Analysis of Construction Trade Worker Body Motions Using a Wearable and Wireless Motion Sensor Network

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Abstract

Biomechanical analysis of construction workers has been considerably improved with the development of wearable sensors. Information delivered by these systems is playing an important role in the evaluation of postures as well as in the reduction of work-related musculoskeletal disorders (WRMSDs). In this article, we present a novel system and data processing framework to deliver intuitive and understandable motion-related information about workers. The system uniquely integrates Inertial Measurement Unit (IMU) devices in a wireless body area network, and the data processing uses a robust state machine -based approach that assesses inadequate working postures based on standard positions defined by the International Organization for Standardization (ISO). The system and data processing framework are collectively validated through experiments carried out with college trainees conducting typical bricklaying tasks. The results illustrate the robustness of the system under demanding circumstances, and suggest its applicability in actual working environments outside the college.

Keywords: MSD, Postures, Construction, Wireless Sensor Network, IMU

1. Introduction

Injuries and poor occupational health resulting from inadequate working conditions impact the wellbeing of the working population as well as countries' economies. Work-Related Musculoskeletal Disorders (WRMSDs)

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are injuries affecting muscles, joints and tendons, that result from repeated 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.

In the construction sector, workers are particularly at risk of WRMSDs because of their high exposure to awkward postures, which are sometimes held for long periods of time, and also to carry heavy loads. According to Labour Force Survey and Reporting of Injuries, Diseases and Dangerous Occurrences Regulations (RIDDOR), in the period 2013-2016 in the UK, 64% of self-reported work-related illnesses were related to WRMSDs, resulting in 1.2 million days off per year. Amongst construction trades, masonry and concrete workers appear the most at risk, with more than 110 cases per 10,000 employees working full time [21]. Furthermore, 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 [21].

These alarming statistics, along with economic and demographic pressures, have pushed the construction sector to consider occupational health as an increasingly important issue, worth the same amount of attention as safety. In a survey by the Constructing Better Health (CBH) Scheme, 97% of the respondents agreed or strongly agreed that health is taken more seriously than 10 years ago [5]. However, in a more recent study [7], 84% of respondents thought that more needs to be done to improve the implementation of occupational health in the industry, and 85% of them agreed that there is a need for industry-wide data to be analysed to spot health trends in the industry. When it comes to WRMSDs, one of the main issue is the lack of reliable and scalable approach to assess their risks.

In this paper, we present a new strategy and system to deliver intuitive and understandable motion-related information about workers in the construction. Accordingly, this paper is structured as follows. Section 2 reviews existing and recent initiatives by governments, companies and universities to develop different strategies to assess WRMSDs risks. In Section 3, we introduce our recently developed system to track the motion of workers, based on wearable Inertial Measurement Units (IMUs) connected through a wireless body area network; we call this system *Activity Tracking with Body Area Network (AT-BAN)*. In Section 4, we then present our novel algorithm to automatically recognise awkward postures in the collected IMU data. Subsequently, Section 5 reports experimental results on the assessment of bricklaying tasks. Finally, Section 6 concludes the article and suggests future developments of the proposed system.

2. Background

The analysis of body motion has been tackled by experts during the last century for different purposes. Lillian and Frank Gilbreth were pioneers of motion study [6] in the field of industrial management. Focused on productivity and efficiency, they reduced all the hand motions carried out by workers in assembly tasks into some combinations of basic operations. They studied the basic operations (or 'therbligs') involved in tasks of bricklaying, reducing the number of required movements from 18 to 4.5 and increasing the number of laid bricks by 3 times [26].

Later on, various public agencies, companies and researchers have been involved in the creation of tools and techniques to reduce health and safety risks in the workplace, especially WRMSDs. Generally, they study the motion of workers during their working day. Amongst the various guidelines, MAC [22] and ART [23] were developed by the British HSE for assessing manual handling and repetitive tasks. OWAS [13] was designed to modify the production line of a steel manufacturing company; and RULA [15] and REBA [14] for upper limbs and entire body assessment, respectively. Almost all these techniques are based on the visual analysis of the motion of workers by experts on ergonomics, who typically fill out a questionnaire or form to assess the performance [2]. Although these methods have proven to be somewhat effective, they are neither objective nor precise, because they generally rely on some form of a subjective assessment of the assessor, which will likely to vary with experience and differ from one expert to another (subjectivity).

During the last decades, aiming to improve the repeatability of tests and deliver more accurate and precise results, numerous measuring devices have been proposed and investigated for biomechanical analysis in construction and other trades. Among those modern devices, marker-based optical motion tracking systems [8] have been widely used due to their precision. Trackers can be easily fit to the workers body, making systems wearable even in the jobsite during a working session. Another advantage of their wearability is that all body parts can be measured simultaneously, which enables more systematic evaluation of postures, something almost impossible for an expert at first sight. Alternatively, markerless optical motion tracking systems have been investigated using video cameras [11] or depth cameras [17]. These systems have been also proved useful to conduct studies of postures and classify different movements. However, a major practical limitation of all these vision-based systems is that a direct line of sight is required to register the movements. In a similar manner, devices such as depth cameras, based on infrared projection systems, are too sensitive to varying lighting conditions and are not recommended for use outdoors. Their short range of operation as well as their narrow field of view are also limitations to be considered.

Recently, the miniaturisation of electromechanical systems has encouraged the development of small wearable devices to register the movements of different parts of the body. These miniature devices integrate several sensors like accelerometers, magnetometers and gyroscopes in so-called IMUs. In addition to delivering results potentially as precise as optical systems, IMU systems are fully worn and so do not require any line of sight. Numerous works have been published in recent years on monitoring of movements of workers from different trades using IMUs. In 2014, Vanveerdeghem et al. [25] presented an IMU wearable system to control the motion of firefighters and detect if they are lying, walking or running. Rawashdeh et al. [16] used IMUs placed on the arms of athletes to help prevent injuries in overhead sports. In the field of construction, several researchers have developed IMU-based systems to study the behaviour of workers around the jobsite. Joshua and Varghese [12] proposed the use of IMUs data to classify workers activity as effective, ineffective or contributory. Very recently, Alwasel et al. [1] used a commercial wireless set of IMU sensors and the 3D SSPP software package [1] to estimate forces and moments performed by the major body joints of bricklaying trainees and workers. That work relates very much to the approach presented in this paper, with similar conclusions drawn on the links between experience, productivity and ergonomic safety. Finally, Yan et al. [27] have developed a warning system for construction workers to prevent WRMSDs. They attach two wireless IMU sensors to the workers head and back to infer the angles described by head, neck and trunk. However, the scope of their setup is limited, since they do not consider the evaluation of limbs movement. Another approach is presented in [3, 4], in which the authors combine video with physiological status monitoring (PSM) technology and ultra wideband (UWB) to track the movements of workers and relate

[1] Center for Ergonomics, University of Michigan, https://c4e.engin.umich.edu/tools-services/3dsspp-software/.

their physical characteristics to their position in the environment.

Selecting and employing internationally standardised rules by the International Organization for Standardization (ISO) is a first step towards a set of uniform criteria to evaluate body motions in the workplace and helps reduce the impact of WRMSDs [27]. For example, ISO 11228 [10] relates to the application of forces and loads handling, and ISO 11226 [9] is oriented to the acceptability of static working postures. Note that, although this paper is linked to tasks involving manual handling, its main objective is to study the postures of workers during their working day. For this reason, we focus on standard ISO 11228, which itself also refers to ISO 11226 for recommendations concerning working postures.

In the following, we present a new strategy to deliver intuitive and understandable motion-related information about workers in the construction field. Building on the approach initially presented in [24] and using the AT-BAN system, a scalable wireless body area network of IMUs developed by the research team, this novel approach evaluates the movement of several parts of the body and identifies postures of interest during bricklaying tasks, which subsequently provides information oriented to minimise the likelihood of WRMSDs. Unlike previous works [27], this system covers all the main limbs of workers and is able to register their activity over an entire day. Although the results presented in this paper correspond to the evaluation of the system for bricklaying tasks, the scalability of the system (both hardware and software) facilitates its use for different activities and trades.

3. Overview of the system

With the objective of recognising key postures and movements of workers, we have developed the Activity Tracking with Body Area Network (AT-BAN) system. This system has already been presented in previous works [20] [19], so we only briefly summarise it here.

Compact wearable IMU devices of dimensions 6 x 4 x 1.5cm are wirelessly connected to a work station, delivering a real-time, precisely synchronised and accurate stream of data, comprising: acceleration, magnetic heading and angular velocity, at a sampling rate up to 50 Hz. These sensors are attached to the subject's body by means of elastic straps, as shown in Figure 1(a), fitting tightly to the limbs, to prevent slippage, which could otherwise result in incorrect recognition of postures and movements. The number of sensors can vary, being adapted to the needs of the particular application.

The system used in the experiments reported here employs 8 sensors, and can be operated continually for approximately 8 hours without the need for a recharge. The 8 sensors are placed in the vulnerable parts of the body associated with the bricklaying activity, i.e. upper/lower back, arms and upper/lower legs [21]. This placement allows us to examine the back, shoulder and knee activities in detail.

(a)

(b)

Figure 1: (a) Location of AT-BAN sensors on the body. (b) Set up of the system.

In addition to the data obtained from the sensors, working sessions were recorded with a video camera (see Figure 1(b)). The acquisition of visual information has two purposes: (1) providing a visual reference point to evaluate the performance of the algorithm developed for postures identification; (2) evaluating the quantity of work carried out (e.g. number of bricks laid down over a specific period), so that health performance can be gauged against productivity. It must be highlighted that the video is not used anywhere in the quantification of the body motions.

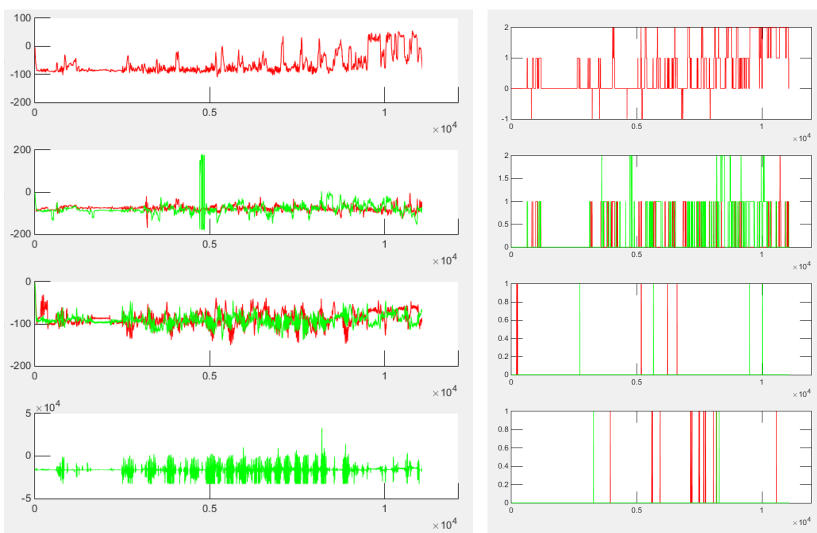
The subsequent data processing technique, the main contribution reported in this paper, is described in Section 4.

4. Analysis of postures

4.1. State Machine

Every task performed by humans involves multiple body parts moving in synchronization. Therefore, assessing the movement of a person requires monitoring various body parts simultaneously. The accuracy and objectivity of current evaluation methods have been improved with the use of sensors attached to the body aiming to acquire data related to movement. However, data obtained from such sensors is a set of continuous/analog signals that can be displayed at best as a set of curves (see Figure 2(a)) that need to be simultaneously analysed and interpreted. Such interpretation is complex, even for professionals.

Thus, the first aim of this approach is to discretise the angular values calculated after the data obtained from the sensors. For each instant of time, analog angular values are converted to discrete data following the principles of a finite-state: each sensor output will take a state depending on its present and past states. As illustrated in Figure 2(b), more understandable plots are delivered after processing the information.



(a) (b)

Figure 2: Angles of several sensors attached to the body of a worker during bricklaying tasks. (a) Continuous signal. (b) Discrete signal. From top to bottom: back, arms and upper legs (red for right limbs and green for left ones)

Depending on the rotation of one or several body joints with respect to an initial orthostatic position (i.e. standing), each body part is assigned a state. For example, considering the flexion of an arm, this can be 'slightly elevated', 'elevated' or 'too elevated'. However, these are fuzzy terms that need to be defined by certain thresholds to provide an objective assessment.

Instead, we use angular thresholds specified in the standard ISO 11226 (see Section 2). Amongst the postures evaluated in that standard, our study more specifically focuses on (Figure 3): trunk inclination, knee flexion, kneeling, and upper arm elevation, that are all determined by an angle. Note that these motions are related to the joints most affected by WRMSDs as mentioned, as discussed in Section 3. The angular thresholds corresponding to those joints are summarised in Table 1.

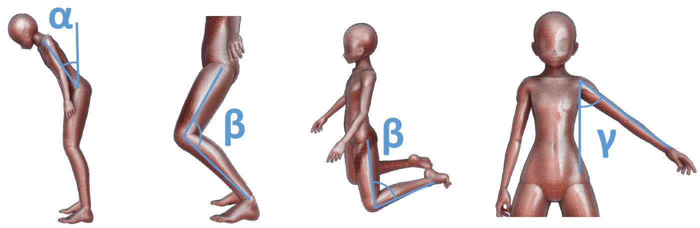


Figure 3: Basic movements and representative angle

These three different angles are measured by the AT-BAN system at 50Hz, and raw values are filtered using a median filter. The angular values are then compared with a reference value, set from the initial standing-up posture of the worker, to establish each individual joint state, as shown on Table 1. To respond to sensor signal noise, we accept a change in the state machine of a primary body position only if it is held for at least one second. This approach is similar in effect to a Schmitt trigger [18]. The result of this state evaluation process is illustrated in Figure 4, where angles and state machine values are noted for a sensor attached to the upper back. Note that values for α are calculated as the difference between the angles plotted in the graph and the reference initial value for that variable, which is around 90° in this particular case.

Following the idea of Gilbreth, this study interprets each task or activity as a combination of simple movements performed by several body parts. For example, the WRMSD risks associated to a task of spreading mortar on a row of bricks can be seen as a mainly involving and combining trunk inclination (back bending), knee flexion (squatting) and upper arm elevation. Therefore, all the primary position states described in Table 1 are combined to infer higher-level body postures, such as the twelve postures shown in Figure 5. Table 2 illustrates how some higher-level postures are inferred from primary position states.

Primary body part position	State	Angle	Definition
Trunk inclination	-1	$\alpha < 0°$	Trunk backward inclination. Not recommended position
	0	$0° \leq \alpha < 20°$	Acceptable trunk inclination
	1	$20° \leq \alpha < 60°$	Trunk forward inclination. The holding time is evaluated according $t > -0.075\alpha + 5.5$ where t is time in minutes and α is angle in degrees. If inequality is true, not recommended
	2	$\alpha \geq 60°$	Trunk backward inclination. Not recommended position
Knee flexion	0	$\beta > 140°$	Acceptable knee flexion
	1	$90° < \beta \leq 140°$	Extreme knee flexion. Not recommended position
Kneeling	0	$\beta > 90°$	See knee flexion
	1	$\beta \leq 90°$ (and calf parallel to floor)	Just one leg kneeling. Squatting movement considered
	2	$\beta \leq 90°$ (and calf parallel to floor)	Kneeling
Arm elevation	0	$0° \leq \gamma < 20°$	Acceptable upper arm elevation
	1	$20° \leq \gamma < 60°$	The holding time is evaluated according $t > -0.05\gamma + 4$. If inequality is true, not recommended
	2	$\gamma \geq 60°$	Not recommended position

Table 1: Static primary positions according to ISO 11226 standard

4.2. Performance Assessment Metrics/Scores

Results obtained during the joint angle and posture state classification stages are complex to interpret overall because of the amount of information that is generated. As a result, we defined Performance Assessment Metrics, or Scoring system, that summarises detailed joint and posture state information in one overall *Posture score* (or *MSD Risk Score*), S_{pos}. Furthermore, we define a *Productivity Score*, S_p, so that posture/WRMSD performance can be interpreted more objectively in light of the actual work performed by the worker. Indeed, assessing health and safety performance (here MSD) really

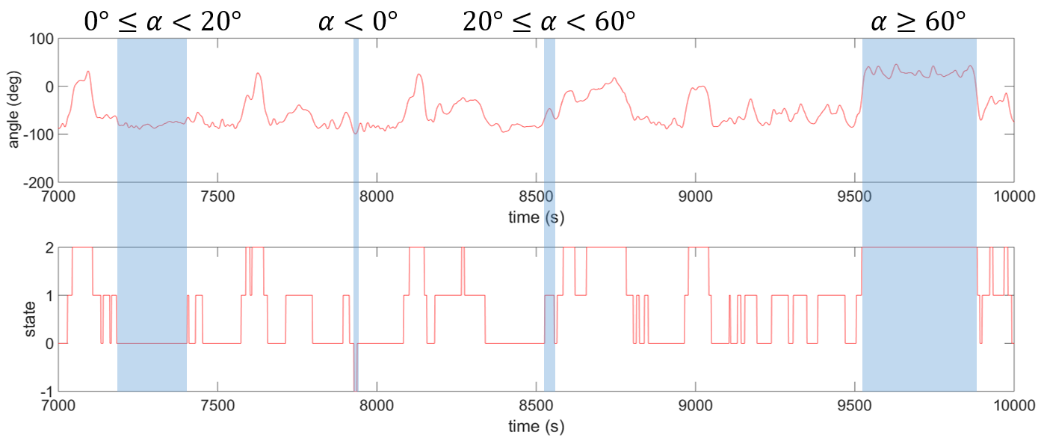


Figure 4: Angles and states of an upper back sensor. Some segments for different states are highlighted

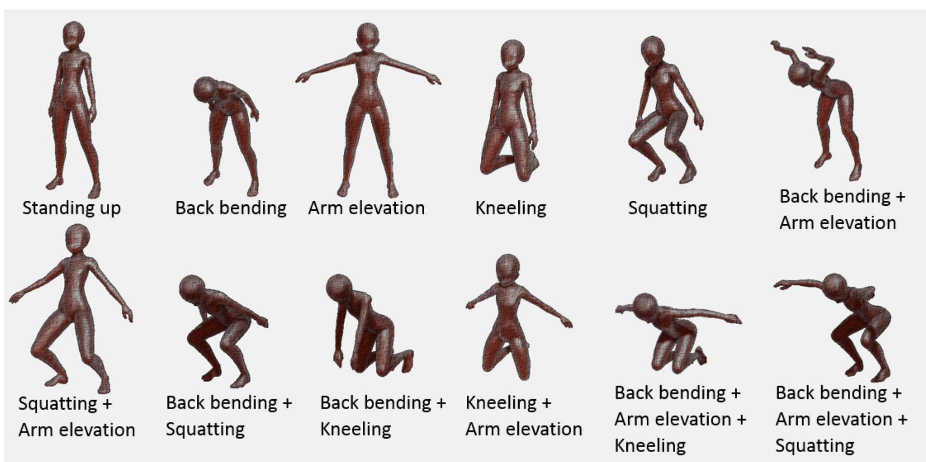


Figure 5: Identified postures

only makes in comparison with productivity. Taking the extreme case of a worker doing nothing but simply standing for 30min, they would have a great posture/MSD score; but clearly this great score should be contrasted with the total lack of work performed. The *Productivity Score* and *Posture Score* are easily presented to and therefore understandable by users and stakeholders.

For the *Productivity Score* S_p, we simply count the number of bricks laid down by the worker in visualising the video (this can be done rapidly by looking at the start and end state of the built wall at the beginning and end

	Trunk Inclination	**Knee Flexion**	**Kneeling**	**Upper Arm Elevation**
Back bending + Squatting	2	1	0	0
Squatting + Arm elevation	0	1	0	1
Back bending + Kneeling	2	0	2	0

Table 2: Inferring posture states (Figure 5) from primary position states (Table 1).

of the video, respectively). Equation 1 is then used to calculate S_p. In this equation, n_b is the number of bricks per minute laid down by the worker, c_b is an adjustment factor that considers the weight of the bricks (or blocks) and the number of items laid down by an average worker, and c_c is a *functional* efficiency factor that reflects the complexity of the wall (e.g. fine works, facing bricks, common bricks, ...). S_p increases with productivity.

$$S_p = n_b c_b c_c \tag{1}$$

The *Posture Score* S_{pos} is calculated as a weighted average of the state machines for all measured body part positions, i.e. all sensors, as summarised in Equation 2 where: $|k_{ij}|$ is the absolute value of the state machine for the joint angle (i.e. sensor) i during the interval j; $\bar{\alpha_{ij}}$ (or alternatively $\bar{\beta_{ij}}$ or $\bar{\gamma_{ij}}$) is the mean value of the joint angle α_i during the interval j; and t_{ij} is the duration of the interval j for the joint i. S_{pos} theoretically increases with the risk of developing MSDs.

$$S_{pos} = \frac{\sum_{i=1}^{m}\left(\sum_{j=1}^{n_i} |k_{ij}|\,\bar{\alpha_{ij}} t_{ij}\right)}{\sum_{i=1}^{m}\left(\sum_{j=1}^{n_i} t_{ij}\right)} \tag{2}$$

5. Experiments

Aiming to validate the proposed AT-BAN system and the new posture detection algorithm, experiments have been conducted at Forth Valley College (FVC), a Scottish further education college. The set of experiments presented in this paper focused on bricklaying apprentices, the construction trade considered to have the highest exposure to body bending/twisting and repetitive motions [21]. In this section, detailed information about data acquisition and analysis is provided.

5.1. Data Acquisition

Six male 1^{st} and 2^{nd} year persons, aged 16-34, between 1.70 and 1.95m tall and not seriously injured in the last year, participated in the trials. All were equipped with a set of 8 AT-BAN sensors, as shown in Figure 1. The test subjects performed routine tasks such as: carrying and spreading mortar and moving and lying different kind of bricks (20 and 14 kg blocks and standard 2kg bricks) in the college workshops, replicating real working environments and using standard tools and materials. Their movements were recorded for 20-minute sessions.

Together with the sensor data, synchronised video streams were also recorded. These are used to establish visual ground truth to qualitatively assess the performance of the proposed algorithms and to produce easily understandable results for the users of the system. Furthermore, the videos are used to extract the amount of work achieved during the recorded sessions, so as to obtain some productivity performance information and score.

5.2. Data Analysis

The generation of a ground truth model to evaluate the proposed system would not be a trivial task at all. Even with video recordings and expert assessment – i.e. current best practice – a reliable identification of postures (e.g. as defined by ISO standards) would be hard to achieve. In fact, this method can be argued to be even less reliable than our proposed system. Using an optical tracking system would probably be the ideal approach to obtain comparative ground truth information for the individual angles. But, the equipment could not be obtained and installed in the college lab where the experiments were conducted. Furthermore, those systems are not perfect either and may not have worked well with the workers wearing their typical working outfits and PPE. As a result, we must rely for now on a qualitative analysis of the performance of our system by comparing the automatically detected motions with those visible in the synchronised video. For example, we refer the reader to one of the sessions results in the videos attached to this manuscript [2] [3].As can be seen, all the steady primary position states are properly identified. A short delay in the detections can be observed during noticeable changes in the posture. This happens because of the time threshold we employ to accept changes in primary body positions (see Section 4.1). This may arguably lead to some false negative posture detections when postures are held only for very short periods (such cases are visible a few times in the videos). But, the time threshold also helped smooth measurement errors or spikes and therefore prevent other detection errors.

Remarkable information related to both posture and productivity can be extracted from the performed trials. Table 3 summarises descriptive parameters along with productivity and posture obtained for the 6 test subjects. While the number of bricks handled in each experiment is not very large, the productivity achieved by the test subjects clearly reflects experience gained over time, with the test subjects with more than 12 months of experience showing similar productivity to that of professionals, that can lay between 15 and 20 20kg-concrete blocks per hour (20 to 30 in the case of 14kg blocks).

Regarding productivity, the results indicate that the more experienced test subjects spend less time per brick in postures not recommended by the ISO 11226 standard. Furthermore, it can be observed how test subjects tend to bend their backs, aiming to increase productivity, instead of approaching blocks with more favourable postures (i.e. squatting). If we extrapolate the observed back bending times to a complete working day, even if we do not consider some factors affecting workers' performance, such as fatigue or recovery time, we find that the persons would cumulatively spend in this detrimental posture durations ranging between 4.5 and 7 hours. These habits will most likely entail back problems and days away from work in the future.

The graphs in Figure 6 show the *productivity* and *posture* scores obtained for the 6 test subjects. While productivity scores increase with experience, it is interesting to note how posture scores do not show such a correlation. Note that the recently published work of Alwasel et al. [1] reaches similar conclusions. This small or even lack of improvement in posture scores over time is interesting in light of the steady improvement in productivity, which could be attributed to insufficient training about harmful postures and best practices.

[2] `http://bit.ly/7C-FVC`
[3] `http://bit.ly/82-FVC`

Test subjects	**1**	**2**	**3**	**4**	**5**	**6**
Experience (months)	30	24	3	3	18	18
Trial duration (min)	20	20	20	20	20	20
Brick weight (kg)	20	20	2	2	14	14
Number of handled bricks	11	12	7	5	6	8
Effective time per brick (s)	82	85	180	240	160	120
Bending time per brick (s)	79	84	151	141	159	119
Kneeling time per brick (s)	0	0	0	85	0	0
Squatting time per brick (s)	0	8	0	17	33	3
Arm elevation time per brick (s)	3	2	87	45	7	8

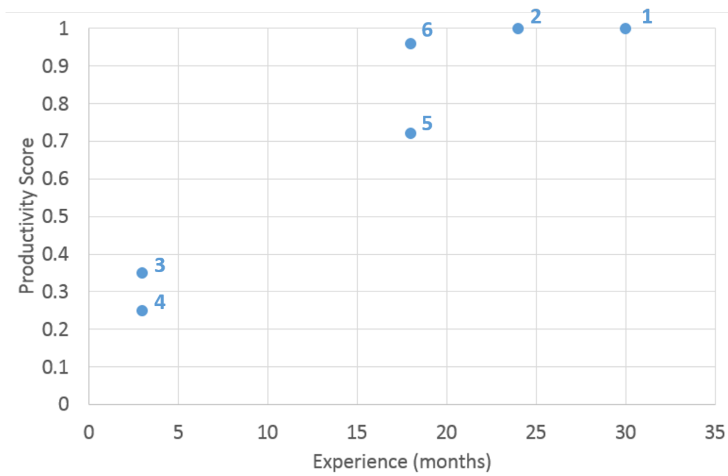
Table 3: Descriptive parameters along with productivity and posture metrics obtained for the 6 test subjects during bricklaying activities.

5.3. Data Visualisation

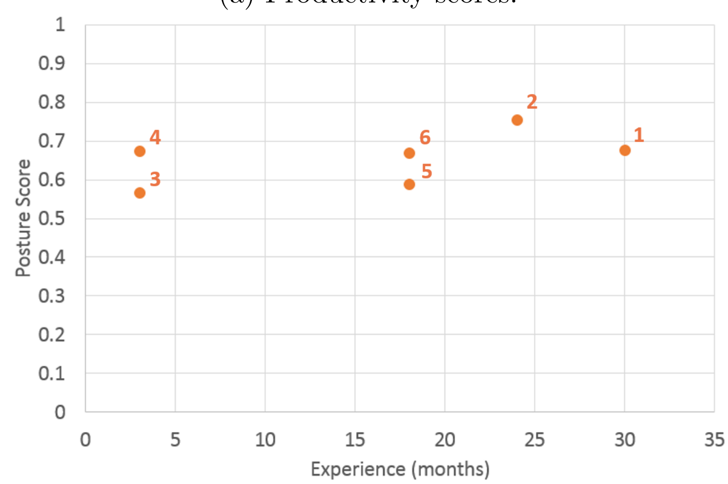
As illustrated in Figure 7 and the two videos attached to this manuscript, two different types of visual outputs have been developed to ease the review of the results by non-technical experts.

The first visual output is a video, showing the higher-level posture detections over time in synchronisation with the captured video stream. A red line moves along the coloured bars, showing the progress of the activity and indicating the identified primary positions. On the right-hand side, a mannequin is used to report the high-level posture detections in real-time. The comparison of this mannequin with the true posture of the worker visible in the video has shown to be valuable not only to our internal validation of the AT-BANs performance, but also to demonstrate its performance to project partners like the staff of the college. It is important to highlight that this visual output is only available for cases when video recording is used, i.e. for stakeholder engagement. In general contexts (e.g. on a real construction site with the worker moving locations during an entire day), video recording would not be feasible, so that this output would not be produced.

The second output summarises the results obtained over the recorded session, delivering information about the number of detections of and time spent in each primary positions during the studied session. In contrast with the first visual output, this second one is obtained from the processed IMU data only, and so is provided when using the system in any context (e.g. on a real construction site with the worker moving locations during an entire



(a) Productivity scores.



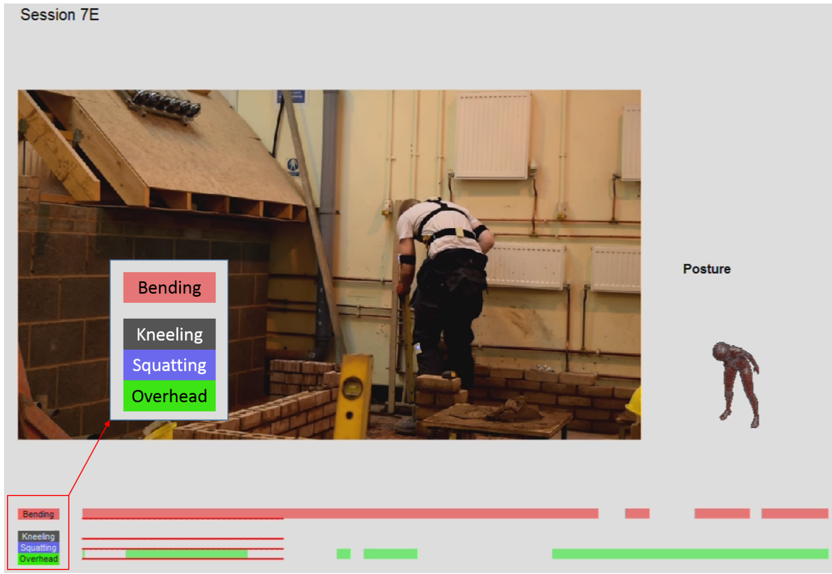
(b) Posture/MSD scores.

Figure 6: Productivity scores (a) and Posture (or MSD risk) scores (b) for the 6 test subjects. The numbers refer to each person ID in Table 3.

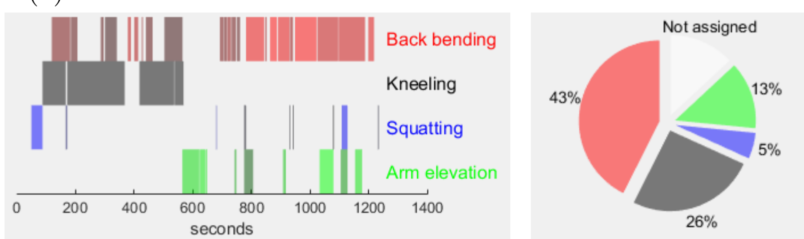
day).

6. Conclusions

The continuous assessment of workers body motion in the working environment can help identify and mitigate the risks of WRMSDs and improve their wellbeing. Although governments, public bodies and researchers have



(a) Frame of the video enriched with the identified motions.



(b) Left: Timeline of a trial session with identified motions. Right: Percentage of time assigned to each primary position.

Figure 7: Visual outputs presenting the session results to non-technical users like trainees and staff of the college.

developed methods to evaluate the movements of workers and correct their movements toward a healthier performance, most of them are based on visual observations and hardly depend on the experience of the assessor.

A novel and more automated approach is presented in this paper to identify detrimental postures in construction jobsites. This method, based on the use of a wearable wireless network of IMU devices, the AT-BAN system, discriminates between basic postures and identify those that are prone to increase the risk of WRMSDs, according to existing ISO standards.

Angular values used as reference for this work have been extracted from the standard ISO 11226, which contains a collection of tables, diagrams and equations to determine the acceptability of static working postures. Even if there exists a standard devoted to dynamic activities (ISO 11228), rules detailed in that document are oriented towards parameters indirectly related to ergonomics and postures, such as loads or repetitions. This highlights a gap in standards available for analysing dynamic activities, which is in fact likely due to the impossibility to establish standards without adequate and stable technologies that can capture data with the required accuracy. The system presented in this paper is intended to push the boundaries further, to eventually enable the development of such standards.

To test and validate the proposed tool, several working sessions were recorded with actual trainees in a local college. Results show that harmful postures can be detected, and suggest that, while productivity performance seems to improve with experience (as expected), our posture score suggests no improvement with experience. However, these results were only obtained with 6 test subjects and more trials, involving a larger population and considering both novice and experts workers both in the college and on site, need to be performed in order to confirm those results and the general usability of our system.

Future works will consider the use of loads for analysis of dynamic postures, and the use of the system will be investigated for other construction trades (e.g. painting and decorating). We will also look into integrating sensors to tools to monitor a wider range of activities and health issues (e.g. vibrations). Finally, through more trials, we should be able to develop a dataset large enough to investigate machine learning algorithms to more potentially more robustly identify postures and motions.

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References

[1] Alwasel, A., Abdel-Rahman, E., Haas, C., Lee, S., 2017. Experience, productivity, and musculoskeletal injury among masonry workers. Journal of Construction Engineering and Management.

[2] Buchholz, B., Paquet, V., Punnett, L., Lee, D., Moir, S., 1996. Path: A work sampling-based approach to ergonomic job analysis for construction and other non-repetitive work. Applied Ergonomics 27 (3), 177 – 187.

[3] Cheng, T., Migliaccio, G. C., Teizer, J., Gatti, U. C., 2013. Data fusion of real-time location sensing and physiological status monitoring for ergonomics analysis of construction workers. Journal of Computing in Civil Engineering 37 (3), 320–335.

[4] Cheng, T., Teizer, J., Migliaccio, G., Gatti, U., 2013. Automated task-level activity analysis through fusion of real time location sensors and worker's thoracic posture data. Automation in Construction 29, 24–39.

[5] Constructing Better Health, 2009. Health in construction research. Accessed 27/03/2017.

[6] Gilbreth, F. B., Gilbreth, L. M., 1917. Applied motion study. Sturgis and Walton, New York.

[7] Heath-Lay, P., 2016. Building a health solution to meet industry needs. `https://bandce.co.uk/wp-content/uploads/2017/01/building-an-occupational-health-solution-to-meet-industry-needs.pdf`

[8] Hwang, S., Kim, Y., Kim, Y., 2009. Lower extremity joint kinetics and lumbar curvature during squat and stoop lifting. BMC Musculoskeletal Disorders 10 (15).

[9] International Organization for Standardization, 2000. ISO 11226: Ergonomics evaluation of static working postures.

[10] International Organization for Standardization, 2007. ISO 11228-3: Ergonomics manual handling part 3: Handling at high repetition on low loads.

[11] Joshua, L., Varghese, K., 2011. Video annotation framework for accelerometer placement in worker activity recognition studies. In: Proceedings of the 28th ISARC. Seoul, Korea, pp. 164–169.

[12] Joshua, L., Varghese, K., Sep. 2014. Automated recognition of construction labour activity using accelerometers in field situations. International Journal of Productivity and Performance Management 63 (7), 841–862.

[13] Karhu, O., Kansi, P., Kuorinka, I., 1977. Correcting working postures in industry: A practical method for analysis. Applied Ergonomics 8 (4), 199 – 201.

[14] McAtamney, L., Hignett, S., 1995. REBA: a rapid entire body assessment method for investigating work related musculoskeletal disorders. Ergonomics Society of Australia, Adelaide, pp. 45–51.

[15] McAtamney, L., Nigel Corlett, E., Apr. 1993. RULA: a survey method for the investigation of work-related upper limb disorders. Applied Ergonomics 24 (2), 91–99.

[16] Rawashdeh, S., Rafeldt, D., Uhl, T., 2016. Wearable IMU for shoulder injury prevention in overhead sports. Sensors 16 (11).

[17] Ray, S. J., Teizer, J., Apr. 2012. Real-time construction worker posture analysis for ergonomics training. Advanced Engineering Informatics 26 (2), 439–455.

[18] Schmitt, O. H., 1938. A thermionic trigger. Journal of Scientific Instruments 15 (1).

[19] Sivanathan, A., Apr. 2014. Ubiquitous Integration and Temporal Synchronisation (UbiITS) Framework A solution for building complex multimodal data capture and interactive systems. Doctor of Philosophy, Heriot-Watt University, Edinburgh, Scotland, UK.

[20] Sivanathan, A., Lim, T., Ritchie, J., Sung, R., Kosmadoudi, Z., Liu, Y., 2013. The application of ubiquitous multimodal synchronous data capture in CAD. Computer-Aided Design.

[21] The Center for Construction Research and Training, 2013. The Construction Chart Book. CPWR.

[22] The Health and Safety Executive, 2002. Manual handling assessment chart (the MAC tool).
http://www.hse.gov.uk/msd/mac/

[23] The Health and Safety Executive, 2009. Assessment of repetitive tasks (ART) tool.
http://www.hse.gov.uk/msd/uld/art/

[24] Valero, E., Sivanathan, A., Bosché, F., Abdel-Wahab, M., 2016. Musculoskeletal disorders in construction: A review and a novel system for activity tracking with body area network. Applied ergonomics 54, 120–130.

[25] Vanveerdeghem, P., Torre, P. V., Stevens, C., Knockaert, J., Rogier, H., 2014. Synchronous wearable wireless body sensor network composed of autonomous textile nodes. Sensors 14 (10), 18583–18610.

[26] Venda, V. F., Venda, Y. V., 1995. Dynamics in Ergonomics, Psychology, and Decisions. Ablex, ISBN: 156750129X 9781567501292.

[27] Yan, X., Li, H., Li, A. R., Zhang, H., 2017. Wearable IMU-based real-time motion warning system for construction workers' musculoskeletal disorders prevention. Automation in Construction 74, 2–11.