UNIONE EUROPEA
Fondo Sociale Europeo

Ministero dell'Istruzione, dell'Università e della Ricerca

PON RICERCA E INNOVAZIONE 2014 - 2020

Università degli Studi di Cagliari

PhD in Industrial Engineering

Cycle XXXIII

Promoting a healthy ageing workforce: use of Inertial Measurement Units to monitor potentially harmful trunk posture under actual working conditions.

Scientific Disciplinary Sector

ING-IND/34: Industrial Bioengineering

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Final exam. Academic Year 2019-2020
Thesis defense: January-February 2021 Session

Acknowledgements

First and foremost I am extremely grateful to my supervisor, Prof. Massimiliano Pau for believe on me for his invaluable advice, continuous support, and patience during my PhD study. His immense knowledge and plentiful experience have encouraged me in all the time of my academic research and daily life.

I would also like to thank Prof. Bruno Leban for his advice, and for his encouragement any time I need it.

I would like to thank my colleague Federico that shared this rewarding, but sometimes hard PhD experience, making it a great time.

I would like to thank all the members at Virginia Tech, Dr. Nussbaum, Dr. Sunkwook, and my lab-mates, Aanu, Saman and Jessica. It is their kind help and support that have made my study and life in Blacksburg a wonderful time.

I would also like to thank all the members of BTS, Bioenigineering. I learn a lot from them, feeling to be part of the group.

Finally, I would like to express my gratitude to my mother, Pippo, my sister, and my fiance. Without their tremendous understanding and encouragement in the past few years, it would be impossible for me to complete my study.

Abstract

Musculoskeletal disorders, particularly those involving the low back, represent a major health concern for workers, and originate significant consequences for the socio-economic system. As the average age of the population is gradually (yet steadily) increasing, such phenomenon directly reflects on labor market raising the need to create the optimal conditions for jobs which must be sustainable for the entire working life of an individual, while constantly ensuring good health and quality of life. In this context, prevention and management of low back disorders (LBDs) should be effective starting from the working environment. To this purpose, quantitative, reliable and accurate tools are needed to assess the main parameters associated to the biomechanical risk. In the last decade, the technology of wearable devices has made available several options that have been proven suitable to monitor the physical engagement of individuals while they perform manual or office working tasks. In particular, the use of miniaturized Inertial Measurement Units (IMUs) which has been already tested for ergonomic applications with encouraging results, could strongly facilitate the data collection process, being less time- and resources-consuming with respect to direct or video observations of the working tasks. Based on these considerations, this research intends to propose a simplified measurement setup based on the use of a single IMUs to assess trunk flexion exposure, during actual shifts, in occupations characterized by significant biomechanical risk. Here, it will be demonstrated that such approach is feasible to monitor large groups of workers at the same time and for a representative duration which can be extended, in principle, to the entire work shift without perceivable discomfort for the worker or alterations of the performed task. Obtained data, which is easy to interpret, can be effectively employed to provide feedback to workers thus improving their working techniques from the point of view of safety. They can also be useful to ergonomists or production engineers regarding potential risks associated with

specific tasks, thus supporting decisions or allowing a better planning of actions needed to improve the interaction of the individual with the working environment.

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Introduction

The demographic changes, in combination with the increasing ageing of the population which is accompanied by a large prevalence of several chronic degenerative diseases, pose significant challenges for the economy development and require specific attention, particularly as regards the quality of life that should be ensured to every citizen. In this context, the European Commission highlights the importance of promoting an active healthy ageing, on the interest of social cohesion and greater productivity (Europe 2020). Even at national level, the document “National Strategy for a Smart Specialization” (Strategia Nazionale Specializzazione Intelligente, SNSI, which is focused on determining investment priorities on strategic thematic areas) identifies as fundamental the capacity of redesign the life environments, including those dedicated to working activities, following an approach centred on the individual and his/her well-being.

As mentioned, the increase of life expectancy which can certainly be considered a significant achievement of the last century, is not always accompanied by a parallel improvement in quality of life, especially in late adulthood. In particular, in the next years greater incidence of chronic degenerative diseases is expected and thus, there is an urgent need to develop comprehensive community-based approaches that include interventions to prevent declines in intrinsic capacity and foster healthy ageing. Among chronic degenerative diseases, of great importance (given their social and economic burden) are musculoskeletal disorders (MSDs) which affect one in two adults in US and other industrialized countries (WHO, 2018) at some point of their life. Such phenomenon directly reflects on labour market, as MSDs are one of the primary causes of work-related disorders, out of which approximately 30% is represented by low back disorders (LBDs) making them the most common MSD. The impact of MSDs in general, and LBDs more specifically, encompasses various employment-related outcomes, ranging from usual paid work, to health-related work loss. In the worst cases, the latter event may cause early retirement or, in some countries, make the individual eligible to receive a state-funded disability pension. Until one of these conditions is reached, workers are often allowed to remain at work with amended or restricted duties, or diminished productivity (the so called “presenteeism”) or maintain their “employed” status but on sick leave. This scenario is further exacerbated in mature workers engaged in highly physically demanding jobs, as the assigned tasks may have a stronger impact on their health (with respect to younger workers) due to their intrinsic higher vulnerability associated to the cumulative effect of occupational exposure during the life course and to a generally reduced physical capacity. Hence, in order to promote longer healthy aging even in the mature worker, it appears important to take into account their physical and cognitive changes and, where possible, to design specific gradual adaptations in terms of assigned tasks, which enable to keep balance the relationship between physical/mental capacities and job requests. (Palmer and Goodson, 2015).

Measurement of physical risk factors for LBDs under actual working conditions is a challenging task. This because differently from the usual concept of exposure (such as exposure to chemical or physical agents in the environment) the assessment of exposure in musculoskeletal epidemiology, cannot be determined independently from the worker. In fact, physical load depends on posture and movements that the worker carries out to interact with machinery and tools, and ultimately from the interaction between the physical work demand and the worker physical capability.

The most commonly employed tools to characterize the level of exposure associated to different occupations are diaries, self-report questionnaires and observational methods (by direct observation or using video). Direct measurement methods, which make use of different kind of devices, are less frequently used despite their superior features in terms of reliability, accuracy and repeatability. This is because while such systems are well suitable for laboratory settings, in most cases their use in actual work environment may result difficult or hardly bearable for tested workers. To enhance the applicability of quantitative assessment under actual working conditions, this research propose the use of wearable miniaturized devices like Inertial Measurement Units (IMUs) and activity trackers to evaluate trunk posture and to monitor the intensity of physical activity. Such simplified setup, which has been proven comfortable for use during regular task performances, is characterized by several advantages, such as the possibility to monitor a large number of workers in a reduced time, the availability of detailed data, which can be summarized in few information easy to interpret, thus giving the possibility to quickly identify those situations who increase the risk for low back injuries, as well as managing high risk jobs and to improve return-to-work strategies.

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Chapter 1

An ageing society

During the last decades, Europe has experienced an outstanding increase of life expectancy due to several factors, including reductions in infant mortality, rising living standards, improved lifestyles and better education, as well as advances in healthcare and medicine (Eurostat, 2020). In fact, since 1950s life expectancy has increased by eight to ten years, leading to an European population that could reach a life expectancy above 80 years of age by 2070 (life expectancy from 78.3 in 2016 to 86.1 for males, from 83.7 in 2016 to 90.3 for females, Economic and Financial Affair, European Commission 2018, Report). Moreover, given the low birth rates, the age structure of the European population is further ageing. In 2001 the "total dependency ratio" was 48.9%, that means that every two people of working age, there were two dependent people (younger than 15 or older than 65). Breaking this down, the old-age dependency ratio (those 65 and over compared to those 15-64) was 23.5%, so there were more than four people aged 15-64 for each person aged 65 or over. The young-age dependency ratio (those aged 0-14 compared to those 15- 64) was 25%, meaning there were four people of working age for each person aged 0-14. In 2017, the total dependency ratio for the EU-28 further increased to 53.9%. Not only there is a growing proportion of people likely to be dependent on the working age population overall, but this is therefore skewed towards those aged 65 plus, rather than towards children aged 0-14, who would at least in the future form part of the working age population potentially supporting others. In this scenario, hypothesizing that patterns of economic activity remain at current levels, projections suggest that the worsening of the total age-dependency ratio will accelerate dramatically, with the ratio reaching 63.5% as soon as 2030. It will continue to increase rapidly, reaching 76.5% in 2050 (Demographic outlook for the European Union 2019).

This social-demographic shift poses pension system under serious financial pressure. Indeed, since the ‘90s, European countries have started to reform their pension systems, increasing the labor-market participation of older people while, at the same time, restricting the possibilities for early retirements. Several authors analyzed the impact of pension reforms (Ardito, 2017; Rebate and Rochut, 2017; Staubli and Zweimuller, 2013; Geyer and Welteke, 2017), founding a modest increase in the employment, counterposed to an increase of applications for unemployment, disability or sick-pay insurance exhibiting a substantial impact on the other public insurance schemes.

Nowadays, a retirement age of 67 years is the most widespread policy in Europe (Ardito and d’Errico, 2018). From an ideal point of view, a longer working life may allow to make available superior resources to counterbalance the higher pension cost and health care costs associated with population ageing. Besides, it will also allow a smaller proportion of total resources to be used for the economic support of the older population and more to be allocated to the young, especially to education and unemployed. However, the duration of working period of an individual depends, among other factors, on health and disability trends. In such a context, the implementation of effective ergonomic solutions specifically designed for older workers appears crucial.

Musculoskeletal disorders (MSDs)

The side effect associated to the pension reforms may be due to the scarce consideration of age-related health issues such as the high presence of chronic disease among the older population (Ardito and d'Errico, 2018). Indeed, older workers may experiment a reduced ability to deal with occupational demands and tasks due to chronic morbidity or functional limitations. In fact, many people aged between 51 and 65 years report chronic diseases such as hypertension (39.2%) dyslipidemia (21.3%), diabetes (9.2%), cancer (4.9%), arthritis (4.9%), stroke (3.3%) along with neurological disease in smaller percentage (d'Errico, 2017; Atella et al., 2019), scenario that is aggravated by the high prevalence of MSDs which are reported by 40% -50% of the people reporting chronic diseases Duffield et al. (2017).

Definition, incidence and prevalence

The term "Musculoskeletal disorders" (MSDs) generically describes both injuries and disorders involving muscles, joints, tendons, ligaments, nerves, cartilage, bones and the localized blood circulation system. For the purposes of the present study, we will consider only MSDs caused by inflammation or degenerations, characterized by an accumulative nature resulting in pain or physical constraints thus excluding the sequelae of systematic diseases such as rheumatoid arthritis, as well as those resulting from traumatic incidents such as falls, motor vehicle accidents and assault (Gillespie et al., 2013).

If MSDs are either caused or aggravated primarily by work and by the effects of the immediate environment in which work is carried out, they are known as "work-related MSDs" (wMSD). It is noteworthy that wMSDs, contrarily to what intuitively thought, affects all forms of working environments, ranging from physically arduous work to low-intensity static work (da Costa and Viera, 2010; Bernard, 1997).

Although wMSDs report trends showed a reduction of their impact in the last decade (European Agency for Safety and Health at Work – EU-OSHA Report, 2018), MSDs remain the most common work-related health problem in the developed countries (Côtè et al., 2013).

Workers in all sectors and occupations are concerned about wMSDs, although more common among specific occupations such as construction, water supply, agriculture, forestry and fishing (where around 69% of workers reported MSDs). However, they are also quite common among working tasks usually identified as "blue-collar" occupations, plant and machine operators and assemblers (66%), craft and related trades workers (65%) and workers in elementary occupations (64%) (Figure 1.1) (EU-OSHA Report, 2018).

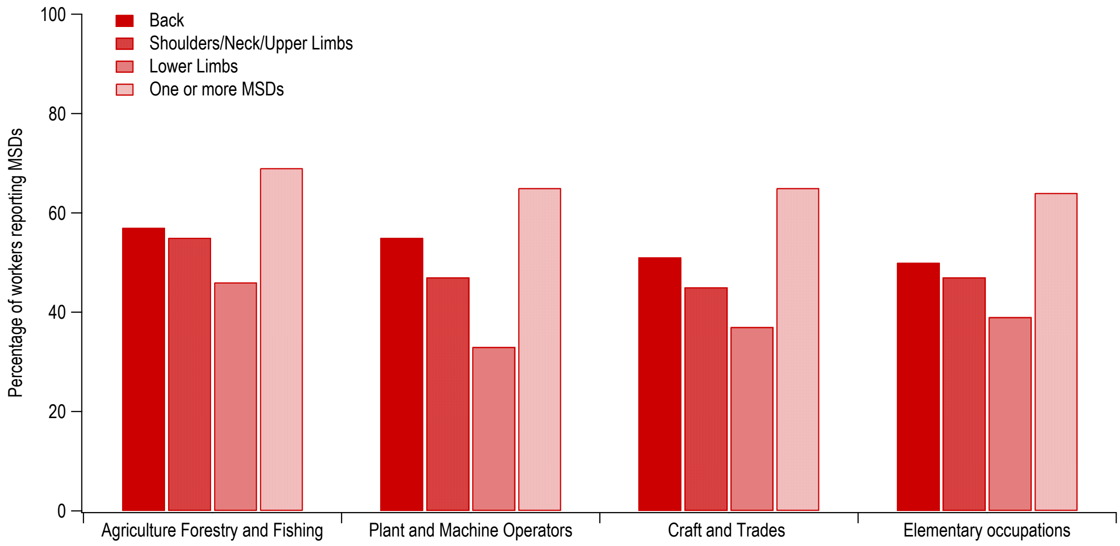

Figure 1.1 Percentage of workers reporting different musculoskeletal disorders in the past 12 months, by occupation (ISCO-08), EU-28, 2015
Adapted from https://www.bls.gov/opub/ted/2018/back-injuries-prominent-in-work-related-musculoskeletal-disorder-cases-in-2016

Low Back Disorders (LBDs)

Among MSDs, those involving the low back are the most common (Global Burden Disease. GBD 2016). The term "low back disorder" (LBD) refers to an inflammatory and/or degenerative form of cumulative trauma that affects muscles, bones, tendons, ligaments and other structures supporting the back (OSHA, 2016). Every year, approximately 30% of the physician's visit are requested based on back complaints (National Research Council, US, 2001). It is common to observe that individuals experience disabling syndromes even in absence of defined radiographic abnormalities. This condition is known as "non-specific back pain" (Hartvigsen et al., 2018). Common signs of LBDs include chronic pain, discomfort during activity or static posture, and loss of mobility (Cooper, 2015; EU-OSHA, 2016). These signs can emerge periodically as result of cumulative trauma and exertions in the workplace and consequently lead to possible muscular failure and physical disability (Konz and Johnson, 2007).

LBDs represent a major problem not only in the general population, but also among many occupational populations (Marras et al., 2009). In 2015, approximately 3/5 of workers in the EU reported MSD complaints and in particular LBP (43%) (Eurofound, 2017). Similarly, in the US in 2016 MSDs involving the back accounted for 38.5% of all work-related MSDs with a variable prevalence among occupations, with the highest rate recorded among health care assistant, material movers, forestry, machine operators (figure 1.2) (US Bureau of Labor and Statistics, BLS, 2016).

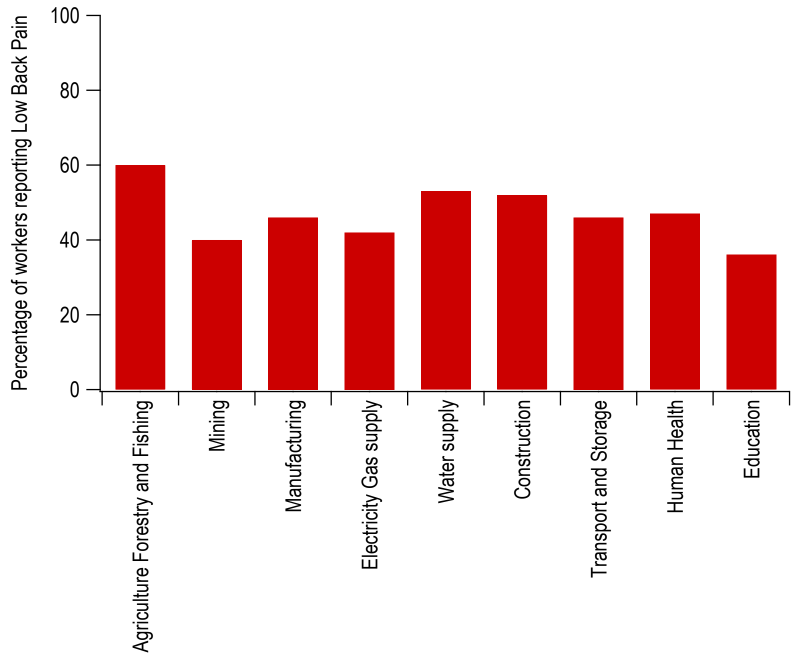

Figure 1.2 Percentage of workers reporting low back pain in the past 12 months, by sector (Statistical Classification of Economic Activities in the European Community, NACE, rev.2) EU-28 2015. Adapted from https://www.bls.gov/opub/ted/2018/back-injuries-prominent-in-work-related-musculoskeletal-disorder-cases-in-2016

Factors involved in low back disorders development

It is generally accepted that the risk of developing LBDs in occupational settings is originated by a combination of individual, psychosocial and physical risk factors (da Costa and Vieira, 2010; Putz-Anderson and Bernard, NIOSH 1997; Trask et al., 2016; Wai et al. 2010; Bao et al. 2016; Waters et al., 2007; Keyserling, 2000; Shelerud, 2006; Burdorf and Sorock, 1997; Hartvigsen et al. 2004; Manek and MacGregor, 2005). Psychosocial factors such as social support, job status, and job satisfaction have been found associated with back injuries (Hoogendoorn et al. 2001), but they may even impact more in the transition from pain to disability, or the chronicity of back pain (Shelerud, 2006) rather than the mechanisms of injury themselves. Similarly, individual risk factors such as, age, anthropometry, previous back injury, and smoking (Burdorf and Sorock, 1997) have been found related to the development of LBDs but they can be only partly controlled in a workplace context.

A number of systematic reviews have suggested a causal relationship between LBDs and occupational risk factors such as non-neutral posture, manual materials handling, and repetitive tasks (Putz-Anderson and Bernard, 2007; Punnet and Wegman, 2004; Marras et al., 1995; da Costa and Vieira, 2010; Punnett et al., 1991). Non-neutral trunk postures, which are defined as mild to extreme deviations from resting positions (Putz-Anderson and Bernard, NIOSH 1997) that include trunk flexion and hyperextension in the sagittal plane, rotation in the transverse plane and lateral bending in the frontal plane. It should be noted that such definition strongly depends on the context of the working task and on the type of posture analysis but in any case, such postures have been suggested to have potential effects on the musculoskeletal integrity of the back in occupational contexts.

The real-world experience suggest that workers often experience non-neutral trunk postures, holding them, lifting objects or people, or twisting to reach tools (Dempsey, 1998).

Putz-Anderson and Bernard (1997), Burdorf and Sorock (1997), Hoogendorn et al. (1999), Beek and Hermans (2000), Lotters et al. (2003), Wai et al. (2010a, 2010b) and Heneweer et al. (2011) found a strong relationship between manual material handling and the development of LBDs. Some of these reviews, found also strong to moderate relationship between non-neutral postures (bending and twisting) and the development of LBDs as well as weak to strong relationship with heavy physical work defined as "work that has high energy demands or requires some measure of physical strength" (Putz-Anderson and Bernard, 1997; Burdorf and Sorock, 1997; Hoogendorn et al., 1999; Beek and Hermans, 2000; Lotters et al., 2003; Heneweer et al.,2011).

When the trunk assumes a non-neutral posture, both spinal loading and intervertebral disc pressure increase, potentially resulting in impairment or injury due to overexertion (Jager et al., 2000; McGill, 1997). In vitro studies which investigated the effects of spinal loading on tissue tolerance (Aultman et al., 2004; Aultman et al., 2005; Parkinson and Callaghan, 2007) show how physical loads culminate in mechanical (e.g. failure of the spinal unit after a number of cycle of compression) and physiological effects (e.g. increase of height loss with increase of cumulative load) (Courville et al., 2005). The results of such experiments led to estimate the mechanical limits of the involved anatomical structures and put the basis for theories on how physical exposures lead to injury (Marras, 2005). Moreover, sustained non-neutral postures can result in a reduction of the blood supply necessary to stabilize the musculature due to the compressive effects on capillaries and veins (Vieira and Kumar, 2004). In practice, the supply of oxygen and other nutrients to the back anatomical structures becomes limited when excessive load exists, thus leading to an accumulation of waste products (e.g. hydrogen ions, diprotonated phosphate etc.) which are cause of fatigue and discomfort (Garg, 1979).

It has also been suggested that highly repetitive postural changes increase tissue fatigue and induce micro-strain on the low back (Adamds and Dolan, 1998). Of course, it is perfectly normal to expect increased spinal loading while in non-neutral posture during regular activities of daily living, but if the necessary recovery is not allowed, the probability of experiencing muscular strain and injury increases (Brinckmann et al, 1988).

Since LBDs have a multifactorial etiology, no consensus on the causal relationship between LBDs development and non-neutral posture exists. There are no specific guidelines unanimously accepted as regard threshold or limits at which trunk posture become an occupational hazard, thus they continue to be undefined (Dionne et al., 2008; Hoy et al., 2010). However, some authors (Hoogendorn et al., 2000; Coenen et al. 2013) reported an increased risk of LBDs development for workers who worked with the trunk flexed over 60° for more than 5% of the working time, or over 30° for more than 10% of the working time and for workers who lifted a load of at least 25 kg more than 15 times per working day.

The prevalence of LBDs is different across different age groups (Rubin, 2007). In particular the highest rate of back pain are found consistently in the adult population between the third and sixth decades, with those experiencing new onset of back pain more likely to be in the third decade (Dionne et al., 2008; Hurwitz and Morgenstem, 1997; Waxman et al., 2000). A systematic review of the literature comparing the prevalence of LBDs in different periods of life found the lowest prevalence among younger adults (20-35 years old) with rates increasing with age until ages 60 to 65. After this age, a decline in the frequency of pain has been observed (Dionne et al., 2008; Loney and Stratford, 1999).

As regards workers, some studies indicate that LBDs prevalence it is typically higher among older worker than younger workers (Okuribido et al., 2011). This phenomenon can be explained by biological changes of body structures related to the ageing process. The organ systems (i.e. cardiovascular, respiratory and musculoskeletal) functionality may decline around 2% per year after the age of 30 (Sehl and Yates, 2001). As result, the physical capacity of a 65 years old can be reduced up to 50% compared with a 25-years old, (Ilmarinen and Rantanen, 1999). The muscle strength peaks occur around the third decade, then strength remains constant approximately until 45 to 50 years of age and then declines at an average rate of 12% to 15% each decade thereafter. The primary factor responsible for the decline of muscular strength is the loss of muscle mass (Bellew et al., 2005; Delmonico et al., 2009), which begins to be observable at the age of 30 years and lead to a 30% of reduction of the muscle cross-sectional area at 65 years of age (Doerthy, 2001). These changes originate a reduction of the concentric muscular strength by 8-10% per decade which is more noticeable in the lower limbs (in particular, knee extensors and flexors) than in the upper limbs. The factors that contribute to this decline are sarcopenia and a simultaneous neuromuscular alteration such that there is a selective age-related denervation of motor units and an increase in the size of the remaining motor units, that lead to an increase of the muscles activation threshold and to a decreased speed of contraction (Miller et al., 2014). During the ageing process, particularly in individuals over 50, it is possible to observe a reduction in the fraction of water present in both the vertebral disc and the surrounding tissues, which causes stiffness of the spine (Galbusera et al., 2014). Moreover, the deterioration of the viscoelastic properties of dorsal ligaments decreases their effectiveness as sensory organs (Solomon, 2006). Accordingly, back muscle reflex latency of older individuals, results delayed in response to spine loading and trunk muscles are characterized by reduced activity performing functional tasks (Hubley-Kozey et al., 2009). Taken together age-related sarcopenia and selective denervation are responsible for reduction in musculoskeletal capacity, flexibility and coordination thus markedly impairing work ability in older workers.

The ageing workers

In older workers, physiological age-related changes and chronic diseases lead to a reduction in work capacity and performances, with possible consequences on their health and safety when the occupational demand is not properly modified (Yeomans, 2011). As result of this phenomena, the prevalence of wMSDs is higher among older workers, even though, there is no conclusive evidence that age itself represent a risk factor (Okunribido and Wynn, 2010). WMSDs are more likely to be developed at old age and this is particularly true under adverse working conditions, including physically demanding work, repetitive work under time constraints and working in awkward postures (Okunribido and Wynn, 2010; Breslin and Smith, 2005).

Notably, while health tends to decline with age, exposure to occupational hazards and to physical and psychological work demands does not. The European Working Condition Survey (2016) reported that exposure to main work-related risk factors does not decrease significantly in workers aged over 50 (Eurofound, 2016). In fact, only small reduction of non-neutral postures, upper limb repetitive movements, and manual handling of heavy loads exists when comparing workers aged over 60 years with those aged between 50 and 60. In addition, even the amount of working hours do not decrease much, remaining, on average, elevated among men regardless their age (mean = 38 hours/week).

Burr et al. (2017a) have found that high physical work demands (i.e. sustained non-neutral posture) have a stronger impact on the health of older workers compared with their younger counterpart, while psychosocial risk exposures (e.g. high work pace, low influence at work, low social support from colleagues) do not have substantially different effects on the incidence of poor self-rated health depending on age (Burr et al. 2017b). A significant interaction between age and physical work demands for worsened self-report health was found also by Aittomaki et al (2005). These findings may indicate a higher vulnerability to the negative effect on health of physical work among older workers. This might be due to the cumulative effect of longer engagement in a given occupation (in terms of years of service) of older employees (Flecther et al., 2011; Blane et al., 2013) or to a lower mean physical capacity of older employees respect to the younger ones, leading to an unbalance between their reduced physical capability and unchanged physical job requirements (Burr et al., 2017a; Savinainen et al., 2004). Hence, in order to promote longer working life, is important to consider health specificities of older workers.

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Chapter 2

Exposure assessment of risk factors for the development of low back disorders

Measurement of physical risk factors for LBDs is a challenging task, particularly under actual working conditions. One of the most important reason that makes complex the assessment of risk factors for the development of LBDs is their nature itself. Indeed, in musculoskeletal epidemiology, the concept of exposure differs from those of occupational exposure, where this term refers to an agent or factor in the environment, external to the workers (Burdorf and van der Beek, 1999). Risk factors, as well as workload associated to the development of LBDs, cannot be determined independently from the worker. In fact, the physical load may depend on posture, movement and the forces resulting from the interaction between the physical work demand and the worker physical capability. The physical loads are stresses that disturb the internal state of the individual, mechanically and physiologically, resulting in cascade responses that start from the application of a load, that causes mechanical modification of tissues (e.g. deformation of connective tissues within the muscles, as well as increases in intramuscular tissue pressure which can affect the muscle blood flow mechanically), that in turn produce physiological changes (that include electrochemical and metabolic changes) which cause a neurological response (shifting concentrations of substrates and metabolites are conveyed to the central nervous system by sensory afferent nerves and cause corresponding sensations of effort and discomfort) (Armstrong et al., 1993). From a macroscopic point of view, the biomechanical stresses refer to tissue forces at each body part that are produced as a result of force exertion and movement of the body. Generating muscle forces leads to physiological disturbances on the human body such as energy consumption, production of metabolic waste and localized or whole-body fatigue. If the biomechanical or physiological responses exceed the individuals' capacity (in terms of strength, endurance or working techniques), one may experience discomfort, pain or incur in injuries.

The relationship between the most common work-related risk factors and the occurrence of LBDs does not follow a linear trend, but is rather U-shaped trend, where at the two extremes are located respectively no exposure at all and extreme exposure (for instance constrained sitting posture and heavy material handling) (NIOSH, 1997, Winkel and Mathiassen, 1994). Moreover, workload is determined not only by external loads, but also by the interaction between the worker and the workplace (Radwin et al. 2001). External loads are affected by the geometry of the workplace, the types of tools used and the environmental conditions (Armstrong et al. 2003). Is therefore important to conduct the exposure assessment in the actual working environment, in order to obtain useful information for the reduction and prevention of development of LBDs.

Exposure assessment for the most common LBDs risk factors previously mentioned (e.g. manual material handling, sustained non-neutral postures, frequent flexion and rotation, etc.) is not simple. Several authors have compared and discussed strength and weakness of different techniques for measuring exposure in musculoskeletal studies (Burdorf and van der Beek, 1999; Genaidy et al., 1993; Spielholz et al., 2001; Janowitz et al., 2006; Li and Buckle, 1999). They can be broadly classified into three categories: self-report methods, observational methods and direct measurement methods.

Self-report methods

Self-report measures on work-related diseases including health complaints, disorders, injuries, and classical occupational diseases, often under the form diaries, interviews and questionnaires are widely used from several decades. They provide workers' perception of ergonomic factors in a workplace and they are commonly employed in epidemiological studies to easily collect data on large sample of workers. Self-report methods can use discrete or continuous scale to obtain data from workers to estimate prevalence of postures, frequency of movements and the presence of level of forces or physical agents, or also ask about organizational, cognitive and psychosocial factors as well as pain perception. Self-report techniques provide useful data, have the apparent advantages of being straightforward to use, applicable to a wide range of working situations and appropriate for surveying large numbers of subjects with a relatively low cost (David, 2005). However, their validity has been questioned by several authors. In fact, the respondents are not always truthfully, and the answers are related to their own feelings, and these might be different for various subjects (Barrero et al., 2009). Furthermore, having severe musculoskeletal pain or psychological pressure regarding work situation or individual life probably impact on reporting work-related musculoskeletal risk factors (Balogh et al., 2004; Barrero et al., 2009). For instance, Balogh et al. (2004) found that the presence of musculoskeletal complaints led to higher estimation of exposure to physical risk factors. Additionally, Stock et al. (2005) explained some possible reasons for the low validity of self-reported questionnaires such as operators' knowledge about work-related musculoskeletal risk factors, capacity to judge, respondents' comprehension of the questions, response scale and methodological limitations of the studies which determine the validity of a questionnaire.

Observational methods

To date observational methods are probably the most used approach in field setting both to evaluate physical workload (in order to identify hazard at work) and to monitor the effects of ergonomic changes. The comprehensive review carried out by Takala et al. (2010) identified a total of 30 available observational methods alternatively useful to assess the general work load, upper limb activities and manual material handling with the possibility to choose among them on the basis of the characteristics of the job to be assessed; the subject/s that must be monitored and who will use the method and the resources available for collecting and analyzing data.

Among the most common applied observational method in the follow part are reported some of the main features and pros and cons in their applicability.

Ovako working posture assessment system (OWAS)(Karhu et al., 1977). OWAS, which is probably the most widespread and documented method, was originally developed to describe workloads associated to the duty of steel industry company and allows to assess force (weight of the loads handled in three categories) and posture (back, arms and lower extremities) exerted. The assessment leads to 252 possible combinations that can be classified in four action categories indicating the need of an ergonomic change. The observations are carried out using fixed time-intervals. This method has shown good intra- and inter-observer variability but low agreement with direct measurements aimed in assessing the time spent in bent postures. Two main limitations are associated with this method: it is time-consuming and does not allow to consider duration and repetitions of sequential postures.

Portable ergonomic observation (PEO) (Fransson-Hall et al., 1995). PEO is a computer based observational method for the continuous monitoring of workers. Each time the observer sees the worker adopts a new predefined posture, performs a task or changes posture, hits the corresponding keys and the software records the starting time of the event. When the worker change posture/task, the observer hits the same keys again. This procedure triggers the software to calculate and store the duration of a particular action. Starting from these data it is also possible to assess the cumulative exposure for a given period (day/week). This method has shown moderate to good agreement with direct measurement as well as intra and inter- observer repeatability. However, this technique is time consuming and if the work-pace is rapid, the assessment of several exposure categories is not possible.

Rapid entire body assessment (REBA, Hignett and McAtamney, 2000). REBA was designed as quick and easy observational and postural analysis tool for the whole-body activities in healthcare and other service industries. The REBA assessment associates increasing scores to positions of individual body segments as they deviate more from the neutral posture. The method provides the assessment of the posture of back, neck, legs, upper and lower arms and wrists for a total of 144 possible posture combinations that are transformed into a total postural score. The assessment of trunk and leg posture is characterized by a moderate intra-observer agreement, but low for the assessment of the upper limbs. This method of assessment does not allow to record duration and frequency of the posture observed and scores only one side (i.e. there is no possibility to combine scores associated with right and left limbs) so that usually only the "worst case" is considered.

US National Institute of Occupational Safety and Health (NIOSH) lifting equation (and its revision, Waters, Putz-Anderson, Garg, & Fine, 1993, 1994). When the focus of the assessment is on manual handling tasks, the most common method used is the NIOSH lifting equation, which has been developed to assess the risk of LBDs among jobs characterized by repeated lifting actions. The NIOSH Lifting Equation considers six factors related to the lifting task, where multipliers are based on biomechanical, psycho-physiological and epidemiological data. The method is based on the calculation of a "lifting index" ($LI = \frac{Load\ Weight}{Relative\ Weight\ Loaded}$) which represents the ratio between the actual lifted weight and the relative weight loaded (dependent on several position multiplier factors). LI values below 1 are considered to be safe for the average population and, as LI increases, the worker is exposed to a greater risk to develop LBD. The strength of this method relies on its clear and simple way to indicate the need of ergonomic actions. Moreover, it is well documented and tested under several laboratory conditions, in contrast, it is difficult to use in practical situations, due to several position metrics that is necessary to take into account in the calculation of the relative weight loaded (e.g. distance of hands on the load from midpoint between ankles; starting height of the hands from the ground; vertical travel distance of the lift etc.)

Although the observational methods are focused on the assessment of biomechanical exposure on the musculoskeletal system, they are not directly comparable, mainly due to the use of different categories to perform the postural assessment (e.g. different angles threshold). Furthermore, their validity is limited to have a level of agreement with other methods since there is not a “gold-standard” to measure workload. But, also neglecting this aspect and assuming these methods being valid itself (because tested in a systematic way) factors such as the level of training of the observer, size of the body segment and rapidity of the movement to assess, lead to unpredictable errors.

Summarizing, if the workplace is characterized by a limited number of postures that can be easily categorized into two or more classes, trained observers can be able to assess body posture with high level of accuracy and precision (van der Beek and Fring-Dresen, 1998). However, these methods provide unsatisfactory estimation when they are requested to classify very dynamic tasks. Also, they can lead to an alteration of the working strategy when the workers are aware about the observation (long observations make this aspect less critical as the worker become accustomed) (Trask et al. 2007). At last, these methods are not feasible for use in clinical settings as the nurse/physician-patient interaction poses critical privacy issues that may arise when a direct observation by a third party is performed.

Direct measurement methods

The third category of exposure assessment methods is represented by direct measurement, which have been used with some success to quantify exposure in field studies and to investigate task simulations. Highly accurate systems such as optical motion capture have been used to record body posture, tracking position and velocity of different body segments, during the performance of simulated activities in laboratory settings. While in field studies, have been applied instruments which can range from simple hand-held devices for the measurement of joint range of motion to more sophisticated electro-goniometers that provide continuous recording of joint movement. In addition, lightweight devices such as inclinometers, accelerometers or Inertial Measurement Units (IMUs) have been applied to record joint/body segment movements, allowing the assessment of the time spent by the worker in different postures during the working day. Another largely used method is the surface electromyography that allows the characterization of muscle activity (Perry and Bekey 1980), or the evaluation of muscle fatigue (Radwin et al. 2001).

Direct measurement systems can provide large amount of accurate data on a wide range of exposure variables. However, they usually require that sensors are attached to the worker's body (as for example occurs in the case of surface electromyography electrodes) and this may result in discomfort and possible modifications in working behavior. Besides, most of these techniques are time and resource consuming and tend to generate dataset not easy to read and practical to interpret by ergonomic practitioners. In particular, if the time required for data collection is excessive, testing large groups of workers in a reasonable amount of time becomes hardly feasible. Last, but not less important, in some cases the initial investment to purchase the equipment is considerable, as well as the resources necessary to cover the costs of its maintenance and the employment of highly trained and skilled technical staff to ensure their effective functioning.

In summary, the choice of the assessment method should be based not only to the specific exposure parameter/s of interest, but also on its resolution, validity and reliability features. High resolution, validity and reliability are usually necessary for laboratory-based studies, but the practical implications of the results or transfer of measurement techniques developed in the controlled environment from the laboratory to actual and complex work environments are often difficult to achieve.

When the goal is collecting data in real-work environments, the choice of a specific measurement method does not only depend on its characteristics (i.e. resolution, validity, reliability), but also on the variability expected within and between workers. A workplace analysis aimed in assessing risk factors for MSDs should collect a enough data to describe exposure patterns in the study population and effectively observe inter/intra-individual differences. In the case of physical workload, given its variability in time and among the strategies adopted by individual workers, is desirable to have information about each worker for an extended period of time so that it is reasonable to expect that a fully representative series of tasks is carried out. In practice, this kind of approach is difficult to use due to several reasons:

- Exposure assessment methods should be applicable to a wide range of working context (e.g. industrial, clinical, etc.);
- Exposure assessment methods should allow comparison between workers, days, occupations and sectors;
- Exposure assessment methods should make use of instruments which are not source of discomfort during the performance of regular activities and sufficiently unobtrusive to allow to the worker to perform its job in a natural manner.

The most common tools used for the assessment of trunk workload (i.e. surface electromyography and inclinometers) are quite difficult to employ in actual working environment, due to the possible existence of adverse conditions including presence of humidity, extreme (high and low) temperatures, etc. For instance, cold storage warehouses may cause condensation in electrical circuits altering the functioning of the surface electromyography. Hot and humid environments may increase the worker' sweating thus reducing the electrode adhesion and making all the surface electromyography measurement setup uncomfortable (Trask 2007). Moreover, since workers often wear protective equipment, the devices used to monitor posture should not alter their efficacy, as workplace safety is priority. In addition, acquired data should ensure enough evidences to support employees' beliefs that the device will bring information helpful for their health in order to improve their compliance (Bergmann and McGregor, 2012; Schall et al., 2018; Jacobs et al., 2019).

The recent advancement in the technology of miniaturized wearable devices greatly solved most of the mentioned issues. In particular, a suitable option to quantitatively assess workload in real work environments, potentially able to overcome some issues associated to commonly applied exposure assessment methods (e.g. obtrusiveness, long preparation time, difficult direct comparisons, subjective bias etc.) is represented by the use of IMUs, which will be described in detail in the next chapter.

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Chapter 3

Inertial sensors, a valid option for the assessment of exposure to physical risk factors related to the development of low back disorders

In the field of human movement analysis, inertial sensor technology exploits the property of inertia to provide either angular velocities or accelerations of selected body segments using devices like accelerometers, inclinometers, gyroscopes, magnetometers and IMUs, the latter being a combination of accelerometers, gyroscopes and/or magnetometers.

A single axis accelerometer consists of a mass, suspended by a spring in a housing (Figure 3.1).

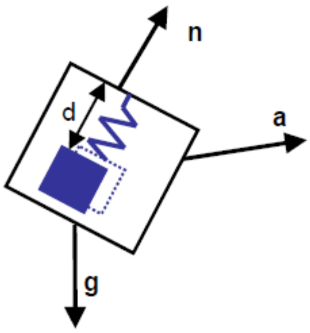

Figure 3.1 Example of single axis accelerometer structure. The sensor contains a mass suspended by a spring. The distance d of the mass with respect to the sensor housing is measured and is a function of acceleration and the direction of the gravity vector **g**, with respect to the direction of distance measurement. The unit vector n represents the sensitive axis of the sensor

The mass is allowed to move in one direction which represents the sensitive direction of the accelerometer. The displacement of the mass is a measure of the difference between the acceleration (imposed) and the acceleration of gravity (**g**) along the sensitive axis. Combining three single axis accelerometers, a tri-axial accelerometer is obtained. A tri-axial accelerometer can be used to measure inclination (inclinometer) for applications in which the expectable acceleration is small compared to **g**. The inclination is determined by calculating the angle of the sensor axes with respect to **g**. In contrast, the use of an accelerometer does not allow the measurement of rotations around its vertical axis.

A gyroscope consists of a vibrating mass. To measure the angular velocity, the vibrating mass undergoes to an additional vibration caused by the Coriolis effect. The displacement of the mass is measured in the direction perpendicular to the actuation direction. If the housing is rotated with an angular velocity perpendicular to the plane, the mass will experience an apparent force (Coriolis force) in the direction perpendicular to the angular velocity and momentary mass speed (Figure 3.2). This force is only apparent in the sensor coordinate system, not in the inertial coordinate system. As for the tri-axial accelerometers, combining three single axis gyroscopes, it is possible to construct a tri-axial gyroscope.

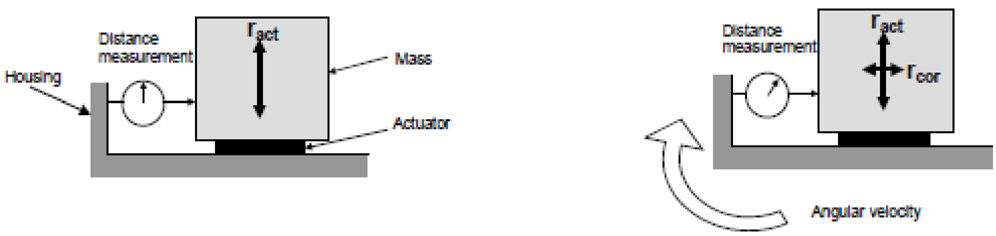

Figure 3.2 Example of gyroscope structure. A gyroscope consists of a mass, which is brought into vibration by an actuator in the direction given by r_{act} When the gyroscope is rotated, the mass will not only vibrate in the actuation direction, but will also undergo a (small) additional displacement in the direction perpendicular to both the original displacement r_{act} and the angular velocity vector. This additional displacement, also known as the Coriolis effect, is used as a measure of angular velocity.

To date these sensors (accelerometers and gyroscopes) are fabricated in small structure in the micrometer scale, where mechanical and electrical components are combined into so called microelectromechanical system (MEMS).

From a mathematical point of view, the integration of accelerations and angular velocity signals, would make possible to completely define the pose of a rigid body on which the sensors are attached. However, in the real-world, signals from micromachined gyroscopes and accelerometers are affected by errors which makes it difficult to obtain a reliable estimation of orientation and position, due to integration drift (Luinge, 2002).

The use of IMUs (that consist of a tri-axial accelerometer, tri-axial gyroscope and possibly a tri-axial magnetometer), in combination with an appropriate sensor fusion algorithm such as Kalman filter or complementary filter (Madgwick et al., 2011) allows to overcome the above mentioned issues as, for instance, the drift error introduced by the integration of the gyroscope signal may be compensated by the accelerometer-based orientation estimate. These devices appear therefore more suitable than accelerometers or gyroscope alone to be employed for prolonged data collection.

In the last decades, the use of inertial sensors (especially accelerometers and IMUs) has become widespread in many applications where fast and reliable quantitative assessment of human movement is required. The current availability of miniaturized lightweight IMUs make them very appealing to collect movement information under ecological conditions. Accelerometers are widely recognized as valid tools to monitor daily life activities for epidemiological or clinical purposes, both in healthy and pathological subjects (Arvidsson et al., 2019). They are commonly used to estimate energy expenditure and classify physical activity or behaviors according to their intensity (e.g. sedentary behavior, light, moderate and vigorous physical activity levels). Also, IMUs are becoming increasingly popular in clinical settings as they have been demonstrated reliable in assessing spatio-temporal parameters of gait (Bugané et al., 2012), and suitable to reproduce instrumented versions of classical clinical tests such as the Timed Up and Go, the 6-minutes walking test, etc. (Iosa et al., 2016)

In the last two decades accelerometers, gyroscopes and IMUs have become popular also in occupational field-based studies (Lim and D'Suoza, 2020), even though the variety of protocols employed for the measurements and the data processing techniques are so variable that a standardization is quite far from being achieved. As a matter of fact, the scientific literature reports studies that differ each other in terms of number of sensors employed (which ranges from 1 to 17), sensor placement locations (Figure 3.3) and parameters assessed (e.g. angular displacement, velocity etc.). Accelerometers have been used to assess exposure to non-neutral working postures with particular focus on low back, neck and shoulders (Jansen et al., 2001; Tesche et al., 2009; Schall et al., 2015; 2016). However, despite their common use, accelerometer-based estimates have been found characterized by poor accuracy in case of complex dynamic motions (Schall et al., 2015). Such issues pushed researchers to explore the potentialities of IMUs.

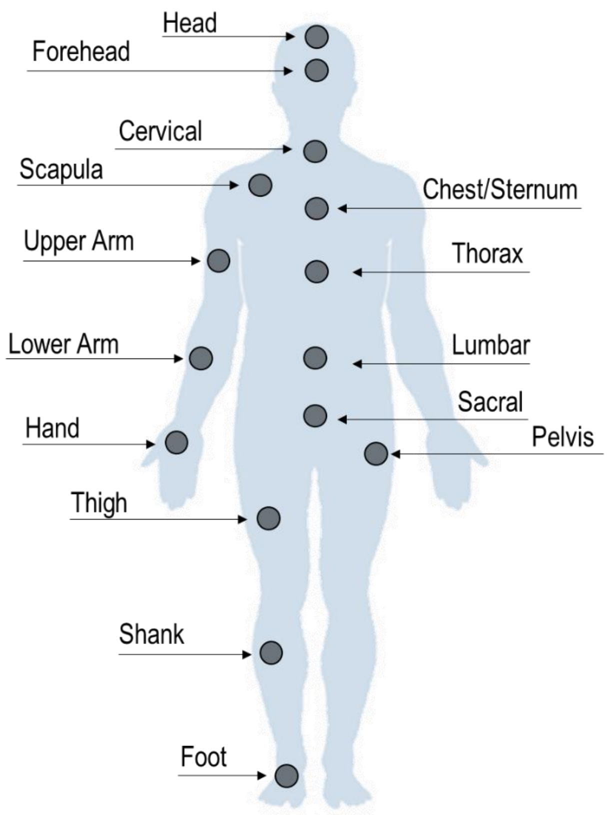

Figure 3.3 Examples of different sensor/s placement locations adopted in different studies.

There are currently several models of IMUs on the market specifically designed for human movement analysis (see Figure 3.4). Being small, light and wearable, IMUs appear the ideal solution to monitor postural changes in field settings and thus, their validity and accuracy for the assessment of body kinematics have been extensively investigated, especially by comparing their performance to gold standards such as optical motion capture system (OMC) (Table 3.1). Such validation studies have been performed, for example, as regards the assessment of upper arms and shoulder kinematics (Cutti et al., 2008; El-Gohary and McNames, 2012), cervical spine (Duc et al., 2014), lower extremities (Picerno et al., 2008; Ferrari et al., 2009), and trunk (Plamondon et al., 2007; Schall et al., 2016).

Figure 3.4 Example of IMUs commercially available. (From Top to bottom) Awinda (X-Sens Technology, Netherlands) and Aktos-t (Myon, Lucerne, Switzerland) allow the use of linked sensors. Shimmer3 (Shimmer Research, Dublin, Ireland), Gait Up (Alp ICT, Plan-les-Ouates, Switzerland), G-Sensor2 (BTS, Bioengineering, Milan, Italy)

In terms of IMUs performances, Cutti et al. (2008) and then El-Gohary and McNames (2012) reported a RMS error <3.6° and <8° when evaluating respectively shoulder and elbow three-dimensional kinematics in terms of joint angles during the performance of flex-extension, prono-supination and intra-extra rotation of the upper limb. Similarly, Duc et al. (2014), who employed IMUs to evaluate the cervical range of motion (ROM) found a mean difference with OMC <5.7° and a mean standard error in the test-retest repeatability <6.2°. At last, Ferrari et al. (2009) and Picerno et al. (2008) who evaluated the kinematics of the lower limb during gait, reported an excellent agreement with the results obtained by means of OMC.

Besides the mentioned applications in clinical field, it is noteworthy that IMUs have been validated in terms of accuracy and precision also in ergonomic applications. The studies carried out by Plandmon et al. (2007) and Kim and Nussbaum (2013) evaluated the validity of using IMUs to assess trunk posture during manual material handling (MMH) tasks in comparison with OMC reference system. Plandmon et al. (2007) found on average an error of 1.5° in trunk lateral bending, 3.2° in trunk flexion and 4.3° in trunk axial rotation. Kim and Nussbaum (2013) investigated 3D joint angles and velocities of knees, hips, trunk and shoulders, in subjects who were requested to perform a range of MMH tasks (i.e. lifting, lowering, pushing, pulling and carrying). The comparison of the results obtained using IMUs and OMC, showed a mean absolute error (MAE) ranging between 0.8° and 3.6° for joint angles and between 0.53 °/s and 1.03 °/s for joint angular velocities. Robert-Lachaine et al. (2017) assessed whole body kinematics during 32 minutes of MMH tasks, using simultaneously an OMC system and a full-body inertial motion capture system in order to determine technological and biomechanical model differences between IMUs and OMC. They found an error due to different technologies generally below 5° of (calculated as RMS error) with coefficient of repeatability ($CR = SEM \cdot \sqrt{2} \cdot 1.96$, value below which the absolute differences between two measurement would lie with 95% of probability) varying from 2.2° to 9.7°, while differences associated to the biomechanical model were found statistically greater than those due to technology. Schall et al. (2016) explored the validity and reliability of an IMU compared with an OMC assessing trunk posture during a simulated 8-hour shift in simulated milk-parlor activities, finding a sample-to-sample RMS difference ranging between 4.1° and 6.6°.

IMUs have been also used to classify posture and types of work task by means of predictive models (e.g. machine learning, artificial neural network etc.) (see Table 3.2). For instance, Brandt et al. (2017) applied a Linear Discriminant Analysis to classify low and high-risk lifting using data acquired by means of inertial sensors placed on the trunk. They found that, on average, the algorithm

Table 3.1 Studies validating IMU-based measurements in clinical and ergonomic application in comparison with optical motion capture system

Study	**Objective**	**Validation**	**Key findings**
Cutti et al (2008)	Measure of scapulothoracic, humerothoracic and elbow 3D kinematics.	Performance of flex-extension, rotation and prono-supination (1 subject tested)	RMS error <3.6°
Duc et al. (2014)	Assessment of cervical spine mobility	Sequences of imposed active head movements (lateral bending, axial-rotation and flexion–extension) (10 healthy subjects and 13 arthrodesis patients tested)	ICC range 0.63-0.99 SEM <6.2° RMS difference <5.7°
El-Gohary & McNames (2012)	Assessment of shoulder and elbow joint angles	Performance of shoulder and elbow flex-extension, rotation and ab-adduction at regular and fast speed (8 subjects tested)	RMS error <8°
Ferrari et al. (2009)	Assessment of thorax-pelvis and lower limb kinematics”	Gait (4 subjects tested)	CMC coefficient of multiple correlation of hip, knee and ankle flex-extension and hip ab-adduction >0.88
Kim & Nussbaum (2013)	Assessment of full body joint angles and angular velocities	20 minutes of MMH tasks performance (14 subjects tested)	MAE joint angles range 0.8°- 3.6° MAE joint angular velocities range 0.53°/s - 1.03 °/s

Picerno et al. (2008)	Repeatability of six examiners in the sensor placement for the evaluation of joint kinematics	Upright posture and walking tasks (1 subject tested)	RMS error walking condition range 2.5% - 4.8% of the ROM in flex-extension; range 13.1%-41.8% of the ROM in internal-external rotation
Plandmon et al. (2007)	3D trunk posture	MMH task in static postures, dynamic motion of short duration (30s) and long durations (30min) (6 subjects tested)	RMS error <3° along flex-extension axis and <6° along axial rotation axis
Robert-Lachaine et al. (2017)	Technological and biomechanical model differences in the evaluation of full body kinematics	Performance of MMH tasks (12 subjects tested)	Differences attributed to the biomechanical model significantly greater RMSE than the technological error. Joint angles RMS error <5°
Schall et al. (2016)	Assessment of trunk angular displacement and upper arm elevation	8 hours of dairy parlour tasks. (10 diary workers tested)	RMS difference range 4.1°-6.6°for the trunk RMS difference range 7.2°-12.1°for upper arm elevation

was able to correctly discriminate 65% of the postural angles estimated. In a laboratory study, Kim and Nussbaum (2014) compared the performances of three different classification algorithms (i.e. Linear Discriminant Analysis, k-nearest neighbor and Multi-layer feedforward neural network) which processed data obtained using different combination of sensors with the purpose to classify MMH tasks (i.e. carrying, walking, lifting/lowering from ground and knuckle eight and push and pulling). The precision of the classification exceeded 90%, while the durations of the task performed were underestimated of approximately 14%. Hosseinian et al. (2019) developed an algorithm based on a random forest model to classify four static activities (i.e., standing, trunk flexion, trunk lateral bending to the left and right side) and seven dynamic activities (i.e., bidirectional trunk twisting, lateral bending, flexion/extension, squatting, slow walking, fast walking, and running) using data features obtained from a single sensor located on the chest. The algorithm classified data from simulated activities with a prediction accuracy of 93%–98.2%. Peppoloni et al. (2016) developed a machine learning segmentation algorithm to identify the starting and ending of different hand activities including neutral posture, reaching, grasping, and moving in a study which investigated the repetitive hand motions of supermarket cashiers. Deviations from neutral posture of the upper limb, neck, trunk, and leg during the segmented activities were used to calculate the RULA score for each activity. The study reported an accuracy of 94.8% within each activity cycle for the RULA scores obtained by the algorithm compared to those assessed by an ergonomic practitioner. Anderson et al. (2019) developed an algorithm based on decision trees to classify sitting, standing, weight-shifting, shuffling, and walking using data from a single accelerometer attached on the thigh. The prediction accuracy of the algorithm adopting a leave-one-subject-out cross-validation method was between 93.3% and 96.8%.

Table 3.2 Studies validating IMU-based measurements to classify ergonomic tasks

Study	Model	Objective	Features	Validation	Key findings
Brant et al. (2017)	Linear discriminant analysis	To classify low and high risk lifting activities	Feature vector composed by 90th, 95th or 99th percentile of sEMG activity level and trunk inclinations	Monte-Carlo cross validation (random sampling of training and test set repeated 100 times)	Accuracy 65.1-65.5%
Kim & Nussbaum (2014)	Linear discriminant analysis; k-nearest neighbor; Multilayer feedforward neural network	To classify MMH tasks type: walking, carrying, lifting, lowering, pushing and pulling	Feature vector composed by joint angular displacement; joint angular velocities, contact pressure (insole)	Three fold cross-validation	Precision >90% and recall >80%
Hossenian et al. (2019)	Random forest	To classify MMH tasks: four static and seven dynamic	Feature vector composed by median trunk angles and area under the curve of normalized with respect to subjects' height) acceleration	NA	Accuracy 93%-98.2%

Peppoloni et al. (2016)	State machine	To classify task types: neutral pose, reach, grasp, and move	NA	Strain Index and RULA score calculated with the measured posture within the identified task duration were compared with human evaluator's ratings	Accuracy of 94.8% for RULA action level, $$.8% for Strain Index
Anderson et al. (2019)	Decision Tree	To classify sitting, standing, weight-shifting, shuffling and walking	Raw acceleration data	Leave-one-subject-out cross-validation	Accuracy 93.3%-96.8%

In the last decade a relevant number of studies proposed the use of IMUs also for "in situ" analysis (see Table 3.3). For instance, Alvarez et al. (2016) measured the joint kinematics of upper limbs (wrist, elbow and shoulder joints), using four IMUs, to assess repetitive movements or sustained awkward postures (such as holding a bent arm position) in industrial settings but also in clinical settings for the joint motion evaluation procedures carried out by doctors in the examination of affected joints for granting medical sick leave. Moriguchi et al. (2013) assessed the upper body posture (arms, head and neck) in a cohort of electricians working in the construction industries. Posture was assessed during a regular shift having the sensors placed bilaterally on the upper arms (sensors were attached on two plastic plates fixed below the deltoid muscle insertion), on the forehead (using a double-side tape) and in correspondence of the cervicothoracic spine (C7-T1). Sigh et al. (2017) evaluated musculoskeletal postural load in surgeons using three IMUs, placed bilaterally on the upper arms and on the chest. Data collected was then used to calculate a modified Rapid Upper Limb Assessment (RULA) score. Brant et al. (2018) used two IMUs placed on the upper back and on the thigh to analyze the workload (in terms of non-neutral posture and number of steps) in construction workers. Blanguier et al. (2017) aimed to characterize trunk posture patterns in vineyard activities recoding amplitude of flexion and time spent in non-neutral posture (>20°), by means of a single

IMU placed on the chest at the sternum level. Similarly, Asante et al. (2018) used a posture measurement system (IMU-based) to assess trunk flexion and lateral bending in different activities (pre-sorting; removal of unwanted/dangerous materials etc.) carried out by recycling workers. Jakobsen et al. (2018) compared the workload on the low back (assessed in terms of trunk posture and muscle activity) among blue-collar workers employed in different sectors (postal workers, machine operators, warehouse workers). Ribeiro et al. (2011) examined the within-day reliability of a commercial device (based on IMU) monitoring lumbo-pelvic trunk posture of healthcare workers, while Villumsen et al. (2016) investigated the association between trunk forward bending, low back pain (LBP) intensity and social support.

Table 3.3 Studies validating IMU-based measurements in field settings

Study	Body district	Biomechanical exposure metrics	Field/occupation	Number of sensor/s
Alvarez et al. (2016)	Upper limb	Amplitude (threshold based), frequency and duration (%time) of non-neutral posture	Industry	4: thorax, upper arm, forearm and hand
Moriguchi et al. (2014)	Arm, head and neck	Arm elevation (threshold based), head and neck flexion angles; duration (%time)	Construction (electricians) (12 Norvegian and 12 Brazilian workers)	4: right and left upper arms; forehead; cervicothoracic spine (C7-T1)
Sigh et al. (2016)	Neck, trunk and shoulder	Neck and trunk flexion (threshold based); arm elevation (threshold based). Duration (%time)	Surgeons (N=4)	3: right and left upper arms and chest
Balanguier et al. (2017)	Trunk	Trunk flexion and rotation (threshold based). Duration (%of time)	Vineyard workers (N=15)	1: chest (sternum level)
Asante et al. (2018)	Trunk	Trunk flexion and lateral bending (threshold based). Duration (%Time)	Recycling workers (N=10)	1: chest

Ribeiro et al. (2011)	Trunk	Trunk flexion (threshold based). Frequency (bends/hour)	Aged-care residential home workers (N=21)	Spineangel postural monitoring
Villumsen et al. (2016)	Trunk	Trunk flexion (threshold based). Duration (time)	Blue-collar workers (N=657)	2: Trunk (T1-T2) and thigh
Schall et al. (2016)	Trunk and upper arm	Trunk flexion and upper arm elevation (Threshold based). Duration (%time). Count of 3s periods in neutral trunk posture or arm position with velocity <5°/s per min	Nurses (N=36)	3: right and left upper arm and thorax (T4)
Jakobsen et al. (2018)	Trunk	Trunk flexion (threshold based). Duration (time)	Warehouse workers(N=39), Operators (N=27); Postal workers (N=24) and slaughterhouse workers (N=20)	1: thorax (T1-T2)

The results of the above-mentioned studies strongly support the idea that IMUs represent an effective and feasible way to assess body postures and to classify MMH activities in occupational contexts. However, when a relevant number of sensors is employed, the application of such techniques to actual working contexts appear difficult. Also, most existing studies do not consider all the main features of exposure, namely amplitude, duration and frequency. To fill, at least partly, this gap, the main purpose of the present study is to propose the application of a simplified setup to assess trunk posture in terms of amplitude, frequency and duration in real work environments.

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Chapter 4

Instruments and methods

As previously mentioned, this study is focused on the characterization of posture and movement of ageing workers, particularly in those engaged in physically demanding occupations which are possibly associated to an increased risk of develop LBDs. In order to simplify the assessment of workload associated with trunk posture and occupational physical activity, the research has been articulated into two main areas:

1. To demonstrate the feasibility of use and the reliability of a simplified setup composed by a single IMU to monitor trunk flexion for prolonged working time in actual occupational settings.
2. To explore the possibility to use the same setup to classify type, frequency and duration of a range of MMH tasks of interest (given their potential hazard for the development of LBDs) by means of specific algorithms that process IMU-derived data.

In the subsequent part of this chapter, will be described in detail the devices employed for the study as well as the data processing techniques.

Inertial Measurement Units (IMUs) and accelerometers to assess motion

To date, there is a wide range of IMUs available on the market, which differ for technical characteristics like sensitivity range, presence of dedicated software to facilitate the data processing in clinical, sport or ergonomic use or for the possibility to acquire data on-board.

For instance, the X-Sens units (The Netherlands) IMUs (Figure 5.1) (see Faber et al., 2009; Kim and Nussbaum, 2013; Alvarez et al., 2016; Merino et al., 2019; Maurice et al., 2019); The I2M SXT, (APDM, Inc., Portland OR) (see Sigh et al. 2017); I4 motion (Technoconcept, Mane, France) (see Balanguier et al. 2017); SXT I2M (NextGen Ergonomics, Montreal, Canada) (see Asante et al., 2018); or the ArduIMU v3 (3D robotics, Inc., Berkeley, CA). The X-Sens units (The Netherlands) IMUs are probably the most widespread for research purposes due to the possibility they offer to collect and process data on full body kinematics by means of an ad-hoc suite. However, their use in the assessment of full body kinematics in actual working conditions is limited due to incompatibility with personal protective equipment and the need to stay close (15 m) to the sensor receiver. The G-Sensor2 (BTS-Bioengineering, Italy) (Figure 5.1) gained popularity especially in clinical and sport settings due to the availability of ready-to-use protocols to calculate parameters of interests for gait analysis, Timed-Up-and-Go, jumps, etc. Moreover, this device allows recording data on-board (up to 512 Mb of data, that is 2 to 8 hours of data collection depending on the acquisition frequency), giving the possibility to the tested subject to freely move (without the need to stay within the range of communication with a PC) appearing thus suitable to long monitoring in actual occupational settings. Actigraph company (USA) produce the GT9X IMU (see for example Brant et al., 2017), but in the literature is easier to find studies which employed the GT3x tri-axial accelerometer (Figure 5.1), a device extensively employed either as inclinometer or activity tracker to estimate levels of physical activity and energy expenditure (some examples are: Jakobsen et al., 2018; Schall et al., 2015; Villumsen et al., 2016).

Different sensors, although based on the same principle of functioning, are characterized by peculiar features that make them more suitable to specific uses and settings. In the case of the present study, the G-Sensor2 was found the most appropriate solution to record trunk movement for prolonged period of time on-board. On the other hand, the X-Sens Awinda system represented a good solution to compare the performance achievable in tasks classification with sensors placed in different locations simultaneously. Finally, the GT3x was a valid option to estimate occupational physical activity in a straightforward way due to its powerful management software.

X-Sens Awinda, Strap and Suite version and recording receiver station | G-Sensor 2 | Actigraph Gt3x

Figure 5.1 In figure are reported the three commercially available IMU, employed in this work

Quantification of angular motion

Assuming body segments as rigid bodies, the quantification of attitude or angular motion consist of three components, which refer respectively to the sagittal, coronal and transverse anatomical planes. Since several kind of parametrization are currently available to represent movement in three-dimension (3D), a given segment attitude can be specified by different components values depending on the parametrization that is chosen. In Cartesian coordinate systems, given a global reference system and a local reference system embedded in the rigid body (body segment), the attitude of the segment can be described relatively to the global reference system by defining a 3x3 rotation matrix [R]. A commonly used parametrization makes use of Cardan/Euler angles, which are easily obtainable starting from a rotation matrix. Indeed, a set of three independent angles is obtained by an ordered sequence of rotations (a,b,c) about the axes of a selected Cartesian coordinate system (which generally is the global reference system) to obtain the attitude of the segment (or, equivalently, of the embedded reference system). The sequence is determined by the assignment of the axes x,y,z to the ordered sequence a,b,c. When all three rotations (a,b,c) occur around different axes (x,y,z) the term Cardan angles is used. For a=c (e.g. x,z,x), the term Euler angles is used. For a given attitude (i.e. a defined rotation matrix), the magnitude of the three angular components changes according on the way axes are assigned to the ordered sequence. Thus, Cardan/Euler angles are characterized by the so-called sequence dependency.

In order to avoid this sequence dependency Cole et al. (1993) proposed a generalized algorithm which overcomes the issues related to the model proposed by Grood and Suntay (1983). In his generalized algorithm Cole et al. (1993) defined the axis of flexion F-axis, the longitudinal axis L-axis and the third axis T-axis, which is obtained by the cross product between F-axis and L-axis with the relative sequence of rotation F-L-T or rotation around the axis of flexion, rotation around the axis of ab-adduction and finally the rotation around the axis of axial rotation (FE-AA-IE).

Quantification of angular motion using G-Sensor2 data

The G-Sensor2 integrates a Digital Motion Processor^{TM} (DMP^{TM}) that provides as output the Cardan angles together with raw accelerations and angular velocities using a proprietary motion fusion algorithm. The Cardan angles are referred to a local reference systems obtained from an autocalibration procedure which is performed each time the sensor is powered on, and thus is not directly usable in the determination of its attitude (or the attitude of the body segment on which it is attached). Following the generalized algorithm proposed by Cole et al. (1993), the attitude and subsequent angular movement of the sensor have been obtained following the next steps.

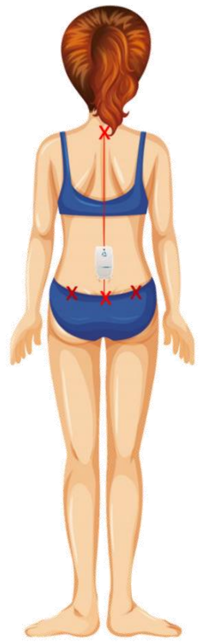
- STEP 1: Definition of fixed and moving reference systems

In order to obtain the sensor attitude, it is necessary to define both fixed and moving reference systems. For convenience, the fixed reference system has been chosen coincident to the reference system embedded in the sensor case which then coincide with the moving reference system before the start of the movement (i.e. during the calibration/stabilization phase).

The x-axis of the fixed reference system is represented by the inferior-superior axis, the y-axis is the medio-lateral axis and the z-axis is the antero-posterior axis (see Figure 5.2a). They correspond respectively to the axis of axial rotation, flexion-extension and ab-adduction or lateral bending, when the sensor is attached to the subject's trunk (the sensor was placed according to Faber et al., 2009).

The moving reference system (local reference system) is based on the Cardan angles calculated by the DMP^{TM} during the stabilization phase, identified using the vertical acceleration signal. This procedure is performed considering the interval of time in which the vertical acceleration values are within ± *2% of g* threshold (*g*: acceleration of gravity), as shown in figure 5.3.

a



b

Figure 5.2 Figure a shows the reference system associated to the case of the sensor. x-axis that correspond to the axial rotation; y-axis that correspond to flex extension and z-axis that correspond to the lateral bending. Figure b shows the sensor location placement according to Faber et al. (2009)

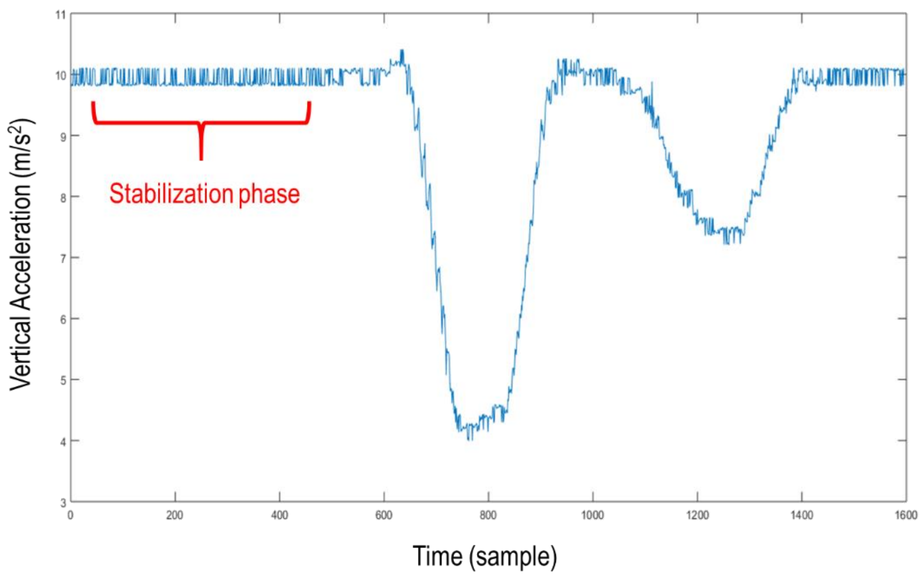


Figure 5.3 Example of vertical of vertical acceleration where is indicated the portion of signal used to find the stabilization phase

- STEP 2: Sensor orientation assessment from IMU Cardan angles output

To obtain the sensor orientation we must recall that the attitude of a rigid body (ρ) in space can be obtained using the relationship between a global (fixed) reference system and a local (moving) reference system (eq. 5.1) **(**Figure 5.4).

$$^{g}\rho = {}^{g}R_{l}\rho + {}^{g}o \tag{5.1}$$

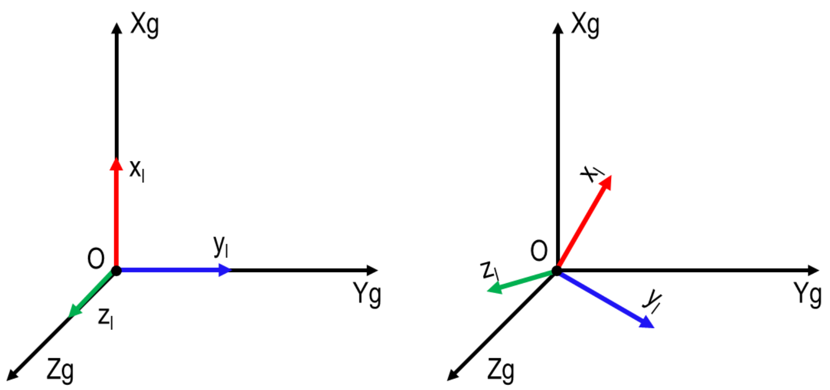


Figure 5.4 Example of global and local reference systems. On the right the two system are overlapped (as during the stabilization phase); On the left the local reference system is rotated respect to the global reference system (as during trunk movements)

Where the rotation matrix ${}^{g}R_{l}\rho$ has been defined as:

$$^{g}R_{l} = \begin{bmatrix} \cos(\theta_{x_g x_l}) & \cos(\theta_{x_g y_l}) & \cos(\theta_{x_g z_l}) \\ \cos(\theta_{y_g x_l}) & \cos(\theta_{y_g y_l}) & \cos(\theta_{y_g z_l}) \\ \cos(\theta_{z_g x_l}) & \cos(\theta_{z_g y_l}) & \cos(\theta_{z_g z_l}) \end{bmatrix} \tag{5.2}$$

Then, the relative movement between the fixed and moving reference systems can be calculated for each time sample, using the rotation matrix parametrization (5.2) and the equation (5.3)

$$R_{angular\ movement} = R_{Moving}^{T} * R_{Fixed} \tag{5.3}$$

Where $R_{angular\ movement}$ is the rotation matrix that represents the angular movement of the sensor; R^T_{Moving} is the rotation matrix representing the moving reference system transposed and R_{Fixed} is the rotation matrix associated to the fixed reference system.

Finally, to represent in a simpler manner the information contained in the rotation matrix $R_{angular\ movement}$ it has been translated using Cardan angles. This transformation has been performed using the Cardan rotation sequence Y-Z-X (corresponding to FE-AA-ROT), as suggested by Cole et al. (1993) to avoid errors associated to the sequence dependency.
All the above-mentioned data processing has been performed using a custom MATLAB routine (R2019a, MathWorks, Natick, Massachusetts, USA).

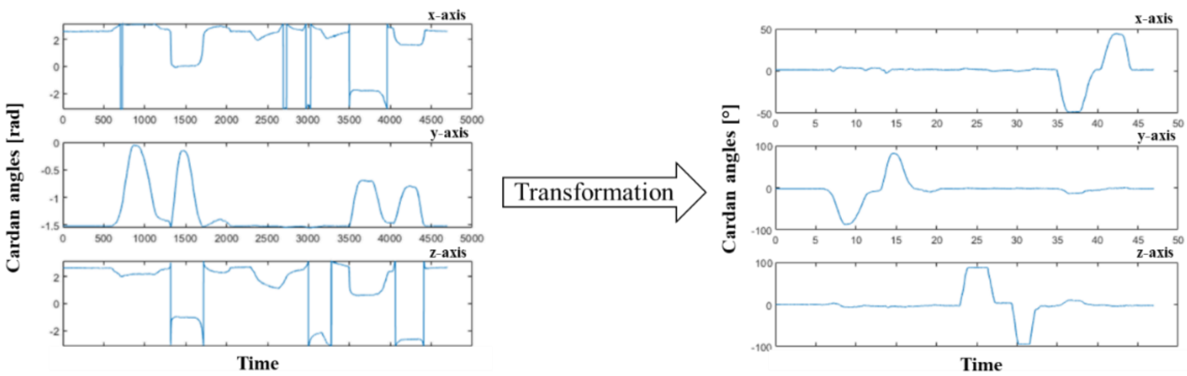


Figure 5.5 Example of transformation from Cardan angles output of the sensor to Cardan angles calculated with respect to the fixed sensor reference system, following the described steps

Comparison of angular motion using G-Sensor2 and an optical motion capture system

Although several studies verified the validity and reliability of the IMU in terms of human body kinematics assessment (Cutti et al., 2008; El-Gohary and McNames, 2012; Picerno, et al., 2008; Ferrari et al., 2010; Plamondon et al., 2007; Kim and Nussbaum, 2013;

Schall et al., 2015), to the best of our knowledge none of them specifically evaluated the performances of the G-Sensor2 (BTS Bioengineering, Milan, Italy). Thus, in order to assess the quality of the output achievable with this device, the Cardan angles measured by means of the IMU with those obtained from an optical motion capture system during simultaneous acquisitions.

To this aim, three non- aligned markers were placed on the G-Sensor2 (as shown in Figure 5.6). They defined a reference system oriented as the embedded reference system of the case of the G-Sensor2 (Figure 5.6).

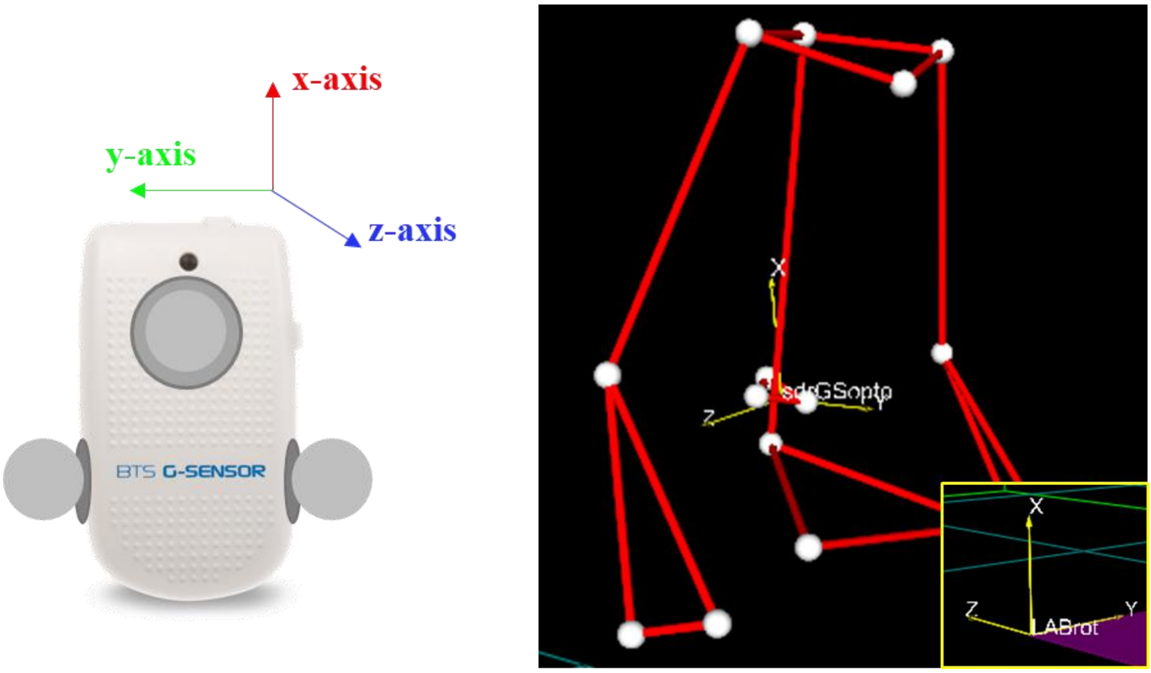


Figure 5.6 Left: three non- aligned markers to build an embedded sensor reference system. Left: Sensor reference system represented in the optical motion capture system point of view.

Labeling the markers attached to the sensor as: L_GS (left side marker), R_GS (right side marker), TOP_GS (top anterior marker), at each time was possible to obtain the 3D coordinates of three non-aligned point in space. Starting from these data we built the rotation matrix that defines the local reference system associated to the sensor as follows:

$$j = \|P_1 - P_2\|$$

$$a = \|P_3 - P_1\|$$

$$k = \|a \times j\|$$

$$i = \|j \times k\|$$

$$Local_{RS} = [i, j, k] \tag{5.4}$$

Where P_1 is R_GS; P_2 is the mid-point between R_GS and L_GS and P_3 is TOP_GS. Also, j is the unit vector that connect P_1 to P_2; k is the projection of P_3 onto the unit vector j and i is the unit vector obtained as cross product between j and k.

As described in equation (5.3) it is possible to obtain the information about the sensor angular displacement (from the optical motion capture system point of view) by comparing the rotation matrix of the local reference system with the rotation matrix associated to the global reference system (the laboratory reference system) suitably rotated so that at the initial time frame the two reference systems are overlapped (figure 5.4).

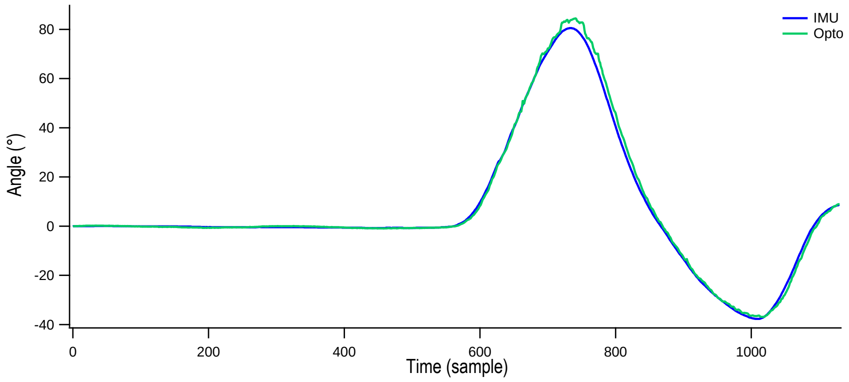
To calculate the differences in angular displacements assessed obtained using the two systems (i.e. optical vs IMU), a sample-to-sample root mean squared distance (RMSD) on 21 trials (7 subjects x 3 repetitions) for three main trunk movements (i.e. flex-extension, lateral bending, axial rotation) was performed.

$$RMSD = \sqrt{\sum_{i=1}^{N} \left(\frac{\theta_{IMU} - \theta_{Optical}}{N}\right)^2} \tag{5.5}$$

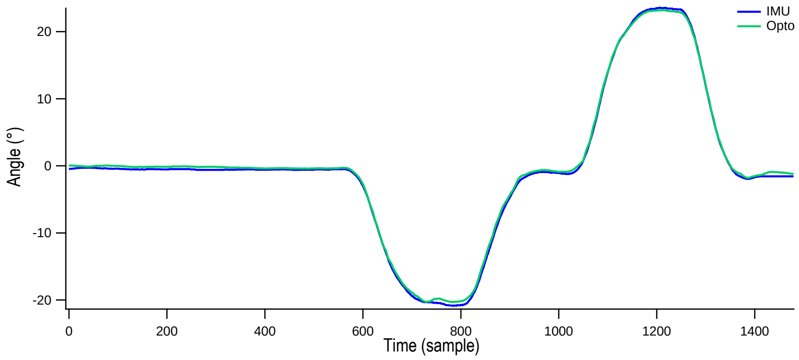
The results showed a good level of agreement between the systems, with a RMSD ranging from 1.6° to 3.8° for lateral bending and axial rotation respectively (Table 5.1).

Table 5.1 sample-to-sample RMS error on 21 trials (7 subjects x 3 repetitions) for each trunk movement. Values are expressed as mean (SD)

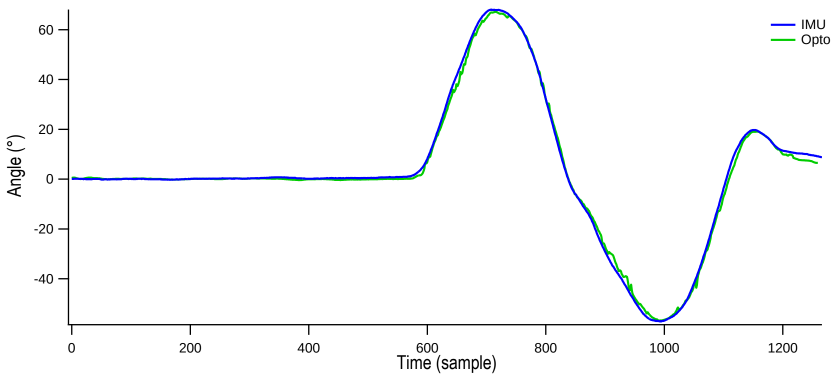
<table>
<tr><th colspan="2">Analyzed Movement</th><th>RMS</th></tr>
<tr><td>Flexion

Extension</td><td>
</td><td>2.1

(1.9)</td></tr>
<tr><td>Lateral

Bending</td><td>
</td><td>1.6

(0.8)</td></tr>
<tr><td>Axial

Rotation</td><td>
</td><td>3.8

(1.3)</td></tr>
</table>

Continuous Monitoring of trunk posture: Exposure Variation Analysis

In field studies, exposure is an observed parameter and the quantification of variation becomes a problem of reducing exposure-vs-time data. The term “exposure” may denote the acute, instantaneous level of physical load, or may refers to a cumulative aspect which described the time-integrated quantity of exposure. In occupational field the exposure is a variable parameter that imply a problem of data processing to yield relevant information. Dynamic and static aspects of postural movements are important in explaining the way in which physical load may cause musculoskeletal problems. In principle, continuous registration of angular trunk position acquired through direct measurement techniques allows to quantitatively describe all three essential parameters of exposure, that is amplitude, frequency and duration. In practical terms, having available a method to easily assess exposure (while still able to discriminate/identify the relevant pattern of exposure), might help to compare exposure at different time or between different occupations (e.g. construction, healthcare, manufacturing etc.) or populations (e.g. young vs old, men vs female etc.).

Matthiassen and Winkel (1991) proposed a method for the reduction of exposure data recorded as a function of time, named Exposure Variation Analysis (EVA). EVA basically translate exposure-versus-time registrations into a data sheet. The procedure to perform such process is the following:

1. The duration of every single unbroken period spent within a certain class limit (a predefined level of exposure) is registered;
2. These periods are sorted into time-period classes (each characterized by a predefined duration of exposure);

3. The accumulated time spent in each of the time-period classes is calculated and expressed as percentage of the total working time;

4. Steps (1) to (3) are repeated for each of the remaining exposure level classes.

In this way a value located in a certain cell of the data sheet represent the accumulated time spent in period of defined length, at the exposure level within the indicated class. The sum of all cells values represents the 100% of the working time. A datasheet with n cells will contain n-1 statistically independent numbers, thus providing a basis for statistical evaluation of the analyzed work operation, as well as for comparison with other work tasks. The contents of the table can also be represented as a bar diagram (Figure 5.7).

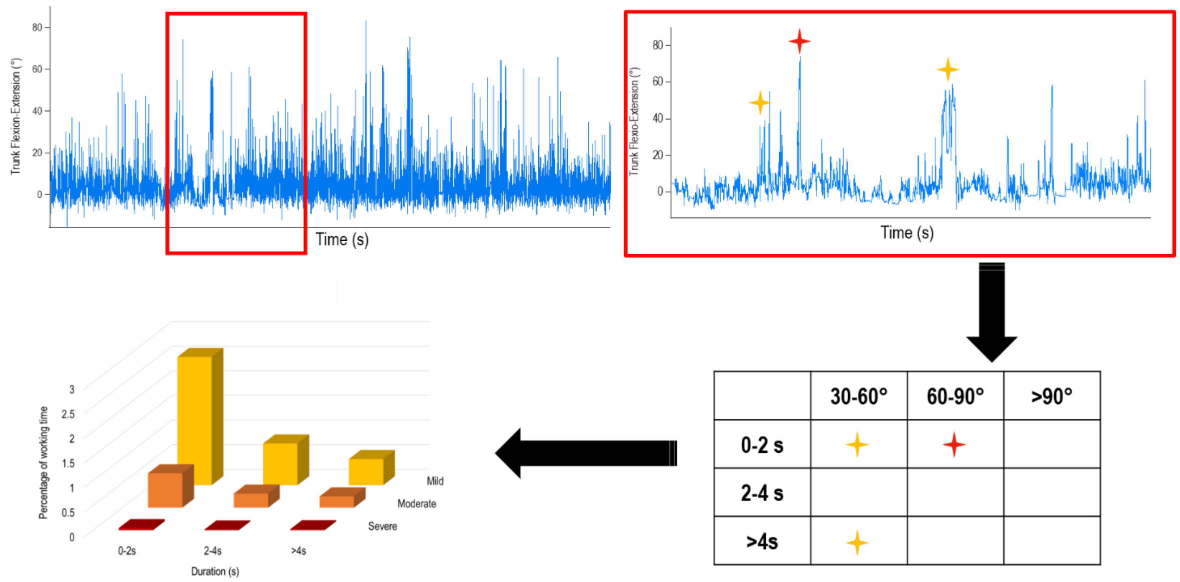


Figure 5.7 Example of EVA methods procedure. From the exposure vs time signals duration of every single unbroken period spent within a certain class limit is registered; periods are sorted into time-period classes; accumulated time spent in each of the time-period classes is calculated and expressed as percentage of the total working time.

The choice of exposure classes

Specific thresholds or limits at which trunk postures become an occupational hazard have not been defined yet, although this issue was debated since a decade ago (Hoy et al., 2010). The attempts to classify mild, moderate and severe trunk postures resulted, so far in many (and even much different) thresholds. Wai et al. (2010) who summarized the results of 35 studies which adopted a variety of categories to evaluate awkward trunk postures, concluded that most epidemiological studies used thresholds of 45° or greater to define extreme postures. The NIOSH suggested that researchers should classify trunk postures into four major categories based on increment of 30° (i.e. 0°-30°; 30°-60°; 60°-90° and >90°, NIOSH, 2014). Although this classification was designed mainly to facilitate the use of observational methods, it also represents an important starting point for standardization of trunk postures and have been also used in subsequent studies (Villumsen et al., 2015; Lee et al., 2017; Coenen et al., 2013). In the present study we decided to adopt the NIOSH classification also to facilitate the comparison of the results with those of previous studies.

Discrimination of different activities in manual material handling tasks

In addition to the evaluation of body kinematics, IMUs have been used also to classify posture and type of work task by means of predictive models (e.g. machine learning, artificial neural network etc.). Since jobs that involve manual material handing (MMH) such as lifting/lowering, pushing/pulling, and carrying have been positively associated with a higher risk of LBDs development (National Research Council, USA, Panel on Musculoskeletal Disorders, Institute of Medicine 2001). In this study has been decided to apply a classification algorithm to estimate frequency and duration of eight MMH tasks namely: 1) lifting from the ground, 2) lifting from knuckle height, 3) lowering to the ground, 4) lowering to knuckle height, 5) pushing, 6) pulling, 7) carrying, and 8) walking.

There are many currently available classifications algorithms and variants (e.g., Naïve Bayes, K-Nearest Neighbors, Decision Tree, and Support Vector Machines), that can be trained using signals obtained with different feature selection methods and, tested using different approaches. For our purposes, the choice of a bidirectional long short-term memory (BiLSTM) recurrent neural network appeared the most suitable. This choice because deep learning (among which BiLSTM) approaches have been found to often outperform conventional classification algorithms (Gjoreski et al., 2016) and can avoid the design and handpicking of features that typically require expert knowledge (Jordao et al., 2018; Wang et al., 2019; Shakya et al., 2018). Additionally, Wang et al. (2019) noted that a LSTM network is effective in classifying highly unbalanced activities in terms of frequency as occurs in MMH tasks (e.g., more lifting from knee level than lifting from ground level).

The following paragraph will present BiLSTM in more detail.

Bidirectional Long-Short Term Memory Network (BiLSTM)

Bidirectional Long Short-Term Memory Network are a particular Artificial Recurrent Neural Network structure, a group of models that take the principle "infer the knowledge from the data". These methods are suitable to study a particular class of problems that are represented by temporal sequences of input-output data pairs (e.g. speech recognition, time series prediction, dynamic control systems etc.).

Given a time series of input data vectors $\boldsymbol{x}_1^T$, a RNN maps a corresponding output data vectors $\boldsymbol{y}_1^T$by means of a set of activation weights and a non-linear activation function. With neighboring data being in some way statistically dependent.

$$\boldsymbol{x}_1^T = \{\boldsymbol{x}_1, \boldsymbol{x}_2, \boldsymbol{x}_3, \dots, \boldsymbol{x}_{T-1}, \boldsymbol{x}_T\}$$

$$\boldsymbol{y}_1^T = \{\boldsymbol{y}_1, \boldsymbol{y}_2, \boldsymbol{y}_3, \dots, \boldsymbol{y}_{T-1}, \boldsymbol{y}_T\}$$

For a given time sequence $\boldsymbol{x}_1^T$ and $\boldsymbol{y}_1^T$ as training data, the aim is to learn the rules to predict the output data given the input data. Inputs and outputs can, in general be continuous and/or categorical variables. In the latter case categorical, they can be named class labels (as in the present study), and the problem is known as “classification problem”. In the case of the classification problem, the goal is to find the most probable class, out of a given pool of possible classes for every time frame *t* given an input vector sequence $\boldsymbol{x}_1^T$. To make this kind of problem suitable to be solved by an artificial neural network, the categorical variables are usually coded as vectors as follows. Consider that *i* is the desired class label for the frame at time *t*. Then, construct an output vector y_t such that its i^{th} component is 1 and other components are 0. The output vector sequence $\boldsymbol{y}_1^T$ construct in this way along with the input vector sequence $\boldsymbol{x}_1^T$can be used to train the network which will result from a maximum likelihood estimation. It has been shown that the i^{th} network output at each time point t can be interpreted as an estimate of the conditional posterior probability of class membership for class *i*, with the quality of the estimate depending on the size of the training data and the complexity of the network.

Different architectures of artificial neural networks use input vector sequence in different ways (Figure 5.8 from Schuster and Paliwal, 1997). A RNN architecture can make use of all the available input information up to the current time frame t_c to predict y_{tc}. The amount of this information is captured by a particular RNN depends on its structure and the training algorithm used. In general for an input sequence $\boldsymbol{x}_1^T$, a RNN compute the hidden sequence $\boldsymbol{h}_1^T$

and the output sequence $\boldsymbol{y}_1^T$ by performing the following operations for time steps t =1 to T (Graves et al. 2013):

$$h_t = H(W_{xh}x_t + W_{hh}h_{t-1} + b_h)$$

$$y_t = H(W_{hy}h_t + b_y)$$

Where H is the hidden layer activation function, W_{xh} is the weight matrix between the input and the hidden layer, $W_{hh}$is the recurrent weight matrix between the hidden layer and itself, W_{hy} is the weight matrix between the hidden and output layer, and b_h b_y are the hidden and output layer bias vectors respectively. H is usually an element-wise application of the sigmoid function. To overcome the vanishing gradient problem of traditional RNN, Hochreiter and Schmidhuber (1997) propose an alternative RNN called Long Shorth-Term Memory (LSTM) in which conventional neuron are replaced with a so-called *memory cell* controlled by input, output and forget gates. In this case, H can be described by the following composite function:

$$i_t = \sigma(W_{xi}x_t + W_{hi}h_{t-1} + W_{ci}c_{t-1} + b_i)$$

$$f_t = \sigma(W_{xf}x_t + W_{hf}h_{t-1} + W_{cf}c_{t-1} + b_f)$$

$$c_t = f_tc_{t-1} + i_t tanh(W_{xc}x_t + W_{hc}h_{t-1} + b_c)$$

$$o_t = \sigma(W_{xo}x_t + W_{ho}h_{t-1} + W_{co}c_t + b_o)$$

$$h_t = o_t\tanh(c_t)$$

Where σ is the sigmoid function, *I*, *f*, *o* and *c* are respectively the input, forget, output gates and cell activation vectors. Future input information, i.e. those coming after t_c, is usually useful for prediction, together with past and present input information. To use all available input information, it is possible to use two separate networks (one of each time direction) and then somehow merge the results (Schuster and Paliwal 1997). A bidirectional LSTM (BiLSTM), process input sequences in both directions with two sub-layers in order to account for the full input context. These two sub-layers compute forward and backward hidden sequences h_f and h_b respectively, which are then combined to compute the output sequence y, thus:

$$h_{t,f} = H(W_{xh,f}x_t + W_{h,fh,f}h_{f,t-1} + b_{h,f}$$

$$h_{t,b} = H(W_{xh,b}x_t + W_{h,bh,b}h_{b,t-1} + b_{h,b}$$

$$y_t = W_{h,f\,y}h_{t,f} + W_{h,b\,y}h_{t,b} + b_y$$

An example of architecture is showed in figure 5.8.

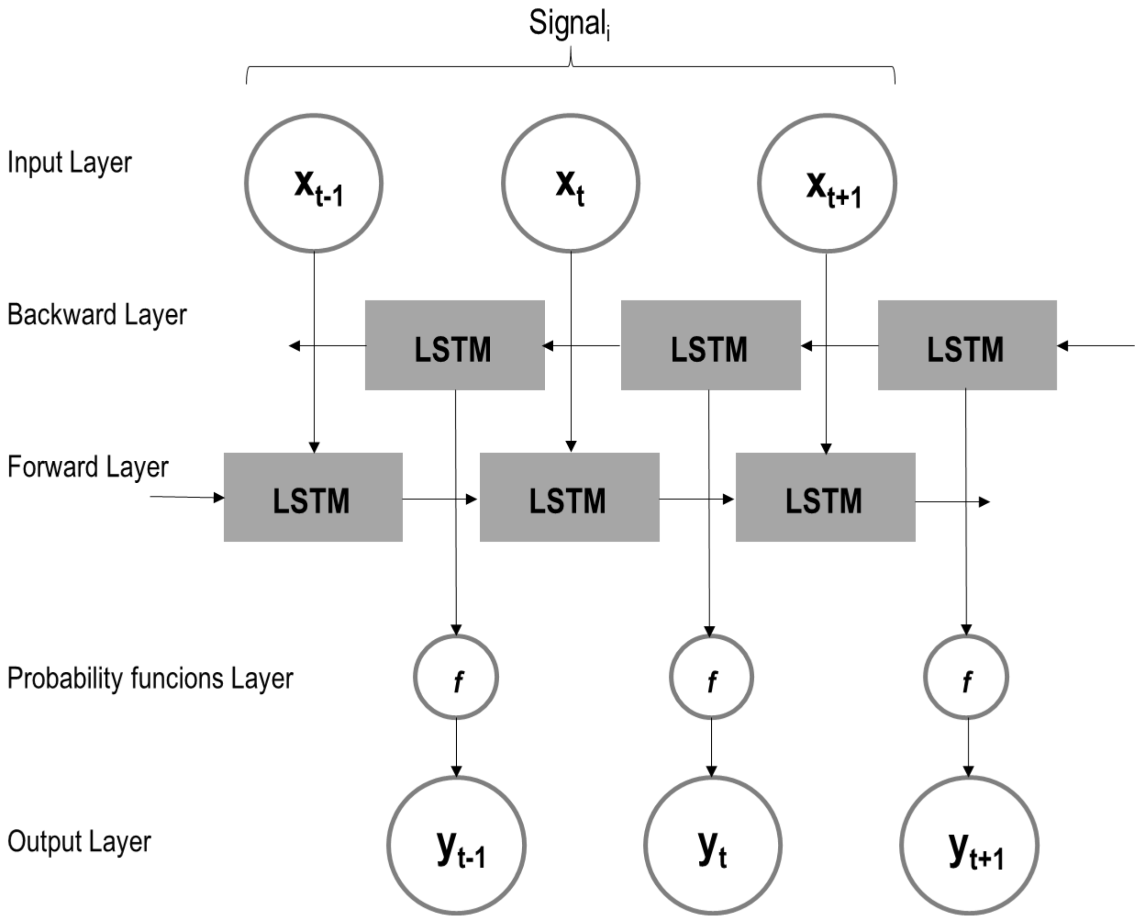


Figure 5.8 Example of BiLSTM architecture. (Figure adapted from Wadawadagi et al. 2020)

BiLSTM was found characterized by good performance in task classification (Wainwright and Shenfield, 2019; Hammerla et al., 2016). Using a forward and a backward LSTM layer, BiLSTM learns bidirectional, long-term dependencies between time steps of time series, thus leading to a better performance than a (forward) LSTM layer that typically learns a long-term dependency from prior time steps (Hammerla et al., 2016; Siami-Namini et al., 2019). We implemented the BiLSTM using the *bilstmLayer* function available in Matlab^{TM} Deep Learning toolbox (R2019a, MathWorks, Natick, Massachusetts, USA). In particular, the architecture (see Figure 5.9) of the network here employed consisted of an input layer, characterized by variable sizes depending on the number of sensors considered for the analysis (3 accelerations signals and 3 angular velocities signals for each sensor).

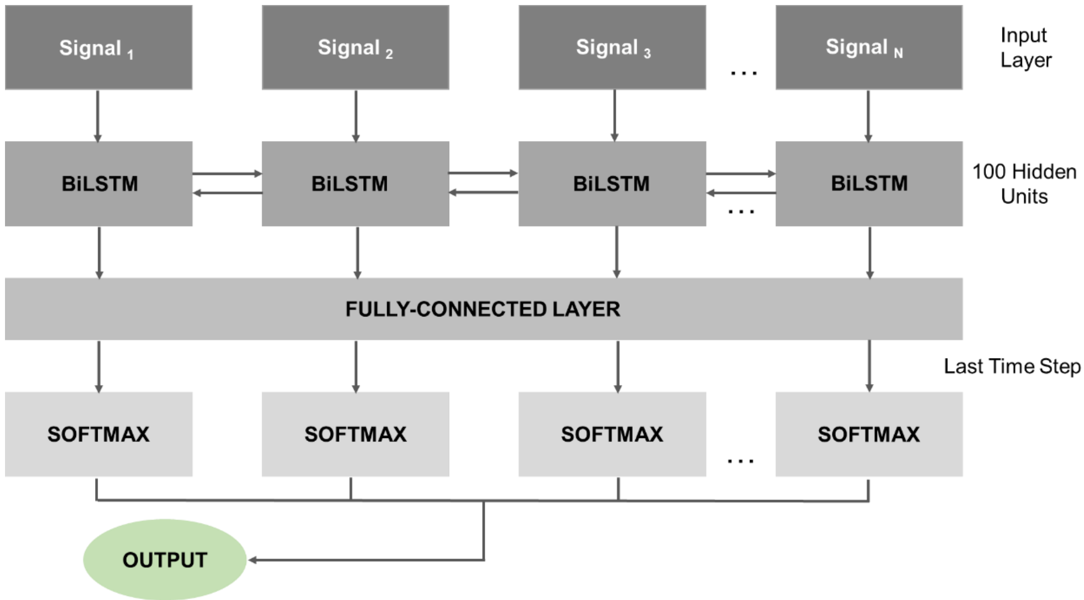


Figure 5.9 Architecture of the BiLSTM network employed for the MMH task classification. The input layer is characterized by variable sizes ranging from 6 to 102 depending on the number of sensors considered for the analysis (3 accelerations signals and 3 angular velocities signals for each sensor). The input layer was followed by the BiLSTM architecture consisted of 100 hidden units. After this layer, the fully-connected layer where have been indicated the number of classes of interest. The last layer provides the probability for each category in the dataset following the softmax function.

The input layer was followed by the BiLSTM architecture consisted of 100 hidden units. After this layer, the fully-connected layer where is indicated the number of classes of interest. The bottom layer provides the probability for each category in the dataset following the softmax function. The maximum number of epochs was set to 300. Decision was made sample to sample.

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Case study 1

Trunk flexion monitoring among warehouse workers using a single inertial sensor and the influence of different sampling durations

A version of this chapter has been published. Porta M., Pau M., Orrù P.F. and Nussbaum M.A. (2020). International Journal of Environmental Research and Public Health. 17(19),7117, pp.1-12.

Introduction

Non-neutral trunk postures, in particular those involving flexion (Wai et al., 2010), represent a risk factor for the onset of low-back disorders (Andersen et al., 2007; DaCosta and Vieira, 2009; Bernard, 1997; Punnet et al., 1991). These disorders represent a major health problem, causing absence from work, with consequent reduction in productivity (Villumsen et al., 2014), and in the most serious cases disability and impairment of the fundamental activities of daily living. Such adverse outcomes, along with their associated social costs (Dunning et al., 2009), have led ergonomists and safety professionals to try to improve job design decisions, and to establish suitable safe work limits that either prevent these outcomes or, at least, mitigate their adverse effects.

A critical issue when planning prevention/mitigation strategies is obtaining an accurate evaluation of the biomechanical risk associated with each working task, which requires a detailed identification of task intensity, frequency, and duration (Burdorf and van Riel, 1996). Traditionally, such assessments have been typically performed by means of self-reports and observational methods. The former method is easy to use and inexpensive, but can be biased by subjective perceptions of physical work demands, while the latter can be inaccurate and substantially time-consuming, with required analysis durations up to 30 times the actual duration of a video segment (Herberger et al., 2012).

In the last three decades, however, several quantitative techniques have been developed and used to obtain direct measurements of trunk postures under actual working conditions, including electro-goniometers (Marras et al., 1992) and inclinometers (Williams et al., 1993). Unfortunately, some of these instruments are not suitable for long-term measurements, since they require additional external structures to be connected to the body. Since they are often attached on the subject's skin, they can also cause discomfort (David, 2005). Moreover, these devices can alter an individual's usual working behaviours.

In recent years, the rapid advancement of technology and a parallel reduction in cost has made it easier to employ substantially smaller devices, such as wearable inertial measurement units (IMUs), to obtain quantitative data on movement kinematics. Such devices have rapidly become popular among human movement researchers, as they provide reliable data, with quality comparable to gold standards (i.e., optical motion capture systems: Faber et al., 2009; Goodvin et al., 2006; Kim and Nussbaum, 2013; Lebel et al., 2017; Schall et al., 2015). IMUs represent an appealing option even for field-based settings, as they do not interfere with worker's task and can acquire a large amount of data, thus being suitable for long-term posture monitoring.

For lumbar posture, the most common parameter in assessing exposure is the angular position of the trunk, commonly expressed using an ordinal scale (e.g., neutral, mild, and severe flexion), even when continuous data are recorded. In most cases emphasis is given to the level of exposure neglecting both frequency and duration, although duration of exposure may be used to evaluate cumulative exposure proportional to chronic damage (Burdorf and van Riel, 1996).

In the last decade, several reports have indicated that IMUs can effectively monitor body posture during the performance of diverse tasks, both in laboratory conditions (Faber et al., 2009; Schall et al., 2015; Faber et al. 2016; Cutti et al., 2007; Godwin et al., 2009; Kim and Nussbaum, 2014; Lim and D'Suoza, 2019; Yan et al., 2017) and in situ (Villumsen et al., 2014; Schall et al., 2015; Arias et al. 2017; Bootsman et al. 2019; Jun et al., 2019; Asante et al., 2018; Balaguier et al., 2017; Jakobsen et al, 2018). However, while these have investigated trunk kinematics, no information was provided about critical aspects of postural exposure, such as the frequency and duration of trunk movements.

Assessing trunk posture is of particular interest among warehouse workers. These workers are often assigned to order-picking processes, in which they perform a variety of physically-demanding tasks, such as restocking shelves and pallets, loading and unloading pallets, and driving forklifts. In many warehouse facilities, it is typical for a worker to spend the majority of their shift picking items from shelves and stacking them onto a pallet to form orders that are then shipped. Since such tasks are not easily automatable, they are still mostly performed manually, with limited (or no) mechanical support. As such, warehouse workers commonly perform substantial manual material handling (MMH) tasks that involve repetitive exposures to non-neutral trunk postures, and experience a relatively high rate of low-back disorders (Marras et al., 1997; Marras et al., 1999; Schneider et al., 2006).

In such a context, IMUs can be considered a valid option to monitor several aspects of movements associated with working tasks, as their interference with regular movements appears negligible and thus their use seems acceptable in workplaces. However, issues related to compliance, protection of personal data, and comfort, as well as the lack of standardized protocol for data acquisition and processing, are still under debate. Thus, the use of such devices in daily practice is not as widespread as expected (Beeler et al., 2018; Schall et al., 2018; Bergman et al., 2012).

To help overcome some of these concerns, this study aimed to assess the feasibility of classifying trunk flexion during actual MMH tasks among warehouse workers using a miniaturized wearable IMU. The main purpose of the study was to determine the potential of a simplified setup, a single IMU, suitable for application in actual working conditions for long-term monitoring, and to provide a reliable classification of trunk postures in terms of frequency and duration. Additional analysis was completed to investigate the influence of the monitoring duration, to explore possible efficiencies in data collection that might help toward improving worker acceptability and enhancing the number of workers that can be included in exposure assessments.

Materials and Methods

Participants

Twelve male, full-time workers participated voluntarily, with mean (SD) age = 35.4 (9.1) years, height = 172.7 (5.3) cm, body mass = 72.3 (12.6) kg, and seniority in service = 9.5 (6.2) years. Each participant was employed at the main regional warehouse in Sardinia of "Conad del Tirreno Soc. Coop. Srl" (the largest Italian retail supplier). At the time of the study, all workers were free from any signs of acute or chronic musculoskeletal conditions and, after a detailed explanation of the purposes and methodology of the study, signed an informed consent form. The study was carried out in compliance with the ethical principles for research involving human subjects expressed in the Declaration of Helsinki and its later amendments. Participants were routinely assigned to the same kind of tasks during a regular shift, namely: 1) refilling shelves with small packages by moving goods from a vertical closet to roller units placed at variable heights; and 2) assembling orders to be delivered to local stores, following instructions received continuously via radio on the type and quantity of the necessary goods that will be subsequently placed on a pallet. Preliminary observations, along with interviews with the operators and their supervisors, indicated that the tasks completed by the workers exhibited distinct characteristics of cyclicity and repeatability. Such aspects were considered to select the monitoring duration in the experimental tests, as described in detail below.

Experimental Protocol

Raw accelerations and angular velocities were recorded onboard the IMU (G-Sensor, BTS-Bioengineering, Italy) at 100 Hz and preprocessed by a Digital Motion Processor (DMP™), which provided rotational angles (i.e., roll, pitch, and yaw) (Further details are provided in Chapter 4). Such data must be further processed to obtain Cardan angles referred to a global reference system. Before data acquisition, during the working tasks, the physiological trunk position (expressed in terms of flexion angle) was assessed by having participants stand for 10 s in a neutral, upright posture. This procedure supported removing subject-specific angular offsets and errors caused by sensor placement. Cardan angles about the IMU axes were then calculated using the YZX sequence (i.e., flexion-extension around Y; lateral bending around Z axis; axial rotation around X axis) as generalized by Cole et al. (1993).

Data processing was carried out by means of a custom routine developed in Matlab (R2019a, MathWorks, Natick, Massachusetts, USA) to classify trunk flexion angles as follows (Jakobsen et al., 2018; Hoogendorn et al., 2000; NIOSH, 2014):

- Class 1: flexion angle = 30°–60°
- Class 2: flexion angle = 60°–90°
- Class 3: flexion angle > 90°

Subsequently has been determined the duration of exposure to each posture class using an approach based on exposure variation analysis (EVA, Matthiassen and Winkel, 1991), which has been applied in previous work to investigate trunk posture in workplaces Jansen et al. (2001), with specific time periods of 0–2s, 2–4s, and >4s. Finally, have been assessed the time spent in each of the combinations of posture and time period classes in terms of either frequency or percentage of the total working time. Data were processed for the entire 2-h period.

These data were also processed separately for different sampling durations, to explore the effects associated with possible reductions of the monitoring time. To do so, we considered moving windows of different durations (from 15 to 90 min, in 15 min increments), each at one-minute steps over the full two-hour sample (Figure 1). Mean values of the percentages spent in each class of flexion obtained for each duration were compared with those calculated using the original 2-h sample (considered as the "true" value).

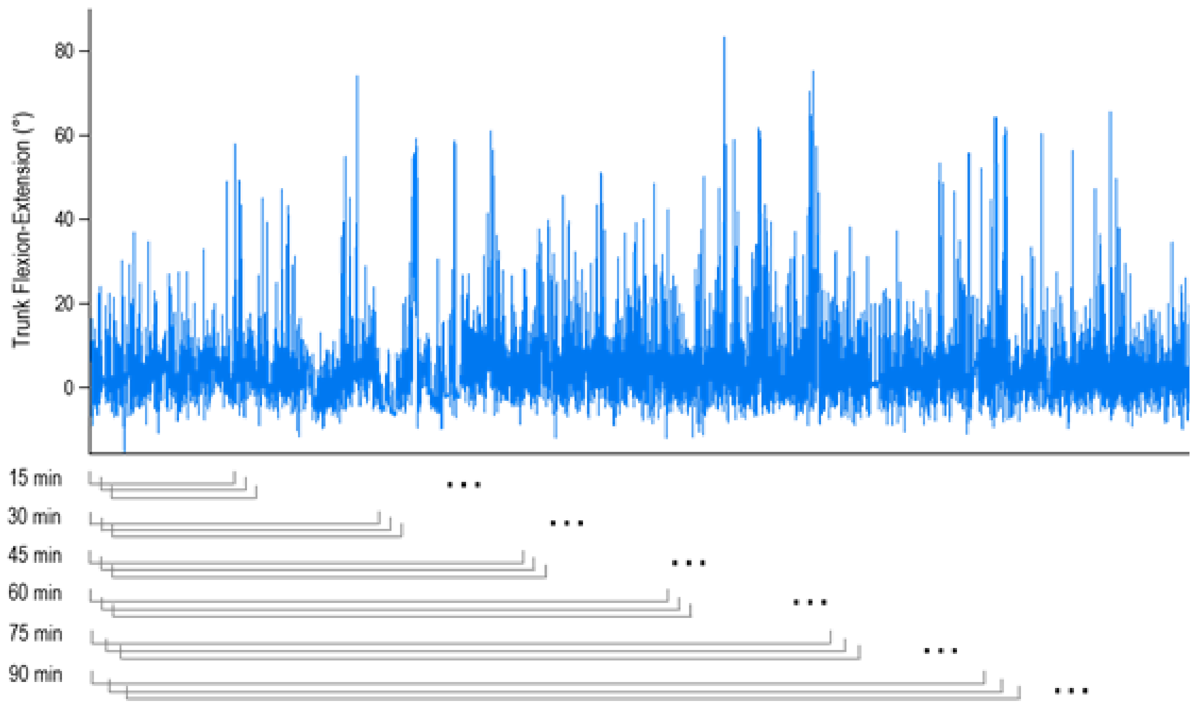
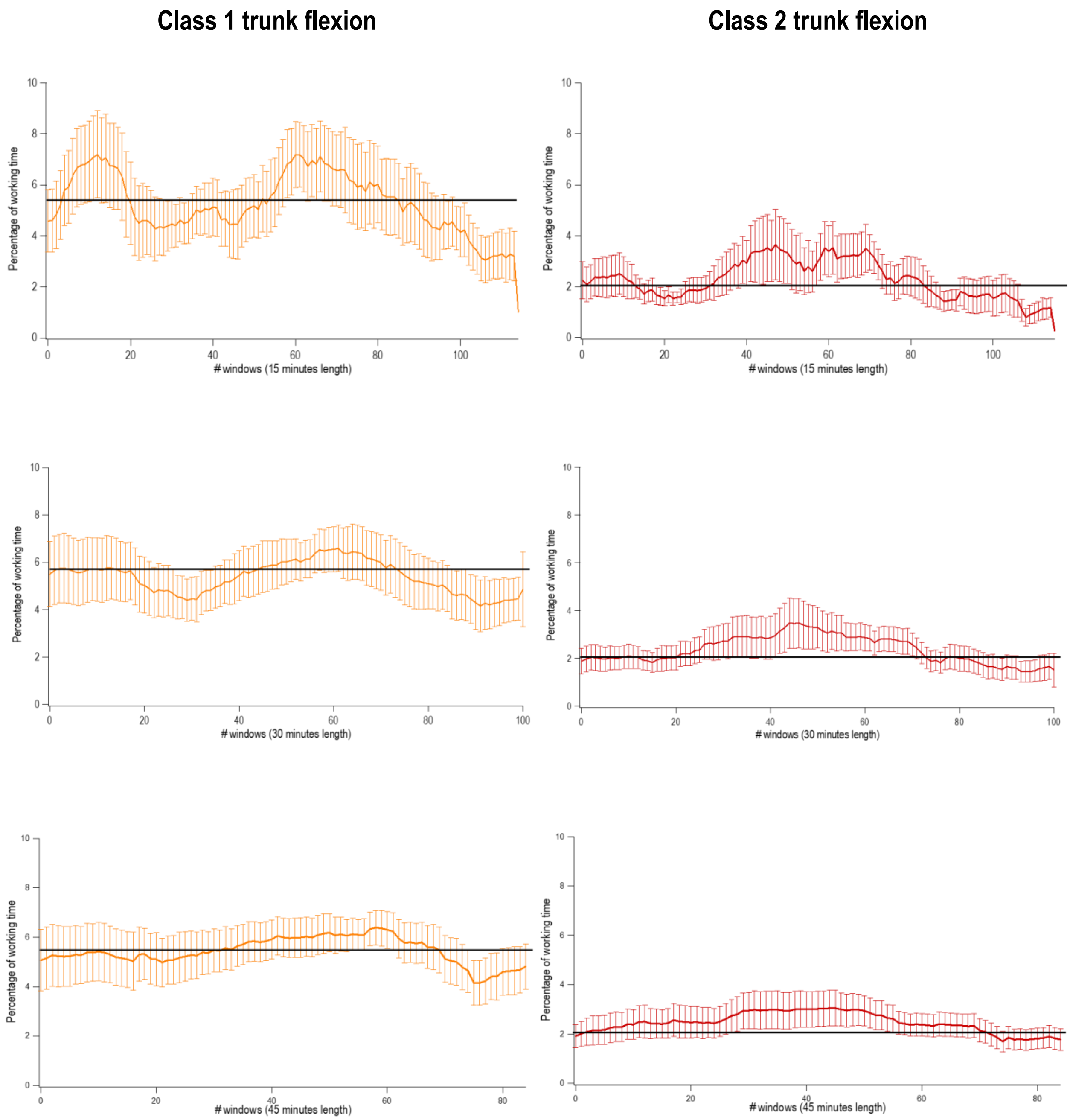


Figure 1 Example of two hours of trunk flexion data obtained from a participant (top). As shown at the bottom, windows of different duration (15, 30, 45, 60, 75, and 90 min) were moved across the entire signal, each in one-minute steps. Positive values indicate trunk flexion, while negative values indicate extension.

A relative mean squared error (MSE) was calculated to capture the error associated with a specific window duration. Figure 2 shows results obtained for each class of flexion and for each of the six window durations, demonstrating how averages across the subjects have been calculated



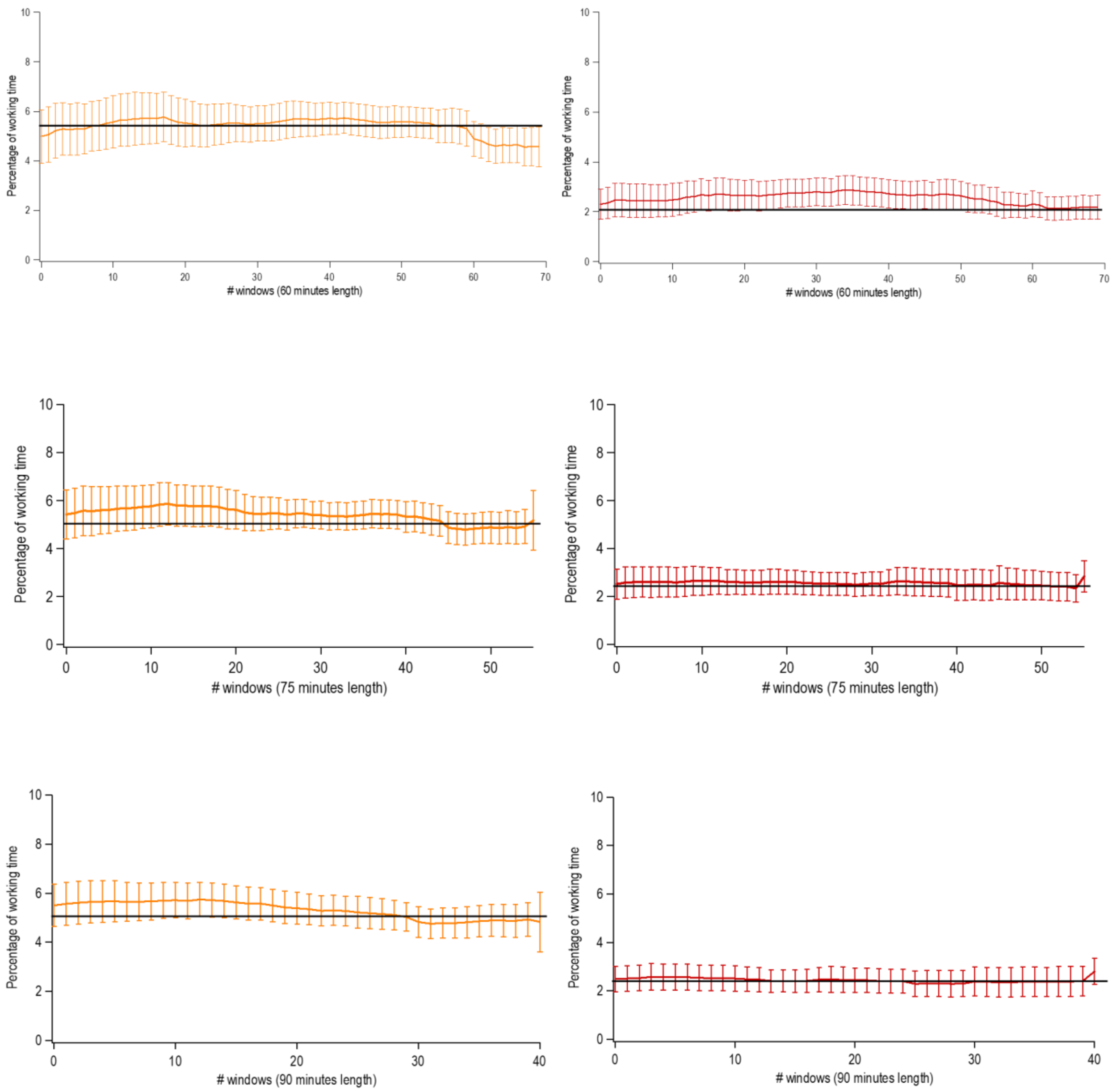


Figure 2 Mean values of the percentage of time spent in two classes of trunk flexion. Each point represents the mean value (standard error) calculated across the workers using windows of different duration, from 15 (top) to 90 (bottom) minutes, using steps of 1 minute. Black lines represent the "True" value calculated as mean exposure obtained from the entire 2 hours of monitoring.

Results

Table 1 summarizes the working time spent in trunk flexion according to the three defined classes, based on the full acquisition period (i.e., 2 h). Participants spent 5.1% of the time in trunk flexion between 30° and 60°, and 2.3% of the time with flexion between 60° and 90°. The percentage of time spent in postures characterized by angles >90° was negligible (0.07%). Results of the EVA analysis are shown in Figure 3. Considering only the angles higher than 30 degrees (which represent approximately 8% of the monitored time, the majority (~70%) of flexion angles ranged between 30 and 60° (i.e., Class 1), while lower percentages were observed for Class 2 (28%) and Class 3 (<1%) flexion. In terms of event duration, most (60%) trunk flexion events lasted ≤2 s, 24% had a duration of 2-4 s, and <10% were maintained for >4 s.

Table 1 Results regarding different classes of trunk flexion. For each class of flexion, means (SD) of the percentage of time spent in different classes of trunk flexion are given from the entire 2-h observation periods and from several shorter window durations

Windows duration	Class 1 (30–60°)	Class 2 (60–90°)	Class 3 (>90°)
	Mean (SD)	Mean (SD)	Mean (SD)
2 h	5.1 (2.2)	2.3 (1.5)	negligible
90 min	5.3 (2.2)	2.4 (1.6)	-
75 min	5.4 (2.4)	2.5 (1.6)	-
60 min	5.3 (2.6)	2.5 (1.8)	-
45 min	5.2 (3.0)	2.5 (1.8)	-
30 min	5.3 (3.4)	2.4 (2.0)	-
15 min	5.3 (4.2)	2.4 (2.5)	-

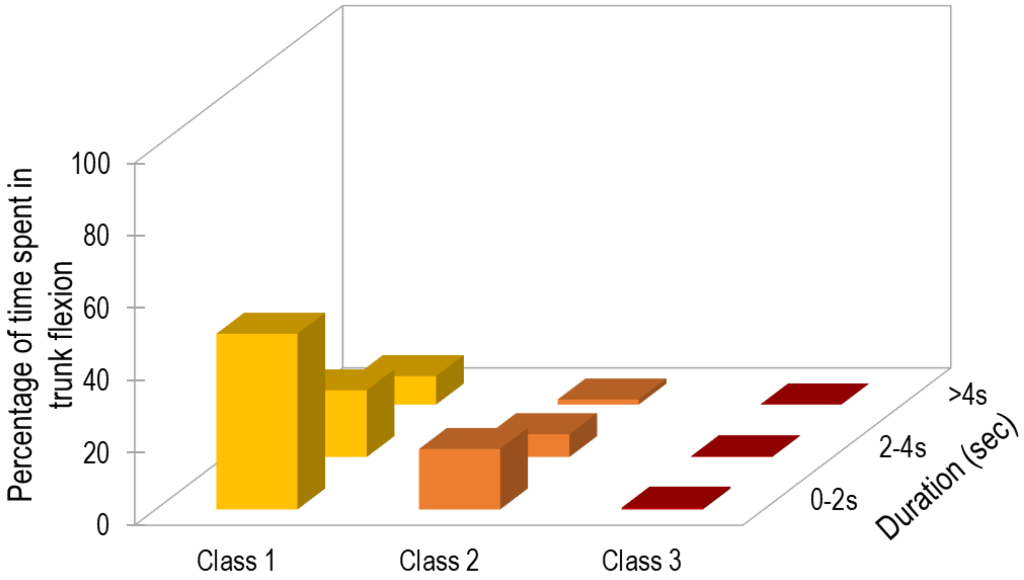


Figure 3 Results from exposure variation analysis of trunk flexion. Bars represent the percentage of time spent in different categories of trunk flexion, based on flexion amplitude and duration. This representation captures the distribution of flexion pattern (e.g., nearly 70% of flexed posture occurred for less than two seconds and most trunk flexion was between 30° and 60°).

Although at the group level the percentage of time spent in trunk flexion appeared relatively low, analysis at the individual level revealed different behaviors, as shown in Figure 4. For example, participant A spent 6.7% of the time with trunk flexed between 30° and 60°, and 5.7% of the time with trunk flexed between 60° and 90°. In contrast, participant B spent 10.1% with trunk flexion between 30° and 60° and only 1.6% of the time with trunk flexion between 60° and 90°. In both cases, the obtained values exceeded those recommended to avoid an increased risk of low back pain (Hoogendorn et al., 2000).

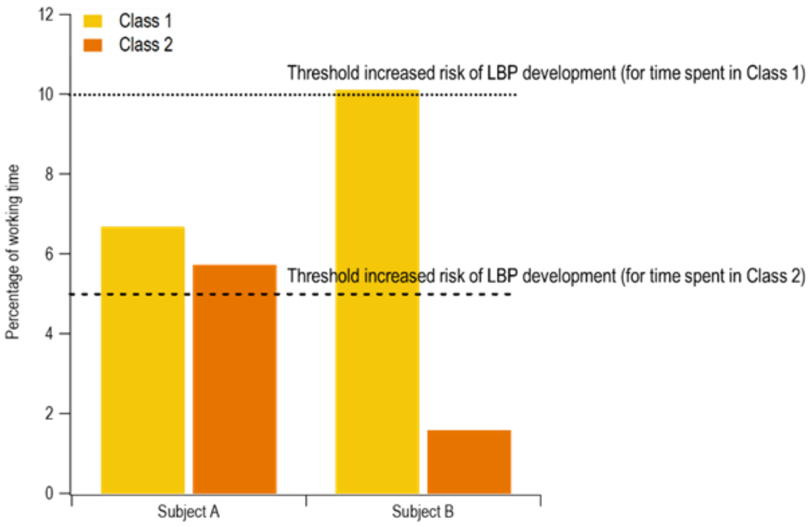


Figure 4 Example of different postural behaviors adopted by two participants performing the same kind of activities. Noted thresholds for low back pain (LBP) are from (Hoogendorn et al., 2000).

Relative MSE values, capturing differences obtained with reduced monitoring durations with respect to the 2-h value, are shown in Figure 5. This error appears to decrease exponentially with increasing window duration. However, MSE values were quite similar for windows durations ranging from 60 to 90 min (between 4.1% and 3.1% for Class 1, and between 4.8% and 1.3% for Class 2).

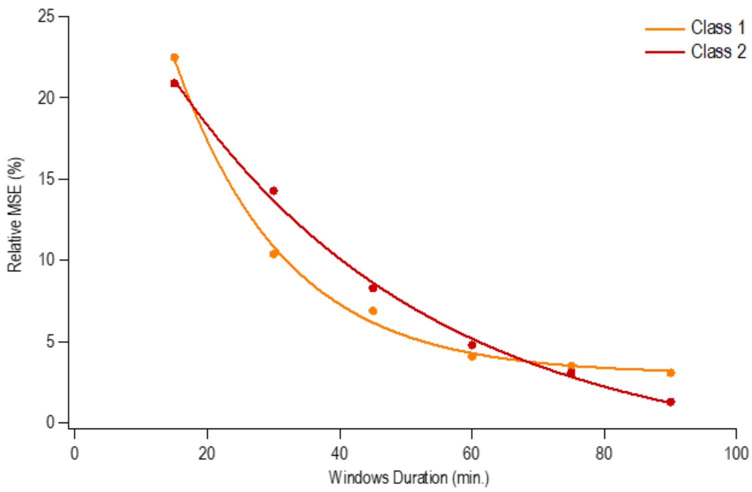


Figure 5 Relative mean squared error (MSE), indicating the difference between mean values of the time spent in trunk flexion and the mean “True” value (from the full 2-h sample). Values are given for several window durations (i.e., 15, 30, 45, 60, 75, and 90 min). Exponential curve fits are indicated by solid lines.

Discussion

The main purpose of the present study was to assess the feasibility of using a simplified setup involving a single miniaturized wearable IMU to characterize a worker's exposure to trunk flexion. The proposed approach is potentially suitable for long-term monitoring under actual working conditions, since it is based on a sensor that is of limited size, is easily positioned, and provides data with a straightforward interpretation. We tested this setup using a sample of warehouse workers, during the execution of tasks characterized by a marked cyclicity for 2-h of an actual shift; this approach may be suitable for application to other tasks characterized by similar features.

IMU data on trunk flexion were reduced using the EVA approach integrated with recommended exposure thresholds. Overall, the current participants spent 5.1% of their working time with trunk flexion of 30–60°, and 2.3% of their time with trunk flexion 60–90°, while the time spent with trunk flexion exceeding 90° was negligible. In their 3-year prospective studies, Hoogendorn et al. (2000) and Coenen et al. (2003) assessed physical load in terms of trunk postures and the number of lifts by means of video analysis. They estimated that workers who spend either more than 10% of their daily shift with trunk flexion exceeding 30°, or more than 5% of the time with trunk flexion exceeding 60°, are at an increased risk of the onset of low back disorders. In contrast, no explicit conclusions were formulated for flexion exceeding 90°. However, it is reasonable to assume that such extreme postures will be associated with an increased risk of low back disorders, given that trunk flexion amplitude is positively correlated with the load sustained by the intervertebral disks (Bayoglu et al., 2019). The patterns of trunk flexion found here are comparable with those reported by Jansen et al. (2001) from a sample of nurses (who spent approximately 9% of the working time with the trunk flexed >30°) and housekeepers (10% of the working time with the trunk flexed > 30°). Similar trends were also reported by Jakobsen et al. (2018) for warehouse workers and machinery operators. Although the workers tested here spent, on average, only 7.4% of the working time with their trunk flexed, it is noteworthy that most of these flexions were in the shortest duration category (duration < 2s, see Figure 3), suggesting that the tasks required relatively rapid activities.

As a group, the tested participants would thus appear to be at low risk based on their trunk flexion exposures. However, for two participants the above-mentioned thresholds were exceeded. This is not surprising, since workers assigned to the same task can adopt distinct postural strategies according to factors such as experience, anthropometry, and optimization of energy expenditure (Kuorinka et al., 1994; Authier et al., 1996; Burdorf, 1992). Thus, the proposed simplified approach might be useful both to identify strenuous tasks and activities in a particular job (at the group level), and to detect potentially critical conditions that may exist even in presence of planned working conditions and suitable training programs, being applicable to a large sample of workers without a significant increase in measurement efforts. Application of the EVA approach (Matthiassen and Winkel, 1991) supports determining how different classes of trunk flexion are distributed as a function of their duration. Such information may also be useful to reproduce more realistic conditions for laboratory simulations, where the pace of the activity is usually determined a priori, along with the distribution and duration of different levels of trunk flexion.

One practical issue in the use of sensors in monitoring working postures (and other outcomes) is determining the duration of monitoring. While reducing the monitoring time would allow testing more workers in a given period and would decrease the degree of interference of measurements with the task, such reductions may be possible only when the working task is characterized by substantial repeatability. If so, once data are obtained for a complete working shift (such as during a characterization study), further periodic monitoring could be shortened without any substantial loss of information. We found that errors (relative

MSE) decrease non-linearly with an increasing monitoring window duration (Figure 5). Although further quantitative investigations with larger samples are needed, our results suggest that 50–60 min periods of monitoring might be sufficient to capture postural exposures without substantial bias for the current task.

Some limitations in the current study should be acknowledged. First, this study analyzed only postural exposure (specifically trunk flexion), although it is known that several other kinematic and kinetic aspects of exposure (e.g., movement velocity and external loads) are important in assessing biomechanical risk. In particular, velocity has been found (Marras et al., 1995) to be a stronger predictor of risk among trunk kinematic factors. IMUs are suitable to provide such information easily, since angular velocities are immediately available as raw output data. However, as pointed out by Burdorf and van Riel (1997), posture is the basic element with which the other factors integrate to yield a complete picture of a worker's exposure. Second, has been analyzed only trunk flexion, even though it would be of interest to consider other trunk movements, such as combined flexion–rotation or flexion-lateral bending, as these are also implicated in the risk of onset of low back disorders (Hoogendorn et al., 2000). Third, although these results suggest that 50–60 min of monitoring among warehouse workers might be sufficient to characterize the task in terms of trunk flexion, further studies are necessary to increase the generalizability of these results to other tasks. Finally, it would be interesting to explore the relationship between individual physical aspects, in terms of trunk range of motion and movement strategies adopted during the working shift, to understand whether limitations/impairments may influence a given workers material handling behaviors. Despite such limitations, the methodology proposed here may be useful especially for rapid in situ screenings of large cohorts of workers, while at the same time ensuring minimal disturbances to the working tasks.

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Case study 2

Do old workers cope with postures which require repeated trunk flexions differently from younger ones?

Introduction

The decline of the birth rates, in combination with increased life expectancy is gradually leading the world population towards an overall ageing. Statistical data report that the number of individuals aged over 60 increased from 9.2% in 1990 to 11.7% in 2013 and to 21.1% in 2015 (UN-World Population Prospects, 2015). Worldwide life expectancy also risen from 65.3 years in 1990 to 78.3 years in 2016 and it is expected to further increase (Murray et al. 2015, The 2018 Ageing Report). In particular, western European countries are characterized by one of the oldest populations (Walker & Maltby, 2012), with a demographic old-age dependency ratio (i.e. number of individuals aged 65 with respect to those aged 15-64) projected to increase significantly in the EU in the next decades. As a result of the pension reforms, the percentage of those aged over 65 (which was approximately 25% in 2010) rose to 29.6% in 2016 and is projected to further increase to reach 51.2% in 2070 (Economic and Financial Affair, European Commission 2018).

Such socio-demographic shift, which put pension system under serious financial pressure, has been somehow faced by many European countries with several consecutive reforms of their pension systems, with the aim to increase the labor-market participation of older people. This approach is leading into a widespread retirement age of approximately 67 years in most of the

European countries (Ardito and d'Errico, 2018). However, to result effective in ensuring actual savings, it is essential that the increase of the average age of workforce is not accompanied by a consequent increase of applications for disability or sick-pay insurance. Thus, the implementation of effective ergonomic solutions specifically designed for older workers appears an issue of critical importance.

In this context, it is useful to recall that, among workers aged between 50 and 64 years (which are classified as "old", McCarthy et al., 2014) the most common cause of sick leave are low back disorders, arthritis and myalgia (31%, 34% and 32% respectively) (Hubertsson et al., 2014), which have been found associated, at least partly, to the physiological decline of the musculoskeletal system due to the ageing process. Several studies reported that, in older individuals, biological tissues such as tendons and ligaments underwent a worsening in mechanical and viscoelastic properties and muscle mass decreases originating a generalized reduction of strength which is marked in body districts like lower limbs and trunk. Besides, the reduction in the fraction of water present in the vertebral disc and the surrounding tissues causes stiffness of the spine (Galbusera et al., 2014) and subsequent reduction in range of motion.

When an individual aged over 50 is engaged in physically demanding occupations (like those typical of construction or metal industries, agriculture, healthcare etc., Karlquist at al., 2003; Proper et al., 2006), the possible negative effects associated with a reduction in physical capabilities are likely to be exacerbated. In fact, they include several tasks characterized by sustained non-neutral body posture, repetitive movements and manual material handling (MMH). Although such aspects are potentially harmful for any worker regardless his/her age, in older workers they have been recognized able to increase the risk of musculoskeletal disorders (MSDs) (Okunribido et al., 2011) according to two main mechanisms. Firstly, as previously mentioned, the individuals' physiological decline with chronological age (Sluiter, 2006) implies a reduced physical capacity as previously mentioned (Faber et al., 2006) and, secondly, older workers are usually characterized by larger adverse occupational exposure merely due their longer engagement in a given occupation (in terms of years of service) compared to their younger colleagues. Thus, they are likely to experience higher degree of cumulative physical strain. In addition, even though most older workers are considered physically suitable to be assigned at the same tasks they performed in younger age, it cannot be neglected the fact that they require longer time to recover from fatigue associated with performed tasks (Kiss et al., 2008; Cotè et al., 2014). Based on these considerations, appears fully justified the need to plan proper monitoring actions and interventions to ensure older workers an “healthy ageing” as well as long working life of good quality. In this context, the accurate assessment of the workload represents a critical issue to control the higher vulnerability of older workers to occupational exposure.

The characterization of jobs associated with high physical demands and the consequent assessment of physical workload, is commonly performed by quantifying the exposure to awkward postures, especially those involving repeated and sustained trunk flexion (because significantly involved in MSD development) and assess the level of occupational physical activity (Arias et al. 2017). It is noteworthy that generally, individuals exposed to repeated trunk flexion are more at risk to develop LBDs (Wai et al., 2010) and some studies attempted to quantify such risk as a function of the time spent in specific postures. For instance, Hoogendorn et al. (2000) found a 22% increase in relative risk of develop low-back pain (LBP) in individuals who spend more than 10% of the working time with the trunk flexed between 30° and 60° and, similarly, Coenen et al.(2013) calculated increased odd ratios for LBP when more than 5% of the time was spent with the trunk flexed between 60° and 90°.

The assessment of workload under actual working condition, is commonly performed using observational methods, video-recording and computer-aided analysis, even though quantitative techniques have been recognized necessary to support such analysis due to their superior accuracy and reliability (David et al. 2005). In particular, the use of wearable miniaturized Inertial Measurement Units (IMUs) is quickly gaining popularity among researchers and practitioners as they are low-cost, relatively easy to use and able to potentially provide accurate data on a wide range of biomechanical parameters. Simple configurations based on the use of a single sensor to collect data about trunk posture (in terms of amplitude and duration of the movement) have been successfully employed in a wide range of occupational contexts characterized by intrinsic risk of development of LBDs (Sigh et al., 2017; Balanguier et al., 2018; Asante et al., 2018; Ribeiro et al., 2011; Villumsen et al., 2016; Schall et al. 2016; Jakobsen et al. 2018, Porta et al. 2020). However, to the best of our knowledge, this approach has never been used to assess the existence of possible differences in postural strategies adopted to perform task typical of metalworking industry, among young and old workers.

On the basis of the above mentioned considerations, the main purpose of the present study is to quantitatively characterize the physical exposure (in terms of trunk flexion) in a cohort composed by young and old (>50 years old) workers employed in a metalworking industry. We aim to address the following three research questions: 1) Are there any differences in the patterns of trunk flexion performed by young and older workers? 2) Are patterns of trunk flexion dependent by the spine mobility features of the workers? And 3) Is working experience (i.e. years of service) a factor able to influence trunk flexion patterns?

Methods

Participants

Thirty-three full-time male workers currently employed at the “IMI Remosa Srl” (Cagliari, Italy) a metalworking company specialized in design and manufacturing of control and shut-off valves used in the oil refineries, were recruited for the study on a voluntary basis. At the time of the study, they were free from any signs of acute or chronic musculoskeletal conditions (in the previous six months) according to self-reports and medical records of the company. After a detailed explanation of purposes and methodology of the study, they signed an informed consent form. The study was carried out in compliance with the ethical principles for research involving human subjects expressed in the Declaration of Helsinki and its later amendments.

Participants were stratified into two groups according to their age as follows: young workers (aged between 18 and 49 years, n = 19) and old workers (aged >50 years, n = 14). Their demographics and anthropometrics characteristics are reported in Table 1. Both groups include a similar proportion of the main tasks performed in the company, namely machine tools operators, welding and assembly, warehousing and preparation and laying of refractory cement.

Table 1 Anthropometric and demographic characteristics of participants. Values are expressed as mean±SD [range]

	Young		Old	
	Mean±SD	Range	Mean±SD	Range
Age (Years)	37.7 ± 7.2	25 – 49	54.7 ± 4.1	50 – 64
Height (cm)	174.8 ± 8.2	155-186	169.0 ± 4.7	160-175
Body Mass (kg)	73.6 ± 11.0	55-93	73.2 ± 11.7	[55-97]
BMI (kg/m^2)	24.0 ± 2.4	20.8-28.7	25.5 ± 3.1	21.1-31.6
Seniority at work (Years)	9.4 ± 5.2	2.0 – 19.8	24.9 ± 8.6	11.0 – 43.0

Experimental protocol

Trunk posture was continuously monitored for 4-hours during a regular 8-hour work shift, using a lightweight miniaturized IMU (G-Sensor, BTS Bioengineering S.p.A., Italy) which integrates tri-axial accelerometer, gyroscope and magnetometer and was previously employed for similar studies (Porta et al., 2020). Raw data was recorded onboard the IMU at 50 Hz and pre-processed by a Digital Motion Processor (DMP™), which provided Cardan angles (i.e., roll, pitch, and yaw). The device was placed on the low back using a semi-elastic belt, approximately at three-quarters of the distance between the C7 vertebrae and the mid-point between posterior superior iliac processes, as described by Faber et al. (2009). Before any experimental session, participants were requested to stand still for 10 s in a neutral, upright posture in order to remove any subject-specific angular offsets and errors caused by sensor placement. Moreover, the active ROM for flexion-extension movements of the trunk was assessed asking participants to perform a maximal trunk flexion followed by the return to neutral posture and then by a maximal extension. This sequence was repeated three times, at self-selected speed advising workers to avoid excessive non-natural movements.

Trunk flexion patterns were assessed by processing IMU data by means of a custom routine developed in Matlab (R2019a, MathWorks, Natick, Massachusetts, USA) (Further details are presented in Chapter 4). In particular, acquired data was classified into three categories according to what proposed in previous similar studies (Hoogendorn et al. 2000; NIOSH 2014; Jakobsen et al., 2018) as a function of the calculated flexion angle as follows:

- Class 1: (30° < flexion angle < 60°)
- Class 2: (60° < flexion angle < 90°)
- Class 3: (flexion angle > 90°)

Then the duration of exposure for each posture class was calculated using an approach based on Exposure Variation Analysis (EVA, Mathiassen & Winkel, 1991), with specific time periods of 0-2s, 2-4s, and >4s. Finally, the time spent in each combination of 'posture-time period' classes was calculated in terms percentage of the total working time.

Participants were also requested to wear a wrist-worn activity tracker (Actigraph GT3x-BT, Acticorp Co., USA) previously validated for use in ergonomic studies (Jakobsen et al.

2018; Schall et al. 2015; Villumsen et al., 2016) to verify the existence of possible differences in the average physical activity (PA) performed by the tested groups, as this might represent a confounding factor for the results. This device, which basically include a tri-axial accelerometer, provides several metrics associated with performed PA such as number of steps, percentage of time spent in activity of light (<3 MET), moderate (3-6 MET) and vigorous (>6MET) intensity, as well as vector magnitude count (VMC) which represents an aggregate measure of movement expressed by the equation:

$$VMC = \sqrt{x^2 + y^2 + z^2} \tag{1}$$

Where x, y and z represent the acceleration vectors.

The raw acceleration data was downloaded and processed using the dedicated software Actlife v6.13.4 (Acticorp Co., USA) by applying the cut-points proposed by Hildebrand et al. (2014) to classify PA intensity.

Statistical Analysis

Three separate multivariate analysis of variance (MANOVA) was carried out to explore the existence of possible differences respectively in trunk flexion ROM, patterns of flexion during the work shift and level of physical activity performed (dependent variables) among the two age groups (independent variable). The level of significance was set at $p = 0.05$ and the effect size was assessed using the eta-squared (η^2) coefficient. Univariate ANOVAs were carried out as a post-hoc test by reducing the level of significance to $p = 0.017$ (0.05/3) after a Bonferroni correction for multiple comparison.

Furthermore, the existence of possible correlation between patterns of flexion and spine mobility (expressed by means of trunk flexion ROM) was explored using Spearman’s rank correlation coefficient rho, by setting the level of significance at $p < 0.05$. Rho values of 0.1, 0.3, and 0.5 were assumed to be representative of small, moderate, and large correlations respectively, according to Cohen's guidelines (1992). Finally, a covariate analysis of variance (ANCOVA) was carried out to understand the influence of seniority at work in the choice of different postural behaviour. All analyses were performed using the IBM SPSS Statistics v.20 software (IBM, Armonk, NY, USA).

Results

Baseline ROM of the participants and flexion patterns assessed based on IMU data are reported in table 2 and 3 respectively. The statistical analysis revealed that young workers are characterized by significantly higher ROM with respect to older workers (121.9° vs 102.2°, p=0.017). In particular, the difference in ROM is mainly attributable to the significant reduction in the amplitude of flexion movement, which passes from 95.7° of young workers to 79.9° of their older colleagues.

Table 2 Values of range of motion (ROM) and separate value of flexion end extension for young and old workers. Values are expressed as mean±SD.

	Young	**Old**
ROM (°)	121.9 ± 20.3	**102.2 ± 20.2***
Flexion (°)	95.7 ± 14.2	**79.9 ± 15.7***
Extension (°)	26.2 ± 9.2	23.3 ± 7.3

The symbol * denotes a significant difference vs. young workers after Bonferroni correction p = (0.05/3) =0.016

Both groups performed most of trunk flexion between 30° and 60° (Class 1), while they spent a lower percentage of time with their trunk flexed between 60° and 90° (Class 2) and over 90° (Class 3). However, MANOVA found a significant effect of age on the percentage of time spent in Class 2 and Class 3. In fact, younger workers spent 1.55% and 0.13% of the time in Class 2 and Class 3 respectively, while older spent 0.65% and 0.03% in Class 2 and Class 3 respectively.

Table 3 Results regarding different classes of trunk flexion. For each class of flexion, means±SD of the percentage of time spent in different classes of trunk flexion are given from the entire 4-hour observation periods.

	Young	Old
Class 1 (%)	4.05 ± 3.0	3.97 ± 3.06
Class 2 (%)	1.55 ± 0.96	**0.65 ± 0.54***
Class 3 (%)	0.13 ± 0.13	**0.03 ± 0.05***

The symbol * denotes a significant difference vs. young workers after Bonferroni correction p = (0.05/3) =0.016

Figure 1, shows the evident differences in pattern of flexion of young and old workers according to the time spent in each class of flexion. Our results revealed that younger workers spent consistently longer time in mild, moderate and severe flexion with duration between 2 and 4 s. While no differences were found as regards the time spent in mild flexion (Class 1) with short duration (0-2 s) and in severe flexion (Class 3) lasting more than 4 s.

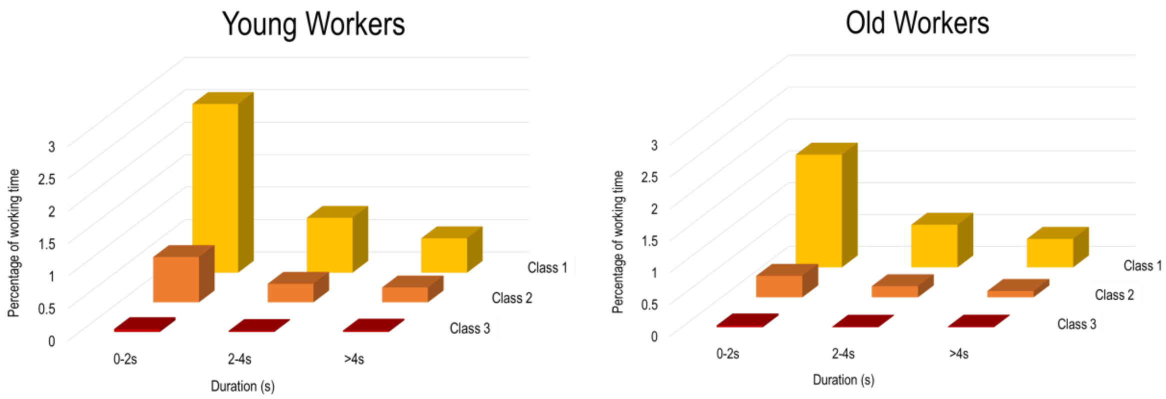

Figure 1 Results from Exposure Variation Analysis of trunk flexion. Bars represent the percentage of time spent in different categories of trunk flexion based on flexion amplitude and duration. This representation captures the distribution of flexion pattern

In terms of levels of occupational PA (see Figure 2), our data show that older workers spent longer percentage of work shift in moderate and vigorous PA, and carried out more steps, but such differences were not found statistically significant.

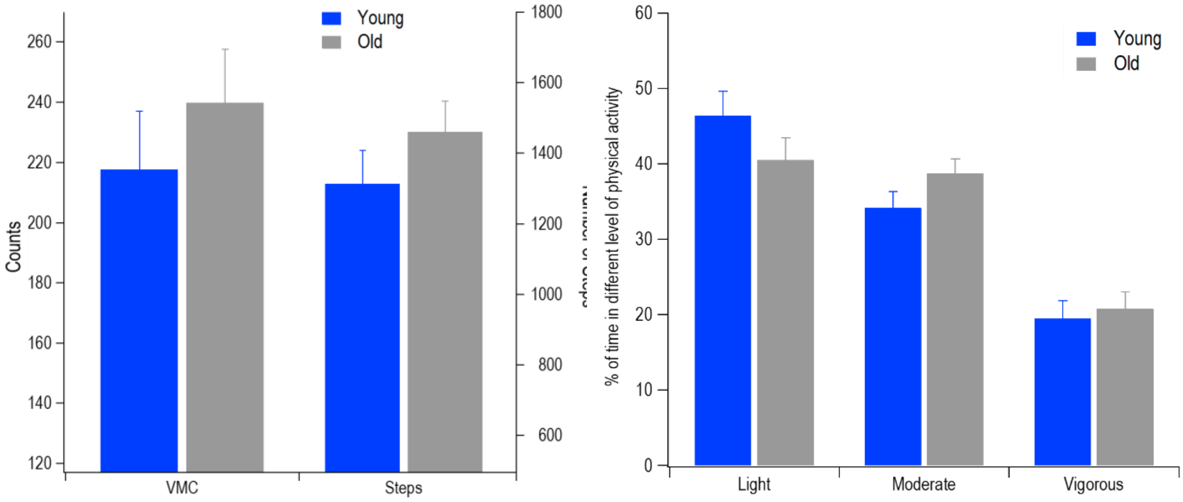

Figure 2 Occupational physical activity parameters. Left: mean value of VMC and number of steps per hour. Right: Percentage of time spent in different level of physical activity intensity

The results of the correlation analysis are reported in Table 3. The only significant correlation was detected between trunk flexion ROM and percentage of time spent in flexion >90° (Figure 3).

Table 3 Spearman's correlation coefficients for correlation between flexion range of motion and percentage of time spent in different class of flexion

		% of Flexion in Class 1	% of Flexion in Class 2	% of Flexion in Class 3
Flexion ROM	*rho*	-0.138	0.342	**0.403**
	p-value	0.484	0.075	0.033

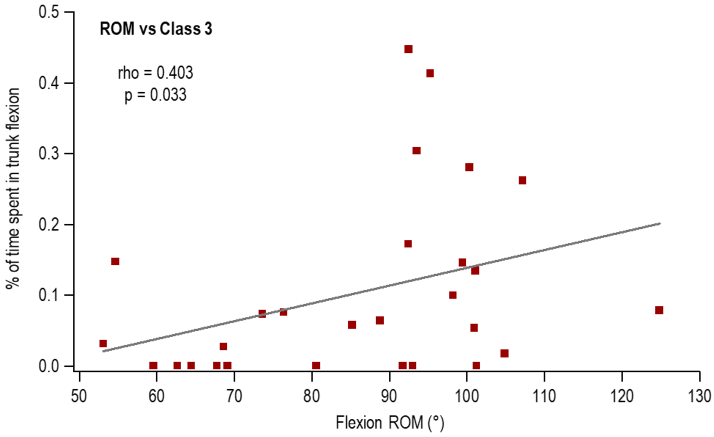

Figure 3 Correlation between flexion range of motion and percentage of time spent in Class 3 of flexion (>90°)

When the flexion patterns were analysed taking into account both age and expertise (seniority at work) no differences between the two groups in trunk flexion patterns were found.

Discussion

The main aim of this study was to quantitatively characterize the patterns of trunk flexion and the occupational physical activity levels of young and old metal workers during a regular work shift, using a simplified setup based on the use of a single IMU located in the low-back. At first, it is noticeable that, generally speaking, the calculated values of trunk flexion (~4.5% in flexion 30°-60°; ~1.5% in flexion 60-60° and ~0.1% in flexion >90°) are in good agreement with those reported for similar tasks by Jacobsen et al. (2018) but lower than those reported by Shahriyari et al. (2018) although, in the latter case, the differences are likely due to a different placement location for the sensor (lumbar trunk vs sternum).

Our initial hypothesis about the existence of age-related differences in trunk flexion patterns was confirmed by the results, especially as regards the percentage of time spent in Class 2 and Class 3 of flexion, which was found respectively 42% and 23% higher with respect to older colleagues. Such results are somehow consistent with those reported by Burr et al

(2017) and Authier et al. (1996) who found that demanding body postures (i.e. those with trunk flexed over 45°) were less common among older workers. Similarly, Plamondon et al. (2012) observed that more experienced workers tent to flex their lumbar trunk less than novice worker. Since the experienced workers were significantly older than novice, they speculated that this difference could be attributed to the chronological age, and in particular to reductions in the trunk flexibility associated with aging (Troke et al., 2005; Intolo et al., 2009). Such aspect seems to be relevant even in the case of the present study, as spine ROM of younger workers was found ~20° larger with respect to older ones. However, the reduced ROM seems to explain only the scarce occurrence of severe flexion among older workers, as confirmed by the significant correlation detected with baseline ROM. Indeed, most of the existing differences between the two groups are probably linked to the adoption of more conservative strategy chose by the older workers. It is known that lumbar flexions which approach the physiologic limits are convenient from an energetic expenditure point of view but, at the same time, it may also increase the risk of injuries. In fact, large trunk flexions due to stretching of the passive lumbar structures are associated with elastic energy storage which is subsequently restored during the recovering of the neutral position (Maduri et al. 2008). Moreover, lumbar flexion balances the external moment by an increase in the contribution of the passive elements thus reducing the internal compressive forces on the disk (Gracovetsky et al., 1989). In contrast, pronounced lumbar trunk flexion originates very high shear stresses (close to the resistance limits of the tissues) and the intervertebral disks underwent a 20-40% reduction in their load support capacity with respect to neutral posture (McGill, 1998). At last, such extreme postures desensitize the mechanical receptors of ligaments (Solomonow, 2007) thus altering the correct proprioceptive input and increasing the risk of injury.

As regards the levels of occupational PA performed by the workers here tested, the results showed that older workers spent 38.7% and 20.8% of time in moderate and vigorous PA respectively and younger workers spent 34.2% and 19.4% respectively. Although, generally speaking, elevated amounts of moderate and vigorous PA have been demonstrated beneficial in preventing non-communicable diseases and in improving quality of life (Anderson and Durstine, 2019), this might not be likewise true in the occupational context. In fact, it has been pointed out that occupational and leisure-time PA have opposite effect on the global health (Holterman et al., 2012). While leisure-time PA is beneficial for health, occupational PA at moderate and vigorous level is rather to be considered harmful, where the most probable reason is that high energetic demands at work continue for hours in comparison with much shorter bouts of leisure-time PA during which both the ability to control the task and the psychological expectations very often differ (Kukkonen-Harjula, 2007). In addition, Villegas et al. (2006) found that high-intensity occupational PA is inversely associated with high intensity leisure-time PA, and this fact tends to enhance the discrepancy between “positive” and “negative” PA. Similarly, Blafoss et al. (2019) found that the duration of leisure-time PA gradually decreased with increased work-related fatigue in individuals engaged in physically demanding jobs, especially in those aged over 50 years, who were found to perform less leisure-time PA compared with younger workers. Unfortunately, we did not assess PA performed by participants during non-working hours, but given the substantial time spent in occupational moderate to vigorous PA, it appears reasonable to suppose that they perform a reduced amount of leisure-time PA, a fact that is likely to contribute to decrease physical capacity, thus resulting in increased work-related fatigue.

Some limitations of the study should be acknowledged. First, we considered only trunk flexion, even though it would be of interest to consider other movements, such as combined flexion–rotation or flexion-lateral bending, as it is known that they are also involved in the risk of onset of LBDs (Hoogendorn et al., 2000). Secondly, as previously mentioned, we did not collect data on PA during non-working hours, and thus we are not able to exactly define the influence of the level of fitness of the participants on the strategies adopted to perform the assigned tasks. At last, since the sample here tested was entirely composed by men, it remains unknown whether age-related effects in terms of trunk flexion strategies are also sex dependent.

In conclusion, this study demonstrated that a simple non-intrusive measurement setup (composed by a single IMU worn on lumbar trunk and one wrist worn accelerometer) is able to provide information about the workload of metal industry workers, allowing to discriminate among different strategies adopted according to chronological age, basic spine mobility features and years of experience. Such data may result useful to highlight potentially harmful behaviors or conditions and suggest early intervention in order to prevent the development of LBDs, especially in individuals with marked signs of decline in their physical capacity.

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Case study 3

Manual Material Handling tasks classification using a single wearable inertial sensor data and Bidirectional Long Short-Term Memory network

Introduction

Work-related musculoskeletal disorders (wMSDs) still remain a major health issue in workplaces (Buckle, 2005, Carrillo-Castrillo et al., 2019), and are reported to cause productivity loss, absenteeism, and disability with a considerable economic burden (Villumsen et al., 2015). wMSDs explained 34% of lost workday in the U.S. (U.S. Bureau of Labor Statistics, 2019) and about 1/3 of work-related health complaints in the EU (European Agency for Safety and Health at Work, 2019). A number of risk factors have been strongly implicated in the aetiology of wMSDs, including manual material handlings (MMHs) such as lifting/lowering, pushing/pulling, and carrying; repetitive motions; and prolonged postures (National Research Council (US), Panel on Musculoskeletal Disorders, Institute of Medicine 2001). Moreover, for a given job, each worker may experience substantially different levels of physical demands due to individual work styles (Authier et al., 1995, Burdorf and van Riel, 1996) and anthropometry differences (Corbeil et al., 2019: Dempsey et al., 1999). To effectively control wMSDs and provide individual specific interventions, there is thus an important need for collecting information required to quantify physical exposures such as what task a worker does, and also when, how long, and how frequently they perform such a task.

Collection of such information can be achieved using diaries or direct observation approach. Though these approaches are straightforward and requires no particular tools, the diary approach is prone to a bias due to subjectivity in self-report measures and recall errors (Heberger et al., 2012). Direct observation is typically labor intensive and difficult to use in real time at workplace (Heberger et al., 2012) and also suffers from biases due to observer's subjectivity and frequency of data logging (Pedersen et al., 2016). An alternative, promising approach can be activity/task classification. This approach has been explored using on-body sensors and vision-based systems (e.g., Chen et al. 2012; Ugulino et al 2012). A representative example of the former is an inertial measurement unit (IMU) that typically includes an accelerometer, a gyroscope and/or a magnetometer (Luinge, 2002). The use of an IMU quickly gained popularity as enabling continuous monitoring of data from the wearer without being limited in a fixed location like vision-based systems (e.g. video and depth cameras) (Cornacchia et al. 2017). Furthermore, with progresses in microelectromechanical systems (MEMS) sensor technologies, IMUs are reasonably affordable and widely available in many consumer products such as smartphone and smartwatches, and which has been viewed as a strength for the application of activity classification (Cust et al, 2019; Nweke et al., 2019, Lim and D'Suoza, 2020).

To date, exiting work strongly supports that IMU use is effective and feasible in classifying activities both in non-occupational (e.g. identifying/detecting activities of daily living, a fall event etc.) and occupational context (Wang et al 2019; Tahir et al., 2020). A good classification accuracy was reported (up to ~97%) for a wide range of daily activities (e.g., walking, sitting, climbing stairs etc.) using IMU data (e.g., Oshima et al., 2020; Parkka et al., 2006). In the occupational context, MMH-related activities (such as, for example, lifting, lowering, pushing/pulling) were classified with accuracy of ~30% – ~100% (Ogris et al, 2008; Kim and Nussbaum, 2014; Bastani et al. 2016; Grzeszick et al. 2017). In these and related studies, accuracy generally varied depending on the number of sensors and classification algorithms used.

However, as argued by several research groups (Chung et al., 2011; David 2005; Neumann et al, 2012), a "practitioner-friendly" approach is needed to promote the application of task classification approach with IMUs (or other wearable sensors) to quantify physical demands in an actual workplace. Two practical challenges in using the task classification approach in real work environments can be the number of sensors and classification algorithm selection. First, though the use of a single sensor such as an activity tracker, smart watch/phone is commonly explored for the classification of daily activities, the existing work on occupational task classification typically used a multiple number of sensors ranging from three (Gholipour and Arjmand, 2016) to 17 sensors (Kim and Nussbaum, 2014), except a recent study of Hosseinian et al. (2019) with an accelerometer positioned on the chest of users. Although having a large number of sensors may improve classification performance, it can be an important practical concern for practitioners to manage and use multiple sensors in the field, and also for wearers (i.e., workers) to keep many sensors on multiple body parts for an extended period in a work environment. Second, there is no straightforward way to optimally select a classification algorithm and features for the selected algorithm. A variety of classification algorithms (e.g., Naïve Bayes, K-Nearest Neighbors, Decision Tree, and Support Vector Machines) with varying feature selection methods was explored previously, and classification performance for a given task was affected by specific algorithms and features. Thus, using the task classification may require expert knowledge in classification algorithms and their feature selection, and which can be a barrier for practitioners.

Thus, to support the use of task classification approach to objectively assess exposures to physical risk factors of WMSDs in an workplace, the current study was aimed to investigate the use of a single IMU to extract task-relevant information (i.e., the task performed, duration of a task, and the number of tasks performed) during several MMH tasks, and while utilizing a bidirectional long short-term memory (BiLSTM) network. Specifically, have been considered different body regions (i.e., the chest, the pelvis, a wrist) for the single sensor attachment location that were commonly used in the existing work on task classification and were suggested to produce high user compliance in wearing sensor(s) on the body (Lim and D'Souza, 2020; Doherty et al., 2017). Additionally, have been explored likely scenarios that one or two sensors are additionally available to use with the single sensor setup, to examine how much performance gain the use of an additional sensor can provide. In the case of classification algorithm, has been employed a BiLSTM that is a variant of LSTM (see the BiLSTM section below), as deep learning approaches are found to often outperform conventional classification algorithms (Gjoreski et al. 2016), and can avoid the design and handpicking of features that typically require expert knowledge (Artur Jordao et al., 2018; Wang et al., 2019; Shakya et al. 2018). Especially, a LSTM network is considered to be effective in classifying highly unbalanced activities in terms of frequency which may be viewed as characteristics of MMH tasks (e.g., more lifting from knee level than lifting from ground level) (Wang et al. 2019).

Material and Methods

Participants, MMH task simulation, and Instrumentation

Details of the experimental procedure were previously reported (Kim and Nussbaum, 2014), thus here will be provide a summary. A total of 10 gender-balanced young adults (19-29 years old) completed four cycles of a simulated job in a laboratory setting. Each job cycle was designed to include major MMH tasks such as lifting/lowering, pushing/pulling, and carrying (Figure 1). Participants were allowed to complete each MMH task using self-selected comfortable styles and speeds. Each of the four job cycles was paced to last 7 minutes, rest was given after each cycle, and the four cycles were repeated three times. For classification purposes, ground truth MMH task labels were manually assigned by direct observation (via video recordings). The MMH tasks performed include: 1) lifting from the ground (LG), 2) lifting from knuckle height (LK), 3) lowering to the ground (LoG), 4) lowering to knuckle height (LoK), 5) pushing, 6) pulling, 7) carrying, and 8) walking (only as required to perform the tasks).

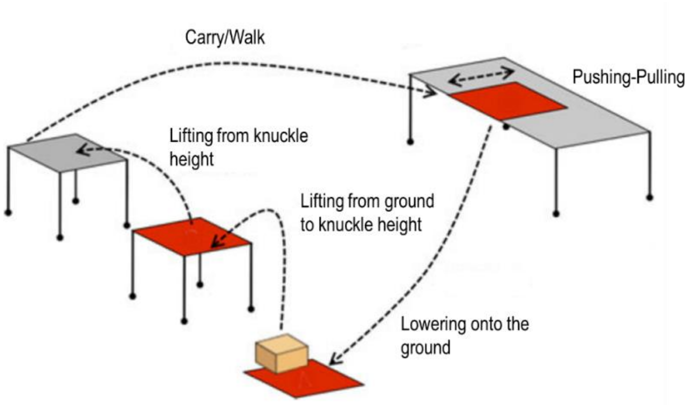


Figure 1 Illustration of the simulated job. Figure adapted from Kim and Nussbaum, 2014

During the simulated job, whole-body accelerations and angular velocities were recorded at 60 Hz using an inertial motion capture system (MVN BIOMECH, Xsens technologies B.V., Enschede, the Netherlands), composed of 17 IMUs positioned on the head, sternum and pelvis; and bilaterally on the scapulae, the upper and lower arms, hands, thighs, shanks, and feet. Kinematic data were subsequently down-sampled to 15 Hz since 98% of the frequency spectrum content in human activities is below 10Hz (Khusainov et al., 2013).

Bidirectional Long-Short Term Memory Network (BiLSTM)

The BiLSTM is a variation of LSTM that includes a forward and a backward LSTM layer to learn information from the previous layer (Schuster and Paliwal, 1997) (an example of architecture is shown in Figure 2). LSTM is a recurrent neural network (RNN) architecture for time series modeling to capture the long-term and short-term dependencies in time series and, has been proved to have good performance in task classification (Wainwright and Shenfield, 2019; Hammerla et al., 2016). Using a forward and a backward LSTM layer, BiLSTM learns bidirectional, long-term dependencies between time steps of time series, and often lead to a better performance than a (forward) LSTM layer that typically learns a long-term dependency from prior time steps (Hammerla et al., 2016; Siami-Namini et al., 2019).

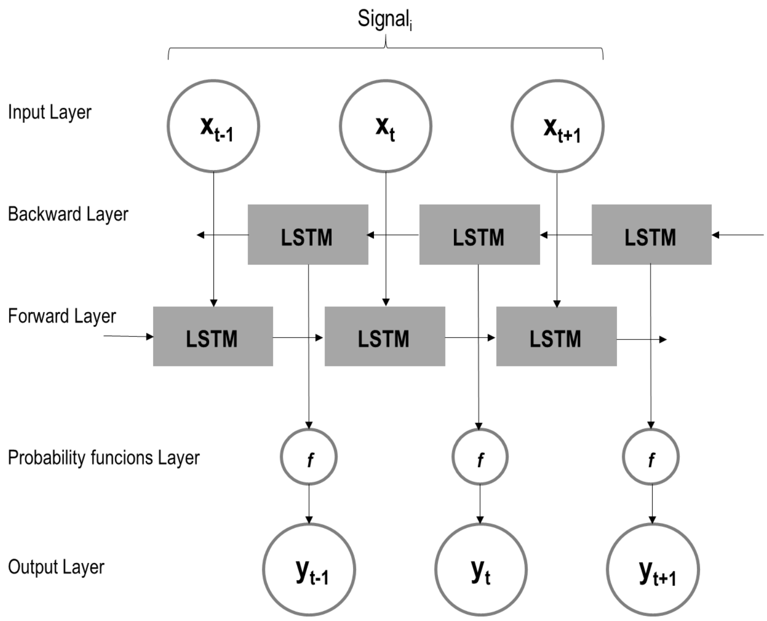


Figure 2 Example of BiLSTM architecture. (Figure adapted from Wadawadagi et al. 2020)

We implemented the BiLSTM using the *bilstmLayer* function in Matlab™ Deep Learning toolbox (R2019a, MathWorks, Natick, Massachusetts, USA). The architecture of the network here employed consisted of an input layer, a BiLSTM, a fully connected layer, a softmax layer, and an output classification layer (Figure 2). The input layer involved input node sizes of 6 to 102, depending on the number of sensors considered for the analysis (3 accelerations signals and 3 angular velocities signals for each sensor). The input layer was followed by the BiLSTM architecture consisted of 100 hidden units. After this layer, the fully-connected layer was to map outputs of BiLSTM layers to the output size (i.e., the number of task classes of interest). The last layer provides the probability for each category in the dataset following the softmax function (see Figure 3). The maximum number of epochs was set to 300. Decision was made sample to sample.

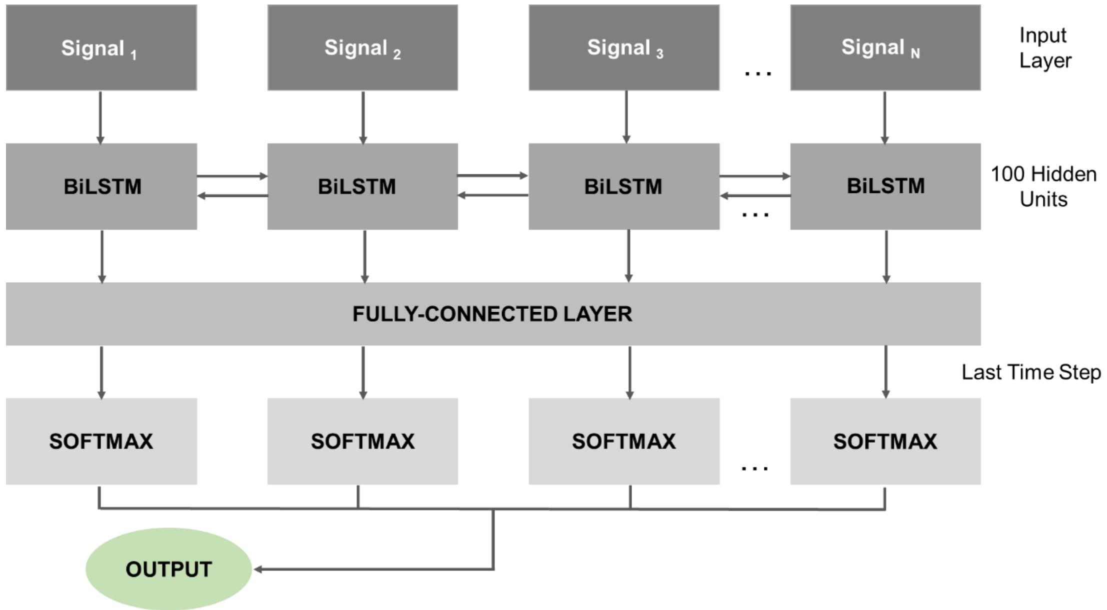


Figure 3 Architecture of the BiLSTM network employed for the MMH task classification. The input layer is characterized by variable sizes ranging from 6 to 102 depending on the number of sensors considered for the analysis (3 accelerations signals and 3 angular velocities signals for each sensor). The input layer was followed by the BiLSTM architecture consisted of 100 hidden units. After this layer, the fully-connected layer where have been indicated the number of classes of interest. The last layer provides the probability for each category in the dataset following the softmax function.

MMH-task classification

Since the choice of on-body sensor placement locations in the workplace may depend not only on the likelihood of a higher accuracy, but also on the practicality of the selected sensor location(s) (i.e., comfortable to wear, not interfering with a work tool, work environment, personal equipment, etc.) (Beeler et al., 2018). To facilitate the ease of IMU use in the field, four different sensor placement locations for a single IMU were considered:

- Pelvis (P): the sensor was placed over the midpoint between posterior superior iliac spines
- Trunk (T8): the sensor was placed over the eighth thoracic spine process
- Right wrist (RW): the sensor was placed over the right forearm close to the wrist joint
- Left wrist (LW): the sensor was placed over the left forearm close to the wrist joint

These locations were frequently adopted in earlier work and were suggested to lead to a high user compliance in wearing sensor(s) (Lim and D'Souza, 2020; Doherty et al., 2017). In addition to a single IMU scenario, we explored several combinations of these sensor locations, to examine how much classification performance gain might be achieved when having one or two additional sensors on the body. Specifically, three of two IMUs scenarios and one of three IMUs scenario were considered. The former includes both wrists (RW+LW), pelvis and right wrist (P+RW), trunk and right wrist (T8+RW). Note that though the LW location can be use with the latter two cases, we chose the RW location given the high prevalence of right-handed individuals in the general population (Papadatou-Pastou et al. 2020). The three IMUs scenario includes pelvis and both wrists (P+RW+LW). To understand the classification performance for these scenarios, we included a full body (FB) scenario (i.e., 17 IMUs) as a comparison reference.

Timeseries of tri-axial accelerations and angular velocities from each sensor were used as input to the BiLSTM. We used the leave-one-out cross validation approach to train the BiLSTM while considering a participant as a fold. As such, the dataset from nine participants was used for training, and the dataset from the remaining one participant was used for validation; this process was repeated 10 times. This validation approach was used since it reflects a realistic scenario where a model is trained offline using the samples of existing subjects and it is tested with samples of an unseen subject (Li et al., 2020), although this approach may lead to high inter-subject variations due to the fact that the same task can be performed in different ways by different subjects (Jordao et al. 2018). The performance of the trained BiLSTM was quantified using the following commonly used metrics:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

$$Recall = \frac{TP}{TP + FN}$$

$$Precision = \frac{TP}{TP + FP}$$

$$F1 - Score = 2 \times \frac{Recall \times Precision}{Recall + Precision}$$

where TP, TN, FP, and FN are, respectively, true positives, true negatives, false positives and false negatives. Though accuracy is often reported in the existing literature, it may be not a proper metric for imbalanced, multiclass classification (Sun et al., 2009; He and Garcia, 2009). To have a better understanding of accuracy, have been also included recall, precision, and a harmonic mean of recall and precision (i.e., F1- score).

In addition, assessing physical exposures during MMH tasks often requires time-related information such as the duration to complete a task, and the frequency of a task during a work shift. For this reason, the time durations and frequency of each MMH task were also used as performance metrics such that percentage errors of time duration and frequency were calculated comparing these estimated from the BiLSTM to the ground truths determined by observations.

Statistical Analysis

Separate, two-way repeated-measures analyses of variances (ANOVAs) were performed to understand how *Sensor configuration* (i.e., single, two, three, and fully-body sensor configurations) and MMH *Task* affect classification performance metrics (accuracy, recall, precision and F1-Score values) and percentage of error concerning the estimation of duration and frequency of MMH tasks. Percentage of error concerning the estimation of duration and frequency were log-transformed prior performance of statistical analysis. Where relevant, post-hoc comparisons were conducted using the Holm-Sidak method. All statistical analyses were completed using SigmaPlot 11.0 (Systat Software Inc., UK) with statistical significance determined when $p<0.05$.

Results

Figure 4 summarizes accuracy, F1-score, precision and recall values of each MMH task with respect to each sensor configuration. ANOVA results indicated significant main and interaction effects of *Sensor configuration* and *Task* on accuracy, F1-Score, precision and recall (all p-values<0.001). Post-hoc tests reveal that single sensor configurations generally yielded classification performance statistically comparable to the FB with some exceptions, depending on single sensor locations and tasks. For example, the RW configuration had statistically similar mean F1-Score values (0.785–0.935) compared to the FB (0.870–0.968), regardless of tasks. F1-Score values of the P configuration (0.737–0.934) were also similar to those of the FB for all the tasks except pulling. The LW configuration, however, generally had lower mean F1-Score values (0.729–0.828) than the FB (0.870–0.968) except for the excluding walking, pulling, and pushing tasks. Additionally, there was no statistical difference in classification performance between the two (or three) sensor and the single sensor configurations. In fact, adding one or two additional sensors to a single sensor configuration appeared to not improve classification performance. Across all the tasks, mean precision, recall, and F1-Score values ranged, respectively, 0.688–0.920, and 0.759–0.820 for the two and the three sensor configurations; and 0.729–0.935, for the single sensor configurations.

In addition, a larger variance in accuracy was often observed when a sensor was placed on the wrist (i.e., either or both of LW or/and RW) particularly during the carrying ranging between 0.900 to 0.991, walking in the range 0.927-0.982, lifting knuckle in the range 0.921-0.993, and pushing tasks in the range 0.954-0.999. Similarly, having a sensor on either or both of the LW or/and RW showed a larger variance in precision, recall, and F1-Score particularly during the pulling and pushing tasks (precision, recall and F1-score ranged between 0.140 to 1.00; 0.121 to 1.00, and 0.126 to 0.988 respectively).

Percentage errors in the duration and frequency of tasks are summarized in Tables 1 and 2 respectively. The median percentage error in the estimation of task frequency was 0.0% in most of the sensor/s configuration and for most of the activities, with the exception of walking activity for which LW, BW and P show a median error of -7.1%. In the estimation. Regarding the estimation of tasks duration, it is possible to observe errors ranging from 0.0% to 13.6%. Comparing the error percentage obtained using data from different sensor configuration, only P+RW showed statistically different results compared to FB.

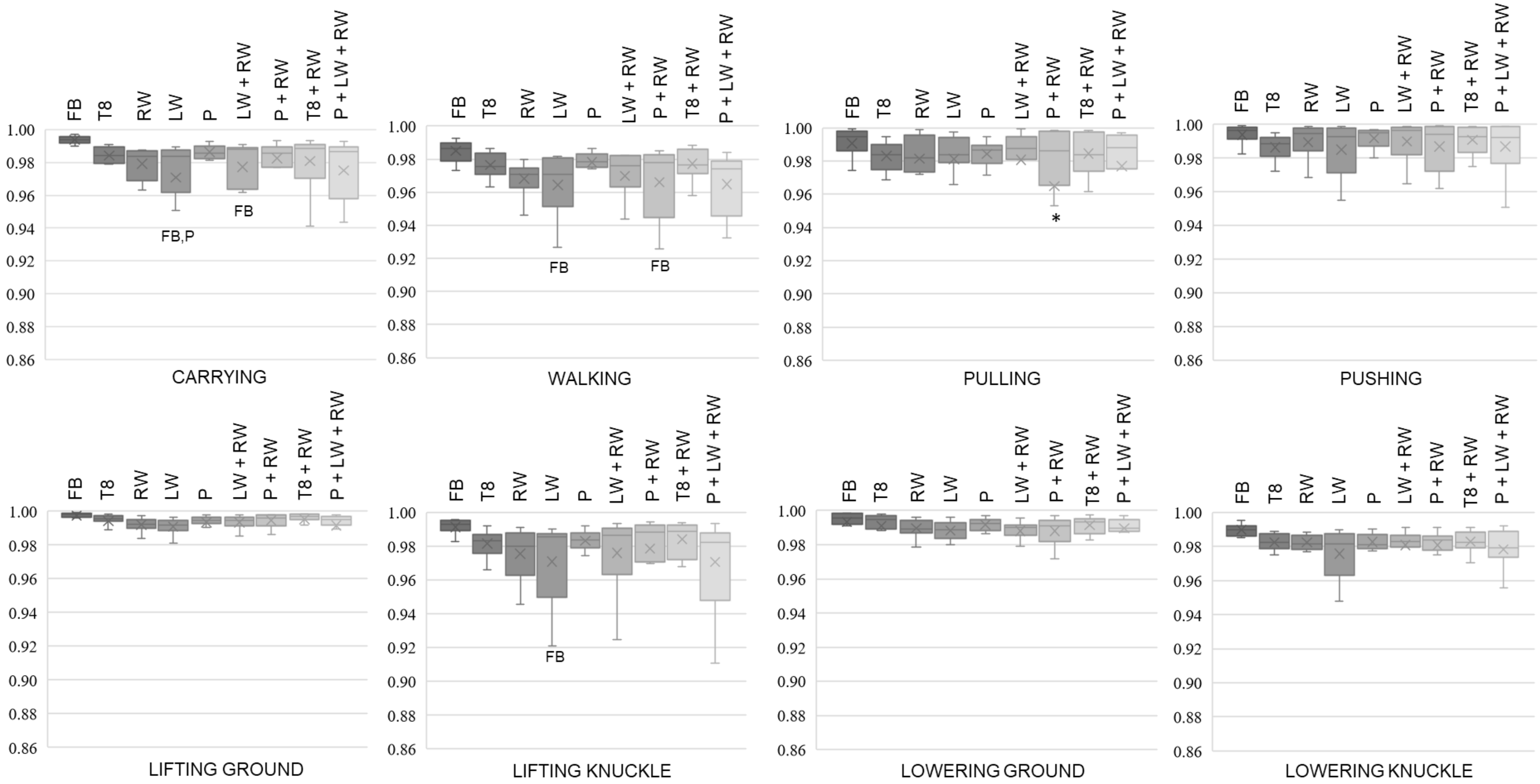
Table 1 Error percentage [(true-estimated)/true]% on estimating task duration: median ([interquartile range=third quartile-first quartile])

	Carrying	LiftingG	LiftingK	LoweringG	LoweringK	Pulling	Pushing	Walking
Ground Truth [s]	25.9 (3.6)	10.7 (1.9)	24.5 (5.0)	11.6 (3.5)	20.2 (3.4)	12.2 (3.3)	11.3 (1.6)	42.1 (10.7)
FullBody	1.6 (9.0)	-0.6 (5.4)	0.0 (9.3)	1.6 (10.4)	3.3 (16.7)	0.5 (30.7)	4.2 (33.3)	2.7 (13.3)
T8	3.9 (16.5)	-1.8 (15.9)	-4.1 (16.8)	-0.5 (16.0)	5.9 (20.6)	-2.7 (60.4)	10.6 (27.35)	1.4 (14.8)
T8+Right Wrist	2.6 (12.3)	0.5 (11.6)	0.2 (9.6)	-0.6 (21.57)	5.1 (18.3)	3.1 (35.8)	4.0 (29.4)	3.5 (12.8)
Pelvis+Right Wrist	3.7 (14.3)	-1.7 (17.6)	1.0 (17.34)	13.6 (41.8)	-5.2 (27.2)	2.3 (22.2)	1.6 (32.2)	0.1 (15.7)
LeftWrist	0.0 (27.84)	9.8 (32.9)	-0.5 (19.5)	4.1 (44.0)	3.1 (19.0)	3.5 (27.4)	5.5 (22.9)	4.2 (16.9)
RightWrist	0.3 (17.0)	-0.6 (18.6)	7.2 (24.9)	12.7 (35.0)	0.4 (16.0)	1.5 (21.0)	-0.5 (14.2)	-1.0 (14.9)
BothWrist	-0.2 (15.3)	0.8 (11.6)	1.3 (17.8)	6.3 (44.1)	4.2 (15.1)	1.4 (22.1)	1.6 (13.4)	4.2 (12.6)
Pelvis	1.5 (12.5)	5.9 (13.2)	-0.7 (18.8)	1.6 (22.3)	3.6 (23.3)	11.9 (39.5)	4.3 (17.0)	0.1 (17.6)

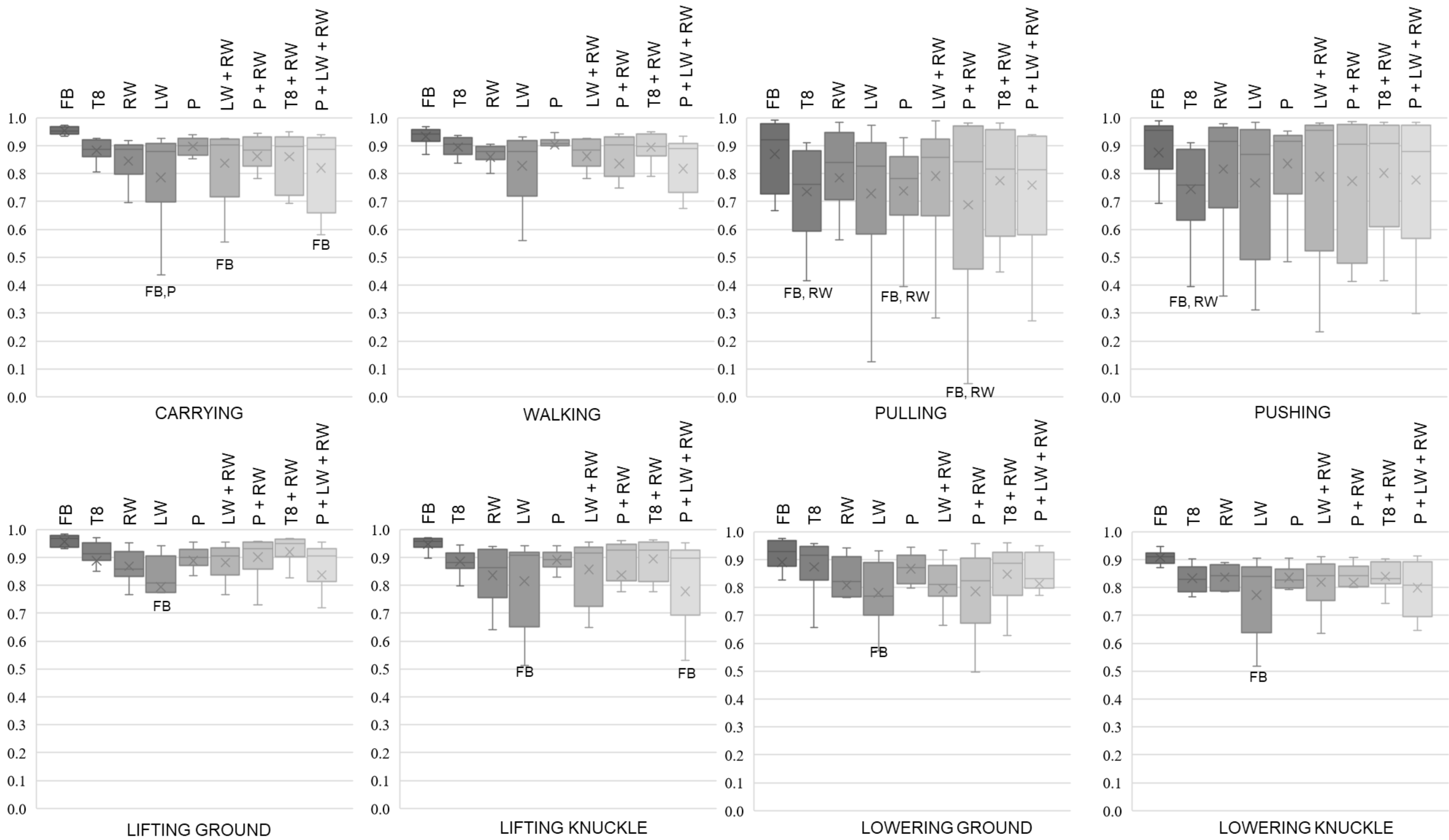
Table 2 Error percentage [(true-estimated)/true]% on estimating frequency of task: median [interquartile range=third quartile-first quartile])

	Carrying	LiftingG	LiftingK	LoweringG	LoweringK	Pulling	Pushing	Walking
Ground Truth [#]	15.0 (5.0)	5.0 (0.0)	15.0 (0.0)	5.0 (1.0)	15.0 (0.0)	5.0 (0.0)	5.0 (1.0)	10.0 (5.0)
FullBody	0.0 (0.0)	0.0 (0.0)	0.0 (0.0)	0.0 (20.0)	0.0 (6.6)	0.0 (20.0)	0.0 (0.0)	0.0 (0.0)
T8	0.0 (13.3)	0.0 (20.0)	0.0 (6.7)	0.0 (20.0)	0.0 (6.7)	0.0 (25.0)	0.0 (60.0)	0.0 (14.3)
T8+Right Wrist	0.0 (6.6)	0.0 (0.0)	0.0 (0.0)	0.0 (25.0)	0.0 (6.6)	0.0 (36.6)	0.0 (20.0)	0.0 (14.3)
Pelvis+Right Wrist	0.0 (12.2)	0.0 (20.0)	0.0 (0.0)	0.0 (45.0)	0.0 (14.4)	0.0 (20.0)	0.0 (0.0)	0.0 (21.4)
LeftWrist	0.0 (13.3)	0.0 (0.0)	0.0 (13.3)	0.0 (25.0)	0.0 (12.9)	0.0 (25.0)	0.0 (0.0)	-7.1 (25.0)
RightWrist	0.0 (20.0)	0.0 (20.0)	0.0 (0.0)	0.0 (20.0)	0.0 (19.6)	0.0 (25.0)	0.0 (20.0)	0.0 (22.2)
BothWrist	0.0 (20.0)	0.0 (20.0)	0.0 (0.0)	0.0 (25.0)	0.0 (6.6)	0.0 (40.0)	0.0 (0.0)	-7.1 (20.0)
Pelvis	0.0 (6.6)	0.0 (0.0)	0.0 (6.6)	0.0 (25.0)	0.0(13.1)	0.0 (20.0)	0.0 (18.3)	-7.1 (14.3)
Wrist+Pelvis	-6.6 (20.0)	0.0 (0.0)	0.0 (13.3)	0.0 (25.0)	0.0 (18.7)	0.0 (50.0)	0.0 (20.0)	0.0 (22.2)
Wrist+Pelvis	-1.7 (19.1)	6.5 (19.0)	2.4 (17.2)	4.5 (26.1)	3.3 (21.7)	-1.8 (27.1)	2.3 (21.1)	1.4 (18.34)

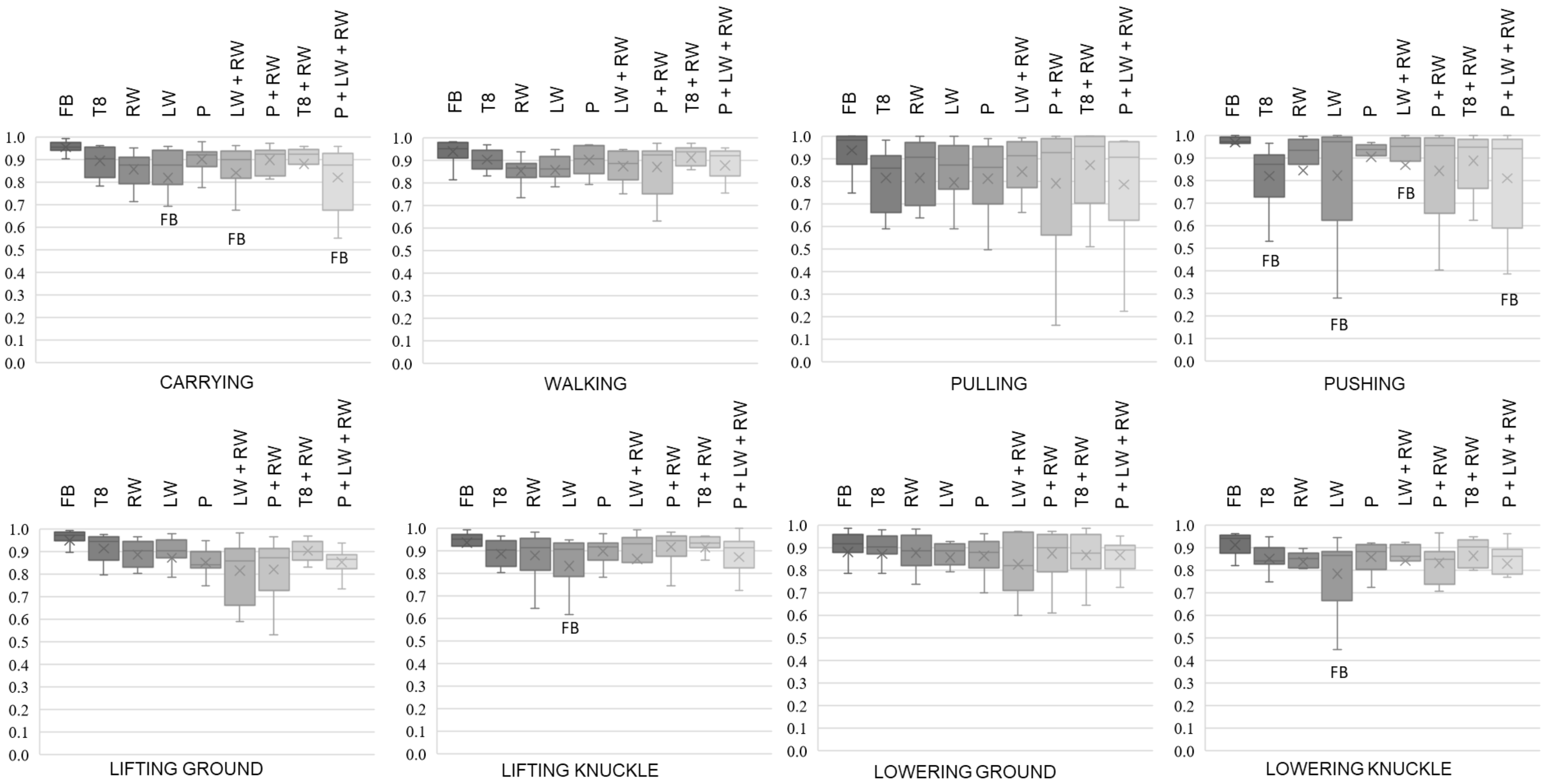
Accuracy


FB
T8
RW
LW
P
LW + RW
P + RW
T8 + RW
P + LW + RW
1.00
0.98
0.96
0.94
0.92
0.90
0.88
0.86
FB,P
FB
*
CARRYING
WALKING
PULLING
PUSHING
LIFTING GROUND
LIFTING KNUCKLE
LOWERING GROUND
LOWERING KNUCKLE

F1-Score


CARRYING
WALKING
PULLING
PUSHING
LIFTING GROUND
LIFTING KNUCKLE
LOWERING GROUND
LOWERING KNUCKLE
FB
T8
RW
LW
P
LW + RW
P + RW
T8 + RW
P + LW + RW
FB,P
FB, RW

Precision


FB
T8
RW
LW
P
LW + RW
P + RW
T8 + RW
P + LW + RW
CARRYING
WALKING
PULLING
PUSHING
LIFTING GROUND
LIFTING KNUCKLE
LOWERING GROUND
LOWERING KNUCKLE
0.0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0.9
1.0

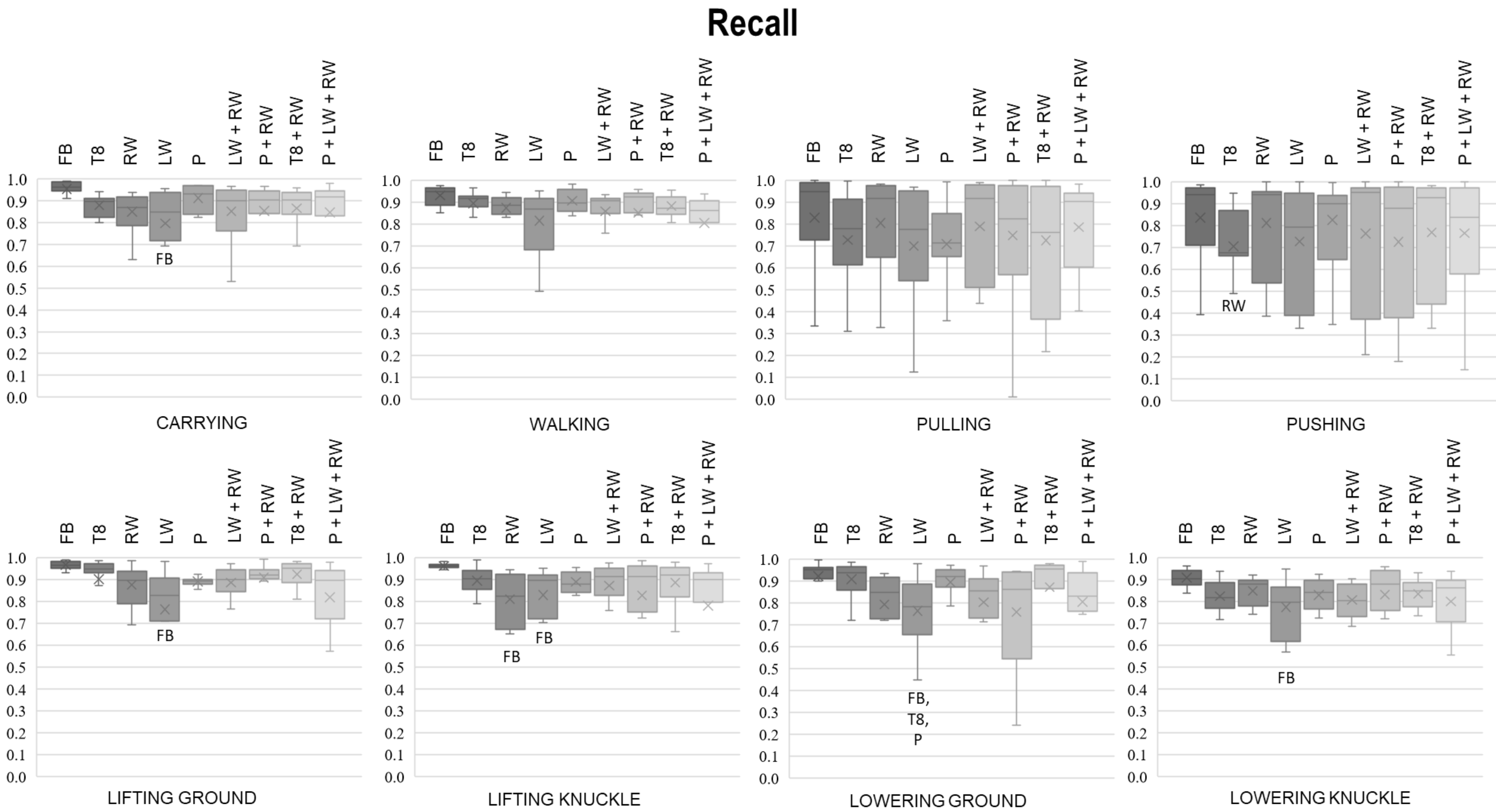


Figure 4 In figure are summarizes accuracy, F1-score, precision and recall values of each MMH task with respect to each sensor configuration

FB: significant difference respect to Full Body configuration
P: significant difference respect to Pelvis configuration
RW: significant difference respect to Right Wrist configuration
T8+RW: significant difference respect to T8+Right Wrist configuration
*: significant difference vs all configurations

Discussion

In this study, to support objective physical exposure assessments in a workplace, has been examined the use of a single IMU with a BiLSTM network to classify MMH tasks to obtain task relevant information (i.e., task type, task duration and the number of a given task). Overall, in many cases, using a single IMU led to classification performance, comparable to using multiple (i.e., 2-3) IMUs and the full-body sensors (17 IMUs). For example, median [5^{th}-95^{th} %ile range] F1-scores for the use of a single IMU were 0.889 [0.396-0.983], depending on specific body locations and MMH tasks, while F1 scores for using two IMUs were 0.897 [0.417-0.988] , three sensors 0.878 [0.127-0.983] and F1 scores for the full-body sensors were 0.942 [0.537 – 0.991]. Earlier study that used the full-body sensors to classify MMH task reported F1 scores of 0.8960 – 0.9599 (Barazandeh et al., 2018) and 0.853 – 0.945 (Kim and Nussbaum, 2014).

MMH-task classification performance was similar when a single IMU was placed either on the pelvis, the right wrist, or the thorax, and was a relatively work when a single IMU was placed on the left wrist (Figure 3). Yet, the left wrist (vs. other locations) configuration had statistically lower MMH-task classification performance only for some MMH tasks. The obtained results demonstrated that depending on a sensor location, using a single IMU can achieve statistically similar classification performance, compared to the FB configuration (17-IMUs). Some comments about the comparison of the performance of the configurations which can be considered more suitable for practical uses. We used the FB configuration as reference, therefore as expected reported the best performances in terms of accuracy and F1-Score as well as precision and recall. Comparison between this (FB) and the other configurations was found statistically significant only in few cases. The worst performances were instead observed for the LW configuration, whose values were statistically lower than FB configuration in six out of 8 tasks classification in terms of F1-Score and in 3 out of 8 tasks classification in terms of accuracy (see Figure 3). At first glance, such findings are somehow expectable since it is known that the sensor placement largely influences the classification performances (Atallah et al., 2011), and better results are usually achieved when the sensor is placed on the body district directly involved in the specific movement analyzed. However, performances were not statistically different with respect to the FB configuration using the same configuration (wrist sensor data) but having the sensor in the dominant limb (RW). Good performances were also achieved from data obtained from T8 (Trunk) or P (Pelvis) locations, although T8 showed significantly lower performance than FB classifying pushing task (F1-sore was 14% lower) and both P and T8 showed significantly lower performance than FB classifying pulling task (F1-sore were 14.3% and 16.5% and lower respectively), appearing less suitable in the classification of such tasks. Although not significant from a statistical point of view, results achieved using wrist sensors showed a greater variability, reflecting the wider choice of strategies possible performing MMH task using hands rather than trunk.

An important aspect in the classification process is the error in the estimation of the duration and frequency of a certain task. This is important because also when the estimation of the duration of a certain task is similar to the ground truth, the number of times that task has been performed may be different from the estimated frequency and vice-versa. Our results showed that tasks duration estimation varied, and in some cases substantially, depending on the specific classification algorithms, sensor setup or task type (see Tables 1 and 2), ranging from -0.5% to 12.2% where typically larger errors are associated with tasks of shorter duration, but the median error in the estimation of the frequency of tasks was often zero.

These findings suggest that even data obtained from a single sensor may lead to satisfactory results in terms of task classification and estimation of its duration, when external conditions like dominant limb and type of performed activity are carefully considered. This statement finds support on the analysis of the results of performances achieved adding one or two sensors. In fact, RW alone achieved an average F1-score of 0.87, while adding LW, T8 or P F1-scores were found lower, 0.83, 0.85 and 0.84 respectively. Although a reduction in performances (not statistically significant) was someway unexpected, a possible explanation might be found in the lower performances of LW (F1-

score = 0.80), T8 (F1-score = 0.85) and P (F1-score = 0.86) compared to those achieved by RW, that instead of improve the overall classification, seems to confuse the one achieved by RW.

These results demonstrate that data from a single IMU can classify simulated activities commonly observed during MMH tasks enabling accurate and efficient ergonomic assessment. Here have been explored the performances of different sensor setup compared with the optimal available condition of the FB setup. Since performances of single sensor setup do not statistically differs from each other, in terms of task type identified, their duration, and the number of a task identified, we would like therefore to leave to the reader the choice of the more feasible placement on the basis of his/her practical need. Circumstances in which, the job does not require frequent pushing and pulling tasks, pelvis can be an optimal unobtrusive placement, as alternative to the wrist placement that in some peculiar circumstances might led to potentially harmful condition (e.g. to hook in some machinery). Furthermore, if the practitioner expects some challenges in data collection, using a combination of sensors he/she may overcome the data collection failure. Of course, although a single sensor allows to reach good classification performances, when possible, the use of a full body configuration allows to extract additional detailed information such as joints kinematics.

The novelty of this study resides in the use of a BiLSTM for the classification of MMH tasks using a single IMU. Some comments about the choice of this particular network need to be cited. An interesting aspect in the choice of a BiLSTM network for the classification of MMH tasks in real work environment is that it is potentially able to process signals collected by consumer devices like smartphone or smartwatch equipped with accelerometers and gyroscopes, due to the fact that it can be fed using raw time-series signals thus avoiding the need for complicated feature extraction processes that usually require expert knowledge and tend to reduce the generalizability of the method (Artur Jordao et al., 2018; Wang et al., 2019). Furthermore, since the frequency of the different tasks associated with MMH can be extremely different (i.e. more lifting from knee level than lifting from ground level), the BiLSTM option seems to be appropriate because exhibit good performances also in presence of task that happened with unbalanced frequency (Wang et al, 2019).

Some limitations need to be accounted. Firstly, an exhaustive exposure assessment provides three levels: intensity, frequency and duration, while our approach allows to assess only frequency and duration. Secondly, the classifier has been trained using data from activities carried out in laboratory settings, although performed at self-selected speed and using the preferred strategy. Another drawback might be related to the relative inexperience of the participants performing MMH tasks compared to professional workers. Linked to the abovementioned limitation, future works might include information about the carrying loads (Lim and D'Suoza, 2019), adding knowledge about the intensity of the MMH tasks performed. Finally, but not less important, future works should consider testing the proposed method in field settings, to assess its performances in real work environment.

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Conclusion

This project was designed to provide a small contribution in bridging the gap between the research typically performed in a laboratory setting, and the possibility to translate the results into practical applications in an actual industrial context. In the last decades, both society and industry have experienced new challenges associated with the huge demographic changes and, in many countries, the change in age composition of the population has been faced through reforms aimed in reducing any possibility of early exit from the work market, thus pushing individuals towards a prolonged working life. However, the increased presence of older people in the workforce is likely to have consequences in terms of health issues since the prevalence of chronic diseases increases with age. Among them, musculoskeletal disorders (and particularly LBDs) represent a serious problem for workers, employees, insurance and public administrations. In this context, this research project has been focused on designing an approach (feasible to be applied in actual working environments) able to provide quantitative reliable data useful to support the monitoring of potential harmful conditions for workers, with the final aim of preserving and promoting an "healthy ageing" of workers.

The development of work-related LBDs is an "old" problem, but despite the large number of studies carried out on this topic, no definitive solutions have been found so far. Some possible explanation may be related to different methods applied in the epidemiological research to characterize exposure to risk factors. In fact, most researches that attempted to explain the existence of a causal relationship between risk factors and symptoms have been carried out in laboratory settings, thus neglecting several aspects of the actual interaction between workers and environment. In other cases, self-reported questionnaires have been used, but such tools are highly biased by the workers perception. As a result, scarce information about quantitative assessment of exposure to risk factors under actual working condition are available.

Driven by these drawbacks, this research attempted to propose a valid tool to collect information about workers' trunk posture, easy to use, feasible for actual working conditions, and able to provide straightforward output.

To reach these goals, this research has been articulated into two main paths:

1. To demonstrate the feasibility of use and the reliability of a simplified setup composed by a single IMU to monitor trunk flexion for prolonged working time in actual occupational settings.
2. To explore the possibility to use the same setup to classify type, frequency and duration of a range of MMH tasks of interest (given their potential hazard for the development of LBDs) by means of specific algorithms that process IMU-derived data.

The obtained results demonstrated that IMUs represent a suitable way to monitor trunk posture, at the same time providing the possibility to discriminate among different strategies adopted to perform a given task. Such features suggest that this technique can highlight potentially harmful behaviors or conditions. In this way, early intervention to prevent the development of LBDs might be planned.

The simplicity of the employed setup and the associated methodology to process IMU-based data here proposed, may be useful specially to perform rapid screenings of large cohorts of workers, with minimal disturbances to the working tasks. Collected data may represent valuable information for ergonomist or production engineers regarding potential risks, to support decisions or type of actions needed to improve the interaction with the working environment, with the final aim of preventing injuries to keep workers healthier and active as long as possible.

La borsa di dottorato è stata cofinanziata con risorse del Programma Operativo Nazionale Ricerca e Innovazione 2014-2020 (CCI 2014IT16M2OP005), Fondo Sociale Europeo, Azione I.1 "Dottorati Innovativi con caratterizzazione Industriale"

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