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(WMSDs issue) A novel wearable system for the online assessment of risk for biomechanical load in repetitive efforts☆

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A B S T R A C T

Work-related Musculo Skeletal Disorders (WMSD) are considered the third main reason for disability and early retirement in the U.S. and are widespread in many occupations, involving both heavy and light biomechanical loads. In Italy, only taking into account the years 2009–2010, it is estimated an exponential increasing in the number of WMSD reports. In particular a 159.7% increment has been reported compared to the 2006 statistics. In this context, it is clear how important correctly diagnosing this kind of pathology is becoming. Traditional methods for WMDS assessment are based on observational techniques, in which experts manually segment, label and evaluate movements with the help of pro-forma sheets. Since these methods are currently based on visual inspection and subjective judgment, they could benefit from objective measurements in terms of both reliability and repeatability. Moreover an automatic tool for ergonomics assessment would vastly reduce the time that an expert needs to carry out the same assessment manually. In this context a novel wearable wireless system capable of assessing the muscular efforts and postures of the human upper limb for WMSDs diagnosis is proposed. The system, being non-obstructive, can be used to monitor workers in ecologic environment while they are carrying on their everyday tasks. A real-time assessment is obtained according to two of the most common indexes for the analysis of risk factors on workplaces: the Rapid Upper Limb Assessment (RULA) and the Strain Index (SI). The system exploits inertial measurement units (IMUs) to reconstruct the upper limb posture, modeled as a 7 degrees of freedom (DoF) kinematic chain. As far as muscular efforts are concerned, surface EMG sensors are used to assess forearm flexor muscles strain. As an example of the proposed system application the results of a first data collection campaign regarding super-market cashiers during everyday real-life operations is reported.*Relevance to industry*: The presented system has a high potential impact on industry as a timely intervention on the WMSD factors may reduce pathologies and reduce the recovery of expert workers.

1. Introduction

According to international statistics, in the last years Work-related musculoskeletal disorders (WMSDs) have become one of the main concern for workers health and safety. The growing interest on WMSD is explained by the increase of case reports and by the impact of WMSD on industry production.

In particular, according to the Italian government agency for the insurance against work-related injuries, WMSDs, differently from other work-related injuries, have shown a constant growth as it is shown in Table 1 (Italian Government Agency for Injured Workers (AMNIL), 2013). More recent data show a further increase of approximately 4.000 cases (+15%) with respect to 2010 (Italian Government Agency for Injured Workers (AMNIL), 2013).

WMSDs usually arise from common movements, such as lifting, intensive keying, forceful pinching and gripping, that are not

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Table 1
WMSDs incidence for the 2006–2010 years interval (Italian Government Agency for Injured Workers (AMNIL), 2013).

Type of WMSD	2006	2007	2008	2009	2010	Var. % 2006–2010
Vertebral disk diseases	2.828	3.276	4.130	6.629	9.368	231.3%
Tendinitis	3.124	3.842	4.461	6.036	8.525	172.9%
Carpal tunnel syndrome	1.731	1.477	1.668	2.435	4.819	178.4%
Arthrosis	1.588	1.938	1.965	2.343	1.971	24.1%
Others	795	907	886	1.057	1.455	83.0%
Total	10.066	11.440	13.110	18.500	26.138	159.7%

particularly harmful, but that become hazardous in specific work situation in which several repetitions of these movements are done without sufficient recovery time or they are done too fast.

Risk factors are usually classified into three main groups: individual, psychosocial, and physical. Examples of individual and psychosocial factors are: job-related stress and dissatisfaction, low organizational support, high work demands.

Considering the physical category the most influential causes are recognized to be workload in repetitive activities and body postures (Aarås et al., 1988; Forcier et al., 2008; Kilbomet al, 1994). For that reason, traditional techniques for assessing WMSDs focus in particular on observing the angular deviation of a body segment form its neutral position, force exertion, and repetition. Those techniques can be gathered in three groups: self-reports, observational inspection or by instrument-based techniques (David, 2005).

Self-reports methods usually consist of questionnaires that must be filled by the monitored workers. Those methods are straightforward and easy to use, but are prone to give a distort information due to the subjectivity of the worker perception. Moreover, factors affecting self-reports answers are eventually pre-existing MSDs and psychosocial factors.

Observational inspection consists of the visual analysis of recording observations with the help of pro-forma sheets. This family of methods focus mainly on postural observation, workload or a combination of the two. Among these methods the Rapid Upper Limb Assessment (RULA) (McAtamney and Nigel Corlett, 1993), which assesses biomechanical and postural loading on the human body focusing mainly on neck, trunk and upper limbs, is one of the most used. Other examples are the NIOSH Lifting Index (Waters et al., 1993) and the Job Strain Index (SI) (Steven Moore and Garg, 1995). The first evaluates the risks related to manual handling of load during lifting tasks, while the latter focuses on the muscular effort component focusing on the wrist-hand complex, and gives a net threshold to rank the risk factors of different jobs. Being practical, inexpensive and not intrusive, observational methods can be used in several workplace conditions, but they heavily rely on the analyst's skills in terms of evaluating quantitative parameters such as joint angles and loads displacement by visual inspection. For this reason the introduction of a measurement tool to capture some or even most of the parameters involved in the calculation can greatly enhance the exploitation of these methods.

Instrument-based techniques rely on direct measurements from sensors attached to the workers body. Since it is crucial to minimize the disturbance caused by instrumentation to the user, the most used solution are wearable and hand-held devices. Very common solutions employ motion capture devices to reconstruct the body posture. Vignais et al. (2013) presented a wearable body sensor network composed of inertial units and goniometers. The body posture is assessed with a 20 Degrees of Freedom (DoF) biomechanical model and joint angles are used for the RULA assessment. The system is capable of giving a visual feedback of the RULA score to the user. In this context only postural risks assessment are considered by the method. In addition to body posture several works monitor also force exertion and load during the task execution. Usually this is done with grip/force sensors (Freivalds et al., 2000) or with surface EMG sensors, which are more suitable to measure hand and finger forces in the workplace without interfering with a worker's normal movement patterns (Mogk and Keir, 2006). In fact, in a comparative study of Trask et al. (2007), several different methods are taken into accounts (observations, interviews, EMG, inclinometry, and vibration monitoring) showing the capability of EMG monitoring equipment to provide data focused on only one risk factor, but with a very high level of detail. Moreover several metrics (mean, peaks, percentiles, cumulative exposure, rate of change) can be investigated through EMG, with the downside of being a costly solution compared to traditional observational methods. EMG can be used as a tool for non-standard assessment (Spyropoulos et al., 2013; Søgaard et al., 2001). In the first case the authors employ video-based tracking methods to capture kinematic parameters and surface EMG sensors to define possible indicators of fatigue accumulation for the shoulder. Two lifting tasks, with different ranges are analysed during common operations in a supermarket. In the second force sensors are added to EMG and optical motion tracking. Considering EMG assessment in the context of standard scoring methods, it has been used both for complementing a modified version of the RULA scoring system (Pérez-Duarte et al., 2014) and as an alternative to the visual inspection according to the BORG scale, since it is shown the two assessments are strongly correlated (Jones and Kumar, 2010). An example of the latter application has been studied by Cabeças (2007), where EMG is used as an alternative to observational methods in computing the SI score. The authors conclude that, once defined appropriate trigger levels for the muscular activation, EMG is a valid alternative to visual inspection in the SI computation. This is true in particular when efforts are not clearly associated to hand/wrist movements and when non-cyclical high-frequency activities are assessed. In the context of assessing WMSDs, several factors interact at the same time, thus it is crucial to monitor all of them. In general it has been shown that methods assessing different factors lead to different risk evaluations. For this reason using more than one method at the same time can help prioritize interventions and ensure a more thorough evaluation of risk factors. On the other hand, the use of more than one method can rapidly lead to unacceptably high costs for the practitioner both from a time and money view point (Chiasson et al., 2012). In this context an automatic online assessment system, taking into account several factors and consequently several different risk scoring methods, would give a meaningful evaluation, without the cost drawback of multiple observational assessments. For this reason the problem of gathering motion and muscular effort data that could serve WMSDs risk assessment has been approached. The authors presented in Peppoloni et al. (2014) a preliminary version of the system discussed in this work, focusing on an offline postural assessment based on RULA. In the present work the precedent offline upper limb WMSD risk assessment is moved to an online assessment, while enhancing the role of EMG by introducing the strain index as a further risk indicator. The RULA and the SI methods were selected as explicitly cited in the ISO 11228-3 and the UNI EN 1005 for the risk assessment of repetitive task. These two methods have been chosen since they focus on two different risk factors, namely postures and effort level, which are equally critical. In particular the RULA action level is based purely on the kinematic assessment, while the SI score is mostly affected by the level of effort, along with the ratio of recovery time and time under effort. In doing so the system presents a deeper capability for analysis, compared to just kinematic or effort-based assessment. The article is structured as follows. Section 2 presents the method that was selected to assess WMSDs risk, along with the techniques that were developed to reconstruct motion from IMU sensors and to determine the effort intensity from EMG signals. Section 2 shows also the method that was selected to achieve an automatic segmentation of the activity. Section 3 shows the assessment of the system along with the obtained results. Sections 4 and 5 conclude the paper with a discussion of the results and the drawn conclusions.

2. Materials and methods

2.1. Motion capture and muscles strain analysis

The proposed method is based on the RULA and the strain index methods for WMSDs risk assessment. These methods require motion and muscular effort tracking as well as a segmentation of the action to detect cycles and to determine when efforts are actually exerted. The system employed is based on the device presented in Avizzano et al. (2014) and comprises a wearable system which communicates wirelessly with a host pc, where the main software is running. Inertial measurement units (IMUs) are used to reconstruct the posture of the human upper limb. This choice has been done because, being self contained and unobtrusive, IMUs represent a solid alternative to classical optical tracking systems (Kim and Nussbaum, 2013). Moreover they do

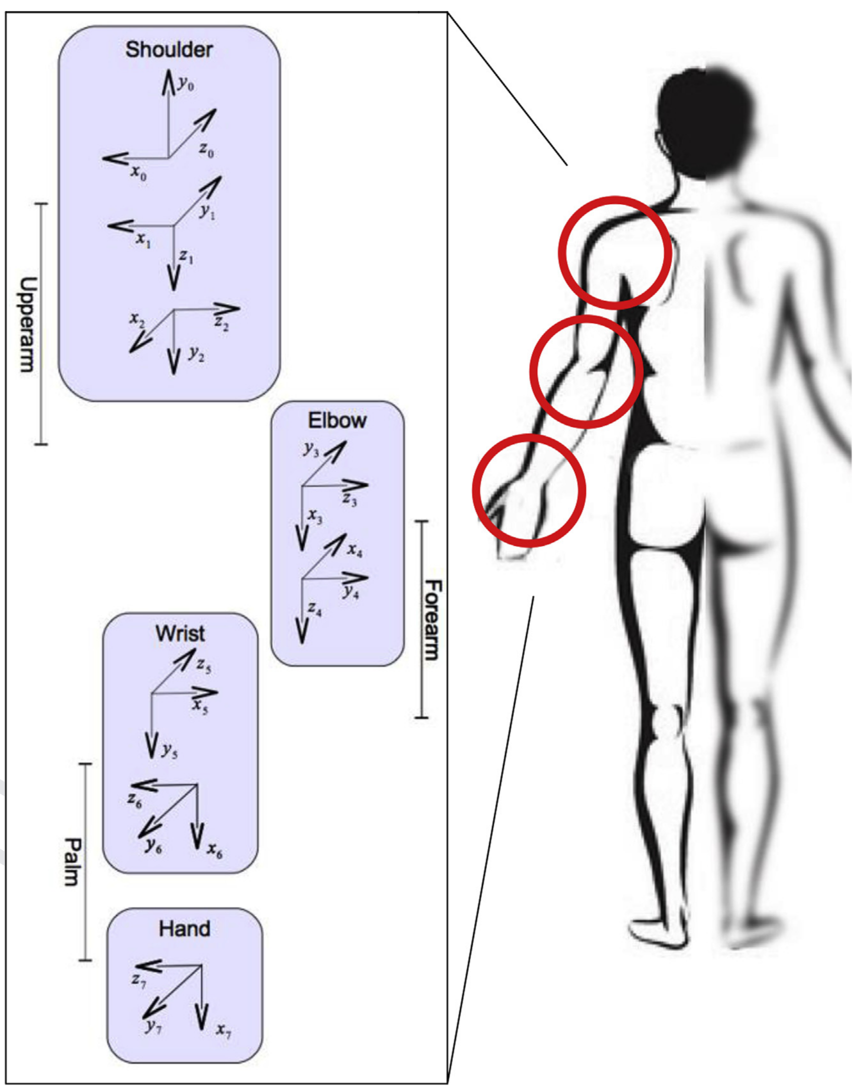

Fig. 1. Schematic representation of the seven DoF model used in our system. The model comprises three revolute joints for the shoulder, two for the elbow and two for the wrist. The Denavit-Hartemberg reference frames for the kinematic chain are represented on the left.

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not require any further instrumentation to be mounted, such as cameras system. To achieve motion tracking the system employs a 7 DoF model (Fig. 1) of the human arm having the chest as root and three links for upper arm, forearm and hand. The state of the model, namely joint angles, angular velocities and angular accelerations are estimated from the measurements coming from IMU sensors using an Unscented Kalman Filter. Further details on algorithms can be found in Peppoloni et al., (2013) and in Ruffaldi et al. (2014).

In addition to the IMUs the system exploits a 8 channel surface EMG. This kind of sensor allows to estimate the muscular effort exerted on the actuated joint, thus the force produced in specific parts of the human body, in our case the hand. Other information, such as the level of fatigue can be estimated from the EMG signal. The common procedure to obtain meaningful data is to firstly filter the EMG signals with a bandpass filter (frequency [10–500] Hz for 1 kHz sampling frequency or [10–250] Hz for 500 Hz sampling frequency), since most of the power is in the [20–200] Hz frequency range. (see (De Luca et al., 2010)).

This pre-processing step allows us to extract the features that scores the muscular effort. Our choice is to use the root mean square (RMS) of the power spectral density (PSD), since it gives objective information about the current effort level.

All the EMG and IMU signals are gathered by the board and sent via Bluetooth to a PC. Posture reconstruction and EMG features software runs on-line on the host PC. The boards also guarantees the synchronization of EMG and IMUs data. The architecture of the system is shown in Fig. 2.

2.2. Task and cycles segmentation

RULA and SI are based on the cycles that the monitored activity consists of. For example, for a grocery cashier activity the basic cycle is composed of: reaching for the object, grasping it, scanning and releasing the object. To assess every single cycle of the task the system is equipped with an automatic segmentation policy using posture and muscle effort compared to the maximal voluntary contraction (MVC) of the subject for the monitored muscles. In particular the task execution is monitored and at every time step a state machine infers the actual phase of the cycle. Since the main focus, in the presented case, is monitoring cashiers during items scanning procedure five possible states are assumed, chosen according to the Methods-time Measurement (MTM) (Maynard et al., 1948) categories of action. The states are *Init*: the initial state of the task, *Neutral pose*: the subject has is arm lying on his side, *Reach*: comprising every movement of the cycle performed without a load (e.g. reaching for the object and returning to neutral pose), *Grasp*: the subject gains control of the object, *Move*: every movement performed with the load. The state machine transitions are performed according to forces and motion (both position and velocities). The state machine with transition conditions is shown in Fig. 3, where $\dot{x}_h$ is the current velocity of the hand, F is defined as $\frac{RMS(t)}{MVC(RMS)}$, while th_v and th_f are chosen thresholds for velocity and force exertion. The *n-pose* and $\dot{x}_h$ are obtained from the reconstructed motion, while F is obtained from the EMG features.

According to the chosen segmentation policy a new cycle

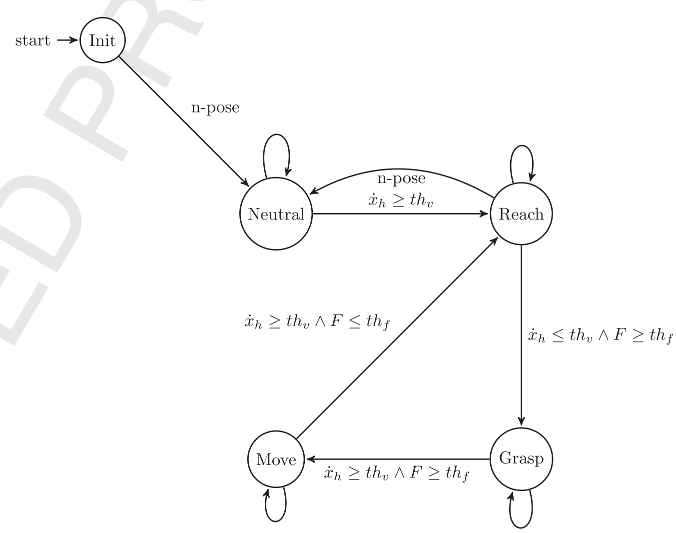

Fig. 3. The state machine employed for the online segmentation of the action cycles. Every state represent a phase of the cycle and the transitions are performed according to the reconstructed posture and the monitored muscles efforts. $\dot{x}_h$ is the hand velocity, F is the ratio between the actual effort and the MVC, th_v and th_f are velocity and force thresholds.

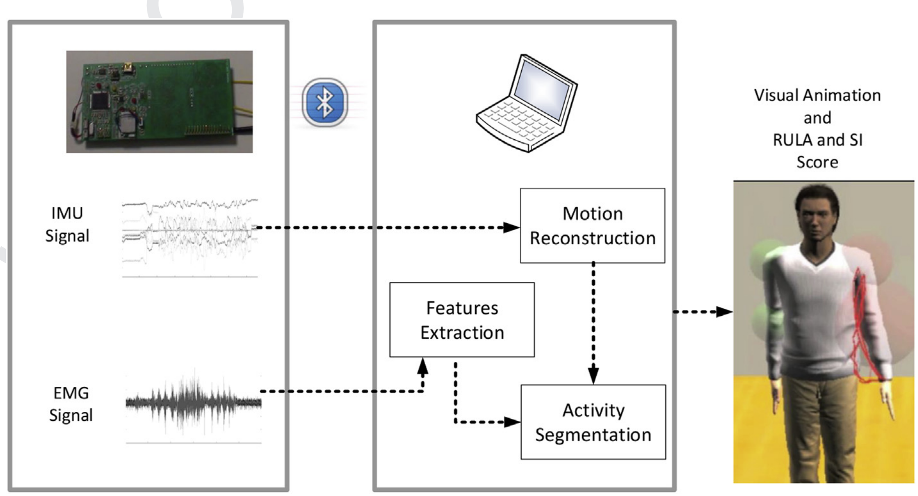

Fig. 2. Architecture of the system. The wearable device acquires EMG signals and 9-axis inertial measurements from the sensors. The measurements are sent via bluetooth to the software running on the host PC, computing motion reconstruction, EMG features and consequent action segmentation. The results are shown by a 3D animated avatar.

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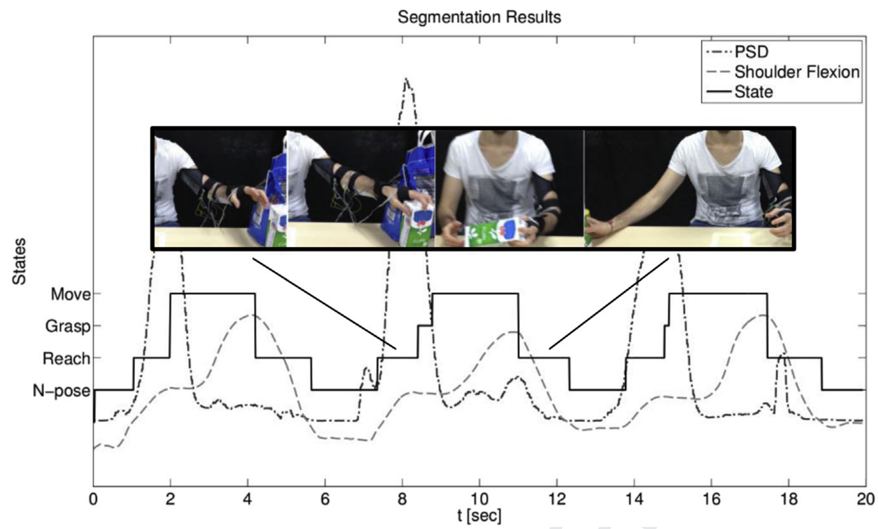

Fig. 4. Example of segmentation for a 3 cycles scanning action. The shoulder flexion angle and the sum of the RMS of the PSD for all che EMG channels are represented to show the performance of the segmentation state machine for every cycle.

begins with the transition from *Neutral* to *Reach* and ends with the transition from *Reach* to *Neutral*. An example of segmentation for a 3 cycles scanning task is shown in Fig. 4. The shoulder flexion is also shown, being as a good index of the motion during the cycles, along with the sum of the RMS of the PSD for all the EMG channels and the states of the state machine.

2.3. RULA and SI scores computation

Given a segmentation of the repetitive activity targeted by the assessment, RULA and SI scores can be computed online. The RULA score computation considers the upper arm flexion, forearm flexion and pronation/supination together with the wrist flexion and abduction. All of these variables are considered as angles of deviation (in degrees) from the neutral position. Those information are easily obtained from the posture estimation. Since in this work tracking is limited to the upper limb, neck, trunk and leg positions are considered to provide a constant contribution to the RULA. This is a minor limitation of the capabilities of the system.

The SI uses both postural and effort scores. The formula to be computed is:

$$\begin{aligned}\text{Strain Index (SI)} = {} & (\text{Intensity of exertion multiplier}) \\ & \times (\text{Duration of exertion multiplier}) \\ & \times (\text{Exertion per minutes multiplier}) \\ & \times (\text{Posture multiplier}) \\ & \times (\text{Speed of work multiplier}) \\ & \times (\text{Duration per day multiplier})\end{aligned}$$

Some of the ratings reported in Steven Moore and Garg (1995) are qualitative and associated to verbal cues. In order to translate the verbal description to an objective measurement the ratings have been interpreted to be calculated from the capture system. Intensity of exertion is computed from the EMG signals at a 100 *Hz* frequency, and it is provided as a percentage of the maximal strength:

$$\%\text{Intensity of effort} = \frac{\text{Exerted effort}}{\text{Worker's MVC}} \tag{1}$$

where the exerted effort and the maximal effort are computed as the sum of all the EMG channels RMS of the PSD:

$$\text{Exerted effort} = \sum_{i=0}^{\#channels} \sqrt{\frac{1}{N}\sum_{j=1}^{N}\left|x_i^j\right|^2} \tag{2}$$

where x_i^j is the $j-th$ value of the FFT of the EMG signal from channel j, computed in a window of size N.

The worker's MVC is computed in a same way. Since the value is subjective it can be obtained from a maximal effort static contraction of the muscle group considered. Finally the Intensity of exertion multiplier value for the cycle is obtained as the mean of the Intensity of effort during the whole cycle. The duration of exertion tells how long an exertion is applied and summed with the duration of recovery gives the exertional cycle time. It is computed as:

$$\%\text{Duration of exertion} = \frac{t_f^e - t_i^e}{t_f^c - t_i^c} \tag{3}$$

where t_i^e and t_f^e are the overall initial and final time for the states under load (*Reach* and *Move*) of the cycle, while t_f^c and t_i^c are initial and final time of the currently evaluated cycle.

The posture rating is evaluated with the estimated wrist flexion

Table 2
Rating criteria for wrist posture.

Rating criterion	Wrist extension	Wrist flexion	Ulnar deviation
1	0°–10°	0°–5°	0°–10°
2	11°–25°	6°–15°	11°–15°
3	26°–40°	16°–30°	16°–20°
4	41°–55°	31°–50°	21°–25°
5	>60°	>50°	>25°

Table 3
Rating criteria for speed of movement.

Rating criterion	MTM-1
1	≤80%
2	81–90%
3	91–100%
4	101–115%
5	>115%

Table 4
Characteristics of the group of participants. Mean (standard deviation).

Characteristics	Value
Age	30.7(8.01)
Gender (Male/Female)	$n = 7/3$
Handedness (Left/Right)	$n = 4/6$

and abduction angles according to Table 2 (Steven Moore and Garg, 1995).

The speed of work rating is computed considering the MTM-1 (Maynard et al., 1948). The ratio between the predicted pace measured in TMU for the complete cycle of movements and the actual pace is used, and the rating is assigned according to Table 3.

The duration per day multiplier is considered for every cycle and equals to 4, according the average working day of 4–8 h. Lastly the effort per minute multiplier is computed online from the exertional cycle time, while in the offline analysis is considered to be:

$$\text{Efforts per minute} = \frac{\text{Number of exertions}}{\text{Total observation time (min)}} \tag{4}$$

Once the RULA and SI scores are outputted by the system, the corresponding action level (RULA) and risk level (SI) can be computed. For the rating criteria computation the reader is referred to (McAtamney and Nigel Corlett, 1993; Steven Moore and Garg, 1995).

An example of RULA and SI scores for the 3 cycles of scanning previously presented are shown in Fig. 5. In the figures the cycles segmentation and the SCORE for the RULA, along with the SI score are represented for each of the three cycles.

2.4. Experimental setup

The system has been tested in an ecological environment to assess the task of the supermarket cashiers. Moving from the experience gathered during the preliminary test described by the authors in Peppoloni et al. (2014) a mockup of the real scenario has been built.

In particular a station ergonomically identical to the real check-out position has been built to assess the system. Ten healthy subjects have been monitored for two check-out operations each. The subjects belong to an age-group between 25 and 50 years, in particular 3 females and 7 males, of which 4 are left-handed and 6 right-handed. Subjects characteristics are shown in Table 4.

The operations have been carried on a shopping bag, composed of ten items of different weight and shape shown in Fig. 6. Items with correspondent weights are reported in Table 5.

Fig. 6. The ten items used for the experiment shopping bag. Every item has a different weight ranging from 0.3 to 7.5 *kg*.

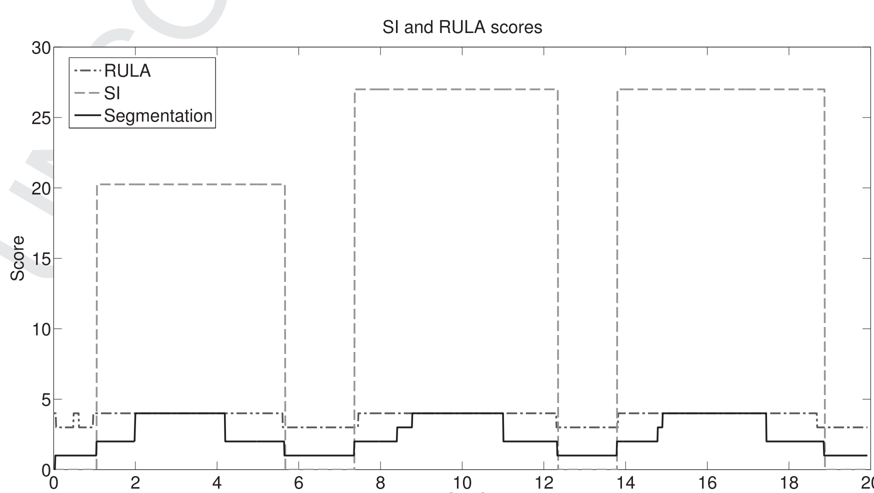

Fig. 5. Examples of results of the RULA score and SI score for the 3 cycles of scanning.

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Table 5
Items composing the shopping bag with their weights.

Item	Weight [kg]
Dog food can	1.25
Milk pack	1.0
Fruit juice pack	2.0
Dish soap	1.5
Beer pack	2.5
Corn flakes pack	0.5
Pasta pack	0.5
Sweet corn can	0.3
Cat litter	7.5
Salt pack	1.0

To assess the capability of the systems against the evaluation of an expert, every experiment was also recorded to have the RULA and SI scores made manually by an analyst. The automatic RULA action level and SI score are compared with the mean scores given by two human evaluators for every cycle with the traditional observational evaluation. The chosen human evaluators are two subjects not involved in the experiment with experiences in human motion analysis. .

2.5. Procedure

Each participant signed an informed consent and were informed that the system will measure their kinematic behavior and muscles effort during the execution. The procedure described to mount and calibrate the system according to the monitored task, is general and represents the same procedure an investigator should follow to use the system. The system is mounted on the participant's upper limb. The wearable device is mounted on the inner part of the subject upper arm with inside an arm-band. IMUs are attached to the subject upper arm, forearm, and hand inside of elastic bands. EMG sensor array is attached to the subject forearm in such a way to monitor flexor carpi radialis, the palmaris longus and the flexor carpi ulnaris. After the mounting phase the calibration procedure is run. The calibration procedure is comprised of two steps:

1. motion tracking system calibration
2. calibration of the Segmentation state flow machine thresholds.

During the first calibration the subject was asked to freely move his arm in the space to calibrate magnetometers according to the local Earth magnetic field, then the subject was asked to hold briefly three static positions of the arm to let the system autonomously compute the actual orientation (due to mounting) of the inertial sensors. After the motion capture system is calibrated the user was asked to perform an MVC static test of the forearm flexors muscles. After these phases the segmentation thresholds can be calibrated. The thresholds th_v and th_f are the only tunable parameters of the system. They have to be set according to the monitored task dynamic. After the subject is given an overview of the task, items and equipment. The participant is asked to perform the scanning task at a normal pace and as naturally as possible, returning in the neutral pose after every scanned object. Online data regarding the reconstructed motion (namely upper limb joints angles and angular velocities) and muscle effort were monitored to understand the task dynamic levels and correctly set the thresholds. After this calibration step the actual acquisition phase start. The acquisition phase was carried on twice for every participant, after the captures participants filled out a final questionnaire composed of two parts, the first characterizing the population (age, gender, handedness and previous experiences), the second concerning the participant's feedback, assessed on a Likert scale from 1 to 7 (see Appendix A for the complete questionnaire). No perceived effort assessment has been carried out, except for the general tiredness sensation at the end of the test.

The experimental setup is shown in Fig. 7.

The graphical interface showing the online analysis is shown in Fig. 8. The experimenter is presented with two panels. The *Score Panel* shows information about the current cycle number, the current phase and the online RULA and SI scores. The *Cycle Score Panel* shows the mean RULA and SI scores for the last completed cycle. The interface is realized as a Matlab® GUI and

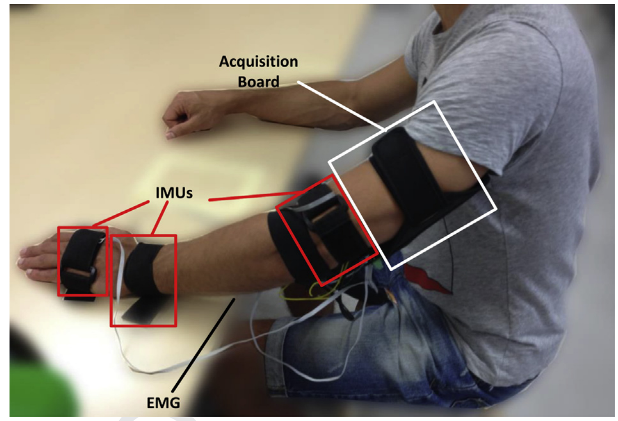

Fig. 7. The experimental setup for every subject. The subject is wearing the system on his left arm and performs the scanning operation in an environment dimensionally and ergonomically identical to a real life check out station.

Fig. 8. The graphical interface showing the online assessment of the system. The *Score Panel* shows information about the current cycle number, the current phase and the online RULA and SI scores. The *Cycle Score Panel* shows the mean RULA and SI scores for the last completed cycle.

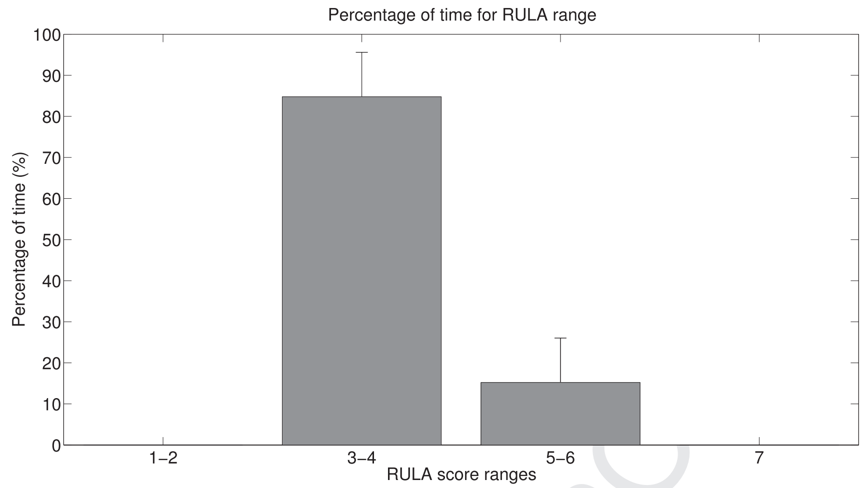

Fig. 9. Percentage of time spent at each range during the task execution for all the subjects.

receives data from the system server through UDP connection.

3. Results

The results of the system for the RULA action level and SI scores for the risk level are reported according to the RULA and SI score sheets and the values given by the system. As an indicator of the system estimation Fig. 9 shows the percentage of time spent in every RULA score range by every subject, considering the whole experiment duration time.

As detailed in Section 2 compared the system results were compared with the human evaluators' score. The score for every cycle given by the human evaluators is averaged and compared to the score given by the system for the same cycle. The total accuracy is computed as:

$$\text{Accuracy }\% = \frac{\text{Number of Correct Assesments}}{\text{Number of Cycles}} * 100 \quad (5)$$

where an assessment of the system is considered correct when it

Table 6
Accuracy of the system obtained comparing system results for every cycle and mean of two human evaluators' results.

Measure	Accuracy %
RULA action level	94.79%
SI	44.79%

Table 7
Intraclass Correlation Coefficients for a 95% confidence interval.

Measure	ICC	95% Confidence interval
RULA action level	0.00	−0.20 to 0.20
RULA action score	0.26	0.06 to 0.43
SI risk level	0.23	0.04 to 0.41
SI score	0.28	0.08 to 0.45

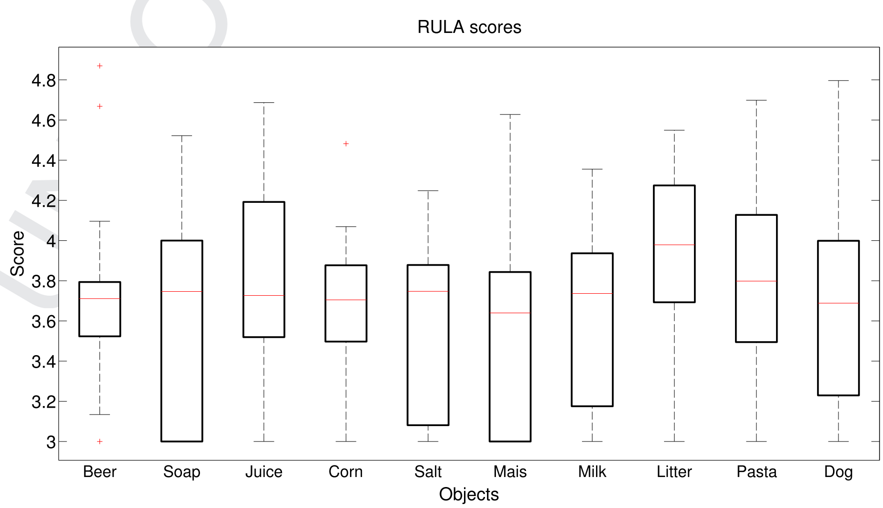

Fig. 10. The figure shows the inter-object variability of the system RULA action level. It can be seen that the minimum variability is found in the *Beer pack* evaluation (4% between *25th* and *75th* percentile), while the maximum is found in the *Washing-up liquid* evaluation (15% between *25th* and *75th* percentile).

presents the same evaluation of the human evaluators. The results are reported in Table 6.

To assess the conformity of the estimations made by the two different evaluators, namely the system and the human evaluators, the ICC (Intraclass Correlation Coefficients) (Doros and Lew, 2010) for a 95% confidence interval is reported in Table 7. In particular the ICC(3,1) is reported. This index is used when every evaluators evaluates every object and the evaluators considered are the only ones of interest for the analysis. ICC is computed both for the output of RULA and SI scores and for the equivalent Action Level (RULA) and Risk Level (SI) to which the scores are converted.

In order to assess the repeatability of the system measurement compared the results obtained in every cycle for every subject for the same object were compared. Results are shown in Fig. 10. The minimum variability of the system assessment is 4% between *25th* and *75th* percentile for the *Beer pack* item, while the maximum variability is 15% between *25th* and *75th* percentile for the *Washing-up liquid* item. The mean variability of the RULA action level is 13%, which must take also into account differences between subjects.

A two-way ANOVA was performed on the RULA action level with factors being objects and evaluator type. Data were tested for homogeneity with Levene's test before applying ANOVA. The levels of the factor objects were 10 as the number of items, whereas two evaluator types were considered, namely the human evaluators and the automatic system. The factor object was found to affect the RULA action level ($p<10^{-4}$), whereas the factor evaluator type was not significant ($p=0.37$). Also the interaction effect is negligible ($p=0.46$). The results of the ANOVA test are shown in Table 8.

The system wearability has also been assessed thanks to the questionnaires given to the subjects. In particular the encumbrance and the comfort of working while wearing the system have been investigated. The results on a scale of 7 have been reported in Table 9.

4. Discussion

According to the results shown in the Results section the system is able to give a RULA score estimation congruent to the one given by the human evaluators. Despite the variability between subjects, which includes different grasps used on the objects and/or a greater support during the task given by the non-monitored arm, the score associated to every object is repeatable, thus demonstrating the precision of the system. Moreover different scores are associated to different objects, as shown in Fig. 10 and from the ANOVA analysis. Although the score is influenced by the subject's grasp that changes the ulnar deviation and the wrist flexion, it can be seen that the Cat litter item, which is the heavier and the less comfortable to grasp, has the highest score. Moreover the lowest score is associated to the Sweet corn can item, that is the lightest and the most easily graspable. As far as the SI score is concerned the system gives a score congruent to the evaluators' evaluation in almost the 50% of the cases. The discrepancy observed between the evaluators, can be due to several factors related to both the human and the procedural sides. First the SI score depends on the intensity of exertion, which is estimated by the system according to MVC test performed at the beginning of the experiment. As pointed out in Cabeças (2007), the goodness of the test varies significantly according to the trigger threshold for the intensity of exertion. Therefore the actual capability of the subject to perform his real MVC for the muscles considered leads to MVC tests more or less informative about the real maximal contraction. Moreover high frequency acyclic movements produce artifacts in the EMG signals, that may affect the SI score, as reported also in Cabeças (2007). It has to be also noted that the human evaluators tend to underestimate the actual efforts exerted by the subjects. This is probably due to the video recording, that did not properly convey the exerted effort. For example one of the evaluators rated the displacement of the Cat litter item as a no-effort activity. This consideration is also supported by the results of the questionnaires. Most of the subjects indeed felt fatigued at the end of the experiment, and this evaluation is not congruent to the generally low values for the intensity of exertion given by the human evaluators. This would lead to further investigation on the subjects' perceived effort using self-assessment sheets.

Table 8
Results of the two-way ANOVA The factors considered are objects and evaluator type.

Source	SS	df	MS	F	Prob > F
Columns	26.83	9	2.981	894.33	0
Rows	0.0067	2	0.0033	1	0.3692
Interaction	0.06	18	0.0033	1	0.4599
Error	0.9	270	0.0033		
Total	27.796	299			

Table 9
Wearability assessment of the system, according to questionnaires given to all the subjects. The mean values are shown on according on a Likert scale from 1 to 7.

Parameter	Score %
Comfort	5.2
Encumbrance	2
Usability for a complete work turn	5.3

5. Conclusions

This work presents a wireless wearable system for online assessment of WMSDs risks for the upper limb. The system performs an online score computation according the RULA and SI scoring methods. The system is capable of autonomously segmenting the cycles and giving a score for each cycle. The system output was compared to a traditional score assigned by analysts through observational inspection. The scores estimated with the proposed approach proved to be congruent with the analysts' scores. The users rated the system to be usable for a whole average working turn, being not obstructive or painful during the movements. Further developments for the system will involve the implementation of a better intensity of effort estimator, working on both technical and procedural aspects. A further improvement will be an automatic calibration procedure to estimate limbs lengths autonomously during the calibration procedure.

Uncited references

Kivi and Mattila, 1991, Colombini and Occhipinti, 2006, Radwin, 2011, Franzblau et al., 2005. . Q3

Appendix A. Ergonomics assessment study questionnaire.

Name:

Surname:

Age:

Handedness:

Gender: M F

1. **Any past exposure to grocery cashier as customer?** Y N
2. **Any past exposure to grocery cashier as cashier?** Y N
   (a) If yes, for how long (months)

   Read the following statements and check the number according to your agreement with the statement.
3. **The device is comfortable.**

Totally Disagree	1	2	3	4	5	6	7	Totally Agree

4. **The motion is not influenced by the device.**

Totally Disagree	1	2	3	4	5	6	7	Totally Agree

5. **The device is painful.**

Totally Disagree	1	2	3	4	5	6	7	Totally Agree

6. **I felt fatigued at the end of the tests.**

Totally Disagree	1	2	3	4	5	6	7	Totally Agree

7. **I had difficulties to reach and move the objects.**

Totally Disagree	1	2	3	4	5	6	7	Totally Agree

8. **I think the device is usable in a workplace during the work activities.**

Totally Disagree	1	2	3	4	5	6	7	Totally Agree

9. **Comments.**

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