HUMAN ACTION DETECTION AND ERGONOMIC RISK ASSESSMENT AT CONSTRUCTION SITES, BY USE OF MACHINE VISION AND DEEP LEARNING

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Abstract

The research work described herein focuses on the real-time detection and pose analysis of human activities at construction sites, as well as on the evaluation of the ergonomics of these activities. The pose detection and ergonomic analysis utilize machine vision (MV) and deep learning technologies for the processing of images and/or video streams, and a "skeletonization" mechanism that upon detection of a worker pose, measures the geometric properties of the pose's keypoints in the skeletal shape and then calculates the corresponding scores according to the Rapid Entire Body Assessment (REBA) methodology. The utilized approach, which was successfully tested on several typical construction activities, (1) has the potential of providing fast ergonomic assessment at construction sites; and (2) it contributes to the knowledge of occupational safety and health in the construction industry, by providing a low-cost and accurate approach for assessing the risk factors of Work-related Musculoskeletal Disorders (WMSDs).

Introduction

Health and safety have always been among the biggest issues in construction, globally. The unsafe way construction workers operate and the non-observance of the necessary protection measures at construction sites, as well as inherent risks in most construction operations, pose a combination that can be catastrophic. Uncomfortable work postures, repetitive and heavy lifting, and excessive force or overexertion are some of the ergonomic risk factors that can lead workers to develop work-related musculoskeletal disorders (WMSDs). According to the International Labor Organization (ILO), every year about 318,000 work-related accidents occur, with a substantial part of them being related to the construction sector, and in 2021 alone, according to the Health and Safety Executive (HSE) there were approximately 40,000 cases of work-related WMSDs in the United Kingdom

The issue of safety at the workplace has always concerned workers and especially workers in the construction sector, where most accidents are usually observed. One of the most recent and important examples of construction site accidents was the preparation for the World Cup in Qatar (2022), where according to an ILO study 50 migrant workers died, 500 migrants were seriously injured and 37,600 suffered mild to moderate injuries. The main causes of serious injuries were falls, car accidents, and falling objects.

Considering all the above, we understand the need for an improved and more effective method of monitoring construction work, which will aim to obtain a more complete picture of work behavior, so that the necessary steps can be taken to minimize accidents. The classic manual (and intermittent) inspections using construction site foremen have proven not only ineffective in terms of time and cost but also less accurate, making the integration of technology in the construction industry necessary.

Literature Review

Over time, several investigations have been carried out for identifying and understanding the causes of accidents, as well as the methods of dealing with this problem. But the investigation of automated assessment methods has, to date, been limited.

Hignett and McAtamney (2000) worked entirely with the Rapid Entire Body Assessment (REBA) postural analysis tool and how to best apply it. REBA is reported to have been developed as a field tool specifically designed to identify the various types of unpredictable working postures encountered in health care and other service industries. The researchers first collected data from over 600 postural examples, to establish the body part ranges in the REBA score sheets, and then the sensitizing concepts of load, coupling, and activity were incorporated to produce the final REBA scores for each pose (in the range of 1–15), with accompanying levels of risk and action levels. The authors concluded that although the initial development of REBA shows promise as a useful postural analysis tool, further validation needed to be carried out.

In the paper by Alwasel et al. (2011), the authors dealt with the overall problem of work-related musculoskeletal disorders (WMSDs) in construction, focusing on what affects a worker's shoulders and presenting background on the kinematics of shoulder movement, the biomechanics and the causes of shoulder injuries. The authors presented preliminary results for a prototype of a simple, low-cost, magnetoresistive-angle sensing solution for automatically monitoring undesirable movements and patterns of motion, which was expected to reduce construction WMSDs.

In Jaffar et al. (2011), an overview is provided of ergonomics risk factors in the construction industry and a conclusion that based on literature, the most significant ergonomics risk factors are awkward posture in handling job task, force, and repetition of specific movement including vibration.

Citing that construction activities performed by workers are usually repetitive and physically demanding, and that execution of such tasks in awkward postures can strain their bodies and can result in fatigue, injuries or in permanent disabilities, Ray and Teizer (2012) focused on developing an automated approach for posture estimation and classification using a range camera for posture analysis and categorizing it as ergonomic or non-ergonomic. Their approach first classified a worker's pose to determine whether a worker is 'standing', 'bending', 'sitting', or 'crawling' and then estimated the posture of the worker using OpenNI middleware to get the body joint angles and spatial locations. A predefined set of rules was then formulated to use this body posture information to categorize tasks as ergonomic or non-ergonomic.

In Guo et al. (2018), the authors discussed the unsafe behavior of site workers and what could be done to prevent construction accidents, presenting a skeleton-based real-time identification method by combining image-based technologies, construction safety knowledge, and ergonomic theory. The proposed method recognizes unsafe behaviors by simplifying dynamic motion into static postures, which can be described by a few parameters.

Antwi-Afari et al. (2018) refer to awkward working postures as the main risk factor for work-related WMSDs in construction. Their study developed a method to automatically detect and classify awkward working postures based on foot plantar pressure distribution data measured by a wearable insole pressure system. In order to apply the method ten asymptomatic participants performed five different types of awkward working postures (overhead working, squatting, stooping, semi-squatting, and one-legged kneeling) in a laboratory setting. Four supervised machine learning classifiers (artificial neural network (ANN), decision tree (DT), K-nearest neighbor (KNN), and support vector machine (SVM)) were compared and the best was used for classification performance using a 0.32s window size.

Golabchi et al. (2018) To simplify and automate the assessment processes, the study by Golabchi et al. (2018) explored the adaptation and integration of various existing methods for data collection and analysis, proposing a framework of data collection, action recognition, and simulation modeling for productivity and ergonomic analysis, and point cloud model generation and human motion animation for output visualization.

Massiris-Fernández et al. (2020) presented a method that performs accurate ergonomic risk assessment and that automatically computes Rapid Upper Limb Assessment (RULA) scores from snapshots or digital video using computer vision and machine learning techniques, reporting that this method can also handle multiple workers simultaneously, even under sub-optimal viewing conditions. The researchers' workflow utilized open-source neural networks to detect the workers' skeletons, after which their body-joint positions and angles are inferred, with which RULA scores are computed. As reported, the method was validated in actual outdoor working situations under the technical supervision of seven experienced ergonomists, who also evaluated the associated RULA scores. The validation methods involved three levels of comparison: (1) Skeleton and joint detection confidences by viewpoint; (2) Angle comparison between lab-controlled and simulated viewpoints, and (3) RULA score agreement across the proposed method and observations from experienced ergonomists. The authors conclude that the experimental results provide positive evidence of the feasibility of the method and that reasonable variations in camera view do not significantly influence the results in real conditions. The paper, though, identifies two potential weaknesses that may lead to errors. Skeleton detection biases in some cases may lead to relevant angle measurement deviations and also, the angular measurements are not computed from 3D body-joint estimates, but from 2D projections, which may raise projective distortions.

Research Methodology

As aforementioned, the methodology on which this research work is based mainly includes the application of several machine vision (MV) and deep-learning (DL) technologies. The objective was to create a software that would receive sensory data (images), process them to recognize all body parts of the imaged (worker), and finally apply the REBA approach to compute the rating of, and thus the hazard in, the body posture in investigation.

The detection and identification of the human body through the input (images or videos) presented to the software code developed, was the most challenging part of the study since for the correct operation of the program the input image needs to be processed in three dimensions (both x,y,z coordinates, and joint angles are required). From the analysis of each input image (such as the one shown in Figure 1a), a skeletonized pose is deduced (Figure 1b) and coordinates (in 3 dimensions) of keypoints are extracted, representing the various body parts and body joints.

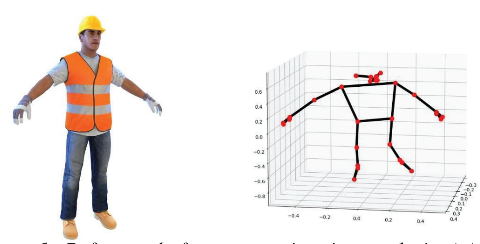
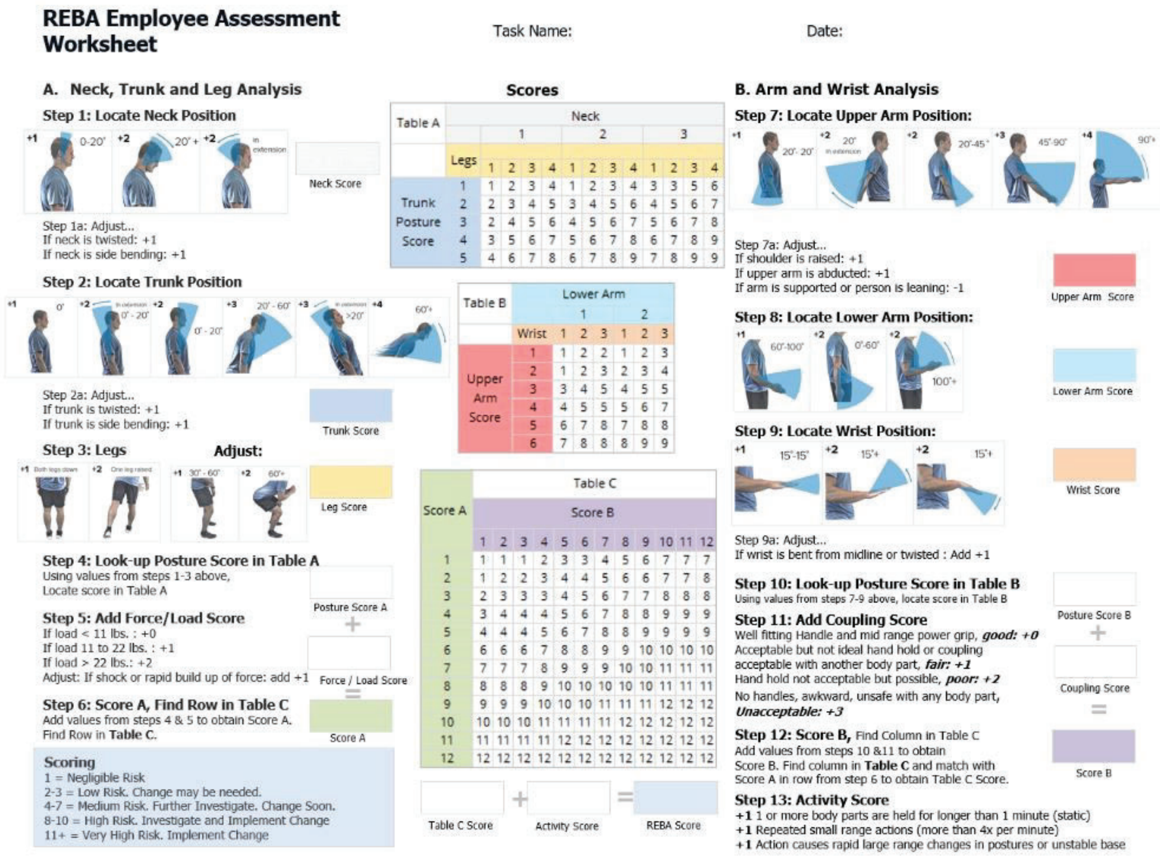


Figure 1: Before and after pose-estimation analysis; (a) Worker pose 1, (b) Skeletonized pose showing body part keypoints.

The developed software code (in the *Python* programming language) is based on readily available code modules and is composed of two key steps: (1) at first, an input image is processed, the human pose in it is extracted in 3D and the coordinates of the various body parts are estimated; (2) then, application of REBA is performed based on the coordinates extracted from the previous step, the sub and total scores are computed, and then the final evaluation is deduced.

REBA Framework

The Rapid Entire Body Assessment (REBA) tool and associated evaluation worksheet (Figure 2) uses a system-



REBA Employee Assessment Worksheet

Task Name:

Date:

A. Neck, Trunk and Leg Analysis

Step 1: Locate Neck Position

+1 0-20° +2 20°+ +2 in extension

Neck Score

Step 1a: Adjust...
If neck is twisted: +1
If neck is side bending: +1

Step 2: Locate Trunk Position

+1 0° +2 in extension 0°-20° +2 0°-20° +3 20°-60° +3 in extension >20° +4 60°+

Step 2a: Adjust...
If trunk is twisted: +1
If trunk is side bending: +1

Trunk Score

Step 3: Legs **Adjust:**

+1 Both legs down +2 One leg raised +1 30°-60° +2 60°+

Leg Score

Step 4: Look-up Posture Score in Table A
Using values from steps 1-3 above,
Locate score in Table A

Posture Score A

Step 5: Add Force/Load Score
If load < 11 lbs. : +0
If load 11 to 22 lbs. : +1
If load > 22 lbs.: +2
Adjust: If shock or rapid build up of force: add +1

Force / Load Score

Step 6: Score A, Find Row in Table C
Add values from steps 4 & 5 to obtain Score A.
Find Row in **Table C.**

Score A

Scoring
1 = Negligible Risk
2-3 = Low Risk. Change may be needed.
4-7 = Medium Risk. Further Investigate. Change Soon.
8-10 = High Risk. Investigate and Implement Change
11+ = Very High Risk. Implement Change

Scores

Table A		Neck 1				Neck 2				Neck 3			
	Legs	1	2	3	4	1	2	3	4	1	2	3	4
Trunk Posture Score	1	1	2	3	4	1	2	3	4	3	3	5	6
	2	2	3	4	5	3	4	5	6	4	5	6	7
	3	2	4	5	6	4	5	6	7	5	6	7	8
	4	3	5	6	7	5	6	7	8	6	7	8	9
	5	4	6	7	8	6	7	8	9	7	8	9	9

Table B		Lower Arm 1			Lower Arm 2		
	Wrist	1	2	3	1	2	3
Upper Arm Score	1	1	2	2	1	2	3
	2	1	2	3	2	3	4
	3	3	4	5	4	5	5
	4	4	5	5	5	6	7
	5	6	7	8	7	8	8
	6	7	8	8	8	9	9

Table C	Score B											
Score A	1	2	3	4	5	6	7	8	9	10	11	12
1	1	1	1	2	3	3	4	5	6	7	7	7
2	1	2	2	3	4	4	5	6	6	7	7	8
3	2	3	3	3	4	5	6	7	7	8	8	8
4	3	4	4	4	5	6	7	8	8	9	9	9
5	4	4	4	5	6	7	8	8	9	9	9	9
6	6	6	6	7	8	8	9	9	10	10	10	10
7	7	7	7	8	9	9	9	10	10	11	11	11
8	8	8	8	9	10	10	10	10	10	11	11	11
9	9	9	9	10	10	10	11	11	11	12	12	12
10	10	10	10	11	11	11	11	12	12	12	12	12
11	11	11	11	11	12	12	12	12	12	12	12	12
12	12	12	12	12	12	12	12	12	12	12	12	12

Table C Score + Activity Score = REBA Score

B. Arm and Wrist Analysis

Step 7: Locate Upper Arm Position:

+1 20°-20° +2 20° in extension +2 20°-45° +3 45°-90° +4 90°+

Step 7a: Adjust...
If shoulder is raised: +1
If upper arm is abducted: +1
If arm is supported or person is leaning: -1

Upper Arm Score

Step 8: Locate Lower Arm Position:

+1 60°-100° +2 0°-60° +2 100°+

Lower Arm Score

Step 9: Locate Wrist Position:

+1 15°-15° +2 15°+ +2 15°+

Wrist Score

Step 9a: Adjust...
If wrist is bent from midline or twisted : Add +1

Step 10: Look-up Posture Score in Table B
Using values from steps 7-9 above, locate score in Table B

Posture Score B

Step 11: Add Coupling Score
Well fitting Handle and mid range power grip, ***good: +0***
Acceptable but not ideal hand hold or coupling
acceptable with another body part, ***fair: +1***
Hand hold not acceptable but possible, ***poor: +2***
No handles, awkward, unsafe with any body part,
Unacceptable: +3

Coupling Score

Step 12: Score B, Find Column in Table C
Add values from steps 10 &11 to obtain
Score B. Find column in **Table C** and match with
Score A in row from step 6 to obtain Table C Score.

Score B

Step 13: Activity Score
+1 1 or more body parts are held for longer than 1 minute (static)
+1 Repeated small range actions (more than 4x per minute)
+1 Action causes rapid large range changes in postures or unstable base

Figure 2: The REBA assessment worksheet (original worksheet developed by Dr. Alan Hedge Hignett and McAtamney (2000)).

atic process to evaluate both upper and lower parts of the musculoskeletal system for biomechanical and MSD risks associated with the job task being evaluated. The single-page worksheet can be used to evaluate required or selected body posture, forceful exertions, type of movement or action, repetition, and coupling. It should be noted that the force/load (step 5), coupling (step 11), and activity (step 13) adjustments to the deduced posture scores are 'post-pose analysis' evaluations.

Computational Framework

Pose estimation is performed by use of the *OpenCV* and *Mediapipe* machine vision libraries. *OpenCV* is a general-purpose machine-vision library and *Mediapipe* is a framework for building machine-learning pipelines for processing time-series data such as video and audio, which offers ready-to-use yet customizable *Python* solutions as a pre-built *Python* package. The aforementioned *Python* libraries allow for the computation and extraction of 3D coordinates (x,y,z) for 33 different points on a human body (shown in Figure 3), which in turn allow for the deduction of the human pose.

It should be noted, though, that the selection of *Mediapipe* for performing the pose estimation presents a problem with regard to the number of body parts it computes. More specifically, *Mediapipe* detects/extracts 33

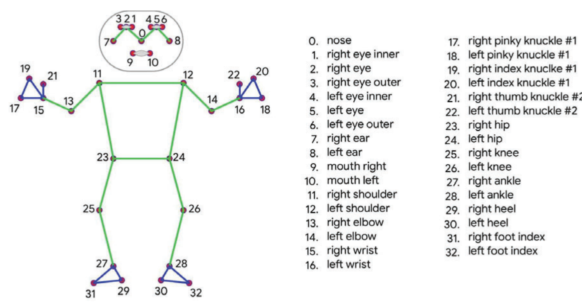


Figure 3: Body parts detected by Mediapipe analysis.

body parts (Figure 3) while the REBA implementation uses 16 of them for its analysis. Thus, a down-sampling and/or remapping of the deduced body parts is required. The problem was solved by creating a mapping between the 33 body parts from *Mediapipe* to the 16 body parts used by REBA so that one gets as a result the coordinates of only the 16 keypoints needed (Figure 4). After the pose estimation process is completed, for each different case of a figure (pose) that is being analyzed, the code returns as a result the 3D coordinates (x,y,z) for each of the 16 body parts that are needed and which constitute a complete human figure. At the outset of this process (Figure 5), the user is able to apply the REBA evaluation code with, as input, the coordinates of the detected keypoints instead of the original image.

Coordinates of REBA joints of interest, AFTER re-referencing w.r.t. hips			
REBA		MediaPipe	
0:	Head	1:	left_eye_inner
1:	Nose	0:	Nose
2:	LShoulder	11:	left_shoulder
3:	LElbow	13:	left_elbow
4:	LWrist	15:	left_wrist
14:	LHand (optional)	19:	left_index
5:	RShoulder	12:	right_shoulder
6:	RElbow	14:	right_elbow
7:	RWrist	16:	right_wrist
15:	RHand(optional)	20:	right_index
8:	LHip	23:	left_hip
9:	LKnee	25:	left_knee
10:	LAnkle	27:	left_ankle
11:	RHip	24:	right_hip
12:	RKnee	26:	right_knee
13:	RAnkle	28:	right_ankle

Figure 4: Coordinates of REBA joints of interest, after re-referencing.

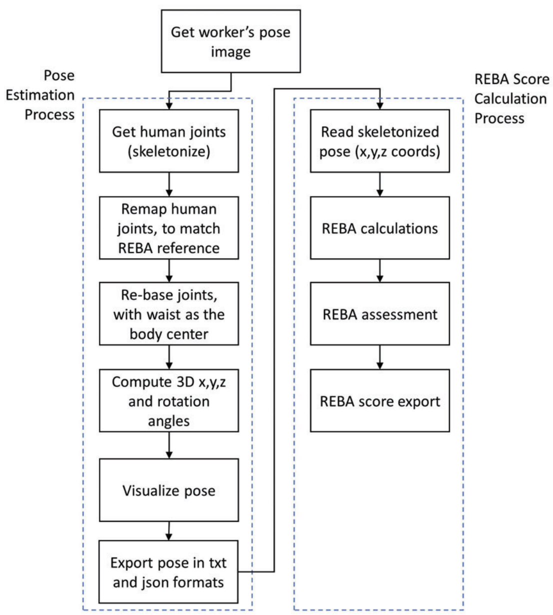


Figure 5: Human pose analysis flowchart.

The REBA calculation is done in six steps (neck, trunk, legs, upper arms, lower arms, wrists), by use of a *Python* code snippet (rs9000, 2022). In each above step, the degree associated with the mentioned body part is evaluated, and its REBA score is derived from an associated table of values as per the REBA worksheet.

Case Studies, Findings and Discussion of Results

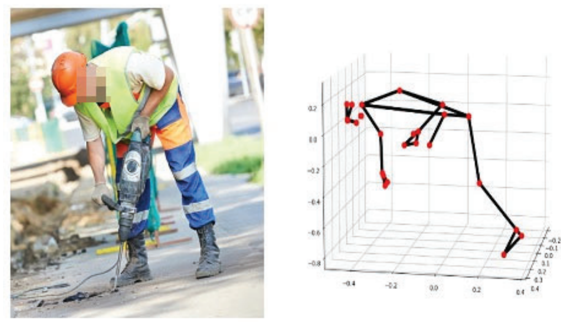
As case studies, several typical construction poses were analyzed (a subset of which is shown in Figures 1, 6- 12 and discussed below).

In studying the results extracted from the analyses of these eight poses, one can note:

1. the high accuracy in the detection of the keypoints in

(a) (b)

Figure 6: Before and after pose-estimation analysis; (a) Worker pose 2, (b) Skeletonized pose showing body part keypoints.



(a) (b)

Figure 7: Before and after pose-estimation analysis; (a) Worker pose 3, (b) Skeletonized pose showing body part keypoints.

the skeletonized representation of the depicted poses, when the pose to be analyzed is not obstructed;

2. the 3D skeletonized representation (x,y,z coords and rotational angles) of the detected keypoints, and thus the enabling of REBA calculations;

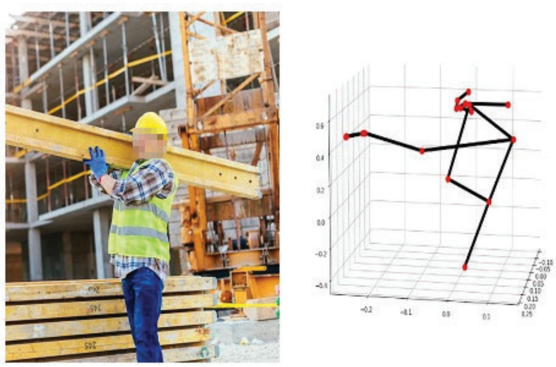
3. the automated and fast skeletonization of the pose (each image analysis is performed in milliseconds, on a generic laptop).

With regard to the accuracy of the REBA evaluation, a comparison of the manual application vs. the automated calculation is listed in Table 1.

In most case-study poses discussed herein, we notice small differences in the REBA scores obtained by the automated MV-based code as compared to the manual application of the method (Table 1). This does not necessarily infer an error in the utilized code but, rather, either a discrepancy in the appraisal (since the results of the manual computation are derived from the evaluator's personal assessment of body posture and thus a level of subjectivity), or an induced error due to an incomplete 'skeletonized pose' during the conversion process (e.g. Figures 8, 9 and 11). The two calculation stages (pose estimation/skeletonization and REBA score calculation) are interrelated and an

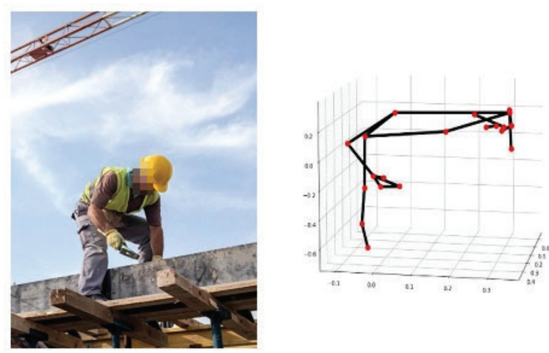
Table 1: Manual vs. MV-based analysis results

Pose	Computation Method	REBA Score A [Neck, Trunk, Legs]	REBA Score B [UpperArm, LowerArm, Wrist]	REBA Score C
Figure 6	Manual	[2,4,2]	[2,2,1]	6 (medium risk)
Figure 6	MV	[2,3,2]	[2,2,3]	5 (medium risk)
Figure 7	Manual	[3,4,2]	[3,2,2]	8 (high risk)
Figure 7	MV	[3,3,4]	[3,2,3]	10 (high risk)
Figure 8	Manual	[3,4,1]	[4,2,3]	9 (high risk)
Figure 8	MV	[3,5,4]	[4,2,3]	11 (very high risk)
Figure 9	Manual	[4,3,6]	[3,2,3]	9 (high risk)
Figure 9	MV	[3,3,2]	[2,2,3]	7 (medium risk)
Figure 10	Manual	[3,3,2]	[3,2,3]	8 (high risk)
Figure 10	MV	[3,3,4]	[2,2,3]	9 (high risk)
Figure 11	Manual	[2,4,2]	[2,2,3]	7 (medium risk)
Figure 11	MV	[2,5,2]	[2,2,3]	8 (high risk)
Figure 12	Manual	[2,4,4]	[3,2,3]	10 (high risk)
Figure 12	MV	[2,3,2]	[2,1,3]	4 (medium risk)



(a) (b)

Figure 8: Before and after pose-estimation analysis; (a) Worker pose 4, (b) Skeletonized pose showing body part keypoints.



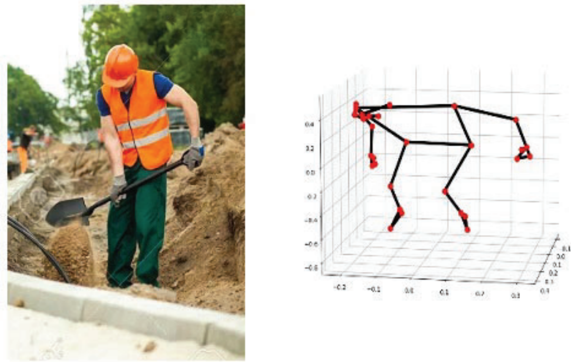
(a) (b)

Figure 9: Before and after pose-estimation analysis; (a) Worker pose 5, (b) Skeletonized pose showing body part keypoints.

incorrect pose estimation leads to an erroneous calculation of the slopes between the body parts of the figure and thus to an incorrect REBA score. This type of error (pose estimation) is, in most cases, due to the “unfavorable” image capture of the pose or even the quality of the image.

A higher difference is observed in the last pose analyzed (Figure 12). While the sub-scores (neck, trunk, legs, arms, wrist) obtained by the two methods do not show high differences between them, the total MV-based score is equal to 4 compared to the manually derived score of 10. The difference is due to an erroneous appraisal of the trunk position. The pose’s neck position has a negative slope resulting in a REBA score of +2, which together with the wrist (+3 for 15+ degrees of inclination and bent from midline) are the only partial scores that are consistent between the two methods. The trunk is inclined more than 60 degrees and, for this reason, it gets 4 points as opposed to the MV calculation which evaluates it with 3 points. As for the legs we have unilateral weight bearing (+2) and an inclination at the knees that clearly exceeds 30 degrees (+2) which gives us a leg score equal to 4, greater than that of the MV-based calculation (+2). Finally, the position of the upper arm varies between 45-90 degrees (+3) and the lower arm between 0-60 degrees (+2). The corresponding scores of the code are +2 and +1.

Achieving a full 3D visualization of the human pose is a serious challenge for the MV method since every different image capture received as input to the MV code must be evaluated so that 3D coordinates for each body part can be extracted from the 2D image. This constitutes the greatest difficulty of the analysis and at the same time testifies to the ability of the MV method to gain an understanding of the environment it “sees” in order to make a decision. Also, as aforementioned, any obstructions of body parts in an image (input) can be detrimental to the accuracy of the



(a) (b)

Figure 10: Before and after pose-estimation analysis; (a) Worker pose 6, (b) Skeletonized pose showing body part keypoints.

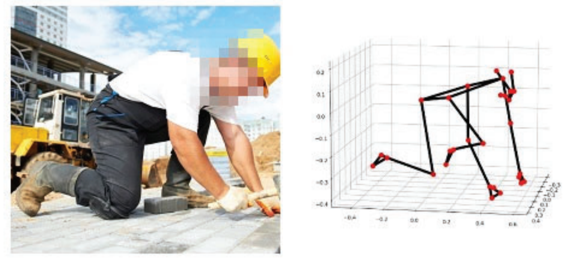
(a) (b)

Figure 11: Before and after pose-estimation analysis; (a) Worker pose 7, (b) Skeletonized pose showing body part keypoints.

method. This issue can be solved by using video streams instead of static images so that through movement there is a better view of the human pose and an improved perception of space by the software. In general, the code can be considered reliable and workable, and the results are reasonable and expected. Discrepancies in the results are experienced but not to the extent that they could affect the reliability of the method. REBA is impractical to be implemented manually and periodically at a construction site because one cannot constantly monitor the movements of the workers and manually calculate their REBA scores.

Conclusions

The automation of a worker's pose assessment and of compliance-checking during construction operations is of paramount importance to not only the health and safety aspects at the site but most importantly the short- and long-term health of the construction workers. The goal is to create a healthier and more progressive environment by using appropriate safety and health techniques during the construction of projects which will significantly contribute to reducing injuries within the construction site, as well as



(a) (b)

Figure 12: Before and after pose-estimation analysis; (a) Worker pose 8, (b) Skeletonized pose showing body part keypoints.

long-term health problems such as WMSD. The execution of construction projects always presupposes a safe workforce, and the use of MV techniques in the field of civil engineering must be perceived as a key part of improving the monitoring of health and safety conditions.

The present study focused on the automated detection of body postures during work at the construction site, and on their evaluation using the REBA method. The whole process was automated by applying a MV-based calculation of the associated REBA scores and the results were compared to the scores obtained by manually applying the REBA methodology. The MV-based scores, even though showing in some cases small deviations from the manually obtained REBA scores, are reliable and better applicable since they are fast and easy to compute by use of the proposed methodology.

As future work, the below actions to improve the accuracy and applicability of the proposed method are scheduled for implementation:

- Use a continuous image stream (video) for the analysis of poses, to increase the accuracy of the 3D skeletonization process and to weight-average REBA scores over time;
- Amend the MV code to include activity detection and classification so that the pose detection is related to an activity and thus a related force/load can be estimated (used in REBA Score A);
- Use on-site cameras (stationary or mobile) to capture and analyze construction poses over time, and a GDPR-compliant anonymization technology to process such images for the extraction of much-needed health and safety statistics.

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