Explaining the Ergonomic Assessment of Human Movement in Industrial Contexts

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Abstract: The repetitive nature of manufacturing processes is identified as a risk factor for the onset of musculoskeletal disorders. For prevention, the operator's exposure risk is measured through ergonomic risk scores which are often associated with a workstation, ignoring the variability among operators. Moreover, the score values hinder a comprehensive interpretation by occupational physicians. Observation methods require significant effort, preventing accurate and continuous evaluation. The conducted study developed a solution using inertial sensors for automatic operator risk exposure in the manufacturing industry. Two experimental assessments were conducted: laboratory validation, performed by 14 subjects, using an optical motion capture system as a reference; and field evaluation, with 6 participants, acquired on a real automotive assembly line, served as the basis for an ergonomic risk evaluation study. Through the research, it was implemented an upper-body motion tracking algorithm relying on inertial information, to estimate the angular orientation of anatomical joints. An adjusted ergonomic risk score, based on direct measurements was developed allowing an ergonomic evaluation which also has an explanation approach, based on the comprehensive analysis of the angular risk factors. Direct measurements fasten the ergonomic feedback, consequently, the evaluation can be extended to more operators, ultimately preventing work-related injuries.

1 INTRODUCTION

Work-related musculoskeletal disorders (WMSDs) represent a significant portion of work-related health problems in the European Union, impacting employees from different working sectors (Irastorza et al., 2010). According to the World Health Organization, musculoskeletal conditions are the second largest contributor to disability worldwide and they are predicted to rise as the global population ages (Luttmann et al., 2003). During 2017-2018, the upper limb or neck disorders accounted for approximately 42% of WMSDs, and within these, elbow diseases are the most prevalent (H. Seidel et al., 2019).

In some industry sectors, e.g. textile and automotive, production processes are typically based on the cooperation between humans and machines. Although the work methods carried out by workers have predefined motions and actions, their repetitive nature can increase the risk of musculoskeletal disorders development, leading not only to absenteeism but also early retirement and loss of productivity (Uva et al., 2008; Varandas. et al., 2019).

On large industrial environments, there are still some unsolved challenges which prevent a more effective ergonomic job analysis. During the work method design, which comprises a set of predefined motions, manufacturing industries rely on ergonomic assessment tools which measure the workers' risk exposure through a risk score value. Thus, for a given work method, the global risk score is calculated taking into account all local scores associated with each motion or action that composes the work cycle. However, those are based on an average worker, meaning that they do not take into account the variability among operators that may exist at the manufacturing

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plant population, such as anthropometric variations, operator's age and work experience. Additionally, ergonomic teams might still rely on observational methods, which involve dedicated personnel to observe or video record operators at work for posterior analysis. Due to the high workload involved in this process, it becomes unfeasible to employ observational methods across the complete manufacturing population. Moreover, the outcome of the ergonomic risk assessment results in a number which quantifies the associated risk yet, when occupational doctors receive their patients and wish to access the history of the assigned workstations and associated ergonomic risk, they only have access to a score to describe the risk, which is insufficient for an adequate analysis to the contributing risk factors that lead to a given global risk score.

Although robots are becoming more common in manufacturing environments, operators are still essential. However, the concept of an operator is undergoing a paradigm shift through the new generation of operators coming entitled "Operator 4.0". These new smart and skilled workers will have "super-strength" provided by exoskeletons, smarter decision capabilities supported by artificial intelligence, and able to age healthily at work supported by a set of wearable body monitoring devices (Romero et al., 2016).

2 RELATED WORK

Wearable devices have attracted considerable attention to industrial environments. By using inertial motion capture systems, data can be collected, and several parameters can be directly measured, e.g. position and velocity of each body segment, postural angles trends and gait parameters, making these fundamental for ergonomics studies (Caputo et al., 2019; Wang. et al., 2019).

Several surveys have been published concerning human motion tracking as in (Filippeschi et al., 2017) and (Pereira et al., 2017). Among the studies which used human motion tracking methods for ergonomic assessment in industrial concepts, (Battini et al., 2014) used solely inertial sensors to perform a full-body ergonomic evaluation based on several ergonomic worksheets. (Peppoloni et al., 2016) and (Vignais et al., 2017) focused on the ergonomic assessment of the upper body regions but combined the inertial measurement units (IMUs) with other methods such as electromyography, goniometers and video system. On the other hand, (Bauters et al., 2018) relied on a video system to perform a full-body analysis to deliver operators productivity indicators.

In general, the studies fail to provide an error estimate for their motion tracking system. This can be achieved by matching the proposed tracking methods against other validated motion capture technique considered as ground truth. Moreover, the overall results of ergonomics worksheets are uniquely a single score value, lacking a more comprehensive analysis of the risk factors.

There are some limitations associated with the use of inertial sensors. For instance, gyroscope's measurements are affected by drift over time due to the integration of device's defects and noise (Beavers, 2017). Furthermore, sensor fusion techniques often require to tune empirically the most adequate filter parameters. Hence, one solution is to use a complementary filter with few tuning parameters to mitigate the impact of gyroscope's drift. Video systems also present some challenges, e.g. the recordings are limited to defined camera angles.

This work comprises the development of a motion tracking framework for a direct and continuous ergonomic risk assessment on industrial contexts. We intended to encompass a cost-effective solution to establish quantitative direct measurements of posture and movement using inertial information, from accelerometers, gyroscopes and magnetometers, for the upper-body. Those measurements will be able to continuously monitor operators individually producing also more comprehensive reports with explanations, concerning the most contributing factors for the calculated risk scores. Herewith, our work presents three major contributions: (1) an upper-body motion tracking algorithm relying only on inertial information, to estimate the absolute or relative angular orientation of anatomical joints; (2) the development of an adjusted ergonomic risk score, based on direct measurements, and (3) an ergonomic risk explanation approach, based on the comprehensive analysis of the angular risk factors. It is expected that in long-term this solution will help in the prevention of upper limb WMSDs arising from repetitive tasks.

3 PROPOSED METHOD

When planning the implementation of a system using direct methods for an ergonomic assessment, there are typically three design considerations: explainability, invasiveness and scalability. Explainability relates to the degree of information that a setup can report. Invasiveness is related to the operator's discomfort level and also to the impact on the operator's performance due to the setup. Scalability establishes how many subjects can, simultaneously, use the setup, depending on invasiveness and cost. We propose a system which allows extracting information at an intermediate level, i.e. calculating low-level metrics of ergonomic risk and not demanding a large number of sensors. Thus, it is expected that the system has an average level of scalability, explainability and invasiveness.

3.1 System Overview

The developed upper body motion tracker system is a sequential algorithm designed to obtain the time-dependent angular information of several anatomical segments. Since the upper limbs and spine are regions with a higher prevalence and incidence of work-related musculoskeletal disorders, the upper body was the main focus of this research. Therefore, four anatomical segments were defined:

- **Arm** segment, as the segment between shoulder and elbow joint;
- **Forearm** segment, as the segment between elbow and wrist joint;
- **Hand** segment, as the segment between wrist and distal region of the third metacarpal;
- **Torso** segment, as the segment between the jugular notch and the xiphoid process of the sternum.

The motion tracker implementation pipeline is depicted in Figure 1.

Data acquisition is the first stage of the process. Four IMU devices were employed and each of them was attached to one of the four considered segments, collecting acceleration, angular velocity and the magnetic field data.

Signal processing methodology comprises pre-processing and orientation estimation. The first was divided into two main processes: temporal synchronisation, where equal sampling frequency and temporal alignment was ensured between the four IMU devices, and noise reduction, through the implementation of a first-order low-pass Butterworth filter with a cutoff frequency of 1 Hz, on accelerometer and magnetic field data. In its turn, orientation estimation describes the applied sensor fusion method and the necessary considerations to obtain the angular information of one segment relative to another or relative to an anatomical plane.

The considered model admits flexion/extension, abduction/adduction, for shoulder joint; flexion/extension and pronation/supination for the elbows; flexion/extension and ulnar/radial deviation for the wrist. Finally, the model also allows for the torso flexion/extension and lateral flexion/extension. Consequently, the whole model admits 8 degrees-of-freedom and considers human movements of the upper limb and torso.

3.2 Inertial Signal Acquisition

In the context of this research, 9-DoF IMUs containing a triaxial accelerometer, gyroscope and magnetometer were employed. The IMU devices collect data sampled at 100 Hz and they were placed at the following regions: IMU 1, IMU 2 and IMU 3 were positioned at the posterior side of the hand, forearm and arm, respectively. Particularly, IMU 2 was placed in the wrist area and IMU 3 was located in the elbow region. IMU 4 was positioned in the thorax area. To assure a common axis alignment, the local axes direction of each device must be known before attaching the device to the subject. It was considered that the Y-axis, of all devices, points up. Figure 2 illustrates the inertial devices placement.

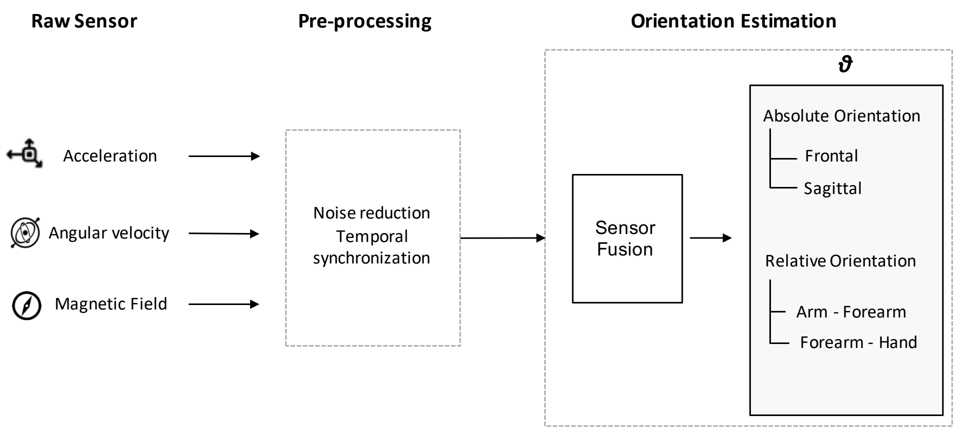

Figure 1: Upper-body motion tracker system framework.

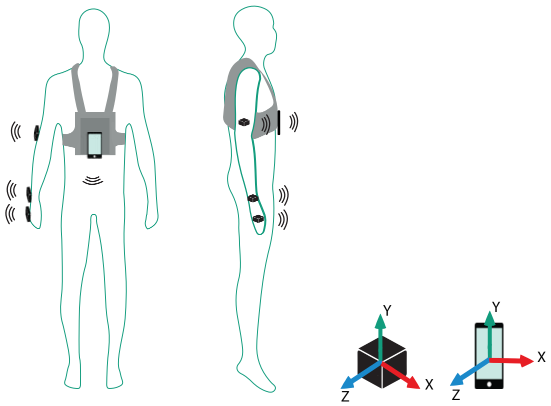

Figure 2: Placement of the IMU devices: three units on the right upper limb and one unit on the torso. The devices were commonly aligned with Y-axis pointing up.

3.3 Orientation Estimation

In order to estimate the anatomical segments attitude, the signals gathered from accelerometers, gyroscopes and magnetometers was combined through a sensor fusion method. An algebraic algorithm, followed by a quaternion-based complementary filter (QCF), derived from (Colton, 2007; Valenti et al., 2015), were implemented.

3.3.1 Algebraic Method

Data from accelerometer and magnetometer sensors were combined using an algebraic algorithm (Lerner, 2012). Throughout the algorithm implementation, the information of these two vectors was combined defining an orthogonal coordinate system with the basis vectors, expressed as a 3×3 rotation matrix. Afterwards, the rotation matrix can be translated into a reference quaternion, which represents the orientation of a segment relative to Earth Reference Frame, following East-North-Up configuration. However, the reference quaternion does not represent the final orientation, once it only relies on accelerometers and magnetometers readings. Nonetheless, this quaternion was presented as measurements to QCF to obtain the final estimated quaternion.

3.3.2 Quaternion-based Complementary Filter

The quaternion-based attitude method updates the estimated quaternion through gyroscope's measurement and rectifies it based on a reference quaternion from the accelerometer and magnetometer measurements.

Using a quaternion representation of gyroscope's data and combining it with a previous instant estimated attitude quaternion, through the Hamilton product, results in an update quaternion which represents the device rotation.

For initialising the filter, the update quaternion is set equal to the reference quaternion. This way, both of them represent the same device orientation. Nevertheless, for every sensor reading interval, a rectification and calculation of the estimated quaternion take place. Next, we used interpolation to the reference and the update quaternions. A Spherical Linear Interpolation (SLERP) (Dam et al., 1998) allows to weight between the two quaternions. Once the gyroscope is very accurate in short intervals it is more weighted. Nevertheless, to stabilise the unwanted sensor drift, a minor amount of the interpolation is directed towards accelerometer and magnetometer, which are sensors more trustworthy in the long term.

The estimated orientation exhibits the QCF characteristics which combine high-frequency measures from gyroscope and low-frequency from accelerometers and magnetometers to deliver reliable motion information.

3.4 Angular Trajectory Reconstruction

After determining the estimated segment quaternion, it is possible to make assumptions on the angular motion. It is assumed that consecutive IMU devices, placed on the upper limb segments, are aligned, i.e., have one local axis that has the same direction. Direction vectors can be expressed through pure quaternions in Sensor Frame. Making use of the dot product between two vectors, the angle between segments is determined.

Angular information between two consecutive segments is defined as relative orientation. On the other hand, the angle between a segment and an anatomical plane is defined as the absolute orientation. The anatomical planes were defined using the local axes of an inertial device placed on a subject's torso. Additionally, the IMU device placed on the torso segment is relevant to estimate the torso flexion and lateral flexion. The angle of these last movements is accomplished by comparing the torso's current state with torso's rest position.

4 RESULTS

Two experimental assessments were conducted: laboratory validation and field evaluation. The laboratory tests enabled the creation of a movements' dataset, where the proposed technique and a computer vision approach were compared with an optical motion capture system. The field evaluation dataset was acquired on a real automotive assembly line and served as the basis for the ergonomic risk assessment study.

4.1 Laboratory Validation

A validation protocol was designed to assess the proposed method performance. Thus, to measure the tracking error, the Vicon optical-passive motion capture system was used as a reference, which has a reported error lower than 2 mm (Merriaux et al., 2017).

The proposed framework is intended to be used through long-term acquisitions, corresponding to the operator's working shifts. However, sensor's may present some change in response over time, which will be an issue. Another layer of information, to periodically correct this sensor drift, might be a solution. Despite video processing is computationally more expensive than inertial sensor processing, it can be used during short iterations to reset the drift from sensors. Therefore, a video collection on the validation protocol is introduced to test and characterise the computer vison-based library OpenPose (Cao et al., 2018). The OpenPose is an open-source markerless technology for multi-person 2D pose detection, identifying in total 135 keypoints, on single image, using convolution neural network.

The acquisition protocol was performed by 14 subjects, nine men and five women, with an average age of 26 ± 3 years. It allowed measuring the angular error across all considered joints in a wide range of different movements. The validation protocol was composed of two main parts: one describes a static movement evaluation and the other details a dynamic evaluation. The concepts static and dynamic denote if the subject was standing or walking while doing the designated movements, respectively.

Subjects wore a motion capture setup composed of four IMUs sampling at 100 Hz and optical markers tracked by Vicon cameras at 100 Hz. The Vicon setup was composed of ten cameras, measuring an acquisition area of 8x4 m, and two standard cameras filming the whole exercise, which were also used as input for the OpenPose algorithm. The optical markers' positions followed Vicon's Upper Limb Model Guide descriptions (Vicon Motion Systems, 2007). Raw data is composed of 2 recording hours.

Several actions were manually segmented, specifically flexion/extension, abduction/adduction/, lateral flexion, ulnar/radial deviation and anatomical position for static evaluation; flexion and anatomical position for dynamic trials. Figure 3 exhibits an example of an angular reconstruction, representing the performance of QCF and OpenPose. It can be observed that both methods reconstruct the motion similarly to Vicon however, it can be noted an offset from OpenPose during abduction and from QCF during anatomical position.

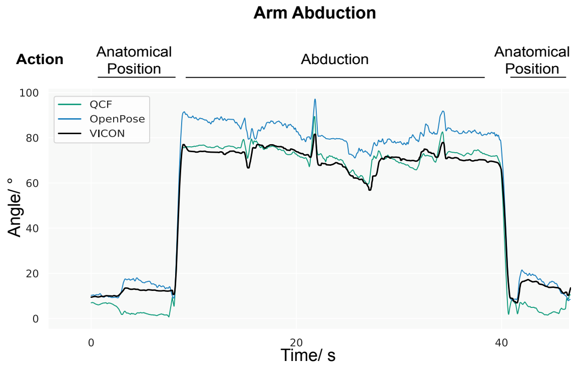

Figure 3: Angular reconstruction of arm's abduction and adduction. QCF (green), Vicon (black) and OpenPose (blue) results.

It is relevant to explain that the procedure adopted to adjust the light conditions of the tests is complex. On one hand, the best conditions for using Vicon require low ambient light, while on the other hand, the conditions for using OpenPose require regular ambient light so that the subject's skeletal image contours can be identified by the model. It was decided to minimise Vicon's error, since it was considered the ground truth of this study and low ambient light conditions were applied. However, this fact degraded the performance of OpenPose algorithm, and consequently the hand segment had to be neglected due to inadequate low light conditions.

To perform a quantitative performance assessment of both methods, two evaluation metrics were used: the Cumulative Distribution Function (CDF) and the Root-Mean-Square Deviation (RMSE). The function represented in equation (1) is the CDF of a real-valued random variable X,

$$F_X(x) = \mathrm{P}(X \leq x) \tag{1}$$

where $\mathrm{P}(\mathrm{X} \leq x)$ is the probability that the considered variable X takes on a value less than or equal to x.

Algorithms can be analysed using their RMSE as a measure of how well they describe a given set of observations. Equation (2) represents the RMSE, where y_t denotes the groundtruth value at time t provided by Vicon and $\hat{y}_t$ denotes the predicted value at time t estimated by the upper-body tracking method.

$$\mathrm{RMSE} = \sqrt{\frac{1}{\mathrm{T}} \sum_{t=1}^{\mathrm{T}} (y_t - \hat{y}_t)^2} \tag{2}$$

Firstly, the CDFs were calculated to assess each segment performance under the QCF and OpenPose

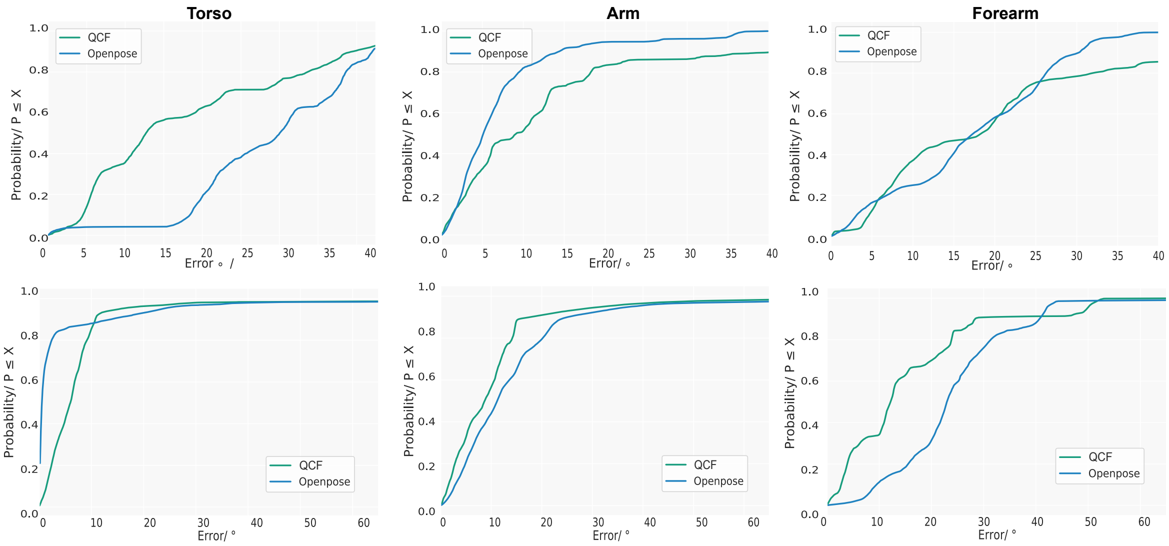

Figure 4: Cumulative distribution function for the absolute error of OpenPose and QCF across torso, arm and forearm segments. **Top:** static evaluation; **Bottom:** dynamic evaluation.

methods. Figure 4 represents the CDF for QCF and OpenPose techniques. Through the analysis of the CDF for the static tests, it is possible to conclude that arm and forearm's movements present a lower error when assessed with OpenPose algorithm. However, the torso's reconstruction shows better results with QCF.

Contrary to static tests, in dynamic trials OpenPose presents better results for torso movements and QCF has a higher performance for arm and forearm exercises.

Table 1 represents the RMSE results for both static and dynamic trials.

Table 1: Root mean square error regarding QCF and OpenPose methods. Static and dynamic evaluations.

	QCF		**OpenPose**	
	RMSE (°)		RMSE (°)	
	Static	Dynamic	Static	Dynamic
Torso	**22**	**21**	25	23
Arm	18	**27**	**13**	29
Forearm	30	**20**	**20**	27

In general, the table allows inferring that QCF and OpenPose have similar performance. The arm segment presents the lowest movement's error in static trials. In its turn, the forearm segment overall results show a higher error in both algorithms when comparing it Vicon's reference.

4.2 Field Evaluation

This section of the study consisted of an ergonomic risk assessment of three workstations at a real automotive assembly line, comprised by repetitive work cycles.

In this study, we recruited six participants, four men and two women, with an average age and height of 31 ± 8 years and 173 ± 6 cm, respectively, without any known musculoskeletal pathology. The operators were asked to perform their working tasks while using IMUs attached to their body. Prior to the experiment, subjects signed and obtained a participation informed consent. This research reports the results from three workstations, Liftgate, Fender and Doors, from the Bodyshop assembly line. Operators wore four IMUs and were asked to perform two calibration positions, N-pose and T-pose, in the beginning, and at the end of the test. The curated dataset is composed of 4.23 recording hours.

4.2.1 General Workstation Risk

Before adopting strategies to improve working conditions, situations that can contribute to operators' risk must be identified. Ergonomic indexes grant information on the main risk factors, allowing to prioritise interventions. The Rapid Upper Limb Assessment (RULA) worksheet can be used to screen and identify harmful postures (McAtamney and Corlett, 1993). In this research, we developed an adapted version of RULA's, named Adjusted Rapid Upper Limb Assessment (AdRULA), which was implemented. The

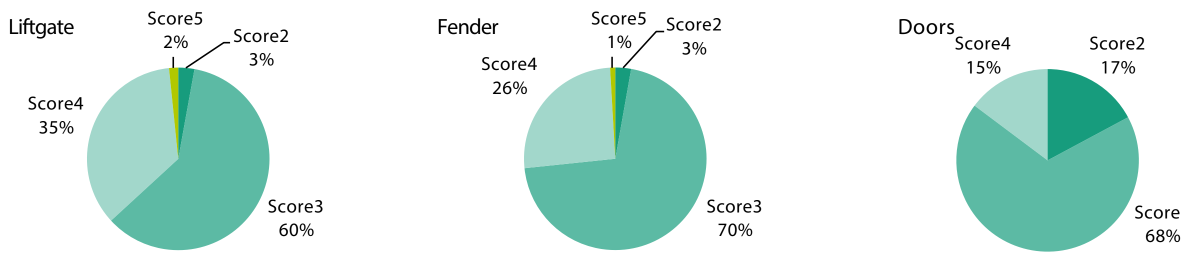

Figure 5: Liftgate, Fender and Doors workstation analysis. Mean score distribution for each workstation.

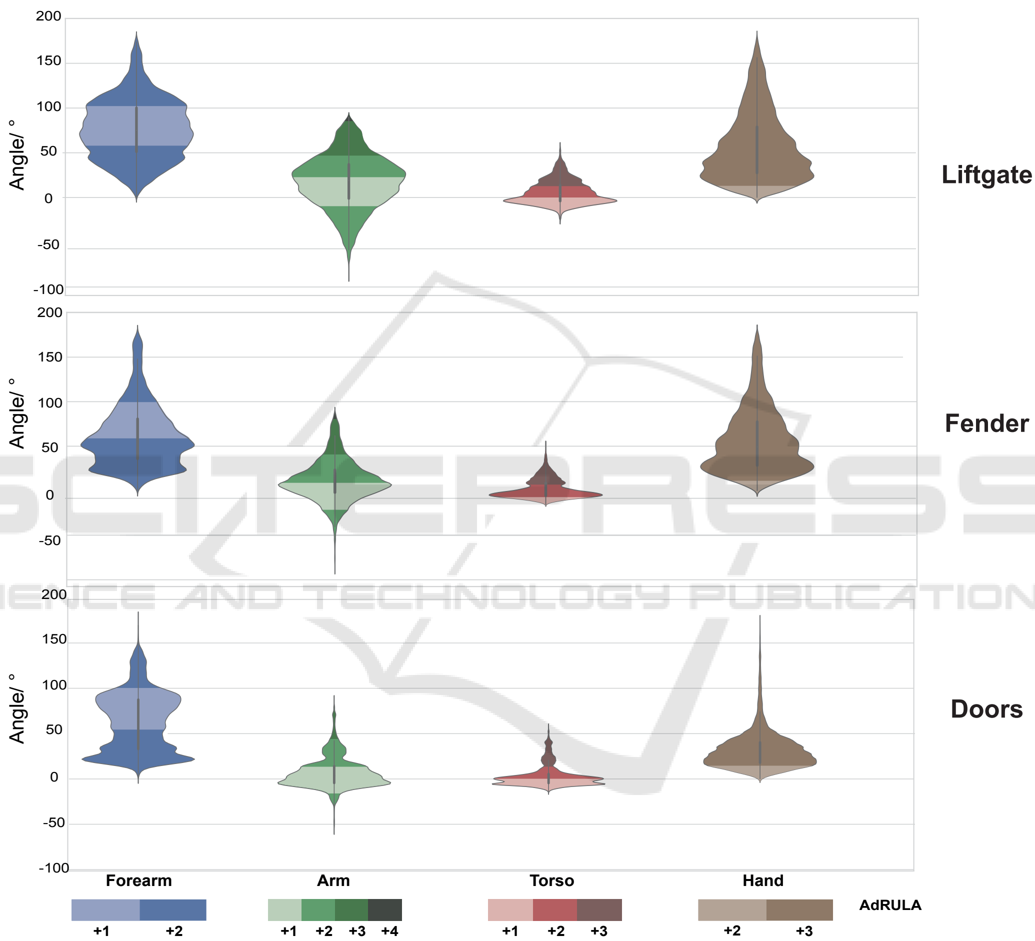

Figure 6: Representation of operator's average flexion and extension movements from Liftgate, Fender and Doors workstations with AdRULA score thresholds.

AdRULA focus on the subject's upper-body selects postures every 0.02 s and apprehends poses via direct measurements, e.g., wearable technology. The local and final scores are determined similarly to the RULA method.

The average workstation's score, using AdRULA index, summarised in Figure 5, was determined through two steps: 1) considering a single operator performing the actions of a selected workstation, in each work cycle, it was determined the percentage of time spent in each score and, afterwards the individual average was obtained; 2) the mean score for a given workstation is finally calculated by averaging all the operators scores (calculated in the previous step).

The charts demonstrate that, in general, when operators perform tasks in the considered workstations they stand for a longer period in a level 3-4 risk zone which represents a low risk. Despite being a small percentage, the Liftgate and Fender workstations present a level 5 risk. Accordingly, those workstations represent a higher risk to operators in terms of postures. We anticipated these results since Liftgate and Fender are workstations which require postures more prone to a higher exposure risk, such as overhead motions.

4.2.2 General Workstation Explanation

From an ergonomic perspective, it is relevant to identify which movements contribute to a higher risk of injuries. For the rest of this section, we present a more detailed analysis of the factors that contribute to the global scores, in order to complement the analysis with a more interpretable and explainable methodology. Figure 6 represents the distribution of extension and flexion movements for each workstation, in the form of a probability density of these data.

It can be observed that the torso's movements have similar angular distribution for the considered workstations. Moreover, for Liftgate and Fender, the hand movements have a higher probability of performing flexion exercises around 50° while in the Doors workstation the highest probability stands in the 25° range. Flexions and extensions distribution between arm and forearm segments present evident unlikeness. While in the Liftgate, the forearm presents a highest density probability between 50° and 100°, Fender and Doors present two prominent probability peaks: 25° and 50° for Fender; 25° and 90° for Doors. Overall, as working conditions are more demanding for arms and hands, the Liftgate is classified with higher scores. Doors workstation, with a larger probability of postures around the segment's neutral zone, is evaluated with lower levels.

4.2.3 Team Explanation

While working in the same workstation, operators might not share the same characteristics, e.g., height, weight, limbs length, and others. Figure 7 represents the probability density of four different subjects performing the tasks assigned to the Liftgate workstation. Subjects' characteristics are also depicted. Throughout the analysis, it can be reasoned that among operators from the same workstation, which have different characteristics, angular movements distribution is not identical. Consequently, the individual's ergonomic risk will be different from the one that could be assigned to an average worker. The score value might not be simple to interpret and consequently, hinder occupational doctors and team leaders to perceive operators' needs. The individual analysis helps to understand if the operator performs tasks within the workstation risk range or if their characteristics intensify/mitigate the risk. Thus, having personal reports, with detailed movements information, can be an advantage for improving injuries-preventive recommendations and for adjusting work conditions.

5 CONCLUSIONS

WMSDs represent a significant portion of work-related health problems, affecting workers from all sectors. This research provided three major contributions. Firstly, an upper-body human motion tracking algorithm using inertial sensor information was used to estimate the absolute and relative orientation of anatomical joints. Secondly, an adjusted ergonomic risk score was developed based on direct measurements. Finally, an ergonomic risk explanation approach, based on the comprehensive analysis of the angular risk factors was presented.

Several conclusions were established using the validation dataset. The OpenPose approach was used as a mocap method, with similar performance to QCF, yet it has some challenges. The first is that OpenPose is a computationally expensive algorithm. Secondly, it is also prone to error in the presence of occlusion (when the algorithm fails to track a limb).

Employing the estimated orientation of anatomical joints, provided by the system, it is possible to conduct an ergonomic risk assessment. The workstations that presented a higher level of risk, Liftgate and Fender, behold actions that, effectively, require positions more susceptible to risk, e.g. overhead work. Nowadays, the global risk score is often agnostic to the variability of operators' characteristics and the scores, assigned based on ergonomics assessments, use as reference an average worker. While completing the risk analysis, it is possible to point out evident motion differences among operators who perform the same workstation's tasks. Hence, an individual ergonomic approach is better suited for preventing injuries, once it can unmask risk factors exposure. The evaluation should be individual-related and not the collective. Whenever risk exposure management is a concern, the ergonomic analysis should be available for each worker. At last, providing explainability to risk assessments is an added value to occupational doctors once it allows a more comprehensive analysis which can be relevant to support the decision-making process for different strategies that can be addressed to the worker by the Team Leader and/or occupational doctor.

Comparing to previous researches presented in literature (Battini et al., 2014; Vignais et al., 2017) this

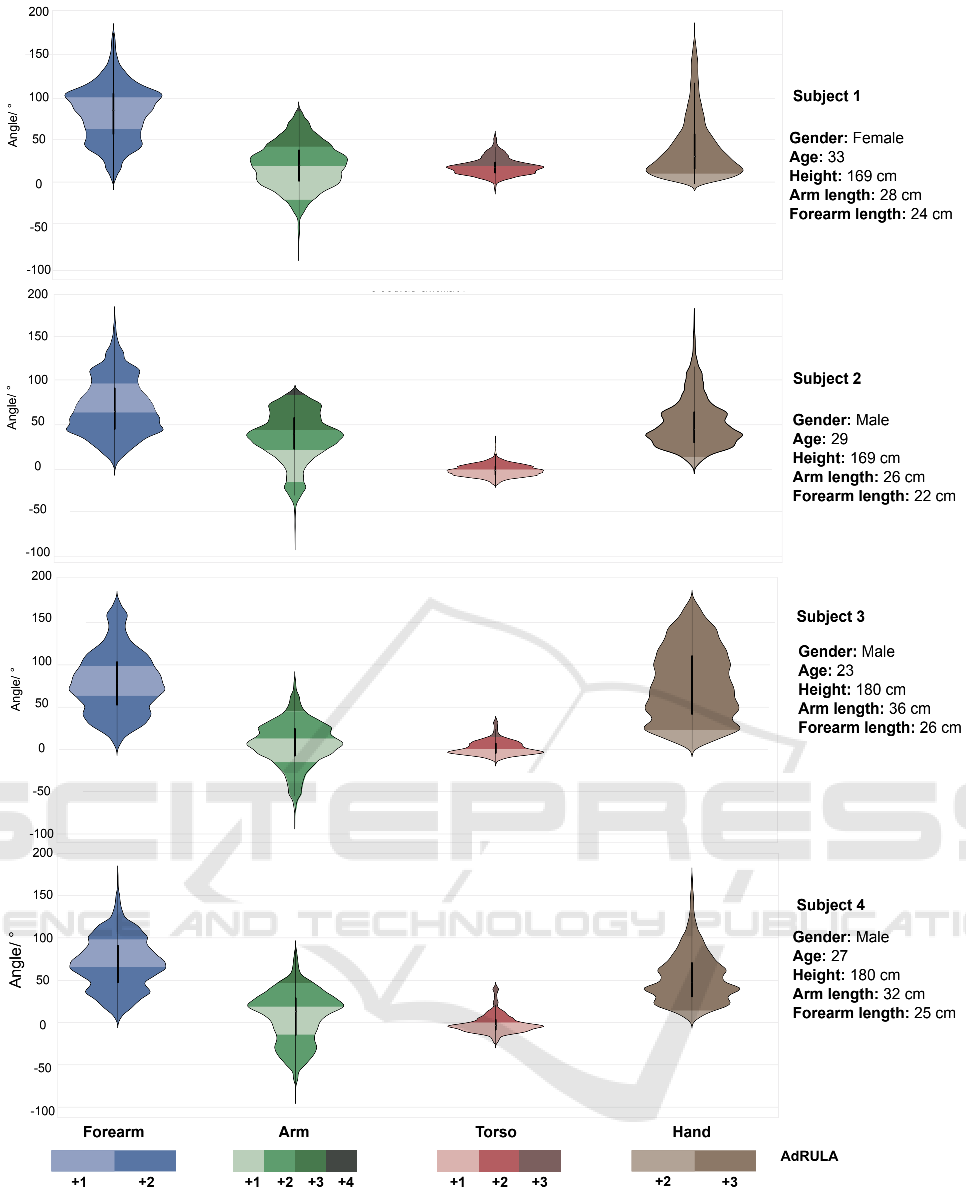

Figure 7: Comparison of average flexion and extension movements distribution from four different subjects while performing Liftgate's tasks, with AdRULA score thresholds. Right side - subjects' characteristics.

study provides a quantitative error estimate of the proposed tracking system, accomplished through a laboratory validation. We combined different analysis tools regarding the two experimental assessments, the laboratory validation and the field evaluation. The trials required to design and organise two protocols in which sensors attachment, calibration and monitoring were detailed and contained guidelines for both participants and specialists. Furthermore, the provided ergonomic study is not only concerned with delivering a global risk analysis of a workstation, but it also reaches the individual level.

With the current work, we can conclude that the proposed method is feasible in a real manufacturing context and provides a faster ergonomic analysis. Accordingly, we encourage the use of inertial sensors as an effective method for detailed ergonomic assessment in industrial environments. Nevertheless, the study has a limited sample size thus, to improve robustness, the data collection should be increased.

As future work, it is expected to reduce the sensor fusion accumulated errors of the long term system which arise from the need of sensors to re-calibrate. A solution would be introducing multimodal sensor fusion approaches, e.g. using video recordings to periodically calibrate the system. Video recordings are limited to defined camera angles however, that shall not be a problem since during repetitive tasks we can anticipate the action places and position the cameras accordingly. Additionally, the explanation approach can be increased through the analysis of three dimensions of risk factors exposure: intensity, duration and frequency.

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