Smartphone Based Freezing of Gait Detection for Parkinsonian Patients

Pepa L., Verdini F., Capecci M., Ceravolo M. G.

***Abstract*— We built a smartphone-based architecture to detect on line Freezing of Gait (FOG) occurrences and send acoustic signals to restore gait. Parameters used for FOG detection and FOG events are stored in a local database and periodically sent to a clinical server. We tested this solution on 18 patients.**

***Index Terms*— Parkinson's Disease, Freezing of Gait Detection, Smartphone, Acceptability**

I. Introduction

Parkinson's disease (PD) is a progressive neurological disorder affecting the basal ganglia [1]. PD often includes motor disorders that significantly impair quality of life. Among these, Freezing of Gait (FOG) is a dramatic, episodic gait pattern common in advanced PD. FOG can be defined as a "brief, episodic absence or marked reduction of forward progression of the feet despite having the intention to walk" and particularly occurs when initiating gait, turning or negotiating an obstacle [2]. FOG pathogenesis is largely unclear, because of the difficulties of observing it in a clinical environment and of the different kinds of FOG observed by clinicians [3]. Such episodic nature and heterogeneous manifestation make arduous assessing FOG severity. Furthermore clinical management of FOG is difficult because of its resistance to standard pharmacological treatment. Clinicians found alternative approaches [4]: evidences show that rhythmic auditory cueing can alleviate FOG and improve patient's gait performance [5]. In literature a number of wireless sensor networks has been proposed to detect FOG occurrence. Moore et al. [6], using vertical linear acceleration data of legs, defined a freeze index (FI) as the ratio between the integral of the power spectrum in the band 3-8 Hz and the integral in the band 0.5-3 Hz. A threshold is applied to detect FOG. Recently the same group of study [7] used this parameter for FOG detection through an architecture composed of 7 inertial measurement units that transmitted data to a computer. Bachlin e al. [8] proposed a wearable assistant, composed of sensors and computing unit, that produces rhythmic auditory cues when a FOG is detected. These authors improved the detection algorithm using an energy threshold to avoid false positives during standing. Energy is defined as the integral of the power spectrum of acceleration signal in the entire band $0.5-8$ Hz. Mazilu et al. [9] proposed a wearable assistant, composed of a smartphone as wearable computer and wearable accelerometers (hip, knee, ankle), for online detecting of FOG. When FOG is detected, the assistant provides rhythmic auditory cueing or vibrotactile feedback. The system is based on machine learning techniques. The classifier must be trained offline on a base station, then is stored in a file and copied to the mobile-phone for its online use. The class of systems discussed above presents some problems in terms of acceptability. All of them need to place sensors on patient's body and often need to transmit data to a computing unit, which must be always nearby the patient. According to [10], usability is "the extent to which a product can be used by specified users to achieve specified goals with effectiveness, efficiency and satisfaction in a specified context of use". Technology acceptance is a quality attribute referring how users come to accept and use a technology taking into account social implications as well as personal satisfaction and effort [11]. For a wider acceptance of healthcare monitoring systems we need to consider important aspects [12]:

- medical monitoring can generate in patients the perception of breaking their privacy;
- medical technology often refers to 'taboo related' areas, associated with disease and illness.

In this scenario, information and communication technology does not elicit oppressive or embarrassing feelings because of its popularity [12]. In particular smartphones offer a customizable user interface to increment perceived ease of use and inertial sensors to collect motion data.

The objective of this study is to present an architecture for FOG detection and able to provide acoustic feedback at FOG occurrence to help patients to resume walk. We aim to focus on acceptability and usability requirements discussed above, in order to maximize patient's ease and convenience in using the system during daily life. In this paper, Section II provides a description of the overall architecture. Section III deals with the evaluation modality, with a description of how the performance of the architecture was evaluated. Furthermore in Section IV we report results of experimentation and in Section V we discuss the results. Finally in Section VI we draw conclusions.

II. System Architecture

The objective of this study is to present and describe an architecture for FOG detection. The architecture can also help the patient to overcome the block providing acoustic feedback. The overall system was developed on a smartphone. The smartphone application was implemented for the

Authors are with the Information Engineering Department, Universita' Politecnica delle Marche, 60131, Ancona, Italy (email: {l.pepa, f.verdini, m.capecci, m.g.ceravolo}@univpm.it).

This work was supported by the Movement Disorders Centre, Department of Neurological Sciences, Neuro rehabilitation Clinic, United Hospitals of Ancona

two main platforms iOS and Android, in order to guarantee the portability of the system. To our knowledge in the literature there are not previous works of FOG detection with the only smartphone. The smartphone was placed at patient's hip through an elastic belt, in order to guarantee the alignment of accelerometer axes with vertical, medio-lateral and antero-posterior axes of the patient (fig. 1(a)). We used a socket to fix the smartphone at the belt. The socket should fit perfectly the smartphone, in order to hold it in vertical position. In fact for the processing purpose the alignment of accelerometer axis is critical only for the vertical one, but visual inspection of the right position for the socket is sufficient to maintain algorithm reliability.

A. Smartphone Application

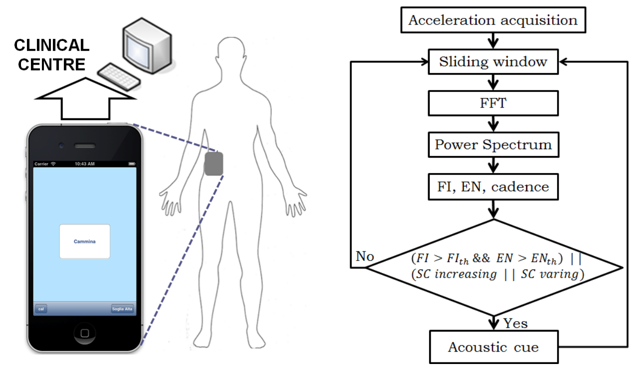
A smartphone application was developed which collects and processes data from the available accelerometer. The application acquires vertical acceleration measurements at a frequency of 100 Hz and then computes features for FOG detection. First the application applies a sliding window (Hamming window) of 256 samples on acceleration data; the window shift is 40 samples. On each window the application computes the FFT and the power spectrum, then features used by the detection algorithm: freeze index (FI) [6], energy (EN) [8] and cadence. The cadence is the step frequency and is calculated as the second harmonic in the power spectrum (continuous component excluded), in fact it is exactly two times the stride frequency. Auvinet et al. [13] confirmed, as expected, that the first power spectrum harmonic concerns stride frequency, while step frequency is the second power spectrum harmonic. Finally a detection rule is applied to features values and when a FOG event is detected acoustic feedback is provided to the patient.

The algorithm detects a FOG event when FI and EN are above their respective threshold values or if cadence is increasing or varying. Hence the detection rule uses two different characterizations of FOG [14]: the former uses the frequency analysis of hip movements (FI, EN) and the latter uses a spatiotemporal kinematic parameter of gait (cadence). The first part of the detection rule is the same of previous works in the literature [6], [8], but while in these works threshold values for FI and EN are chosen to be universal for all subjects, our application adopts user-specific thresholds computed as the mean plus one the standard deviation of parameters acquired from 20 sec of standing posture measures [15]. The second part of the detection rule refers to cadence increment or variation. We considered cadence variation and increase according to the following binary rules respectively:

$$(SC(i) \neq SC(i-1)) \wedge (SC(i-1) \neq SC(i-2)) \quad (1)$$

$$(SC(i) \geq SC(i-1)) \wedge (SC(i-1) > SC(i-2)) \quad (2)$$

where $SC(i)$, $SC(i-1)$, $SC(i-2)$, are the values of step cadence in the last three window. When condition (1) or (2) becomes true, the application detects a cadence variation or increase respectively. We introduced this second part of the detection rule, according to studies [16] that demonstrate the relation of FOG to the disruption of temporal, other than spatial, characteristics of gait. Based on these findings, we consider step cadence an important feature in FOG monitoring, that could increment sensibility of FOG detection and reduce the variability of performance among different patients found in previous studies [17], [8], [15], where it was related to different walking styles across subjects, the presence of tremor and different kinds of FOG in term of phenomenology. In fig. 1(b) a flow chart of the algorithm is presented.



(a) System architecture (b) Software flow chart

Fig. 1: (a) Overview of the overall architecture. (b) Algorithm flow chart

All the informations collected by the smartphone app (features calculated, FOG events detected and threshold values) are stored through an sqlite database internal to the smartphone and used later for statistical analysis. During daily living usage the application transfers all these data to a server at the clinical center periodically.

The user interface of the application was designed extremely intuitive and simple, in order to satisfy usability requirements. When the app is lunched the patient can start the algorithm only pressing a button.

III. Test and Evaluation

In this section we will explain the set up used to test the proposed architecture and the parameters used to evaluate its performance.

A. Experimental set up

Throughout the assessment protocol, the constant aim of the investigators was to obtain a sequence of videos depicting a wide range of FOG types and severities. In this way we could define the reliability and the external validity of the study, hence the transferability of results to all daily living situations. Therefore, patients were assessed, in the morning and under the effect of their own chronic dopaminergic therapy, while they were performing different types of video-recorded Time Up and Go (TUG) test, as described in the following. Patients performed three kinds of TUG tasks designed to provoke FOG on a standardized course of 5 meters:

1) the standard TUG test modified (5 meters) [18];
2) the Cognitive Dual Task Timed Up and Go test [19];
3) the Manual Dual Task Timed Up and Go test [20].

Each kind of TUG test was repeated for 3 times. Walking trials were recorded on a digital video camera from a consistent vantage point for later analysis, and each video showed a complete TUG trial starting and ending in the seated position. Simultaneous acceleration data were acquired from the trunk during the TUG trials described above.

Eighteen patients consecutively referred to the Movement Disorders Centre, Department of Neurological Sciences, Neurorehabilitation Clinic, United Hospitals of Ancona, were recruited. The study was approved by local Ethics Committee and written informed consent was obtained.

B. Evaluation criteria

The parameters used to evaluate system performance are the sensibility and specificity of the detection. In order to compare our results with the literature, sensibility and specificity are defined according to previous works in the literature [8], [9]. Sensibility is described by the following formula:

$$Se = tp/(tp + fn) \tag{3}$$

Where true positives (tp) were the windows correctly classified as FOG and false negatives (fn) the windows classified as non-FOG despite the patient manifests the symptom in that time instant. In order to have a better overview of the system, sensibility is calculated also as the ratio between the number of FOG events detected by the application and the total number of FOG events observed during all the trials. For what concerns specificity, we defined true negatives (tn) the windows correctly classified as non-FOG and false positives (fp) the windows wrongly classified as FOG despite its absence. Based on these definitions specificity was calculated as:

$$Sp = tn/(tn + fp) \tag{4}$$

IV. Results

Out of the 18 enrolled patients, fourteen (77.78%) showed at least one FOG episode during the proposed video assessment. We observed 73 FOG events in total, as recognized by clinicians based on video recordings. We obtained 82.34% of sensibility and 76.75% of specificity. During the online performance the application failed to recognize only 2 FOG events, which means that sensibility calculated as the ratio between number of FOG recognized and total FOG observed reached 97.26%. Applying offline the detection rule used in [8], which considers only FI and EN, we obtained 68.24% of sensibility and 82.38% of specificity.

V. Discussion

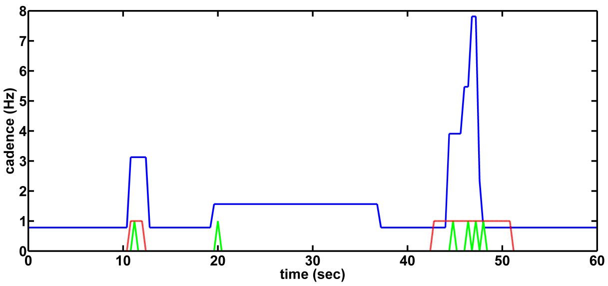
System performance in terms of sensibility and specificity is comparable to previous works in the literature. This is an important finding given the novelty of the architecture which uses the only smartphone. Bachlin e al. [8] obtained 73.1% of sensibility and 81.6% of specificity. Mazilu et al. [9] during the online performance reached a sensibility of 66.25% and a specificity of 95.38%. Instead Moore et al. [6] evaluated system sensibility only as number of FOG detected divided by number of FOG in total. They obtained 78.3% sensibility with a universal FI threshold and 89.1% with an individual threshold. In a more recent work [7] Moore et al. reached 84.3% sensibility and 78.4% specificity with a seven-sensors configuration. Furthermore they found 86.2% sensibility and 82.4% specificity for the single lumbar sensor, recommending this placement as an optimal configuration for autonomous FOG detection. It must be specified that in this work sensibility and specificity are assessed as a binary classification test [7], and thus they should be compared with our sensibility score of 97.26%.

As expected, with the addiction of a further FOG condition concerning cadence the specificity of our system decreased from 82.38% to 76.75%, but sensibility significantly increased from 68.24% to 82.34%. In fact according to the work [3] clinicians observed that three kinds of legs motion can occur during FOG: (i) small shuffling steps with minimal forward movement (shuffling with small steps), (ii) legs trembling in band $3 - 8$ Hz but no effective forward motion (trembling in place), and (iii) complete akinesia, i.e., no observed legs motion. The detection rule based on FI is indicated for only one kind of FOG and it seems difficult that it could be effective in the other cases. FOG episodes characterized by complete arrest of gait or by small, disturbed, and rapid steps could be detected in relation to cadence information [2]. Fig. 2 reports temporal trends of cadence and FI during a TUG trial of patient 14, who presents an akinetic FOG. The red line represents in both graphs the real instants of FOG as assessed by clinicians from video recordings. Particularly, in fig 2(a) it takes value 1 during a FOG and 0 in the other time instants, while in fig. 2(b) during a FOG the red line takes the value of the FI threshold. The blue line in fig. 2(a) is cadence trend, while in fig. 2(b) it represents FI variation. In fig. 2(a) the green line takes value 1 when the algorithm finds an increase in cadence or a cadence variation. With the only information of FI the system would not detect anyone of the two FOG events, while cadence augment permits our algorithm to detect both the events and to give the acoustic feedback to the patient.

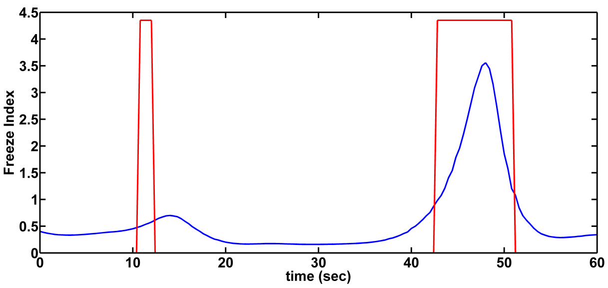
Sensibility and specificity could be improved by adding further information on gait, such as step length, which is another important parameter in FOG characterization. In fact in fig. 2(a) there is one false positive, due to a voluntary increment of speed and hence cadence. According to studies [3], [2], [14] the period just before FOG is characterized by an increased cadence, decreased stride length, and decreased angular excursion of leg joints. Hence with step length information a FOG event could be distinguished by a voluntary increment of gait speed, which generally causes an increase in both cadence and step length.

VI. Conclusions

We introduced a new architecture for online FOG detection, designed according to acceptability and usability



(a) Cadence trend



(b) Freeze Index trend

Fig. 2: (a) Cadence trend during the first TUG trial of patient 14: the blue line is cadence as calculated by the application; the green line shows cadence variation or increase; the red line shows the time interval of FOG as assessed by video recordings. (b) FI trend during the first TUG trial of patient 14: the blue line is FI as calculated by the application; the red line shows the time interval of FOG as assessed by video recordings, during the FOG the red line take the value of FI threshold

requirements. The core of the system was implemented on a smartphone, which is easy to use and does not elicit embarrassing feelings because of its popularity. Furthermore a smartphone does not limit patient's movement. The system functionalities are mostly achieved in an autonomous way in order to facilitate its use: the only action left to the patient is to start the system. Tests on 18 patients revealed a good reliability of FOG detection (71 events detected on a total of 73), that reached 82.34% of sensibility and 76.75% of specificity. The system represents a valid assistive tool as well as an alternative FOG assessment tool, especially for situations where clinicians have no information such as daily living. Hence it would be very interesting to test the system in a daily living situation. The performance could be improved by adding further information, such as step length, and using a more intelligent FOG detection rule, for example based on fuzzy logic [21]. Given the low impact on patient's movement and the absence of social implications, our architecture could be successfully applied to other chronic diseases.

References

[1] H. Braak, E. Ghebremedhin, U. RÃŒb, H. Bratzke, and K. Del Tredici, "Stages in the development of parkinson's disease related pathology," *Cell and Tissue Research*, vol. 318, no. 1, pp. 121–134, 2004.

[2] N. Giladi and A. Nieuwboer, "Understanding and treating freezing of gait in parkinsonism, proposed working definition, and setting the stage," *Mov Disord*, vol. 23, no. 2, pp. s423–25, 2008.

[3] J. D. Schaafsma, Y. Balash, T. Gurevich, A. L. Bartels, J. M. Hausdorff, and N. Giladi, "Characterization of freezing of gait subtypes and the response of each to levodopa in parkinson's disease," *Eur. J. Neurol.*, vol. 10, no. 4, pp. 391–398, 2003.

[4] S. H. Keus, M. Munneke, M. J. Nijkrake, G. Kwakkel, and B. R. Bloem, "Physical therapy in parkinson's disease: evolution and future challenges," *Mov Disord*, vol. 24, no. 1, pp. 1–14, 2009.

[5] C. L. Tomlinson, S. Patel, C. Meek, C. E. Clarke, R. Stowe, L. Shah, C. M. Sackley, K. H. Deane, C. P. Herd, K. Wheatley, and N. Ives, "Physiotherapy versus placebo or no intervention in parkinson's disease," *Cochrane Database Syst Rev*, vol. 6, no. 2, pp. 144–176, 1995.

[6] S. T. Moore, H. G. MacDougall, and W. G. Ondo, "Ambulatory monitoring of freezing of gait in parkinson's disease," *J Neurosci Methods.*, vol. 167, pp. 340–348, 2008.

[7] S. T. Moore, D. A. Yungher, T. R. Morris, V. Dilda, H. G. MacDougall, J. M. Shine, S. L. Naismith, and S. Lewis, "Autonomous identification of freezing of gait in parkinson's disease from lower-body segmental accelerometry," *J Neuroeng Rehabil*, vol. 10, no. 19, 2013.

[8] M. Bachlin, M. Plotnik, D. Roggen, I. Maidan, J. M. Hausdorff, N. Giladi, and G. Troster, "Wearable assistant for parkinson's disease patients with the freezing of gait symptom," *Information Technology in Biomedicine, IEEE Transactions on*, vol. 14, no. 2, pp. 436–446, 2010.

[9] S. Mazilu, M. Hardegger, Z. Zhu, D. Roggen, G. Troster, M. Plotnik, and J. M. Hausdorff, "Online detection of freezing of gait with smartphones and machine learning techniques," in *6th Intern. Conf. on Pervasive Computing Technologies for Healthcare (PervasiveHealth) and Workshops*, 2012.

[10] R. M. Schumacher and S. Z. Lowry, "Nist guide to the processes approach for improving the usability of electronic health records. national institute of standards and technology," *NISTIR 7741*, 2010.

[11] V. Venkatesh, M. G. Morris, G. B. Davis, and F. D. Davis, "User acceptance of information technology: Toward a unified view," *MIS Quarterly*, vol. 27, no. 3, pp. 425–478, 2003.

[12] M. Ziefle and W. Wilkowska, "Technology acceptability for medical assistance," in *Pervasive Computing Technologies for Healthcare (PervasiveHealth), 2010 4th International Conference on*, 2010, pp. 1–9.

[13] B. Auvinet, G. Berrut, C. Touzard, L. Moutel, N. Collet, D. Chaleil, and E. Barrey, "Reference data for normal subjects obtained with an accelerometric device," *Gait and Posture*, vol. 16, no. 2, pp. 124–134, 2002.

[14] A. Delval, A. Snijders, V. Weerdesteyn, J. Duysens, L. Defebvre, N. Giladi, and B. Bloem, "Objective detection of subtle freezing of gait episodes in parkinson's disease," *Mov Disord*, vol. 25, no. 11, pp. 1684–93, 2010.

[15] L. Pepa, F. Verdini, M. Capecci, M. Ceravolo, and T. Leo, "An architecture for reducing the freezing of gait during the daily life of patients with parkinson's disease," *Gait and Posture*, vol. 40, p. S2, 2014.

[16] A. Nieuwboer, R. Dom, W. De Weerdt, K. Desloovere, S. Fieuws, and E. Broens-Kaucsik, "Abnormalities of the spatiotemporal characteristics of gait at the onset of freezing in parkinson's disease," *Mov Disord.*, vol. 16, no. 6, pp. 1066–1075, 2001.

[17] L. Pepa, F. Verdini, M. Capecci, M. Ceravolo, and T. Leo, "Can the current mobile technology help for medical assistance? the case of freezing of gait in parkinson disease," in *Ambient Assisted Living: Italian Forum 2013*, S. Longhi, P. Siciliano, M. Germani, and A. Monteriu', Eds. Springer, 2014, pp. 177–185.

[18] A. Shumway-Cook, S. Brauer, and M. Woollacott, "Predicting the probability for falls in community dwelling older adults using the timed up and go test," *Phys Ther.*, vol. 80, no. 9, pp. 896–903, 2000.

[19] M. Hofheinz and C. Schusterschitz, "Dual task interference in estimating the risk of falls and measuring change: a comparative, psychometric study of four measurements," *Clin Rehabil*, vol. 24, no. 9, pp. 831–842, 2010.

[20] L. Lundin-Olsson, L. Nyberg, and Y. Gustafson, "Attention, frailty, and falls: the effect of a manual task on basic mobility," *J Am Geriatr Soc*, vol. 46, no. 6, pp. 758–761, 1998.

[21] L. Pepa, L. Ciabattoni, F. Verdini, M. Capecci, and M. Ceravolo, "Smartphone based fuzzy logic freezing of gait detection in parkinson's disease," in *Mechatronics and Embedded Systems and Applications (MESA), 10th IEEE/ASME International Conference on*, 2014.