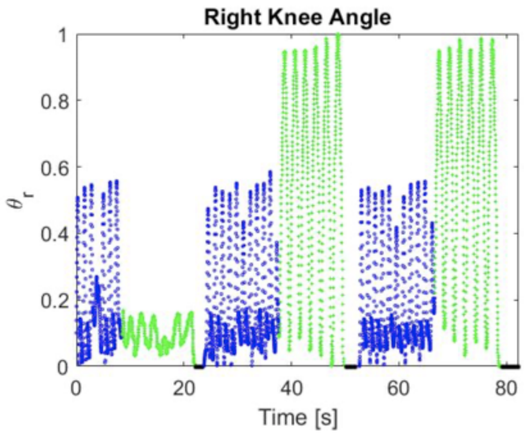
$$\gamma = \frac{1}{\#features}$$

$$K(x_i, x_j) = e^{-\gamma||x_i - x_j||^2} \tag{6.4}$$

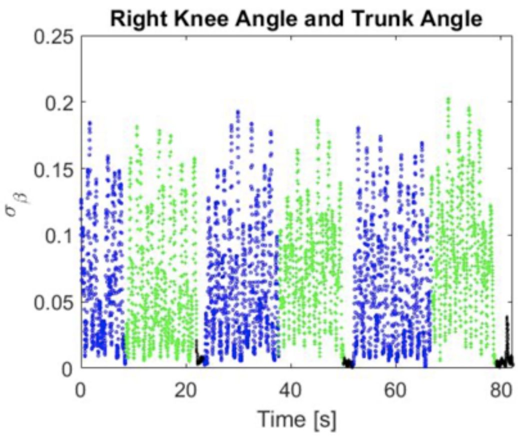
The SVM was trained using Matlab software. Accuracy (ρ), was selected as a first index to compare the performance between the two different classifiers. Confusion Matrices (CM) can provide a more detailed understanding of the classifier performance. Each CM row represents the predicted output, whereas the columns represent the true classes. Precision (μ) and recall (ν) represent the percentage of all the examples correctly predicted to belong to each class and the percentage of all the examples belonging to each class that are correctly classified, respectively (Powers (2011)).



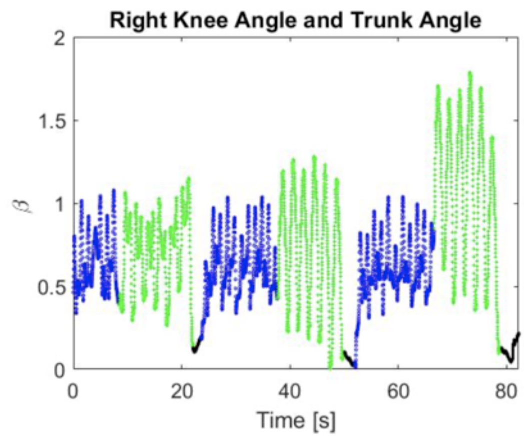
(a) Example of σ_{θ_d} distribution.



(b) Example of θ_d distribution.



(c) Example of σ_{θ_β} distribution.



(d) Example of θ_β distribution.

Figure 6.3 In the figure the kinematic variables corresponding to walking (blue circles), bending (green crosses) and standing (black diamonds) for subject 2 are reported. These data come from session *B* where the user was required to perform the following sequence: walk, stoop, walk, squat, walk, freestyle. Each activity separated by a standing phase.

6.2 Results

The classifier $svm(x|y)_a$ outscores $svm(x|y)_n$ in terms of accuracy, with an average accuracy increase of 21.06%, as reported in Table 6.1. Focusing only on the best classifier, Table 6.2 summarizes its performance by means of the CM.

Walking and bending present good results for all the four considered sessions. Indeed, μ values are above 90% in all cases. Recall is always above 90% apart from two cases where it drops down to

Table 6.1 Classification accuracy results

	$svm(A\|A)$	$svm(A+B\|A+B)$	$svm(B\|B)$	$svm(A\|B)$
ρ_n	71.08%	69.92%	74.41%	64.83%
ρ_a	92.01%	90.95%	93.78%	87.73%

Table 6.2 Confusion matrices

$svm(A|A)_a$

	W	**B**	**S**	Precision (μ)
W	2561	29	0	98%
B	354	4377	115	90%
S	0	0	0	0%
Recall (ν)	88%	99%	0%	

$svm(B|B)_a$

	W	**B**	**S**	Precision (μ)
W	7131	227	0	97%
B	421	9393	166	94%
S	259	467	4491	86%
Recall (ν)	91%	93%	96%	

$svm(A+B|A+B)_a$

	W	**B**	**S**	Precision (μ)
W	9778	288	0	97%
B	606	13325	223	94%
S	342	880	4549	79%
Recall (ν)	91%	92%	95%	

$svm(A|B)_a$

	W	**B**	**S**	Precision (μ)
W	2693	175	0	94%
B	154	3829	79	94%
S	68	402	36	7%
Recall (ν)	92%	87%	31%	

87% and 88%. Considering standing, ν is always higher than μ and $svm(A|B)_a$ and $svm(A|A)$ present apparently bad results, as discussed in the next section. Finally, it is possible to note that the classifiers involving session A are characterized by worse performance with respect to $svm(B|B)_a$.

6.3 Discussion

From the point of view of feature selection, x_a carries more information with respect to x_n, as reflected by the accuracy results. This was quite expected considering that θ_l is the same as θ_r, just with a phase delay. Moreover, while x_n focuses only on the punctual value of the variables, x_a also takes into account their evolution, by introducing the evaluation of the moving standard deviation. Considering that a window of $w = 15$ samples was used, it has to be taken into account that the algorithm has a $250ms$ estimation delay. Further tests are needed to understand whether users accept or not this delay.

Secondly, it emerges that the classifier performance are better related to session B. Indeed, while precision values for walking are, as expected, comparable, $svm(B|B)_a$ has bending precision value that is 4% higher than $svm(A|A)_a$, even considering that the bending style in session B was more varying. Recall values for walking are almost comparable, but for bending, $svm(A|A)_a$ has a 6% higher value. This can be justified by the fact that bending style is just one and, therefore, easier to recognize. These are very interesting results, since they can be used to design new testing scenarios based on the protocol of session B, rather than session A. Concerning standing, it is possible to understand how the first protocol is too unbalanced and, therefore, standing classification becomes very difficult. Better results are obtained with the second protocol, suggesting, once again, to use for further developments this protocol.

Third, from the results analysis, when testing and training are performed on the same subjects, the results are better, i.e., $svm(A|A)_a$, $svm(B|B)_a$ and $svm(A+B|A+B)_a$ present a better outcome than $svm(A|B)_a$. However, analysing walking and bending the result is very positive also for the last classifier, considering that training was performed on 4 subjects and testing on 6 different ones. Moreover, the standing low values of precision and recall for $svm(A|B)_a$ ($\mu = 7\%$ and $\nu = 31\%$) are probably related to the experimental protocol. Indeed, while training is performed on Session B where standing represents 20.87% of the data, in the testing data (session A) only 1.55% of the samples represent standing.

Fourth, the trained classifiers work independently from the exoskeleton architecture, require to use only an IMU on the trunk and sensors to measure knee angles. These measures could be retrieved using IMUs on both lower and upper legs or introducing soft sensors like those proposed in Totaro et al. (2017), where sensorized knee pads could be integrated in the user's working suit. A recent work has shown that it is possible to optimize the set of IMUs used for activity classification, relying on Deep Learning techniques, Porta et al. (2021). In the work presented in this chapter, however, rather than optimizing the IMUs set, it was chosen to rely on those sensors that could allow for a satisfying hand-crafting of the features. An additional remark is that testing is performed on different bending

Table 6.3 Confusion matrix for $svm(x|y)_a$ considering quasi-passive exoskeletons

$svm(A|B)_a$

	W	**B/S**	Precision (μ)
W	2693	175	94%
B/S	222	4346	95%
Recall (ν)	92%	96%	

$svm(B|B)_a$

	W	**B/S**	Precision (μ)
W	7131	227	97%
B/S	680	14517	96%
Recall (ν)	91%	98%	

techniques and that performances are expected to improve if focusing only on freestyle bending, as in Chen et al. (2018).

From the exoskeleton control point of view, as discussed many times, HAR is fundamental to determine when to start or stop delivering assistance. Based on the exoskeleton actuation architecture (quasi-passive or active), in the following sections further considerations are reported.

6.3.1 Quasi-Passive Exoskeleton Control

Considering a quasi-passive exoskeleton where the active elements are used only to engage or disengage the passive actuators, the distinction between standing and bending is not so relevant. Indeed, as many examples in literature show, if the exoskeleton wearer is standing, no force is exerted by the device since there is no elastic/spring elongation (Abdoli-e et al. (2006), Imamura et al. (2011), Lamers et al. (2017)). The actuators are only elongated when walking or bending. This means that, as an example, the confusion matrix of $svm(A|B)_a$ and $svm(B|B)_a$ would become as the ones in Table 6.3, where both precision and recall improve. From the studies conducted in Baltrusch et al. (2018), it is important to provide a tool for switching off passive actuators when walking. Therefore, analyzing the tasks performed, if walking is misclassified with bending/standing this will reduce user comfort wearing the exoskeleton, whereas misclassifying bending/standing with walking means that assistance is switched off when needed. Defining the first error as *type-I* and the second as *type-II*, Table 6.3 reports that the 5% of type-II error is more relevant than the 6% type-I error, for $svm(A|B)_a$. A possible solution to deal with type-II error is to introduce some inertia in the switching, i.e., switching from an assistive state to one without assistance only after a given number of consecutive predictions.

6.3.2 Active Exoskeleton Control

Of course, for active control, it is important to distinguish also between standing and bending. This is due to the fact that, since motors are involved, it is possible to provide assistance even though the user is not bent. As an example, it is possible to consider the consequences of an accidental contraction of one of the muscles driving EMG based controllers (as that proposed in Kawai et al. (2004) and in Toxiri et al. (2018a)) when the user is standing and taking a rest. One possible consequence could be the delivery of impulsive torques that could seriously affect the device acceptance. Moreover, introducing inertia, as discussed for quasi-passive exoskeletons, could affect the timing of the assistive torques that, being provided by active actuators, are generally bigger than in quasi-passive devices. Therefore, if user's motion and exoskeleton assistance are not properly synchronized, also this could negatively impact user acceptance. An alternative solution could be to train the data based only on subject specific trials. Indeed, in doing so, preliminary analysis show an accuracy increase of more than 2% with respect to Table 6.1 and, also, misclassification errors reduction. Once again, it can be stressed that in industrial applications, bending and lifting occur with a user-specific style. Therefore, training and testing the SVM based on the user style is expected to improve the performance.

6.4 Conclusions on Training a SVM classifier

To perform the classification of standing, walking and bending, a *SVM* classifier was trained and tested. In order to decide which features to select, 10 healthy subjects were asked to wear a $3D$ motion tracking wearable system (Xsens) and perform walking and bending. Additionally, the users were divided into two groups and had to follow precise instructions according to the associated protocol. These instructions concerned lifting style and activities separation by means of standing phases. Data collection showed that using knee and trunk features works well even for different bending styles. From the protocol point of view, it is possible to conclude that session B better approximates an actual scenario and has very good performance ($\rho = 93.78\%$, $\mu = 97\%, 94\%, 87\%$ and $\nu = 91\%, 93\%, 96\%$ for walking, bending and standing, respectively). To verify how good the classifier is with respect to unseen data, it was also tested on subjects completely different from the training ones ($svm(A|B)_a$). The discussion focused also on how these results are expected to impact active or quasi-passive devices control.

The study presented in the following describes how the classifier performance change when implementing it on a specific exoskeleton architecture (XoTrunk). As a preliminary assessment, only a subject is tested. In particular, to perform online recognition a faster system is needed and, therefore, only exoskeleton embedded sensors are used, increasing the sampling frequency from $60Hz$ to $100Hz$. Section 6.5 presents how the previous algorithm is modified, Section 6.6 briefly summarizes the data collection and the experimental protocol for training and testing the new classifier. Results are presented and discussed in Section 6.7 and Section 6.8. Eventually, Section 6.9 concludes this chapter.

6.5 Feature Selection and SVM Training for Online Classification

The previous algorithm, presented in Poliero et al. (2019a), is modified by using sensors that are already used in the exoskeleton control, by adopting a smaller window of samples ($w = 10$, instead of 15) and by resorting to a higher sampling frequency ($f = 100Hz$, instead of $60Hz$). This is expected to deteriorate the classification performances and, so, the opportunity of introducing an additional feature is investigated. Equation (6.5) defines the two sets of features that have been used in this study. $\vec{x}_{noMyo}$ has the same number of features as $\vec{x}_a$, defined in eq. (6.1). However, there is a major change: instead of using the difference of the knee angles (θ_d) the hip angles difference (ξ_d) is considered. This is because XoTrunk does not offer sensors to measure the knee angles, whereas relative encoders readings are available from its actuation units on the hips. Also the second feature changes, since it is no more related to the sum of right knee and trunk pitch, but, instead, to the sum of right hip and trunk pitch angle (α). In the second set of features $\vec{x}_{Myo}$, the sum of eight rectified surface EMGs (Σ) acquired by the Myo armband is included. All the features are normalized between $[-1,+1]$, dividing the data by its uniform norm $||x||_\infty$. Maximum values were acquired during the normalization phase presented in Section 6.6.2.

$$\begin{cases} \vec{x}_{noMyo} = & [\sigma_{\xi_d}, \sigma_\alpha, \ddot{\Theta}_x, \ddot{\Theta}_y, \ddot{\Theta}_z] \\ \vec{x}_{Myo} = & [\sigma_{\xi_d}, \sigma_\alpha, \ddot{\Theta}_x, \ddot{\Theta}_y, \ddot{\Theta}_z, \Sigma] \end{cases} \tag{6.5}$$

The same kernel function defined in eq (6.3) and the same convention

$$\gamma = \frac{1}{\#features}$$

were chosen (see eq (6.4)). The SVM was trained using the *Libsvm* software (Chang and Lin (2011)) that had been integrated in the exoskeleton single-board computer. Finally, accuracy (ρ), precision (μ) and recall (ν) were studied to compare these results with those obtained in Poliero et al. (2019a).

6.6 Materials and Method

In the following, data collection and the experimental protocol for training and testing the new classifier are presented.

6.6.1 Experimental Set-up

The experimental set-up consisted of a 10kg box and the XoTrunk prototype. At the time of the experiments, the development of XoTrunk was at an earlier stage than what presented in Chapter 3. Particular differences are the weight and that the actuation unit were assembled including relative encoders for measuring hip angle. The exoskeleton prototype is pictured in Figure 6.4. This exoskeleton is a modification of the trunk module developed within the framework of the EU project *Robo-Mate*[1]

[1] http://www.robo-mate.eu

and presented in Toxiri et al. (2018a). The device overall weight is $11Kg$. For the whole experiment duration, the exoskeleton was in *transparent* mode, meaning that the control gains in eq. (3.1) are set to zero. In such way, the exoskeleton is controlled to provide null interaction torques between the wearer and itself.

Figure 6.4 The Robo-mate mk2b prototype is an intermediate version of the evolution from the Robo-Mate prototype to XoTrunk, as presented in Chapter 3.

6.6.2 Experimental Protocol

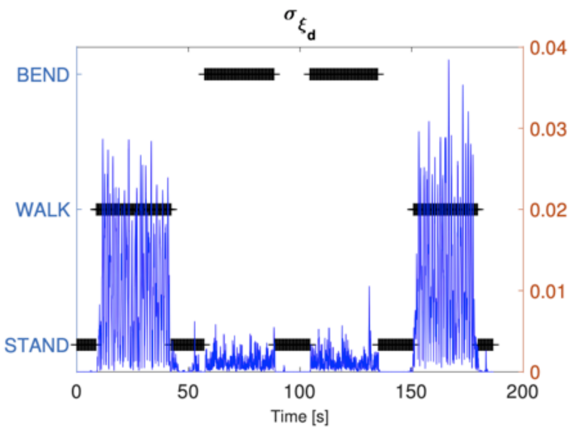
The test subject was given instructions to perform three different activities. As in Poliero et al. (2019a), those were *walking*, *standing* and *bending*, since they are considered representative of the tasks a worker might perform while performing manual material handling. The test was divided into two phases: *training* and *testing*. During the first phase the subject was instructed to concatenate a specific sequence of tasks:

- *walk (W)*. The subject was required to walk from point A to a point B, roundtrip. How to reach point B and, then, A was not specified. Therefore the user could follow a straight path, a curvy one or a mix of them. The two points were located 3.60m one from the other.
- *bend (B)*. The subject had to perform the same bending sequence defined in Poliero et al. (2019a). This routine consists in bending towards the 10kg box, starting from an upright position, grasping it, rising it returning to upright position, then lowering it, releasing it and, finally, returning to upright position. The user was asked to adopt a freestyle bending (Burgess-Limerick (2003)).
- *stand (S)*. The user was asked to stand upright, as close as possible to a relaxed posture.

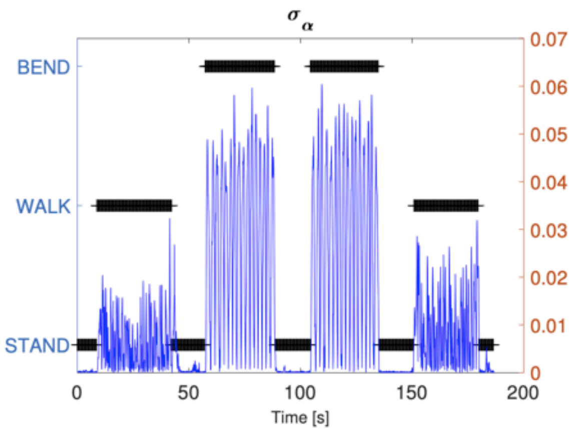
During training, the subject executed the following sequence of tasks: W (x4), B (x4), B (x4), W (x3). Each of these activities was separated by standing phases (S). In testing phase, the sequence was B (x3), W (x5), B (x4), W (x3), again separated by standing (S). The examiner manually assigned labels, by means of keyboard input, that were used to perform the training. Instead, during testing, labels were used as a ground truth to compare the online classification result. One final remark is that, before this protocol was run, the subject followed a brief ($\sim 10s$) phase of normalization in which the requirement was to take a few steps, squat twice and contract the arm wearing the Myo armband.

6.7 Results

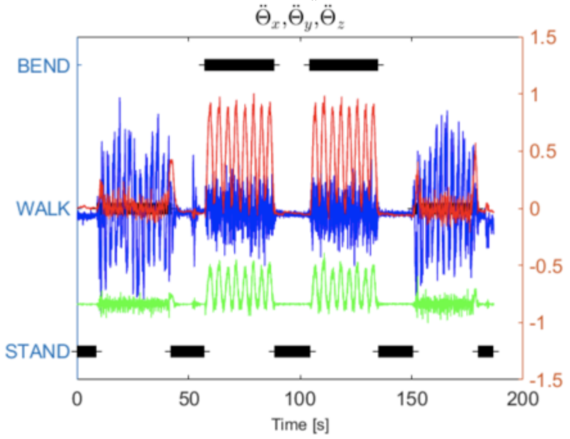
Figure 6.5 represents how the main features varied across the execution of the training phase. For the



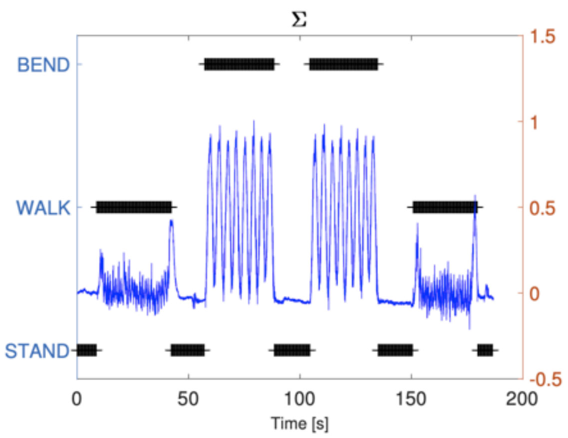
(a) Example of θ_{ξ_d} distribution.



(b) Example of θ_α distribution.



(c) Example of $\ddot{\Theta}$ distribution.



(d) Example of Σ distribution.

Figure 6.5 This figure displays in blue the time plot of the considered features ($\vec{x}_{Myo}$) and how they change according to the activity. Black crosses identify the training label (either bend, walk or stand). In (c) the blue plot represents the trunk acceleration along the x direction, while the y and z direction are reported in green and red, respectively.

Table 6.4 Training Classification accuracy results

	ρ
$\vec{x}_{noMyo}$	80.87%
$\vec{x}_{Myo}$	89.99%

Table 6.5 Training Confusion matrices

$\vec{x}_{noMyo}$

	W	**B**	**S**	μ
W	4040	368	57	90.46%
B	384	5051	163	90.23%
S	1833	767	6022	69.84%
ν	64.51%	81.65%	96.48%	

$\vec{x}_{Myo}$

	W	**B**	**S**	μ
W	5722	720	295	84.93%
B	324	5287	150	91.77%
S	201	179	5797	93.85%
ν	91.60%	85.47%	92.87%	

first feature (Figure 6.5a), the highest values of the moving standard deviation are given by walking tasks. Bending produces a quite low output, while during standing the moving standard deviation is zero or close to it. Considering the second feature (Figure 6.5b), both the trunk and hip angle increase - during bending - and this produces a much higher variation than walking or standing.
Trunk accelerations are mostly stable when the subject is standing, while bending and walking result in significant variations (Figure 6.5c). Finally, it is possible to note that the muscular activity of the subject changes significantly when grasping the box (Figure 6.5d). Table 6.4 reports values of the accuracy comparing the two set of features and Table 6.5 summarizes precision (μ) and recall (ν) values. The introduction of the Myo based feature (Σ) helps increasing both accuracy ($+9.12\%$), bending and standing precision ($+1.54$ and $+24.01\%$, respectively) and walking and bending recall ($+27.09$ and $+3.82\%$, respectively). However, the walking accuracy and the standing recall decrease (-5.53% and -3.61%, respectively). Figure 6.6 reports the online classification provided by the *SVM* trained based on the training data. The accuracy of the testing-data online classification is $\rho = 81.72\%$ and Table 6.6 resumes the online classification performance.

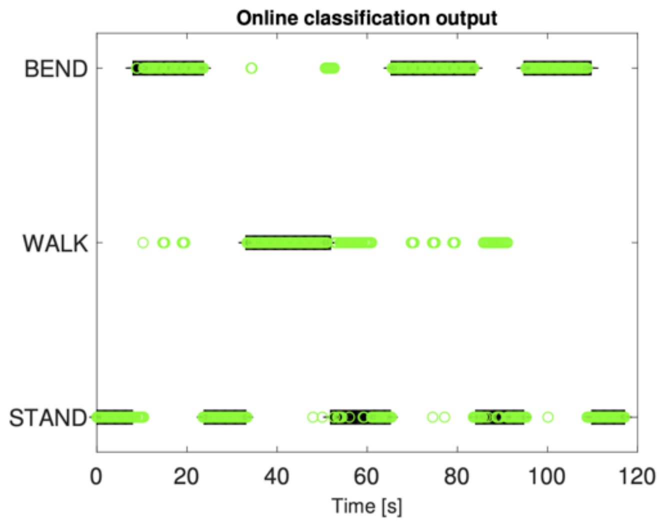


Figure 6.6 Time series plot of the online classification. Green circles represent the prediction while black crosses represent the true label.

Table 6.6 Testing Confusion matrices

	$\vec{x}_{Myo}$			
	W	**B**	**S**	μ
W	1731	308	1189	53.62%
B	103	4236	80	95.86%
S	45	418	3616	88.65%
ν	92.12%	85.37%	74.02%	

6.8 Discussion

In the following, it is discussed how this work proves the feasibility of online classification exploiting exoskeleton embedded sensors. Therefore, as a consequence of a faster and more reliable system, a new control architecture can be implemented.

6.8.1 Online classification

The increase in the sampling frequency, together with the reduction of the window over which the moving standard deviation (σ) is computed, implies that the features are computed over a window of 100ms instead of the previous 250ms. This improves the response time of the system by a 2.5 factor and should, also, increases the user acceptance to the system, since the delay in the classification is low.

6.8.2 Classification reliability

As expected, to obtain a satisfactory level of training accuracy in a faster system, it is necessary to increase the features vector dimensionality. As reported by the accuracy levels, there is evidence that introducing feature Σ helps improving the classification. This result is supported also by the analysis of the confusion matrices. Slightly lower results obtained for standing recall and walking precision are due to the fact that, in the second case ($\vec{x}_{Myo}$), the SVM predicts more walking labels (6737 with respect to 4465, an increase in excess of 50%) and this yields more misclassification.
With regards to the online classification performance, it is clear that the low level of accuracy is strongly influenced by the poor precision in detecting *walking*. This is particularly evident in Figure 6.6 around time $t = 60$s where, for almost 5 seconds *walking* is predicted in place of *standing*. A similar solution occurs at time $t = 80[s]$. As in both cases this misclassification happens when switching from one phase to another, it is reasonable to think that the transition points are not captured well enough by the classifier during training. As a matter of fact, it is possible to improve the SVM training accuracy by varying the parameter γ, defined in the kernel function ϕ. Indeed, setting $\gamma = 2$ or $\gamma = 20$ improves training accuracy up to 92.73% and 95.46%. Nevertheless, considering that the training set is neither large nor representative of many subjects, a low value of γ was selected to prevent overfitting and, therefore, bias all the results.
Given that introducing a new feature seems promising, it is also interesting to understand how further this upgrade can be exploited. Indeed, it emerges that applying some sort of rules it is possible to identify sub-classes starting from the three considered so far. As an example, *carrying* can be detected by understanding whether the user is walking and, if so, whether the muscle activity in the forearm is high or not. Another example is related to discriminating if the user is bending with the load, or not. As shown in Figure 6.7, it is possible to state that if the activity is *bending* and muscle activity is low (below a given threshold), then the user is *lowering without load*. Once the muscle activity rises, it implies that the user is *lifting and lowering with the load* and, once the activity level drops below a given threshold and the activity is, still, *bending*, then the user is *rising with no load*.

6.8.3 New control architecture

The ability of understanding which task the user is performing can help enhancing the exoskeleton versatility. The above presented algorithm has paved the way towards the extension of XoTrunk control from a two-level hierarchy to a three-level one, as presented in Chapter 3. Some further considerations: since motors are torque-controlled, the objective of the mid-level is to define appropriate scaling gains for the signals coming from the human and the exoskeleton. If no high-level is implemented, the gains have to be as generic as possible. For instance, if K_{myo} is too high, it might happen that simply handling or grasping a tool, the user receives very high - and undesired - torques. In addition, in Chapter 5 it was presented how K_{myo} defines the amount of assistance provided during carrying. If this assistance is too high, the gait would be further hindered by the exoskeleton symmetrically

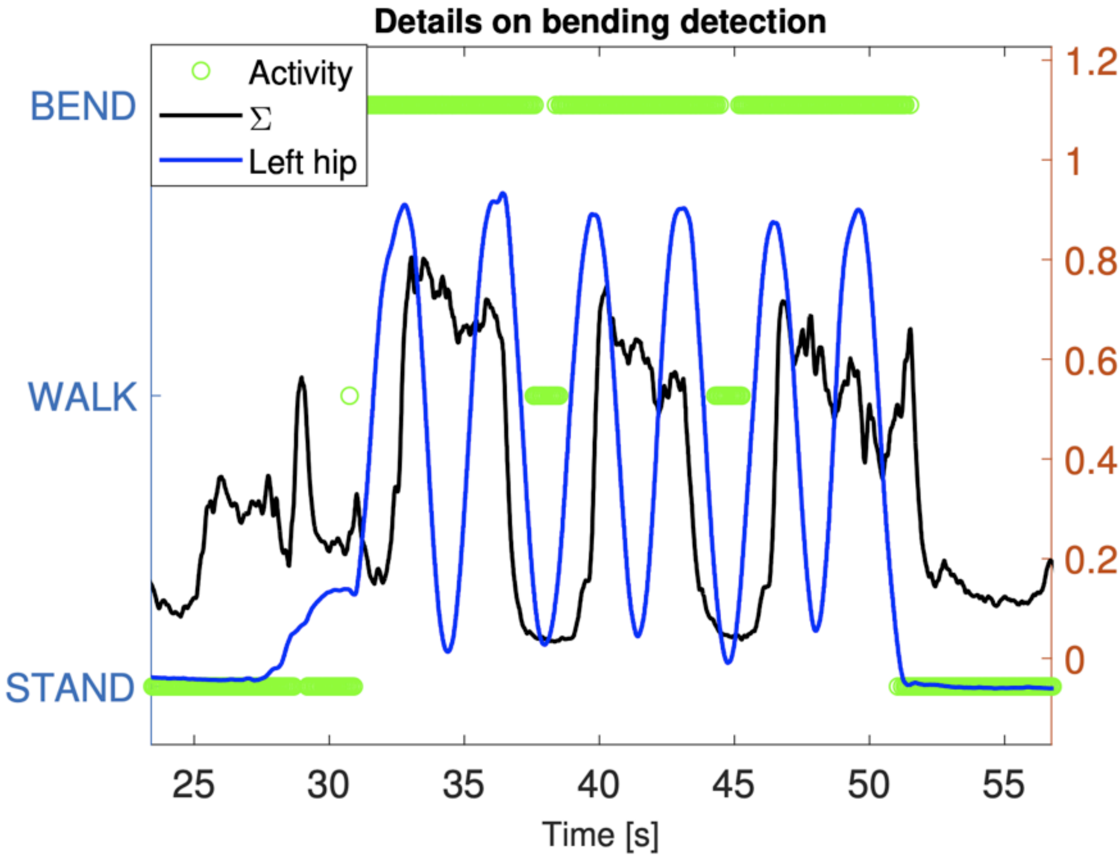


Figure 6.7 Particular of the online classification output, considering forearm muscle activity (black solid line) and left hip angles (blue solid line) during bending. The classified activity is represented by means of green circles.

pushing both hips towards extension. On the contrary, if K_{myo} is too low, the exoskeleton would loose its muscle activity reduction efficacy. This trade-off is removed by inserting a further control level that recognizes the activity. Moreover, this additional layer, as discussed in Part I, allows not only to perform gain tuning, but also to implement completely different control strategies based on the activity. However, if activity recognition is involved in the control, an additional problem, that emerges in the online classification, has to be highlighted. Indeed, there are predictions in which the algorithm produces switches between classification labels that last for very short time intervals (e.g., $20-50ms$). This is clearly an error since there are no meaningful activities that last so little time. However, if not dealt with, this strongly affects the exoskeleton behaviour because it might be required to jump from a transparent mode (e.g., during standing) to a state were motors are engaged and providing assistance (e.g., during bending) and, then, back again to transparent mode. This non ideal behaviour, can be dealt with by introducing an "inertia-rule" in which a transition from a state i to state j occurs if and only if the classifier predicts state j for N consecutive steps. Of course, this yields a prediction delayTherefore, a trade-off between responsiveness to fast transitions and avoiding high-frequency switches has to be found.

6.9 Conclusion

This contribution extends the work presented in Poliero et al. (2019a), showing that it is possible to have an online and reliable activity classifier for the XoTrunk exoskeleton. The classifier is based on Support Vector Machines algorithm and recognizes walking, standing and bending activities. Knowledge of which of these activities is being performed, could be very valuable to the control of quasi-passive exoskeletons (see Section 5.4). Active exoskeletons have the additional possibility of taking specific actions if carrying is recognized. Therefore, in the work presented above, it was shown how the introduction of the forearm muscle activity in the feature vector, not only improved classification performance, but also allowed to discriminate between walking and carrying.

In order to obtain online classification ability, the sampling frequency was increased from $60Hz$ to $100Hz$: the moving window, over which features are computed, reduced from 15 samples to 10, and only exoskeleton embedded sensors were targeted. Satisfactory online performance can be obtained by tuning the Support Vector Machine parameters. However, given that this study was intended to be a preliminary assessment and only one subject was involved, to avoid overfitting and biasing all the results, this tuning was omitted.

Thanks to the obtained results, it is possible to include in XoTrunk a high-level hierarchical controller. This enhances its versatility, shaping the assistance based on the task. Among the limitations of this study it has to be mentioned that the classifier performance was tested only on a single subject and that the exoskeleton was controlled only in transparency mode.

Part III introduces a study that simulates a task seen in a production site, where not only lifting, but also carrying is involved. Moreover, it presents the advantages of exploiting exoskeleton versatility, addressing online switching between control strategies.

Part III

Assessing the benefits and the impact of a versatile exoskeleton

Chapter 7

Exoskeleton versatility assessment

Reviewing the state of the art associated with exoskeleton evaluation (Section 2.3) it was noted how only the efficacy of the exoskeleton is addressed and, most of the times, only considering lifting. *Efficacy* is usually proved by showing the ability of the exoskeletons to reduce the activation of the muscles involved in the task. However, it is also important to understand how the exoskeleton and its wearer move and interact with each other. This type of study is defined *dynamic fit*, Stirling et al. (2020). In Chapter 5 it was shown that the effects of assisting with carrying activities - exploiting the same control strategy employed for lifting - is not ideal, as it restricts the natural gait and does not take full advantage of the exoskeleton potential. Therefore, Part II of this work detailed how, by means of a HAR algorithm it is possible to recognize which activity the user is performing and, consequently, change assistive profile. This chapter presents the effects and the impact that a versatile exoskeleton can have for workers using it. This is assessed via a laboratory testing, simulating the execution of a complex task scenario, as seen in industrial plant visits (Section 7.1). To effectively quantify the advantages of versatility, the study compares the performance of XoTrunk (with and without high-level control) and the quasi-passive exoskeleton Laevo (Section 7.2). Section 7.3 presents how data was collected, processed and which metrics were analysed. Also, to the author's knowledge, for the first time, the exoskeleton control mode changed online according to the classification output. Due to changes in the XoTrunk hardware (motor encoders were removed), it was not possible to use the algorithm developed in Chapter 6. For such reason, a simplified rule-based version of it was developed and used in this assessment. This algorithm is the same that has been used during field testing of the device. Therefore, after the presentation and discussion of the laboratory study results (Section 7.4 and Section 7.5), Section 7.6 reports preliminary findings on the impact that the algorithm had in this field testing. The details of this algorithm are not discussed because of a currently ongoing evaluation of the best way to exploit this IP. Section 7.7 concludes this chapter. As a final remark, preliminary findings of the study presented in this chapter have been accepted for the the PErvasive Technologies

Related to Assistive Environments (PETRA) conference[1], while a more thorough study has been submitted to the special issue *Exoskeletons for Workers* by the Wearable Technologies Journal[2].

7.1 Task Description

An experiment, approved by the Ethics Committee of Liguria (protocol reference number: CER Liguria 001/2019), was conducted on 10 subjects (5 males, 5 females, 1.72 ± 0.1 m height, 67.5 ± 15.7 kg weight, 29.4 ± 4.5 years old and no previous history of back-pain) with no prior experience in back-support exoskeletons usage. Because of the lack of exoskeleton usage experience, an initial familiarization phase - as long as needed for the users to feel confident with the device - was included in the protocol. It took always less than 10 minutes for the test volunteers to become acquainted with the exoskeleton. Following this phase, the subjects were required to simulate the working activity that is performed in a food production site were workers have to lift, carry and unload animal parts that are slippery and not easy to handle. The payload varies in a range between 6 kg and 15 kg. More in particular, the subjects were instructed to perform the following sequence of actions:

1. starting from a standing position, **reach** for a payload (W, 11.4 kg) placed on a surface (B1) at 0.5 m height from the ground;
2. **lift** the payload with self-chosen motion style and turn to an upright posture;
3. **turn** 180° to change direction;
4. **carry** the weight for a 3.5 m distance until a second surface (B2) is reached;
5. **lower** the weight onto B2, at 0.5 m height from the ground;
6. **return** to upright posture;
7. rest in **standing** position.

Sequence $1-2$ are referred to, in the following, as *lifting*, $3-4$ as *carrying*, $5-6$ as *lowering* and 7 as *standing*. Furthermore, the subjects were given 10 s to complete the whole sequence. The rhythm matched that of the actual working operation. The lifted object was a backpack stuffed with foam and payloads, and covered with fabric. This was done in order not to offer evident handling points and, again, to match the industrial scenario. Figure 7.1 summarizes the task description. The task was repeated 10 times for each of the four following conditions, in randomized order:

- *noExo*: subject not wearing the exoskeleton;
- *XoLift*: subject wearing XoTrunk exoskeleton constantly providing assistance;

[1] http://www.petrae.org/index.html
[2] https://www.cambridge.org/core/journals/wearable-technologies

- *XoHar*: subject wearing XoTrunk exoskeleton switching between assistance and transparency, based on HAR;
- *Laevo*: subject wearing the Laevo exoskeleton.

Section 7.3 reports more details about the exoskeletons and the control conditions. No rest phase was planned between each of the 10 task repetitions, so that the faster the *lifting-carrying-lowering* sequence execution, the longer the standing phase duration. Following the10 s interval, the subjects were instructed to start with the successive repetition. On the contrary, 15 minutes of rest were planned between the 4 conditions. During the resting time, the subjects filled-in a custom questionnaire, as detailed in Section 7.3.3. Now, it is important to state that while the task sequence, the execution rhythm and the payload form-factor were selected in order to mimic the industrial scenario, changes were done in the heights, distances and movement constraints to ensure safety of the test volunteers. As an example, the weight was placed on an even surface so that it could be easily reached. In the real scenario, instead, the loads are collected in a sort of tub that requires workers to significantly lean forwards before collection. The weight and the surface heights were double checked by means of the revised NIOSH lifting equations (Waters et al. (1993)). The NIOSH lifting index was 0.81 for males, and 0.99 for females. Being both of these values lower than 1, the task can be marked as safe.

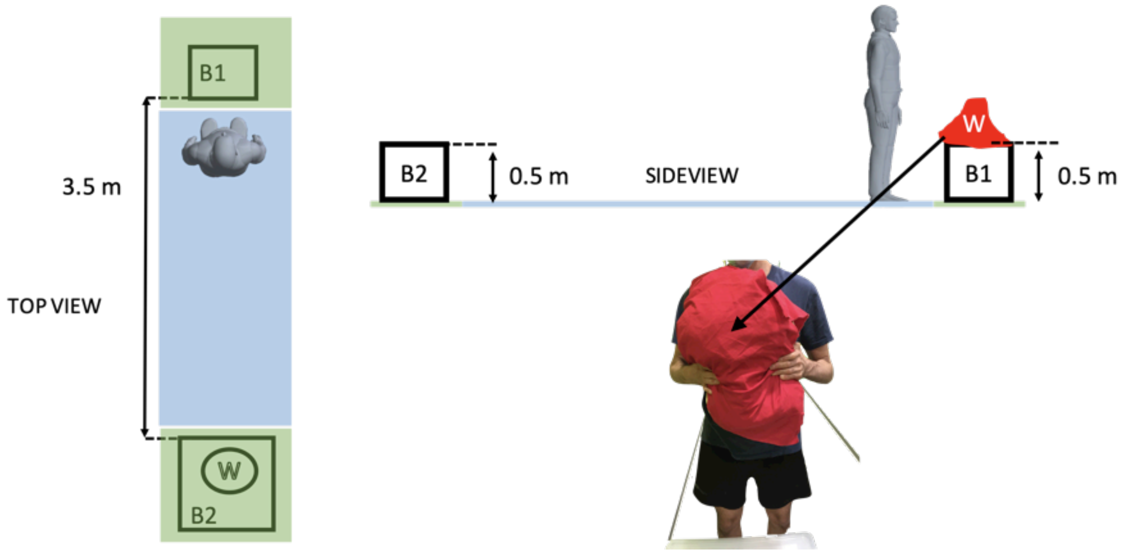


Figure 7.1 Schematic representation of the experimental task. W represents the 11.4 kg weight, B1 and B2 are the two boxes onto which the weight was placed. Carrying task was performed within the light blue area (3.5 m) and lifting in the light green zones. Note that to move from B1 to B2 and viceversa, the subject needs to perform a 180° rotation. At the bottom, the picture shows a subject while holding the load.

7.2 The exoskeletons

Two different exoskeletons were involved in this study: XoTrunk and Laevo v2.5 (see Figure 7.3). The Laevo, a commercially available device, delivers torques, by means of gas springs, according to the profile represented in Figure 7.2. The maximum torque assistance value is 40 Nm. In addition to this, a support-cam can be used to offset the spring-torque profile. In this study, a value of 15° was set. This allows comparison with XoTrunk, as discussed later. Laevo was chosen, also, because its passive elements can be disengaged by means of a manual switch on the device side (see Figure 7.2). As a consequence, during lifting and lowering, the test participants were instructed to always engage the passive elements. On the contrary, during carrying, they could optionally disengage the assistance by means of the switch. This allowed comparing whether the participants preferred manual switching or the automatic one offered by XoTrunk. This latter, was controlled according to two different strategies:

- *XoLift*: only middle and low level of control are used. Thus, regardless of the activity performed, assistance is always computed combining trunk inclination and forearm activity (see Chapter 3).
- *XoHar*: all the three levels of control are used, and, so, the high level recognizes the activity. More in details, if a *lifting* or *lowering* activity is recognized, the exoskeleton provides assistance modulating the output torques via the two lower levels of control, as in *XoLift*. However, if a *carrying* activity is recognized, the exoskeleton enters *transparency* mode. This strategy commands for torques that generate null torque interaction between user and exoskeleton, so that no assistance is provided. As discussed in Poliero et al. (2020a), this strategy is expected not to hinder the natural gait.

For both conditions, the mid-level control strategy was set to

$$\begin{cases} \tau_{exo}(t) = & +sin(\theta(t))K_{IMU} \\ & +\Sigma_{fa}(t)K_{EMG}, \qquad \text{if } \theta(t) > \theta_0 \\ \tau_{exo}(t) = & +\Sigma_{fa}(t)K_{EMG}, \qquad \text{if } \theta(t) \leq \theta_0 \end{cases} \tag{7.1}$$

where K_{IMU} and K_{MYO} were equal to 13 and θ_0 to 15°. This modification, with respect to what defined in Chapter 3, allows unassisted movements for θ_0 degrees if no load is handled. Now, it is worth mentioning for which activity the different conditions are expected to provide the same assistance and for which not. In lifting and in lowering, the control strategy is the same, hence, torque provisions should not change. Of course, changes in the subject's kinematics and delays in the lifting/lowering detection could be sources of differences. The major difference is in carrying: in this task, XoLift provides an extensive torque $\tau_{exo} \leq 13$ Nm per side, whilst XoHar is commanded in transparency.

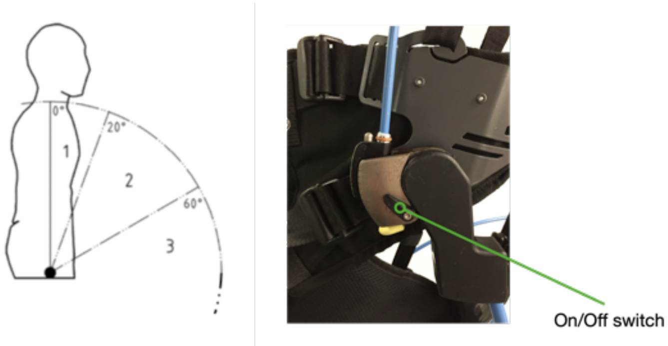


Figure 7.2 Laevo details and working principle. According to trunk flexion, the Laevo exoskeleton delivers a torque between 30 and 40 Nm, as reported in the Laevo v2.56 manual (https://www.laevo-exoskeletons.com/en/manuals). On the right, it is highlighted the position of the switch.

Figure 7.3 Picture of a test subject lifting the load with XoTrunk (left) and Laevo (right).

7.3 Methods

At first, it is worthy recalling why specific metrics can be associated with efficacy or dynamic fit evaluation. Then, how these variables were collected and processed.

7.3.1 Assessment metrics

Efficacy

Back-support exoskeletons have their main effect on the muscles responsible for the back extension, namely the *Erector Spinae* (ES) muscles. Therefore, to evaluate the efficacy of these devices the standard approach is, firstly, to replicate the working scenario in the lab and, then, measure to what extent the exoskeleton usage reduces the activation of these muscles. Common metrics were presented in Chapter 2. In this study, as done in Chapter 4 and Chapter 5, the 90^{th} (P) and the 50^{th} (M) percentile of EMG signal distribution are taken into account. Many studies (de Looze et al. (2016), Grazi et al. (2019)) have assessed the ability of back-support exoskeletons to reduce Erector Spinae (ES) activation during lifting. However, because of their versatility, back-support exoskeletons can have effects also on other relevant MMH activities. This is the reason why, in this study, efficacy is assessed considering not only lifting, but also carrying and lowering tasks. Splitting the bending motion analysis into lifting and lowering is expected to highlight the potential of active and versatile exoskeletons that can modulate assistance accordingly.

Dynamic fit

As introduced in Stirling et al. (2020), dynamic fit is about how the exoskeleton and its wearer move and interact with each other. There are several factors that can be taken into account. Here, the spotlights are on the final user's capability to continue working in a natural way and receive appropriate assistance, according to the task. Therefore in this work, to show how exoskeleton versatility can improve dynamic fit, the following metrics are proposed:

- **Kinematics**: to assess whether workers are experiencing constraints in the movements, a typical metric is the Range of Motion (RoM) of joints like trunk, hip and knee. Moreover, it is worth pointing out that RoMs might be influenced by trajectory changes and, so, also joint angles median values and trajectories should be considered. Finally, the Time required to Complete the Task (TCT) can provide a valuable information on how the exoskeleton interaction is affecting the movements.

- **Intuitiveness and ease of use**: to evaluate these aspects, it should be checked if the exploitation of exoskeleton versatile capabilities is intuitive and easy to use. As an example, requiring the user to manually switch between different control strategies might not be the best solution when performing MMH activities and, thus, automatic switching could be preferred. On the contrary, automatic switching could be worst than manual one, if it is not working properly. Those aspects can be assessed through questionnaires - relying on well established tests like SUS or Nasa TLX or on custom defined ones, Shore et al. (2020), Sposito et al. (2020a).

- **Activity recognition performance**: the first check should be on the device or the user's capability to recognize the activities being performed. Secondly, the assessment should consider how long it takes for the device, or the user, to recognize that a given activity is being performed. Relevant metrics to answer these questions are represented by confusion matrices (CM) that identify precision, recall and accuracy, and the estimation-time delay (ETD).

Versatile exoskeletons are expected to deliver different assistive profiles according to the performed task and, thus, the above mentioned metrics should be evaluated for each of the user activities.

7.3.2 Data collection

As proposed in Section 7.3.1, to assess efficacy sEMG signals were recorded bilaterally at 1KHz sampling frequency from both *Erector Spinae Longissimus* and *Ileocostalis* muscles. The acquisition was done by means of surface electrodes (BTS FREEEMG, BTS Bioengineering, Italy). Electrodes placement was based on SENIAM guidelines [3]. Prior to the task execution start, maximum voluntary contraction (MVC) values for these muscles were acquired.
To assess kinematic metrics, motion data were collected, thanks to a 3D motion tracking system (MTw Awinda, Xsens, The Netherlands), at a 60Hz sampling frequency. To track lower limbs and trunk movements, 8 inertial trackers were placed, respectively, on the sternum, the pelvis, right and left thighs, shanks and feet. Before the task start, a calibration of the inertial system was performed.
For the classification performance evaluation, during the task execution, the experimenter manually performed labelling of the activity carried out by the subject, classifying it as *lifting*, *carrying* or *standing*. To facilitate the manual labelling, the subject was required to spell out each of the performed activities. From the classifier point of view, both lifting and lowering tasks were classified as *lifting*. This choice was related to the fact that the same stategy was used to assist with these activities (see ection 7.3).
Acquisitions of sEMG signals, motion data, manual activity labelling and exoskeleton data were all synchronized.
At the end of each tested condition (excluded the noExo one), the subjects were asked to fill-in a custom 7 anchor Likert-scale questionnaire answering the questions in the following:

Q1 Overall, do you feel less fatigued with respect to the noExo (control) condition?

Q2 Did you feel that the exoskeleton action was constraining/hindering the natural leg movements, with respect to the noExo (control) condition?

[3] http://www.seniam.org/

Q3 Did you feel that the exoskeleton action was providing assistance during the carrying activity?

Q4 Did you feel that the exoskeleton action was constraining/hindering the natural trunk movements, with respect to the noExo (control) condition?

Q5 Did you feel that the exoskeleton action was providing assistance during the lifting activity?

Q6 Is it useful that the exoskeleton automatically recognizes the activity being performed?

Q7 How often would you like to manually set the activity being performed?

Questions $1-6$ were associated with the following anchors: *Totally Disagree*, *Somewhat Disagree*, *Slightly Disagree*, *Neutral*, *Slightly Agree*, *Somewhat Agree*, *Totally Agree*. Question 7, instead, with the following ones: *Never*, *Rarely*, *Seldom*, *Sometimes*, *Occasionally*, *Frequently*, *Always*.

7.3.3 Data Processing

The data processing is divided in two groups: efficacy and dynamic fit.

Efficacy

First, sEMG signals were band-pass filtered ($35-350Hz$), smoothed and rectified in order to extract envelopes, and subsequently normalized with respect to MVC values. Second, the overall lumbar extensor activity was computed averaging the right and left side activity of Iliocostalis and Longissimus Lumborum muscles, as in Poliero et al. (2020a). Therefore, all the efficacy analysis is done with respect to this new variable. Third, the extensor activity was segmented, based on the manual activity labelling, into lifting and carrying. Since each subject performed 10 times the *lifting-carrying-lowering* sequence, at the end of data segmentation, 10 carrying segments and 20 lifting segments were obtained, for each subject. Even though manual labelling did not discriminate between lifting and lowering (as defined in Section 7.1), this was possible taking advantage of how the task was performed. Indeed, each lifting always preceded a lowering. Therefore, all the even sequences labelled as lifting, were actually associated with lowering. Fourth, to consider only steady state carrying, for this task the analysis was limited to data belonging to the $[20\%, 80\%]$ interval of each sequence. Fifth, 90^{th} (P) and 50^{th} (M) percentiles of the EMG signal distribution were calculated for each segmented data. Eventually, these metrics were grouped and averaged according to activity and condition (*noExo*, *XoLift*, *XoHar*, *Laevo*).

Dynamic fit

As seen before, dynamic fit includes several metrics that, for processing purposes, can be divided into three categories: kinematic data, exoskeleton data and subjective data.

Kinematic data The joints under analysis were hip, knee and trunk. The angles of these joints were reconstructed by means of the Xsens system and segmented based on the manual activity labelling performed during the experiment. Again, data segmented as lifting were further discriminated into lifting and lowering. For each carrying segment, the analysis was limited to data belonging to the $[20\%, 80\%]$ interval. Then, RoMs, TCTs and joint median values were computed for each individual phase and, then, averaged according to activity and condition. For the hip nd knee angles, left and right angles were averaged together. Furthermore, based on information about feet contacts with the ground provided by the *XSens* software, hip and knee joint angle profiles related to carrying phases were further segmented into single steps. This procedure was done to extract an average gait profile for each condition.
Finally, TCT were computed as the time each user spent performing a given activity, thanks to the manual labelling.

Exoskeleton data To evaluate activity recognition performance, the classification confusion matrix (CM) was extracted. The manual labelling was taken as the true class, whereas the activity recognized by the exoskeleton as the predicted one. Precision (μ), recall (ν) and accuracy (ρ) were then calculated. For each activity transition, the estimation time delay (ETD) was computed as the difference between the occurrence of a manually labelled transition and the corresponding automatic one. The values obtained for transitions of the same type were, then, averaged. If the automatic transition precedes the manual one, ETD is negative. However, to simplify the analysis, the absolute values of each transition was considered.

Subjective evaluation Subjective data was collected by means of the questionnaire presented in Section 7.3

7.3.4 Statistical Analysis

In this experiment, the same participants are observed under four different conditions yielding a within-subjects study design. For such reason, to investigate whether the changes in means between two paired observations are statistically significant, the paired samples t-test was applied, Altman (1990). This analysis was conducted on the muscle activation metrics comparing only noExo condition with the test ones. For kinematics data, instead, the differences were also tested between exoskeleton conditions.
The questionnaire is based on Likert data that are ordinal, discrete, and have a limited range. This means that data is non-parametric and, so, the Wilcoxon signed rank test was selected. Defining x and y as the vectors collecting the observations of a given metric, under two different conditions (like noExo and XoHar), for both the paired sample t-test and the Wilcoxon signed rank test, the null hypothesis H_0 that $x - y$ comes from a distribution with zero mean is rejected at a significance level set at a standard value of 5%.

7.4 Results

Results are presented first for what concerns efficacy and, then, dynamic fit. Given the amount of presented results, for sake of clarity, punctual discussions are reported right after the result. Overall considerations are, instead, reported in the Discussion section.

7.4.1 Efficacy

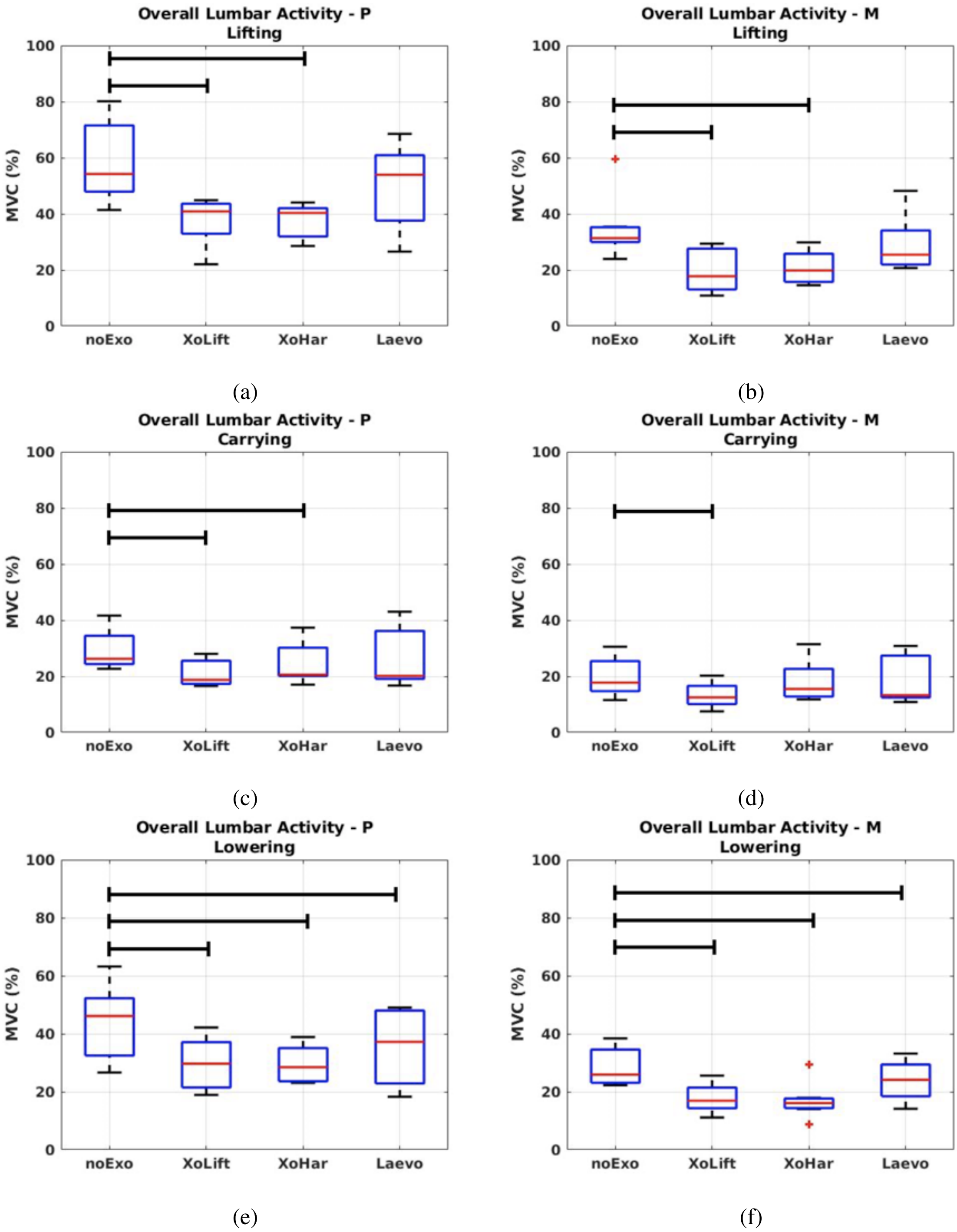
Out of the initial pool of 10 subjects, 3 were excluded. The first due to signal recording issues and the other two as their muscle reductions were around 80%, much more than the expected outcome ($20-30\%$).

Table 7.1 presents the obtained results as variations of the metrics (P and M) in the test conditions (XoLift, XoHar, Laevo) with respect to the noExo one. It is possible to note that for lifting and lowering, there is a big difference between XoTrunk and Laevo. In particular, considering lifting, XoTrunk reduces by an additional 19% considering P and by an additional 25% considering M. In lowering, these values become 10% and 22%, respectively. In carrying, XoHar and Laevo conditions are quite similar (4% difference) and much lower than XoLift, that reduces the muscle intensity by 27% and by 41%, according to the considered metric. This is an expected outcome as, in the two former conditions the exoskeletons are controlled in order not to provide assistance. Nevertheless, XoHar and Laevo yield P reductions by up to 16%. This could be linked with postural changes, namely less pronounced trunk inclinations, suggesting that the backwards push of the exoskeleton in lifting, might help maintaining better carrying postures.

Also, it is very interesting to note how considering M, the differences between XoTrunk and Laevo become more pronounced. This is probably related to the fact that XoTrunk, thanks to its control strategy, can better modulate assistance according to the handled weight.

Figure 7.4 represents the results as boxplots. All the values are normalized with respect to the MVC intensity. In carrying, the muscle activation are around $15-30\%$ of the MVC value, in lowering around $20-40\%$ and in lifting around $30-60\%$. This, once again, stresses how carrying is a relevant task that should not be neglected. Also, investigating the interquartile ranges (the height of the blue rectangles in the figure) it is interesting to point out how noExo and Laevo conditions are more variable than XoLift and XoHar. This might indicate that XoTrunk assistance is more constant across subjects.

Lastly, Table 7.2 reports the p-values of the statistical analysis comparing noExo with the test conditions. Bold values indicate where the null hypothesis was rejected and so, for which conditions the difference was statistically significant. While for XoTrunk, significant differences were found in all activities, for Laevo this happened only in lowering.



(a) (b)

(c) (d)

(e) (f)

Figure 7.4 Boxplot representation of the P (left) and M (right) metrics associated with the overall lumbar activity, during lifting (top), carrying (middle) and lowering (bottom). Red crosses identify outliers. Black segments on the top indicate conditions that reached statistically significant difference.

Table 7.1 Efficacy results

Activity	P			M		
	XoLift	XoHar	Laevo	XoLift	XoHar	Laevo
Lifting	-33%	-33%	-14%	-41%	-38%	-14%
Carrying	-27%	-16%	-12%	-32%	-4%	-8%
Lowering	-29%	-29%	-19%	-37%	-41%	-17%

Table 7.2 Efficacy statistical analysis

Activity	P			M		
	XoLift	XoHar	Laevo	XoLift	XoHar	Laevo
Lifting	**<0.01**	**<0.01**	0.11	**<0.01**	**<0.01**	0.07
Carrying	**<0.01**	**<0.05**	0.13	**<0.01**	0.56	0.28
Lowering	**<0.01**	**<0.01**	**<0.05**	**<0.01**	**<0.01**	**<0.05**

7.4.2 Dynamic fit

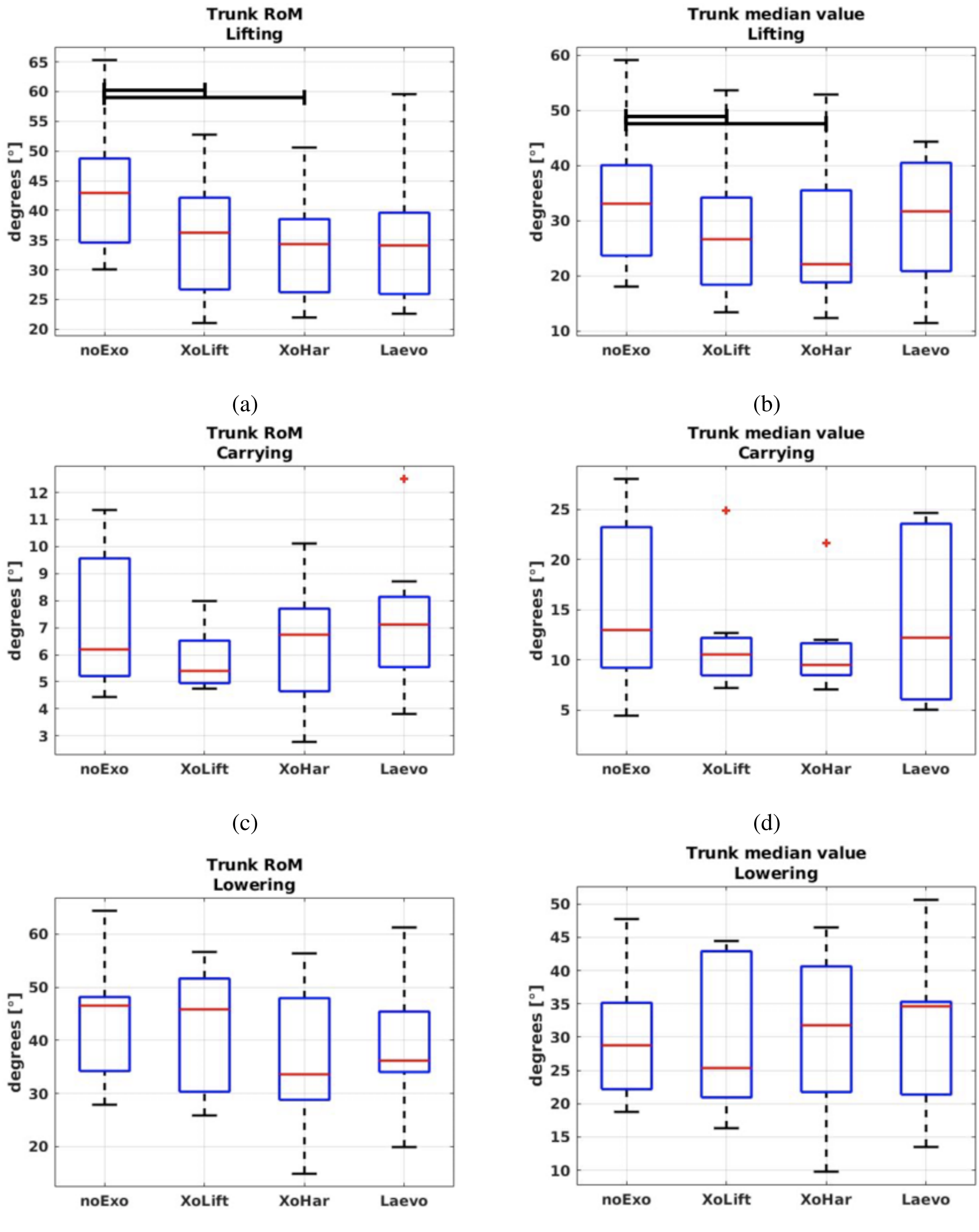
First kinematic data, second classifier performance and third results associated with the subjective questionnaire are presented.

7.4.3 Kinematic Data

Figure 7.5, Figure 7.6 and Figure 7.7 report the boxplot representation of how the trunk, hip and knee joints varied across tasks and conditions. The large interquartile ranges indicates that this data is characterized by high variability, among subjects. As an example, Figure 7.8 depicts how the subjects reacted differently to the analysed conditions. In particular, for subjects 2 and 8 the XoLift condition is associated with the highest hip flexion, whilst for subject 3 and 5 this happens in the noExo condition. Due to this variability, rather than commenting the single metrics values, it is worthy considering general trends.

A first analysis shows that the use of an exoskeleton (either XoTrunk or Laevo) reduces both the RoMs and the median values. Focusing on the trunk, the three activities show interesting results. In lifting, the difference between XoTrunk and noExo condition are always statistically significant and the exoskeleton assistance appears to reduce trunk flexion. Considering Laevo, instead, the posture is less affected and this could partially explain the greater efficacy of XoTrunk (lower flexion, lower muscle activation). In lowering, the data variability appears to be greater than in the other conditions and displays less clear trends. In carrying, even though statistical significance is never reached, it is interesting to point out that when wearing the exoskeletons, not only the trunk RoM decreases, indicating more stability, but also the median value. This implies that, while carrying the load, the

subjects assumed a more ergonomic posture and, thus, confirms the hypothesis made analysing the efficacy.
Together with the trunk, the hips are the joints mostly affected by the exoskeleton. Again, both in lifting and lowering, there is a clear reductive trend for RoMs and median values. This suggests that, thanks to the assistance provided by the devices, the users felt less need of bending. Statistical significance indicates that these trends are common to both devices and can be generalized. During carrying, the expectation was that XoHar would have hindered less the motion with respect to XoLift. This is, slightly, evident by the analysis of the RoMs, that higlights how XoHar is closer to the noExo values and that XoLift is statistically different to noExo. However, as stated in Section 7.3.3, only the RoM information is not sufficient, per se. Indeed, as an example, the same RoMs could be obtained even if the hip trajectory is drastically offset. The information provided by the median values, from this point of view, confirms that XoLift condition offsets the hip trajectories towards negative values, due to the exoskeleton constant delivery of symmetric extensive torques. XoHar, instead, thanks to its transparency mode, appears to be more respectful of the natural gait patterns. Statistical significance further stresses the differences between this two conditions. The last remark is that, in this task, Laevo and XoHar appear to have similar behaviours.
Finally, the knee joint results describe a trend mostly equivalent to what discussed above. In lifting and lowering both RoMs and median values appear to be lower when the exoskeleton is worn. This result is quite unexpected as, a knee RoM increase could have compensated reductions in trunk and hip RoMs. This suggests that, even though users adopted a bending motion with less trunk and hip flexion, they did not compensate by squatting more. Again, this might be due to users grasping the load from a higher height, relying more on the exoskeleton assistance than on their lower limb upwards push.
Overall, while the efficacy analysis showed a clear and evident trend in the data, this is not the case for the kinematic analysis. A further explanation of the large variability in the data could be also explained by the changes in the task speed execution, as reported in Table 7.3. Here it is possible to see that during carrying, both with XoTrunk and Laevo, the execution time increased. The worst condition is represented by XoLift and the best by Laevo. As expected, XoHar appears to be faster than XoLift, suggesting a reduced impairment. Considering lifting and lowering executions, the fastest condition was Laevo, followed by noExo, XoLift and XoHar. Slower execution times associated with XoTrunk, might contribute to the explanation why this device proved to have better efficacy than Laevo. At last, considering standing, Laevo was the condition that allowed for more resting time, confirming the impression that subjects increased the execution speed when wearing this device. As stated before, this could be associated with reduced impairment. Given that standing lasted longer for the XoHar condition than the XoLift one, it is possible to state, as for Laevo, that this is due to reduced impairment. It is worthy pointing out that, also in this case, the executions with XoTrunk were slower than the noExo condition. Figure 7.9 reports the boxplots associated with this metric.



(a) (b)

(c) (d)

(e) (f)

Figure 7.5 Boxplot representation of the RoM (left) and median value metrics associated with the trunk joint angle, during lifting (top), carrying (middle) and lowering (bottom). Red crosses identify outliers. Black segments on the top indicate conditions that reached statistically significant difference.

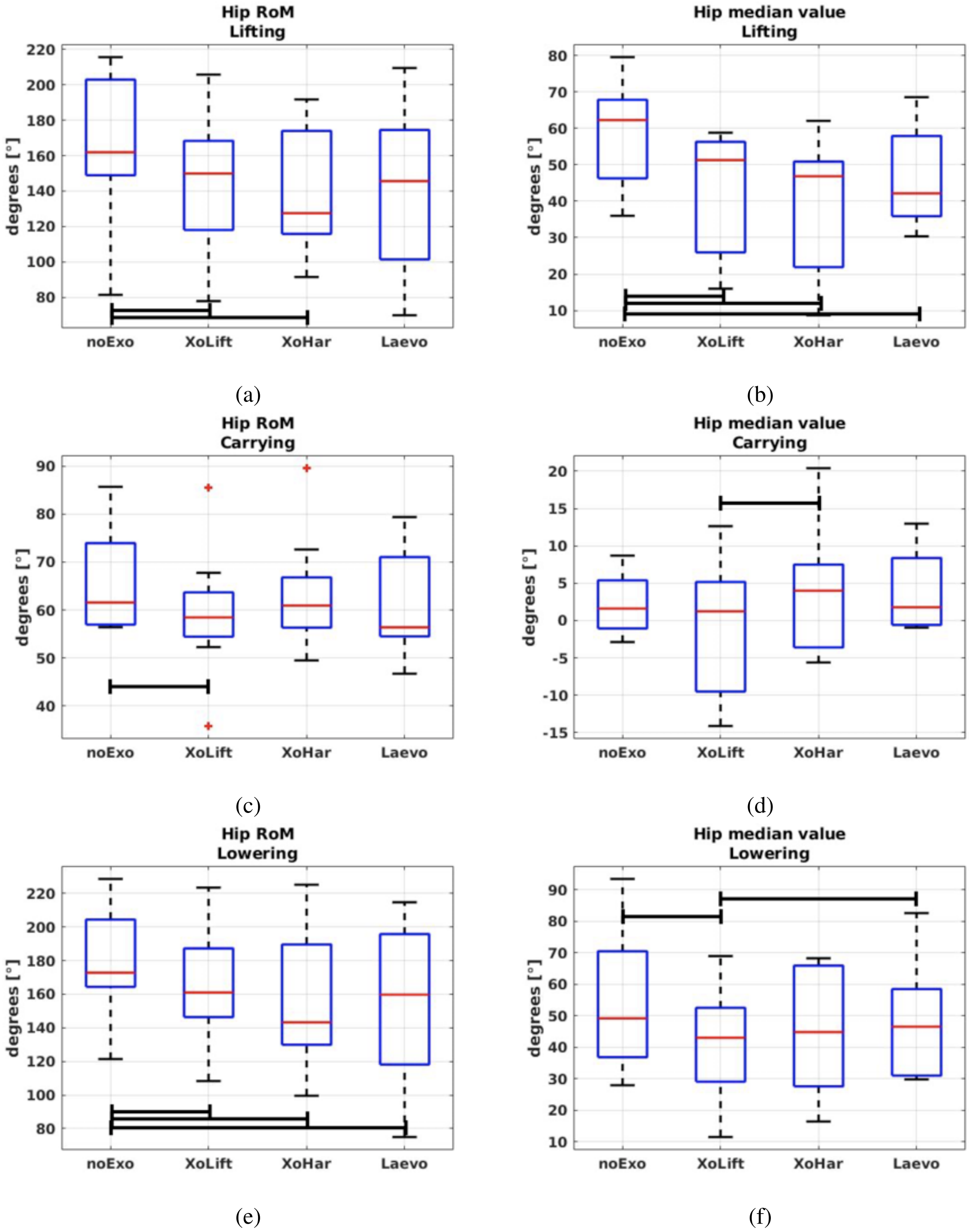


Figure 7.6 Boxplot representation of the RoM (left) and median value metrics associated with the hip joint angle, during lifting (top), carrying (middle) and lowering (bottom). Red crosses identify outliers. Black segments on the top indicate conditions that reached statistically significant difference.

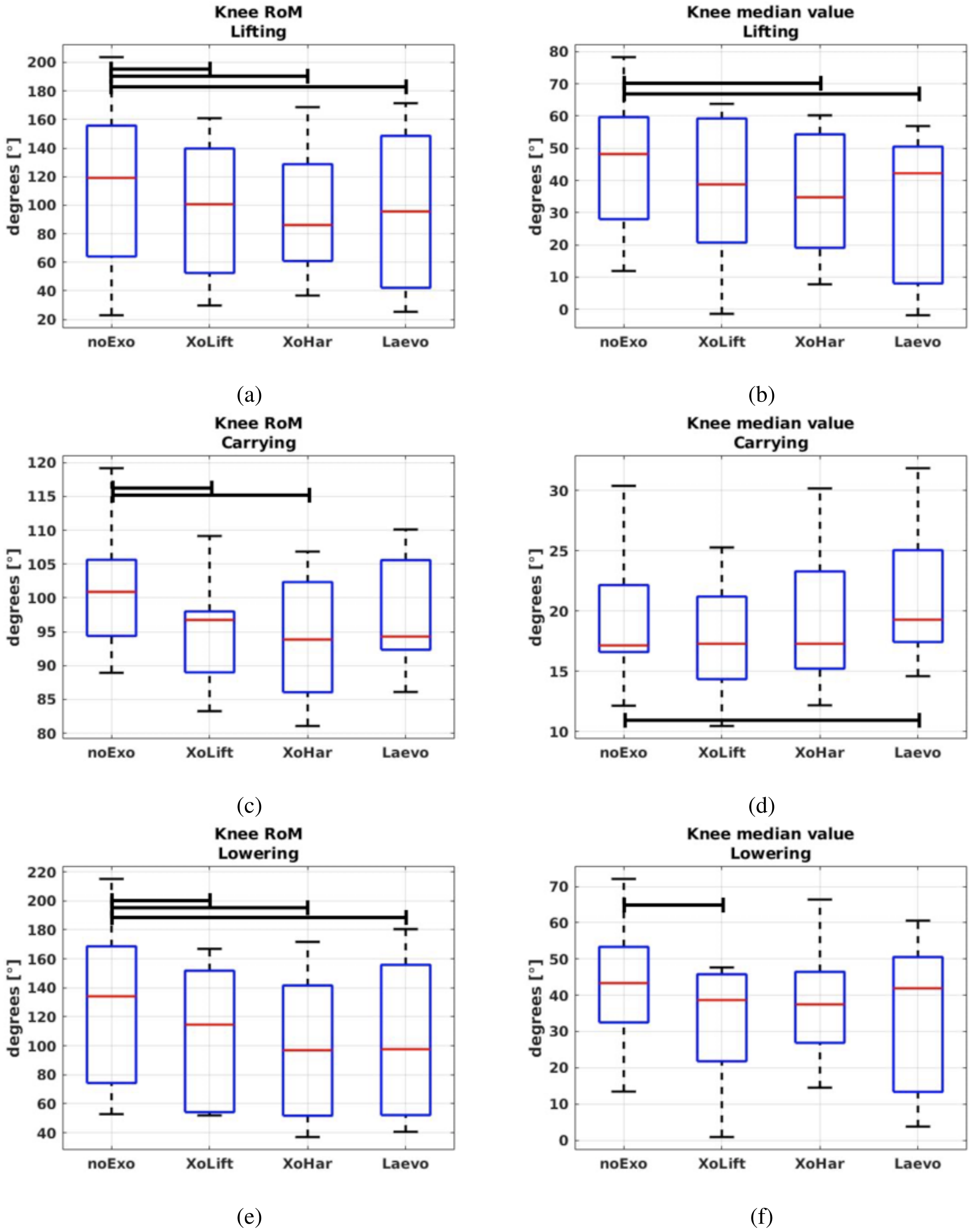
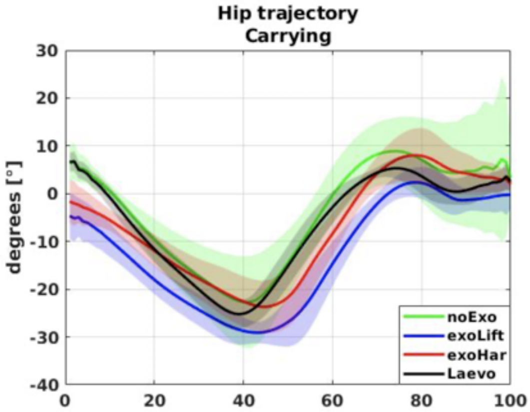
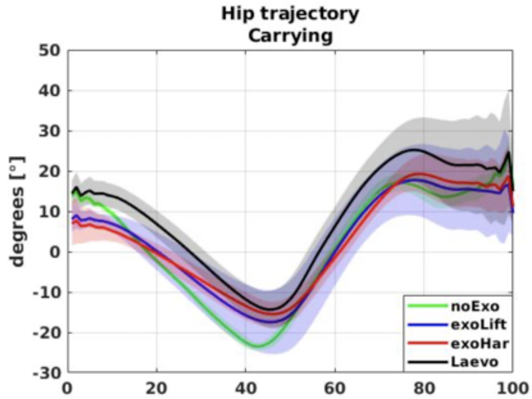


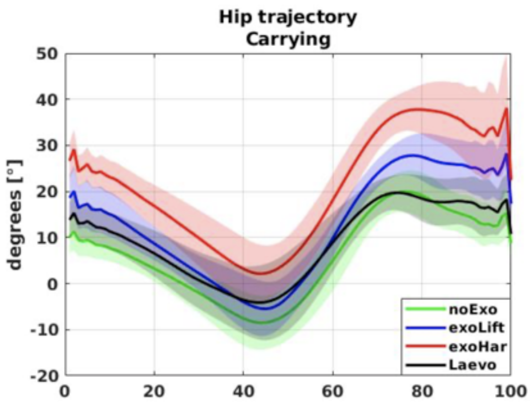
Figure 7.7 Boxplot representation of the RoM (left) and median value metrics associated with the knee joint angle, during lifting (top), carrying (middle) and lowering (bottom). Red crosses identify outliers. Black segments on the top indicate conditions that reached statistically significant difference.



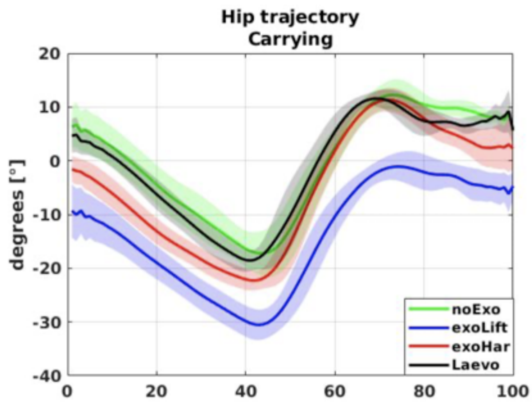
(a) Subject 2



(b) Subject 3



(c) Subject 5



(d) Subject 8

Figure 7.8 Plot of the hip trajectories during carrying for 4 subjects, with respect to the gait phase. 0% corresponds to heel strike and 100% to the successive. Left and right hip trajectories are averaged. noExo condition is represented in green, XoLift in blue, XoHar in red and Laevo in black. Solid lines indicate the mean trajectories, whilst shaded areas indicate the variations.

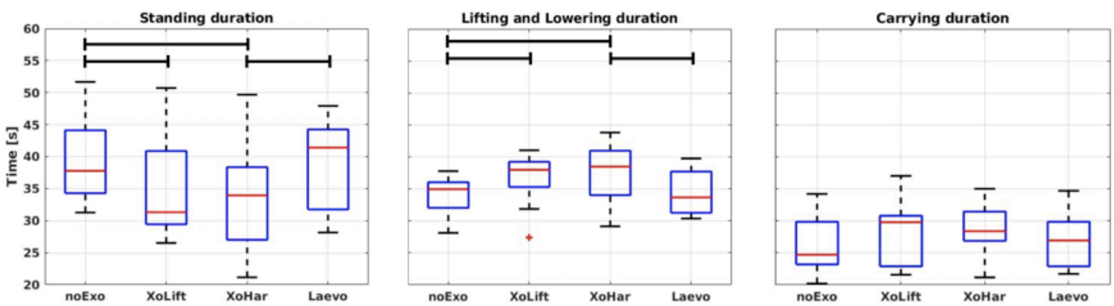


Figure 7.9 Boxplot representation of the total time to complete the 10 repetitions.

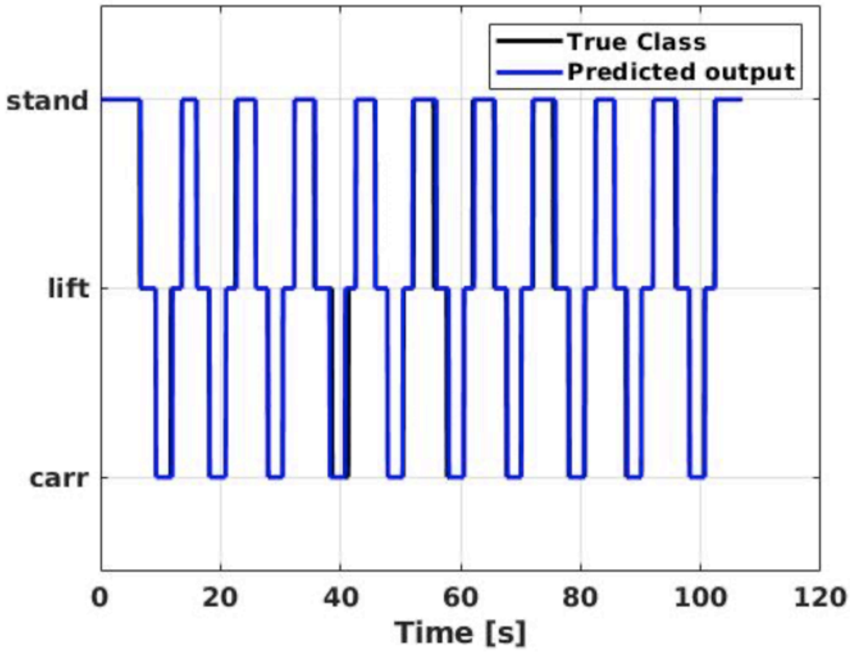
Table 7.3 Median value of the total Time to complete the task (TCT)

Activity	noExo	XoLift	XoHar	Laevo
Standing	37.79 s	31.32 s	33.95 s	41.40 s
Lifting/Lowering	34.96 s	37.98 s	38.49 s	33.67 s
Carrying	24.71 s	29.80 s	28.41 s	26.95 s

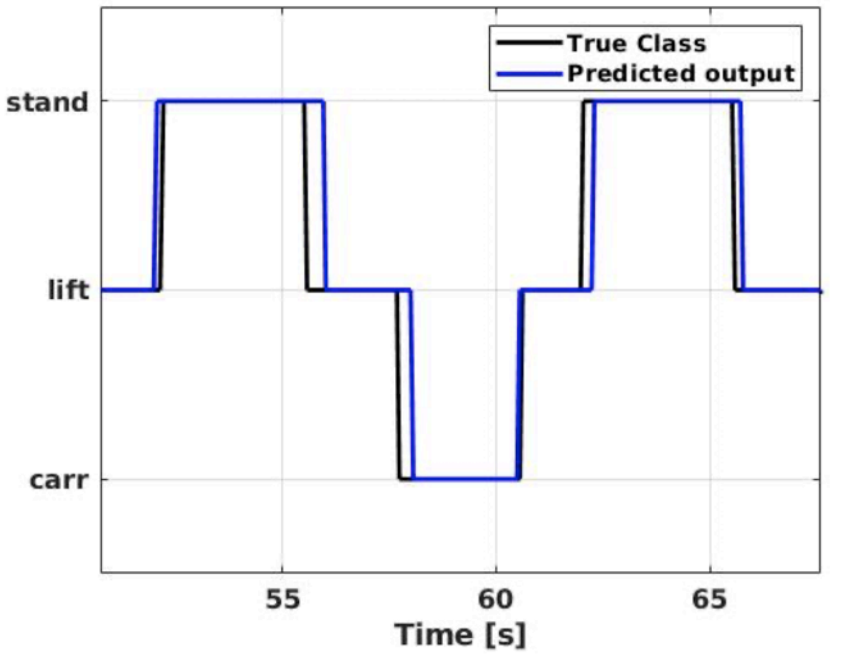
7.4.4 Classifier performance

Considering the task description and, also, the time to complete each task (see Table 7.3), it emerges that the classification problem is well balanced and that, as a consequence, it is important to properly recognize each task. Analysing the Confusion Matrix (CM) reported in Table 7.4, it is possible to extract the classifier performance. The accuracy value, computed analysing the CM diagonal terms, is $\rho = 91.72\%$. Apart from lifting precision ($\mu = 86.95\%$), precision and recall values are always greater than 91%. More in details, when the subjects were performing lifting, the classifier almost misclassified the same amounts of samples (274, corresponding to 6.7% of the total lifting labels and 257, corresponding to the 6.3%), interpreting them as standing or carrying, respectively. This is a problem because, due to wrong activity recognition, the exoskeleton did not deliver the proper torque assistance. However, taking into account the efficacy results (see Table 7.1) this might also explain why XoHar had — considering the 50^{th} percentile of muscle activation — a 4% higher reduction than XoLift. Indeed, not recognizing the start of the lowering activity, might have yield initial unassisted movements, reducing the muscle activation needed to counteract the backward push of the exoskeleton. This was the rationale behind the choice of introducing an initial offset in the assistance but, as shown in eq (7.1), θ_0 did not affect the assistance related to the forearm muscle activity that, in turn, was zeroed by wrong classification. Another element that should be taken into consideration is that the classification errors are not due to completely wrong recognitions (e.g., in standard problems wrongly recognizing a dog picture as a cat), but rather classification delays. As an example, the classification online performance for subject 3 is reported in Figure 7.4. For this particular subject, it appears like the predicted lift→stand transition (LiftStand) sometimes anticipates the true transition ($t \sim 52$ s) and sometimes is delayed ($t \sim 62$ s). The stand→lift (StandLift) transition ($t \sim 56$ s and $t \sim 6$ s) and, slightly, the carr→lift (CarrLift) one ($t \sim 61$ s and $t \sim 61$ s), instead, are delayed, confirming the hypothesis made above on the unassisted initial movements. For more details on the ETD of the classifier, Figure 7.11 reports the Boxplot representation of the average ETDs for all the subjects, calculated without discriminating between anticipations or delays. It is worth pointing out that the CarrLift transition apperars to be the one with less variability among the subjects.

Finally, the presented metrics reflect the reliability of the online classification performance of this classifier, based only on exoskeleton embedded sensors. This, as will be presented in Section 7.6, allowed extensive usage also during field testing.



(a) Subject 3 - total overview of XoHar condition



(b) Subject 3 - particular of XoHar condition

Figure 7.10 Plot of the online classification performance of the classifier, for subject 3. The black line represent the ground truth labelling done manually, whereas the predictions are marked in blue.

Table 7.4 Classifier online performance. Rows represent the true output and columns the predicted output.

	Standing	**Lifting**	**Carrying**	Precision (μ)
Standing	3305	174	9	94.75%
Lifting	274	3539	257	86.95%
Carrying	2	164	2911	94.61%
Recall (ν)	92.29%	91.28%	91.63%	

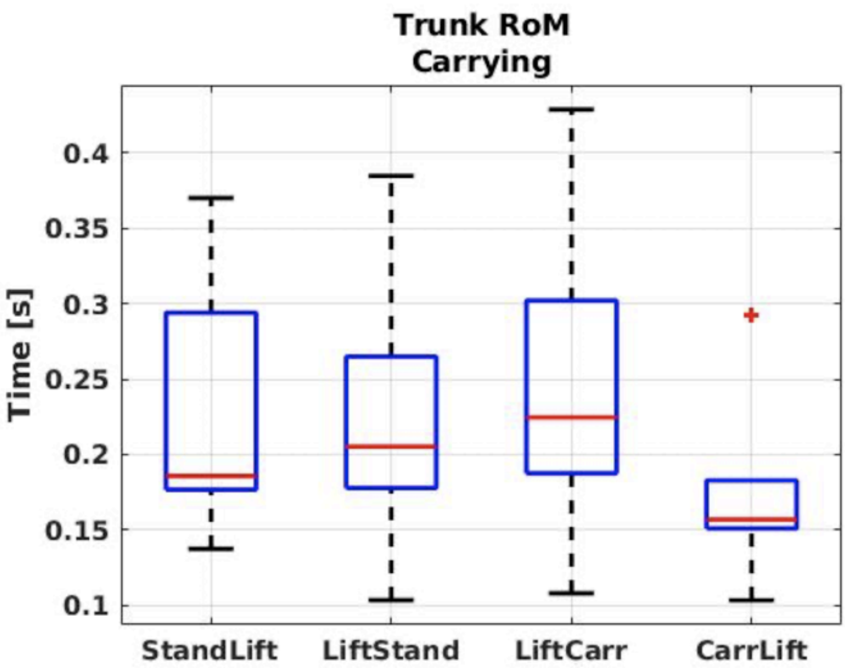


Figure 7.11 Boxplot representation of the classifier ETD for all the subjects.

7.4.5 Subjective questionnaire

The subjective questionnaire analysis, confirms the general trends discussed referring to the kinematic and muscle activity data. The results are reported in Figure 7.12. Q1 confirms that both wearing XoTrunk and Laevo the subjects perceived assistance. In the Laevo case, the most frequent answer was *Slightly Agree* indicating a mild perceived assistance. For XoHar case, instead, the most frequent answer was *Totally Agree*, underlining a stronger perceived assistance. The difference between these latter conditions reached statistical significance.

Q2 investigated whether the test subjects felt that the exoskeleton assistance was hindering the leg movements. Here, as expected, the worst perceptions are associated with XoLift, whereas XoHar is the condition were the users reported less hindrance. The differences between the two conditions reached statistical significance.

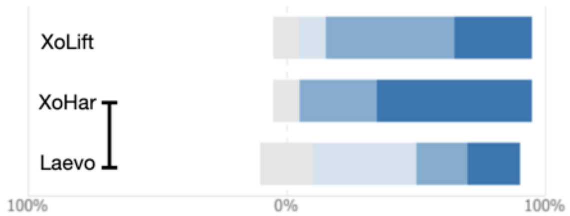
Q3 was related to the assistance that users experienced during the carrying activity. Again, in line with the expectations, XoLift appears to be the condition delivering the highest assistance, while Laevo the lowest. Once more, the differences were statistically significant.

Q4 was on trunk hindrance and there are no significant differences among the three conditions. However, it should be noted that Laevo appears to be the one associated with the least trunk constraints. Additionally, only for XoLift and XoHar, there are occurrences of *Somewhat Agree* and *Slightly Agree*.

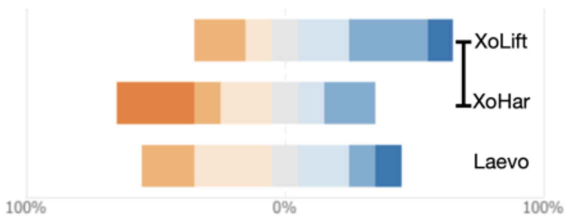
Q5 was about the lifting perceived assistance. In this case, both XoLift and XoHar are statistically different from Laevo, stressing out that XoTrunk was perceived as stronger than the Laevo exoskeleton. Interestingly, while in XoLift and Laevo conditions there are occurrences of *Neutral*, this never happens in the *XoHar* condition.

Q6 and Q7 did not compare different conditions but tested whether the automatic activity recognition is a valuable feature to the users. It appears that none of the test subjects felt that HAR was superfluous and that manually operating a switch is an operation that, if possible, should be avoided. This questionnaire was done after replicating a real working condition scenario and, thus, the findings appear to be encouraging towards an adoption of versatile exoskeletons in the workplace. However, it should not be forgotten that in this study the subjects did not wear the exoskeleton for long time intervals and, so, generalizing these results to the actual industrial scenario is non trivial.

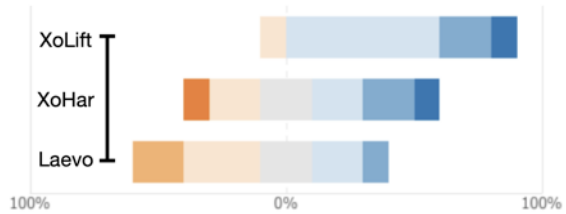
(a) Likert anchors for Q1-Q6



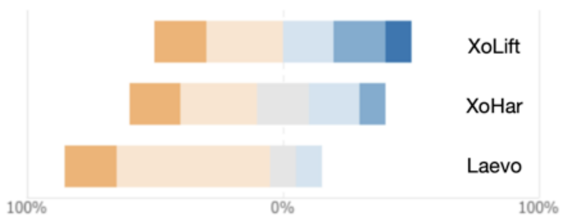
(b) Q1



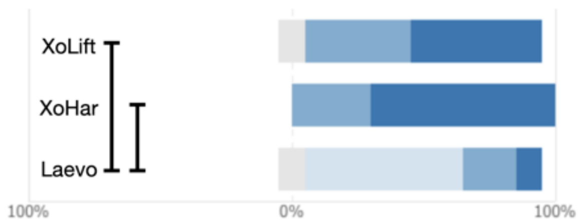
(c) Q2



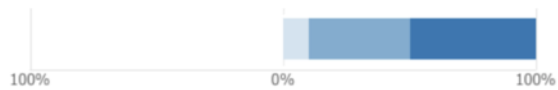
(d) Q3



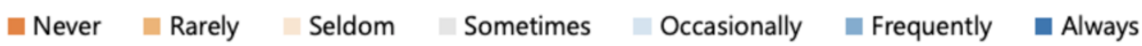
(e) Q4



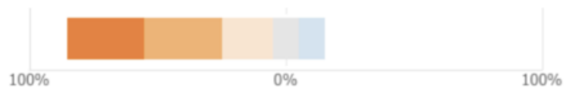
(f) Q5



(g) Q6



(h) Likert anchors for Q7



(i) Q7

Figure 7.12 Questionnaire results. The questions are reported below for an easier interpretation. Vertical segments link conditions where the difference was statistically significant.
Q1: Overall, do you feel less fatigued with respect to the noExo (control) condition?
Q2: Did you feel that the exoskeleton action was constraining/hindering the natural leg movements, with respect to the noExo (control condition)?
Q3: Did you feel that the exoskeleton action was providing assistance during the carrying activity?
Q4: Did you feel that the exoskeleton action was constraining/hindering the natural trunk movements, with respect to the noExo (control condition)?
Q5: Did you feel that the exoskeleton action was providing assistance during the lifting activity?
Q6: Is it useful that the exoskeleton automatically recognizes the activity being performed?
Q7: How often would you like to manually set the activity being performed?

7.5 Discussion

This study was meant to highlight the advantage of exoskeleton versatility, underlying which metrics should be considered when analysing not only the efficacy but also the dynamic fit of a device. Considering the efficacy with respect to lifting and lowering activities, it emerges that XoTrunk yields higher muscle activation reductions than the Laevo (33% vs 14%, 29% vs 19%, cosidering P; 41% vs 14%, 37% vs 17%, considering M, for lifting and lowering, respectively). Versatility, namely XoHar versus XoLift, does not add value in this situation as the mid level control for lifting and lowering is the same. However, interestingly, some of the differences between XoLift and XoHar, especially in lowering, can be explained as an unwanted classification side effect. Indeed, due to delays in the carry→lift transition, the XoHar condition was associated with initially unassisted movements and this, considering the median muscle activation, appears to have had a beneficial effect (41% reduction in XoHar vs 37% reduction in XoLift). Taking carrying into consideration, having chosen different control strategies for XoLift and XoHar, shows the greatest difference due to versatility. Indeed, while the versatile condition (XoHar) did not offer assistance, the XoLift condition showed that exploiting active actuators it is possible to reduce muscle activity, even in non-lifting activities (27% considering P and 32% considering M). This result is different from what found in the previous study presented in Poliero et al. (2020a) and in Chapter 5. Possible explanations might be the different carrying length (3.5 m in this study, 7.5 m in the previous); the payload being in a weight range were, according to the results presented in Poliero et al. (2020a), the exoskeleton was found to have the most beneficial effects; and the inclusion in the task of an initial lifting phase rather than starting directly from an upright posture. This latter modification might have promoted more ergonomic postures. A more detailed comparison between the test protocols should help clarify the differences. Up to this point, taking only in consideration the efficacy, the advantage of versatile exoskeletons does not emerge. On the other hand, this changes once dynamic fit is analysed. Indeed, even though subject to high variability, the kinematic data analysis stresses out that XoHar, with respect to XoLift, is associated with a lower movement hindrance. Furthermore, in this analysis, very good results are obtained by employing the Laevo device, but it should be recalled that the springs were offset in order not to provide assistance for hip flexions lower than 15°. Ideally, in carrying, the only difference between XoHar and Laevo was the device weight (6.5kg XoTrunk vs 2.8kg Laevo). With regard to the execution speed, both XoLift and XoHar conditions were slower than the noExo condition, but this did not prevent the subjects from completing the task in the allocated time. Additionally, if the users got more acquainted to the device (they had no prior experience with it), the speed would have increased. An interesting remark is that in the XoHar condition, the speed appeared to be higher than in the XoLift. The subjective questionnaire analysis confirms that the users preferred using XoTrunk with respect to Laevo and that XoHar condition was preferred to the XoLift one. Furthermore, the users also found the automatic HAR a very useful feature, probably correlated with the good online classifier performance ($\rho = 91.72\%$, $\mu \geq 91\%$ (excluding lifting ($\mu = 86.95\%$), $\nu \geq 91\%$)). This encouraged field testing exploiting this particular classifier.

Overall, for carrying, the efficacy analysis showed the advantage of XoLift over XoHar, but dynamic fit displayed the opposite behaviour. Furthermore, XoHar performance can strongly improve by developing a specific carrying control strategy. The goal would be designing an assistive profile that can support carrying equivalently to the device potential (up to 30%), but without hindering the gait.

Final remarks are concerning the questionnaire and the task design. More in particular, it should be stressed out that the questionnaire was custom defined and should be compared to more standard ones. This could validate the obtained results or point out missed dynamics. Concerning the task design, a closer control of task parameters, as carrying speed or bending style, should diminish the kinematic data variability, but would also deteriorate the actual working condition simulation.

7.6 Field testing: HAR impact

The algorithm analysed in this study was also used during the field testing of XoTrunk. The testing involved 3 companies were MMH activities are performed daily. In these sites, several tasks where exoskeleton assistance would be beneficial were tested. In this section, some preliminary results related to the activity, simulated and presented above, are detailed.

The field trials involved 4 workers for a duration of 9 hours. To collect feedback from the final users, at the end of the trials a questionnaire analysing *assistance*, *comfort*, *usability* and *acceptance* was administrated. Among the questions investigating assistance, it is worth pointing out that the users were asked whether the system was providing proper assistance profiles and whether there were movements that felt hindered. The first trial was done in the XoLift condition and the workers complained about hindrance — when carrying the load — and sudden torque spikes. According to these feedbacks, the following tests were done with the XoHar condition and an improvement of the users' feedbacks was noted. As an example, Figure 7.13 shows 20 s of recorded data that are quite informative on the benefits associated with the versatility. Indeed the torque that would have been provided considering XoLift condition was simulated and compared with the actual torque delivered according to XoHar. It is possible to note that task recognition suppressed several sudden torque spikes while the user was standing and, also, removed assistance during carrying. In the time interval $[2793-2798]$ s, it is clear that carrying recognition was not very stable, as it was often misclassified with standing. This is also confirmed by the analysis of the activities recognized by the classifier. Indeed, even though as discussed for the simulated task, lifting/lowering, carrying and standing appeared to be well balanced, this was not the case for on-site testing as lifting was identified for 37% of the time, carrying for only 11% of the time and standing for 52% of the time. Therefore, it is possible that some carrying activities were misclassified as standing. However, it should also be mentioned that in the actual scenario, workers did not always have to travel 3.5 m and, sometimes, the carried distances were lower, partially explaining why carrying was not as frequent as the other activities.

On average, the workers reported that XoHar condition improved their perception on the exoskeleton.

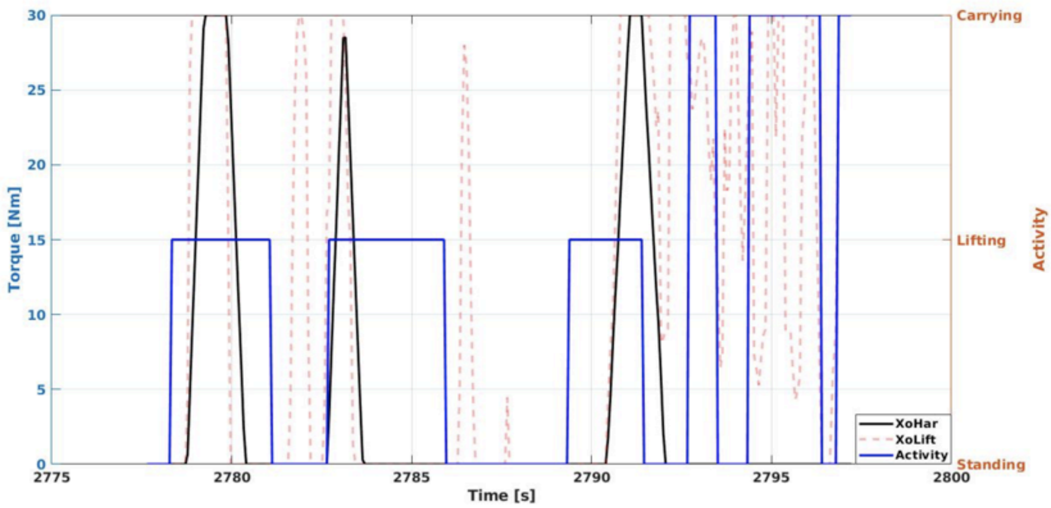


Figure 7.13 This plot represents 20 s of activity recorded during the field testing. It is possible to see how XoHar condition (black line) was able to suppress sudden torque spikes that XoLift would have commanded for (red dashed line). Solid blue lines represent the online classified activity.

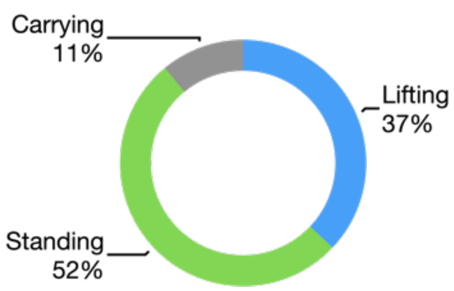


Figure 7.14 Recognized activities distribution during field testing.

7.7 Conclusion

The aim of this chapter was to assess the effects and the impact that a versatile exoskeleton can have simulating a real working activity. This activity was seen in an industrial plant and replicated in the laboratory simplifying some constraints (like accessibility to the load to be handled) in order to ensure safety to the volunteers involved in the study. 10 subjects (5 males and 5 females) were required to perform successive repetitions of lifting, carrying and lowering of a 11.4 kg load, under 4 conditions: noExo, XoLift, XoHar and Laevo. The first, not involving any exoskeleton, was used to have a baseline to compare the exoskeleton effects with. Two exoskeletons were involved in the study: Laevo, a quasi-passive commercially available device (2.8 kg), and XoTrunk, the active prototype described in Chapter 3 (6.5 kg). This latter was controlled in two different modes, namely XoLift and XoHar. XoHar is the control mode that takes advantage of the developed HAR algorithm and, so, is the condition that should highlight versatility potential. Before presenting the results, it was discussed which metrics should be considered when analysing not only the efficacy of a device but also its dynamic fit, i.e., how user and device interact one with the other. Efficacy was evaluated focusing on the reduction of back muscle activity during the execution of lifting, lowering and carrying. The results showed that XoTrunk offers better performance than Laevo and that, also during carrying, XoLift condition is associated with a reduction of muscle activity intensity (30%). This did not happen in XoHar that, for carrying activities, was controlled in order to provide null interaction torques between user and the device itself. Apparently, this result seems to penalize the versatile exoskeleton condition. However, once dynamic fit is considered the situation changes. Indeed XoHar was the condition were users perceived less hindrance, assessed via subjective questionnaires. Also the kinematic analysis of trunk, hip and knee joints, even though subject to high variability, confirms this trend. Efficacy and dynamic fit results should be used to guide the design of an assistive strategy for carrying. This strategy, exploiting versatility, should aim at consistent muscle activity reductions (XoTrunk potential is around 30%) with low or null movement impairment. Of course, in order to develop carrying strategies it is necessary to properly recognize when this activity is taking place. The classifier used in this study proved to be reliable (online classification accuracy $> 91\%$) and, hence, suitable for field testing. The final section of this chapter presented some preliminary results related to the field testing of the HAR algorithm, showing how exploiting versatility, the workers acceptance to the device increased.

Chapter 8

Conclusions and Future works

Occupational back-support exoskeletons have been studied by many practitioners, in the framework of MMH, as a possible solution towards mitigation of back-related MSDs. There is scientific evidence that these devices can accomplish this goal (de Looze et al. (2016), Toxiri et al. (2018b), Theurel and Desbrosses (2019), Grazi et al. (2019)), but most of the times, the evaluation is done only considering lifting tasks. This implies that other relevant activities such as pulling, pushing or carrying are neglected. Nevertheless, in real working scenarios, workers will never perform only lifting. Hence, if back-support exoskeletons prove to be extremely efficient in the latter task, but hinder or obstacle the worker when other activities are performed, their adoption would probably be limited. For such reason, this work addressed the *lack of exoskeleton versatility*, here defined as the ability of an exoskeleton to recognize which task the user is performing and, thus, trigger the appropriate control strategy. Among the relevant MMH tasks that are indicated in the ISO 11228, carrying was selected as the first activity that could benefit from exoskeleton versatility. The choice was also done considering that most of the times carrying occurs right after a lifting task and, hence, is quite frequent in industrial scenarios. Furthermore, carrying proved to be a task for which, considering spinal loading, the impact is comparable to that generated by lifting. As a consequence, a study was conducted to understand if back-support exoskeletons could assist also with this particular activity. More in details, the effects that assisting carrying, with the same control strategy normally used for lifting-assistance, were assessed. The study showed that while this type of assistance might be beneficial for the back, it does hinder gait movements. This results stress the importance of designing an algorithm for activity recognition in order to select the best assistive strategy, according to the task. Two studies were presented in which SVM algorithms were trained based on kinematics and forearm muscle activity. These algorithms proved to be reliable and, so, the XoTrunk control could be expanded from a two-level to a three-level one. This means that, in this newest control, the device can recognize the activity being performed and select the most appropriate controller. In other words, the device is now versatile. Due to hardware changes, it was not possible to extensively test the previous algorithms and, so, in the final assessment on the benefits of exoskeleton versatility, a simplified rule-based classifier was defined. The assessment consisted in the evaluation of efficacy and dynamic fit of two exoskeletons, namely Laevo and XoTrunk. XoTrunk was controlled in two ways: a non-versatile control mode (XoLift) and a versatile one (XoHar). The assessment showed that from an efficacy viewpoint XoLift had results comparable to XoHar if considering lifting and lowering, but better performance in carrying. However, as soon as dynamic fit is considered the situation changes and XoHar becomes the condition that has better results. Also, the HAR algorithm proved to have very good online classification performance and, for this reason, it was also used in the field testing carried out with XoTrunk. At the first trial, the workers had the chance to try XoLift, but reported some negative feedbacks that, however, were resolved by XoHar. This results did confirm the hypothesis underlying this thesis, namely that exoskeleton acceptability in a workplace can be enhanced by exploiting their versatility.

Future works should try to address two different aspects. The first concerns the design of a specific assistive strategy for carrying. Indeed, during the assessment of the versatility, it emerged that XoTrunk had the potential to strongly reduce the muscle activation during this task. However, this assistance should be designed in order not to hinder the gait. The second future challenge would be the extension of the HAR algorithm also to pulling and pushing tasks. In this way, it would be possible to assist, with the same device, many of the MMH activities that are performed, daily, in an industrial scenario.

8.1 Contributions

The core contributions of the thesis here presented, could be summarized in:

- Quantifying the impact on spinal loading of carrying activities, compared to lifting;
- Highlighting that assisting with carrying activities requires specific control strategies and that, simply using the same strategies adopted for lifting does not work;
- Designing an SVM-based HAR algorithm for the identification of carrying, lifting, standing and walking. This algorithm was, at first, designed without considering a specific exoskeleton architecture and, then, applied to XoTrunk. In this way, the control architecture of the device was improved and expanded to a three-level one (versatile controller);
- Assessing the benefits that a versatile controller has with respect to current state-of-the-art devices or control strategies.
- On-field testing of the proposed developments.

8.2 Related scientific publications

- **Poliero, T.**, Toxiri S., Caldwell D.G., Ortiz J. (2018). Actuator Optimization for a Back-Support Exoskeleton: The Influence of the Objective Function. The International Symposium on Wearable Robotics.
- Toxiri S., Calanca A., **Poliero T.**, Caldwell D.G., Ortiz J. (2018). Actuation Requirements for assistive exoskeletons: exploiting knowledge of task dynamics. The International Symposium on Wearable Robotics.
- **Poliero, T.**, Mancini, L., Caldwell, D. G., & Ortiz, J. (2019). Enhancing Back-Support Exoskeleton Versatility based on Human Activity Recognition. In 2019 Wearable Robotics Association Conference (WearRAcon) (pp. 86-91). IEEE
- Toxiri, S., Näf, M. B., Lazzaroni, M., Fernandez, J., Sposito, M., **Poliero, T.**, ... & Ortiz, J. (2019). Back-Support Exoskeletons for Occupational Use: An Overview of Technological Advances and Trends. IISE Transactions on Occupational Ergonomics and Human Factors, 1-13.
- **Poliero, T.**, Toxiri, S., Anastasi, S., Monica, L., & Ortiz, D. G. C. J. (2019). Assessment of an On-board Classifier for Activity Recognition on an Active Back-Support Exoskeleton. In 2019 IEEE 16th International Conference on Rehabilitation Robotics (ICORR) (pp. 559-564). IEEE.
- Calanca, A., Toxiri, S., Sartori, E., **Poliero, T.,**, Di Natali, C., Caldwell, D.G., Fiorini, P., Ortiz, J. (2020). Actuation selection for assistive exoskeletons: matching capabilities to task requirements, Transaction on Neural Systems & Rehabilitation Engineering.
- **Poliero, T.**, Lazzaroni, M., Toxiri, S., Di Natali, C., Caldwell, D. G., & Ortiz, J. (2020). Lifting and Carrying: do we need back-support exoskeleton versatility? (weRob 2020)
- **Poliero, T.**, Lazzaroni, M., Toxiri, S., Di Natali, C., Caldwell, D. G., & Ortiz, J. (2020). Applicability of an active back-support exoskeleton to carrying activities. Front. Robot. AI - Biomedical Robotics (2020)
- **Poliero, T,**, Iurato, M., Sposito, M., Di Natali, C., Toxiri, S., Anastasi S., Draicchio F., Monica, L., Caldwell, D.G., Sanguineti, V., &Ortiz, J. (2021). A case study on occupational back-support exoskeletons versatility in lifting and carrying. (in press, Petra21).
- **Poliero, T,**, Sposito, M., Toxiri, S., Di Natali, C., Iurato, M., Sanguineti, V., Caldwell, D.G., &Ortiz, J. (2021). Versatile and non-versatile occupational back-support exoskeleton: a comparison in laboratory and field studies. (submitted, WTC).

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