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A Minimally Invasive Electromyography-based System for Pre-fall Detection

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***Abstract*— Fall events are one of the main causes of injuries among the elderly. The purpose of this study has been to identify a computational framework for the real-time and automatic detection of the fall risk, allowing the fast adoption of properly intervention strategies, to reduce injuries and traumas due to the fall. A wearable, wireless and minimally invasive surface Electromyography (EMG)-based system has been used to measure four lower-limb muscles activities. Eleven young healthy subjects have simulated several fall events (through a movable platform) and normal Activities of Daily Living (ADLs) and their patterns have been analysed. Highly discriminative features extracted within the EMG signals for the pre impact fall evaluation have been explored and a threshold-based approach has been adopted, assuring the real-time functioning. The threshold level for each feature has been set to distinguish an instability condition from normal activities. The proposed system seems able to recognize all falls with an average lead-time of 840ms before the impact, in simulated and controlled fall conditions.**

***Index Terms*—Electromyography sensors, fall risk evaluation, features extraction, wearable devices.**

I. INTRODUCTION

Falls remain one of the major and common types of accident and wellness issues among older people. The injuries due to a fall can cause physical and psychological consequences, such as: a long-term hospitalisation and a "Post-fall" syndrome, induced by the fear of fall resulting in the loss of their independence [1]. This can lead to a clear deterioration of their quality life and a related increase of the social and economic costs [2], [3]. During the last decade, the European population over 65 has increased s and this trend forced the care-holders institutions to employ more efficient and optimized methods in order to develop the required service at lower cost. The use of the current technologies, such as smart sensors, could help especially through the creation of intelligent environments to reduce the medical assistance and to support the elderlies at home. In particular, several automatic, miniaturized, wireless and wearable fall detectors have been developed for the daily activities monitoring [4], [5], [6], [7]. Even if this kind of technology is more invasive regarding to the vision or acoustic sensors, it presents some important advantages, such as: the re-design of the environments is not required, The possibility of an outdoor operation and the ethical issues (e.g. privacy) are always satisfied. The fall detectors appear very important for minimizing the time of medical intervention, however it is desirable the development of a system able to detect falls before the impact on the floor, which working together with an impact reduction systems, prevents some injuries. Several solutions have been proposed in the prevention of falls and high-quality reviews have been presented [8], [9]. They use inertial sensors (placed above all on the upper part of body) and threshold or machine learning techniques for the classification of the events. Their performance suggest that specificity and sensitivity values are high, but the lead-time before the impact is low (less than 400ms), for this reason a new EMG-based system to detect the risk of fall in a faster mode, has been investigated. To reduce the invasiveness, only four EMG sensors, placed through the gelled electrodes, have been considered and used for the measuring of the lower limb muscles activities. The main purpose of the work, deals with the development of a low-power, wireless, automatic and effective risk of fall detection EMG based framework. The realized prototype uses a threshold-based approach to permit a real-time functioning. The lead-time before the impact has been evaluated simulating imbalance condition and fall events through a moveable platform activated by a pneumatic piston. The obtained results shown that the system, in simulated and controlled conditions, is able to detect all falls about 840ms before the impact on the floor

II. EMG-BASED SYSTEM

The acquisition setup system has been made up of four wireless, wearable surface EMG probes and an USB receiver, produced by the BTS Bioengineering [10]. The data acquired are stored and elaborated on a stand-alone PC. The used BTS FREEEMG1000 system supports up to twenty low invasive probes: the weight of each sensor is about 10 gr and the dimensions are 41.5 × 24.8 x 14mm for the mother electrode and 16 x 12 mm for the satellite electrode. In Fig. 1 the BTS FREEEMEG1000 devices are shown. The sensors can be worn through the common pre-gelled electrodes by using clips, allowing fast, simple and resistant wear ability to the user's movements, reaching a high level of usability.

Each probe integrates:

- two low noise active electrodes to cancel any common mode noise;
- the sensor conditioning circuit (low-pass filter, programmable gain amplifier and Analog/Digital converter) to interface the sensing part to the Microcontroller Unit (MCU)
- The RF transmitter to send the data according to the Zigbee protocol;

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- The memory unit for data acquisition out of transmission range;
- A voltage regulator to supply the rechargeable Lithium battery.

It has been tested that the system can correctly work in indoor and outdoor environment, considering a range of more than 20 meters in free space and up to about 10 meters in presence of two 25 cm thick walls. The data can be sent during a period of about 8 hours in streaming mode, through the rechargeable lithium-ion integrated batteries. The 1 KHz frequency used in the sampling rate and the 16 bit resolution permit a high degree of accuracy. The algorithmic framework for the EMG signals acquisition and elaboration is located on a PC, that receives the data through the compact (dimensions 82 × 44 × 22.5 mm, weight 80gr), wireless and USB interfaced receiver. In the Table I the main characteristics of the EMG sensors and the USB receiver are summarized.

Fig. 1. EMG FREEEMG1000 System.

Table I. Main features of EMG FREEEMG1000 System.

Wireless Probes	Technical Features
Resolution	16 bit
Data Transmission	Wireless IEEE 802.15.4
Battery	Rechargeable Lithium-Ion
Autonomy	8h battery life in streaming mode
Acquisition range	Up to 20 meters in free space
Memory	On board solid-state
Certification	Class "IIa"
Weight	10 gr
Dimensions	41.5 × 24.8 × 14 mm mother electrode 16 x 12 mm the satellite electrode
USB receiver	
EMG channels	Up to 20 probes
Dimensions	82x44x22,5mm
Weight	80 gr

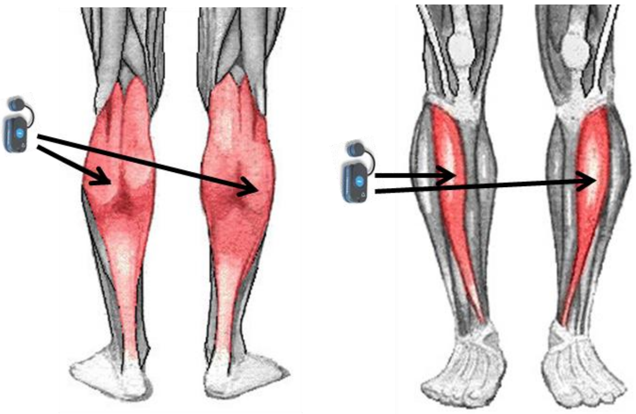

Fig. 2. EMG sensors mounting.

III. DATA COLLECTION

A data collection has been defined in controlled conditions during the simulation, in order to analyse the EMG signals, for each muscle considered, in presence of falls and other kind of events (ADLs). The research has been focused on the electromyography patterns evaluation of the two lower limb tibialis and of the gastrocnemius muscles groups, that have proved to be important in preventing falls [11]. The EMG data have been acquired wearing the sensors as it is shown in Fig. 2.

To develop and to test the fall risk assessment algorithm, a sufficiently large dataset has been created, conducting a study on eleven young healthy actors with different age (29.5 ± 8.2 years), weight (65.4 ± 11.1 kg), height (1.77 ± 0.2 m) and sex (8 males and 3 females) who have simulated:

a) ADLs, that belong to the following categories: sitting down on a chair and then standing up, lying down on a camp bed (height 45 cm) and then standing up, lying down on a mat (height 15 mm) and then standing up, kneeling on a mat (height 15 mm) and then standing up. In Fig. 3 it is shown the experimental scene realized;

b) Walk and sedentary behavior, in normal conditions and in the presence of deviant auditory stimuli (Oddball sequences);

d) Fall events using the movable platform [12] shown in Fig. 4. The actor is on a movable platform with the dimension of 40 x 40 cm. This system has been activated through a pneumatic piston with a variable compressed air pressure (from 4 to 8 bar). The movable platform has been equipped with the IMU Xsens MTi10 device, produced by XSENS Company [13], placed in the bottom of the platform. The Xsens MTi10 device integrates a gyroscope, an accelerometer and 3D magnetic sensors to measure linear motion with a sampling frequency up to 512 Hz and an angular resolution of 0.05 deg. Through its serial interface, the Mti10 device has been connected to the PC and the XSENS MT Software Suite has been used for the recording and the evaluation of the linear speed of the platform and the onset of platform motion.

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Fig. 3. Experimental Set-up for ADLs simulation.

Fig. 4. Movable Platform for fall events simulation.

The platform velocities (minimum recorded were 25 cm/s) changed proportionally with the air pressure value and they were able to cause several slow and fast backward falls of the actors. Each actor was equipped by wireless music headphones to isolate himself and to limit the platform activation noise. The simulated falls have been performed by using also two crash mats, height 20 cm, knee/elbow pad protectors, meeting safety and ethical requirements.

The actors performed more than 215 ADLs and 72 fall events. The data acquired during the campaign have been used to develop and to evaluate the computational framework of the system described in the following section.

IV. COMPUTATIONAL ARCHITECTURE

The preliminary study of the system has been developed on the Math works Matlab, and then the real-time application has been realized using Microsoft C# programming language. The main computational steps of the software architecture are:

a) Pre-processing;
b) Calibration;
c) Feature extraction;
d) Classification.

During the pre-processing phase, the raw data, coming from each sensor, have been band-pass filtered using a 12th order FIR filter, with cut frequencies between 20Hz and 450Hz, to reduce the artefacts and to avoid signal aliasing. Then, to compare the EMG-tension relationship the signals have been processed by generating their full wave rectification and their linear envelope, using a 10th order low-pass Butterworth filter, with cut-off frequency of 10Hz. The calibration procedure has been accomplished by recovering the initial condition after device mounting. In particular, to calculate the baseline of the signals, the signals average for each sensor was calculated while the user wore the devices in a still standing position for 5 seconds. Moreover to reduce the inter-individual variability of EMG the maximum signal amplitude values for the right and left gastrocnemium/tibialis muscles have been evaluated. These values have been used to normalize the pre-processed sensor data. In Fig. 4 It is reported an example of normalized signal for the gastrocnemius and Tibialis muscles of one leg, obtained during an instability trial.

V. FEATURE EXTRACTION

Several time-frequency domain features present in literature have been evaluated [11], [14], [15], [16] and to guarantee a real time functioning, for the first prototype, only one feature with high degree of discrimination and low computational cost have been selected. Based on the experimental results, the muscle Co-Contraction Indices (CCI) for the pair of gastrocnemius-tibialis muscles, using a sliding window of 100ms have shown higher performance. The CCI give an estimation about the simultaneous activation of the muscles pair for each data point of the pre-processed data and they were calculated using (1):

$$CCI_i = \frac{lowEMG_i}{highEMG_i} \times (lowEMG_i + highEMG_i) \times 100 \qquad (1)$$

Where low EMG_i is the EMG signal value for the less activity muscle, while the high EMG_i is the corresponding activity of the higher active muscle. The CCI can range from zero, when there is no muscle activity to a maximum of 200, when both muscles are at the maximum of their activity. In Fig. 6 and Fig.7 some examples of the waveforms for the CCI features for one leg, obtained for ADLs and fall events simulated, have been reported. From the figures the differences between the normal activities and critical events could be inferred: the maximum CCI values for ADLs activities are always less than 50, while for the fall events this value is more than 70. Moreover in Fig. 6 it is shown that the first relevant CCI is detected after about 200ms, after the start of the platform motion and about 860ms before the impact on the mat.

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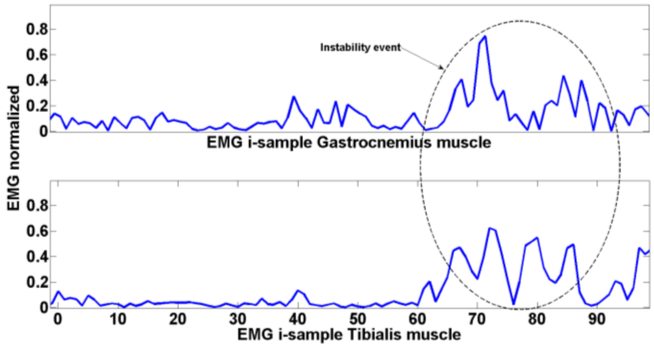

Fig. 5. Example of normalized EMG signals for the gastrocnemius and Tibialis muscles of one leg.

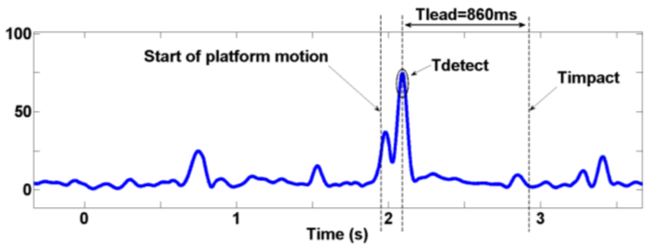

Fig. 6. Example of CCI for one leg for a fall event.

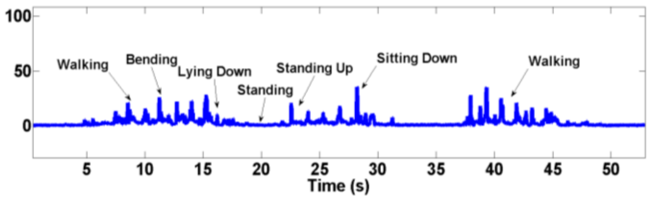

Fig. 7. Examples of CCI for one leg for some ADLs.

VI. RESULTS

The classification of the fall risk has been performed through a simple and low computational cost threshold approach. In this way the real time functioning [17] has been obtained to the detriment of generalization ability. For the evaluation of the system, the CCI have been calculated for more than 280 ADLs and instability events simulated during the acquisition campaign. To evaluate the performance of the system, the 10-fold cross-validation statistical method has been considered. It allows to give a good estimation about the generalization performance of the algorithm [18]. The data have been portioned into 10 equally sized folds and 10 iterations of training and validations are performed; within each iteration, a different fold of the dataset has been used for the algorithm test and the remain part has been considered to calculate the threshold values. They are calculated considering the minimum CCI values for the fall events. The algorithm recognizes the risk of a fall only when CCI thresholds have been over passed.

The metrics considered to evaluate the detection performance of the proposed system are the sensitivity and the specificity [19], defined in (2) and (3) .

$$sensitivity = \frac{TP}{TP+FN} \times 100 \qquad (2)$$

$$specificity = \frac{TP}{TP+FN} \times 100 \qquad (3)$$

Where TP (True Positive) indicates that a fall event happens and the algorithm detects it; FP (False Positive) indicates that a fall event does not occur and the algorithm send an alarm; TN (True Negative) means that a daily event is performed and the algorithm does not detect it; FN (False negative) reveals that a fall event occurs but the algorithm does not detect it. From the test appears that the system presents a significant performance, indeed, considering all iterations of cross-validation technique described above, the average measured value are 77.6% for sensitivity and 75.8% for specificity. These results have been obtained considering 1 KHz frequency sampling for the EMG signals. To reduce the computational cost, a performance evaluation on the system according to the down sampling EMG has been conducted. In particular the signals coming from each sensor channel has been digitally down sampled at 500, 250 and 125 Hz and CCI features have been calculated. The same size of the sliding window for all frequencies have been maintained, in this way the number of points available for each frequency value changes and, consequently, the accuracy can be modified depending on it [20]. To evaluate the effect of the down sampling frequency on the system performance, it is important to consider the change of the sensitivity and specificity on frequency variation. The analysis has been conducted using Matlab and in Table II the sensitivity variation (ΔSE) and the specificity variation (ΔSP), with respect to the 1 KHz sampling rate performance, have been reported. From the table, it is evident that the performance remains the same from 250 Hz up to 1 KHz sampling frequency; instead significant changes have been measured for 125 Hz. Consequently the computational cost evaluation has been conducted to find the best trade-off between performance and execution time for the frequencies of interest. The study has been conducted on the real time fall risk evaluation application realized in Microsoft C#. The system has been tested on a stand-alone PC, composed by a CPU i7@2.40 GHz with a RAM of 8 GB DDR3. The maximum execution time value measured is below the 1 ms, allowing a 1 KHz and below functioning. The execution time variation (ΔExecution Time), with respect to 1 KHz sampling rate, are reported in Table II. Moreover, in Fig. 8 and in Fig. 9 the performance in terms of sensitivity, specificity and relative execution time for the considered sampling frequency are reported. The best trade-off is acquired by using a 250 Hz sampling rate and for this reason it has been chosen for the application.

To evaluate the lead-time before the impact, the equation (4) [21] has been considered:

$$T_{lead} = T_{\mathrm{detection}} - T_{landing} \qquad (4)$$

Where $T_{detection}$ indicates the time when the fall is detected, $T_{landing}$ denotes the time when there is the impact on the mat and T_{lead} is the lead-time before the impact. A negative or positive T_{lead} indicated the fall was recognized before or after the impact respectively. For the evaluation of $T_{landing}$ a sensorized garment, integrating a triaxial accelerometer was

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used [4]. The average time-lead has been measured in about -840ms, considering all fall events recognized.

Table II. Performance variation with respect to the sampling frequency rate.

Frequency Rate (Hz)	ΔSE	ΔSP	ΔExecution Time
1000	-0 %	-0 %	-0 %
500	-0 %	-0 %	-15%
250	-0.8 %	-1.2 %	-38%
125	-8.3 %	-7.8 %	-46%

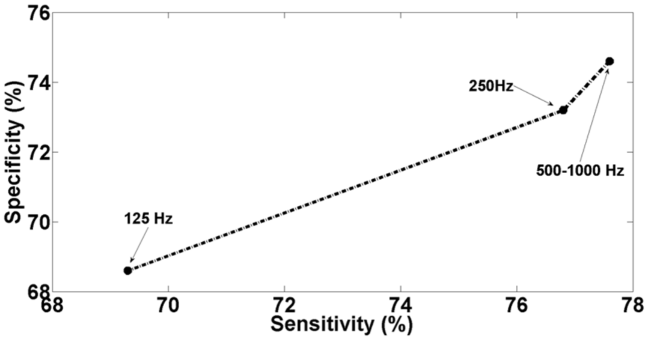

Fig. 8. Performance of the pre-fall detection system.

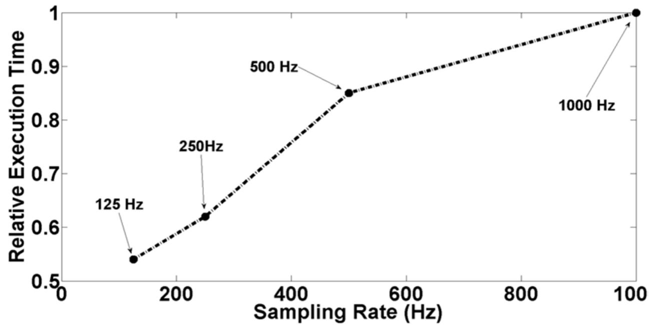

Fig. 9. Relative execution time of the pre-fall detection system.

VII. CONCLUSION

The research presents a study on a real-time and minimally invasive pre-fall detection surface Electromyography-based system. Significant performance in terms of detection time, sensitivity and specificity have been measured, in simulated conditions, by using only four EMG probes. The frequency rate with the best trade-off between the performances and execution time has been evaluated. Future works will be focused on the performance improvements of the system increasing the number of the EMG sensors.

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