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ScienceDirect

Procedia Engineering 120 (2015) 455 – 458

Procedia Engineering

www.elsevier.com/locate/procedia

EUROSENSORS 2015

A Wearable EMG-based System Pre-fall Detector

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Abstract

The paper presents a wearable system able to evaluate real time the risk of fall in elderly people, promoting the fast adoption of properly intervention strategies for reducing injuries (e.g. by activating an impact reduction system). A wireless and minimally invasive surface Electromyography-based system (EMG) has been used to measure four lower limb muscles activities. This work deals with the identification of highly discriminative features extracted from the EMG signals for the automatic detection of people instability. The framework prototype uses a threshold-based approach assuring real time functioning and permitting the detection of a typical imbalance condition about 200ms after the stimulus perturbation, in simulated and controlled fall conditions.

Peer-review under responsibility of the organizing committee of EUROSENSORS 2015

Keywords: surface Electromyography (EMG); features extraction; co-contraction index; risk of fall; Wearable system;

1. Introduction

Fall event is one of the main causes of trauma and death among older people [1,2]. Several automatic fall detectors have been developed and the availability of miniaturized, wireless and reliable sensors on the market allows the realization of affordable wearable systems useful for the daily activities monitoring [3,4,5]. This kind of technology is more invasive with respect to the vision or acoustic sensors, but it presents some important advantages, such as: the re-design of the environments is not required, outdoor operation is possible and ethical issues (e.g. privacy) are always satisfied. The fall detectors appear very important for minimizing the time of medical intervention, but it is desirable the development of a system able to detect falls before the impact on the floor to reduce injures, working together with an impact reduction systems. Several solutions have been proposed in prevention of falls and high-

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Peer-review under responsibility of the organizing committee of EUROSENSORS 2015
doi:10.1016/j.proeng.2015.08.667

quality reviews have been presented [6,7]. 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 in terms of specificity and sensitivity appear high (close to 100%), but the lead-time before the impact is low (less than 300ms), 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 for the measuring of the lower limb muscles activities. The main purpose of the work, supported within Innovaalab Apulia Project, deals with the identification of highly and computationally low-power discriminative features, extracted within the EMG signals for the automatic and real time detection of people instability. The framework prototype realized a threshold-based approach assuring real-time functioning and allowing the detection of a typical imbalance condition about 230ms after the stimulus perturbation (in simulated and controlled fall conditions).

2. System Overview

The hardware setup has been developed by using the wearable surface EMG system FREEEMG1000, produced by the BTS Bioengineering [8]. The system is made up of a USB receiver and up to 10 wireless EMG probes. The considered sensors are minimally invasive: no wire is used, dimensions are 41.5 × 24.8 × 14 mm and the weight is about 10 gr. They are attached to the common pre-gelled electrodes by using clips, allowing a fast, simple and robust mounting for the user's movements at the highest level of usability. The probes integrate the active electrodes which reduce the noise and an on-board solid-state buffer memory system, which guarantees the data safety in case of signal loss during the acquisition. The range of the wireless data transmission is about 20 meters in free space, according to the IEEE802.15.4 protocol. It is possible to acquire the data for more than 8 hours in streaming mode, through the rechargeable lithium-ion integrated batteries. The sampling rate of up to 1000 Hz and the 16 bit resolution permits a high degree of accuracy. The algorithmic framework for the acquisition and elaboration of the EMG signals is on a stand-alone PC, which receives the data through the compact (dimensions 82 × 44 × 22.5 mm, weight 80gr), wireless and USB interfaced receiver. In Fig.1 the overview of the EMG-based system is reported. The preliminary study of the system has been developed on the Mathworks Matlab, and then the real-time application has been realized using Microsoft C#.

Fig. 1 Overview of EMG-based system.

3. Set-up and data acquisition

The research focused the attention on the evaluation of the electromyography patterns of the two lower limb tibialis and gastrocnemius muscles groups, that have proved to be important in preventing falls [9]. The EMG data have been acquired wearing the sensors as it is shown in Fig.2. To create a sufficiently large dataset for the development and testing of risk assessment of fall algorithm, 7 young healthy actors with different age (28.8±7.6), weight (63.7±12.3), height (1.76±0.2) and sex have been involved simulating, under controlled conditions:

- ADLs - Activities of Daily Living (sit, stand, bend and lie down);
- walk and sedentary behaviour, in normal conditions and in the presence of deviant auditory stimuli (Oddball sequences);

- situations of instability (typical of a fall event), under controlled using a tilting platform equipped with an inertial sensor IMU Xsens MTi10, necessary for the detection of the angle and speed of simulated unbalance.

Fig. 2. EMG probes mounting.

4. Computational Framework

The main computational steps of the software architecture are: Data pre-processing, Calibration, Feature Extraction and Classification. The raw data, coming from the sensors, have been band-pass filtered using a 12^{th} order FIR filter with cut frequencies between 20Hz and 450Hz to reduce the artefact and to avoid signal aliasing. Then, the signals have been full rectified and linear enveloped to compare the EMG-tension relationship, using a 10^{th} 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. The calibration routine is achieved by the following steps:

1. The average of the signals for each sensor is calculated while the user wears the devices in a still standing position for 5 seconds. In this way the baseline of the signals is obtained;
2. The maximum signal amplitude measured in a period of 10 seconds is recorded, while the user performs the maximum contraction of the right and left gastrocnemium.
3. The maximum signal amplitude measured in a period of 10 second is recorded, while the user performs the maximum contraction of the right and left tibialis.

The values obtained in 1. and 2. are used to normalize the EMG signals referring to the maximum activation of the muscles of the user, reducing the inter-individual variability. According to the discrimination power for the instability event detection, several time-frequency domain features presented in literature [9,10] have been evaluated and selected. Based on the experimental results, the muscle Co-Contraction Indices (CCI) show higher degree of discrimination using a sliding window of 100ms. The CCI gives an estimation about the simultaneous activation of the pair of muscles for each data point of the pre-processed data and they were calculated using the equation (1):

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

Where $lowEMG_i$ is the EMG signal value for the less activity muscle, while the $highEMG_i$ is the corresponding activity of the higher active muscle.

5. Classification and Experimental Results

For the classification of the fall risk a threshold approach has been adopted. This method has been chosen to guarantee a real time operation to detriment of generalization ability. The CCI have been calculated for all ADLs and instability events simulated during the acquisition campaign described in section 3 and, through the analysis of the 265 recorded simulated events, the performance of the algorithm has been evaluated. Half of the dataset has been used to calculate the CCI threshold values to detect the instability events, while the remaining part has been considered to test out the performance in terms of sensitivity and specificity [11]. Three threshold values have been found (16.3, 27.2, 48.4) and the results are reported in Table 1.

Table 1. Performance of the system for fall risk evaluation.

Threshold	Sensitivity	Specificity
16.3	87.3%	64.8%
27.2	83.2%	72.4%
48.4	76.9%	81.5%

From Table 1 it appears that the alarm generated with the low threshold gives the possibility to recognize almost all instability events simulated, but generates several false alarms. Otherwise, with the high one value false alarms are reduced, however many situations of imbalance are not recognized. Finally, the mean threshold is the best trade-off for the recognition of fall risk. To increase the system robustness, further studies are in progress in order to assess the expected benefit from the use of a significantly higher number of probes (8 or 16) and to grow the data necessary to improve the validity of the threshold parameters selection. To evaluate the detection time, the average delay, with respect to the stimulus perturbation of the plane, has been measured in about 230ms; it means that the risk of fall can be recognized in very fast way, before other accelerometer-based pre-fall systems. The platform used introduces lateral, fast and sufficiently large (more than 16 degrees of amplitude) perturbations, bringing the users beyond their limits of stability.

6. Conclusion

A real time and minimally invasive surface Electromyography based system for the assessment of the risk of fall has been presented. Several time-frequency domain features presented in literature have been investigated and the low computational cost and the effective Co-Contraction Indices have been chosen. The classification has been performed through a real time threshold-based approach to guarantee a fast detection of the risk. Good performance in terms of detection time, sensitivity and specificity have been measured in simulated conditions. Future works will be devoted to increase the robustness and the performance of the system through the use of more sensors and increasing the dataset for the values of threshold calculation.

References

[1] M.C. Chung, K.J. McKee, C. Austin, H. Barkby, H. Brown, S. Cash, J. Ellingford, L. Hanger, T. Pais, “Posttraumatic stress disorder in older people after a fall”. Int J Geriatr Psychiatry 2009;24(9): pp.955–64.

[2] S. Sadigh, A. Reimers, R. Andersson, L. Laflamme, “Falls and fall-related injuries among the elderly: a survey of residential-care facilities in a Swedish municipality” J. Community Health 2004;29: pp.129–40.

[3] F. Bagalà, C. Becker, A. Cappello, L. Chiari, K. Aminian, J.M. Hausdorff, W. Zijlstra, J. Klenk, “Evaluation of Accelerometer-Based Fall Detection Algorithms on Real-World Falls”, PLoS One, 7 (2012), pp. e37062.

[4] P. Siciliano, A. Leone, G. Diraco, C. Distante, , M. Malfatti, L. Gonzo, M. Grassi, A. Lombardi, G. Rescio, P. Malcovati, “A networked multisensor system for ambient assisted living application”, Advances in sensors and Interfaces. IWASI 2009, pp. 139-143.

[5] G. Rescio, A. Leone, and P. Siciliano, “Supervised Expert System for Wearable MEMS Accelerometer-Based Fall Detector,” Journal of Sensors, vol. 2013, Article ID 254629, 11 pages, 2013.

[6] A.K. Bourke, K.J. O’Donovan and G.OLaighin,”The identification of vertical velocity profiles using an inertial sensor to investigate pre-impact detection of falls,” Medical Engineering & Physics, vol. 30, pp 937-946, 2008

[7] G. Wu,” Distinguishing fall activities from normal activities by velocity characteristics,” Journal of Biomechanics, vol.33,pp.1497-1500, 2000.

[8] http://www.btsbioengineering.com

[9] A. Phinyomark, G. Chujit, P. Phukpattaranont, C. Limsakul, Hu Huosheng, "A preliminary study assessing time-domain EMG features of classifying exercises in preventing falls in the elderly," Electrical Engineering/Electronics, Computer, Telecommunications and Information Technology (ECTI-CON), 2012 9th International Conference on , vol., no., pp.1,4, 16-18 May 2012.

[10] B. Horsak, et al “A. Muscle co-contraction around the knee when walking with unstable shoes”, J Electromyogr Kinesiol., vol.25, 2015

[11] N. Noury, P. Rumeau, A.K. Bourcke, G. Olaighin, J.E. Lundy, “A proposal for the classification and evaluation of fall detectors”. IRBM 2008;29(6):pp.340–9.