Musculoskeletal Disorders in Construction: A Review and a Novel System for Activity Tracking with Body Area Network

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Abstract

Human body motions have been analysed for decades with a view on enhancing occupational well-being and performance of workers. On-going progresses in miniaturised wearable sensors are set to revolutionise biomechanical analysis by providing accurate and real-time quantitative motion data. The construction industry has a poor record of occupational health, in particular with regard to work-related musculoskeletal disorders (WMSDs). In this article, we therefore focus on the study of human body motions that could cause WMSDs in construction-related activities. We first present an in-depth review of existing assessment frameworks used in practice for the evaluation of human body motion. Subsequently different methods for measuring working postures and motions are reviewed and compared, pointing out the technological developments, limitations and gaps; Inertial Measurement Units (IMUs) are particularly investigated. Finally, we introduce a new system to detect and characterise unsafe postures of construction workers based on the measurement of motion data from wearable wireless IMUs integrated in a body area network. The potential of this system is demonstrated through experiments conducts in a laboratory as well as in a college with actual construction trade trainees.

Keywords: WMSDs, construction, Health, Well-being, biomechanics,

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inertial measurement unit

1. Introduction

Deterioration of workers' physical health and loss of workdays not only impact their well-being and quality of life, but also the country's economy. For example, in 2011 more than 400,000 people in the United Kingdom suffered from illness caused by their work, resulting in 7.5 million lost days (The Health and Safety Executive, 2014).

Musculoskeletal Disorders (MSDs) are injuries or pain affecting muscles, joints and tendons. MSDs result from daily awkward postures and handling tasks, such as: forceful exertions in lifting or carrying loads, bending and twisting the back or limbs, exposure to vibration or repetitive movements (including keyboard typing). If these activities are work-related, then the resulting injuries and disorders are referred to as Work-related Musculoskeletal Disorders (WMSDs).

1.1. WMSDs in Construction

Construction workers are particularly at risk of WMSDs because they are frequently exposed to awkward postures and motions, such as lifting, bending or twisting, sometimes for long periods of time. Comparing the different industries in the UK, the Health and Safety Executive (HSE) shows that, despite some improvement over the last 10 years, the rate of self-reported work-related illness in the construction sector remains the second highest behind transport and storage (see Figure 1).

With the construction sector employing almost twice more people than the transport sector (2.3 million and 1.47 million respectively, according to the British Office for National Statistics), the number of self-reported work-related illness in the construction sector is likely the highest among all sectors. Note that these figures do not take account of the additional large number of unreported injuries.

The extent to which certain construction occupations are exposed to awkward positions is well summarized by the Center for Construction Research and Training (CPWR) in the United States which reported that carpet and tile installers are on their knees, crouching or stooping more than the 80% of the time, and bricklayers spend 93% of their time bending and twisting the body or doing repetitive motions (The Center for Construction Research and Training, 2013). Figure 2 summarizes the rates of WMSDs reported due to

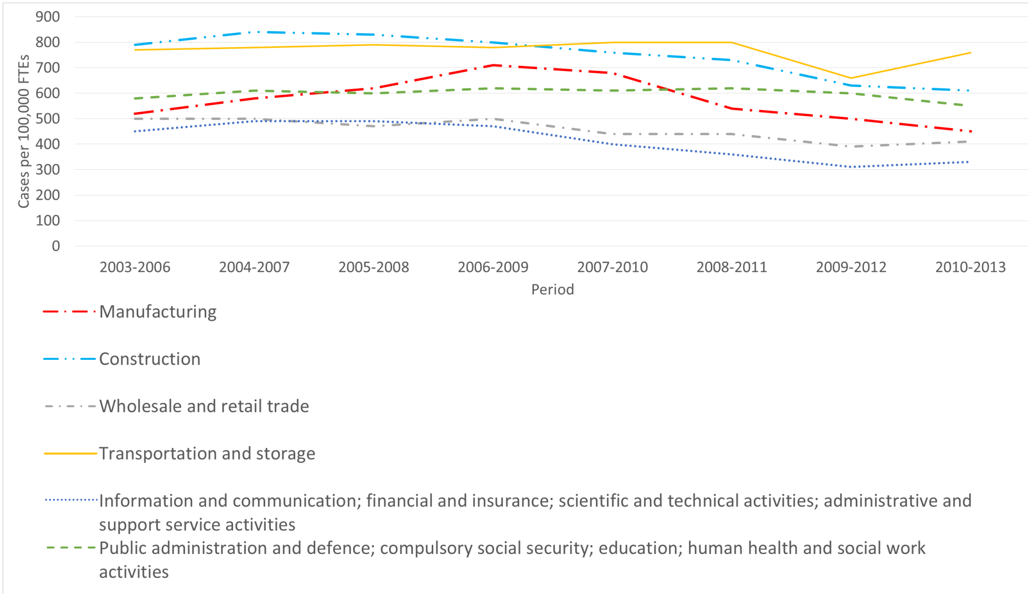

Figure 1: Rates of self-reported WMSDs, by industry, for people working in the last 12 months (data source: The Health and Safety Executive (2014)).

overexertion per construction occupation, in 2013 in the United States. Masonry workers, for example, appear particularly exposed to WMSDs. Memarian and Mitropoulos (2012) conducted a detailed study of incidents and risk activities in a large masonry company and concluded that the tasks resulting in most incidents (and consequently an important number of days away from work and days with modified tasks) were: laying bricks (19%), scaffold erection (18%) and material handling (14%).

Focusing on the postures resulting in WMSDs, Zimmerman et al. (1997) identify the top five ergonomic problems in construction as: working in the same position for long periods, bending or twisting the back in an awkward way, working in awkward or cramped positions, working when injured or hurt, and handling heavy materials or equipment. Figure 3 illustrates the percentage of non-fatal injuries (*i.e.* resulting in days away from work) for each body region, as reported by The Center for Construction Research and Training (2013). The upper body, and particularly the back, appears to be the most impacted.

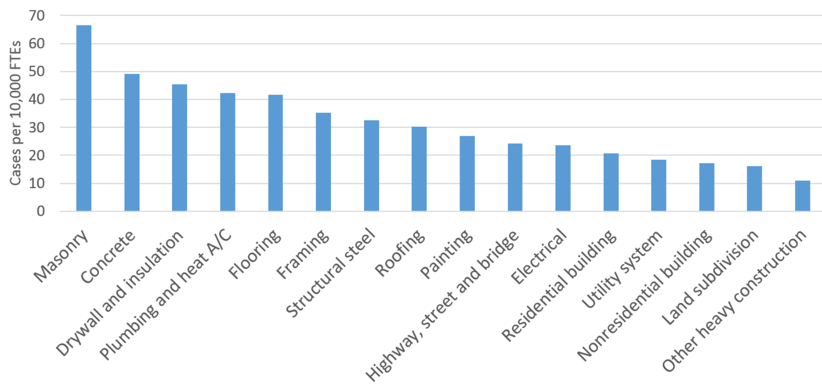

Figure 2: Rate of overexertion injuries resulting in days away from work, by construction subsectors (data source: The Center for Construction Research and Training (2013)).

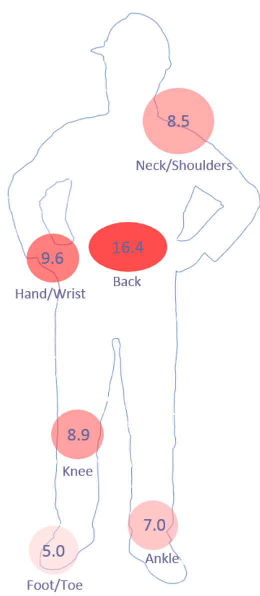

Figure 3: Distribution (in %) of non-fatal injuries resulting in days away from work in construction (source: The Center for Construction Research and Training (2013)).

1.2. Contribution and Structure of the Article

Occupational health has been recognized as an important problem since Gilbreth started his motion studies in the early 20^{th} century (Gilbreth and Gilbreth, 1917). Yet, despite advancements in technology and the development of many tools and initiatives, WMSDs persist as statistics reflect. Better monitoring the body movements of workers, including during their training period, could help correct bad postures and raise awareness about good practice, and consequently improve their quality of life and save working days and money.

Focusing on the construction sector, this article first reviews tools currently employed by government and companies to assess the postures and motions of workers with regard to their long-term health, including the risk for WMSDs (Section 2). Next, Section 3 provides an in-depth review of measurement tools that have been proposed and used for human biomechanical analysis. The use of Inertial Measurement Units (IMUs) is particularly studied as this relates to the system proposed here. Section 3 concludes with the identification of the need for developing and assessing non-invasive wearable systems for continuous body motion monitoring to support assessors and workers in improving construction tasks and preventing WMSDs. Section 4 then presents our proposed Activity Tracking system based on IMUs integrated in a novel wireless Body Area Network (called AT-BAN) and reports experimental results on the recognition of body postures related to lifting, an activity well-known to be problematic. The experiments are conducted both in a laboratory and in a college with actual construction trade trainees. Section 5 concludes this article with an analysis of the contributions made and suggestions for further development and assessment of the proposed system.

2. Current practice for evaluating postures and body movements in the workplace

The postures and body movements of workers can impact their health and well-being and also affect productivity. F. B. Gilbreth was a pioneer of motion study in the field of industrial management (Gilbreth and Gilbreth, 1917, 1924), focusing mainly on better coordinating the body motion of workers to improve productivity. Ever since, practitioners, physiotherapists and ergonomists, from both public and private organisations, have taken a keen interest in the study and evaluation of tasks and workers, developing various assessment methods with focus on productivity and/or health. These methods consider different parameters to be measured, from motion amplitude and frequency to muscle activity.

Section 2.1 reviews the main risk assessment methods that have been developed and applied in various sectors. Section 2.2 then reviews how most of these methods have particularly been applied within the construction sector. Section 2.3 summarizes the strengths and limitations of these methods, with particular focus on the posture and motion measurement techniques they employ.

2.1. Current WMSD risk assessment method

Government agencies dedicated to health and safety issues across industries (such as the Health and Safety Executive (HSE) in the UK or the National Institute for Occupational Safety and Health (NIOSH) in the United States), universities as well as some companies have been developing techniques and proposing guidelines to assess the daily tasks of workers and alter them to reduce the number of work-related injuries and illnesses. Some of these techniques focus on assessing the task, in order to infer its impact on posture and body motions and as a result the level of risk of WMSDs. These methods include the *Work Practices Guide for Manual Lifting* developed by NIOSH (NIOSH, 1981; Waters et al., 1994) to help practitioners assess and minimize the risks associated to lifting jobs, as well as the method of Snook and Ciriello (1991) to assess the risk of lower back disorder (LBD) in lifting, lowering, carrying, pushing and pulling tasks. While practical, these methods however infer postures and body motions as opposed to directly measuring them, which adds a layer of potential error in the overall risk assessment.

Other methods have been developed that are instead based on the direct measurement of actual postures and body movements. Since direct measurement is preferable to identify the source of WMSDs and this is the approach considered in the system presented later in this manuscript, these methods are reviewed in more detail below.

Assessment of Repetitive Task (ART) and Manual Handling Assessment (MAC). One of the methods developed by the HSE in the UK, the *Assessment of Repetitive Task* (ART) tool (The Health and Safety Executive, 2009), assesses repetitive tasks typically carried out by factory workers (*e.g.* packaging). A scoring method is established that takes into account the posture of the upper limbs, neck and trunk, evaluated by a risk assessment expert who is observing the worker. The final score rates the level of exposure of the worker, helping to identify the risk factors that contribute to the development of WMSDs. A traffic light coding system is also introduced to report performance in a way easily understood by users.

The HSE also proposes the *Manual Handling Assessment* (MAC) tool (The Health and Safety Executive, 2002) to evaluate other tasks involving risks to the lower back. Motion parameters related to lifting and carrying movements are considered, such as back bending, torso twisting, and the distance between the hands and the lower back. These movements are assessed by an expert watching the workers in the jobsite.

Note that ART and MAC evaluation tools are based on the subjective (qualitative) judgement of the assessors, as opposed to the quantitative direct measurement of body motions.

Ovako Working Analysis System (OWAS). The (OWAS) was developed by the steel-manufacturing company Ovako with the goal to redesign their production line. It identifies and evaluates bad working postures based on the visual observation of the daily routine of workers (Karhu et al., 1977). Postures are classified in more than 250 different poses by assessing the position of trunk, arms and legs, as well as the weight of the load. Every posture is coded to enable the evaluation of the overall risk of WMSDs.

Posture, Activity, Tools and Handling (PATH). The (PATH) assessment method, proposed by Buchholz et al. (1996), codes the postures as originally suggested by Karhu et al. (1977) in the OWAS method, adding new codes for different activities, loads and equipment. By evaluating images recorded during work activities, assessors identify the proportion of time workers spend in the coded postures that are classified as 'neutral' or 'non-neutral'.

Rapid Upper Limb Assessment (RULA) and Rapid Entire Body Assessment (REBA). McAtamney and Nigel Corlett (1993) present the *Rapid Upper Limb Assessment (RULA)* survey to evaluate certain postures of the neck, trunk and upper limbs. Ergonomists code each posture by visually evaluating the angles between the studied body parts, and obtain a *grand score* that is used to decide whether a movement is considered acceptable (based on the criteria derived from the relevant literature) or some changes have to be made.

The *Rapid Entire Body Assessment (REBA)* method (McAtamney and Hignett, 1995; Hignett and McAtamney, 2000) was developed to improve and extend RULA. Like RULA it evaluates and scores the postures of workers, but extends it by visually evaluating the positions of the legs, considering postural loading factors and evaluating awkward positions in upper limbs (*e.g.* if arms are abducted or rotated or if shoulders are raised).

Quick Exposure Check (QEC). The QEC tool, proposed in (Li and Buckle, 1999), consists of a questionnaire and a scoring sheet. The scoring sheet is used by experts to assess the movements of the trunk and upper limb joints to identify those postures leading to WMSDs. To create this tool, Li and Buckle registered the movements of workers by means of a vision-based platform for motion capture, and, with the opinions of experts assessors, they defined the different postures to be considered and the range of movements leading to WMSDs.

In contrast to the previous tools, not only practitioners are involved in the evaluation but workers also play their role by filling out in a questionnaire related to the studied movements.

2.2. Application in Construction

Most of the above-mentioned works have actually been applied and validated in the construction sector. McGorry and Lin (2007) study grip strength in the handling of tools used in construction trades using the RULA method as a basis to evaluate the posture of the arms obtained from different tools configuration. Kim et al. (2011) apply the REBA method to study the movements of workers during the installation of prefabricated walls in order to improve panel design and construction processes. Wall panel installation is also evaluated by means of the QEC method in (Rwamamara, 2007). Kivi and Mattila (1991) were pioneers in the application of the OWAS method to the field of construction, developing a basic portable computer system to manually score the observed tasks; the computer then calculates an overall score. The same group later used that same system to evaluate the use of tools, such as hammers (Mattila et al., 1993). More recently, the OWAS method has also been used in (Saurin and de Macedo Guimaraes, 2008) as a tool to assess the body position of operators working on scaffolds and painting or coating bulding façades. Finally, Forde and Buchholz (2004) have evaluated the movements of ironworkers by means of the PATH method in order to develop improved tools and work techniques, reducing non-neutral postures.

2.3. Summary

The assessment methods reviewed in this section are summarized in Table 1 that compares them based on the posture characteristics and means of measurements they consider. While they consider various body parts and motion characteristics, it is interesting to point that they were all initially designed, and often are still used in practice, using visual observations by experts as the main means of measurement of posture and body movement. Yet, visual observations tend to be imprecise and result in excessively subjective evaluations (Kemmlert, 1995), including when conducted by expert observers (*e.g.* ergonomists). Even when observing video recordings of activities (as opposed to live), it is quite complicated to identify patterns, compare movements or establish individual differences.

This subjectivity and lack of accuracy leads to the need to replace or supplement visual observations with other more accurate and precise posture measurement devices and methods. The development of those is discussed in the following section.

	Body part	**Posture characteristics**			**Means of measurement**
		Ampl.	**Durat.**	**Freq.**	
RULA	Upper limbs	✓	–	✓	Visual assessment Video/Picture Software/Table
REBA	Whole body	✓	–	–	Visual assessment Video/Picture Scoring sheet/Tables
MAC	Upper limbs and back	✓	–	✓	Visual assessment Scoring sheet
ART	Upper limbs	✓	✓	✓	Visual assessment Scoring sheet
OWAS	Whole body	✓	–	✓	Visual assessment Scoring sheet
PATH	Whole body	✓	–	✓	Visual assessment Video/Picture Data collection sheet
QEC	Upper limbs and back	✓	✓	✓	Visual assessment Scoring sheet

Table 1: Comparison of the assessment methods to evaluate workers postures in their workplace.

3. Biomechanical measurement devices

Biomechanical assessments based on visual observations (either in real time or using video recordings) are not accurate and precise. In terms of *accuracy*, a difference of ten degrees in a posture is not easily noticeable while observing a worker in real time. *Precision*, or *repeatability* or *reproducibility*, refers to how much measurements produce the same results when repeated numerous times by the same or different assessors (Li and Buckle, 1999) — note that Li and Buckle (1999) refers to this reproducibility criterion as *reliability* but we find this term too vague, confusing. Visual measurements are well-known to be imprecise, particularly when conducted by different assessors.

Accurate and precise results can be better achieved by means of (modern) measuring devices, facilitating experts' diagnostics. Section 3.1 provides a general overview of measurement devices that have been developed over time for biomechanical analysis. Then, Section 3.2 focuses on the devices that have been more specifically considered in the construction sector. Sections 3.1 and 3.2 both particularly investigate the recent development and increasing usage of IMUs. Finally, Section 3.3 summarizes these previous works, identifying limitations and specifying a need.

3.1. Overview

Figure 4 presents the evolution of measuring instruments used for biomechanical analysis. Tapes and goniometers (West, 1945; Robson, 1966; Miller, 1985) are the most simple instruments and have been used clinically for centuries to register linear movements and rotations. However, since they have to be operated by the assessors, employing these instruments is time consuming and very intrusive (*i.e.* leading to motion restrictions or discomfort), preventing their use outside controlled, clinical environments.

Further progress in biomechanical measurement has only really been made since the mid-1900s. Tracking devices driven by analog circuits were developed in the 1970s (Flowers, 1976) and by digital/analog converters on computers in the following decade (Miall et al., 1985). These devices have provided more precise and rapid results, making the analysis of movement patterns easier. In the early 1990s, Marras et al. (1993) used an electrogoniometer to evaluate WMSD risks with focus on LBDs, while Nimbarte et al. (2010) recently used electromyographic (EMG) systems to study the major neck muscles in handling and lifting tasks. Also Jia et al. (2011) proposed

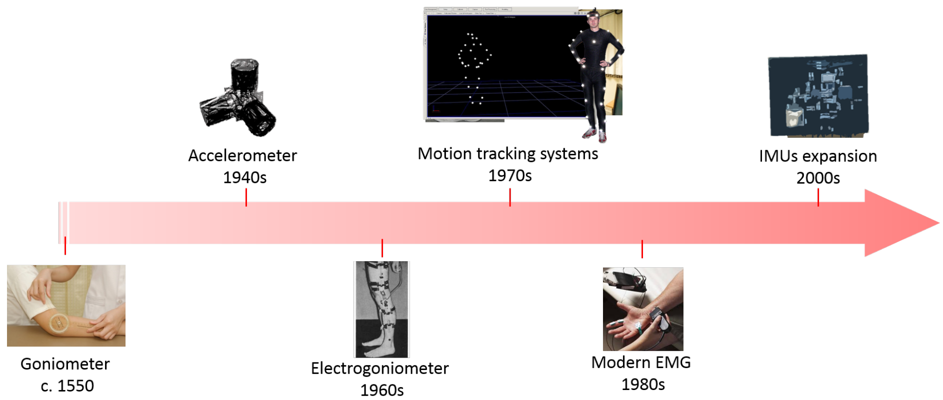

Figure 4: Timeline of measurement solutions for biomechanical analysis.

the use of EMG devices to predict lower lumbar region loads during carrying, erecting, lifting and moving tasks. These devices delivered improved levels of wearability and reduced intrusiveness compared to previous technologies, although these were still far from ideal.

Various authors have carried out biomechanical analyses by means of vision-based motion tracking systems that track the body parts with or without the help of markers attached to those parts (Ray and Teizer, 2012). For example, as mentioned in subsection 2.1, Li and Buckle (1999) used a vision-based tracking system to produce the QEC tool for assessing the movements of workers. Systems based on electro-magnetic fields can similarly be used as alternatives to vision-based motion tracking systems (Wong and Lee, 2004; Theodoridis and Ruston, 2002; Hwang et al., 2009). Vision and electromagnetic systems can be less intrusive than previous technologies because they work wirelessly. However, this is achieved at the cost of significant external infrastructure, (*e.g.* calibrated camera network) which prevents setup outside dedicated environments.

Nowadays, the reduction in size of electronic devices (*e.g.* microelectromechanical systems (MEMs)) has allowed the creation of small and wearable sensors which can register the movement of different parts of the body. These devices, when integrating sensors such as accelerometers, magnetometers and gyroscopes, are called *Inertial Measurement Units (IMUs)* and enable the measurement of acceleration, velocity, orientation, and the Earth's gravitational forces and magnetic fields in real time. These capabilities have raised significant interest among researchers aiming to measure postures and body motions in various contexts, from daily activities (*e.g.* walking, running and sitting) to complex work-related tasks (*e.g.* climbing, hammering and lifting). The rest of this section reviews the already extensive literature on the use of IMUs for posture and body motion measurement.

One of the initial areas of investigation for the application of IMUs has been gait analysis. Simcox et al. (2005) study the movement of lower limbs and trunk during walking and sit-stand trials. They compare the angle measurements calculated by a camera motion analysis system and those inferred from IMUs, and conclude that these sensors are accurate to measure trunk and lower limbs in real time. However, in their system the sensors were wired to a hand-held computer which is clearly invasive and would prevent its usage by workers. Recently, Novak et al. (2014) have presented an algorithm for detecting turns during walking activities by means of a wireless and wearable sensors network. The authors also reflect upon the optimal position of IMUs to evaluate such movements.

Karantonis et al. (2006) classify different postural orientations (*i.e.* possible falls, lying, sitting, standing or walking) and the transitions between those by studying data from a small accelerometer worn on the waist. Vanveerdeghem et al. (2014) have recently proposed a wearable wireless body sensor network integrating four IMU sensors into a firefighter garment to control the trunk movements and detect whether a person (in fact, up to four people) is walking, running or lying.

Other daily activities, such as morning and eating tasks (*e.g.* dressing, breakfast, brushing teeth or combing hair) can be controlled for disorder evaluation or rehabilitation. For example, Luinge et al. (2007) track arm kinematics by means of IMU devices. They compare the obtained results with the reference values determined by a vision-based motion tracking system, concluding that the accuracy of their system may be sufficient for the assessment of activities of daily living. In (Yang et al., 2008), a learning algorithm is proposed to recognize scrubing, vacuuming or brushing teeth in data obtained from an accelerometer worn on the dominant wrist.

Sport activities are also studied by means of accelerometers and IMUs. Parkka et al. (2006) recognize the sport a person is practising by means of a wireless body sensor network integrating more than ten different sensors (*e.g.* IMU, GPS, light sensors or microphones). And Namal et al. (2006) analyse soccer actions (walking, jogging, passing and dribbling) in data from twelve wireless accelerometers located on the legs, arms, waist and head, to establish a soccer gait pattern recognition system.

In the context of work, maintenance or assembly tasks have mainly been considered. Lukowicz et al. (2004) evaluate different working processes in a wood workshop. In this work, the user wears a system consisting of three accelerometers (two on the dominant arm and one in the other) and two microphones (wrist and chest), and certain operations are recognized by means of correlation between frequency and intensity of sounds and the user's motion. The system as presented is however somewhat intrusive because the user has to wear a computer attached to their trunk. In (Zappi et al., 2008), tasks related to a car assembly line are recognized in data acquired by accelerometers placed on the workers' arms. Similarly, Koskimaki et al. (2009) present a work in which hammering, screwing and drilling operations are recognized by analysing the acceleration and angular speed from an IMU sensor located on the wrist.

3.2. In construction

As mentioned earlier, construction is a sector particularly affected by work-related injuries, with WMSDs being a recurring problem which has contributed to create a bad image of this industry. Due to the high rate of WMSDs, the control of activities carried out by construction workers has attracted research interest in recent years.

Alwasel et al. (2011) present the prototype of a magneto-resistive system to measure joint angles and they test it for shoulder movements. In (Alwasel et al., 2013), they propose another solution to register different angles by mounting an optical encoder to an exoskeleton. This system can be used to measure shoulder, elbow and knee joint angles. But the size of the system makes it rather intrusive, and thus does not allow workers to wear it over long periods of time such as during entire working days.

Nimbarte et al. (2010) study neck disorders amongst construction workers by means of EMG systems wired to a computer, and conclude that lifting and holding loads at shoulder height affect neck muscles and can be a source of WMSDs. Unfortunately, because they have to be fixed directly to the skin, EMG sensors are somewhat intrusive. Furthermore, as presented the system is not wearable. In a similar manner, Jia et al. (2011) propose a method based on EMG systems to evaluate the movements and efforts perfomed by the lower back in activities related to prefabricated panels erection. Although EMG and force measurements provide direct measurements of muscle activations and the forces involved, EMG systems may be considered as intrusive (as noted above) and cannot be used outside the laboratory set up or in a real work site.

Joshua and Varghese (2011b) propose to use video cameras to record the movement of construction workers on site and conduct an initial study of the movements of arms and waist to determine the appropriate location of accelerometers to track those body parts. Ray and Teizer (2012) propose to use depth sensors (also called range cameras) to study the posture of construction workers and classify their movements as 'ergonomic' or 'non-ergonomic'. Unfortunately, like video camera -based systems, the field of view and depth of current range cameras makes this system only usable for the study of stationary activities. Furthermore, range cameras are sensitive to varying lighting conditions, which means that the system should preferably be used indoors.

Accelerometers and IMUs are increasingly being promoted in various studies (Wang et al., 2015). Kim et al. (2011) present a load measuring tool for construction workers based on four accelerometers located on the arms. The size of this wired solution makes the system intrusive and difficult to wear, and so cannot be considered for long-term usage. Jebelli et al. (2014) propose to use an IMU sensor attached to the ankle to characterise the fall risk of workers on the jobsite and prevent accidents. Although focused on productivity assesssment, Joshua and Varghese (2011a) present a system that classifies masonry activities (fetch and spread mortar, lay bricks, and filling joints) by processing acceleration data from two accelerometers placed on the waist of bricklayers. Finally, in their most recent work Joshua and Varghese (2014) classify the activity of experienced workers as 'effective', 'ineffective' or 'contributory' by analysing data from accelerometers located on the head (hardhat), arms and waist of workers.

3.3. Summary

This literature review shows how new technologies are facilitating body posture and motion measurement. The evolution of technologies has been driven by not only improvement in measurement accuracy and precision, but also reduction in intrusiveness and enhanced wearability. A large majority of construction-related studies reported to date acquire data using systems that are either intrusive or not sufficiently wearable, and so can only be used for assessing stationary activities (even in somewhat 'controlled' environments), over short periods, and often in supervised manners (the subjects are constantly aware of being observed). Yet, it would be desirable to have body posture and movement measurement systems that are sufficiently wearable and non-intrusive to enable their use over long periods of time, ubiquitously (*i.e.* anywhere on any jobsite) and without physical external presence.

IMUs offer great potential in all these aspects, in addition to data quality, robustness and low cost. As a result, as reported above and in (Wang et al., 2015), these devices are increasingly being promoted in various studies. Yet, the literature review also shows that, while some initial works have been reported on the use of IMUs for tracking the motion of construction workers in the fields of productivity or health, no work to date has been conducted to assess body posture or motion more completely to reduce WMSDs.

In the remaining of this article, we present a scalable IMU-based wearable system with a low level of intrusiveness and real-time processing that has the potential to fill these gaps. The system is developed with the aim of delivering continuous WMSD risk assessment over long periods of time and for non-stationary work activities. The proposed system, detailed in Section 4 below, differs from that of Namal et al. (2006) in that it does not use accelerometers only, but IMUs that integrate various motion sensors delivering more precise motion data. Furthermore, the system is developed entirely in-house, which offers great flexibility to shape it to varying needs, including integrating sensors other than biomechanical ones. In that sense, our system resembles that of Parkka et al. (2006), but their focus is on sport biomechanics while we focus on worker biomechanics for WMSDs risk assessment.

This work also differs from that of Joshua and Varghese (2011a, 2014) who focus on productivity. In fact, we note that the biomechanical measurements required by WMSDs risk assessment need to be much more precise than those required for their productivity assessment.

4. Real-time and automated assessment of construction work postures. A new system

We present the *Activity Tracking with Body Area Network (AT-BAN)* system, a novel wearable system that aims to quantitatively, accurately and ubiquitously measure the postures and body motions of workers, in order to detect potentially unhealthy ones. Following the original concept presented in (Sivanathan et al., 2014), this system operates around a cyber-physical body area network with real-time activity tracking capabilities. This system is unobtrusive, wireless and wearable, and is primarily designed to operate autonomously. We foresee that it could first be used to augment the observations of trainers in colleges, through both individual assessments and benchmarking, but it is not unreasonable to consider that such a system could be used by workers to autonomously monitor themselves on actual job sites over long periods of times (*e.g.* entire workdays). This would provide an opportunity for *life-long training*.

An overview of the AT-BAN system is given in Section 4.1, and its differences with other measurement systems (strengths and shortcomings) are further discussed. Results of experiments carried out so far are then reported and discussed in Section 4.2.

4.1. System Overview

As illustrated in Figure 5, the AT-BAN architecture is a generic infrastructure that can accommodate any type of sensors and devices. The low-level technical features of the AT-BAN system, such as connectivity, interfacing and synchronisation, are built upon the UbiITS framework (Sivanathan et al., 2013; Sivanathan, 2014).

Wearable, wireless IMU devices are the basic blocks of the version of the AT-BAN system reported in this article. These proprietary devices of dimensions $6cm \times 4cm \times 1.5cm$ contain sensors (accelerometer, gyroscope, and magnetometer), a micro-processor, components for wireless transmission, built-in storage and power supply (Figure 6). The sensors enable the real-time measurement of acceleration, angular velocity and heading in 3-axes. This data can be streamed wirelessly in real-time to a work station where it is analysed, also in real-time, by algorithms that aim to infer parameters related to the physical motion of limbs (speed, displacement, joint angles, inclination, even force and torsion), recognize specific motions of interests, and characterise them with regard to their severity in terms of body health. The number of sensors and sampling frequency are variable and only limited by the maximum available bandwidth of the wireless network. Our current system can for example comfortably manage 10 sensors at a sampling rate of $50Hz$, which would enable full body tracking. Furthermore, our sensors are powered by rechargeable batteries that can last for a minimum of 8 hours, which means that the system can be used to track the activity of workers over entire workdays.

As stated in previous sections, the body parts most affected by injuries among construction workers are: back, neck and shoulder, hands and wrists and knees. We thus propose to attach the sensors to the limbs and back.

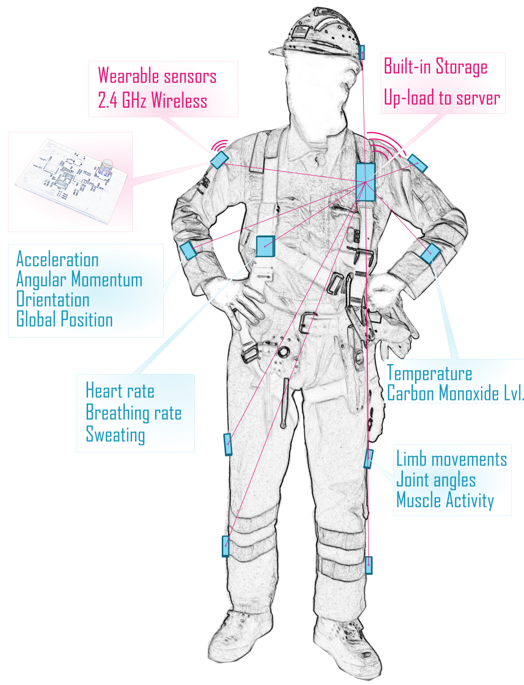

Figure 5: AT-BAN infrastructure and parameters obtained from the sensors. For the sake of simplification, the sensors are shown attached to the worker's garment. In practice, IMUs should be worn tight to the body to avoid errors resulting from the slack of the overlay garment.

Figure 6: Wearable device attached to the wrist of the trainee.

We currently attach them by means of elastic belts, as illustrated in Figure 7. Four sensors placed on the arms (*i.e.* two on each arm) would provide information about reaching loads and identify if the user is working overhead. One sensor on the back and two sensors on the shins would provide sufficient information to distinguish squatting and stooping postures.

The capacity of our system to process data in real-time supports the de-

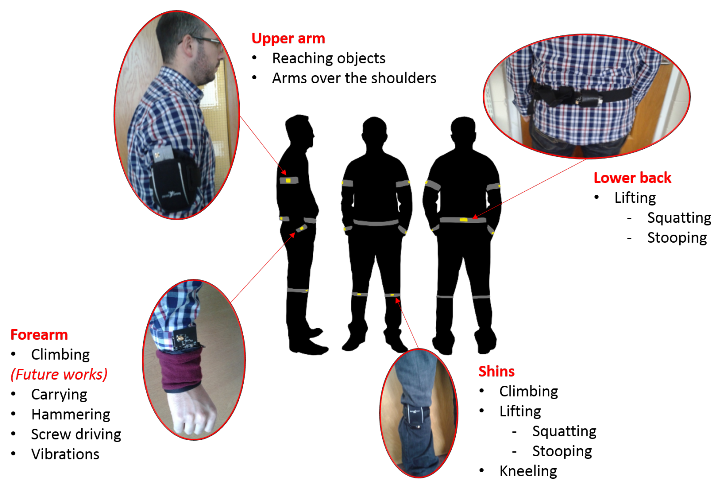

Figure 7: Placement of the sensors on the body of the user.

livery of feedback to workers at various frequencies most appropriate to the context, *e.g.* in real-time or on a daily basis. For instance, the feedback can be in the form of an instantaneous alert (*e.g.* a warning beep or vibration), or else a summary report could be provided at the end of a work session, summarizing statistics about the occurrences of "unhealthy" motions detected by the system. In the experiments shown in Figures 10 and 11, only the summary feedbacks were provided, as the instantaneous alert feature was not required on this instance. Nonetheless, the processing of the data is conducted as if it is provided in real-time, which naturally enables the generation of instantaneous alerts.

This system presents multiple advantages over conventional vision-based motion analysis systems. Predominantly, vision-based systems are restricted to a capture scenario and affected by lighting and occlusions, whereas the AT-BAN can operate in any work space, *i.e.* work sites with harsh conditions and limited visibility. Although IMUs suffer drifts over time when used with global coordinates (*i.e.* with a fixed external reference) and vision-based systems do not present this issue, IMUs produce better accuracies when used for relative measurements (*i.e.* using two IMUs), such as instantaneous acceleration, change of speed of a limb or joint angle of a hand/leg. Our system is based on the analysis of those relative motion measurements.

4.2. Evaluation and Preliminary Results

In an initial evaluation of the proposed system, we have designed a simple experiment to assess lifting-related motions and postures, more specifically stooping and squatting. As mentioned earlier, the low back and legs play an important part in these motions, and two posture variables particularly need to be measured to detect and recognize them: the angle rotated by the back of the user on the sagittal plane, α_B, and the angle(s) described by the leg(s), α_L (see Figure 8). Our system calculates these (and other) angles by combining acceleration and velocity data provided by the accelerometers and gyroscopes of the IMUs located in the low back and legs respectively. The IMUs' magnetometer information is also used to compensate for the effect of magnetic distortions (Madgwick et al., 2011).

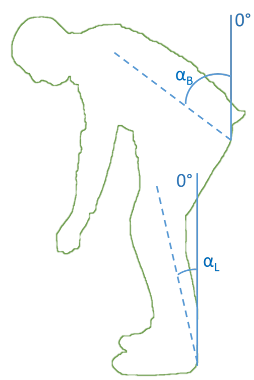

Figure 8: Illustration of the back angle (α_B) and leg angle (α_L) considered for detecting and distinguishing stooping and squatting motions.

Table 2 summarizes the criteria — *i.e.* thresholds for α_B and α_L — employed here to detect and distinguish stooping and squatting motion/postures. These thresholds have been defined in an *ad-hoc* way. While they have worked well in our experiments, when used in practice they should be revisited taking into consideration expert opinion. Note that we do not distinguish just two postures (squatting and stooping) but also a third one that refers to some form of 'combination' of both (where the user partially stoops and squats), a situation likely encountered in practice.

As illustrated in Figure 9, different subjects were solicited to lift several concrete blocks located on the floor and place them on a desk at knuckle height. The size of the blocks was $10 \times 10 \times 10$ cm and the weight 2 kg. Each participant was asked to repeat this task several times: some of them

Trunk movement	Leg movement	Pose	Code
$20° \leq \alpha_B$	$0 \leq \alpha_L < 30°$	Stooping	
	$30° \leq \alpha_L$	Squatting with back bending	
$0 \leq \alpha_B < 20°$	$30° \leq \alpha_L$	Squatting without back bending	
	$0 \leq \alpha_L < 30°$	Other	

Table 2: Angle ranges for detecting and distinguishing squatting and stooping motions/postures.

on instinct and other ones by flexing their legs and keeping the load close to the body, as manuals advise (National Institute for Occupational Safety and Health, 2007).

Figure 9: Lifting movement executed by a user.

Figure 10 shows the results for a 40-second recording during which several liftings were conducted. The upper graph shows the value of α_B and the lower graph illustrates the angle described by the leg, α_L. To facilitate the understanding of the performance results, and as proposed in other previous assessment tools, we code the results by means of the universal traffic light coloring system. A green segment corresponds to a properly executed movement (*i.e.* squatting without significant back bending), the red movements require prompt corrective action (*i.e.* stooping), and the yellow-marked movements should be examined further (*i.e.* intermediary combinations of squatting and stooping). The results in Figure 10 show that the back and leg sensors together provide discriminatory information for both the detection and distinction of squatting and stooping motions/postures — although, as shown later, that discrimination would be further strengthened by considering the motion data from all tracked body parts.

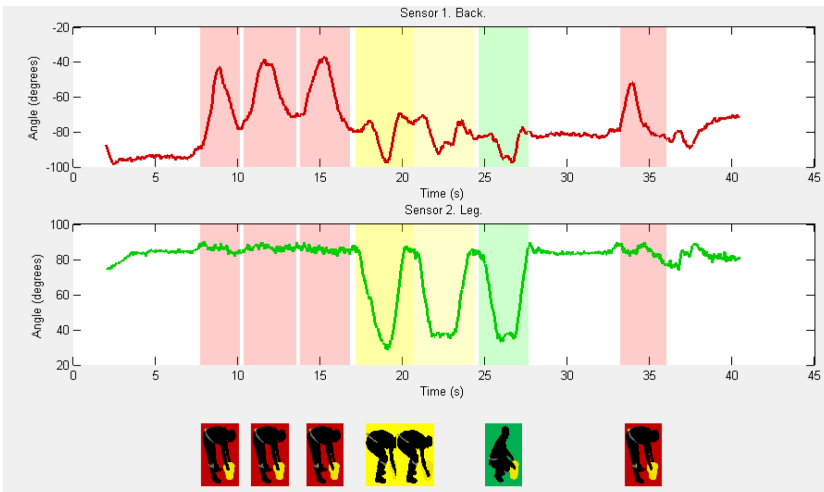

Figure 10: Interface of the software analysing the motions of construction workers. The upper graph shows the angle described by the back of the user on the sagittal plane, α_B; the lower graph illustrates the angle rotated by the leg, α_L.

The positive results obtained with that first experiment have led to the setup of a second set of experiments conducted in the more realistic context of a training college, with trainees performing their normal training activities over 15-minute periods. These experiments were aimed at better assessing the detection and classification performance of the proposed system. Furthermore, to improve our assessment and also demonstrate to users (*e.g.* trainees, assessors) the potential and performance of our system, we have video-recorded the trainees and synchronised the videos with the AT-BAN motion data.

Figure 11 shows the right leg and back motion data for a trainee carrying out paperhanging works. As can be appreciated in the top left image (extracted from the synchronised video) and marked with a blue rectangle in the graphs, a stooping motion is correctly recognised while the trainee was indeed stooping. It is also worth noting that the trainees reported that they quickly "forgot" about the systems, which indicates that they did not find them intrusive to conducting their work effectively and efficiently.

While the system showed good performance in terms of false negative (*i.e.* no stooping and squatting motions were missed), many more false positives were noticed. As a typical example of such false positive, the top right image of Figure 11 illustrates a situation where the system wrongly detected a bending motion when the trainee was in fact standing up but with a knee flexed on a bench. The reason for this error (which constituted the wide majority of the experienced false positives) is that the experiment was carried out using just one leg sensor worn on the right leg (*i.e.* with no sensor worn on the left leg). This showed that one sensor was clearly not sufficient and that squatting/stooping motions should be detected by considering the motions of both legs. As mentioned earlier, our infrastructure is scalable, being able to simultaneously consider many sensors; future iterations of the above experiments will thus be conducted with more sensors simultaneously capturing motions from the two legs and the back (as well as the arms and head).

As discussed earlier, while the current system can be used to provide feedback on individual movements, the assessments of all motions can also be aggregated to generate a global performance over a defined period, such as a workday. In the lower part of Figure 11, a tachymeter-type diagram employing a colormap based on the same traffic light colors as earlier is shown, that could be used to provide overall performance information over an entire day (*e.g.* average score). Projections of the number of detected motions (here stooping and squatting) for an entire working day are also provided.

5. Conclusions

Proper postures and body motions on the jobsite help workers maintain a good health and improve their well-being. They prevent the appearance of WMSDs and other work-related illnesses, avoiding days away from work or days with modified task, which consequently enhances performance and saves money.

Currently employed methods are often based on visual observations (*in-situ* or post-evaluated using videos) which is not very acucrate and precise. Research has been conducted to replace or supplement visual observations

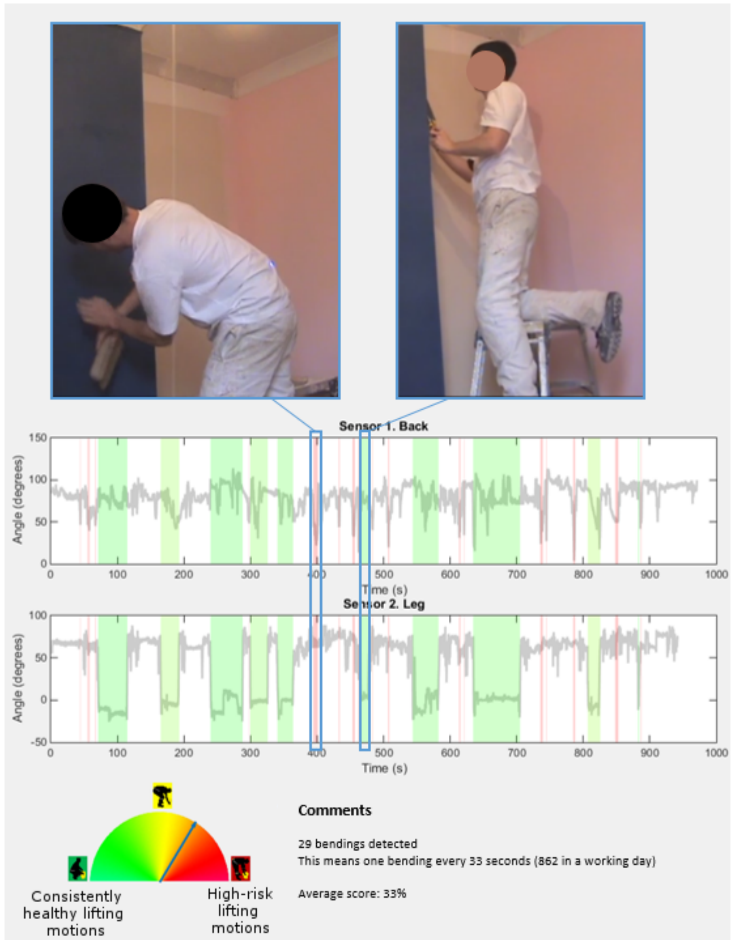

Figure 11: Illustration of the evaluation of the squatting and stooping motions/postures of a paperhanging trainee conducting normal training activities in a college over a 15-minute period. Frames from a synchronised video recording are used to better visualise and validate the performance of the motion detector and classifier.

with more accurate body posture measurement devices but many of the reviewed works used systems that are either not wearable, invasive and/or infrastructure-intensive, possibly requiring usage in controlled environments. More recently, the development of small IMUs has open the possibility of developing wearable systems that are not invasive and so could be employed for reliable assessments over long periods of times and in diverse working environments. However, no work seems to have yet focused on developing and using such systems for WMSD risk assessment among construction workers.

In this article, we present a novel wearable wireless system based on IMUs which provides non-invasive, long-term and ubiquitous tracking of body postures and motions. The data captured is processed in real time to recognize certain postures and evaluate them.

Experiments have been reported that have focused on the study of low back and legs for tracking the lifting-related motions of squatting and stooping. This preliminary validation of our system was conducted in our laboratory as well as with actual trainees in their college over periods of 15 minutes and more. The results are very encouraging, so future work will aim at assessing the system in real work environments (*i.e.* on actual jobsites) and over entire working days. Furthermore, future work will attempt to calibrate the system with the help of experts to characterise various motions of interest (*e.g.* lifting), and take into account not only posture characteristics (*i.e.* angles, distances) but also motion characteristics such as speed and acceleration (which is readily available from the sensors).

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