Available online at www.sciencedirect.com

ScienceDirect

Procedia Engineering 120 (2015) 324 – 327

Procedia Engineering

www.elsevier.com/locate/procedia

EUROSENSORS 2015

Smart sensing systems for the detection of human motion disorders

P. Lorenzi[a], R. Rao[a], G. Romano[a], A. Kita[a], M. Serpa[a], F. Filesi[a], R. Parisi, A. Suppa[b], M. Bologna[b], A. Berardelli[b], F. Irrera[a]*

[a]*Department of Information Engineering, Electronics and Communications, Sapienza University of Rome, Italy*

[b]*Department of Neurology and Psychiatry, Sapienza University of Rome, Italy*

Abstract

We propose a wearable wireless sensing system for the home monitoring of specific symptoms of the Parkinson's disease. The system is composed of inertial sensors, a station for the real time processing (smartphone/PC/tablet) and dedicated algorithms. The recognition algorithms use fusion of raw signals from accelerometers and gyroscopes. The system provides a robust and reliable detection of the involuntary freezing of gait, which is a common and dangerous symptom of the Parkinson's disease causing falls. The proposed system provides an early detection of the freezing of gate at its outset with excellent performance in terms of sensitivity and precision, and timely provides an audio feedback to the patient for releasing the involuntary block state.

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

Keywords: wearable wireless inertial sensors; home monitoring of motion features; Parkinson's disease; freezing of gait; auditory feedback.

1. Introduction

Motion symptoms of the PD include a wide variety of movement disorders [1]. In particular, the freezing of gait (FOG) is a paroxysmal block of movement which takes place in advanced stage of the PD, when the patient is not properly covered by the therapy. It typically starts with a progressive step shortening (*pre-freezing state*) [2] and a stop, during which patients refer that their feet are "stuck to the ground" (*FOG state*) [3]. During the FOG patients make attempts to complete the step, oscillating and thrusting forward the trunk, which can cause catastrophic events as falls [4]. It has been demonstrated that rhythmic auditory stimulation can bring patients out of the FOG state [5].

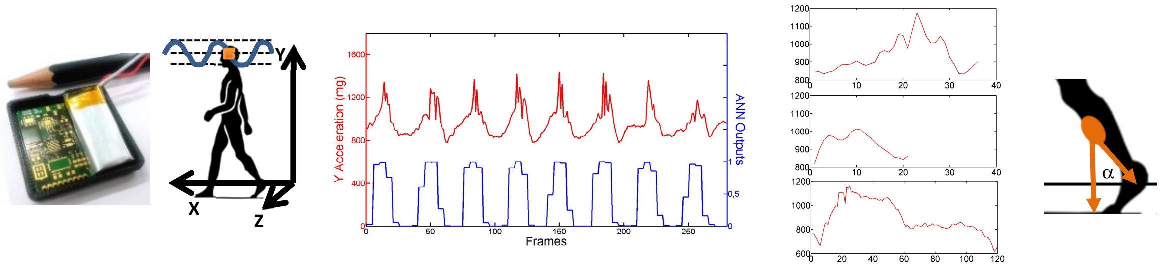
* Corresponding author. Tel.: +0390644585440.
E-mail address: Fernanda.irrera@uniroma1.it

Peer-review under responsibility of the organizing committee of EUROSENSORS 2015
doi:10.1016/j.proeng.2015.08.626

In the last few years, a number of systems for the FOG detection have been proposed, all based on the use of inertial sensors positioned on the patient body [6-11]. In this paper, we propose the realization of a wearable wireless sensing system based on MEMS inertial sensors able to recognize in real time specific kinetic features associated to motion disorders typical of (but not limited to) the PD and eventually give an auditory stimulation to the patient to release the block. Two different solutions are proposed here, one of which has the sensor in a headset (SHESS), while the other has two sensor on the shins (S3). They both were designed to be used at home or outdoor, during the normal activity of the patient. Respect to the other systems proposed in literature, SHESS has the advantage to be a single package (the headset), very easy to wear. This makes the system compact and energy efficient since no wired/wireless connection is required to give the audio-feedback. On the contrary, S3 requires an additional device in the ear for the audio-feedback, but guarantees the best performance presented in literature to date in terms of sensitivity, specificity, precision and accuracy. The board used for the two solutions is a prototype called neMEMSi [12]. It integrates an ultralow-power 32 bit microcontroller by STMicroelectronics (STM32L1) with 33.3 DMIPS peak computation capability and very low power consumption (down to 233 uA/MHz). The Cortex™ M3 architecture and the 32 MHz clock frequency make this microcontroller suitable for advanced and low-power embedded computations. The sensor unit LSM9DS0 integrates a ±16 g (g-force) 3D accelerometer, a ±12 Gauss 3D magnetometer and a ±2000 dps 3D gyroscope. Bluetooth communication is supported. The device size (with battery) is 25x30x4 mm^3 (see Fig. 1a).

2. The Smart Headset Sensing System (SHESS)

The headset contains the board and the audio feedback device. The framework is sketched in Fig.1b. The recognition algorithm uses raw data of the vertical acceleration (Ay) which has an oscillatory behaviour during a regular walk, as displayed in Fig.1c (upper curve, where peaks are steps) and an artificial neural network (ANN) with two layers (the hidden and the output ones) [13]. The ANN algorithm was chosen because is extremely light and fast. The ANN training starts with a *known* signal, in which specific reference patterns with a known size are identified. In Fig.1d there are shown the reference patterns of a regular step (top), a short step (mid) and a trunk oscillation (bottom). The known signal is partitioned in subsequences having the same size of the reference pattern. A cost function is calculated with a warping function [14], which represents the cumulative distance between the two time series. Sequences having a cost function below an optimized threshold are positive inputs to the ANN (1). An example of the ANN output in the case of successful recognition of regular steps is shown in Fig.1c (lower curve).



a b c d e

Fig. 1. (a) picture of the NeMEMSi board; (b) reference framework in SHESS; (c) SHESS: the upper curve is Ay during a regular walk, the lower curve is the ANN output after training with the reference pattern of a regular step; (d) reference patterns of a regular (top) and short (mid) step and a trunk oscillation (bottom); (e) S3: angle between the vertical axis and the shin.

Once the training of the ANN was complete, its capabilities were tested with *unknown* signals relative to states of particular interest for the PD: the stop state, short and irregular steps, trunk fluctuations. First test: Fig.2a shows the signals associated to the vertical acceleration (upper curve) during a voluntary stop state (region I), a regular gait (regions II and IV), while turning (region III). The ANN Output (ANN_O) is reported in the same figure, after training with the pattern of regular steps (lower curve). Second test: the Ay signal corresponding to an irregular gait is sketched in Fig.2b, with short steps in region III and regular steps in region II (upper curve). The short steps are typical of a pre-post-freezing state [2]. The ANN was trained with the reference pattern corresponding to short steps.

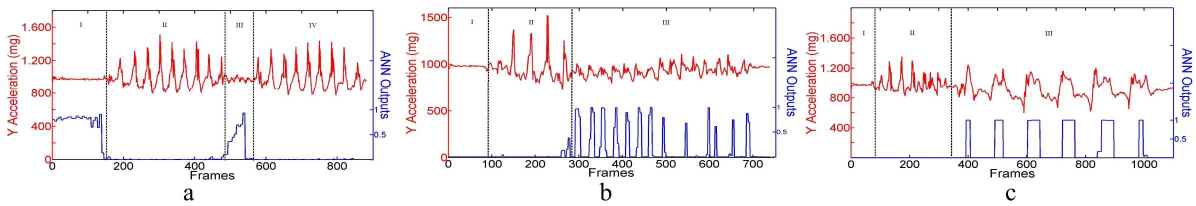


Fig. 2. (a) First test: recognition of the stop state (ANN_O=1 in region I and III, lower curve); (b) Second test: recognition of short steps (ANN_O=1 in region III, lower curve); (c) Third test: recognition of trunk oscillations (ANN_O=1 in region III, lower curve).

As one can see, short steps are clearly identified and distinguished from the regular ones (ANN_O curve of Fig.2b). No false positive/negative are present and the recognition is totally successful. We can affirm that SHESS can identify the pre-FOG state, which is an excellent result because an audio-feedback timely provided to the PD patient in that state would prevent the FOG onset. Anyway, in the case that FOG occurs, it is important to prevent falls, caused mainly by back and forth trunk oscillations. Therefore, the third test regards the recognition of trunk oscillations in the XY plane. The Ay signal in is reported in Fig.2c (reference pattern in Fig.1d). Of course, the position of the sensor emphasizes the sensitivity of the system to this symptom, in fact the ANN_O is really excellent (lower curve in Fig.2c).

3. The Sensing System on the Shins (S3)

In this solution, a sensor is positioned on each shin. The recognition algorithm is based on a time domain analysis of the sensor signals. The raw signals of accelerometer and gyroscope are fused together through the attitude and heading reference system (AHRS) and the Madgwick's algorithm (β =0.15) [15]. The data reading frequency from the sensor is 60Hz, which allows a correct sampling of the signal during FOG events since the relevant spectrum of FOG is 3 – 10 Hz. A quaternion based representation of the limb orientation and position is calculated. The angles α_{right} and α_{left} between the vertical axis and the right/left shin are sketched in Fig.1d. The angular velocities ω_{right}, ω_{left} obtained after angle derivation are used as the input for the FOG detection. The algorithm calculates the low-pass of the angular velocities: k_{right}=lowpass($|\omega_{right}|$) and k_{left}=lowpass($|\omega_{left}|$), and introduces an index $K = k_{right} + k_{left}$.
A group of ten patients of different age and sex, and at different stages of the disease was asked to wear the two sensors and make an exercise several times. The exercise was always the same: walking some steps, passing through an open door, turning and going back. FOG events occurred frequently during the exercises. In order to classify properly the states, a preliminary calibration of the system was performed. To this aim, the whole exercise was filmed with a camera and the sensor signals were recorded. The films were studied by doctors, who indicated the exact timing of the freezing events. Then, the calculated K curves were compared with the clinical observation by the doctors. This allowed to define three threshold values of K (T_{1-3}) which classify the four states: regular gait ($K>T_3$), pre-post freezing-state ($T_3>K>T_2$), involuntary freezing state ($T_2>K>T_1$) and voluntary rest state ($K<T_1$). It is worth noticing that the values of T_{1-3} are the same for all the patients. From a clinical side, distinguishing the involuntary freezing state from the rest state is crucial, but fortunately using inertial sensors it relatively simple, since in the involuntary freezing state the muscle activity is always present and gives rise to lots of small movements which are clearly detected by the sensors. Typical behaviors of α, ω and K are shown in the three top diagrams of Fig.3. Clinical report by doctors about the exact FOG timing is sketched in the bottom diagram. The comparison between the K curve and the clinical reports allowed to define the T thresholds and the four classified states. In the example of Fig.3, a few FOG and pre-FOG events were identified by both doctors and S3. In one case (time=23-28 s), S3 distinguished between pre-FOG and FOG states, whereas doctors reported just a FOG in the whole time interval. Values of T_{1-3} remained the same along all the measurements. Subsequent cross-checks outlined an excellent agreement between the doctors reports and the automatic recognition of FOG performed by S3. An extremely low number of errors (false positive or false negative) were found. This leads to the best performance published to date in terms of sensitivity, precision, accuracy and specificity. The average results on more than two hours recording time and ten patients are shown in Table 1.

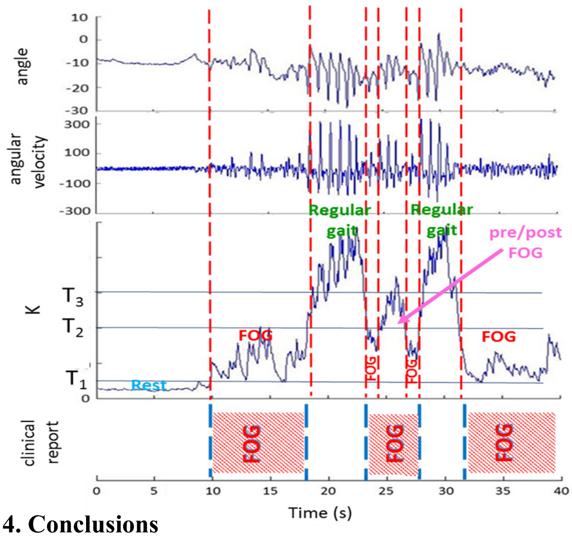


Table 1. Recognition performances of the system.

Sensitivity	Specificity	Precision	Accuracy
94.5%	*96.7%*	*93.8%*	*95.6%*

Fig.3 An example of angle and angular velocity measured by the sensor on the shin during the exercise. The calculate K index is also displayed. The bottom diagram reports the clinical observation of the FOG events timing. The comparison between the K curve and clinical report allows definition of the $T_{1\text{-}3}$ threshold values and, definitely, the four states.

4. Conclusions

Wearable wireless sensing of specific symptoms of the Parkinson's disease (PD) for the home monitoring has been proposed. The hardware is composed of inertial sensors and a station for real time processing (smartphone/PC/tablet). Two different solutions are proposed both operating in real time, one of which has the sensor in a headset, while the other one fixes two sensors on the shins. The recognition algorithms use fusion of raw signals from accelerometers and gyroscopes. The systems are extremely versatile and provide robust and reliable detection of the gait freezing state. The proposed systems provide an early detection of the freezing of gate with excellent sensitivity, precision, accuracy and specificity. An audio feedback can be timely given to the patient at the block onset.

Aknowledgements

Authors thank the patients for credit and forbearance, and STMicroelectronics for providing the NeMEMSi boards

References

[1] A. Nieuwboer et al. "Abnormalities of the spatiotemporal characteristics of gait at the onset of freezing in Parkinson's disease." *Movement Disorders* 16.6 (2001): 1066-1075.
[2] P. Arias and J. Cudeiro "Effects of rhythmic sensory stimulation (auditory, visual) on gait in Parkinson's disease patients" *Experimental Brain Research,* vol.186, pp.589-601, 2008.
[3] J. Spildooren et al "Freezing of gait in Parkinson's disease: the impact of dual-tasking and turning" *Movement Disorders*25.15 (2010)2563-70
[4] B. R. Bloem et al. "Falls and freezing of gait in Parkinson's disease: a review of two interconnected, episodic phenomena." *Movement Disorders* 19.8 (2004): 871-884.
[5] P. Arias, J. Cudeiro "Effect of Rhythmic Auditory Stimulation on Gait in Parkinsonian Patients with and without Freezing of Gait" PLoS ONE. Vol.5 (2010)
[6] P. Lorenzi et al. "Wearable Wireless Inertial Sensors for Long-Time Monitoring of Specific Motor Symptoms in Parkinson's Disease" BIODEVICES 2015 - 8th Int. Conference on Biomedical Electronics and Devices, Proceedings; Part of 7th International Joint Conference on Biomedical Engineering Systems and Technologies, BIOSTEC 2015, Lisbon (P) pp.168-173
[7] S. Mazilu et al. "GaitAssist: A Daily-life Support and Training System for Parkinson's Disease Patients with Freezing of Gait", *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems* 2531–2540 (2014)
[8] M. Bachlin et al. "A wearable system to assist walking of Parkinson s disease patients" *Methods Inf Med,* vol.49, pp.88–95, 2010.
[9] S. Moore et al. "Autonomous identification of freezing of gait in Parkinson's disease from lower-body segmental accelerometry" *Journal of NeuroEngineering and Rehabilitation,* vol.10, pp.19, 2013.
[10] B. Sijobert et al. "IMU Based Detection of Freezing of Gait and Festination in Parkinson's Disease" *IFESS MALAYSIA*, 2014
[11] S. T. Moore et al. "Ambulatory monitoring of freezing of gait in Parkinson's disease" *J. of neuroscience methods,* V.167, pp.340–348, 2008.
[12] D. Comotti et al. "neMEMSi: One step forward in wireless attitude and heading reference systems" *Inertial Sensors and Systems (ISISS)*, International Symposium on 1–4 (2014).
[13] C. M. Bishop et al. "Neural networks for pattern recognition", Clarendon, Oxford 1995.
[14] E. Keogh, C. A. Ratanamahatana "Exact indexing of dynamic time warping" *Knowledge and information systems,* vol.7, pp.358–386, 2005
[15] S. O.H. Madgwick, A. J.L. Harrison, R. Vaidyanathan , "Estimation of IMU and MARG orientation using a gradient descent algorithm", IEEE International Conference on Rehabilitation Robotics , Rehab Week Zurich, ETH Zurich Science City, Switzerland, 2011