Motion Data Based Construction Worker Training Support Tool: Case Study of Masonry Work

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Abstract –

Construction work involves a number of repetitive and physically demanding tasks. Exposure to these labor intensive tasks with awkward postures result in an increase in biomechanical risk factors that may lead to work-related musculoskeletal disorders (WMSDs). Thus, it is essential to provide training for apprentice-level workers to adopt safe working postures. Recent advancements in sensing technologies have enabled us to automatically collect body motion data and analyze posture. The present work presents an automated posture assessment method using inertial measurement units (IMUs) allowing for in-depth ergonomic analysis via kinematic data. A case study on masonry work was performed and body motion data from masons with varying experience levels were collected. For the posture analysis, we first investigated the risk of working posture between experience groups using observation-based posture assessment methods (RULA and REBA), then compared the assessment scores between experience groups. Finally, a prototype training tool based on working posture was introduced. The experimental results show that the automated collection and analysis of motion data can provide greater understanding of working postures adopted by workers with different experience levels with the potential to be used as a training tool in apprenticeship programs.

Keywords –

Construction management; Automation; Masonry; Risk assessment method; RULA; REBA; Training tool; Motion capture system

1 Introduction

In the construction industry, workers are frequently exposed to tasks that contribute to work-related musculoskeletal disorders (WMSDs), including overexertion during lifting, repetitive tasks, and awkward postures [1, 2]. Among construction workers, masons are more prone to WMSDs due to frequent lifting and static postures used while handling heavy building materials [3]. In 2010, the masonry trade was found to have the highest rate of overexertion injuries (66.5 per 10,000 full-time equivalent workers) and the second highest rate of back injuries (45.3 per 10,000 full-time equivalent workers) within selected construction subsectors [1]. Furthermore, repetitive tasks have shown to be related to an increase in physical fatigue levels, which can result in greater incidence of accidents and lowered productivity. Hence, it is of great importance to analyze ergonomic risks associated with construction tasks to mitigate the prevalence of WMSDs among construction workers.

Observation-based posture assessment methods have been widely used to identify and monitor potential ergonomic risks associated with WMSDs [4]. These methods include the Rapid Entire Body Assessment (REBA) [5], Rapid Upper Limb Assessment (RULA) [6], and Ovako Working posture Analyzing System (OWAS) [7], which produces risk levels based on input elements such as posture, work duration, and repetition [8]. Traditionally, observation-based assessments require an ergonomist or task analyst to visually assess a worker's posture during an activity in real-time or post-evaluate using a video recording [9]. Body joint angles are the primary input element to describe posture; however, is difficult to obtain precise and reliable input values due to human errors in visual assessments [10].

Recent advancements in motion capture systems have spurred their use in several applications from visual effects in entertainment to biomechanics and sports performance. Motion capture systems based on wearable inertial measurement units (IMUs) can automatically and accurately track motion data. Wearable IMUs are less expensive compared to other motion capture systems, can be used in most site conditions, and do not obstruct the natural motion of wearers. Thus, these wearable IMUs can be used to collect input elements (i.e. body joint angles) with greater accuracy for observation-based assessment methods.

Previous research efforts reported that less experienced workers showed higher lost-workday claims

[1] and significantly lower productivity than experienced workers [11]. Specifically, Alwasel et al. [11] investigated the joint force and moments of masons who were grouped based on experience level, during a bricklaying task. The results showed that joint forces and moments were lowest in the group with the highest level of experience compared to the groups with less experience. Given that the experienced masons adopted safer and more productive methods in their work, it is possible to identify proper, task-specific working postures to develop training tools for inexperienced, apprentice-level workers.

This paper first compares WMSD risk levels of masons with varying levels of experience using existing posture assessment methods (i.e. RULA and REBA). Secondly, a prototype training tool based on working posture is introduced. A case study on masonry work was performed to demonstrate the motion data collection process during a bricklaying task. Based on the motion data, working postures were determined and used as inputs to the RULA and REBA posture assessment methods. Potential issues about the posture assessment methods are discussed.

2 Literature Review

Many ergonomic assessment methods require inputs that describe posture since they are associated with joint force and moment generation contributing to the risk of WMSDs [12, 13]. Posture-based ergonomic assessment methods such as the RULA and REBA posture assessment methods evaluate the stresses on the musculoskeletal system and risk for WMSDs primarily using joint angles with reference to movement planes. RULA and REBA have been commonly applied in the construction industry to study the movement of workers. McGorry and Lin [14] used the RULA method to compare and demonstrate the utility of a proposed methodology that evaluates arm posture and grip strength in tool handling. Kim et al. [15] used the REBA method to estimate the risk of WMSDs in panel erection to improve panel specifications and workplace design. Using the RULA and REBA body part diagrams, a risk score and its prescribed action level for ergonomic intervention can be found. However, since these assessments are traditionally based on visual observations of joint angle, the results are prone to inaccuracies across different observers [10].

Due to the development of sensing technologies, various types of motion sensing systems have been introduced to improve the efficiency and accuracy of posture assessments. Popular among these sensing technologies are vision-based assessments, which use video cameras for object identification and tracking, and inertial measurement units (IMUs), which obtain motion data with accelerometers, gyroscopes, and magnetometers. For example, Ray and Teizer [16] used a Kinect range camera to classify work tasks as ergonomic or non-ergonomic. Alwasel et al. [11] used an IMU-based sensor suit and 3D Static Strength Prediction Program [17] to estimate joint forces and moments in a bricklaying task. Research efforts in WMSDs in the construction industry utilizing sensing technologies, to date, have been focused on posture detection, posture classification, and comparison of working posture to ergonomic standards. However, few studies have examined the differences in working postures adopted by workers with growing levels of experience. In this research, we investigate risk levels associated with working postures adopted by masons of varying levels of expertise using an automated risk assessment tool.

3 Methodology

In Ontario, Canada, the three-year masonry apprenticeship consists of on-site and in-school training. Upon completion, the apprentice can apply to become certified as a journeyman. Forty-five participants were recruited from the Brick and Stone Masonry Apprenticeship Program offered by the Ontario Masonry Training Centre. The experiment was conducted at two institutions: Conestoga College in Waterloo, Ontario, and the Canadian Masonry Design Centre (CMDC) in Mississauga, Ontario. The participants were separated into four cohorts based on years of experience: novice with no experience, apprentice with 1-year experience, apprentice with 3-years of experience, and journeyman with 5 or more years of experience (Table 1).

Table 1. Number of participants

	Novice	1 Year	3 Years	Journeymen	Total
Conestoga	5	4	7	5	21
CMDC	12	5	6	1	24
Total	**17**	**9**	**13**	**6**	**45**

Wireless motion capture suits, MVN Awinda from Xsense [18] and Perception neuron from Noitom Ltd. [19] were used to collect participants' motion data. The suits contain seventeen inertial measurement units (IMUs), and each sensor is composed of a three-axis accelerometer, three-axis gyroscope, and three-axis magnetometer. The suits collected motion data at a 125 Hz sampling frequency. The experiments were recorded using camcorders to label and segment the data in the data processing phase. Prior to the experiment, a calibration session was performed for each participant to ensure conformity between the models generated from the motion data and the participant's body. Each participant was instructed to complete a pre-built lead wall using forty-five concrete masonry units (CMUs), thus each bricklaying task consisted of forty-five individual lifts. Figure 1 shows the experimental setup with the lead wall. The pre-built lead wall was six-courses high and consisted of twenty-seven blocks. The participants completed the wall using CMUs from the second course to the sixth course. The CMU blocks were placed on three pallets approximately 1 meter away from the lead wall. Two panels of mortar were positioned between the three pallets and were continuously supplied by helpers. The CMUs are CSA"A" - Type "A" concrete units and each weigh 16.6 kg with dimensions of 390 x 190 x 100 mm (Canadian Concrete Masonry Producer Association).

Figure 1. Experimental setup.

After the completion of the bricklaying task, motion data from the IMU suits were extracted as Biovision Hierarchy (BVH) type files containing 3D joint orientation over time. Then, joint angles required for the RULA and REBA posture assessment methods were calculated using the International Society of Biomechanics (ISB) recommendations [20, 21]. As shown in Figure 2, a local coordinate system is defined for each body segment using joint centers, then the Euler angles between adjoining segments' coordinate systems were calculated [22].

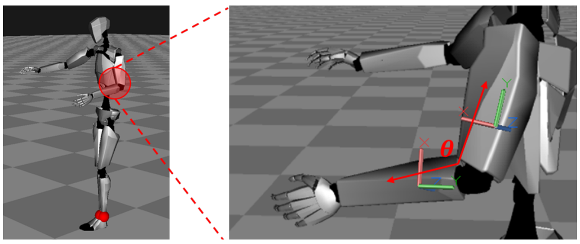

Figure 2. Joint angle based on Local coordinate system

The calculated joint angles were used to assign posture scores in both assessment methods. The RULA and REBA assessment methods consist of two body region sections to obtain a final score representing the risk for MSDs: 1) arm and wrist analysis, 2) neck, trunk, and leg analysis. The posture score according to the segment angle is first obtained, and then the score of each section is calculated considering additional adjustments such as external force and frequency. A final score is assigned by combining the previous two posture scores. The final RULA score ranges from 1 to 7 and final REBA score ranges from 1 to 15, which correspond to four and five risk levels respectively. Table 2 shows the final score range and corresponding risk level.

Table 2. Score range of RULA and REBA

RULA	
Score	Level of MSD risk
1-2	Acceptable posture
3-4	Further investigation, change may be needed
5-6	Further investigation, change soon
7	Investigate and implement change
REBA	
Score	Level of MSD risk
1	Negligible risk, no action required
2-3	Low risk, change may be needed
4-7	Medium risk, further investigation, change soon
8-10	High risk, investigate and implement change
11+	Very high risk, implement change

In this study, both the right- and left-side of body segment angles were obtained, however only the side with the higher score contributed to the final score. Since the wearable IMU suits collected 125 frames of motion data per second, a RULA and REBA score was assigned to each frame. Since each lift varies in duration, the maximum assessment score was selected for each lift. Considering more than 70% of all lift motions were two-handed lifts, the assessment scores were analyzed by selecting only two-handed lifts. Finally, the average final scores of each experience group were used for comparison.

4 Result and Discussion

4.1 Average RULA and REBA scores

Table 3 shows the average RULA and REBA score of four groups with different levels of experience. The overall average score of RULA is 6.95 and of REBA is

10.94, both indicating high risk for MSDs. In the score comparison between experience groups, the average RULA score was highest in the 3-years group, while the average REBA score was the highest in the journeymen group. The novice group showed the lowest score in both assessment tools. It is important to note that the variance of average scores among experience groups were not significant in both assessment tools. Specifically, the difference between the highest score and the lowest score is only 0.11 and 0.35.

Table 3. Average final score of RULA and REBA

Group	**RULA**		**REBA**	
	Average	SD	Average	SD
Novice	6.88	0.39	10.74	0.97
1 Year	6.96	0.22	10.89	0.97
3 Years	6.99	0.11	11.02	0.81
Journeymen	6.98	0.14	11.09	0.78

To build the lead wall, participants placed forty-five CMUs in five courses, from the second course to the sixth course. A detailed risk assessment score by course is shown in Table 4. Both assessment tools showed a lower final score when placing CMUs in the third and fourth courses in all groups. Since the third and fourth course are approximately at hip-height, the result may be due to less back- and arm-bending.

Table 4. Average score of RULA and REBA by course

Groups	**Average RULA score by courses**				
	2	3	4	5	6
Novice	6.94	6.84	6.80	6.89	6.92
1 Year	7.00	6.94	6.90	6.95	7.00
3 Years	7.00	6.99	6.97	7.00	6.99
Journeymen	7.00	7.00	6.92	6.98	7.00
Groups	**Average REBA score by courses**				
	2	3	4	5	6
Novice	10.98	10.62	10.44	10.67	10.99
1 Year	10.72	10.71	10.95	10.93	11.07
3 Years	11.18	10.90	10.90	10.89	11.21
Journeymen	11.07	10.67	10.92	11.22	11.34

The added external load in RULA and REBA is one of the important adjustment factors for the final score. In particular, when an external load greater than 22 lbs (10 kg) is applied, an additional 2 or 3 scores were applied resulting in a higher final score. The CMUs used in this study was 16.6 kg, and both assessment tools showed a very high-risk final score regardless of the various segment angles obtained by the participants. Therefore, in the case of heavy material handling tasks such as masonry work, the practicality of posture assessment methods may be limited since they do not provide significant results to differentiate between experience groups.

4.2 Prototype training tool

Although the average RULA and REBA scores were not able to provide results with significant differences between experience groups, the tools can indicate the risk of each body segment according to the joint angles. Thus, we developed a prototype training tool that provides independent joint scores and adopts the joint angle ranges used in the REBA scoring system since it provides whole body postural risk reflecting both upper- and lower-limbs joint angles. The training tool uses a color-map to reflect risk levels at selected joints. The angle range and risk level indicator is shown in Table 5.

Table 5. REBA Score-based Tool - Risk Level Indicator

Body Segment	Angle (degree)	Score	Risk Level Indicator
Shoulder	0 – 20	1	
	20 – 45	2	
	45 – 90	3	
	> 90	4	
Elbow	60 – 100	1	
	0 – 60 or > 100	2	
Wrist	0 – 15	1	
	> 15	2	
Neck	0 – 10	1	
	10 – 20 or 0 <	2	
Truck	0	1	
	0 – 20 or 0 <	2	
	20 – 60	3	
	> 60	4	
Leg	0	1	
	30 – 60	2	
	> 60	3	

Figure 3 shows a snapshot of the training tool applied to Participant #2 in the journeymen group. As shown in Figure 3, the red color indicates that the back and arm angles are unsafe for the participant. To correct the posture and maintain low risk levels, the participant must reduce the flexion angle of the back and shoulder by bending more at the knees and reduce the flexion angle of the arm by keeping the CMU block closer to the body.

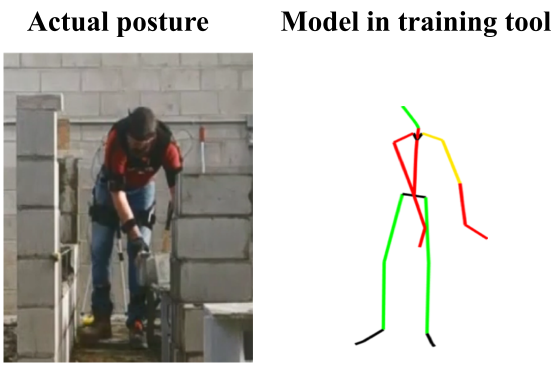

Figure 3. The snapshot of prototype training tool

As demonstrated, the training tool which continuously collects motion data, can inform its user of safe and unsafe working postures for the entire work duration. This allows the user to proactively correct unsafe postures and reduce the risk of WMSDs. The training tool has the potential to be used in apprenticeship programs to establish safe working postures.

5 Conclusion

The practice of safe working postures in construction work help workers maintain good health and productivity levels. Current observation-based posture assessment methods are subject to human error and lack precision. Recent developments of IMUs allow for the continuous collection of motion data which are more reliable for use in posture assessments. In this paper, motion data was collected from forty-five participants with different experience levels ranging from novice to more than 5-years of masonry experience. We analyzed the working postures of the participants while performing a bricklaying task using IMU suits.

Risk levels for WMSDs were determined and compared for each group using posture assessment methods, RULA and REBA. The results showed that the average maximum assessment scores across experience groups for RULA is between 6.88 and 6.99, and REBA is between 10.74 and 11.09. The results of the assessment methods showed that the assessments may not be able to differentiate between the working postures of workers with different levels of experience. Both assessment methods indicated that the risk levels for WMSDs were lowest when the participants were handling CMUs between the knee and hip level. We also presented a prototype training tool that was developed based on joint angle inputs used in the REBA scoring system. The training tool identifies unsafe postures using motion data collected during a work task so that its user can make necessary adjustments.

Future work will compare results obtained from the posture assessment tools presented in this study, with those obtained using biomechanical analysis (e.g., using 3D Static Strength Prediction Program). The biomechanical analysis will be used to determine joint forces and moments generated during the bricklaying task and to develop a biomechanical-based training tool. In addition, studies on work proficiency and productivity using training methods will be conducted.

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