A Wearable Assistant for Gait Training for Parkinson's Disease with Freezing of Gait in Out-of-the-Lab Environments

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People with Parkinson's disease (PD) suffer from declining mobility capabilities, which cause a prevalent risk of falling. Commonly, short periods of motor blocks occur during walking, known as freezing of gait (FoG). To slow the progressive decline of motor abilities, people with PD usually undertake stationary motor-training exercises in the clinics or supervised by physiotherapists. We present a wearable system for the support of people with PD and FoG. The system is designed for independent use. It enables motor training and gait assistance at home and other unsupervised environments. The system consists of three components. First, FoG episodes are detected in real time using wearable inertial sensors and a smartphone as the processing unit. Second, a feedback mechanism triggers a rhythmic auditory signal to the user to alleviate freeze episodes in an assistive mode. Third, the smartphone-based application features support for training exercises. Moreover, the system allows unobtrusive and long-term monitoring of the user's clinical condition by transmitting sensing data and statistics to a telemedicine service.

We investigate the at-home acceptance of the wearable system in a study with nine PD subjects. Participants deployed and used the system on their own, without any clinical support, at their homes during three protocol sessions in 1 week. Users' feedback suggests an overall positive attitude toward adopting and using the system in their daily life, indicating that the system supports them in improving their gait. Further, in a data-driven analysis with sensing data from five participants, we study whether there is an observable effect on the gait during use of the system. In three out of five subjects, we observed a decrease in FoG duration distributions over the protocol days during gait-training exercises. Moreover, sensing data-driven analysis shows a decrease in FoG duration and FoG number in four out of five participants when they use the system as a gait-assistive tool during normal daily life activities at home.

Categories and Subject Descriptors: H.1.2 [**Models and Principles**]: User/Machine Systems; C.3 [**Special-Purpose and Application-Based Systems**]: Real-Time and Embedded Systems

General Terms: Design, Algorithms, Performance, Human Factors, Empirical Studies in Ubiquitous and Mobile Computing

Additional Key Words and Phrases: Wearable assistant, user centered, gait impairment, on-body sensors, freezing of gait, out-of-the-lab studies, system's acceptance

1. INTRODUCTION

Parkinson's disease (PD) is a degenerative neurological disorder characterized by postural instability, rigidity, reduced movement range, and tremor. Worldwide prevalence is estimated to be between 4.0 and 16.1 million people [Muangpaisan et al. 2011] and is expected to double by 2030 [Dorsey et al. 2007]. Current treatment is mainly pharmacological and focuses on relief of motor symptoms, but there are symptoms that do not respond to Parkinsonian drugs. Freezing of gait (FoG) is a severe PD symptom that is frequently unresponsive to medication. FoG is a paroxysmal, episodic gait disturbance. It is typically sudden and transient, with episodes lasting usually from a few seconds up to a minute, during which the motor system is blocked and walk cannot be continued. People with PD frequently report that during FoG their feet are *frozen* or *glued* to the ground and they are unable, inexplicably, to move forward [Nutt et al. 2011]. These unexpected motor blocks severely impinge on the functional independence and health-related quality of life [Tan et al. 2012]. FoG increases the risk of falls, anxiety, loss of mobility and independence, and mortality [Gray and Hildebrand 2000].

Training and rehabilitation interventions that help in alleviating FoG include group exercise and treadmill training with rhythmic auditory and visual cues [Allen et al. 2010]. Such rhythmic cues, in the form of an external stimulus, have been shown to facilitate the continuation of a repetitive movement such as gait. Providing a rhythmic external cue, such as an auditory signal, can reinitiate neurological rhythm as a pacemaker and thereby helps to overcome a gait freeze episode more quickly [Thaut et al. 1996; Hausdorff et al. 2007; Lim et al. 2005]. However, existing techniques have to be performed in the clinic or require medical staff to assist in the training exercises. With limited resources in terms of personnel and infrastructure, the healthcare sector is challenged to develop novel instrumentation and therapy methodologies to cope with an increasing number of people with PD [Dorsey et al. 2007].

The first contribution of this work addresses this problem and aims to deliver a wearable computing-based solution for independent motor training and assistance. We present a detailed overview of GaitAssist, a wearable sensing and feedback system that detects the FoG episodes in real time. The system has two main functions: (1) as a gait trainer with personalized exercises and (2) as a gait assistant during daily life activities. The components consist of motion sensing units that are attached to the ankle and communicate wireless to a smartphone for data storage and processing. Based on computationally efficient machine learning techniques, FoG episodes are detected using the smartphone as a processing unit. Upon FoG detection, a rhythmic auditory signal can be triggered that serves as gait stimulation and supports the user to alleviate the FoG and to resume walking. Additional support is offered for motor-training exercises, which consists, for example, of added cognitive load at different difficulty levels for the gait-training exercises. We designed all components in a closed loop with patients and clinicians before the final deployment and evaluation study in the home.

The second contribution is an acceptance study conducted in the homes of the people with PD and FoG. Assistive systems designed for at-home use obtain high scores in terms of acceptance, wearability, and performance when assessed in the lab. However, in natural conditions, acceptance rates are typically lower than in laboratory settings [Steele et al. 2009]. We see two critical aspects for technology research in PD that require an acceptance study in out-of-the-lab environments. First, confronted with an unknown wearable system, the potential users may yield a high boarding hurdle or

the risk of quickly abandoning the system—when the system usage is voluntary and not accompanied by the clinician. Since symptoms of PD are burdening the execution of daily routines, any additional intervention (i.e., using such systems) may add more load to the user. Therefore, such systems require a low user compliance and immediate visibility of its benefits to support sustained use. Furthermore, the people with PD are usually elder and are not early adopters of new technology. Second, there is evidence in clinical literature that walking patterns of people with PD are different in natural environments compared to laboratory settings [Okuma and Yanagisawa 2008]. For instance, FoG is difficult to trigger in the clinics [Nieuwboer and Giladi 2008], such as because of the so-called white coat syndrome, when often people experience a higher number of FoG episodes in daily life than within the lab. Despite these observations, recently proposed wearable systems for gait training and assistance in PD, and in general in healthcare, lack validation in the user's natural environments (e.g., at home) or in public areas [Jovanov et al. 2009; Bächlin et al. 2010; Mazilu et al. 2012]. We specifically investigate the performance of the proposed system in the habitual environment of the user, where she or he is not supervised and assisted by a technician or clinician [Allen et al. 2012]. To this end, we formulate the following research question:

—Can the system be mounted and operated independently by the user with satisfying comfort?

To answer this question, we asked nine PD subjects with FoG, from two sites in two countries, to participate in an *out-of-the-lab* study. Setup and operation of GaitAssist has been performed by the participants without any clinician help. The system was used in two different scenarios: while performing gait-training exercises and in assistive mode during natural walking at home. After the experiment, participants were asked to fill in scores for statements regarding the operation and wearability of the system, and related to the exercise content. At the end of the trial, participants also held discussions with a clinician to have a more detailed feedback and input regarding the acceptability of the system in home settings. Based on the grades and comments given by the participants, we analyze and discuss the wearable system's acceptance and usability at home.

The third and final contribution is a data-driven analysis of the FoG distributions during the study for the participants in the first clinical site. To this end, we formulate the following research question:

—Can we measure an observable short-term effect on FoG episodes when using GaitAssist while performing motor-training exercises or as a gait assistant in the homes?

For this purpose, we collected sensing data and FoG-detection output of GaitAssist during the home usage of the system from the five participants in the first site. We then performed a data-driven analysis to observe if there are any trends observed in the FoG durations and FoG number during the protocol.

The rest of the article is organized as follows. In Section 2, we situate this work into the research landscape. We specifically focus on wearable systems in PD and acceptance studies of technological artifacts in the healthcare domain. Section 3 presents in detail the GaitAssist system and how its components have been implemented. Section 4 presents the study design at home, with acceptance results given in Section 5 and the data-driven analysis on FoG distributions in Section 6. We conclude in Section 7 with a summary of the findings.

2. RELATED WORK

People with PD can improve motor functions and decrease FoG severity by performing rehabilitation exercises [Tomlinson et al. 2012; Pelosin et al. 2010]. In the same

direction, clinical research in motor training in PD shows that rhythmic auditory or visual cueing while walking helps to decrease FoG severity [Allen et al. 2010; Donovan et al. 2011; Nieuwboer et al. 2007]. Continuous cueing has a positive impact on the gait but wears off over time [Nieuwboer 2008], as users get used to the stimuli. A solution to mitigate this effect is to give the cue only in the case of a FoG event for a limited period of time.

Wearable systems for FoG detection. Several research groups have proposed wearable systems for FoG detection, and some of them include feedback to the user. Table I contains an overview of the characteristics and evaluation settings of such systems. Most wearable systems involve accelerometers and/or gyroscopes mounted on the body [Jovanov et al. 2009; Djurić-Jovičić et al. 2010; Bächlin et al. 2010; Mazilu et al. 2012; Tripoliti et al. 2013] or integrated in garments [Niazmand et al. 2011], extended with electroencephalography (EEG) [Handojoseno et al. 2012] or electromyography (EMG) [Cole et al. 2011].

One standard feature that is extracted from the raw signals is the Freeze Index (FI), defined as the ratio between the power contained in the so-called freezing and locomotion frequency bands (i.e., 3 to 8 Hz and 0.5 to 3 Hz, respectively) [Moore et al. 2008; Bächlin et al. 2010; Jovanov et al. 2009]. This feature is convenient because it requires only FFT computation. Other feature extraction approaches involve mixed time-frequency features [Zhao et al. 2012] and entropy [Tripoliti et al. 2013]. In Mazilu et al. [2012], the authors investigated the use of time-domain and statistical features, together with FFT features. Overall, the different proposed approaches reach detection sensitivities that often exceed 80%, and the detection is performed with at best with a latency of a few hundreds milliseconds.

However, these solutions were focused on the technology choices and the feasibility of FoG detection offline or in real time and did not take into account the effect of the system and the interaction with it from a user point of view. In all of the previous studies, the final users did not participate in the design process of the systems, as the systems were not developed for unsupervised environments use. Moreover, all studies up to now, from our knowledge, were not including evaluation of the systems during daily living activities or in the homes of the users.

As a step further, we proposed GaitAssist [Mazilu et al. 2014a], a wearable FoG assistant for gait training in out-of-the-lab and unsupervised settings, co-designed with people with PD, clinicians, and engineers. GaitAssist uses wearable sensors mounted on the body and machine learning techniques to detect the FoG episodes in real time. To develop our system, we arranged an exploratory data recording session with 18 PD patients, and we performed participatory design meetings with clinicians, engineers, and the patients: we asked our prospective users to fill in questionnaires regarding the wearability of on-body sensor placements and had open-ended discussions with the patients about how the system would look from their point of view. Further, we used the feedback given by the users to the first version of the system tested in the lab settings, to refine it and to incorporate new requirements from clinicians and patients.

Healthcare systems in out-of-the-lab environments. People with PD often exhibit a different behavior between being in a lab or hospital and in their natural environment, such as at home. People who experience FoG at home in various conditions do not necessarily experience it in a clinical setting [Nieuwboer and Giladi 2008; Okuma and Yanagisawa 2008]. Under laboratory conditions, they tend to experience increased stress (i.e., white coat syndrome [Geh et al. 2011]) or give more attention to the gait tasks when being observed. Under natural conditions, people with PD do not focus as much on their walking performance [Giladi and Hausdorff 2006]. GaitAssist has been tested in laboratory conditions [Mazilu et al. 2014a]: under supervision of clinicians,

Table I. Related Work on Wearable Systems for Detecting Freeze of Gait in Parkinson Disease

Reference	Sensors	Features and methods	Realtime	Dataset characteristics and detection performances	Experimental setting	Investigation goal
[Moore et al. 2008]	Accelerometer on the left shank and dedicated wearable computer for data collection	FFT-based dedicated feature – freeze index and threshold algorithm	No	11 subjects (in off medication state); 46 FoG detected. Performance: 78% true positive rate, 20% false positive rate	In the lab with clinical protocol	FoG characteristics
[Jovanov et al. 2009]	Accelerometer and gyroscope (either on belt, knee, ankle or shoe) and a wireless headset	Freeze index from [Moore et al. 2008] and threshold algorithm	Yes	4 experiments of simulated FoG and 1 subject. Detection performance unknown	unknown	System performance
[Djurić-Jovičić et al. 2010]	6 Inertial Measurement Units on each leg segment of both legs and a non-wearable computer	Energy of the sensor signals, stride length, neural networks and manually set thresholds	No	4 subjects with PD and FoG. Error in diverse walking patterns of 16%	In-the-lab with clinical-designed walking protocol	System performance
[Bächlin et al. 2010]	3 accelerometers on ankle, thigh and lower back, and one dedicated wearable computer	Freeze index from [Moore et al. 2008], power on the $[0 – 8]$ Hz frequency band and manually set thresholds	Yes	10 subjects, 8 hours of data with 237 FoG episodes. Performance: 73.1% sensitivity and 81.6% specificity (per data-window basis)	In the lab with clinical protocol	System performance
[Niazmand et al. 2011]	5 accelerometers integrated in a garment (shanks and belt) with a non-wearable computer	Power spectral density features and 3 threshold-based algorithms	No	6 subjects. Performance: 88.3% sensitivity and 85.3% specificity (per data-window)	In the lab with unknown protocol	System performance
[Cole et al. 2010]	3 accelerometers (shank, thigh, and arm) and Electromyography (EMG) device	Energies with dynamic neural networks	No	10 subjects. Performance: 83% sensitivity and 97% specificity (per second)	Setting not mentioned. Protocol: unconstrained activities	System performance
[Zhao et al. 2012]	5 accelerometers integrated in a garment (shanks and belt) with a non-wearable computer as in [Niazmand et al. 2011]	Frequency-based features	Yes	8 subjects, 54min of data, 82 FoGs. Performance: 81.7% sensitivity	In the lab with clinical protocol	System performance
[Tripoliti et al. 2013]	6 accelerometers (wrists, ankles, waist, chest) and 2 gyroscopes (waist, chest)	Entropy of the raw signals with supervised machine learning algorithms (Naive Bayes, Decision Tree, Random Forest)	No	5 subjects, 93 FoG events. Performance: 81.9% sensitivity and 98.7% specificity (per data-window basis)	In the lab with clinical protocol	FoG characteristics & System performance
[Mazilu et al. 2012]	3 accelerometers (thigh, ankle, lower back) as in [Bächlin et al. 2010]	Statistical and FFT features with supervised machine learning methods	Yes	Dataset from [Bächlin et al. 2010]. Performance: 66.2% sensitivity and 95.3% specificity (per data-window basis)	In the lab with clinical protocol	System performance
[Mazilu et al. 2014a] & [Mazilu et al. 2014b]	2 Inertial measurement units (acceleration, gyroscope, magnetometer) on the ankles and a smartphone	4 FFT-based features and C4.5 decision trees	Yes	Two datasets: (1) 18 subjects; 24 hours of data; 110 of 182 FoGs detected. (2): 5 subjects with FoG; 10 hours of data; 99 of 102 FoGs detected, detection latency ≤ 0.5 seconds	In the lab with clinical protocol	System performance & User acceptance

gait exercises have been performed and a scenario has been mocked up to reflect normal walking to investigate the assistive mode. However, it remains unclear if and to what extent the system impacts gait quality and the user perception in a daily life setting outside the lab (e.g., at home).

Allen et al. [2012] identify 53 relevant trials showing evidence that exercise, motor training, and rhythmic cueing strategies delivered individually in out-of-the-lab environments are beneficial for motor training in PD [Frazzitta et al. 2010] and to reduce the severity of freezing [Nieuwboer et al. 2007; Pelosin et al. 2010]. However, the authors argue that the training programs were closely supervised by the clinicians, even when the training was taking place in the participants' homes. This may cause a bias in the positive results from the studies, as the motor training setting is different from a daily life naturalistic scenario, even if it takes place outside the clinics. Moreover, the enumerated trials do not include, to our knowledge, the usage of an intelligent wearable system to assist the participants with cueing upon gait difficulties during the gait-training protocol.

In this work, we ask the participants to set up and use GaitAssist in their homes without any clinical or expert supervision. The wearable system is shipped with a step-by-step guide of how to deploy and operate the system to perform gait exercises and to use it as a wearable assistant. Thus, we made sure that the setup is as naturalistic as possible, being identical to the real usage scenario. In other words, the user buys a commercial wearable assistant and follows the gait-therapy protocol independently, guided only by a manual.

Another issue related to the home use of wearable sensor systems for healthcare is the difference between acceptance of such systems in out-of-the-lab environments compared to in-the-lab settings [Steele et al. 2009]. Often, systems that are highly appreciated in lab conditions have difficulties being adopted at the user's home environment. Recent studies analyze the implications of using and accepting home-based healthcare systems [Grönvall and Verdezoto 2013]. Social, emotional, and environmental factors play a key role in the adoption and use of healthcare systems in the home settings [Patel et al. 2012; Alemdar and Ersoy 2010]. As suggested in Schuler and Namioka [1993], the perception of a healthcare technology by its users has a strong impact on the outcome of a treatment. People who need care often have a lower barrier of acceptance than expected by caregivers and researchers. In addition, varying technical expertise may lead to differences in perception. Technology artifacts may even be associated with negative effects on their well-being [Sponselee et al. 2008]. Experience with patients in managing and accepting the body-worn technology highlights the issue of stigmatization and the need for a constant feedback from the system to the patient [Patel et al. 2012]. Further issues that came up in the acceptance of healthcare systems are related to privacy, trust, security, reliability, and battery lifetime [Grönvall and Verdezoto 2013]. Thus, in this work, we analyze how well the system was accepted in an out-of-the-lab setting, and we investigate potential differences between the perception of the system in the lab versus at home.

A recent survey [Patel et al. 2012] concludes with the observation that wearable sensor systems have been successfully applied in various rehabilitation scenarios (e.g., back and upper limb, stroke rehabilitation). We follow this direction and analyze whether using GaitAssist at home might help in motor training and in decreasing the FoG severity.

3. THE GAITASSIST SYSTEM

In this section, we give details about GaitAssist, our personalized wearable assistant for FoG support and motor training at home or in other unsupervised environments. The core module of the GaitAssist system provides audio feedback, a rhythmic sound

Fig. 1. GaitAssist system setup: (1) up to two wearable sensors attached on the ankles, (2) the sensor attachments, (3) a smartphone with the GaitAssist preinstalled app, and (4) optional earphones. The user of the system can choose whether to use the phone's loudspeakers or earphones to receive the audio feedback.

much like from a metronome, for a certain period of time (i.e., 8 to 10 seconds). This feedback is initiated at moments of *gait freeze* or of gait patterns that may lead to FoG during walking. To start the rhythmic feedback in real time when a FoG occurs, the system continuously monitors and evaluates the gait (i.e., the motion of the user).

In the following, we present the technical details of GaitAssist, including the system components and the communication between them. We describe the FoG detection framework and algorithms, describe the design of the user interfaces (UIs), and give details about the telemedicine service. We then present the results from a preliminary evaluation of the system in a laboratory setting, which provided the incentive for the out-of-the-lab evaluation.

Figure 1 shows the GaitAssist setup: it comprises a smartphone as the processing unit and between one or two wearable sensors, which are attached on the ankles with Velcro stripes. The wearable sensors sample data that is sent in real time to the smartphone via Bluetooth. The sensors are Inertial Measurement Units (IMUs) and were designed and developed by EXEL[1] for the Cupid project,[2] under which GaitAssist was developed. We aim for a minimum number of sensors attached on the body, thus the limitation of the system in connecting up to two IMUs. For this project, we chose a Samsung S3 mini model as the GaitAssist phone, because of its small shape, while providing enough computing capabilities to analyze the IMU data in real time. However, the system code is based on Android API, thus Samsung S3 can be changed with another phone model that runs Android. GaitAssist is the result of incremental design and development carried out by interdisciplinary teams of engineers and clinicians that used feedback and data collected during extensive design and testing sessions with 23 people with PD involved in in-the-lab settings [Mazilu et al. 2014a].

3.1. System Architecture

The main functions of GaitAssist are (1) *training support* for the gait-training exercises and (2) *gait assistant* during natural daily life walking in out-of-the-lab settings. The GaitAssist software consists of an Android application supporting the motor-training exercises and the assistive rhythmical cueing given upon FoG detection. Figure 2 shows the main modules of the GaitAssist app and the intercommunication between them:

(1) *IMU sensors* stream 3D acceleration, 3D gyroscope, and 3D magnetometer data at $N_f = 32$Hz to the smartphone via Bluetooth in real time. We chose 32Hz as a trade-off between the IMU's battery power and the amount of data needed to

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[1]www.exelmicroel.com.

[2]www.cupid-project.eu.

Fig. 2. The GaitAssist system with its components and modules: (1) wearable sensors, (2) FoG-detection module, (3) Motor-training exercises module, (4) Preferences module, (5) auditory feedback, and (6) Logging and telemedicine module.

observe changes in the gait properties. As the human movement range is between 0.5 and 16 Hz, a larger sampling rate will only waste precious battery power needed for a long-term usage of the system as an assistive device.

(2) The *FoG-detection* module detects the FoG episodes in real time, based on the data from the wearable sensors.

(3) In the *Motor-training exercises* module, the system supports exercises such as *gait initiation*, *cognitive loading*, and *turns*, as designed by physiotherapists.

(4) In the *Preferences* module, the clinician can set the preferences for the provided feedback. This includes different options for the exercises, such as exercise completion time, metronome settings, and the option to fine-tune the detection sensitivity of FoG detection models.

(5) The *Auditory feedback* module produces different types of rhythmic auditory cueing following the input of the FoG-detection module.

(6) The *Telemedicine and logging* module stores the raw IMU readings and the output of the FoG-detection algorithm during the system's use to phone's internal memory. These data are sent periodically to a telemedicine server and can be accessed later by the clinicians.

We will further describe the FoG-detection module, the Motor-training exercises module, and the Telemedicine and logging service.

3.1.1. FoG-Detection Module. The main functionality of GaitAssist is the real-time detection of FoG episodes from the continuous motion data collected by the ankle-worn IMUs. The module works with up to two IMUs. To detect the FoG episodes in real time from the IMU ankle data of the users, we considered a machine learning approach. Machine learning models have been proven to be useful in accurately detecting human activities such as walking, sitting, standing, and falling [Bulling et al. 2014; Choi et al. 2011]. A couple of recent studies show that FoG can be accurately detected with machine learning models and wearable sensor data [Mazilu et al. 2012; Tripoliti et al. 2013].

Training dataset. To accurately detect FoG in real time, we built a user-independent FoG-detection model using IMU data from the ankle collected from 18 subjects with
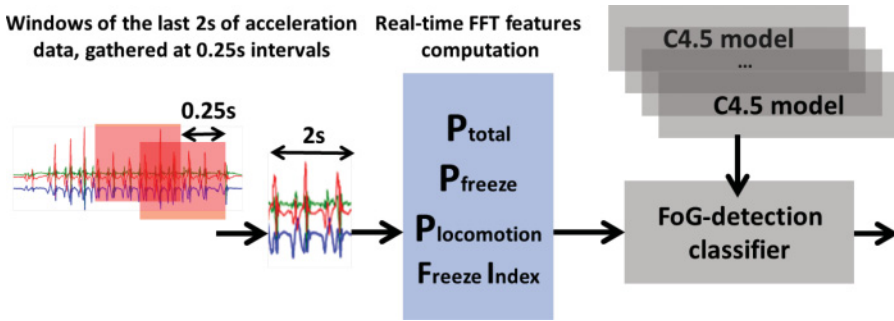
Fig. 3. The real-time FoG-detection framework from the GaitAssist system.

Table II. Features Extracted from Acceleration Magnitude Vectors

Feature	Description
Power on locomotion band (PL)	Power on the 0.5 to 3 Hz band of the acceleration magnitude signal in the window
Power on freeze band (PF)	Power on the 3 to 8 Hz band of the acceleration magnitude signal in the window
Total Power (TP)	The sum of the power in the freeze and locomotion bands. This feature was used by Bächlin et al. to distinguish volitional standing from FoG [Bächlin et al. 2010]
Freeze Index (FI)	Power of the freeze band 3 to 8 Hz divided by the power in the locomotor band 0.5 to 3 Hz as used in the FoG-detection algorithm from Moore et al. [2008]

PD and FoG, a subset of the Cupid dataset [Mazilu et al. 2013a]. The Cupid dataset consists of 24 hours of multimodal sensing data collected from people with PD experiencing FoG in a lab setting. Cupid dataset contains physiological information such as electrocardiography (ECG), galvanic skin response (GSR), or functional near-infrared spectroscopy (FNIR) data, and IMU data from different body positions—foot, ankle, thigh, back, and arms. More technical details about the sensors setup and overall flow of the Cupid experiment can be found in Mazilu et al. [2013a].

In total, clinicians labeled 182 FoG episodes with durations between 0.2 and 98.8 seconds. The FoG labels were obtained from clinicians' annotations using a stopwatch and videos, and later synchronized with the sensors data stream. Clinicians considered the moment of arrested gait pattern (i.e., stop in alternating left–right stepping) as the start of a FoG episode and the instant when the patient resumed a regular gait pattern as the end.

We choose the ankle position for the wearable sensors to be attached based on previous studies [Bächlin et al. 2010; Tripoliti et al. 2013; Mazilu et al. 2012], but also from our prior analysis [Mazilu et al. 2014b], which shows that inertial data from the ankle position gives the best information to characterize FoG and distinguish it from other types of human gait. Moreover, in Mazilu et al. [2014a], the ankle position received the highest wearability scores to attach on-body sensors for a wearable assistant.

The FoG-detection machine learning framework. The real-time FoG-detection chain implemented by GaitAssist is presented in Figure 3. Raw 3D acceleration data from the Cupid ankle dataset is segmented in windows of 2 seconds, with an overlap of 0.25 seconds. These values were selected as a trade-off between FFT-based descriptive power of the human gait and the latency of the real-time FoG-detection. We compute the acceleration magnitude vectors in each window. From the vector of magnitudes, we compute the following FFT-based features described in Table II to capture the FoG
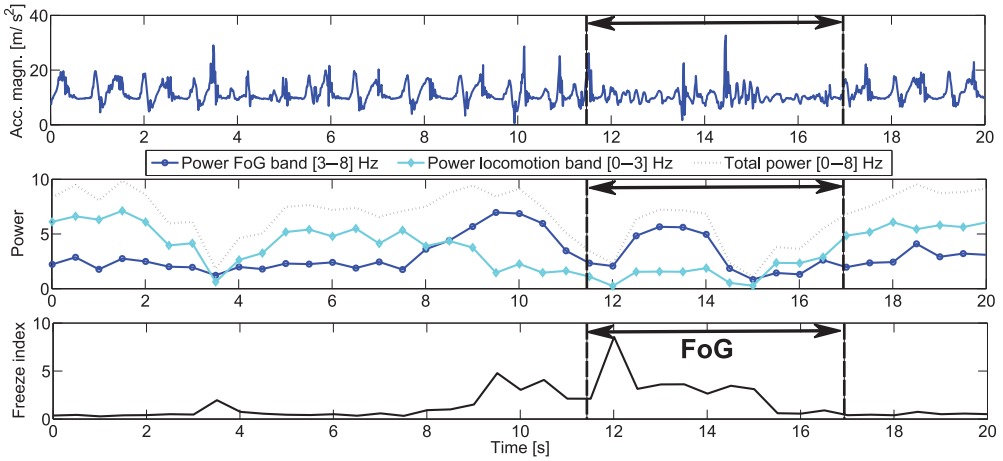
Fig. 4. A sequence of 20 seconds of walking, containing a FoG episode. The sequence contains the acceleration magnitudes from IMU raw data and in the four features extracted from the sliding window vectors: power on FoG band, power on locomotion band, total power between 0.5 and 8 Hz, and the FI.

characteristics compared to the normal gait. The resulting feature vector is fed into a FoG-detection algorithm, which decides in real time whether the user is in FoG or not.

Figure 4 contains 20 seconds of walking and turns, including a FoG episode as example. From the ankle, we capture the raw-acceleration magnitude (top) and compute four FFT-based features. We observe that *power on freeze band* (PF) and *freeze index* (FI) features increase prior to or during the FoG onset compared to the walking periods, whereas *power on locomotion band* (PL) values decrease before or during FoG. Although the PL feature is similar in cases of turning, standing, sudden stops, and FoG, the *total power* (TP) feature helps in distinguishing between turns and FoG, for example.

The FoG-detection algorithm consists of instances of C4.5 pruned trees, trained offline on labeled ankle acceleration data from the Cupid dataset. The procedure to build the C4.5 models follows the same first steps as in the FoG-detection framework: all 3D acceleration data from each ankle of the subjects is added together and is split in windows of 2 seconds. From each window, the acceleration magnitude vector is computed, then the four FFT features are extracted. A label from the groundtruth annotations, whether the window time frame is labeled as FoG or normal walking, is added to the features, which together create a training instance. These instances computed from each window of acceleration data are then used to train a C4.5 model. A second C4.5 model for FoG detection was trained only on a selection of Cupid ankle data, which consists only from the sessions of walking that contain at least one FoG episode. This second model was built as a more sensitive version of the first classifier in detecting FoG. The classification models were then integrated in the GaitAssist framework on the smartphone.

Before deploying them in the GaitAssist framework, the FoG-detection performances has been evaluated offline in a person-independent setting: for each PD subject in the Cupid dataset, we considered the other data collected from the remaining subjects, built a FoG-detection model following the same steps as in the framework detailed before, and tested it on the selected subject data. We then computed the following measures for each of the subjects: the number of FoG events successfully detected and the number of false FoG detections. A FoG event is considered detected if during the period of time marked with a FoG label in the ground-truth annotations at least once the algorithm

detects two times FoG from three consecutive data windows. A false FoG-detection event is considered when the algorithm detects a FoG in the way detailed before while the ground-truth label shows no FoG for that period of time/data. Overall, 110 from a total of 182 FoG episodes were successfully detected on the entire Cupid dataset, with 20 false FoG detections.

We also considered statistical features such as mean, max, min, standard deviation, variance, and energy of the magnitudes of both accelerometer and gyroscope data as an addition for the FFT features from accelerometer, as in Mazilu et al. [2012, 2013b]. However, the FoG-detection results obtained by taking into account different combinations of the new added acceleration and gyroscope features did not outperform the results obtained when using the four FFT features from accelerometer alone.

Rhythmic cueing feedback. In response to the detection of a FoG event, we provide a cueing signal to the user. Previous studies [Nieuwboer 2008; Lim et al. 2005] showed that auditory cueing is the most effective for improving gait in people with PD. We therefore chose to provide rhythmic auditory stimulation (RAS) in the form of a metronome ticking sound at the onset of FoG episodes [Rubinstein et al. 2002]. The FoG detection and RAS feedback generation can be used together for day-long FoG support, but they are also essential for the training component.

3.1.2. Training Exercises. The implemented exercises of GaitAssist are designed by clinicians and should encourage the patient to practice the use of FoG-aware cueing in FoG-provoking situations, and to train the gait in these situations. Experiments and clinical studies suggest that exercises for FoG-provoking situations are beneficial for gait training in people with PD, and to reduce the freezing severity [Allen et al. 2010; Nieuwboer et al. 2007; Pelosin et al. 2010].

Table III presents a brief review of the exercises supported by GaitAssist. There are two classes of exercises: (1 to 2) gait initiation exercises (e.g., weight shift while standing or stepping), with the additional option of dual tasking, and (3 to 6) turning exercises. Clinicians choose these two types of exercises as training because step initiation and different types of turns (e.g., 180-degree turns or 360-degree turns) are among the main causes that provoke FoG in people with PD [Schaafsma et al. 2003; Ziegler et al. 2010].

For each of the six exercises, GaitAssist signals the start and the stop of each exercise with a human voice asking the user to start the movement or to stop it. In between exercises, the system does not collect or analyze the data from the sensors.

For exercise 2 (i.e., gait initiation with cognitive load), GaitAssist randomly shows different shapes and colors, with higher probability for green circles and red squares to appear, to support the cognitive load task. Motor training with cognitive load is used to reproduce the natural daily life condition—usually people do not pay attention to their walk, but do parallel activities (e.g., having a conversation while walking) [Bloem et al. 2004].

Exercises 3 and 5 differ from the whole target of the GaitAssist system—to provide RAS upon FoG in FoG-provoking situations. During these exercises, the RAS is delivered continuously except in the case of FoG and a limited period of time after FoG. The idea behind this is that the users are encouraged to follow the rhythm given by the system and learn how to synchronize their gait with the rhythmic auditory cueing from GaitAssist. These two exercises function as learning tasks for the actual FoG-provoking exercises 4 and 6.

Each exercise has three subtypes corresponding to the exercise complexity: *easy, medium*, and *hard*. The difference between each subtype is given by the exercise parameters set by the clinician, such as the exercise time, the RAS time, and the BPM settings.

Table III. GaitAssist Training Exercises as Designed by Clinicians

#	Exercise	Training Type	Description	GaitAssist Support
1	Weight shift standing/ stepping	Gait initiation	The user needs to shift his weight between his legs or weight to one foot and step forward and backward with the other leg, according to the rhythm imposed by the system.	GaitAssist provides in the first minutes of the exercise (as set by the physiotherapist) a continuous rhythmic auditory stimulation (RAS) tone to help the user establish the rhythm. The next minutes until the end of the exercise, the system provides RAS upon FoG.
2	Cognitive task	Gait initiation	The user should start walking only when a specific shape, such as a green circle, appears on the GaitAssist screen. He needs to make 5 steps and then stop, or stop when a red square shape appears, during the exercise time.	Randomly shows different shapes and colors, with higher probability for green circles and red squares to appear; the system provides RAS upon FoG detection.
3	Figure 8 (1)	Turning	The user needs to walk according to the rhythm in a figure 8 shape for 5 rounds through the right side and then 5 rounds through the left side. The user needs to continue this until the exercise end tone is given.	The system provides continuous RAS during the exercise, except during FoG and short periods of time after FoG (e.g., 10 seconds).
4	Figure 8 (2)	Turning	The same as in the previous exercise.	The system starts RAS only upon FoG.
5	Chairs (1)	Turning	The user is asked to place two chairs facing each other at 3m apart. The the user needs to arise from one chair and walk according to the rhythm provided by GaitAssist to the other chair, circle it from the right, return to the first chair, and sit on it. This movements need to be repeated until the exercise end tone is given.	GaitAssist provides continuous RAS during the whole period of the exercise, except during FoG and short periods of time after FoG (e.g., 10 seconds).
6	Chairs (2)	Turning	The same as in the exercise no. 5.	GaitAssist starts RAS only upon FoG detection.

3.1.3. Telemedicine. In parallel with the FoG-detection and gait-training support, GaitAssist saves the app settings, the raw sensing data collected from the IMUs, and the synchronized output of FoG-detection algorithms together with the features computed from the IMU data for each exercise done by the user. These data are sent to a telemedicine server and are uploaded to the account of the user. The data synchronization between the telemedicine server and GaitAssist is made when the phone starts a new WiFi connection. Once the WiFi connection is established, GaitAssist sends all new data.

The telemedicine service stores the raw data and the output of the FoG-detection classifier, then computes FoG-related statistics such as average FoG duration or the number of FoG detected episodes per exercise or overall during the training day. Besides such aggregated information, clinicians underline the importance of having access to raw motion data for further visualization and analysis. By collecting continuous data during GaitAssist usage sessions, physiotherapists will be able to monitor the long-term effects of motor training on disease progression. The clinicians can visualize the raw IMU data and the statistics for each training day and thus can adapt the

exercise settings or even the pharmacological treatment of the patient. The data and the statistics sent to the telemedicine server are useful to monitor not only the gait training of the user but also disease progression during longer periods of time. IMU-collected data containing a 3D accelerometer, 3D gyroscope, and 3D magnetometer can be used further for deploying and refining new FoG-detection methods.

An additional service of the telemedicine is that clinicians can upload a file with new settings for GaitAssist and gait-training exercises to the telemedicine service. During the synchronization between GaitAssist and the telemedicine service, these settings will be updated in the GaitAssist app. This allows the clinicians to remotely change and adapt the gait-training procedure for each user without having to visit the patient at home or invite the user to the hospital.
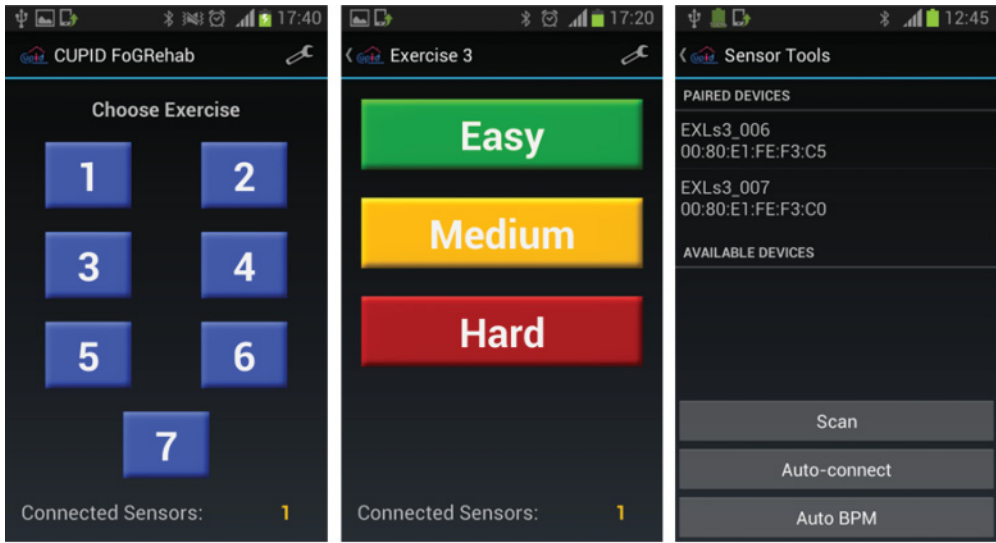
3.2. User Interface

GaitAssist comes with two role-dependent user interfaces. First, the *patient UI*, has simple large buttons for each of the gait-training options. This is shown by default when starting the app. Second, the *clinician UI* contains all ptions and settings of GaitAssist and training exercises. To enter in the clinician interface, a user needs to tap five quick times on the screen of the patient interface. Figure 5 shows screenshot examples of the two UIs.

3.2.1. Patient UI. People with PD usually have issues with using the touchscreen of smartphones when touching the phone's buttons or apps' buttons. To ease the usage of the GaitAssist app, the patient UI has seven large buttons in the main tab, with large text size, corresponding to the six motor-training exercises (buttons 1 through 6), and to the gait-assistive option for daily life activities (button 7), as shown in Figure 5(a). For the gait-training exercise, when pressing each of buttons 1 through 6, a new screen will appear where the user has the option to choose the exercise difficulty. The difficulty option buttons are also large and have different colors to make them easier to distinguish the message they have. When an exercise difficulty is selected, an exercise screen will appear with a large green button for Start. During the exercise, the button changes into a red Stop button. The exercises end either when the exercise time, as set by the clinicians in the clinician UI, is completed or when the user presses the Stop button. Once the exercise is finished, the UI comes back to the main screen with the seven button options. In the case of exercise 2, corresponding to gait initiation with cognitive load, in the exercise screen there are differently colored shapes that appear randomly during the exercise for a period of 2 to 3 seconds each to support the cognitive load part of this exercise.

To ease the system setup and improve usability, the sensors automatically connect to the system once the GaitAssist application started. Only at the first usage of the application does the user need to pair the sensors manually. At the first connection, the MAC addresses of the IMU will be saved, and next the app will automatically connect to the sensors, once started. In addition, when the user exits the app, this will send a Turn Off message to the sensors. In the patient UI, there also is a Sensor Tools interface, which gives the user the option to reconnect the sensors in case of a failure of the sensor connection or to connect new sensors.

This interface also provides the option of automatically adjusting the beats per minute (BPM) setting necessary for establishing the rhythmicity of the auditory cueing given during FoG. When selecting the Auto BPM option, the user will be asked to walk in a natural way in a straight line, for 30 seconds, between a Start and End signal given by the app. Then the system analyzes the gait data collected from the 30 seconds to automatically count the number of steps during this period and to compute the gait rhythmicity of the user, and thus the BPM value. The BPM value is central for the

(a) Patient user interface.
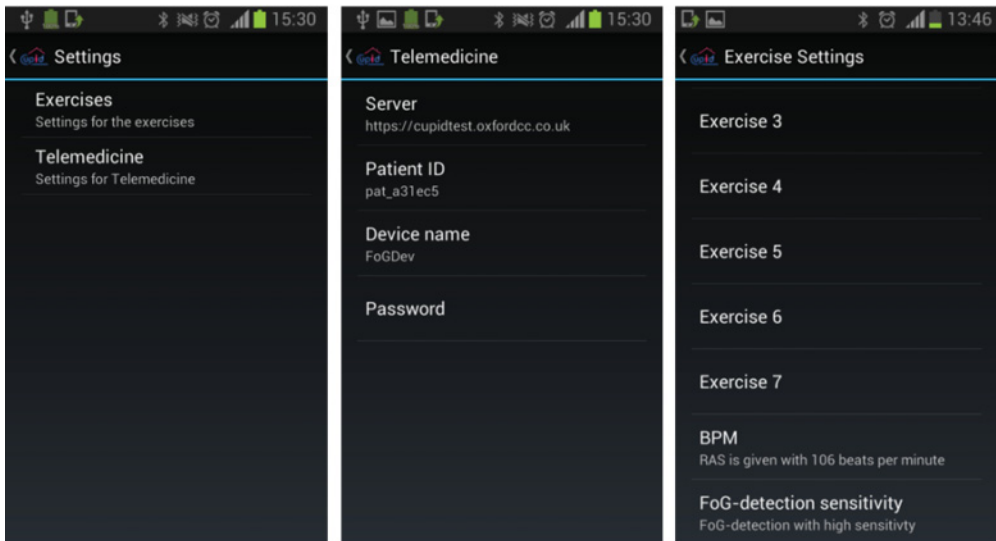
(b) Clinician user interface.

Fig. 5.   The two UIs of the GaitAssist app: patient UI (a) and clinician UI (b).

cueing given by the system during FoG, as the rhythmicity of the cue needs to be the same as the normal gait of the patient to help him resume the walking.

3.2.2. Clinician UI. By quickly tapping the patient UI screen five times, the app enters into the clinician UI, shown in Figure 5(b). The UI will change back to the patient interface if the Return button is pressed. The clinician UI contains two types of settings that can be changed by the physiotherapist: settings regarding the exercise and global gait-related variables, and the telemedicine parameters.

Exercise Settings contains the settings for each of the exercises, such as the exercise time for each of the difficulty options and general settings such as the BPM value,

or the sensitivity of the FoG-detection model. The BPM value is usually set by the physiotherapist after analyzing and assessing the user's gait. However, the Auto BPM setting from the patient UI offers the user the possibility to update this value in case she thinks the RAS is not synchronized with her gait rhythm (i.e., people with PD may change their gait properties from day to day, or even during the same day, depending on medication, physiological and psychological factors) [Okuma and Yanagisawa 2008; Hausdorff et al. 2003].

In Telemedicine Settings, clinicians need to set the telemedicine server, the name of the GaitAssist device, and the user account credentials from the telemedicine service. All data gathered during the GaitAssist usage will be then uploaded to the user's account from the telemedicine service.

3.3. Functionality Evaluation

Before deploying the system at home, we performed a final evaluation in terms of power consumption and performance. Since smartphones are commonly used, by the elderly as well, we wish to leverage the used phone as the processing and feedback platform for GaitAssist. Critical to this is a low impact on the smartphone battery life when continuously in use.

Phone resources consumption. The total time required for computing the FFT features and making a decision with regard to the FoG algorithm is at most 6 milliseconds, measured in real-time settings on the Android application running on the Samsung Galaxy S3 mini phone. A profiling of the GaitAssist app with PowerTutor[3] shows that the CPU usage of the phone during these operations does not exceed 50%. In a realistic usage setting, GaitAssist consumes less than 1% from the battery power per hour. However, the IMU batteries last for at most 4 hours, which limits the time of the GaitAssist usage as an assistive device.

System preliminary in-the-lab evaluation. Before deploying GaitAssist with people with PD and FoG in their homes, we performed a preliminary testing of the system in the lab. We asked five people with PD and FoG to perform a set of walking tasks in the hospital while supervised by the clinicians. A detailed description of the trial with details about the people participating and descriptions of the walking tasks and exercises is given in Mazilu et al. [2014a]. The limited number of participants in the preliminary study is a result of the nature of the targeted population (i.e., elderly subjects) with PD and FoG, but also due to the requirement that subjects participating in this study should not have been previously included in any of the participatory studies for GaitAssist. Participants were invited to come to the hospital for three sessions during different days in 1 week, with each session lasting approximately 30 minutes. Each of the five participants used the system during gait-training exercise and naturalistic walking protocols as follows. In the first 2 days, the participants performed gait-training exercises following the instructions of a physiotherapist and with GaitAssist providing cueing during FoG episodes. On the third day, subjects used the system in a real-life walking task in the hospital corridors and the park nearby. The protocol tasks were designed to test the feasibility and a preliminary acceptability of the GaitAssist system.

The entire in-the-lab study was video recorded, and videos were synchronized with the sensing data from GaitAssist sensors. The FoG labels were obtained from clinicians' annotations using a stopwatch and videos. Clinicians considered the moment of arrested gait pattern (i.e., stop in alternating left–right stepping) as the start of a FoG

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[3]http://ziyang.eecs.umich.edu/projects/powertutor/.

episode and the instant when the patient resumed a regular gait pattern as the end. In total, clinicians observed 102 FoG episodes from the five participants during the three trial days.

The GaitAssist FoG real-time hit rate was 97% (99 out of 102 FoG episodes correctly detected), with a detection delay of ≤0.5 seconds after the start of a FoG. FoG events shorter than 0.5 seconds could not be detected. As such, 27 false FoG detections occurred in total during the study, meaning that GaitAssist started cueing at moments without a FoG in progress. This was usually in response to unusual motions that resembled FoG, such as during gait festination, turning with very small steps, sudden stops, or during sit-to-stand and stand-to-sit movements. The latter ones were due to the lack of these types of movements in the training data.

Participants stated that the system helps them in resuming the gait earlier upon FoG and that they feel comfortable wearing it [Mazilu et al. 2014a]. Discussions of participants with the clinicians and their observations and advice regarding GaitAssist helped us improve different system components, such as the UI, sensor attachments, sensor case, and automatic connection of the IMUs with the phone. Details about the overall participatory design and development steps are given in Mazilu et al. [2014a]. The final system, as presented in this section, integrates all input received from patients, clinicians, and engineers in the different stages of system design, deployment, and testing.

4. THE AT-HOME STUDY

To study the user acceptance and a potential effect of the system on the user's gait in the natural environment of the user, we performed a study with new PD patients who were not involved in the design or in-the-lab evaluation of GaitAssist.

4.1. Participants

For our study, we included people with varying motor abilities reflecting different stages of PD. This wide range of inclusion was meant to better inform us about the potential utility of the system throughout the course of the disease. People with PD selected for the study were diagnosed with PD, were cognitively intact, had adequate vision and hearing abilities, lived with a caregiver or a family member, and were deemed computer literate by having an email account. We excluded people who suffer from psychiatric co-morbidities, such as major depression, or had a history of stroke, traumatic brain injury, brain tumor, or other neurological disorders. Participants underwent a clinical physical and neurological examination using the Unified Parkinson's Disease Rating Scale test UPDRS—part III [Goetz et al. 2008]. Subjects who suffered from FoG were asked to rate their FoG severity using the new FoG questionnaire [Giladi et al. 2009].

Nine people with PD from two medical sites in two countries (five subjects from Israel and four subjects from Belgium) participated in the study (mean age: 68.3.8±10.7 years; 78% men). Table IV summarizes the participants' characteristics from the two medical sites. Participants had moderate (four participants) or mild (five participants) PD severity and mean disease duration of 12.8 ± 8.5 years. All participants were cognitively intact, and except one subject from site 2, all suffered from FoG based on the FoG questionnaire [Giladi et al. 2009], suggesting severe freezing. Eight out of nine subjects were under their regular medication treatment for PD and FoG, and they did not change their medicines during the study. One subject used only medical marijuana.

The nine participants were representative of people with different PD ranges with FoG, were volunteers, and expressed motivation to participate in this study. Besides suffering from PD, the participants were elderly people, and even if they were computer literate, they were not early adopters of novel technologies such as wearable devices. Furthermore, users were required to set up the system and perform the protocol without

Table IV. At-Home Study: The Participants' Characteristics

Subject Site 1	Gender (Israel)	Age (years)	PD Duration (years)	FoGQ Score [Giladi et al. 2009]	H&Y score [Hoehn and Yahr 1967]	UPDRS3 [Goetz et al. 2008]
PD1	F	64	19	24	3	23
PD2	M	79	5	24	2	24
PD3	M	76	12	28	3	40
PD4	F	73	4.5	30	2	51
PD5	M	82	12	18	2	46
Site 2	(Belgium)					
PD1	M	51	4	0	2	42
PD2	M	65	30	8	3	56
PD3	M	54	18	20	3	37
PD4	F	71	11	19	2	23

any clinical assistance or supervision there or in their homes. All these parameters contributed to having a limited number of participants in the study.

4.2. Procedure

The training program at home consisted of three protocol sessions delivered during three different days in 1 week, as designed by the clinicians. On the first day, participants underwent a clinical physical, neurological, and cognitive examination and were asked to rate their FoG severity. The clinicians explained the operation of the system and provided the users with a manual for self-use. Only during the first protocol day did the clinician remain with the users to make sure they understood the manual and the exercises. However, the clinician refrained from taking part in the training program unless a critical problem emerged (e.g., the participant fell) or clarification was needed (e.g., the user could not take off the sensors at the end of the training). In the subsequent two protocol days, the clinician was not present, and the exercises were performed alone by the participant or under the supervision of the caregiver or family member who accompanied the participant every day.

At the beginning of the procedure, the user was asked to set up the system on the body (attach the sensors and the straps, turn on the sensors, turn on the phone, and start the GaitAssist app). Then the user needed to perform the designed protocol tasks. At the end of the session, users needed to exit the GaitAssist application, turn off the phone, and detach the sensors from the ankle. Each step of the procedure (set up and protocol tasks) was detailed with a short description and pictures in the self-use manual. Figure 6 shows the participants during the protocol, operating the GaitAssist system on their own using the provided manual.

4.3. Protocol

In each of the protocol days, the participants used the system for approximately 60 minutes. During each day, the participants were asked to perform motor-training exercises and some of their usual daily life activities while wearing the GaitAssist system. Rest breaks were included between parts of the session, and the subjects could also rest between the sessions if needed. The protocol included two parts mapped on the two functions of the GaitAssist: (1) a gait-training exercise part and (2) a daily life activities part.

Gait-training exercises. In the first part, the participant was asked to perform motor exercises that have been shown to provoke FoG, such as gait initiation, dual-task conditions, and turnings [Schaafsma et al. 2003] (Figure 7(a) and 7(b)). The suggested

Fig. 6.   Participants following the user manual and operating the GaitAssist system.

(a)   (b)   (c)

Fig. 7.   Users practicing exercise 2, step initiation with visual cognitive load (a); exercise 3, the figure 8 (b); and free walking in the home environment (c).

motor-training exercises were the same as the ones suggested by the clinicians in Section 3.1.2 and implemented in the patient UI of GaitAssist (exercise options 1 through 6).

Daily life activities. The second part of the protocol included walking during common daily life activities, such as rising from chairs, passing through different narrow spaces between furniture, walking around different rooms, and walking outdoors (Figure 7(c)). This corresponds to the option 7 in the patient UI of GaitAssist (Section 3.2). The system assists the user by providing gait-synchronized RAS upon FoG or when the user encounters difficulties in walking.

5. USER FEEDBACK

At the end of the deployment week, participants were asked to complete a questionnaire regarding the usability and the comfort of the GaitAssist system. The structured questionnaire was constructed specifically for the study based on validated questionnaires

Table V. Satisfaction Questionnaire

#	Statement	Site 1 Average	Site 2 Average	Global Average
	System operation	**4.2**	**3.9**	**4**
1	I can turn on the sensors easily	4.2	3.2	3.7
2	I can turn on the mobile phone easily	4	4.5	4.3
3	I can turn on GaitAssist Android app easily	4.6	4	4.3
4	I can switch between the training modes of the app easily	4	4	4
	Wearability	**4**	**4.2**	**4**
5	I can attach the sensors easily	1.8	2.7	2.2
6	It is possible to remove the sensors independently	3.2	4.5	3.8
7	The weight of the earphones does not interfere with the exercises	4.2	4.5	4.4
8	It is possible to put on the earphones independently	5	4.2	4.6
9	It is possible to take off the earphones independently	5	4.7	4.8
10	The auditory feedback is heard well	5	4.7	4.8
	Exercise content	**4.1**	**3.5**	**3.8**
11	I understand *gait initiation* exercise	4.2	2.8	3.4
12	I understand *response inhibition* exercise	4.2	3.7	3.9
13	I understand *figure 8* and *turns* exercises	4.2	3.5	3.8
14	I can easily do these exercises	4	4	4
	Subjective opinions	**3.8**	**3.8**	**3.8**
15	I think GaitAssist is simple to use	3.6	3.2	3.4
16	In my opinion, GaitAssist is suitable for people with Parkinson's disease	3.6	4.2	3.9
17	The manual is clear and simple to understand	4.2	4	4.1

Note: Statements and average scores were on a scale from 1 to 5, where 5 is the best score for participants in site 1 (Israel), site 2 (Belgium), and the overall average across all nine participants.

assessing techniques [Demers et al. 1996]. Each statement has five possible answers: 1, strongly disagree with the statement; 2, mostly disagree; 3, neither agree nor disagree; 4, mostly agree; and 5, strongly agree. The results of the usability questionnaire are divided into four categories:

—*System operation* relates to the participant's ability to operate the system: to turn the smartphone and the sensors on and off, to switch between the modules, and to enter training parameters.
—*Wearability* relates to the ability to independently attach/detach the sensors and the comfort of using the smartphone and the earbuds.
—*Exercise content* includes questions related to the training methodology and the way in which the participants in the study understood and did the exercises.
—*Subjective opinions* included questions about participants' opinions and their overall impressions about this system and its potential for use by people with PD.

In Table V, we present the mean score over all nine participants for each statement. In general, participants stated that they were highly satisfied with the system and its potential for use, and they enjoyed using it in most of the training sessions. In the following, we summarize the relevant feedback and lessons learned for each category.

System operation. Despite the high grades given by the participants on the statements regarding system operation (Table V), five of them had difficulties in turning the sensors on or off. This action required bending and was particularly difficult for participants with tremor, rigidity, or fine motor impairments, which are common symptoms of PD. In the second and third training sessions, however, participants learned

(a)   (b)
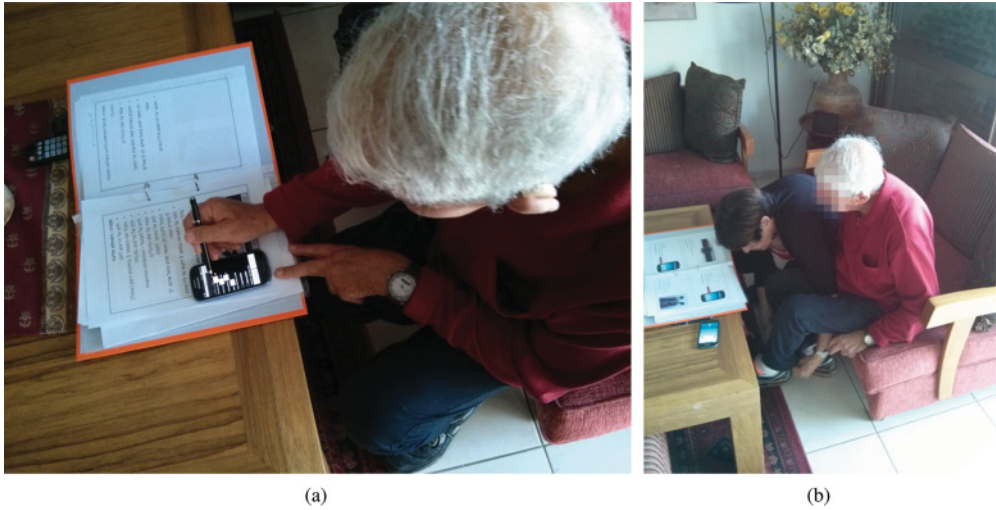
Fig. 8. Using GaitAssist at-home: a participant operating GaitAssist with a stylus pen (a) and a family member helping the participant to attach the sensors (b).

how to use the system, and it was easier for them to operate it. They even reported improvement in the ability to work with the sensors.

In the first session, participants complained that turning on the mobile phone was not easy, and usually they needed more than one attempt to turn it on. However, for 80% of the users, this was the first experience with a smartphone, and it seemed that during the progression of the training, the use of the phone became easier and more intuitive. After turning on the smartphone, users needed to press the GaitAssist app icon on the phone's home screen. This action requires fast movement of the index finger or thumb. Because of lack of experience with the smartphones and as an effect of the disease, which can make it difficult to quickly tap a screen, many of the participants pressed the icon for a longer time during the first usage of the phone. In response to such a long press, the phone activated icon rearrangement instead of starting GaitAssist. For the next sessions, we changed the parameter controlling the duration of the long press. As a result of this feedback from the participants, users received a stylus pen, which enabled them to press the icons more accurately (Figure 8(a)) for the next protocol sessions.

Wearability. Operating the sensors received low wearability scores compared to interaction with the other external modules of the system, such as the earphones, which received maximum grades. One explanation is that the earphones were known to the participants, being long-established commercial devices, whereas wearing sensors is a new concept for the public and especially for elderly people, such as our participants in the study. Putting on or taking off the sensors and their attachments was a difficult operation, as it required bending down. In addition, even if it was not a limitation, they were elderly people with PD. Common PD symptoms such as tremor or fine motor impairments made this action even more difficult. Therefore, a caregiver or a family member helped the participant to complete this task (see Figure 8(b)).

Users were offered earphones for auditory cueing. They successfully managed to introduce the plug of the earphones into the phone's socket. Although they heard the feedback better using the earphones, they preferred not to use them because they could also hear the mobile phone. One of the participants was using hearing aids, making it hard for him to wear earphones in parallel.

Exercise content. This category included four questions regarding the training methodology and the way in which the users understood the exercises and how they performed them. During the first and second sessions, participants encountered various issues. They had problems because they did not follow all of the instructions in the user's manual or did not read the manual completely. However, by the last session, users understood the exercises and performed them appropriately. A solution for this issue is to provide videos examples with clinicians practicing each exercise in addition to the using the user's manual.

In the case of visual cognitive load exercise, such as exercise 2, despite the high average score given by the participants, most of them did not perform it correctly. Common mistakes were walking during the entire period or walking more steps than required in the instructions. As also was observed in Mazilu et al. [2014a] during in-the-lab evaluation, GaitAssist generated erroneous detections and provided RAS during sit-to-stand and stand-to-sit situations, or during turning with small festinated steps in the absence of FoG. When such a false positive generated rhythmic cueing, users were confused, as they were not sure whether to stop or continue when performing the cognitive load exercise.

All users said that the auditory feedback was well heard from the phone. The phone was held in hand by the participants or placed in a pouch or pocket.

Subjective opinions. The statements in this category refer to all aspects the participants needed to deal with when they activated and used the application. Even if they gave average to positive scores for the statements in this section (a 3.6 to 4.2 grade out of 5), overall participants were satisfied with the system, stating that it is suitable as a gait-training and gait-assistive tool, and that it has the potential to decrease FoG severity. Users found the user's manual for GaitAssist to be clear and comprehensive. One user had difficulties in turning the pages and suggested adding sticky notes browse more easily between the pages.

However, in its current form, there are still disadvantages that influence the ability to operate GaitAssist easily. The most common comment from the participants referred to the possibility of independent use. In their opinion, it is imperative to have the support of another person during the training for dealing with the system, such as assistance for sensor placement or typing.

Discussion. GaitAssist received an average of 4 out of 5 as a wearability score (i.e., for statements 5 through 10) when being used and tested in the user's natural environment without clinical support or assistance. The score obtained is a positive result, given (1) the user's background—that is, elderly people with PD and FoG who are not early adopters of technology and are not using wearable technology, and (2) the specific testing scenario—that is, the users were asked to set up and use the system by themselves in their home environments without any clinical support. However, we observed one common wearability drawback—participants needed a family member to help them set up the system on the body, mainly in attaching the sensors on the ankles, suggesting that the users cannot independently setup the system by themselves.

In terms of comfort when using the phone and the earphones (statements 2 through 4 and 7 through 10), the scores obtained are in the range of 4.2 and 5 out of 5, suggesting a positive opinion and openness in adopting these electronics. The usage of the phone and the application has been received positively and reported to be intuitive to use. Even the users who did not operate a smartphone before answered statements 2 and 4 with scores equal to or higher than 4. However, using the wearable sensors received low scores in the user's natural environment scenarios. Participants in the study reported difficulties in attaching the sensors, requiring help from another person. This wasbecause a phone,

even if not used as an assistive device, was already present in the daily life of the participants, and hence the low barrier of acceptance. On the other hand, the wearable sensors were novel to the participants. In addition, sensors must be attached to the ankles—an unusual position for wearable accessories. In the specific case of elderly people with PD, this is a difficult task, as it requires bending. Indeed, the sensors may have been well accepted in the in-the-lab setting [Mazilu et al. 2014a]: the mental link between rehabilitation equipment and hospital settings together with a sporadic use results in a higher acceptance of the device. However, for daily life usage, users demand minimal compliance, even if the rehabilitation tools have a positive effect.

Thus, *sensor wearability is critical* to the acceptance of the system for home use. The long-term goal is to integrate sensing into a garment to minimize the compliance of GaitAssist.

For statement 16—"GaitAssist system is suitable for people with Parkinson's disease"—participants rated it with 3.9 out of 5 on average. This still suggests an overall positive opinion toward using the system in their daily life. Participants expressed their willingness to continue training and using GaitAssist after the end of the trial, stating that they feel it helps them improve the gait.

For some statements, there are differences in scores given between the groups of subjects from the two sites. The four participants in site 2 had mild disease severity compared to the five subjects from site 1. The FoG questionnaire values overall were lower for the participants in site 2 compared to the participants in site 1 (refer to Table IV in Section 4). Moreover, the average age was higher for the group in site 1 compared to the participants in site 2, and participants in site 1 overall had more advanced disease severity. This explains why, for example, in the case of statement 5, the group of subjects in site 2 gave higher grades than the group from site 1 when asked how easy was to attach the sensors on the body: participants in Site 2 found it easier to bend and attach the sensors due to the milder effects of the PD on the motor functions.

But overall, the grades given by the participants in site 2 were lower than those given by the participants in site 1. Surprising, if we consider that the participants in site 1 have a higher average age and are suffering from a higher disease severity than the subjects from the second site, one would expect to have lower acceptability grades of the system from the participants in site 1 due to these group characteristics. On the other hand, people suffering from PD and FoG are people who have continuous difficulties in walking, feel constrained during their daily life activities due to the pervasive nature of FoG, and usually depend on a caregiver or member of a family for support with motor activities. Thus, this explains somewhat why the system was more easily accepted by the people in site 1. As also stated by the participants, people can bypass some limitations of the system if GaitAssist offers the user walking assistance and support for motor training. The success in accomplishing the main function of GaitAssist, such as offering rhythmic cueing upon FoG, overcomes the eventual wearability limitations in the case of participants in site 1. Participants stated that *the system helps them walk better*—this being in line with their main expectation from such an assistive device. On the other hand, participants in site 2, younger on average and with a milder disease severity, tended to have a more critical view and value more the wearability and the operationality of the system besides the assistive function of the system—thus, the slightly decrease in the scores given for GaitAssist.

6. SHORT-TERM IMPACT ON THE GAIT: A DATA-DRIVEN ANALYSIS

Starting from the subjective opinion of the participants in the study that using the system *helps them in improving the gait*, and linked to the in-the-lab evaluation of GaitAssist, where users subjectively stated that it *supports in decreasing the FoG duration* [Mazilu et al. 2014a], we performed a second experiment. During the 1 week

Table VI. Number of Detected FoG episodes by GaitAssist during the Gait-Training Sessions
for Each Protocol Day and Each of the Five Participants

Participant	Day 1 (#)	Day 2 (#)	Day 3 (#)	Total (#)
PD1	28	35	27	90
PD2	31	39	35	105
PD3	11	7	27	45
PD4	39	28	14	81
PD5	22	29	20	71

out-of-the-lab protocol, we collected sensing data from the five participants in site 1. We then performed a data-driven analysis on the FoG distributions over all 3 days of the protocol to observe if there were any trends or variations in FoG duration and FoG number when using the system. We performed the analysis on a total of more than 12 hours of sensor data from the five participants.

Objective assessment and detection of FoG episodes. The protocol was not videotaped due to its complex settings and privacy issues (i.e., experiments were executed in the participants' homes, where other members of their families also reside). To compute the FoG statistics, we considered the output of the FoG-detection module from GaitAssist, which uses acceleration data to detect and measure FoG in real time. The system provides the number of FoG episodes synchronized with the time and the duration for each FoG event. The system was shown to provide robust performance when tested in in-the-lab settings (see Section 3.3). Moreover, FoG detection using wearable sensing data is considered a valid objective assessment of the FoG in the clinical practice [Moore et al. 2008].

Metrics. To analyze whether there is an effect on the participants' gait when using Gait-Assist for motor exercises or as an assistant, we considered the following metrics:

(1) *Total number of detected FoG* in each of the 3 days for each of the two protocol parts.
(2) *FoG duration* statistics for each gait-training or assistive session in three different days.

As also mentioned in the description of the study, we included participants with varying motor abilities reflecting different stages of PD and FoG. Thus, each participant might react differently in terms of FoG when using the system. Therefore, we chose to analyze the results in the case of each subject instead of an overall statistical analysis.

As detailed earlier, the GaitAssist system was used by participants in two different settings mapped on the two functions of the system: (1) as wearable support for motor-training exercises and (2) as an assistive device used during daily life at-home activities. In the following, we presents the results of our data-driven analysis for the two parts of the protocol.

6.1. Training Exercises Support

(1) Trends in detected number of FoG episodes. Table VI contains details about the numbers of FoG episodes during the gait-exercises protocol as detected by GaitAssist. The detection algorithm also makes false detections (i.e., detects a freeze when there is none), and thus the computed numbers in the table incorporate false FoGs and do not represent the real number of FoG events. Still, these numbers are approximations of the real FoG and help us in observing trends in the data, if any. For example, if during a day a participant has fewer FoG episodes than compared to the previous training day, then GaitAssist will also detect fewer FoGs compared to the previous day, even if the number of detected FoGs is not the same as the real number of FoGs.
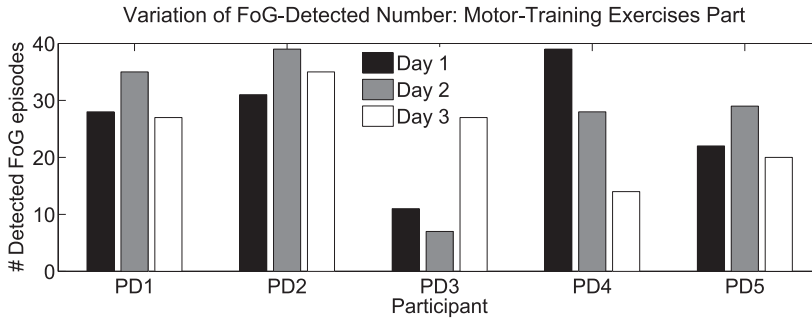
Fig. 9.   FoG number trends for gait-exercise protocol part over all 3 days for each of the five participants.

Figure 9 shows the trends in the detected FoG numbers during the 3 days of exercise sessions. Except for one subject, we did not find a clear trend in reduction of the number of FoG episodes. Only for patient PD4 did we observe a decrease of the number of detected FoGs as the training progressed. A special case is PD3, which due to the disease severity had difficulties in performing the gait-training exercises during the first 2 days. The subject performed the training for shorter periods of time than was required (i.e., the total exercise time was approximately halved from the required daily exercise training). However, on the third day, PD3 could perform the training protocol with almost full exercise times. This might be an explanation for the sudden and high increase in the number of detected FoG episodes on the third day compared to the first 2 days of training. However, these statistics do not show any consistent effect of GaitAssist on the number of experienced FoGs when performing gait-training exercises.

Trends in detected FoG durations. Figure 10 presents the overall FoG duration distributions during the motor-training exercises for each of the three training days as boxplot representations.

For participants PD1 and PD4, we observe a decrease of the upper hinge (75th percentile) and of the upper whiskers (91st percentile) from the first day to the third day of training. In addition, on the first day of training, the FoG-detection algorithm detected exceptionally long FoG episodes (i.e., 8 to 12 seconds for PD1 and 15 to 25 seconds for PD4). Until the last day of training, there are no such long FoGs detected, and the distribution of the FoG duration overall decreases and becomes more compact. This suggests a possible positive effect on the gait induced by GaitAssist (i.e., users react to the RAS given by GaitAssist at the onset of FoG, and by following the rhythmical cues, they resume walking, thus shortening the FoG duration). As well, this decrease of the maximum FoG duration with the training day suggests that the participants might get more and more used to the cueing given by the system, accept it, and learn to respond to it by following the rhythmic pattern to resume gait.

In the case of PD2, a similar decrease in the 75th and 91st percentiles is observed. The median FoG duration is also decreasing with the training day. Overall for PD2, we also observe a reduction in the duration of FoG episodes during the exercises sessions, except two FoG episodes on the last day of training, which are reaching 10s. This suggests that PD2, as PD4 and PD5, might react positively to the GaitAssist real-time cueing and gait-training exercises.

For PD3 and PD5, we observe an inverse trend: the FoG durations increase with training. Thus, they might react negatively to the RAS started upon FoG, which makes it harder to resume walking during FoG. However, these two participants had difficulties in performing all required exercises due to advanced PD motor symptoms.
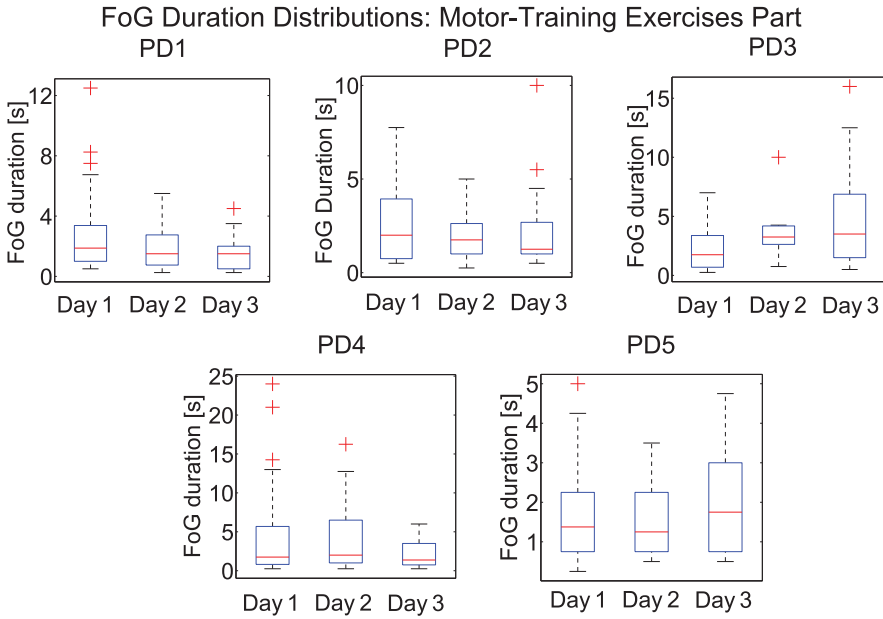
Fig. 10. Boxplots of FoG-duration distributions for each of the three training days for each of the five participants during the exercise sessions of the protocol. The boxplot includes the *median* value of FoG durations; the 25th and 75th percentile as *lower hinge* and *upper hinge*; the *H-spread*, which is the difference between the 75th and 25th percentile; and the 9th and 91st percentile as the *whiskers*. For PD1, PD2, and PD4, we observe an overall decrease in the detected FoG-duration distributions with the training day. For PD3 and PD5, the detected FoG-duration distributions tend to increase with training.

Table VII. Number of Detected FoG Episodes by GaitAssist during the Daily Life Walking Sessions for Each Day and Each of the Five Participants

Participant	Day 1 (#)	Day 2 (#)	Day 3 (#)	Total (#)
PD1	10	11	8	29
PD2	19	6	6	31
PD3	8	11	9	28
PD4	13	8	10	31
PD5	12	8	3	23

In summary, for three out of five participants, data analysis shows a general decrease in the overall FoG duration, as measured by the FoG-detection algorithm. This suggests a short-term training effect on the gait by performing exercises assisted by GaitAssist rhythmical cueing in the users' home environment. For PD5, a slightly negative effect is observed on the FoG duration, whereas for PD3, the FoG episodes tend to be longer with every training day.

6.2. Daily Life Assistive Function

Trends in the number of detected FoG episodes. Table VII contains information about the detected FoG during the daily life walking protocol part. The detected FoGs are lower than in the gait-exercises part of the protocol. This is because the motor-training exercises are specially designed to provoke FoG, being more complex than the usual daily life walking. In addition, the daily life walking part of the protocol was shorter in duration than the gait-exercises part.

Figure 11 shows the trends in the FoG numbers during the 3 days of using GaitAssist as a walking assistant during the daily life activities protocol. For all participants
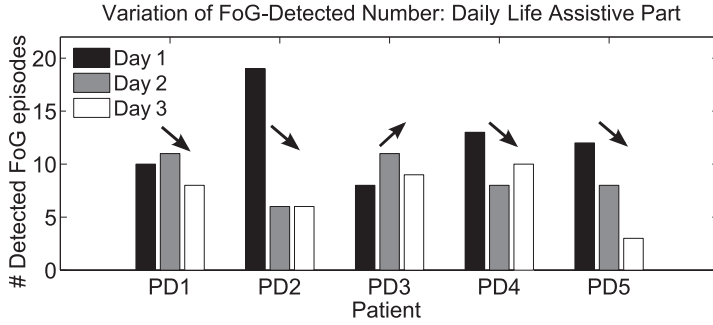
Fig. 11.   FoG number variation over the 3 days of the assistive part of the study.
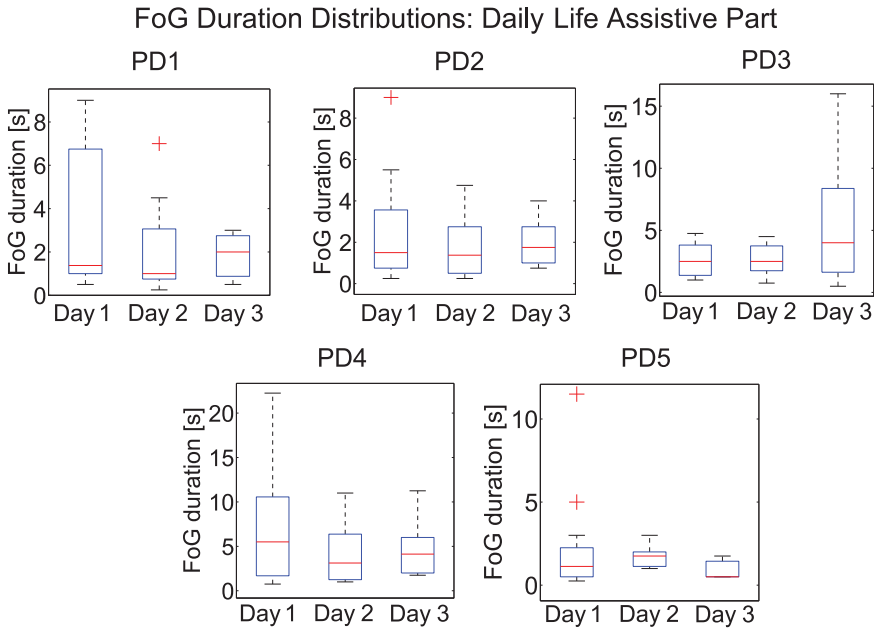

Fig. 12.   Boxplots of FoG-duration distributions for each of the three training days for each of five participants during the daily life walking sessions of the protocol. The boxplot includes the *median* value of FoG durations; the 25th and 75th percentile as *lower hinge* and *upper hinge*; the *H-spread*, which is the difference between the 75th and 25th percentile; and the 9th and 91st percentile as the *whiskers*. For PD1, PD2, PD4, and PD5, we observe an overall decrease in the detected FoG-duration distributions with the training day. For PD3, the detected FoG-duration distribution increases with training.

except PD3, we observe a decreased trend in the number of FoGs. The most significant improvements have been measured for PD2 (with a decrease from 19 detected episodes on Day 1 down to 6 FoGs on Day 3) and for PD5 (from 12 detected episodes on Day 1 down to 3 FoGs on Day 3). Same as before, for PD3, the number of FoGs slightly increases during the training days—from 8 FoGs on Day 1, to 11 FoGs on Day 2, and to 9 FoG events on Day 3.

Trends in detected FoG durations. Figure 12 presents the FoG duration distributions in compact boxplot representations when the users perform daily life walking sessions while wearing GaitAssist. For all participants except for PD3, we observe a reduction of the tail of the distribution (decreasing FoG duration values for the 75th

and 91st percentiles) corresponding to shorter detected FoG episodes as the protocol progresses. In addition, the *h-spread* for PD1, PD2, PD4, and PD5 gets smaller with the training day, suggesting a more compact distribution of the majority of FoG durations (i.e., FoG events tend to have similar durations that decrease overall with the protocol day). This suggest that GaitAssist might help its users as an assistive device during walking. For PD3, similar to the results from the gait-exercises part, the FoG durations increase with the training day. This suggests that the user might react negatively to the feedback of the system, with the RAS making the exit from FoG more difficult.

6.3. Discussion

Overall, the results lean toward a positive effect on the gait of participants when using the wearable training support. Three out of five users (i.e., PD1, PD2, and PD4) responded positively to the gait-training exercises with wearable support cueing, with results suggesting a reduction in FoG *duration* with progressing training. In the case of PD5, the analysis suggests that he reacted negatively to GaitAssist's cueing during the exercise sessions but responded positively and followed it during the daily life walking sessions. An explanation of such a different reaction for gait exercises and daily life walking sessions is that gait exercises are specifically designed to train the gait of people with PD and to provoke FoG. It often requires more attention than the normal walking tasks, and these situations might trigger a different reaction to the GaitAssist cueing.

For four out of five users (i.e., PD1, PD2, PD4, and PD5), the statistical results show a reduction in the FoG durations when participants used GaitAssist during natural daily life walking in assistive mode. This suggests that GaitAssist could be suitable for use by participants as an assistant in their natural environments beyond using it for gait exercise sessions only.

For a single participant only (i.e., PD3), we observed that the duration of FoG events increased during both the exercises part and the natural walking part of the protocol. A possible cause could be the negative reaction of the user to the auditory cue in the moment of FoG. This participant also had troubles in performing all protocol sessions because of the Parkinsonian gait symptoms. This is in line with previous findings regarding RAS in lab settings, where not all patients participating in the studies reacted positively to the rhythmic cueing, but some were bothered by the sound during FoG [Lim et al. 2005]. Moreover, before the trials, clinicians assessed a high score in the FoG questionnaire (see Table IV in Section 4) for PD3 compared to the scores of the other four participants, meaning that PD3 has an advanced PD and FoG stage. This suggests that GaitAssist might have a positive impact on the gait of people with PD with low to moderate FoG questionnaire scores.

To sum up, our analysis on FoG-duration variability suggests that the use of GaitAssist has a positive short-term impact on the participants' gait. This might contribute to improving the quality of the walk in PD, especially when used as an assistant to support natural daily life walking. However, we analyzed only the statistics during the 1-week protocol, which are related to the short-term effect of the system on the users' gait. Moreover, the analysis is made on sensing data from five participants, and thus we cannot generalize if GaitAssist has a positive short-term effect in general in PD. However, the data-driven analysis still suggests promising results toward using the system in the daily life settings of the user. These results gave the base and the motivation for a large clinical study including 40 PD subjects who will use the system in their homes for 6 weeks. Physiotherapists will further assess the long-term effect of GaitAssist on the user's gait using specific clinical protocols and tools (e.g., Ramaker et al. [2002]).

7. CONCLUSION

We present a wearable system for motor training and gait assistance for people with
PD and FoG. We investigate the system acceptance in the natural environment of its
users, as well as the system's impact on the gait quality. We involved nine people
with PD in different stages of the disease. The limitation in the number of subjects
is given by the task difficulty (people with motor impairments are required to use a
novel technology without any qualified assistance) and by the nature of the population
targeted (mostly elderly people diagnosed with PD and FoG). Participants deployed
and used the system in their homes following a system's user manual, without any
clinical help or supervision, during 3 days in 1 week—a period similar to the training
delivered in the lab under clinical supervision. They used the system independently
for gait-training exercises and as an assistive device during natural daily life walking.

The overall feedback suggests a positive opinion of the participants toward adopting
and using the system in their daily life. Participants stated that they wish to continue
using the system in the future, considering it suitable for home use. The study also
revealed some limitations in using the system in its current design. For example,
attaching the sensors at the ankle using straps remains too difficult, even while sitting,
and often users needed the help of a caregiver to attach them.

During the home deployment of the system, we also collected the sensing data and
FoG statistics from the five participants in the first site. The analysis of the FoG-
number and FoG-duration distributions over the 3 days of use suggests that three out
of five participants might react positively to the independent training exercises with
support from GaitAssist. Data-driven analysis shows a decrease in the detected FoG
duration for the three users as the protocol progressed. Moreover, the analysis shows
a decrease in detected FoG number and FoG duration for four out of five participants
when the system is used as an assistive device during daily life activities at home.

Given both positive feedback from participants and suggested positive effect on the
Parkinsonian gait for the majority of the users, we believe that this wearable system
for PD is a suitable tool to support—or even replace—the motor-training sessions in
clinics with unsupervised gait-training exercises delivered at home. By supporting ex-
isting rehabilitation techniques, people with PD are less burdened by clinical visits,
and the healthcare sector resources are relieved. Besides motor-training exercises sup-
port, GaitAssist can be efficiently used by people with PD as an unobtrusive assistive
device during their daily life activities in habitual settings. Moreover, GaitAssist allows
unobtrusive and long-term monitoring of the users' clinical condition by transmitting
sensing data and FoG statistics (i.e., FoG duration and number of FoG episodes) to a
telemedicine service. These data are useful for remote monitoring of the motor-training
progress of the user, as well as for monitoring disease progression during longer periods
of time.

GaitAssist is a finished system that can be deployed to the masses. Following our
short-term findings from the acceptance study and data-driven analysis, clinical re-
searchers are designing a long-term study with 40 PD people to monitor the gait
properties during longer periods (i.e., 6 weeks) and to investigate sustained gait im-
provement when using GaitAssist.

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