Wearable Assistant for Parkinson's Disease Patients With the Freezing of Gait Symptom

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***Abstract*—In this paper, we present a wearable assistant for Parkinson's disease (PD) patients with the freezing of gait (FOG) symptom. This wearable system uses on-body acceleration sensors to measure the patients' movements. It automatically detects FOG by analyzing frequency components inherent in these movements. When FOG is detected, the assistant provides a rhythmic auditory signal that stimulates the patient to resume walking. Ten PD patients tested the system while performing several walking tasks in the laboratory. More than 8 h of data were recorded. Eight patients experienced FOG during the study, and 237 FOG events were identified by professional physiotherapists in a *post hoc* video analysis. Our wearable assistant was able to provide online assistive feedback for PD patients when they experienced FOG. The system detected FOG events online with a sensitivity of 73.1% and a specificity of 81.6%. The majority of patients indicated that the context-aware automatic cueing was beneficial to them. Finally, we characterize the system performance with respect to the walking style, the sensor placement, and the dominant algorithm parameters.**

***Index Terms*—Assistive cueing, context awareness, freezing of gait (FOG), Parkinson's disease (PD), personal health assistant.**

I. Introduction

WEARABLE health assistants are electronic coaches that help patients to negotiate specific problems related to their disease. In this paper, we evaluate a context-aware *wearable health assistant* to help Parkinson's disease (PD) patients experiencing freezing of gait (FOG). The *wearable health assistant* aims at reducing the number and length of their motor blocks, and thus, increase their safety while walking.

PD is a common neurological disorder caused by the progressive loss of dopaminergic and other subcortical neurons [1]. PD patients often suffer from impaired motor skills [2]. Besides a flexed posture, tremor at rest, rigidity, akinesia (or bradykinesia), and postural instability, motor blocks are a common negative effect of PD. Motor blocks (freezing) most commonly affect the patients' legs during walking, and are, generally, referred to as FOG. Clinical assessment of PD is largely based on subjective patient reports. The Hoehn and Yahr (H&Y) scale is commonly used to describe symptoms of PD progress. The scale uses five stages to indicate the relative level of disability [3]. The five stages are as follows.

Stage 1: Symptoms on one side of the body only.
Stage 2: Symptoms on both sides of the body; no impairment of balance.
Stage 3*:* Balance impairment; mild to moderate disease; physically independent.
Stage 4: Severe disability, but still able to walk or stand unassisted.
Stage 5: Wheelchair-bound or bedridden unless assisted.

A. Freezing of Gait

FOG typically manifests as a sudden and transient inability to move. About 50% of all PD patients regularly show FOG symptoms [4]–[6]. Ten percent of PD patients with mild symptoms and 80% of those severely affected regularly experience freezing. FOG occurs more frequently in men than in women, and less frequently in patients whose main symptom is tremor [7]. PD patients who experience FOG frequently report that their feet are inexplicably glued to the ground during the FOG episodes [8]. FOG is difficult to measure, as it is highly sensitive to environmental triggers, cognitive input, and medication. For example, FOG occurs frequently at home and much less frequently in the doctor's office or in a gait laboratory [9]. Evaluation of FOG conditions is usually done using a FOG questionnaire (FOG-Q) [10]. Five subtypes of freezing have been described by Schaafsma *et al.*: start hesitation, turn hesitation, hesitation in tight quarters, destination hesitation, and open space hesitation [8]. FOG has substantial social and clinical consequences for patients. It is a common cause of falls [11], interferes with daily activities, and significantly impairs quality of life [12].

B. Limits of Pharmacological Treatment for FOG Prevention

Pharmacological management of PD is difficult and often ineffective at relieving FOG. The most common form of treatment used to manage motor symptoms in PD patients is levodopa (LD). The effect of LD on parkinsonian symptoms wears off over time and the effective periods varies between 2 and 6 h. In some patients, this wearing off effect is expressed in a gradual deterioration in motor performance; in others, deterioration is

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relatively sharp and unexpected. The later patients are known to exhibit *motor response fluctuations*. For these patients, clear ON and OFF periods can be distinguished, where ON periods refer to times when the medication is effective and OFF periods refer to times when it is no longer effective. As the disease progresses, the effective duration of each drug dose shortens, and more frequent LD administration is necessary [7]. In addition, the development of involuntary movements (i.e., *dyskinesia*) and the OFF/ON phenomena further limit mobility and complicate dosing.

Although FOG episodes generally appear more frequently during the OFF state, gait deficits in PD patients are often resistant to pharmacologic treatment [11]. Therefore, effective nonpharmacologic treatments need to be developed as an adjunct therapy to relieve symptoms and improve mobility.

C. State of the Art in Nonpharmaceutical Treatment of FOG

Various behavioral "tricks" were developed by clinicians and patients to overcome freezing attacks. These tricks include marching to command, stepping over a walking stick or cracks in the floor, walking to music or a beat, and shifting body weight. Such external cues are commonly considered effective in alleviating FOG symptoms in PD patients [13], [14].

Lim *et al.* [15] performed an extensive review of the effects of external rhythmical cueing on gait in PD patients and found strong evidence for improvements in walking speed with the help of auditory cues. Insufficient evidence was found for the effectiveness of visual and somatosensory cueing. Similarly, Nieuwboer *et al.* showed that auditory cueing is advantageous with respect to visual and somatosensory cueing [16].

Rhythmic auditory stimulation (RAS) was shown to be particularly effective at improving gait among PD patients. Regular metronome ticking sounds were applied as RAS with a rate of 110% compared to the natural walking rate of the tested patient. This served to enhance their gait speed and reduced gait variability (i.e., it improved gait stability [17]). But, there was no relative advantage of using this method to improve gait in patients with PD that also suffer from FOG (PD+FOG) compared to PD patients who do not suffer from FOG (PD-FOG) [16]. Interestingly, a study in which PD+FOG patients used the metronome recordings for cueing at home showed no effect in reducing the freezing symptoms [18].

Therefore, the reason for investigating the proposed device is to combine the incidental effect of external cueing to alleviate freezing with the effect of auditory pacing to improve gait in PD patients. Such a device will provide RAS only during an actual or impeding FOG event.

D. Contribution

Previous work using RAS either relied on an experimenter to trigger cueing or on continuous cueing during the training session. In order to help PD+FOG patients during daily life, we propose a device that can provide context-aware acoustic feedback to assist the patient. Such a wearable assistant will provide RAS only during an actual or impeding FOG event. Thus, the device acts as a context-aware wearable assistant that activates only when necessary and remains transparent in the other situations. Specifically, we present the following contributions:

1) a personal wearable assistant, including algorithms to detect FOG online and provide RAS;
2) a study with ten PD patients to evaluate the system;
3) an objective evaluation of the FOG-aware assistant by analyzing the accuracy in detecting FOG;
4) a subjective evaluation of the study by analyzing the patients' perception of the automatic context aware RAS;
5) a detailed *post hoc* performance analysis and assessment of potential optimizations.

II. Wearable Assistant for Online FOG Detection and Rhythmic Auditory Cueing

A. Wearable Assistant Research Hardware

The wearable assistant is based on a tiny computer capable of recording data and online signal processing. It is a customized research platform based on an Intel XScale family processor and uses a Linux operating system designed for rapid prototyping. It offers processing power comparable to an ultraportable PC with power consumption below 2 W. The system runs for more than 6 h on a 3.7 V, 3.3 Ah battery. The packaged wearable computer is $132 \times 82 \times 30$ mm^3 in size and weights 231 g. The system is modular in order to realize different feedback and sensing modalities. By default, it offers universal serial bus (USB) and Bluetooth as extension interfaces, allowing connections to diverse physiological and nonphysiological sensors [19]. The system can be extended using Zigbee or ANT wireless interfaces with USB dongles. To avoid protruding parts, as well as unintended disconnection of these dongles, the system provides an internal USB bay within the system's housing. There is also space and an interconnection possibility for an internal printed circuit board (PCB) extension board. The extension board is interfaced to a 3.5-mm jack at the front and is intended to be used to prototype various signal acquisition and conditioning hardware (e.g., for ECG or galvanic skin response sensing), or to provide user feedback. In this study, the wearable assistant was implemented by extending the system with an auditory feedback module and earphones connected to the 3.5-mm jack.

Two sensors used to measure 3-D acceleration were attached to the patients' leg; one at the shank, just above the ankle, and the other to the thigh, just above the knee. A third 3-D accelerations sensor was attached to the belt, at the lower back of the patient. The acceleration sensors are $25 \times 44 \times 17$ mm^3 in size and weigh less than 22 g, including a rechargeable 300 mAh Li-ion battery with 6 h battery life. The acquired data is transmitted to the wearable computer over a wireless Bluetooth link (64 Hz) for online data processing. The earphones are placed loosely around the patient's neck. The computing system produces a 1-Hz ticking sound starting whenever a FOG episode is identified and ending when the patient resumes walking. Fig. 1 shows the wearable system worn by a patient.

B. Principle of the FOG Detection Algorithm

Bonato *et al.* presented the first evidence that data mining and signal processing allow to recognize the presence and severity of

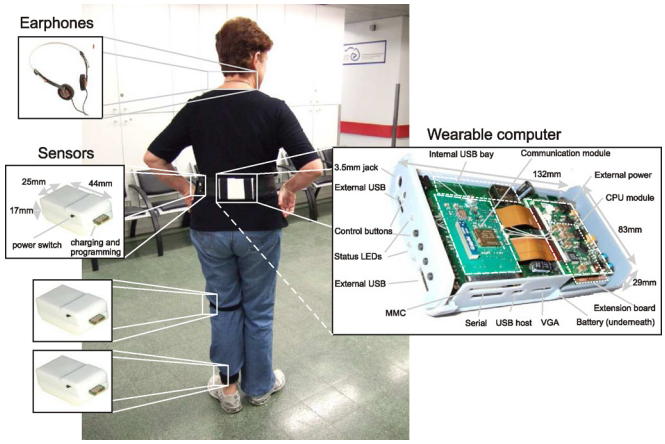

Fig. 1. FOG detection and feedback assistant worn by one patient. Sensors are attached to the shank (just above the ankle) and the thigh (just above the knee) using an elasticized strap and Velcro. A third sensor is attached to the lower back to the same belt that the wearable computer is attached to.

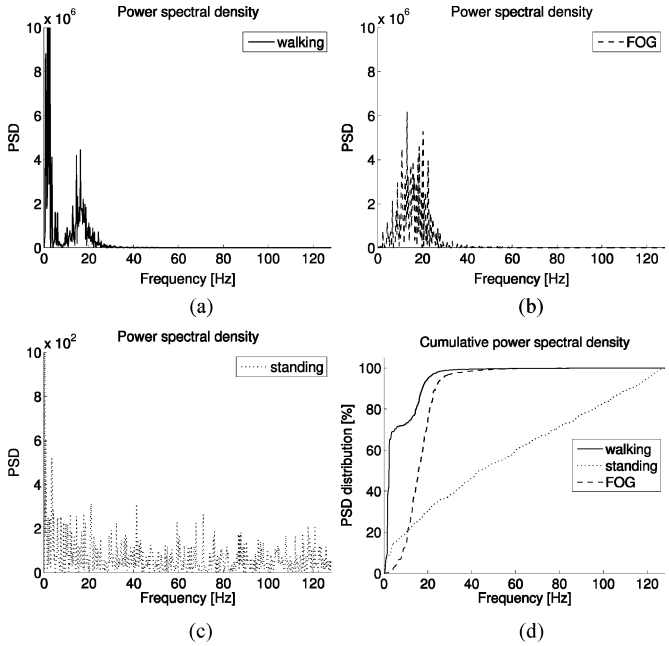

Fig. 2. PSD and cumulative power distribution from 0–128 Hz for walking, FOG, and standing. Note the different scale in (c). (a) PSD for walking. (b) PSD for FOG. (c) PSD for standing. (d) Cumulative power distribution.

motor functions in PD patients [20]. Hausdorff and colleagues examined the ground reaction force signal measured with force-sensitive insoles in the shoes worn by PD patients that were walking normally or experiencing FOG episodes. Using time series and fractal analysis methods, they found that FOG is not a frozen akinetic state, nor is freezing a random, uncorrelated attempt to overcome motor blockades [21]. Instead, the measured forces signal oscillated in a fairly organized pattern. More recently, Moore *et al.* measured the vertical acceleration of the left shank of 11 PD patients and analyzed the power spectra over 6 s signal intervals [22]. They discovered that high-frequency components of leg movement in the [3–8 Hz] band during FOG were not apparent during normal standing or walking. Moore introduced a freeze index (FI) to objectively identify FOG offline. This FI is defined as the power in the "freeze" band [3–8 Hz] divided by the power in the "locomotor" band [0.5–3 Hz]. FOG is detected using a "freeze" threshold. FI values above this threshold are identified as FOG events.

C. Online Implementation of the Algorithm

We developed an online FOG detection algorithm based on the principle described by Moore and introduced the following improvements: 1) a reduced latency; 2) inclusion of an energy threshold; and 3) real-time online operation.

Fig. 2(a)–(c) shows the power spectral density (PSD) derived from a signal of walking, FOG, and standing sampled at 256 Hz. Fig. 2(d) depicts the cumulative percentage of total power in the PSD. One can see that human movement mainly has frequency components between 0 and 30 Hz. More than 96% of the total energy is within this range for walking and FOG. For standing, there is hardly any movement, and therefore, the PSD is dominated by sensor noise. About 10% of the signal energy is below 0.5 Hz, the rest is approximately equally distributed over the whole frequency spectrum (*white noise*). Apart from the frequency distribution, the total energy content of standing is substantially lower than for FOG or walking. This fact allows us to define an energy threshold, which we called *PowerTH*, to distinguish between standing and the other states.

We used the *Context Recognition Network* (CRN) Toolbox [23] for the algorithm implementation on the wearable device. During the study, we only used the shank sensor data for online FOG detection. In order to avoid aliasing, the leg motion was sampled at 64 Hz. A rectangular window function with a window length of 4 s is used. The windowing itself is done in steps of 0.5 s. For the PSD, a 256-point fast Fourier transform (FFT) is calculated. The locomotion band between [0.5 and 3 Hz] and the freeze band between [3 and 8 Hz] have been chosen, as suggested in [22].

The flow chart of the algorithm, including the algorithms' parameters, is given in Fig. 3.

III. Proof of Concept Study

A. Participants

For our study, idiopathic PD patients with a history of FOG, who were able to walk unassisted in the OFF period, were recruited. Patients were excluded if they had severe vision or hearing loss, dementia, or signs of other neurological/orthopedic diseases. The study was approved by the local Human Subjects Review Committee, and was performed in accordance with the ethical standards of the Declaration of Helsinki. Ten PD patients (seven males) diagnosed with PD (66.5 ± 4.8 years; H&Y score in ON (2.6 ± 0.65; see Table I) took part in this study. Motor performance among PD patients generally shows large variability. This was also the case among the group of patients who participated in this study. For example, during nonfreezing episodes, some patients maintained regular gait that could hardly be

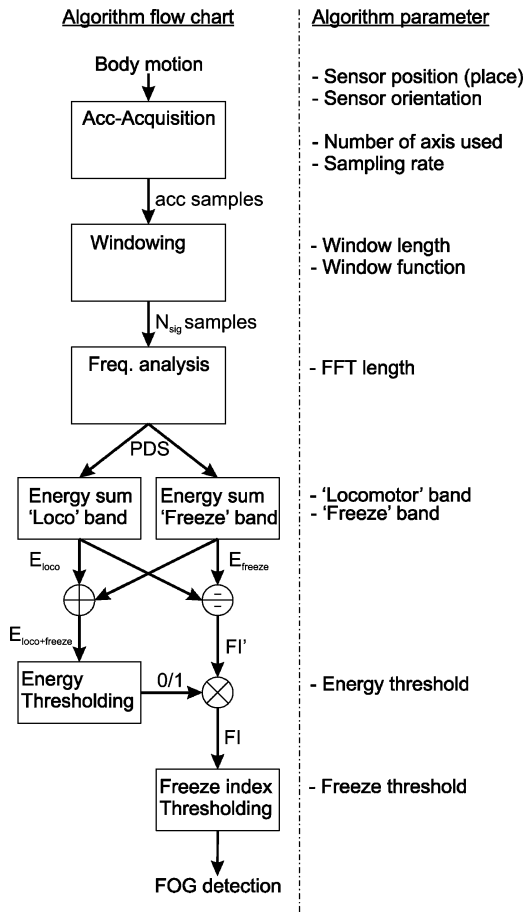

Fig. 3. Flow chart describing the FOG detection algorithm including all parameters.

TABLE I
GENDER, AGE, DISEASE DURATION, AND H&Y RATING OF THE PATIENTS

Subject ID	Gender	Age [years]	Disease duration [years]	H&Y in ON	Tested in
01	M	66	16	3	OFF
02	M	67	7	2	ON
03	M	59	30	2.5	OFF
04	M	62	3	3	OFF
05	M	75	6	2	OFF
06	F	63	22	2	OFF
07	M	66	2	2.5	OFF
08	F	68	18	4	ON
09	M	73	9	2	OFF
10	F	65	24	3	OFF
Mean ± STD		66.4 ± 4.8	13.7 ± 9.67	2.6 ± 0.65	

distinguished from that of healthy elderly people, while others had a slow and unstable gait.

B. Protocol

The study was carried out in the Laboratory for Gait and Neurodynamics, Department of Neurology, Tel Aviv Sourasky Medical Center (TASMC). Patients were tested in the morning during the OFF stage of the medication cycle (more than 12 h after their last anti-Parkinsonian medication intake). Two patients, who reported frequent FOG episode during the ON state, were not asked to avoid medication intake. After signing an informed consent form, the patients were shown how the device works and how to take advantage of the RAS in case of freezing. The study protocol was based on two sessions, one without RAS feedback and one with RAS feedback that sounded whenever the wearable device detected a freezing episode online. Each session consisted of three basic walking tasks designed to represent different aspects of daily walking. Fig. 4 depicts a sketch of the path taken by the subjects during the study. The walking tasks included the following.

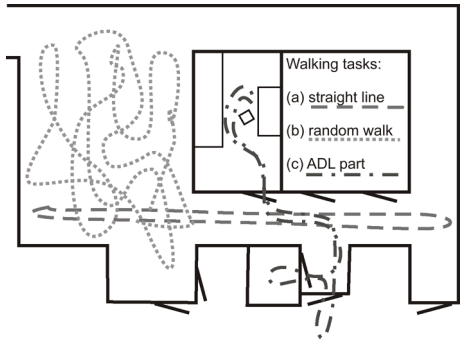

Fig. 4. Sketch of the path taken by the subjects during the study.

1) Walking back and forth in a straight line along the laboratory hallway, including several 180° turns (dashed line in Fig. 4).
2) Random walking in a reception hall space, including a series of initiated stops and several 360° turns (dotted line in Fig. 4). The experimenter issued instructions to the subject to stop or to turn in different directions (at least six turns, three in each direction).
3) Walking simulating activities of daily living (ADL). The ADL part included entering and leaving rooms, walking to the laboratory kitchen, getting something to drink, and returning to the starting room with the cup of water (dash–dotted line in Fig. 4).

During the first session, the device recorded all necessary data and performed online FOG detection; however, the RAS feedback was deactivated.

The second session was a repetition of the first one, with the exception that the RAS feedback was now activated. The length of each walking session was about 10–15 min. Patients walked at their own natural pace without assistance, but a therapist remained close by for safety reasons (see Fig. 5).

At the end of the study, patients returned to the examining room, took their medication, and were debriefed by a therapist. The protocol was approved by the ethics institutional review board of the TASMC. All participants completed the protocol, no side effects were observed or reported, and no special accommodations were needed.

C. Annotation of Ground Truth

All walking trials were recorded on a digital video camera. The leg movement data were synchronized with the video

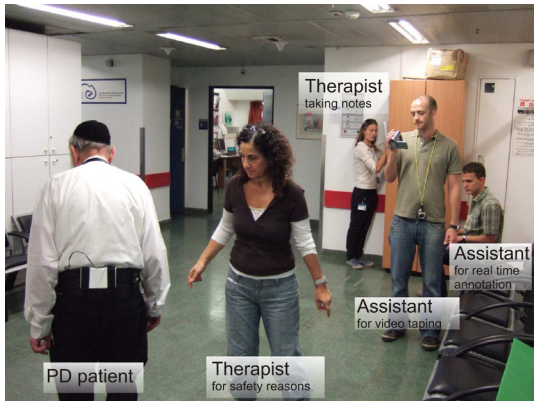

Fig. 5. Snapshot of a typical experimental session, (left) depicting one PD patient equipped with the wearable system performing random walks in the hall. The therapist (right of the subject) instructs the PD patient and cares for his safety. The research assistants (right back) document the session.

recordings using three synchronization steps at the beginning of each recording session. One physiotherapist took notes of relevant events during the session. Another assistant annotated the patients' current activity (e.g., standing, walking, turning, and freezing) in real time by pressing corresponding keys on a laptop computer.

In a *post hoc* analysis, physiotherapists analyzed the video recordings to identify FOG events and determine the exact start times, durations, and end times. The beginning of a FOG event was detected when the gait pattern (i.e., alternating left–right stepping) was arrested, and the end of FOG was defined as the point in time at which the pattern was resumed. This procedure was similar to an earlier established one [8].

D. Subjective Evaluation of the Study

For a subjective evaluation of the system, we asked the participants to fill out a standardized self-report of patient satisfaction and a questionnaire to qualify the systems' operation. The *visual analogue scale* (VAS) and the *clinical global impression change scale* (CGIC) were used.

The VAS is a visual sliding scale with two anchor points, one at each extreme. One anchor point is at "0" (i.e., "worst") and the other at "10" (i.e., best). Respondents specify their level of agreement to a statement by indicating a position on the VAS between the two endpoints [24]. Using the VAS, patients had to grade their walking performance before and after the study, the comfort of the system components, and the usefulness of the system for their everyday life.

The CGIC is a seven-point scale that assesses how much the patient's performance or illness improved or worsened relative to a baseline state at the beginning of the intervention [25]. For example, in our questionnaire, we used the scale to report the change in FOG duration due to using our system. The scale had the following seven anchor points: $+3$: much longer, $+2$: longer, $+1$: minimally longer, 0: no change, -1: minimally shorter, -2: shorter, or -3: much shorter. Furthermore, the CGIC was used to rate the number of FOG events and if patients preferred to hear the RAS more or less frequent. To evaluate the experiment form another perspective, the physiotherapists answered a complementary questionnaire at the end of the completed study. The physiotherapists were asked how they would rate the usefulness of the system, the influence on the patients' gait, and the suitability for use in everyday life. Furthermore, the physiotherapists were asked if they saw that patients benefited from the context-aware cueing and used it or if it was disturbing [26].

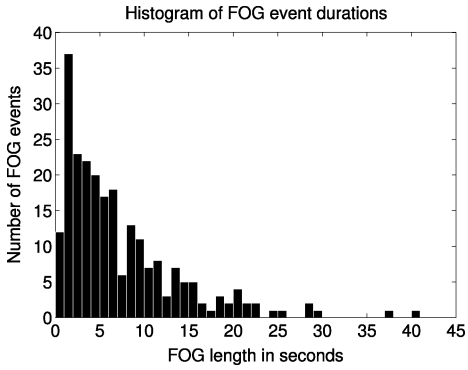

Fig. 6. Distribution of the number of FOG events of a specific duration rounded to the nearest second.

IV. Results of the Study

A. Study Statistics

In total, 8 h 20 min of data were recorded. Eight patients out of the ten exhibited FOG during the study; two patients did not have any freeze events. The walking distance and number of turns depended on the patient's gait speed. One patient could not perform the ADL part. Two hundred and thirty-seven FOG events were identified from the video recordings by the physiotherapists ranging from 0–66 per patient with a mean of 23.7 [standard deviation (S.D.) 20.7].

The length of FOG events ranged from 0.5 to 40.5 s (mean 7.3 s [S.D. 6.7 s]). Fifty percent of the FOG episodes lasted less than 5.4 s, and the majority (93.2%) were less than 20 s long (see Fig. 6). These results are similar to earlier FOG duration characterizations [8].

We did not experience technical problems during the recordings. RAS started properly whenever a FOG episode was detected and stopped again when FOG was no longer detected by the algorithm.

B. Online FOG Detection Performance

Detection performance was evaluated using 0.5 s time frames. The video annotations from the physiotherapists were used as reference for all our algorithm performance evaluations. The system was required to recognize FOG in less than 2 s after it's onset in order for it to be reported as a successfully detected FOG event.

Fig. 7 presents the detection accuracy with reference to sensitivity and specificity for each individual patient. On average, the sensitivity and specificity of the online FOG detection were 73.1% and 81.6%, respectively.

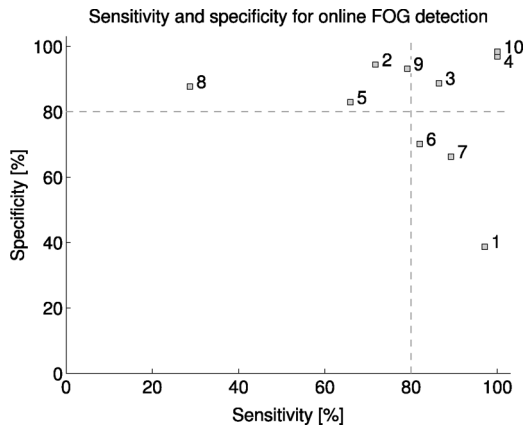

Fig. 7. Sensitivity and specificity distribution for online detection accuracy. Numbers correspond to each specific patient.

The system did not perform equally well for all patients. The best results were obtained for patients *04* and *10*. The worst result in terms of specificity was obtained for patient *01* (38.7% specificity and 97.1% sensitivity). The worst result in terms of sensitivity was obtained for patient *08* (28.7% sensitivity and 87.7% specificity).

We identified that these large variations were caused by different walking styles of the patients. Patient *01* suffers from foot drop while walking, which is characterized by intense stepping movements along the vertical axis. For patient *01*, the system was mostly not able to distinguish between walking periods and very short freezing events when using the global algorithm parameter settings.

Patient *08* was the patient most affected by PD (H&Y stage: 4) and had the most difficulties to walk. She had the slowest and most limited mobility. This made it hard for the device to distinguish between voluntary standing and FOG, which explains the low sensitivity of the system for patient *08*. For the remaining patients, sensitivity and specificity values were close to or higher than 80%, as shown in Fig. 7.

C. Subjective Questionnaire Results

All patients reported that the system was unobtrusive and did not interfere with locomotion. Also, the physiotherapists did not see any indication that the patients' normal gait was disturbed by the physical size and weight of the sensors, and the wearable computer. However, two physiotherapists pointed out that the size of the computing system and the attachment method to the belt should be improved for use in everyday life studies.

Regarding benefits of the device, five out of eight patients who experienced FOG during the study said that they had less freezing events with the device. The three other patients could not see any change. Five patients had the impression that their freezing episodes were shorter with the device. Only one, thought his episodes were longer than usual, and two could not determine any change. Half of the patients who experienced FOG during the study observed fewer and shorter FOG events. The physiotherapists rated the influence of the automatic identification of FOG events and RAS feedback as beneficial, especially for patients with severe FOG. With respect to the occurrence of the feedback, two patients expressed their preference to hear the RAS less often. In their case, the system was too sensitive, resulting in too many RAS occurrences. Their reaction tends to support the observation that continuous cueing is not appreciated by the patients and that RAS should be context-aware. Participants for whom the detection sensitivity was low, demanded to have RAS assistance more often. Low sensitivity resulted in missed FOG events in these patients, and therefore, they did not always get the auditory assistance when experiencing FOG events. This tends to support the previous observation that patients felt a benefit from RAS. Three participants reported that the feedback occurrence was just right. One participant suggested introducing variations in the audio tone and rhythm to avoid becoming used to the system, since he believed this could make the RAS feedback even more effective.

Similarly, one physiotherapist suggested adjusting the tempo of the RAS according to the walking speed of the patient.

Six participants were optimistic that such a personal assistant could be helpful in their everyday life. The other four participants said the trial was too short and they could not really judge the usefulness. The physiotherapists also saw potential in the system to support PD patients in their everyday life. They thought the context aware automatic RAS will be especially helpful for PD patients experiencing long FOG events, but are much aware of the RAS and capable to adapt to the rhythm. Overall, the self-assessment indicates that some of the patients benefit from the assistive device.

V. System Performance Optimization

In this study, we used our modular research platform to first investigate performance of the algorithm and perception of the PD patients. However, the applicability of a FOG assistant in daily life depends on multiple factors. As shown previously, the system should be adjusted to the walking style of each user. To maximize functionality and minimize cost, it is desirable to enable a fast, simple and robust setup of the parameters by care personal or the user themselves. Comfort is an important aspect that directly relates to the on-body placement of the sensor, but may result in a tradeoff with system performance. Finally, the perceived response time must be minimized while maintaining robust performance. In this section, we characterize the system with reference to these aspects and show how it may be improved.

A. Subject-Dependent Parameter Optimization

We analyze the influence that the two detection threshold parameters *PowerTH* and *FreezeTH* have on the performance of the detection algorithm, when using the sensor data of the ankle position on the vertical axis. When optimizing the detection performance, there is a tradeoff between sensitivity and specificity. For our study, we chose to take minimum sensitivity and specificity min(Sens, Spec) as a performance measurement, because the maximum point in the min(Sens, Spec) data space corresponds to the parameter combination where the performance *equal error rate* (EER) is at a minimum. The EER is commonly

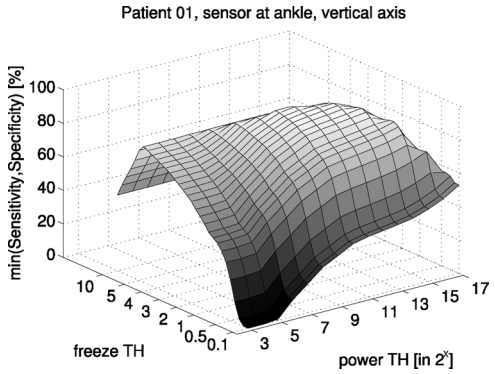

Fig. 8. Min(Sens, Spec) plot for patient 01 (vertical axis of the sensor at the ankle).

used to compare two systems, because it gives a single scalar value. The lower the EER, the more accurate the system is considered to be. In our performance evaluation, the EER is given by

$$\mathrm{EER} = 1 - \max_{\mathrm{freezeTH,powerTH}} \{\min(\mathrm{Sens}, \mathrm{Spec})\}$$

where $\max_{\mathrm{freezeTH,powerTH}} \{\min(\mathrm{Sens}, \mathrm{Spec})\}$ is the maximum point in the $\min(\mathrm{Sens}, \mathrm{Spec})$ data space.

Fig. 8 shows the performance evaluation for patient *01*. By optimizing the parameters for each individual user, we can compute the maximum performance achievable with the given algorithm.

Fig. 9 shows the evaluation of possible parameter combinations for each individual patient. The black dots mark the optimal parameter combination. Gray areas mark all parameter combinations with a detection accuracy that is less than 5% below the maximum. For some patients (e.g., patients *01*, *03*, and *07*), the algorithm performance is relatively insensitive to small threshold variations. For some patients (e.g., patients *02*, *05*, and *06*), the algorithm performance is only insensitive to the *PowerTH*. For patient *08*, the algorithm performance is most sensitive to the *PowerTH*. As discussed previously, patient *08* is the patient most effected by PD and with akinesic ("without motion") FOG. The akinesic FOG is an explanation for the *PowerTH* sensitivity.

When optimizing the two parameters for each patient, we achieved on average a sensitivity of 88.6% and a specificity of 92.4% This is the optimal sensitivity $\mathrm{Sens}_{\mathrm{opt}}$ and specificity $\mathrm{Spec}_{\mathrm{opt}}$ that can be expected with optimized user-specific parameters, as shown in Fig. 10(a).

Next, we evaluated two other sets of parameters. First, we evaluated parameters optimized globally for all users (user-independent optimization). Then, we evaluated two parameter sets for "smooth" and "intensified stepping" walking styles. Performance is quantified with respect to the user-specific performance using the equation $\mathrm{Perf}_{\mathrm{test}} = (\mathrm{Sens}_{\mathrm{opt}} - \mathrm{Sens}_{\mathrm{test}}) + (\mathrm{Spec}_{\mathrm{opt}} - \mathrm{Spec}_{\mathrm{test}})$, where $\mathrm{Sens}_{\mathrm{test}}$ and $\mathrm{Spec}_{\mathrm{test}}$ are achieved using the parameter set being evaluated. A smaller $\mathrm{Perf}_{\mathrm{test}}$ is correlated to an improved performance of the tested parameter set.

For the performance evaluation using global, user-independent parameters, we performed a leave-one-out cross

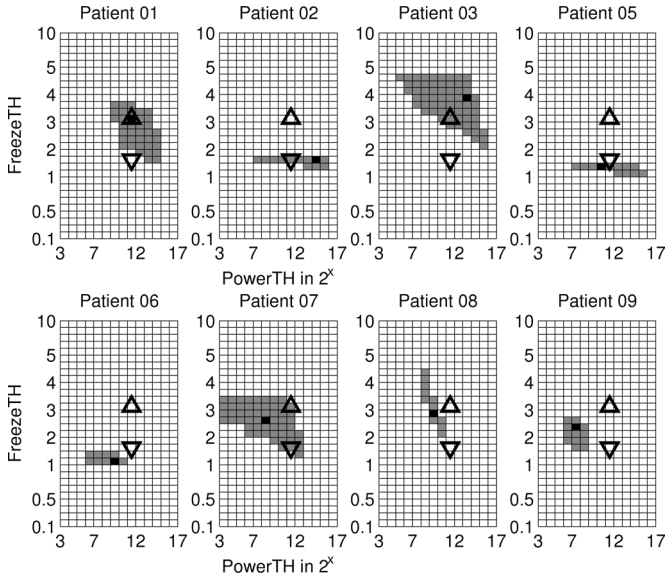

Fig. 9. Evaluation of parameter combinations: The black dots mark the optimal parameter combination; the gray areas mark all parameter combinations with a detection accuracy less than 5% below the maximum. Upward and downward pointing triangles mark group parameter sets for smooth and saccadic walking styles. Patient *04* and *10* are excluded because they did not have FOG during our study.

validation, which means that the global parameters are optimized for $N-1$ subjects and performance is tested on the remaining subject. This step is repeated until the performance was tested for all subjects. Cross validation allows us to evaluate how well the system behaves when it is applied to patients whose data were not used during the parameter optimization. In other words, it indicates how well the system can be generalized. User-independent performance is indicated in Fig. 10(b). On average the algorithm performance with global parameters is 11.1% (STD $\pm$ 5.3%) below the optimal user-specific performance.

Finally, we analyzed the detection performance when separating the patients into two groups with group parameter sets. In the plots of Fig. 9, we identified two main groups: group 1) patients with smooth walking and an optimal *FreezeTH* below 2.5 and group 2) patients with intensified stepping and an optimal *FreezeTH* above 2.5. Based on these findings, we analyzed the detection performance when grouping the ten patients into these two groups. *FreezeTH* and *PowerTH* for the two groups were chosen manually as the visual average of the observation in Fig. 9. The two parameter sets are marked in the plots of Fig. 9 using upward and downward pointing triangles. Fig. 10(c) presents the sensitivity/specificity of the two parameter sets for the patients with smooth walking and intensified stepping. On average, the performance is 3.7% (STD $\pm$ 2.8%) below the optimal user-specific performance.

These results indicate that even with a simple method, e.g., a switch to select between two parameter sets, the system is able to perform at a level close to the optimum performance. This allows personnel care to rapidly setup the system and still maintain good performance. It may also be used by the patients themselves to adjust the sensitivity and specificity of the system.

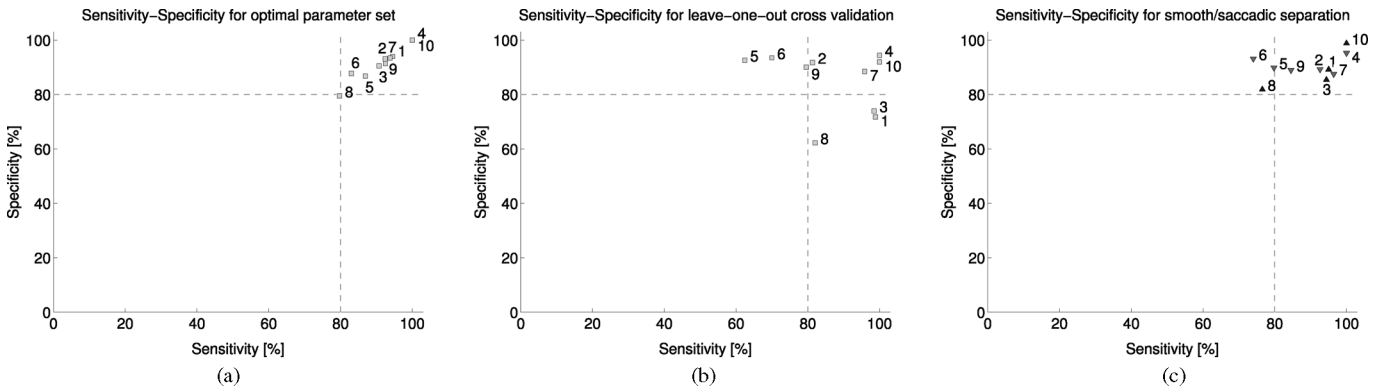

Fig. 10. Sensitivity and specificity plots for different parameter sets evaluated using the data of the vertical axis of the ankle sensor.

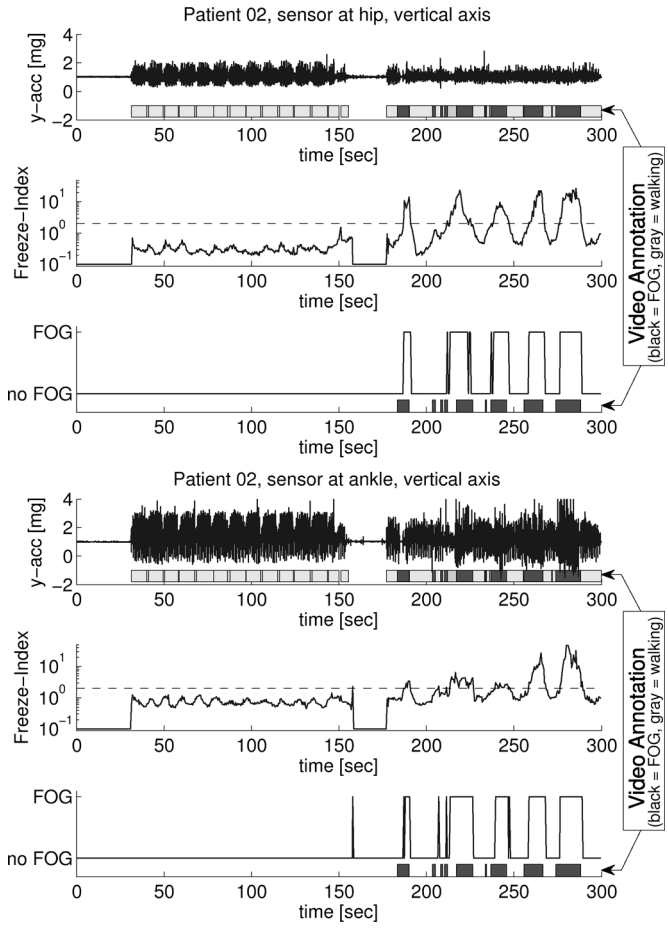

Fig. 11. Five minute signal extract from patient 02 using data from (upper plot) the sensor at the hip and (lower plot) at the ankle together with the FI and the FOG detected parts.

TABLE II
SENSOR POSITION EVALUATION: SENSITIVITY AND SPECIFICITY (± STD) FOR EACH COMBINATION OF SENSOR POSITION (ANKLE, KNEE, AND HIP) AND AXIS ORIENTATION (x = HORIZONTAL FORWARD, y = VERTICAL, z = HORIZONTAL LATERAL, AND $n = \sqrt{x^2 + y^2 + z^2}$ = MAGNITUDE OF ALL THREE AXIS)

	x	y	z	n
Sensor at ankle				
Sens	87%(16%)	81%(14%)	80%(13%)	79%(15%)
Spec	87%(14%)	87%(11%)	81%(19%)	86%(9%)
Sensor at knee				
Sens	76%(20%)	85%(13%)	82%(18%)	82%(15%)
Spec	85%(16%)	88%(13%)	84%(20%)	83%(13%)
Sensor at hip				
Sens	81%(19%)	71%(25%)	78%(32%)	78%(19%)
Spec	84%(28%)	79%(20%)	79%(22%)	80%(24%)

B. Sensor Placement Characterization

In this section, we analyze the detection performance of the system for different sensor placements and orientations to determine the best sensor location while considering the tradeoff between wearability and performance.

For example, Fig. 11 shows a 5-min-long section of a signal measured by the sensor at the hip and at the ankle of patient *02*. Clearly, there is a difference between the signals—the signal of the sensor at the hip is much smaller (damped), but the motion is still very well visible. Table II lists the average performance of the system for all ten patients using the algorithm with global parameters (leave-one-out cross validation). Results are listed for 12 combinations of three sensor positions (ankle, knee, and hip) and four axes combinations, which are the horizontal forward axis x, the vertical axis y, the horizontal lateral axis z, and the magnitude of all three axes $n = \sqrt{x^2 + y^2 + z^2}$.

The best results are achieved when using the vertical axis of the sensor at the knee. However, placing sensors on the thigh just above the knee is the most inconvenient position to wear a sensor. The detection accuracy for the sensor placement at other positions is nevertheless quite good. These results are very promising, because sensors can be placed at a more convenient body position without losing much accuracy.

C. Latency Optimization

Latency refers to the time between the onset of FOG and the time it takes the system to react. In this section, we analyze the potential for latency optimization. The latency of the algorithm is dominated by the data sampling window length used.

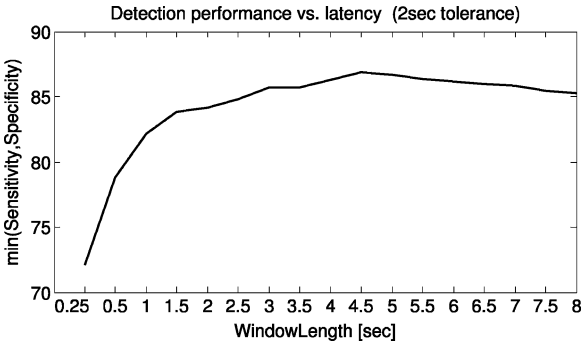

Fig. 12. Detection performance versus window length (latency).

For this analysis, we plotted the accuracy of FOG detection versus window length (see Fig. 12)—keeping the frequency resolution identical by zero padding [27]. When increasing the window length up to a maximum of 4.5 s, the detection performance increases. Further increases in the window size reduce the detection performance again. This behavior can be explained as follow: An increasing window length improves the calculation of the correct frequency spectrum by reducing the leakage effect and resulting in an upward sloping curve. Additionally, an increasing window length also increases the latency of the algorithm, resulting in more missed FOG events and a reduction of the detection accuracy. Therefore, the optimal window length for the best detection performance when taking latency into account is 4.5 s.

VI. Discussion

The limitations of this study are the short time available for the patients to test the system, the limited number of patients, as well as its execution in a medical center, and not an actual daily life environment. Although all ten patients reported a history of FOG, only eight experienced freezing during the experiment. The controlled environment of the study and the presence of the physiotherapist may have reduced the likelihood of FOG in the two patients who did not experience any FOG event during the study. Both patients reported many FOG events at home and could not explain why they did not have any FOG during the study. They expressed a desire to test our device during their natural daily activities.

Further investigations are required to analyze and demonstrate real-world performance. We still do not know how patients will judge the benefit of the system after using it for hours over several days. We speculate that after an initial training period, the machine–human interface will become more automatic and subconscious.

In this study, we used a customized general-purpose modular research platform. There are several areas for technical improvements [28]. This modular platform could be turned into a specialized system specifically designed for our task. It could be miniaturized into a single sensor node that includes the FOG detection algorithm. Roggen *et al.* have shown that complex calculations such as FFT, which are used in the online detection of FOG, can be processed with low power consumption on a device of the size of a button [29]. Such a system could be entirely integrated into or attached to normal shoes of the patient, and only the trigger signal for the RAS is transmitted to the feedback device. The RAS could be given via a hearing-aid-like device or even a hearing aid itself. This implementation remains the object of future work. However, a complexity analysis of the algorithms shows that this is a realistic goal. Future research needs to address different RAS sounds in more detail. While regular rhythms are an important feature of the auditory stimulation, they may be embedded within musical elements, or include other sounds than the metronomic type.

VII. Conclusion

In this study, we evaluated the feasibility of using a wearable health assistant to support PD patients with FOG. To the best of our knowledge, this is the first time that FOG has been automatically detected online using a wearable device in order to provide RAS to patients. The system detected FOG events with a user-independent sensitivity of 73.1% and a specificity of 81.6%.

Due to the large variability between patients' gait, we showed that a user specific parameter optimization improves the detection performance up to 88.6% sensitivity and 92.4% specificity. A rough segmentation of the patients into smooth and intensified stepping walkers, together with a specific sensitivity adjustment improved the detection performance to 85.9% sensitivity and 90.9% specificity. With a global threshold, a detection accuracy of 78.1% sensitivity and 86.9% specificity was achieved.

We received promising feedback from the participants. Some patients even expressed the motivation to wear the system for several weeks. However, this has to be taken carefully because the patients did not use the system for more than 1 h. Further miniaturization potentially increases acceptance by patients. The answers obtained from studying the influence and effects of automatic cueing were also promising. At least half of the participants saw a positive effect. The demand for more frequent RAS feedback of the participants for whom the system had a low sensitivity shows that these patients felt that the feedback helped them. On the other hand, the demand for less auditory feedback of the participants for whom the system had a low specificity suggests that continuous RAS may be annoying and that a context-aware triggering of the RAS is preferable.

The analysis of three different sensor locations showed that all three locations could be used for FOG detection although there are minor differences in detection performance. The ankle position is especially promising because it could enable integration of the sensor into a shoe. At the hip position, the sensor could be integrated into a belt. However, the sensor location at the hip is much more parameter-sensitive, and therefore, less preferable for real-world applications. Performance may be further increased by using sensor fusion, especially for patients where freezing does not result in tremor in both legs. In our preliminary investigation, we have used our flexible, yet bulky general-purpose wearable computing platform. However, the algorithmic complexity suggests the design of a specialized

system that is miniaturized to the size of a button, and includes the FOG algorithm integrated directly into the sensor note itself.

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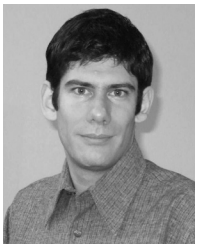

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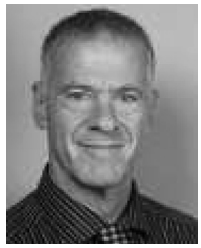

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