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A smartphone-based architecture to detect and quantify freezing of gait in Parkinson's disease

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ABSTRACT

Introduction

The freezing of gait (FOG) is a common and highly distressing motor symptom in patients with Parkinson's Disease (PD). Effective management of FOG is difficult given its episodic nature, heterogeneous manifestation and limited responsiveness to drug treatment.

Methods

In order to verify the acceptance of a smartphone-based architecture and its reliability at detecting FOG in real-time, we studied 20 patients suffering from PD-related FOG. They were asked to perform video-recorded Timed Up and Go (TUG) test with and without dual-tasks while wearing the smartphone. Video and accelerometer recordings were synchronized in order to assess the reliability of the FOG detection system as compared to the judgement of the clinicians assessing the videos. The architecture uses two different algorithms, one applying the Freezing and Energy Index (Moore-Bächlin Algorithm), and the other adding information about step cadence, to algorithm 1.

Results

A total 98 FOG events were recognized by clinicians based on video recordings, while only 7 FOG events were missed by the application. Sensitivity and specificity were 70.1% and 84.1%, respectively, for the Moore-Bächlin Algorithm, rising to 87.57% and 94.97%, respectively, for algorithm 2 (McNemar value = 28.42; p = 0.0073).

Conclusion

Results confirm previous data on the reliability of Moore-Bächlin Algorithm, while indicating that the evolution of this architecture can identify FOG episodes with higher sensitivity and specificity. An acceptable, reliable and easy-to-implement FOG detection system can support a better quantification of the phenomenon and hence provide data useful to ascertain the efficacy of therapeutic approaches.

1. Introduction

Parkinson's disease (PD) is among the most common neurodegenerative disorders [1]: it imposes an increasing social and economic burden due to the progressive disability mainly related to gait and balance impairments. The freezing of gait (FOG) is a very distressing gait disorder affecting up to 80% of patients in the advanced stage of PD [2] and leading to a high risk of falls [3]. It is resistant to dopaminergic medication [4], though improves through external sensory cues [5,6]. It is generally defined as an episodic absence or marked reduction of forward progression of the feet, despite having the intention to walk [7], with different features being dominant: "shuffling" steps, "trembling" legs or akinesia [8]. Due to its erratic nature, FOG is difficult to be studied in the clinical setting [9,10].

A number of wearable sensors recently proposed for providing quantitative assessment of FOG during the real life [11–16]. Moore et al. [11] defined a freeze index (FI) using power spectrum analysis of vertical linear acceleration of the shank [13] during gait and implement it in an complex architecture (composed of 7 Inertial Measurement Units) that was able to transmit data wireless to a computer for processing. The FI is the ratio between the power in the "freeze" band (3–8 Hz) and the power in the "locomotor" band (0.5–3 Hz). Bächlin et al. [12] updated the FOG detection algorithm based on the FI proposing a lighter architecture in which acceleration data from three sensors attached to the body (shank, thigh and belt) were transmitted to a wearable computer through wireless Bluetooth link.

We developed a smartphone-based architecture for real time monitoring of FOG during daily living taking into consideration acceptance and usability requirements. [17] Our controlled cross-sectional study was aimed at verifying the reliability of this system in FOG detection by using two algorithms: an accredited algorithm of the literature (Moore-Bächlin algorithm), and a modification of this algorithm.

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2. Methods

2.1. Subjects

Twenty consecutive subjects, referred to the Movement Disorders Centre for counselling, were enrolled if they met the following eligibility criteria and signed an informed consent prior to the study: diagnosis of probable idiopathic PD [18]; independent ambulation, at least gait needing verbal supervision or help from one person without physical contact in the ON-state, i.e. under the effects of chronic antiparkinsonian treatment (either drug therapy or neuro-stimulation or a combination of the two); clinical history of FOG confirmed by a third person, i.e. caregiver (“probable freezer” [19]); age ≤ 80 years. Patients suffering from concomitant severe neuro-muscular and orthopedic disorders or from moderate to severe cognitive impairment (Mini-Mental State Examination—MMSE- score < 18) were excluded.

The study conformed to the Helsinki protocol for clinical trials and was approved by the local ethics committee.

Patients were assessed under the effect of their own chronic dopaminergic therapy. They underwent a standard clinical neurological assessment, before the execution of the experimental protocol. Hoehn and Yahr staging (H&Y), Unified Parkinson’s Disease Rating Scale (UPDRS), MMSE, Frontal Assessment Battery (FAB) were applied.

Subjects were: 5 female and 15 males, mean age 67.6 years (±9.1), disease duration 15.5 years (±6.6), H&Y stage 3.6 (±0.8) (median: 4), UPDRS total score 40.0 (±15.8), UPDRS Section II 18.5 (±6.2), UPDRS Section III 18.8 (±8.3), UPDRS Section II item “Freezing of gait” 2.4 (±0.7), LEDD (Levodopa equivalent daily dose) 707.3 (±242) mg, MMSE 25.9 (± 3.1), FAB 11.7 (±2.6). No subject was under chronic neuro-stimulation.

2.2. Experimental assessment protocol

Patients were asked to perform three different kinds of video-recorded modified Time Up and Go (TUG) tests: (1) TUG test without dual tasking [20], (ii) Cognitive Dual Task TUG test (Cognitive TUG) [21] and, finally, (iii) Manual Dual Task TUG test (Manual TUG) [22]. In line with Shumway-Cook et al. [20] description of the TUG test, the patient sits on the chair, then rises on the command “go”, walks 3 m at a comfortable and safe pace, turns, walks back to the chair and sits down. The chronometer is started at the instruction “go” and stopped when the patient seats again. In order to maximize the chance of FOG occurrence, the original TUG test [20] was modified asking patients to walk 5 instead of 3 m. In the Cognitive TUG, patients were asked to count backwards by threes, during walking, starting at a number selected by the assessor each time. In the Manual TUG, participants had to complete the task while carrying 2 full cups of water on a tray. Water levels in the cups and cup position on the tray were standardized. The patients had to perform three repetitions of each task, in a random sequence. If the clinical condition did not allow them to complete three repetitions, we accepted a lower number of trials, because the analysis was performed on the whole sample of FOG episodes.

Walking trials were video recorded and used for later analysis. Each video showed a complete TUG trial starting and ending in the seated position. During trials the patient wore the smartphone with the application running and hence performing real-time FOG detection. An elastic belt and a socket hold the smartphone attached to the hip joint (Fig. 1) The application stores all the data collected (gait parameters and FOG episodes) on an internal database.

2.3. The architecture and data processing

The architecture is composed of a smartphone with an application for FOG monitoring. The application was developed for iOS and Android operating systems, although tests were executed with an iPhone 5 (dimensions: 123.8 × 58.6 × 7.6 mm; weight: 112 g). The graphic user interface was designed in order to enhance usability. Just pressing the big central button in the display (see Fig. 1a), the application runs the FOG monitoring function, without requiring any further user interaction (Fig. 1a). The application acquires vertical acceleration data from the onboard sensor at 100 Hz. A sliding window (256 samples Hamming window) is applied to the acquired data; the window shift is 40 samples. On each window, the Fast Fourier Transform (FFT) and the power spectrum are calculated, and the following gait features are extracted: FI, as defined by Moore et al. [11], EI, in the version proposed by Bächlin et al. [12] and step cadence, computed as the second harmonic in the power spectrum. Considering human gait a periodic phenomenon, Auvinet et al. [23] showed that stride frequency represents the first harmonic in power spectrum, while step frequency (cadence) is the second. A peak detection algorithm finds the step cadence by identifying the second peak in the power spectrum acquired data do not include continuous component since the application retrieves user acceleration, without gravity. Two trapezoidal integrations are performed on the frequency intervals characterizing the ‘freeze’ and ‘loco’ bands. The obtained values are divided to find FI and summed to find EI. Although the three features can be computed using any acceleration component (vertical, antero-posterior or medial-lateral), the vertical one is the most significant for the FI [11,13]. Hence, only the vertical component was used for feature extraction, in order to avoid CPU and RAM wasting, thus enhancing real time performance.

Two FOG detection algorithms were tested.

1) **Algorithm 1** (**Moore-Bächlin Algorithm**, **A1**) is the same described by Bächlin et al. [12], which uses FI and EI. FOG is detected when both FI and EI exceed a threshold value, as expressed in the next equation:

$$mb \equiv \left(\left(FI(i) > FI_{th} \right) \wedge \left(EI(i) > EI_{th} \right) \right) \tag{1}$$

Where $FI(i)$ and $EI(i)$ are FI and EI values of the current window, FI_{th} and EI_{th} are FI and EI threshold values.

2) **Algorithm 2** (**A2**) adds step cadence information to A1. In particular, step cadence variation and increase are evaluated according to the following binary rules respectively:

$$a \equiv (SC(i) \neq SC(i-1)) \wedge (SC(i-1) \neq SC(i-2)) \tag{2}$$

$$b \equiv (SC(i) \geq SC(i-1)) \wedge (SC(i-1) > SC(i-2)) \tag{3}$$

where $SC(i)$, $SC(i-1)$, $SC(i-2)$, are cadence values in the last three windows, and the symbol $\wedge$ stands for logical conjunction (“AND” operator). When condition (2) or (3) becomes true, the application detects a cadence variation or increase respectively.

A2 detects a FOG start through a combination of different binary rules:

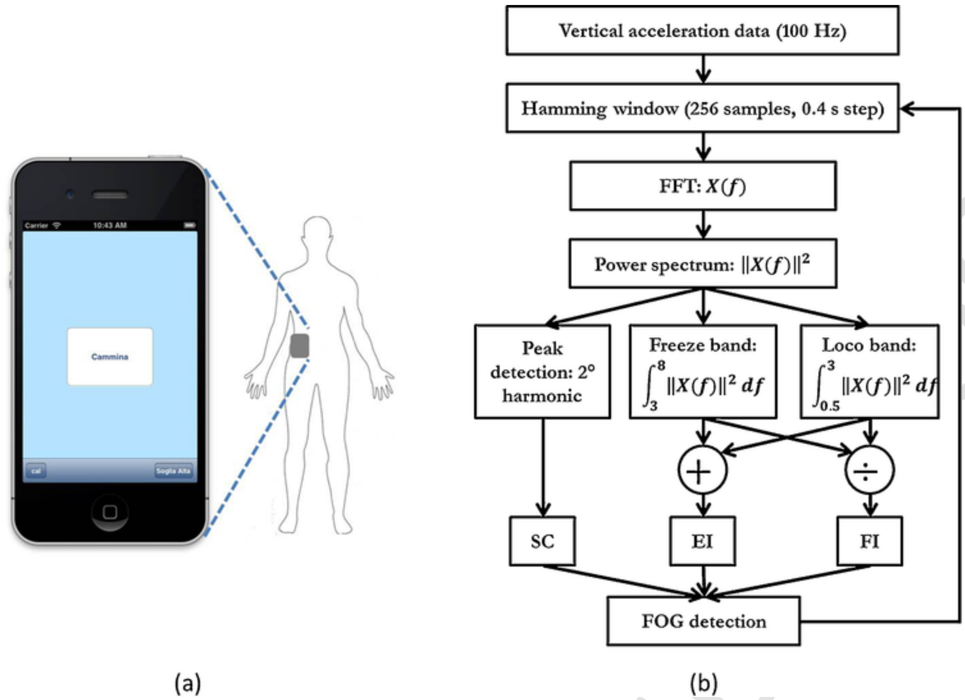

Fig. 1. (a) The hardware of the FOG detection system: a smartphone with the proper application installed. This structure was chosen to enhance usability and acceptability requirements. (b) The block scheme of the FOG detection app. Vertical acceleration data are acquired at 100 Hz sample frequency, then a sliding window is applied for real time processing. On each window, the Fast Fourier Transform (FFT) is computed and successively the power spectrum. The second harmonic of the power spectrum is taken as the step cadence (SC), the integrals between 3 and 8 Hz (Freeze band) and 0.5–3 Hz are computed. The sum of Freeze and Loco band is the EI, while the ratio of Freeze and Loco band is the FI. SC, EN and FI are sent in input to the FOG detection algorithm. It must be specified that the Moore-Bachlin algorithm does not have the "2° harmonic" and "SC" functional blocks. Furthermore, the "FOG detection" block is different in Algorithm 1 and 2.

$$mb \wedge (a \vee b) \tag{4}$$

Where mb stands for A1 (Eq. (1)), a and b are the binary rules reported in Eqs. (2) and (3), and the symbol $\vee$ stands for logical disjunction ("OR" operator).

After detecting a FOG start, the smartphone app starts a concurrent processing thread with the task of detecting the FOG end when the following rule becomes false:

$$mb \vee (a \vee b) \tag{5}$$

Both the algorithms adopted the same user-specific thresholds for FI and EI, in order to adapt the algorithm to patient's characteristics and hence to increase system reliability in FOG detection. Customized thresholds (FI_{th}, EI_{th}) are set as the mean plus one standard deviation of parameters (FI, EI) computed during 20 s of standing posture.

The smartphone locally stores gait features, FOG time of occurrence, FOG duration and threshold values.

A2 was applied in real-time during the experimental trials, while A1 was applied offline on the same data records.

2.4. Data analysis

System reliability was assessed measuring Sensitivity, Specificity, Accuracy, and Precision. These measures were calculated by matching smartphone data recorded to the judgement of two expert clinicians (MGC and MC) who scrutinized the videos and marked the start and end of each FOG event occurring during the TUG trials. Clinicians also took note of the following features of each trial: time of TUG execution (time taken to perform all trials of each TUG), number of freezing episodes, duration of each freezing episode (seconds), total FOG duration (FOG duration per number of FOG episodes), type of freezing (trembling, shuffling, akinetic), gait phase of FOG occurrence (initiation, turning, ending, midway).

The distribution of demographic and clinical variables in the whole sample was described using mean, standard deviation (±SD), median, range and interquartile range (IQR) for continuous variables, while rates were used to describe categorical parameters.

Data analysis was performed on the whole sample, including both patients who showed FOG episodes during video recordings and those who did not, although complaining of FOG daily at home.

Sensitivity (Se), specificity (Sp), precision (Pr) and accuracy (Ac) were used to assess the smartphone reliability and they were calculated according to the following formulas:

$$Se = tp / (tp + fn)$$

$$Sp = tn / (tn + fp)$$

$$Pr = tp / (tp + fp)$$

$$Ac = (tp + tn) / (tp + fn + tn + fp)$$

Here, tp = true positives are the windows correctly classified as

FOG, *fn* = false negatives are the windows classified as not-FOG despite the patient showed FOG in that time instant, *tn* = true negative, are the windows correctly classified as not-FOG and *fp* = false positives are the windows classified as FOG despite its absence. Values were computed for each score, and for each patient (considering all the trials together), as well as for the whole patients

The ROC analysis and the McNemar's test were carried out to assess and compare algorithms performance. FOG episode durations measured by A1, A2, and clinicians were compared through a Kruskal Wallis test. The reliability of the system was also checked with respect to the detection of FOG episodes occurring at the turning; in fact, step cadence spontaneously changes on turning even in the absence of FOG, possibly producing ambiguous results. The system sensitivity to acknowledge turning FOGs was calculated by the number of turning FOGs correctly detected out of the total number of turning FOGs. Conversely, specificity was defined by the number of turns where the system correctly ruled out a FOG episode out of the total turns without FOG. Finally, the relation between some clinical variables, possibly interfering with gait patterns, (Hoehn & Yahr stages, FOG and PD types) and Sp and Se was tested (both with Kruskal Wallis test for continuous data and Chi square test classifying Se and Sp > or < 50%).

3. Results

3.1. Clinical assessment of gait trials

Sixteen (80%), out of 20 enrolled patients, showed at least one FOG episode during the trials. A total 98 FOG events were recognized by clinicians based on video recordings. Inter-rater agreement was perfect with respect to FOG episode acknowledgment, and fair (ICC > 0.80) concerning FOG duration. Table 1 shows descriptive statistics of clinical features. Patients performed the standard TUG faster than the Cognitive ($z = -2.3$; $p = 0.01$) and Manual ($z = -2.3$; $p = 0.01$) TUG tests. During Standard and Manual TUG, FOG episodes most frequently recurred on turning (42% and 46% respectively) and on gait initiation (31% and 27% respectively), whereas during the Cognitive TUG, they recurred equally at the initiation (26%) as well as at midway, turning point and destination (24% respectively). Considering FOG subtypes, 52% were akinetic, 31% shuffling and 17% trembling. The percentages did not change across the three kinds of TUG tests.

3.2. Algorithm reliability

The application correctly detected 91 of the 98 FOG events (92.86%) diagnosed by clinicians. The same result was obtained both with A2 running in real time, and with A1 applied offline.

The reliability scores, obtained on the whole sample of subjects, were: 70.11% (±21.22) sensitivity, 84.13% (±21.99) specificity, 63.45% (±13.57) precision, 81.69% (±17.86) accuracy as for A1; whereas 87.57% (±12.81) sensitivity, 94.97% (±7.79) specificity, 69.55% (±12.43) precision and 84.37% (±10.83) accuracy for A2.

The reliability values were also separately computed on the subgroup of freezers (Table 2: last row).

Fig. 2 shows ROC curves of the two algorithms Area Under the Curve (AUC) was 0.81 for A1 and 0.90 for A2 on the whole sample. The comparison between the two tests was carried out on the whole data sample obtaining a McNemar value of 28.42 and a p-value of 0.0073.

FOG duration values (median, IQR) slightly differed according to detection type: they were 4 (7.7) s for the clinical assessment, 1.6(1.6) s and 2.8(4.5) s for A1 and A2 respectively. Clinical and A2 measurements of FOG duration proved to be significantly correlated (Kruskal Wallis test: $p = 0.01$), whereas no relationship was observed between clinical assessment and A1

Table 1
FOG features as determined upon the clinical assessment of videos. Values refer to the whole group of subjects.

		Mean	Standard deviation	Median	Minimum	Maximum	IQR
TUG time (seconds)	Standard TUG	83.76	52.55	61.08	28.12	198.63	88.73
	Cognitive TUG	118.98	149.75	68.89	42.62	728.98	56.09
	Manual TUG	91.10	93.62	67.37	29.81	437.43	30.98
FOG episodes	Standard TUG	1.6	2.0	1	0	6	2
	Cognitive TUG	2.4	2.1	2	0	9	4
	Manual TUG	2.3	2.7	1.5	0	9	4
FOG episode duration (seconds)	Standard TUG	6.64	5.54	4.5	0	14.1	10.5
	Cognitive TUG	18.02	30.86	4.8	0	11.3	17.5
	Manual TUG	47.9	135	4.6	0	433	6.2
Total FOG duration per subject (FOG duration per number of FOG episodes)	Standard TUG	33.43	39	7.7	0	127	41
	Cognitive TUG	65.99	164.8	10	0	667	55.4
	Manual TUG	66.97	135.6	15	0	433	54.2
		Trembling (%)	Shuffling (%)	Akinetic (%)			
FOG type	Standard TUG	20	31	49			
	Cognitive TUG	10	36	54			
	Manual TUG	23	23	54			
		Initiation (%)	Turning (%)	Midway (%)	Ending (%)		
Distribution of FOG episodes by gait phase	Standard TUG	31	42	11	16		
	Cognitive TUG	28	24	24	24		
	Manual TUG	27	46	11	15		

Table 2
Results. Se1, Sp1, Pr1 and Ac1 are sensitivity, specificity, precision and accuracy of algorithm 1, while Se2, Sp2, Pr2 and Ac2 are sensitivity, specificity, precision and accuracy of algorithm 2. Mean and standard deviations are reported at the bottom lines for all the patients ("All" row) and for the only ones who manifested FOG ("Freezers" row).

Pat. id	Gender	PD Type	N° FOG	Se1	Se2	Sp1	Sp2	Pr1	Pr2	Ac1	Ac2
1	M	Akinetic	2	81.25%	93.75%	98.94%	99.75%	50.00%	60.00%	95.18%	96.09%
2	M	Akinetic	14	65.54%	78.00%	58.21%	87.49%	61.32%	68.52%	56.30%	68.62%
3	M	Akinetic	3	81.11%	93.33%	98.46%	99.23%	71.43%	74.14%	97.94%	96.60%
4	F	Akinetic	1	40.00%	90.00%	96.52%	98.30%	58.00%	62.26%	94.74%	92.66%
5	F	Tremoric	9	49.16%	74.08%	98.36%	99.43%	88.79%	89.23%	88.45%	88.08%
6	M	Akinetic	1	100.00%	100.00%	38.79%	68.80%	44.27%	47.57%	79.11%	73.17%
7	M	Akinetic	7	64.86%	85.38%	90.57%	96.06%	61.02%	70.08%	82.50%	88.22%
8	M	Akinetic	8	48.81%	72.77%	91.23%	98.39%	67.78%	75.85%	88.13%	76.49%
9	F	Akinetic	13	92.68%	97.29%	31.55%	81.72%	65.50%	76.13%	63.64%	68.85%
10	M	Akinetic	–	–	–	85.64%	91.58%	–	–	85.64%	91.58%
11	M	Akinetic	–	–	–	99.51%	99.79%	–	–	99.51%	99.79%
12	M	Akinetic	1	100.00%	100.00%	89.74%	94.93%	62.14%	64.41%	91.40%	87.11%
13	F	Tremoric	–	–	–	43.49%	87.81%	–	–	43.63%	87.81%
14	M	Tremoric	4	38.59%	76.63%	95.62%	97.59%	67.33%	78.11%	88.38%	73.85%
15	F	Tremoric	6	76.79%	100.00%	90.40%	98.04%	72.50%	75.25%	89.05%	84.59%
16	M	Tremoric	–	–	–	97.47%	99.25%	–	–	97.47%	99.25%
17	M	Akinetic	2	87.50%	100.00%	98.35%	98.87%	42.35%	49.56%	89.43%	88.04%
18	M	Akinetic	2	80.00%	100.00%	95.40%	97.99%	56.67%	61.31%	96.75%	87.67%
19	M	Akinetic	14	75.26%	81.71%	99.10%	98.05%	91.38%	93.84%	41.82%	63.60%
20	M	Akinetic	11	40.13%	58.13%	85.22%	96.41%	54.70%	66.57%	65.08%	75.24%
All subjects			98	70.1 ± 21.2%	87.6 ± 12.8%	84.1 ± 22.0%	95.0 ± 7.8%	63.5 ± 13.6%	69.6 ± 12.4%	81.7 ± 17.9%	84.4 ± 10.8%
Freezers			98	70.1 ± 21.2%	87.6 ± 12.8%	84.8 ± 21.8%	94.4 ± 8.4%	63.5 ± 13.6%	69.6 ± 12.4%	81.7 ± 16.4%	81.8 ± 10.4%

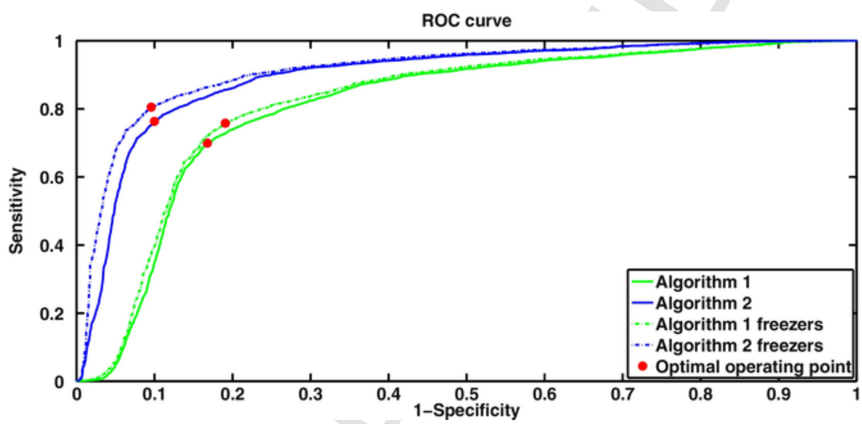

Fig. 2. ROC curve of algorithm 1 (green lines) and algorithm 2 (blue lines). The curves were built with the whole data set (continuous lines) and with the trials of the only freezers (dotted lines). Red dots indicate optimal operating points. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

For what concerns system reliability at the turning, sensitivity and specificity were 80.63% and 75.87%, respectively for A1, while 94.87% and 90.33% respectively, for A2.

PD type, FOG type or Hoehn & Yahr stage did not influence the reliability of the two algorithms.

4. Discussion

We described a smartphone-based architecture, developed to detect and quantify FOG in patients with PD. In a laboratory setting, we have proved the high reliability of the system in FOG monitoring, in particular after the implementation of A2.

Our sample is representative of "PD freezers" as described by different authors [3,4,7,8]: the incidence of freezing in the laboratory was higher than in previous reports [7,8] probably because we used a longer and dual-task TUG test protocol.

A1 reliability (Se and Sp mean scores) was found comparable with previous works [12,24,25], although it was tested on a different system of accelerometers. In fact, Moore et al. [13] obtained a sensitivity of 86.8% and specificity of 82.4%, whereas Bächlin et al. [12] obtained a mean sensitivity of 73.1% and specificity of 81.6%.

In our sample, the standard deviation is high for A1, revealing a possible loss of performance in some patients. This was observed also in previous works [12,14], where it was related to different PD types (tremoric versus akinetic). In the present study no correlations were found between Sp or Se and the clinical data (PD and FOG types, Hoehn & Yahr stages), possibly due to the small sample size.

A2 adds to A1 the computation of the step cadence and the evaluation of its variability or increase through two binary rules (Eqs. (2) and (3)). This upgrade was decided on the basis of studies relating FOG to the disruption of temporal, rather than spatial, characteristics of gait [26,27]. With A2, the mean reliability values increased while the standard deviations decreased McNemar test, applied to the whole data sample, confirmed that these improvements are statistically significant. With rule (4), A2 can avoid false positives due to a wrong increase of FI and EI (i.e. in patients affected by tremor of distal limbs) or a wrong variation of step cadence (i.e. while approaching to a turn). Actually, the normal cadence increases to higher values in shuffling and trembling FOG, making condition b true. In akinetic

FOG, the second harmonic in the power spectrum (step cadence) should change randomly without the periodic contribution of walking, making condition a true. Furthermore, rule (5) ensures that the frequency content comes back in the 'loco' band and the step cadence regularity is restored before detecting the end of the episode, thus improving sensitivity and the quantification of FOG duration. The ROC analysis and the Kruskal Wallis test on FOG durations confirmed these correlations between step cadence and FOG.

Finally, system reliability at the turning does not deteriorate with respect to the overall performance, making it useful in the most challenging and recurrent situation.

A large part of previous architectures [11–13] challenge the acceptability criterion, [17] since they need to place intrusive sensors on patient's body and to transmit data to a computing unit, which must be near the patient. Conversely, we chose the smartphone as our sensing and processing unit for its popularity (socially accepted), ease of use and growing computational capabilities. The choice of a smartphone-based architecture gives patients the opportunity to use the device in the community during everyday life [28,14,15]. Ginis et al. [16] proposed a wearable architecture for FOG detection and training composed of three sensors and a smartphone. To our knowledge, only Kim et al. [15] led both sensing and processing on a smartphone. However, our system differs for the adopted algorithm and for the use of user-specific thresholds, rather than a standard threshold for all subjects.

The study has some limitations, mostly represented by the sample size, which may reduce the reliability of the Se and Sp comparison among the three different FOG/PD subgroups (akinetic, shuffling and trembling) or within PD types and stages.

5. Conclusion

The smartphone-based architecture presented in this study is a not-intrusive system that proved to be highly reliable for FOG monitoring. The promising results obtained in a laboratory context encourage further evaluations in a real life scenario, in order to implement a more complete system useful to monitor and, eventually, manage FOG. In fact, the smartphone app could be easily updated to comprise the functionality of delivering real time cues, whenever FOG episodes manifest and challenge gait progression and patient's safety.

Disclosure

The authors declare that there is no conflict of interest regarding the publication of this paper.

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