Vision-Based Ergonomic Risk Assessment of Back-Support Exoskeleton for Construction Workers in Material Handling Tasks

Yizhi Liu, S.M.ASCE[1]; Amit Ojha, S.M.ASCE[2]; and Houtan Jebelli, Ph.D., A.M.ASCE[3]

[1]Ph.D. Candidate, Dept. of Architectural Engineering, Pennsylvania State Univ., State College, PA. Email: ykl5505@psu.edu
[2]Ph.D. Student, Dept. of Civil and Environmental Engineering, Univ. of Illinois Urbana-Champaign, Champaign, IL. Email: amito2@illinois.edu
[3]Assistant Professor, Dept. of Civil and Environmental Engineering, Univ. of Illinois Urbana-Champaign, Champaign, IL (corresponding author). Email: hjebelli@illinois.edu

ABSTRACT

Work-related musculoskeletal disorders (WMSDs) are a leading cause of injury for workers who are performing physically demanding and repetitive construction tasks. With recent advances in robotics, wearable robots are introduced into the construction industry to mitigate the risk of WMSDs by correcting the workers' postures and reducing the load exerted on their body joints. While wearable robots promise to reduce the muscular and physical demands on workers to perform tasks, there is a lack of understanding of the impact of wearable robots on worker ergonomics. This lack of understanding may lead to new ergonomic injuries for workers wearing exoskeletons. To bridge this gap, this study aims to assess the workers' ergonomic risk when using a wearable robot (back-support exoskeleton) in one of the most common construction tasks, material handling. In this research, a vision-based pose estimation algorithm was developed to estimate the pose of the worker while wearing a back-support exoskeleton. As per the estimated pose, joint angles between connected body parts were calculated. Then, the worker's ergonomic risk was assessed from the calculated angles based on the Rapid Entire Body Assessment (REBA) method. Results showed that using the back-support exoskeleton reduced workers' ergonomic risk by 31.7% by correcting awkward postures of the trunk and knee during material handling tasks, compared to not using the back-support exoskeleton. The results are expected to facilitate the implementation of wearable robots in the construction industry.

INTRODUCTION

The construction industry plays a vital role in the US economy by providing a wide range of employment opportunities and driving economic growth (Liu et al. 2021b). However, construction work is known to be physically demanding and often requires workers to perform tasks in dynamic environments with repetitive movements and unusual postures. These factors increase the risk of work-related musculoskeletal disorders (WMSDs) for workers (Zhu et al. 2021). Investigations have shown that construction workers are prone to WMSDs, including back and shoulder pains (Kazar and Comu 2021; Zhu et al. 2021). Back pain can be caused by lifting heavy construction materials or working in awkward postures for prolonged periods of time, while shoulder pain can be caused by using tools that require repetitive arm movements (Kazar and Comu 2021). Furthermore, according to the U.S. BLS, WMSDs account for around 37% of nonfatal injuries and illnesses experienced by construction workers (Bureau of Labor Statistics 2020). Therefore, it is essential to identify effective solutions to mitigate the risk of WMSDs for construction workers.

Recently, wearable robots, also known as exoskeletons, have emerged as a promising solution to reduce the risk of WMSDs for workers (Bosch et al. 2016; Liu et al. 2021a; b). Exoskeletons can be broadly categorized into two types: active and passive (de Looze et al. 2016). Active exoskeletons are powered through actuators such as electric motors, pneumatics, or hydraulics, which actively provide lift support, weight dispersion, and posture correction for workers (de Looze et al. 2016). Passive exoskeletons, on the other hand, do not include actuators and instead rely on materials or springs to store energy from human movements and provide assistance when required by the worker (Bosch et al. 2016). In the construction industry, active exoskeletons are generally preferred over passive exoskeletons due to their ability to actively aid workers in handling physical workloads (Antwi-Afari et al. 2017). Specifically, active back-support exoskeletons (BSEs) are emerging as a major option for reducing the risk of WMSDs for workers (Zhu et al. 2021). By transferring the load from the worker's spine to the exoskeleton, BSEs can reduce the load exerted on the worker's back and shoulders. In addition, BSEs can provide physical support to workers' upper body and spine, which can further help align the spine in a more natural position. All these functions allow BSEs to reduce the stress and strain on the worker’s back and shoulders (Abdoli-E and Stevenson 2008; Zhu et al. 2021), mitigating the risk of WMSDs for construction workers.

While BSEs can potentially reduce the risk of WMSDs for workers, their implementation on construction sites may raise new safety concerns related to workers. The current body of knowledge does not provide a comprehensive understanding of the impact of BSEs on worker ergonomics, which may increase the possibility of new ergonomic injuries for workers wearing exoskeletons. For instance, active BSEs may induce changes in postural strategies adopted by users (e.g., BSEs may push body joints beyond their normal range of motion), potentially increasing the risk of joint hyperextension (Theurel and Desbrosses 2019). Therefore, to ensure that workers are not exposed to new ergonomic risks, it is critical to conduct ergonomic risk assessments of workers using BSEs. Unfortunately, few studies have been conducted in the construction industry to assess the ergonomic risks of workers wearing BSEs.

To bridge this gap, this study proposes an ergonomic risk assessment approach that integrates computer vision, artificial intelligence, and Rapid Entire Body Assessment (REBA) method (Hignett and McAtamney 2000). This approach will evaluate the workers’ ergonomic risks while performing construction tasks with and without wearing BSEs. To be more specific, the study will develop a pose estimation network using computer vision techniques, to estimate the workers’ 2D posture. Next, based on the estimated posture, the method will calculate the joint angles between connected body parts. Finally, the REBA method will be applied to the calculated joint angles to generate a REBA score, which serves as the metric to assess the worker's ergonomic risk; a higher score indicates a higher ergonomic risk. This study will apply the developed method to a common construction task, a material handling task. Twelve subjects will be recruited to perform the task under two scenarios, with and without BSEs. The comparison results between the two scenarios will reveal the impact of the BSE on workers’ ergonomic risks. This study has the potential to contribute to the understanding of the impact of BSEs on worker ergonomics. The findings of the study should facilitate the implementation of wearable robots in the construction industry.

METHODOLOGY

The aim of this study was to evaluate the ergonomic risk of workers using a back-support exoskeleton (BSE), and the methodology, illustrated in Figure 1, involved three main steps.

Firstly, the authors developed a computer vision-based algorithm to estimate the postures of workers while wearing the exoskeleton to perform construction tasks. To achieve this, a multi-stage convolutional neural network was built based on the authors' previous investigation (Liu and Jebelli 2022) to extract 2D postures of workers from 2D images. In the second step, the authors leveraged the estimated poses to calculate the joint angles between two connected body segments, such as the angle between the neck and shoulder, and the angle between the trunk and thigh segments. Finally, in the third step, the authors assessed the workers' ergonomic risks while wearing the exoskeleton by applying the REBA method to the calculated joint angles from step two. The following sub-sections will provide detailed explanations of each step.

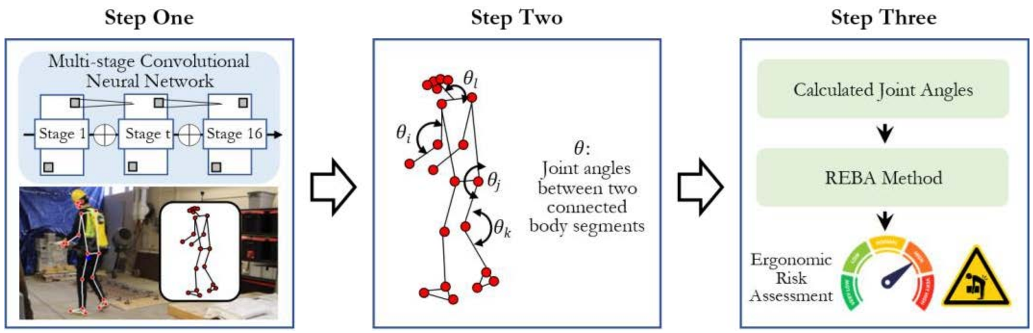

Figure 1. Steps for assessing the ergonomic risks of workers wearing or not wearing BSEs.

COMPUTER VISION-BASED POSE ESTIMATION

The architecture of the multi-stage convolutional neural network (CNN) developed for pose estimation is shown in Figure 2. The developed network consisted of 16 stages, with the first eight stages trained to generate a set of 2D vectors, $\mathbf{L} = \{\mathrm{L}_1, \dots, \mathrm{L}_\mathrm{p}\}$, that connected the body joints of workers; and the remaining eight stages trained to generate a set of confidence maps, $\mathbf{S} = \{\mathrm{S}_1, \dots, \mathrm{S}_\mathrm{q}\}$, that detected 21 body points of the worker. Each of the first eight stages contained three convolution blocks ($\mathrm{C_B}$) and two additional convolutional layers ($\mathrm{C_L}$) with a kernel size of 1×1. As shown, $\mathrm{C_B}$ was comprised of four convolutional layers ($\mathrm{C_L}$) with a 5×5 kernel, and the outputs of all $\mathrm{C_L}$ were concatenated ($\bigoplus$) as the output for the block. Similarly, the following eight stages each contained three convolution blocks ($\mathrm{C_B'}$) and two convolutional layers with a kernel size of 1×1. Each of the $\mathrm{C_B'}$ comprised four convolutional layers ($\mathrm{C_L'}$) with a 9×9 kernel. In this study, the design of each stage followed the design of the OpenPose method (Cao et al. 2021) and the authors' previous investigation (Liu and Jebelli 2022). Between every two adjacent stages of the above architecture, the authors applied an LSTM module with 128 hidden units. The LSTM module processed the outputs from the prior stage (stage t) and sent the processed results to the following stage (stage $\mathrm{t} + 1$) as input. Previous studies have shown that this LSTM module could enhance the geometric stability and continuity of the 2D postures extracted from the input 2D images (Liu et al. 2020). At the last stage of the network, the set of confidence maps $\mathbf{S}$ was paired with the set of corresponding 2D vectors $\mathbf{L}$ to generate the 2D postures of workers. Furthermore, the training process of the developed pose estimation network was conducted according to the steps employed in the authors' previous study, as described in (Liu and Jebelli 2022; Ojha et al. 2022). The training outputs consisted of the set of trained confidence maps $\mathbf{S}^{\mathrm{trained}}$, the set of trained 2D vectors $\mathbf{L}^{\mathrm{trained}}$, and the estimated 2D human pose generated by matching $\mathbf{S}^{\text{trained}}$ and $\mathbf{L}^{\text{trained}}$. An example of the estimated 2D pose of a worker is presented in Figure 2 as well.

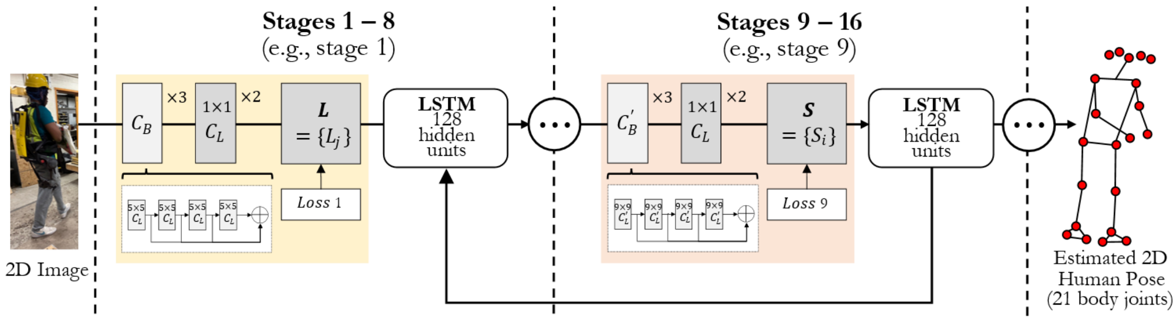

Figure 2. Overall architecture of the multi-stage (16 stages) convolutional neural network.

JOINT ANGLE CALCULATION AND ERGONOMIC RISK ASSESSMENT

Based on the estimated 2D worker posture, we calculated the joint angles related to the position of the worker's neck, torso (trunk), upper arms, lower arms, wrists, and lower limbs (upper leg, lower leg, and knee) using the following equation:

$$\theta = \cos^{-1}\left[\frac{a_i^j \cdot b_k^l}{|a_i^j||b_k^l|}\right], where\ i, j, k, l \in \{1, \ldots, 16\};\ i \neq j\ and\ k \neq l \tag{1}$$

Where a_i^j is the vector obtained from the set of trained 2D vectors $\mathbf{L}^{\text{trained}}$, pointing from joint i to joint j. Likewise, b_k^l is another vector from the set of $\mathbf{L}^{\text{trained}}$, starting from joint l to joint k. "$|a|$" function calculates the norm of the vector a, and "·" indicates the dot product between the two vectors, a_i^j and b_k^l. After calculating the required joint angles from the estimated 2D posture, the authors used them to assess workers' ergonomic risk (with and without wearing an exoskeleton) based on the REBA approach (Hignett and McAtamney 2000). First, we applied the calculated joint angles to generate the assessment scores of trunk flexion, trunk lateral flexion, neck flexion, knee flexion, upper-arm flexion and abduction, and lower-arm flexion according to the REBA method. For example, if the angle of neck flexion falls within 0-20 degrees, the score is increased by 1; if the degree exceeds 20 degrees, the score is increased by 2. Once the assessment scores of each body part were obtained, these scores were combined to calculate a score of whole-body posture using Table A, Table B, and Table C in the REBA worksheet (Hignett and McAtamney 2000). These three tables are REBA decision tables, which can generate an initial REBA score for the ergonomic risk of the whole-body posture. We then adjusted this score using the Activity Score in the REBA worksheet, giving the final REBA score for ergonomic risk assessment. If the final score is 1, the ergonomic risk is negligible, indicating that the worker has a safe posture. Scores between 2 and 3 indicate low risk; 4 – 7 represent medium risk; 8 – 10 indicate high ergonomic risk, and scores above 11 suggest very high ergonomic risk for workers. For more information on using the REBA method to assess ergonomic risks, please refer to (Hignett and McAtamney 2000).

CASE STUDY

To assess the impact of the exoskeleton on worker ergonomics, the authors designed a material handling task. During the task, the authors first collected a 2D image dataset to train the developed pose estimation network. Subsequently, using the trained network, the authors applied the proposed method (as depicted in Figure 1) to the task, with the aim of evaluating the ergonomic risks of workers wearing the BSE.

More specifically, the designed material handling task was performed by twelve subjects, including ten male subjects and two female subjects, with a mean age of 24.3 years and a standard deviation of 1.66 years. The subjects' mean weight was 159 lbs with a standard deviation of 29.2 lbs, and their mean height was 5' 9" with a standard deviation of 2.88 inches. The task was conducted in two scenarios: in the first scenario, each subject was required to perform the material handling task with the assistance of a BSE; in the second scenario, they were asked to perform the same task without the aid of the BSE. Each scenario involved ten rounds of material handling activities, with subjects required to lift a 25-pound bag of cement from the material staging area and deliver it to a cart in each round. The total duration of each session lasted approximately 5 minutes. Figure 3-a illustrates the performed material handling task, and Figure 3-b shows an image of the applied back-support exoskeleton.

Figure 3. Illustrations of the designed material handling tasks.

A digital camera was leveraged to record videos of subjects performing the material handling task. These videos were then processed to generate images at a frame rate of 0.25, resulting in a 2D image dataset applied to train the developed pose estimation network. 4681 images were collected from all twelve subjects, with each image annotated using the approaches mentioned in the OpenPose method and the authors' previous study (Cao et al. 2021; Liu and Jebelli 2022). Each image was annotated with 21 joints, including 12 body joints (left wrist, right wrist, left shoulder, right shoulder, left hip, right hip, left elbow, right elbow, left knee, right knee, left ankle, and right ankle), 4 joints for the foot (left toe, right toe, left heel, and right heel), and 5 joints in the facial area (left and right ears, left and right eyes, and nose). The collected images with the corresponding labeled joints were used to train the developed pose estimation network to generate $\mathbf{S}^{\text{trained}}$ and $\mathbf{L}^{\text{trained}}$ as mentioned in the METHODOLOGY. Figure 3-c illustrates one example of the training image collected from the material handling task as well as its corresponding annotations. In addition, the training performance of the network will be reported in the RESULT section. After obtaining the trained network, the proposed method was applied to the material handling task. Each subject performed five additional rounds of the material handling activities with and without wearing the BSE. The proposed method was used to generate the REBA score to assess subjects' ergonomic risk in each scenario. By comparing the REBA score generated from the two scenarios, the authors could assess the impact of the exoskeleton on worker ergonomics. The comparison results will also be reported and discussed in the RESULTS section.

RESULTS

Figure 4 illustrates the training performance of the proposed network in estimating subjects' 2D postures (with and without a BSE) during the material handling task. In this study, the pose estimation performance of the network was measured using the Percentage of Correct Keypoints with a 0.5 threshold ($PCK^{0.5}$) metric. The $PCK^{0.5}$ metric is a commonly accepted measure for assessing pose estimation accuracy, which measures the percentage of estimated joint locations within a certain distance of the true location (Yang and Ramanan 2013). Higher values indicate better performance. As depicted in Figure 4-a, when the subjects performed the material handling task without wearing the exoskeleton, the method achieved an average $PCK^{0.5}$ value of over 82.0 for all joints for twelve subjects. Among them, the method had the lowest precision for assessing the left ankle joint ($PCK^{0.5}$ = 77.2), and the highest precision for assessing the left and right hip joints ($PCK^{0.5}$ = 87.3). Likewise, when the subjects performed the material handling task with the exoskeleton (Figure 4-b), the method achieved an average $PCK^{0.5}$ value of over 81.5 for all joints for 12 subjects. According to the investigations reported in (Cao et al. 2021; Jiang and Messner 2023; Liu and Jebelli 2022), these results suggest that the proposed method is capable of accurately estimating the subjects' 2D postures when subjects execute the material handling task with and without the BSE, which is crucial for assessing ergonomic risks.

Pose Estimation Performance

$PCK^{0.5}$	**Left Wrist** 84.6	**Right Wrist** 86.1	**Left Shoulder** 81.1	**Right Shoulder** 87.1	**Left Hip** 87.6	**Right Hip** 87.6
$PCK^{0.5}$	**Left Elbow** 79.2	**Right Elbow** 80.4	**Left Knee** 82.6	**Right Knee** 79.9	**Left Ankle** 77.2	**Right Ankle** 78.9
$PCK^{0.5}$	**Left Toe** 79.9	**Right Toe** 83.7	**Left Heel** 82.2	**Right Heel** 79.6	**Left Ears** 80.9	**Right Ears** 82.4
$PCK^{0.5}$	**Left Eyes** 84.5	**Right Eyes** 81.1	**Nose** 81.7	**Average** 82.3		

Note: the $PCK^{0.5}$ value for each body joint is the averaged of all 12 subjects

Pose Estimation Performance

$PCK^{0.5}$	**Left Wrist** 84.9	**Right Wrist** 83.7	**Left Shoulder** 80.9	**Right Shoulder** 79.5	**Left Hip** 87.2	**Right Hip** 83.7
$PCK^{0.5}$	**Left Elbow** 77.9	**Right Elbow** 79.5	**Left Knee** 81.7	**Right Knee** 75.6	**Left Ankle** 79.2	**Right Ankle** 80.3
$PCK^{0.5}$	**Left Toe** 79.9	**Right Toe** 84.6	**Left Heel** 83.4	**Right Heel** 78.4	**Left Ears** 81.1	**Right Ears** 82.9
$PCK^{0.5}$	**Left Eyes** 85.5	**Right Eyes** 82.6	**Nose** 83.2	**Average** 81.7		

Note: the $PCK^{0.5}$ value for each body joint is the averaged of all 12 subjects

Figure 4. Training performance of the developed deep network in 2D pose estimation.

Once the trained network was obtained, the authors applied the proposed method to assess the impact of the BSE on worker ergonomics during the material handling task. As introduced, the proposed method estimated subjects' postures and generated the REBA score accordingly, with higher values indicating higher ergonomic risks. Figure 5-a reports the REBA scores across all 12 subjects while they were performing the task with the BSE (scenario 1). The score for each subject was the average of all REBA scores assessed during the 5-round material handling task. Additionally, Figure 5-a includes several examples of the estimated 2D postures with the corresponding REBA score under this scenario. Likewise, Figure 5-b shows the REBA scores across all twelve subjects without the BSE (scenario 2) and examples of the estimated 2D postures with the corresponding REBA score. By comparing the REBA scores assessed from these two scenarios, the results showed that, on average, the exoskeleton reduced the workers' ergonomic risk by 31.7% for twelve subjects. This improvement is attributed to the BSE's ability to correct awkward postures of the trunk and knee, as indicated by red circles in Figures 5-a and 5-b, compared to not using the BSE during the material handling task.

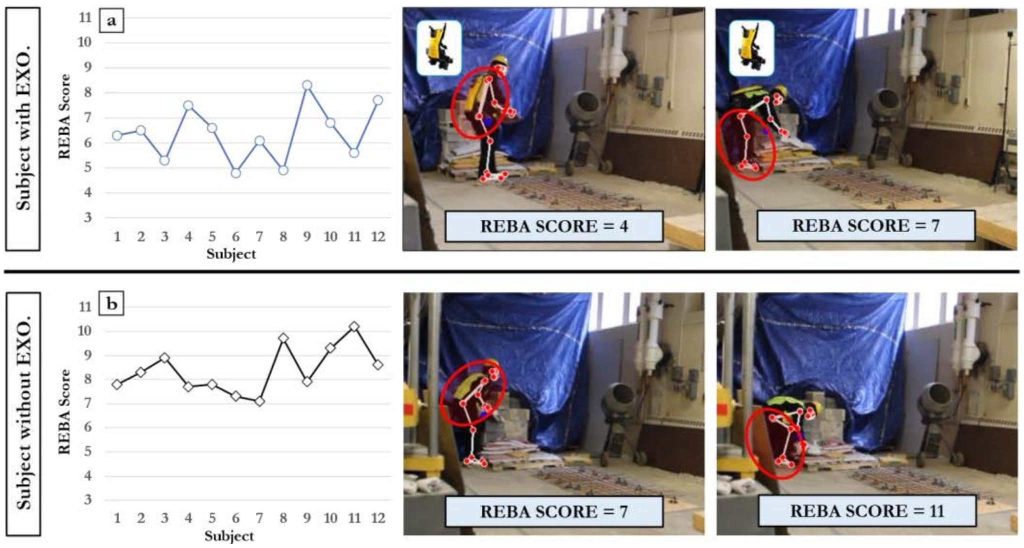

Figure 5. REBA scores for subjects performing construction tasks with and without BSEs.

CONCLUSION

This study aimed to assess the impact of the back-support exoskeleton (BSE) on worker ergonomics when performing physically demanding construction tasks. To achieve this, the authors developed a vision-based ergonomic risk assessment method capable of estimating workers' postures during the task and generating the ergonomic risk assessment based on joint angles calculated from the estimated postures. By applying the developed method to a material handling task, the study demonstrated that the BSE could correct subjects' awkward postures in the trunk and knee during the task. Relying on this, the BSE reduced workers' ergonomic risk by over 30.0% compared to not using the BSE. The results of this study contributed to the understanding of the impact of wearable robots (e.g., BSEs) on worker ergonomics. The implementation of exoskeletons in the construction industry has the potential to enhance workers' health and safety, as well as improve productivity. Future research can investigate the impact of BSEs on worker ergonomics in various construction tasks, including rebar-tying and bricklaying tasks. In addition, the authors also suggest involving more subjects in these tasks to generate more robust investigations on the impact of BSEs on worker ergonomics. In conclusion, this study designed an approach to evaluate workers' ergonomic risks while performing construction tasks with and without BSEs. The results provide insight into the potential benefits of the exoskeletons for enhancing worker ergonomics and can facilitate the safe and efficient implementation of wearable robots in the construction industry.

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