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Smart Vest for Real-Time Postural Biofeedback and Ergonomic Risk Assessment

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ABSTRACT Work-related musculoskeletal disorders (WRMSDs) are a serious worldwide health concern, that can result in the worker's permanent disability and an economic burden of up to 2% of the Gross Domestic Product (GDP). This paper presents the design and development of an innovative smart garment for real-time ergonomic risk assessment. It aims to empower operators with posture awareness and provide objective data to ergonomists. The system is based on inertial sensors and implements a biofeedback strategy that uses haptic stimulus to warn the user about hazard postures, enabling more ergonomic postures. To allow an easy data analysis, a graphical interface was developed in MATLAB. This framework was validated with 5 subjects, in a simulated scenario with 5 tasks that included a collaborative robot arm. The results showed that providing real-time biofeedback to the subject improves posture awareness, and has a significant impact on reducing the ergonomic risk, with reductions of up to 39.8% of the time spent in hazard postures. The wearable technology and developed methodologies are a promising tool to complement the ergonomist diagnoses of hazard tasks and workspaces and to reduce the risk of musculoskeletal disorders.

INDEX TERMS Ergonomic risk assessment, biofeedback, inertial measurement units, wearables design, WRMSDs.

I. INTRODUCTION

The industry is moving towards the 4th revolution, seeking for the smart, skilled, and healthy operator 4.0 [1]. However, work-related musculoskeletal disorders are still a central problem for public health, as it represents the major element in occupational diseases, namely in Europe [2]. Thus, it stands as one of the main priorities of the European Agency for 2013-2020, with associated costs of up to 2% of the Gross Domestic Product [3]. Additionally, severe WRMSDs can result in permanent disability and, consequently, preclude the workers' return to their work and/or limit their daily lives [4]. Higher reported injuries occur at the back, shoulders, and neck. In fact, the low back pain prevalence was esteemed at 25.7%, among the US workers, costing around \$635 billion, annually, in the USA [5]. Regarding the Portuguese working population, about 30.7% manifest backache [6]. One of the major risk contributors to the high number of WRMSDs is sustaining an awkward body posture, while performing a given task, which consists of a deviation from the natural neutral position, namely excessive bending and twisting.

To reduce the exposure of workers to hazardous environments and tasks, ergonomists and engineers have

been putting their efforts into developing risk assessment methods for quantification of the risk of WRMSDs. These tools can be divided into self-reports, observational methods, and direct/instrument-based methods [7]. Self-reports collect risk exposure data from the worker, through interviews and questionnaires. However, despite the direct and initially inexpensive application, it relies on the worker's perception, which is, usually, imprecise and subjective. Observational methods evaluate the workplace risk exposure by observation on the field or by replaying videos and can be divided into simpler and advanced. The simpler ones consist of paper sheets that guide the ergonomist during the ergonomic assessment. A non-exhaustive list includes the Ovako Working Posture-Analysis System (OWAS), the Occupational Repetitive Actions (OCRA), the Rapid Upper Limb Assessment (RULA), the Rapid Entire Body Assessment (REBA), the NIOSH lifting equation and the Postural Ergonomic Risk Assessment (PERA) [7]. Despite being affordable and non-invasive, these tools highly rely on the ergonomist expertise when evaluating parameters such as the worker's joint angle, which diminishes the objectiveness, precision, and repeatability of the methods. For instance, a

difference of 10° in the worker's posture is hardly noticed by the ergonomist, when observed in real-time. The advanced methods, in turn, use dedicated software for analysis of the video-records captured during the workers' shift. Even though the results are more precise, the costs are substantially higher, time-consuming, and require highly specialized staff [7].

Instrument-based methods, in turn, can provide, in real-time, accurate, and objective measurements. Thus, the time required for an ergonomic assessment is reduced and dynamic tasks can be assessed. As the measuring devices should cause the minimum disturbance and restriction of the worker's mobility, in the last years, researchers have been focusing their efforts on ergonomic assessment using motion capture technology, namely, depth cameras, such as the Microsoft Kinect, and wearable devices such as inertial measurement unit (IMU) [8]. IMUs are becoming a very popular choice [9]–[16], due to their capability of capturing 3D movements, their small size, and lightweight, which allow the integration on wearables. Further, these methods do not suffer from drawbacks present in camera-based methods, such as the possibility of occlusion and environmental restrictions like light conditions.

Usually, workers are unaware of their posture and also tend to forget good postural practises in order to meet the constraints of time. Biofeedback is a self-regulation technique that can tackle this problem, through the use of meaningful cues to provide postural awareness to the worker [17]. In 2013, Vignais et al. developed a promising system, composed of 2 goniometers synchronized with 7 Colibri IMUs. The system performed ergonomic risk assessment, in real-time, based on the RULA method. The computed risk scores were fed to the user using an augmented reality headset and auditory warnings, addressing visual and auditory feedback [14]. Owalia et al. also explored the potential of providing postural biofeedback to the user and developed the PostureCoach aiming caregiver's training. The system instrumented two IMUs placed at the mid-thoracic level and in the sacrum to measure the flexion angle of the lumbar spine and provide an auditory warning when the pre-set thresholds were exceeded [15]. Both studies' results evidenced an improvement in the workers' posture and risk awareness, derived from the implemented feedback strategies. Notwithstanding, these types of feedback technologies present some drawbacks. For example, auditory signals can be muffled by the often-noisy industrial environments, or in the case of using earphones the user is more likely to ignore external warning signals associated with his safety. As for visual feedback, the use of augmented virtual goggles and headsets can be uncomfortable, cause eye fatigue, and may limit the worker's field of view. In turn, haptic feedback is a common practice in rehabilitation devices [18], and would not require visual attention nor limit the auditory capacity of the user to detect, identify, and localize environmental cues.

This paper presents a non-intrusive system that aims at real-time upper body posture monitorization, ergonomic

assessment, and improvement of risk and posture awareness. The work is based on the hypothesis that predicting unhealthy body postures and providing immediate biofeedback to workers will lead to healthier, safer working habits and consequent reduction of medical expenses for musculoskeletal-system related injuries. To achieve this end, we developed a smart garment combining the potentialities of IMUs and haptic interfaces, as sensing and biofeedback technology. The thresholds used for the development of the biofeedback strategy were primarily based on the RULA tool and complemented with LUBA. A graphical interface was developed to allow a fast and easy to use ergonomic risk assessment of the tasks and/or workspace. This approach was tested with 5 subjects. Results indicate the impact of the proposed biofeedback strategy and overall system on the user, and show that the haptic biofeedback provides postural awareness and entails a change and correction of posture.

II. SMART VEST DESIGN

The smart garment was developed with two users in mind: (i) the worker, who needs a practical and simple solution, capable of distinguishing awkward postures and provide posture awareness, and (ii) the ergonomist, who requires objective and accurate data, presented in an intuitive way.

A. SYSTEM REQUIREMENTS

One of the main concerns, when designing a smart garment, is to satisfy usability requirements, as a system with low usability will be rapidly abandoned by the user. It is of utmost importance to guarantee a steady fixation of the IMU sensors and haptic vibrators in the right position, even during abrupt movements [18]. Moreover, the wearable fitting should be tight, but without compromising the user's comfort. Other aspects have to be considered, such as weight, comfort, easy donning and doffing, and the wearable's sensation/feeling on the user, i.e., if the system feels weird and external to the user and he cannot abstract from it. In fact, the human body perceives an aura around the body of 0 to 12.7 cm off the body, known in proxemics as intimate space, and forms should remain within this area to be perceived as part of the body [19]. Additionally, the system shall not restrict the user movement nor jeopardize his normal working behavior.

Most human movements occur within the range of 0.5 to 3.5 Hz. The developed system should ensure the required feasibility, without excessive energy consumption, and assure at least an 8-hour work shift. A form of feedback/warn shall be provided to the worker, in real-time and on-site. The user's data must be available to the ergonomist and enable offline risk assessments. Also, a user-friendly interface must be granted.

B. SENSOR PLACEMENT

1) IMU PLACEMENT

Regarding the positioning of the IMUs on the Human body, there is no standard established protocol and each author proposes different locations for the sensors.



FIGURE 1. Back, side and interior view of the developed system and its graphical user interface (GUI).

The spine is divided into 3 main regions: cervical, thoracic, and lumbar. Many models have been proposed to study its movement, dividing it into 8-line segments [20], 4-line segment [21], 2-line segments [22], and one segment. Withal, more segments mean more sensors, which, in turn, means a bulkier and heavier system, which affects the wearability of the system and raises its complexity. Regarding wearable designing, the focus is using the minimum number of sensors, without compromising the system's performance. In observational ergonomic assessment methods, the back's movement analysis is based on a one segment model. This reflects on instrument-based methods. For instance, [14] monitored the back with one IMU placed on the chest, [10] placed the sensor on the upper back, and [15] used 2 IMUs at the mid-thoracic level and sacrum.

The shoulder complex is the joint with the largest mobility range and is frequently simplified and treated as a 3 DOF spherical joint. Thus, only 1 IMU is required to monitor this segment, which is typically placed in the upper arm [23]. The neck, in turn, is usually monitored by placing a sensor in the forehead, or vertebrae C4. However, a sensor in the cervical region could affect the user comfort, while in the forehead would not be aesthetical pleasing for the user.

Thus, in this work, 4 sensors were used and placed on T4 (point where the outward curvature of the back is well pronounced), on each upper arm and back of the head, due to usability issues. Fig. 1 shows an overview of the proposed solution. Each sensor is protected by a 3D-printed case. The sensors' modules are attached to a skinny fitted shirt using Velcro straps. The total weight of this first prototype, electronics, and shirt, is 740 g.

2) HAPTIC MOTORS PLACEMENT

We hypothesize that biofeedback should provide straightforward information about the body part that is prone to ergonomic risk. Therefore, the developed system embodies 4 haptic motors, stitched to the smart garment on both upper arms, cervical and lumbar region, giving haptic cues on the arms, neck, and back, respectively. This approach minimizes cognitive effort from the user since it provides local biofeedback. The vibration frequency is within the 80 and 250 Hz range, as the human cerebral cortex is capable of discriminating frequencies within this range.

III. SYSTEM DEVELOPMENT

A. HARDWARE ARCHITECTURE

The system is composed of 4 MPU-9250 IMUs (Invensense, USA), a highly available and widely used sensor due to its low cost and reliability. It combines a 3-axis accelerometer, a 3-axis gyroscope, and a 3-axis magnetometer. For this work, only the accelerometer and gyroscope data were acquired, with a full range scale of $\pm 4g$ and ± 2000 °/s, respectively. All sensors were interfaced with a high-performance microcontroller, the STM32F4 Discovery, via I2C, and sampled at 100 Hz. The inertial data is stored in an OTG USB driver, with reduced dimensions. 4 coin-style ERM motors (Precision Microdrives™, London) were used as haptic motors, vibrating at approximately 200 Hz, and with a vibration strength of 2.2 g. Each motor is controlled by a DRV2605L haptic driver (Adafruit). The system is powered by a power bank, with a 6.9 mm thickness and a capacity of 3000 mAh, providing a maximum autonomy of around 12h.

B. SOFTWARE FOR DATA PROCESSING

IMUs are affected by sensor bias errors. Therefore, it is necessary to calibrate these sensors before data acquisition. Each IMUs' accelerometer was calibrated by the 6-position method, an easy and fast method [24]. The IMUs' gyroscope was calibrated following an initialization routine, during which the user must stand still for 10 seconds. The angular velocities acquired during this time are averaged and used to calculate an offset, which is removed from the following samples to be acquired.

After the calibration stage, the Euler angles are computed using a Kalman filter to fuse the inertial data from the accelerometer and gyroscope, providing the joint's orientation in the sagittal and coronal plane. Movements were defined following the movement signal convention depicted in Fig. 2.

The system's angle estimation was validated using the UR3, a collaborative robot arm from Universal Robots [25]. The sensor was placed in the robot end-effector oriented at 0°. The robot end-effector was rotated by 45°, at an angular velocity of 90°/s, await 2 seconds, and repeated these movements until reaching 360°. Then, the movement was reversed until reaching the initial position. Results were assessed through the Root Mean Squared Error (RMSE) and listed in Table I. As observed, the obtained RMSE is between 2.57° and 4.95°, corresponding to an error between 1.43% and 2.5%, in relation to the full angle range. These results are comparable with other wearable technologies as demonstrated in [18].

TABLE I
RMSE OF THE ANGLE ESTIMATION OF EACH SENSOR

Sensor RSME	T4	Head	Right Arm	Left Arm
Pitch (°)	2.57	4.95	3.78	3.10
Roll (°)	3.22	4.19	3.39	3.67

C. ERGONOMIC RISK ASSESSMENT TOOL

Upper body posture can be assessed by a set of angles from various body segments. However, the simultaneous analysis of all angles can be a complex and discouraging task, even for professionals. Discretizing the angle values acquired by the sensors is a simple procedure that can ease the analysis. Therefore, it was implemented a finite state machine (Table II) to analyze posture and monitor the ergonomic risk level, where each sample is converted from an analog angular value to a state. To calculate the ergonomic risk level, we used the angles' ranges specified by the RULA index [26], one of the most cited methods in the literature, as thresholds. However, RULA only specifies angles in the sagittal plane, paying little attention to the movements in the coronal plane. The LUBA method [27], in turn, scores all the movements, in all the planes, in an angle range. However, according to [28], RULA is generally more appropriate for the assessment of WRMSDs. Consequently, the signal was discretized using the thresholds set by RULA and complemented with LUBA regarding the coronal plane. Fig.2 illustrates the movements and corresponding measured angle representation. To each state, a risk level was assigned - Low (LR), Medium (MR),

Medium-High (MHR), and High (HR) - along with a time interval that establishes the maximum period of time that a position can be held in that angle range. These times intervals were defined as 1, 5, and 10s for HR, MHR, and MR states, respectively. The used thresholds are all referent to a neutral posture, which is set user-dependent, and given by the alignment of the spine with the extremities, namely, ears and shoulders aligned, and shoulder blades retracted [29]. Consequently, after dressing and calibrating the system, angles are reset. The user is asked to stand with his back straight, arms parallel to his trunk, look forward, and hold that position for 10 s, in order to average the angle of each body part and withdraw those values from future measurements.

D. ERGONOMIC RISK ASSESSMENT TOOL

After performing the angle reset, the system calculates the ergonomic risk. If the recommended time is exceeded, a vibrotactile signal will be given on the risky body segment. The 4 vibrating motors can be activated at the same time (if the awkward posture results from the combination of more than one body part) or one at a time (if just one element is positioned in a hazardous posture). Consequently, local biofeedback is provided to the user, requiring low cognitive effort to acknowledge his posture. For biofeedback purposes, any movement with a duration lower than 1 second is not considered, as it can result from a sporadic movement with no analysis interest.

E. GRAPHICAL USER INTERFACE

To provide an easy access to the data stored in the OTG USB driver and an intuitive stats visualization to the ergonomist, a GUI was created using MATLAB® with two purposes: a Posture State analysis, which consists on a time-analysis, where the user can observe the sequence of posture states of each body part and combine the states to estimate an upper-body posture; a Risk Percentage assessment, which provides an overview of the ergonomic risk exposure of each body part in a pie plot. This strategy aims at a rapid task analysis, specially designed for a first ergonomic diagnosis of the task or workspace and/or postural improvement checks.

IV. EXPERIMENTS

D. SUBJECTS

For a proof-of-concept, 5 individuals, 1 female and 4 males, participated in this study. The participants' age, height, and body mass were 24 ± 1.1 years, 1.75 ± 0.07 m, and 73.5 ± 6.5 kg, respectively. All participants signed a written consent to participate in the studies to be presented.

D. EXPERIMENTAL PROTOCOL

The experimental scenario (Fig. 3) comprises 5 tasks, selected to be as general as possible, that contain different working postures, not only industrial but also of other

TABLE II
FINITE STATE-MACHINE BASED ON RULA AND LUBA METHODS.

Body Part	Plane	State	Angle (°)	Risk level	Definition
Trunk	Sagittal	-1	$\alpha_s < -10$	High	Trunk is inclined backward. Not recommended position if $\Delta t > 1s$.
		0	$-10 < \alpha_s < 20$	Low	Acceptable trunk inclination
		1	$20 < \alpha_s < 60$	Medium	Trunk is leaning forward. Not recommended position if $\Delta t > 10s$.
		2	$\alpha_s > 60$	High	Trunk is leaning forward. Not recommended position if $\Delta t > 1s$.
	Coronal	-1	$\alpha_c < -10$	Medium-High	Trunk is left bent. If time $\Delta t > 5s$.
		0	$-10 < \alpha_c < 10$	Low	Acceptable trunk side bending.
Neck	Sagittal	1	$\alpha_c > 10$	Medium-High	Trunk is side bent. Not recommended position if $\Delta t > 5s$.
	Sagittal	-1	$\gamma_s < -5$	High	Neck is tilted back. Not recommended position if $\Delta t > 1s$.
		0	$-5 < \gamma_s < 10$	Low	Acceptable neck inclination
		1	$10 < \gamma_s < 20$	Medium	Neck is leaning forward. Not recommended position if $\Delta t > 10 s$.
	Coronal	2	$\gamma_s > 20$	High	Neck is leaning forward. Not recommended position if $\Delta t > 1s$.
		-1	$\gamma_c < -5$	Medium-High	Neck is bent to the left. Not recommended position if $\Delta t > 5s$.
Arm	Sagittal	0	$-5 < \gamma_c < 5$	Low	Acceptable neck side inclination
	Sagittal	1	$\gamma_c > 5$	Medium-High	Neck is bent to the right. Not recommended position if $\Delta t > 5s$.
	Sagittal	-1	$\beta_s < -20$	Medium-High	Shoulder is adducted. Not recommended position if $\Delta t > 5s$.
		0	$-20 < \beta_s < 20$	Low	Acceptable shoulder position.
	Coronal	1	$20 < \beta_s < 45$	Medium	Shoulder is abducted. Not recommended position if $\Delta t > 10s$.
		2	$45 < \beta_s < 90$	Medium-High	Shoulder is abducted. Not recommended position if $\Delta t > 5s$.
Arm	Sagittal	3	$\beta_s > 90$	High	Shoulder is abducted. Not recommended position if $\Delta t > 1s$.
	Sagittal	-1	$\beta_c > 20$	Medium-High	The shoulder is flexed. Not recommended position if $\Delta t > 5s$.
	Coronal	0	$-20 < \beta_c < 20$	Low	Acceptable shoulder position
		1	$\beta_c > 20$	Medium-High	The shoulder is extended. Not recommended position if $\Delta t > 5s$.

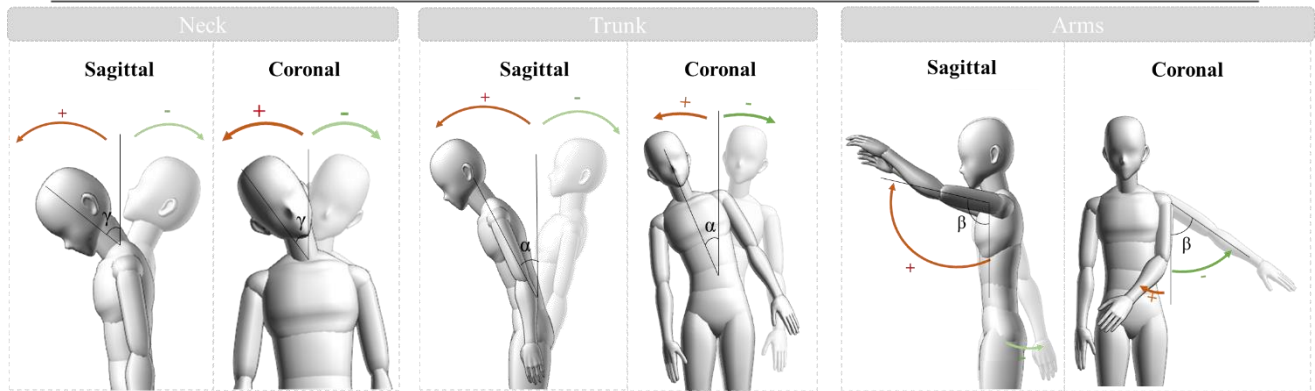


Figure 2. Illustration of the movements and signal convention.

professions such as hairdressers, when trimming hair, for example. The tasks are performed sequentially, the first task followed by the second one, and then repeated without a resting break. In the first 4 tasks, the participant has to drive two screws into the robot end-effector. The robot moves along 4 positions at different heights as soon as the participants finish to screw the screws: around the neck level (task 1), chest level (task 3), waist level (task 2), and hip level (task 4), considering a subject with 1.75 m. The 5th task involves the manual handling of a box (mass = 1 kg), where the participant lifts the box and places it at the top of the cabinet. All the necessary equipment was provided to the subjects, along with a chair that can be used to help reach a more comfortable working position, either to sit or to step on it.

Each trial was performed 4 times: 2 trials without biofeedback, to evaluate the natural response of the subject; and 2 with biofeedback to understand how the subject reacts to the stimulus. At the beginning of the trial, after putting on the smart vest, the tasks' instruction and necessary tools

(screws and chair), were given to the participants. They were explained that the system assesses their kinematics and, during the last 2 trials, they receive vibrotactile biofeedback when their posture was considered incorrect. No other information was provided regarding posture, namely what would be considered a good posture or how to correct it. Also, no advice concerning the use of the chair was given. All participants' trials were filmed for posterior analysis. At the end of the trials, questionnaires with 9 questions trying to assess the system's usability (Fig. 7) were handed out to the subjects to be answered anonymously. The questions were chosen considering the guidelines of System Usability Scale (SUS) [30].

V. RESULTS

Aiming to understand if and how providing biofeedback to the user entails a change in his behavior, a comparative analysis of the subject's behavior, with and without biofeedback, was conducted.

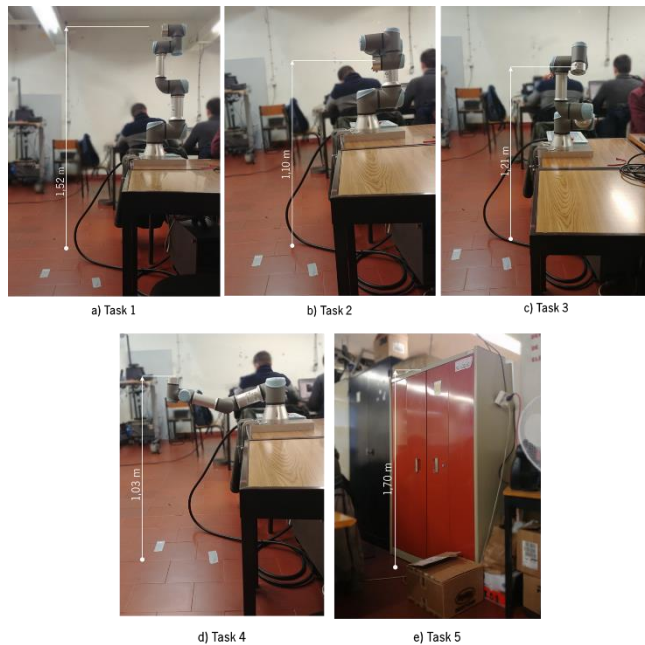


Figure 3. Tasks scenarios.

Fig.4 depicts the average time percentage of each body segment spent at each ergonomic risk levels, without and with biofeedback, of all subjects, for tasks 1-5. Overall, a reduction of the higher risk levels was observed when using biofeedback. Regarding the neck, subjects reduced the time spent in HR level in 36.6%, 43.6%, 45%, and 26% during tasks 2-5, respectively. For the trunk, these reductions were of 1.8%, 22.4%, 39.8%, 28.6% and 4.6% for tasks 1-5. The arms, in turn, did not present HR level during all 5 tasks execution, with or without biofeedback. Notwithstanding, the MHR level was only reduced in task 1, by a percentage of 14.1% (left arm) and 17.4% (right arm), and in task 5 by a percentage of 7.4% for the left arm and 6.5% for the right arm. In tasks 2-4, the MHR level of the arms increased 27.2%, 15.7%, and 21.6% for the left arm and 18.3%, 8.4%, and 7.8% for the right arm, respectively.

Fig. 5 presents time segments acquired during the execution of the first trial of task 4, with biofeedback. A video of this trial is available online¹. Fig. 6 presents the Risk Percentage assessment of the same trial, with the same subject.

The average time for the execution of the overall trial for the 5 participants, was slightly longer for the experiments with biofeedback ($M = 343,98 \pm 47.27$ s) than for the ones without biofeedback ($M = 263.98 \pm 46.47$ s).

Fig. 7 depicts the results of the user's appreciation questionnaire. All participants strongly agreed on the system's easy understanding of the functioning (Q2), no-restriction of the movements (Q4), posture awareness (Q7), the usefulness of the system (Q8), and overall satisfaction (Q9). Also, all participants agreed on the practicality and easy don-doff (Q1), the comfort of the system (Q5), and the

vibration intensity suitability to be noticed by the user (Q3). Most of the participants ($N=4$) agreed on the biofeedback clarity (Q6). In the comment section, the subject that disagreed with Q6 specified that he was able to understand which body part was poorly positioned, but he could not understand exactly how to correct it, so he tried by trial and error.

VI. DISCUSSION

From the results presented, we can infer that providing biofeedback to the user entails a change in his posture and can have a positive impact on the reduction of the task's ergonomic risk. The results demonstrated that the most exposed body part in the assignments is the neck followed by the trunk. These results were expected because the robot's end-effector was, in tasks 2-4, below the eye level of the participants.

Consequently, since the participant has low visibility, he tends to flex his neck, a position with a high ergonomic risk level. For each inch the head leans forward from the neutral position, its weight on the neck increases 4.5 kg [29]. Even though the neck and trunk had a considerable reduction in the HR ergonomic risk level, the exposure of the arms in the trials with biofeedback was slightly higher for tasks 2-4. This is explained by the fact that most of the participants reached for the chair when they were warned by the smart vest of their posture incorrectness. However, the height of the chair was not adequately adjusted to the task's needs.

Fig. 5 allows a better understanding of the changes in behavior ensued by the biofeedback. As observed, at first the participant emulates the past task execution, with the neck flexed (represented at light yellow, panel (a), at $t=[4, 9]$ s). When he receives the haptic cue regarding his posture, at $t \sim 10$ s, the user lifts his head, as highlighted in light blue, panel (b), maintaining a neutral posture. However, with the head lifted, the user has poor visibility. As consequence, he lowers his head to gain visibility (highlighted at light yellow, panel (c), at $t=[10,15]$ s), which results in a new warning from the system, concerning the HR level of his neck posture. His response is to pull the chair available next to him, sit and continue the task.

Notwithstanding, the subject still lifts his right arm (represented at light orange, panel (d) at $t=[16, 24]$ s) which, again, generates a warning that makes him correct the posture of the arm to a more neutral one successfully reducing the risk (represented at the light green in panel (e) at $t=[25, 30]$ s). Observing the correspondent risk percentage assessment, depicted in Fig.6, the subject shows a reduction of 39% the neck's HR, 40% of the trunk's MHR, and 15% of the right arm's MHR. However, the MHR risk of the left arm increased due to the fact that the end-effector was positioned a little too high, and the chair height was not adequately adjusted.

Concerning the total time of the task execution, results show that performing the same task with biofeedback takes more time than when performing without biofeedback. On average, the time difference was of 80 seconds,

¹https://drive.google.com/file/d/1hyL2_qbKNxghLjdd5giQbNbOzbNGmY58/view?usp=sharingGmY58

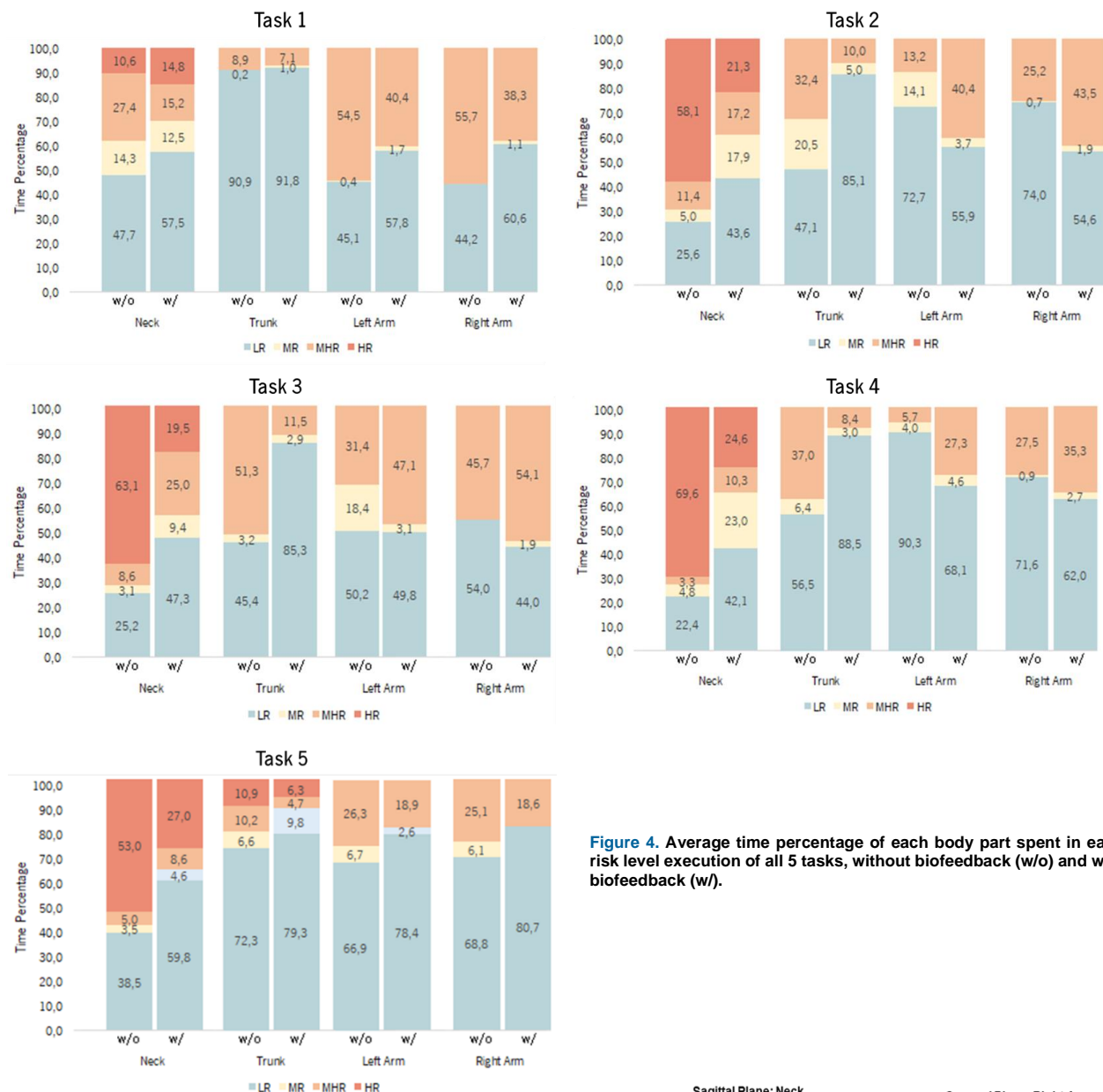


Figure 4. Average time percentage of each body part spent in each risk level execution of all 5 tasks, without biofeedback (w/o) and with biofeedback (w/).

corresponding to an increase of 30%. However, it is believed that with training, as the user gains more conscience of his posture and good ergonomic practices, this difference would be reduced.

Regarding the results from the user's appreciation questionnaires, the answers demonstrate that the system does not restrict movements nor conditionate the normal working behavior of the user. Also, even though wearability improvements should be considered, the smart garment was considered comfortable. The findings suggest that the biofeedback is intuitive but requires training to maximize the user performance and help the user to gain posture consciousness. Notwithstanding, a new validation protocol should be conducted to understand the learning curve of the user regarding posture awareness and understand if the biofeedback strategy needs to be improved. Moreover, the system had high acceptance and satisfaction between the

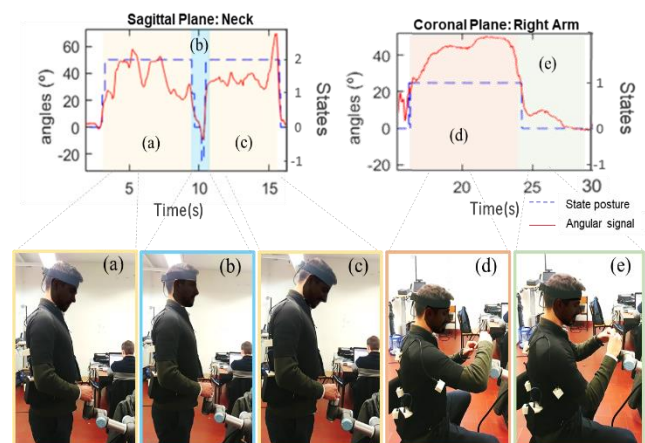


Figure 5. Execution of task 4 with biofeedback. At top: time-segments of the angular values (red line) and posture states (blue dashed line) of the Neck in Sagittal plane and Right Arm in Coronal plane. At bottom: video samples of the identified moments, related by color.

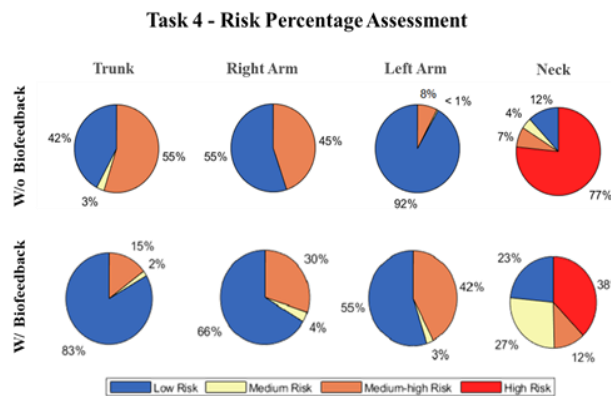


Figure 6. Ergonomic risk level percentage for task 4 without and with biofeedback, as presented in Figure 5, respectively.

participants, and the feasibility of the vibrotactile biofeedback was demonstrated.

One of the main advantages is the valuable information added to the ergonomist analysis. For example, the risk percentage analysis presented on the graphical interface allows a rapid overview of the task and could be a useful tool to first diagnose tasks and/or workspaces that need deeper analysis and possible redesigns. For example, this tool could be used for the assessment of a task and/or workplace with the monitorization of the operators that perform the same task in the same workspace. If the results are discrepant between subjects, this is indicative that the workers' posture needs correction and training. If, however, all the operators' results present high-risk levels, then task/workspace requires a deeper analysis. Along with the provided local risk level scores, it could be used as a complementary tool for the diagnose of hazard tasks and/or workspaces and help in the redesign. Additionally, this tool can help to prevent the occurrence of WRMSDs, as the users have shown to gain posture awareness, which is often forgotten by the workers to comply with the demanding working pace. Moreover, this system could be used in the training of new collaborators, in

order to avoid bad postural habits and maximize productivity.

VII. CONCLUSION AND FUTURE WORK

This work presents a smart garment for online ergonomic assessment and posture biofeedback. The system combines the RULA and LUBA thresholds for ergonomic risk calculation of four body parts, in both sagittal and coronal planes, during task execution. The system also provides intuitive and localized biofeedback, that is activated when the reference angles values are exceeded for more time than the one recommended. The system was tested with 5 subjects, that performed 5 tasks, with and without biofeedback, to understand the impact of the technology. The results evidenced an overall reduction of the time percentage spent in a high ergonomic risk level when executing the tasks with biofeedback. The smart garment, along with its interface, suggested being a promising tool to complement the ergonomist diagnosis of hazard tasks and workspaces. Future work should address validation in a real industrial context, performing more operational tasks, with a considerable number and wide age range of operators, to perceive the acceptance of the product between the workers and start an iteration process, where aspects such as aesthetics, wearability, and comfort can be improved. Experimental tests must be conducted to evaluate the usability of the GUI interface, although the consultation of an ergonomist received excellent feedback. Also, it is intended to explore the use of artificial intelligence algorithms for ergonomic risk assessment, study the influence of continuous haptic biofeedback on the user, with the intensity proportional to the risk level, and add two more IMUs in the back to allow the implementation of a 2-segment model for the spine monitoring. Being this prototype the first iteration of the system, improvements in the hardware and wearability should be conducted and technologies such as conductive thread and flexible PCBs should be tested in order to reduce dimensions and embed the sensing

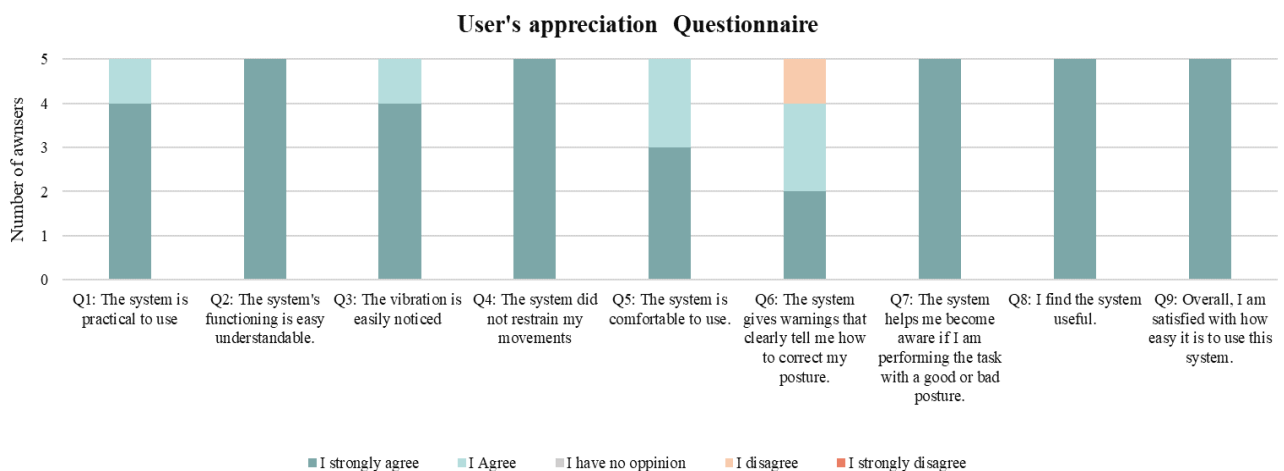


Figure 7. User's appreciation questionnaire answers.

technology into the garment, improving issues such as weight, proxemics, fit and fixation, and aesthetics.

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