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Video analysis for ergonomics assessment in the manufacturing industry: initial feedback on a case study

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The manufacturing industry is being benefited from the new technologies developed in the field of artificial intelligence. However, as part of the European AI strategy, the role of workers in the industry must be protected by including human-centered ethical values. The TEAMING.AI project is developing a revolutionary human-AI teaming software platform comprised of interconnected utilities. This work reflects the preliminary results of some of the methodologies that are being developed within the project.
An ergonomics assessment of manual activities performed by operators in a manufacturing workplace is carried out. The data for the assessment comes from video recordings obtained with cameras installed in strategic points of the shop floor. In this work, the assessment is done by manually selecting the images from the videos and scoring them based on the *Rapid Upper-Limb Assessment* and *Rapid Entire Body Assessment* methods. Once a scored is computed, an analysis of the activity is provided. The preliminary results show that distortion in the image from recording can affect the assessments. A method to enhance the video analysis in two major directions is proposed. The first direction focuses in the automatic operator detection. The second, on generating 3D information for ergonomic assessment with undistorted images. Some details related to the use case are omitted to preserve the anonymity of the operators in the company.

Keywords: Ergonomics assessment, REBA, RULA, 3D Pose Estimation, Deep Learning, TEAMING.AI

1. Introduction

The ongoing Industry 4.0 Revolution has proved its maturity with the digital transformation and announced the beginning of the Industry 5.0 Revolution. The new technologies developed in Artificial Intelligence have played an important role in this revolution and the manufacturing industry has being benefited from these developments Mocan et al. (2022). Furthermore, although the flexibility problem is a big worry for global competitiveness, there is a significant cultural acceptability barrier caused by the fear that humans will be supplanted by over-intelligent AI systems in the short to long term. However, AI systems can be used to handle the math and basic analysis, such as absorb data, classify and prioritise information, which can relieve skilled operators of a tedious burden of these tasks Buchmeister et al. (2019). In light of this, a European AI strategy faces two seemingly contradictory challenges: first, protecting the role of workers in the industry based on human-centered ethical values, and second, seeking a competitive position in the global market.

To achieve this goal, the TEAMING.AI[a] project is developing a revolutionary human-AI teaming software platform comprised of interconnected utilities.

Within human-centered systems, it is funda-

[a]https://www.teamingai-project.eu/

mental to take into account the human factors in the workplace. One important aspect of the human factors is the Ergonomics. This term refers to the scientific field concerned with the knowledge of interactions between humans and other system elements, as well as the field of study that uses theory, concepts, data, and methodologies to enhance human well-being and overall system performance Wilson (2014). Furthermore, ergonomists participate in the design and assessment of tasks, occupations, products, settings, and systems in order to make them compatible with people's requirements, skills, and limits Bridger (2017).

Workplace ergonomic issues and poor work organisation are significant risk factors to occupational safety and health issues DeMichela et al. (2014). A variety of workplace situations are thought to contribute to the rising prevalence of musculoskeletal disorders (MSD) among workers, including postural stress from prolonged sitting, standing, or awkward positions; stereotyped and repetitive work resulting in chronic injury; peak heavy load incidents to the axial or peripheral skeleton; environmental factors; and psychosocial factors such as psychological stress and pressure, lack of job satisfaction, and complacency Niu (2010).

This work aims to highlight an example of the needs in the manufacturing sector when adapting to the Industry 4.0. The potential solutions to ensure a human centered AI collaboration are discussed.

1.1. *Use case description*

For this study we are focusing in the case of GOIMEK which is a manufacturing company that produces high-precision machining of large-sized parts by either milling or grinding on the basis of cast materials or machine-welded structures. The operators at GOIMEK have to manipulate and manually clamp the milling parts before they are machined with the high precision manufacturing machines. This process takes an important part of the total cycle time of a working order and workers are exposed to occupational risks.

The machine of interest for this case study is an industrial milling machine for large parts such as torque arms, and bearing house of wind turbines. These parts are mounted on a mobile line that allows to transversely move between the two machining tables where the parts to be manufactured are clamped to. The so-called machining tables are structures where special supports can be adapted to create the appropriate mooring areas to clamp the metal parts. Each table can move in a two-dimensional plane, allowing it to accommodate parts of different sizes (i.e., place them closer or further from the milling machine).

2. Methodology

2.1. *Video recording of a selected task*

The hardware setup for video recording consists of three cameras, two mounted on the lateral corners of the manufacturing area, and a third mounted on a wall dividing the two milling tables. The places of the cameras are selected such that they can cover the whole area of interaction. Furthermore, they have overlapping areas, where 3D reconstructions would be possible.

From a technical perspective each camera delivers a gray-scale image at the size of 16 MPixel with a frame rate of 10 frames per second. They use a global shutter and are synchronised on a nano-second scale. One speciality are the utilised wide-angle lenses, which on the one hand allow a maximum field of view, but on the other hand introduce high distortions on the images. A high-performance PC collects the three images and merges them to a single one, which then is encoded in real-time on the GPU[b].

Currently a person is manually detected in an image and the image area around it is undistorted with an open-source implementation of Scaramuzza et al. (2006). These undistorted images form the basis for the further ergonomic assessments.

2.2. *Ergonomic Assessment*

The **Rapid Upper-Limb Assessment** (RULA) is a rating method of musculoskeletal loads for tasks

[b]`https://developer.nvidia.com/nvidia-video-codec-sdk`

where people have a risk of neck and upper-limb loading, McAtamney and Corlett (1993). The tool allows to provide a single score as a “snapshot” of the task, which is a rating of the posture, force, and movement required.

After score is computed, the risk is calculated using a defined groups where a score of 1 represents ”low risk” and 7 represents ”high risk”. Such scores are grouped into four action levels to indicate the time frame in which it is reasonable to expect risk control to be initiated. The groups are shown in Table 1.

Table 1. RULA Action Levels.

Action Level	Description
1	A score of 1 or 2 indicates that the posture is acceptable
2	A score of 3 or 4 indicates that further investigation is required and changes may be required
3	A score of 5 or 6 indicates that investigation and changes are required soon
4	A score of 7 indicates that changes are required immediately

Source: Handbook of human factors and ergonomics methods, McAtamney and Corlett (2004).

After deciding the upper arm to be assessed (whether the left, right, or both) the posture can be scored with using the free software found online at `http://www.ergonomics.co.uk/Rula/Ergo/index.html` or the paper version, McAtamney and Corlett (1993). The overall score may be compared to the action level list (shown in Table 1). In most situations, the activities lead to a more extensive examination to guarantee that this guide is utilised as a help in the efficient and effective control of any risks detected.

The **Rapid Entire Body Assessment** (REBA) method was created to evaluate the types of unexpected working postures common in the service sectors. Body position, forces employed, kind of movement or activity, repetition, and coupling are all recorded. The REBA score is calculated to indicate the level of risk and the priority with which response should be done Hignett and McAtamney (2000). The early development was based on limb position ranges adopting RULA principles. The functionally neutral posture is the baseline posture recommended by of Orthopaedic Surgeons (1965). The risk score rises when the posture shifts away from the neutral position. The 144 posture combinations can be converted into a single score that shows the amount of musculoskeletal risk.

To grade the posture, use the scoring sheet and body-part scores using the tables provided in McAtamney and Hignett (2004).The first round of scoring is done by group. First, the Group A includes the trunk, neck, and legs. Then, Group B consists on upper arms, lower arms, and wrists. The left and right sides of Group B postures are scored individually using the scoring sheet. Note that depending on the position, more points might be added or deducted. In Group B, for example, the upper arm may be supported in its current posture, hence 1 point is subtracted from the score. Once the load/force, the coupling, and the activity scores are computed at this step. This process can be repeated for each side of the body and for various positions. When all scores have been processed, the kind of muscle activity is then represented by an activity score (Table 8.3), which is added to the final REBA score to obtain the final REBA score as shown in Figure 4. These ratings are then grouped into five action levels shown in Table 2. This levels indicate how urgent it is to prevent or reduce the risk of the evaluated posture.

Table 2. REBA Action Levels.

REBA Score	Risk Level	Action Level	Action (including further assessment
1	negligible	0	none necessary
2-3	low	1	may be necessary
4-7	medium	2	necessary
8-10	high	3	necessary soon
11-15	very high	4	necessary now

Source: Handbook of human factors and ergonomics methods McAtamney and Hignett (2004).

2.3. *Ergonomics assessment procedure*

Video process. A seven hours video recording of an operator working a normal shift was provided by an applied production research company (PROFACTOR GmbH). The video shows the two milling tables and an automatic industrial milling machine (as described in Section 1.1) where the operator is working. The operator is, thus, visible to the cameras in all of his movements and displacements and we can also understand what the operator is working on.

Task identification. We examined the entire video, to search for movements that did not seem to follow the correct ergonomic procedure. This first identification was approximative for two reasons: first, we selected all the times the operator's ergonomic positions appeared incorrect without doing any detailed analysis. This first exploration helped to understand the nature of the operator's job and to detect incorrect positions. The second reason, and a premise for this ergonomics assessment, is the need of a constant front view of the operator to be absolutely certain that the ergonomic assessment is incorrect, which is a hard task with only three cameras. As a result, this assessment is based on a few landmarks that will be thoroughly explained in this section. The moments of interest (according to our above mentioned approach) were identified for later analysis by screening them from the video and zooming in on the operator's actions.

Image selection. After the filtering process, we selected the snapshots where the operator was visible and performing an ergonomically incorrect task (moments of interest). As the operator performed repetitive tasks throughout the shift, many of the snapshots represented very similar positions. Therefore, for this assessment only one snapshot per different activity carried out by the operator was selected. Furthermore, when the best picture to analyse seemed to be a challenging task, we chose the one displaying the operator performing the most pronounced ergonomically incorrect activity among the repetitions. Considering these criteria, our investigation began with 14 images that represented the operator ergonomic assessment. We time-labelled (start time, finish time, duration of performance, action description) each snapshot and performed three types of analysis: the first was based on the angles measured from the vertical axis, the second and third were based on the calculation of RULA and REBA scores. It is important to note that the entire analysis was done without taking the operator's strength into account.

Image analysis. The first step of the analysis is to observe each snapshot individually and identify the vertical axis using perspective rules. Then, to calculate the angle between that vertical axis and the operator's back line. The snapshot of the Figure 1, shows the operator cleaning the work surface after dismounting a milled part. A reference line parallel the crane's hook that descends vertically from the ceiling was used to determine the vertical axis. Following that reference, we traced the back line. We used an angle-measuring software (Online Protractor[c]) to calculate the angle's size. The same procedure was followed for all the selected images. Please note that the measures on the angles are approximated due to the distortions and point of view of the cameras. We present these images to exemplify the method and those distortions will be corrected in the future work.

RULA analysis. The following analysis uses the RULA tool (Section 2.2), which involves assigning a score to the operator's posture based on his upper limb disorders.

In this work, the risk factors investigated are numbers of movements, static muscle work, force and work postures determined by the equipment and furniture. Only one side of the individual is examined at a time (right or left) and a coding system is used to identify what level of intervention is required.

Following these rules, from Table 1, we assigned a score to each of the collected images in order to determine the level of intervention required based on the angle measured. This process was repeated per snapshot for each operator's action.

[c] https://www.ginifab.com/feeds/angle_measurement/

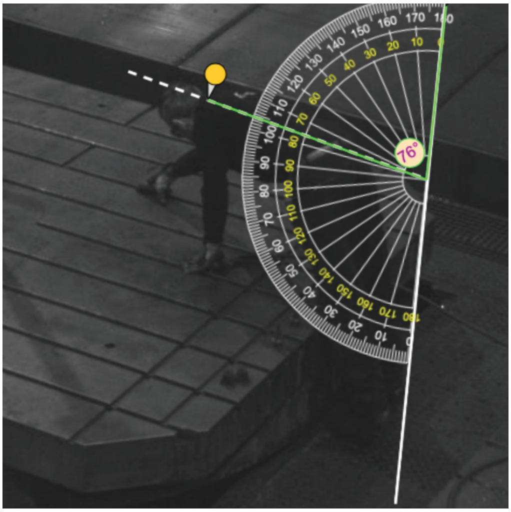

Fig. 1. Superposition of virtual angle measuring tool operator cleaning milling table.

As an example he operator working on top of a ladder to remove supports from the vertical wall as shown in Figure 2, is assessed. The RULA scores obtained for this activity are shown in Figure 3.

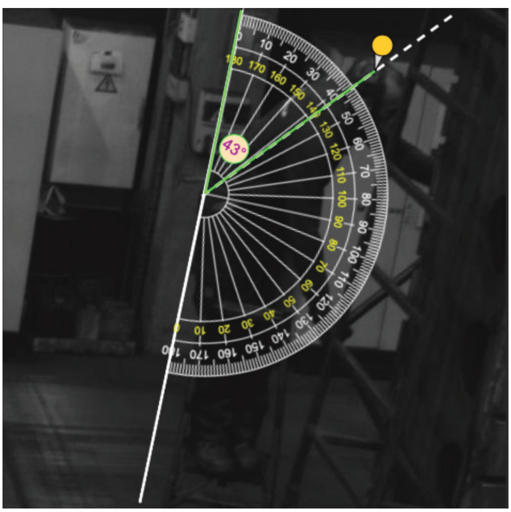

Fig. 2. The operator is working on the vertical support, on top of a ladder applying force using a tool.

REBA analysis. This analysis was done with the REBA method as described in Section 2.2. A similar procedure to RULA was adopted for this part of the analysis. We choose one snapshot

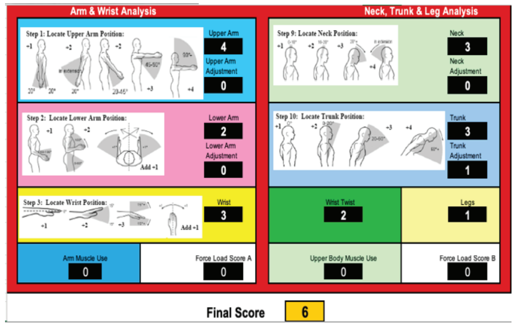

Fig. 3. The final RULA's score for that position calculated from the spreadsheet, where each score is explained with a drawing.

for each operator action and use REBA's scoreboard to calculate the corresponding score. For this method the body is divided into segments and coded individually with reference to movement planes: section A, covers neck, trunk and legs while section B covers arm and wrist.

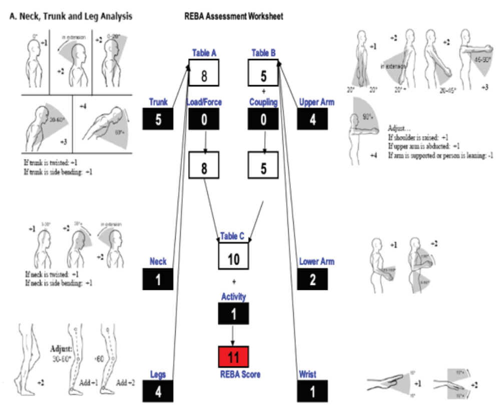

Fig. 4. The REBA tool shows the correspondent body part that is being scored to get the final score.

3. Results and discussions

3.1. *RULA assessment*

The Table 3 contains the scores obtained with the RULA tool. The high scores shown represent the activities with higher risk of injury.

The activity scoring 4 in Table 3, corresponds to RULA action level 2. This indicates that further

Table 3. Table summarising RULA's scores detected.

RULA Score	Activity
6	Stand on a ladder applying force through an instrument. Trunk rotated and inclined to the left.
6	Kneels on the surface with one knee/bent down, applying force through an instrument.
6	Carries heavy weights from. one side to the other.
6	Works crouched on the floor, applying force through an instrument.
4	Cleans surface with broom.
5	Kneels on the surface with both knees, crouched on top of the support wall. Unclamping part.

interaction changes may be required. However, the activities scoring 5 and 6, in Table 3, correspond to a RULA action level 3 out of 4. This means that investigations and changes are required more urgently than cleaning the surface with a broom.

3.2. *REBA assessment*

The Table 4 contains the scores obtained with the REBA tool. The high scores shown represent the activities with higher risk of injury.

The results show 4 out of 5 activities in Table 4 have scores 9 and 10. Therefore, according to Table 2, these activities fall in the REBA Action Level 3 which implies that the activities need an investigation and a change to implement soon. However, the operator working crouched on the floor applying force through an instrument leads to a REBA score of 11, as shown in Table 4. This represents a very high risk that needs an implementation of a change immediately.

4. Conclusions

The RULA score represents the level of MSD risk for the job task being evaluated. The minimum RULA score = 1, and the maximum RULA score = 7. The design goal for the RULA assessment is a score of 3. The Risk Index answers the question "How significant is the risk?". As mentioned before, the RULA's score was calculated for each one of the screenshots. At the end, we revised the highest scores and summarised them in the following table: two of them has in common that the operator is crouched, but, in general, in all the actions the operator has a bad posture of the back: those positions could cause a long-term disease for the operator' health. If the score exceeds the level 2 means that the risk for a MSD is becoming significant and a change in working conditions is recommended. In view of prevention would be advisable that the operators would be educated on proper lifting techniques, ergonomic principles, body mechanics and self-care tools and techniques.

Table 4. Table summarising the highest REBA's scores detected.

REBA Score	Activity
9	Stand on a ladder applying force through an instrument. Trunk rotated and inclined to the left.
9	Kneels on the surface with one knee/bent down, applying force through an instrument.
10	Carries heavy weights.
11	Works crouched on the floor, applying force through an instrument.
9	Kneels on the surface with both knees, crouched on top of the support wall. Unclamping part.

5. Future Work

5.1. *Video analysis*

It is planned to enhance the video analysis in two major directions, see Figure 5 for the envisioned automatic image analysis pipeline.

First, the detection of people should be done automatically. Here, a prototype based on Xiao et al. (2018), which detects first heads and then the whole body is currently evaluated. The major challenge here is to make the detector robustly working on the high-distorted images.

Second, wherever possible 3D information

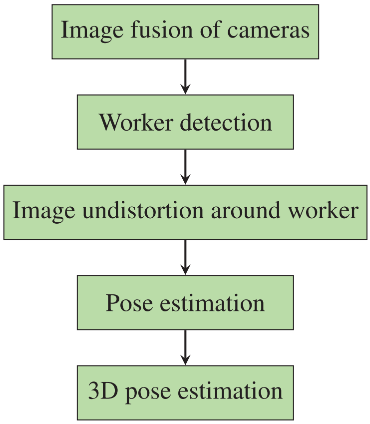

Fig. 5. Envisioned automatic image processing pipeline. People should be detected automatically and 3D information should be generated on estimated poses either through triangulation or with the help of deep-learning algorithms.

should be generated, to enable a real ergonomic assessment. Here two sources of 3D could be used, either via triangulation of the undistorted images in the overlapping areas of the cameras, or via deep-learning-based 3D estimation as shown e.g. in Bazarevsky et al. (2020). Figure 6 depicts a demonstration on an example image.

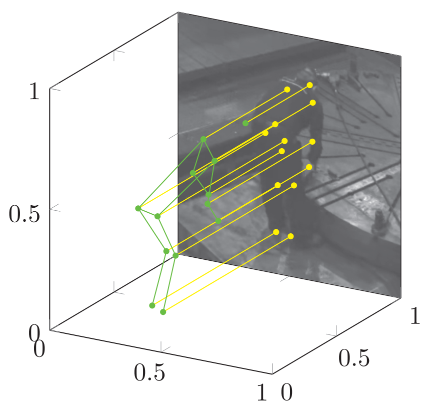

Fig. 6. 3D estimation of a workers pose, calculated with the work of Bazarevsky et al. (2020).

5.2. *Proposed Machine Learning approach*

Assessment of ergonomic risk can be further automated by using machine learning (ML) models, which enables online detection of dangerous movements and can serve as integral part of an early warning system. The proposed architecture of the ML model is presented in Figure 7. The algorithm takes a sequence of human poses as inputs, and uses deep neural networks Yan et al. (2018) to process these multivariate time series signals to compute ergonomic predictions. Depending on the application, the prediction problem can be either formulated as a classification problem (where the output of the model is either "high" or "low" risk) or a regression problem where the REBA/RULA score is estimated directly.

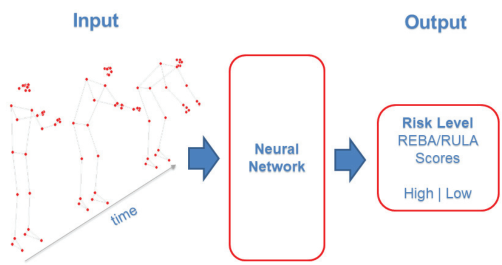

Fig. 7. General scheme of the machine learning algorithm for the prediction of the ergonomic risk score or class based on sequence of human pose data.

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