2014 22nd Mediterranean Conference on Control and Automation (MED)
University of Palermo. June 16-19, 2014. Palermo, Italy

Assessment of task ergonomics with an upper limb wearable device

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Abstract— **Upper Limb Work-related Musculo Skeletal Disorders (ULWMSD) are constantly increasing every year in developed countries. It is estimated that in Italy, in 2007 ULWMSD were the 41,6% of all the work-related pathologies. In this context, the importance to correctly diagnose and treat this kind of pathology is growing. Traditionally the assessment is done using pen-and-paper observational techniques in which movements are manually classified, labelled and compared integrating the results with subjective questionnaires given to the monitored subjects. The main problem with those traditional methods is the lack of objective assessment regarding the motion and the forces exerted, which are inferred by subjects inquiry and the body posture, manually extracted from video tapes. In this context we propose a novel wired system for assessing the muscular effort and posture of the human upper limb for ULWMSDs diagnosis in ecologic environment. The system is composed of inertial units to reconstruct the upper limb posture and EMG sensors to assess the muscle effort. The upper limb is considered as a kinematic chain comprising three degrees of freedom (DoFs) for the shoulder, two DoFs for the elbow and two DoFs for the wrist, while forearm flexor muscles are monitored through EMG. We propose a preliminary validation of the system testing it for assessing posture and muscle effort of a check-out operator during everyday real-life operations.**

I. Introduction

Upper Limb Work-related Musculo Skeletal Disorders (ULWMSD) are one of the most common health problems for workers. It is estimated that in Italy, in 2007 ULWMSD were the 41,6% of all the work-related pathologies. The risk factors causing ULWMSDs are multiple and usually they can be classified into three main groups: individual, psychosocial, and physical. In particular, considering the physical category workload in repetitive activities and body postures are recognized to be among the most influential causes for pain and diseases-related problems [1], [2], [3].

Traditional techniques for assessing the postural stress and its relation to ULWMSDs consist of observing the angular deviation of a body segment form its neutral position, force exertion, and repetition. This can be done by self-reports, observational inspection or by instrument-based techniques [4]. Self-reports methods usually consist of questionnaires that are filled by the monitored workers. Despite being straightforward and easy to use, those methods can give a distort information due to the subjectivity of the worker perception that can be affected by eventually pre-existing MSDs.

Observational inspection consists on the visual analysis of recording observations with the help of pro-forma sheets.

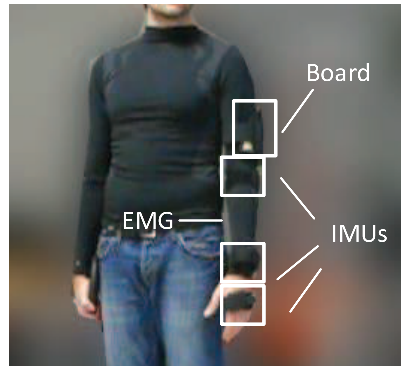

Fig. 1. Male subject wearing the presented system. The system comprises 4 inertial sensors and up to 32-channels EMG sensor array. The signals are gathered and precessed by a board .

Several methods are available for this kind of analysis. One of the most used is the Rapid Upper Limb Assessment (RULA) [5], which assesses biomechanical and postural loading on the human body with particular attention to the neck, trunk and upper limbs. Another technique for posture classification from recordings is the Ovako Working Posture Analysing System (OWAS) [6], developed by the Ovako Oy Steel Co. in Finland. In this system the movements of body segments around the lower back, shoulder and lower extremity (including the hip, knee and ankle) are categorized in different classes: bending, rotation, elevation and position. During assessment, the analyst uses a four digit code to represent the positions of the back (four choices), the arms (three choices), the legs (seven choices) and force. The system takes into account also action categories to reflect the magnitude of the risks. The National Institute for Occupational Safety Health (NIOSH) has proposed the NIOSH Lifting Index [7], for evaluating the risks related to manual handling of load during lifting tasks. A quantitative method for assessing the risk related to manual handling repetitive tasks was proposed by Colombini and Occhipinti [8] that allows us to evaluate the ratio between the technical actions actually performed by the worker and the number that would be recommended. These latter methods are cited by the ISO 11228 and UNI-EN 1005 regulations and guidelines for upper limb risk related to manual handling.

Observational methods are practical and inexpensive and can thus be used in several workplaces, being also not intrusive. On the other hand they heavily rely on the observer skills in terms of evaluating quantitative parameters such as joint angles and loads displacement by visual inspection. These methods would greatly benefit form instruments that

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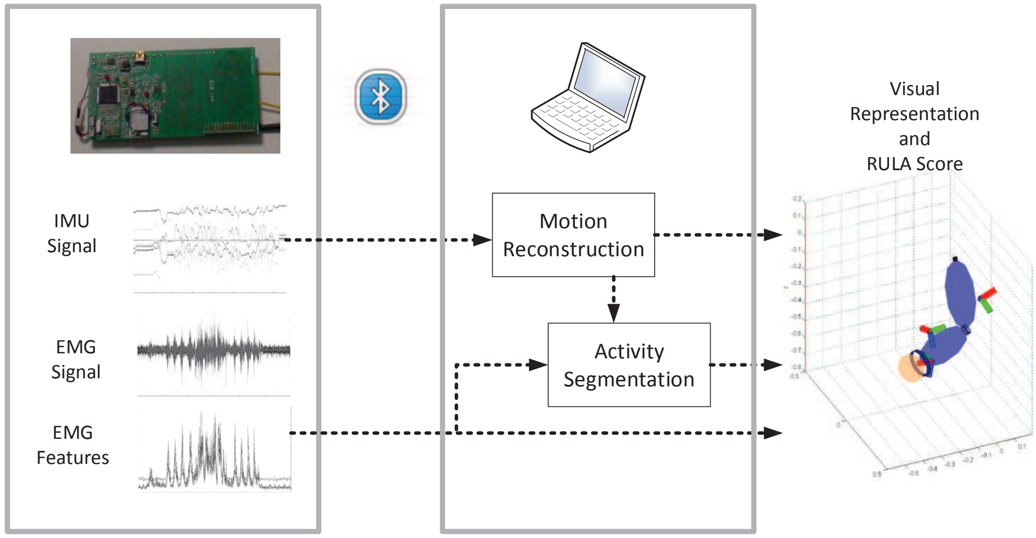

Fig. 2. System architecture representation. The board acquires all the raw signals and computes the features. The data sent to the host PC is further analysed and the arm motion is reconstructed along with the computation of the RULA score

allow us to measure some or even most of the parameters involved in the calculation while minimizing the disturbance caused to the user. Instrument-based techniques rely on direct measurements from sensors attached on the workers body. Several solutions have been explored ranging from wearable to hand-held devices. In [9] the authors present a portable system where a three-axis accelerometer is used as an inclinometer for measuring postures and movements over time. The aim of the work is evaluating risks for neck and shoulder disorders during sustained or frequent work with elevated arm. A similar approach is presented in [10] where a body sensor network composed of inertial units and goniometers is attached directly to the worker upper body. A 20 DoFs biomechanical model is used to assess body posture and estimated joint angles are used for RULA assessment. A visual feedback of the RULA results are given to the user. The system takes only into account postural risks. In [11] the authors presents a model to determine the likelihood of incurring ULWMSDs for the upper limb. Hand motion and exerted force are monitored through a commercial CyberGlove and a UniForce pressure sensor. In particular wrist and grip measurements are gathered to predict diseases incident rate. A different tracking technique is used in [12], where hand kinematics is reconstructed with a marker-less single-camera video tracking algorithm. The risk is evaluated with an automated estimation process using the Hand Activity Level [13]. Several different methods (observations, interviews, EMG, inclinometry, and vibration monitoring) are compared by the authors in [14], with the focus on lower back injuries. The work assesses 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, though being a more costly solution compared to traditional observational methods. In assessing ULWMDs, it is crucial to take into account several factors at the same time, in particular both posture and load have to be considered and how they relate during the task execution. In this context we present a novel wearable system for the assessment of risk factors for ULWMSDs, with the focus on the upper limb. The system exploits inertial sensors and a biomechanical model to reconstruct the posture of the upper limb, taking into account shoulder, elbow and wrist motions. Muscle efforts for the fore arm flexors are measured with a 8-channel EMG array sensor and compared to the maximum voluntary muscle contraction. The posture and the load are then used by the system to give a real time estimation of risks, using the RULA assessment. A preliminary visual analysis of the results is given in the form of an animated avatar, where there RULA score risk level is represented. The paper is organized as follows. Section II gives an overview of the system and of the algorithms used. Section III describes the experimental tests used for the preliminary validation of the system and their results. Section IV discusses the results obtained with the system during tests and describe future developments for the system.

II. Methodology

Wearable motion tracking systems based on inertial motion units (IMUs), being self contained and unobtrusive, represent a solid alternative to classical optical tracking systems. Motion reconstruction based on strapdown integration of the IMU's data is unsuitable, because of the drift problem. Filtering algorithms can be employed to address this issue. We combine a 7 DoFs model of the human arm having the chest as root and three links for upper arm, forearm and hand. The shoulder is modelled as a 3 DoFs spherical joint, two revolute joints model elbow flexion and forearm pronosupination and the same for wrist abduction

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and flexion. The Denavit-Hartenberg (DH) convention is used to model the kinematic chain, where a homogeneous matrix A^i_{i-1} dependent on i^{th} link parameters and the joint angle ϑ_i represents the relationship between two consecutive $i-1^{th}$ and i^{th} frames. The set of joints' angles and their first and second derivatives compose the state of the filter used in our reconstruction algorithm:

$$\Theta = [\vartheta_1, \dot{\vartheta}_1, \ddot{\vartheta}_1, \ldots, \vartheta_7, \dot{\vartheta}_7, \ddot{\vartheta}_7] \quad (1)$$

Given the measurements sensed from IMU sensors (namely angular velocity, linear acceleration and Earth magnetic field), the relationships between measures and the chosen state is non-linear. For this reason we use an Unscented Kalman Filter to estimate joint variables. Further details on algorithms can be found in [15] and in [16]. Figure 3 shows a schematic representation of the kinematic model that was used.

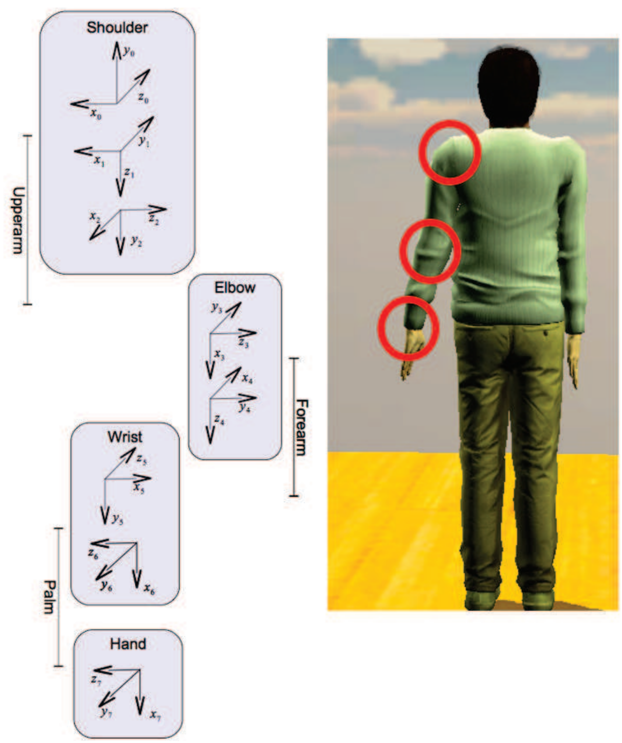

Fig. 3. Schematic representation of the seven DoFs model used in our system. The model comprises three revolute joints for the shoulder, two for the elbow and two for the wrist. DH reference frames are represented along with the model .

Surface EMG signals allow us to determine several features related to the task carried out by the user. In particular, they allow to estimate the torque on the joint that the muscle exerts on the actuated joint and, as a consequence, the force produced in specific points of the human body such as hands. Moreover it is possible to estimate the fatigue status of the measured muscle fibres. EMG signals are typically filtered with a bandpass filter (frequency $[10-500]$ Hz for 1kHz sampling frequency or $[10-250]$ Hz for 500 Hz sampling frequency) to keep the frequency band that contains most of the power i.e. $[20-200]$ Hz (see [17]).

Typically from the raw EMG data, first the power spectral density (PSD) is computed, as the square of absolute value of the Fourier transform of the signal divided by the signal length. Then two features are evaluated: the RMS (root mean square) and the MNF (mean frequency) or the MDF (median frequency) of the power spectrum. The first is related to the magnitude of the force that is exerted as a consequence of the muscle activation. Given the RMS values during 0% and 100% of maximum voluntary contraction (MVC), the force produced is estimated based on the current value of the RMS [18]. MNF and MDF are instead mostly related to muscle fatigue as both MNF and MDF decrease as the monitored muscle get fatigued [19]. MNF is defined as:

$$MNF = \sum_{i=1}^{N} f_i P_i / \sum_{i=1}^{N} P_i \quad (2)$$

where f is the frequency and P is the PSD. The MDF is defined as the frequency at which the PSD is devided into two region of equal amplitude, mathematically:

$$\sum_{i=1}^{MDF} P_i = \sum_{i=MDF}^{N} P_i = \frac{1}{2} \sum_{i=1}^{N} P_i. \quad (3)$$

In our system we use up to 32 electrodes for surface EMG. EMG signals are filtered and processed to obtain RMS. The RMS of the signal allows us to determine some of the values that are required for the RULA such as the frequency of repeated tasks (e.g. grasping for load manual handling) and the force produced.

All the EMG and IMU signals are gathered by the board and sent via Bluetooth to a PC. EMG features are computed by the board, while the posture reconstruction software runs off-line on the host PC. The time synchronization of the IMU and EMG's data is guaranteed by the acquisition board. Conversely, the camera stream is manually aligned to the sensors data. After this alignment phase the different actions are manually segmented according to the camera stream.

The segmentation allows us to select the features in a desired window that corresponds to a specific activity in which the loads and the other parameters needed for the RULA where constant.

Figure 2 shows the system architecture along with all the computational phases. The preliminary visualization comprises the computation of the RULA score for the manipulation of known objects and an animated avatar of the monitored arm. The avatar includes a jet color map representation of the wrist, according to a chosen EMG feature intensity.

The communication between the board and the host PC is implemented as a web interface, managed by a C webserver, while the reconstruction algorithms and RULA score computation are implemented both in C++ and in Matlab/Simulink.

III. Experimental Results

The preliminary test of the system has been carried out in the real-life scenario of a check-out operator during everyday

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activity. The participant, a healthy women, was monitored for approximately 20 minutes for each arm. The participant was sensorized with 4 inertial units MPU9150 (Invensense, Borregas Ave Sunnyvale, CA, USA) placed on the back, upper arm, fore arm and back of the hand, while a 8 channel EMG sensors array is used to monitor the fore arm flexors.

Figure 4 shows the setup for the sensors system along with the actual placements of the EMG sensors array. The setup for the system is non-intrusive and does not effect at all the normal procedures carried on by the subject.

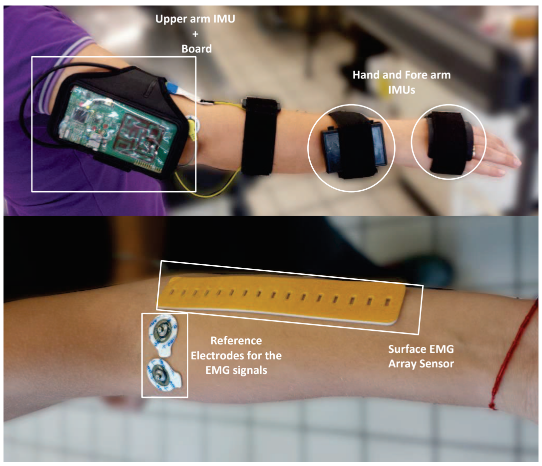

Fig. 4. On the top the setup for the system is shown, the board and three of the four IMUs (Upper arm, fore arm and back of the hand) are highlighted. Below the actual placement for the EMG sensors is shown. The sensors are placed in such a way to monitor the activity of the fore arm flexors.

In addition the scene was captured with two cameras, one RGB camera and RGB-D sensor (Microsoft Kinect Camera). Figure 5 shows the setup and the views of the two cameras.

Fig. 5. Three views of the setup in the preliminary test. On the right the main scene captured with a camera. On the left the views of the RGB-D sensors that allow to understand the organization of the workspace. The RGB-D could be used for improving the tracking of body motions and interaction with the objects.

During the experiment two different groups of items were presented to the participant. The first one (*known bag*) consists of a combination of preliminarly weighted items, while the second one comprises (*customer bag*) random items, purchased by real costumers. The list of the items with their correspondant weights is reported in Tab I.

TABLE I
ITEMS AND WEIGHTS FOR THE KNOWN COLLECTION COMPOSITION

Item	Weight [Kg]
Coke cans pack	2.160
Bisquits pack (small)	0.270
Tuna cans pack	0.440
Cornflakes pack	0.365
Tea bottle	1.620
Potato bag	4.020
Bisquits pack (big)	0.510

The results of the motion reconstruction step for the capture of the left arm are shown in Figures 6, 7 and 9.

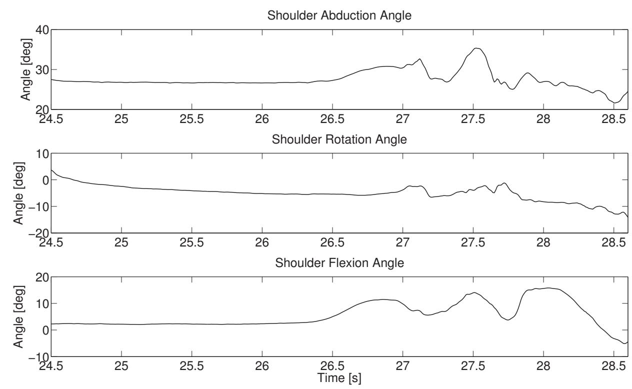

Fig. 6. Reconstruction of shoulder angles, for the left arm.

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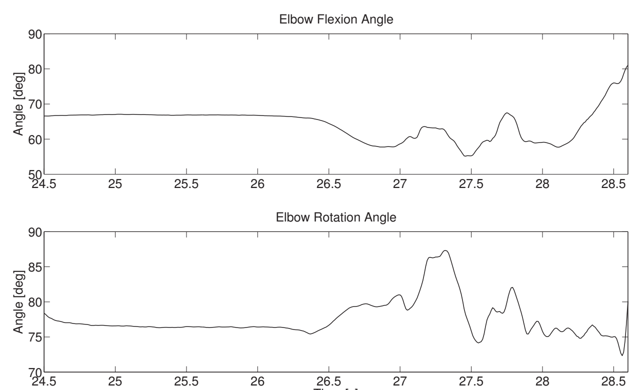

Fig. 7. Reconstruction of elbow angles, for the left arm.

The data from the motion reconstruction were related to the EMG features. In particular fore arm flexors muscle effort were associated to the wrist flexion. An example taken from the test for the left arm is shown in Figure 8, where RMS of the EMG signals for every channel and wrist flexion angle are represented.

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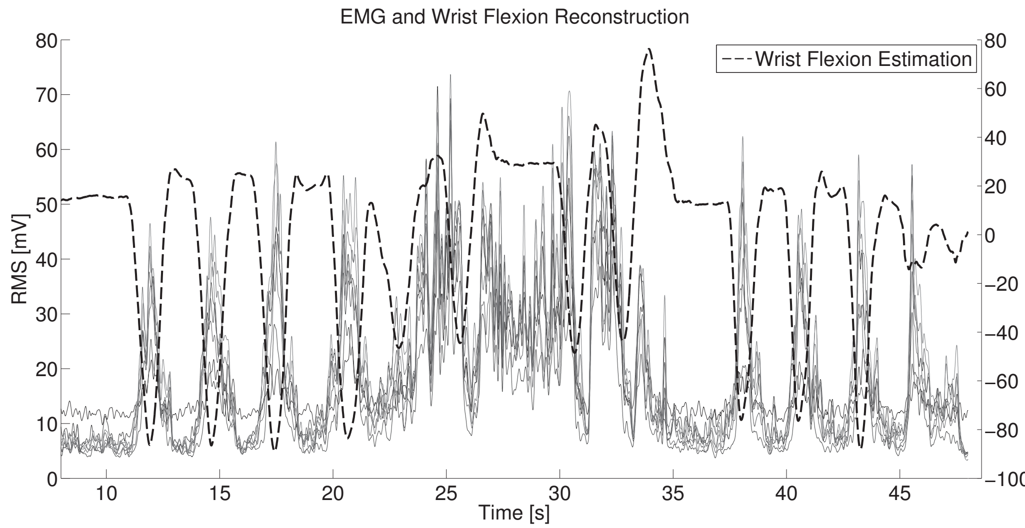

Fig. 8. Wrist flexion angle and the corresponding RMS of the EMG signal for the fore arm flexors.

The results from the motion reconstruction and the known weights from Table I, were used to give the RULA score of the movements involved in the experiment. The RULA assessment (RS) can be computed as a function of several variables, in particular:

$$RS = f(sh, e_f, wr, a_{ms}, l_{ms}, F, F_{fl}, a_{sup}, n_f, n_e, t_e, t_f, l_{sup}). \quad (4)$$

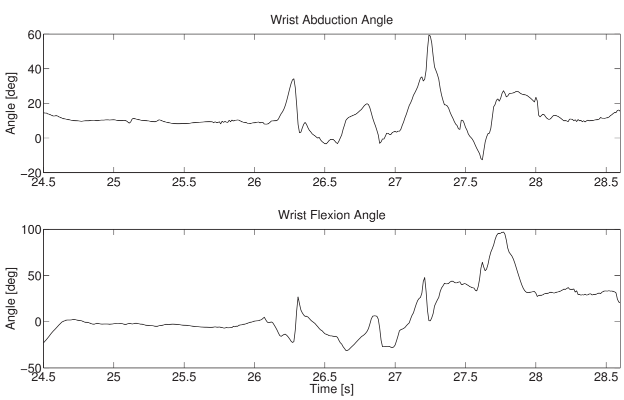

Fig. 9. Reconstruction of wrist angles, for the left arm.

Where sh are the angles of the shoulder three DoFs, e_f is the elbow flexion angle, wr are the flexion and abduction angles of the wrist, a_{ms} and l_{ms} are the muscle scores for arms and legs according to numbers of repetitions per minute, F is the load to be handled, F_{fl} is 0 or 1 if the load is handled intermittently or statically, n_f is the neck flexion angle, n_e and t_e are flags for neck and trunk bending, t_f is trunk flexion angle and a_{sup} and l_{sup} are the flag for arms and leg support.

An example of the RULA score assessment is shown in Figure 10, where the score is computed for the manipulation phases of two known objects (highlighted in red). In particular the objects considered are che Coke cans pack and the

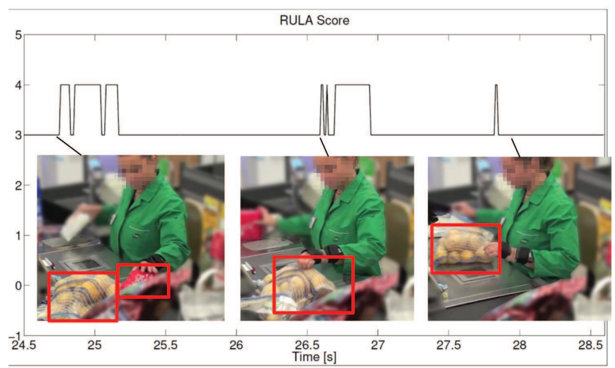

Fig. 10. RULA score for the manipulation phase of two known objects. The computation starts from the beginning of the manipulation of the first objects and ends after the end of the manipulation of the second object. The objects involved are highlighted in red

potato bag. As it can be seen from the figure, during some portions of the manipulation phase the RULA score increases according to the movements of the subject.

The correctness of the obtained scores was checked by visual inspection of the recorded tape of the experiment, as it happens in traditional observational methods.

IV. Discussion

We presented a system for the assessment of ULWMSDs. The system exploits both surface EMG and IMU signals to reconstruct the human motion and relate EMG features and RULA score to it. The system is composed of a board for acquiring raw data signals and compute EMG features, in particular RMS and MNF/MDF of the power spectrum are considered. The data is then sent to a host PC via Bluetooth, where the motion reconstruction pipeline runs. The resulting motion analysis is related to the EMG features to give an estimation of the ULWMSDs risk, along with the RULA score computation when known objects are involved in the task monitored.

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The system have been employed, as a preliminary, test to monitor a check-out operator during everyday operations. The results of the test have shown the capability of the system to correctly estimate the ULWMSDs risks, exploiting both postural and muscle effort information.

Up to date several other tests have been successfully carried on, in such scenarios as plaster cast application and nursing home operators. All the tests have shown the ULWMDs assessment capabilities of the system.

Further development of the system will involve adding more features to the computation and the possibility to reconstruct also the motion of the lower limbs.

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