Wearable Systems and Methods for Treatment of Freezing of Gait in Parkinson's Disease

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Wearable Systems and Methods for Treatment of Freezing of Gait in Parkinson's Disease

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Zürich, January 2016 Sînziana Mazilu

Contents

Abstract

An estimated number of 16.1 million people worldwide suffer from Parkinson's disease, and up to 81% develop Freezing of Gait (FoG) as a symptom. FoG is a severe gait impairment, characterized by unexpected and transient periods during which subjects loose control over their gait, and cannot move their feet. FoG and falls are two interconnected phenomena, with FoG being the common cause of falls and mortality in Parkinson's disease. Currently there is no cure for Parkinson's disease, drug treatments focusing on temporary ameliorating its motor manifestations. Medication effects on gait freezing are variable in the early stages of the disease, and not helpful in advanced stages. Even if freezing of gait is considered a mysterious phenomenon, clinical evidences suggest that gait training exercises and external rhythmical cueing upon FoG are successful in improving gait and alleviate the freezing episode. However, this requires a reliable system that detects in real-time the FoG onset and triggers the cueing. Moreover, a clinical hypothesis suggests that rhythmic cueing with few seconds prior to a FoG episode might help subject improve their gait and even avoid entering FoG. This requires real-time prediction of FoG.

Motivated by clinical evidences, we aim to build a wearable personal assistant to support users to overcome gait freezing during gait rehabilitation protocols and in their naturalistic daily-life environments. Our research contributions are: (1) Description and automatic detection of FoG from human movement captured with wearable sensors, (2) Characterization of the prior-to-FoG periods and prediction of gait freezing from on-body sensor information, (3) Development of a real-time FoG detection wearable system, and (4) Study of the short-term effect of a gait-training assistive device on the users' walk in real-life scenarios.

To describe, detect and even predict FoG in natural conditions, we collected information from a multitude of wearable sensors, such as acceleration, rotation, electrocardiography (ECG), and galvanic skin response (GSR), from 18 subjects diagnosed with Parkinson's disease. Each subject performed approx. 2 hours of realistic in-the-lab gait protocols and a daily-life walking task.

We characterize and model detection of FoG by means of activity recognition methods and inertial sensors attached on lower body. FoG was successfully detected in real-time with supervised machine learning algorithms implemented in a wearable system with a FoG hit-ratio of 97% (99 out of 102 episodes) from 5 subjects in ON medications

state in a laboratory setting, at a cost of 27 false alarms and a detection latency of ≤ 0.5 seconds. We propose unsupervised extracted features and domain-specific features to capture FoG and gait degeneration prior to FoG from lower limb movements. Moreover, we show evidences of specific upper limb movements correlated with FoG, and detect 89% of FoG episodes with 81% specificity from wrist-attached inertial measurement units.

We introduce and model the prediction of FoG, and analyze the periods of few seconds prior to freeze episodes from the gait deterioration and changes in the physiological information perspectives using inertial and physiological wearable sensors. We found evidences of subject-dependent gait changes with up to 6 seconds prior to FoG incorporated in unsupervised extracted features from lower limb acceleration. Moreover, ECG and GSR attributes have statistical significant changes in the 3 seconds period prior to FoG. These findings contributed to prediction of approx. 70% of FoG episodes with an average of 4.2 seconds prior to FoG, by modeling prediction of gait freezing as an anomaly detection problem.

Prior findings are a base for developing a real-time FoG monitoring wearable assistant. The system is composed up to two inertial sensors attached on the ankles and a smartphone, and starts a rhythmic auditory cueing for a limited period of few seconds upon a detected FoG onset. The system acts both as a walking and gait-training assistant in the natural environments of subjects.

Preliminary results from an one week laboratory study and an one week training protocol in the homes of the subjects show that using the system during gait training and daily-life activities decreases the detected FoG duration with each training day for 3 out of 5 subjects. Moreover, analysis show a steady decrease of both number and duration of FoG detected on 4 out of 5 subjects, during daily-life protocol sessions.

We conclude that wearable sensors are a valuable tool to describe, automatically detect and predict FoG episodes in Parkinson's disease. Additionally, wearable FoG assistants are promising to help in the treatment of FoG with gait training exercises and rhythmic cueing support.

Résumé

Plus de 16 millions de personnes dans le monde souffrent de la maladie de Parkinson (MP), et jusqu'à 81% d'entre eux développent le *Blocage de la Marche* (BM) comme un symptôme. BM est un trouble sévère de la marche, caractérisée par des périodes soudains mais transitoires pendant lesquelles les sujets perdent le contrôle sur leur fonction locomotrice, et ne peuvent plus déplacer leurs pieds. BM et chutes sont interconnectés, le BM étant la cause commune de chutes et de décès des personnes atteintes de MP. Actuellement, il n'y a pas de guérison de la maladie de Parkinson, les traitements médicamenteux en mettant l'accent sur l'amélioration temporaire de ses manifestations motrices. Les effets de médicaments sur le blocage de la marche varient dans les premiers stades de la maladie, puis deviennent nulles dans un stade avancé. Même si le blocage de la marche est considérée comme un phénomène encore mystérieux, preuves cliniques suggèrent que des exercices de la marche et les signaux sonores rythmiques externes pendant le BM sont parvenus à améliorer la marche et atténuer BM. Cela nécessite un système fiable qui détecte en temps réel l'apparition de BM et déclenche la signalisation acoustique. En outre, une hypothèse clinique suggère que les signaux sonores rythmiques, déclenches avec quelques secondes avant un épisode de BM pourrait aider le sujet d'améliorer la marche et même éviter le blocage. Mais cela nécessite la prévision en temps réel de BM.

Motivé par des preuves cliniques, notre objectif dans cette thèse est de construire un assistant personnel portable pour aider les sujets à surmonter le blocage de la marche et faire des exercices de rééducation de la marche, dans l'ambiance de leur maison. Nos contributions scientifiques sont les suivants: (1) Description et détection automatique de BM basé sur les informations sur les mouvements de sujet, mesurées par des capteurs portables, (2) Caractérisation des périodes avant-BM et la prévision du blocage avec capteurs portables sur le corps, (3) Développement d'un système portable pour la détection du BM en temps réel, et (4) Etude de l'effet à court terme d'un dispositif d'assistance et entraînement de la marche, dans la vie quotidienne de sujet.

Pour décrire, détecter et même prédire le BM dans des conditions naturelles, nous avons recueilli des informations à partir d'une multitude de capteurs portables, qui mesurent l'accélération, la rotation, l'Électrocardiogramme (ECG), la Réponse Galvanique de la Peau

(RGP), à partir de 18 sujets diagnostiqués avec MP. Chaque sujet a effectué 2 heures de marche dans des conditions de laboratoire suivi par marche comme dans la vie quotidienne.

Nous caractérisons la détection du BM au moyen des algorithmes de reconnaissance d'activités et des capteurs inertiels attachés sur le bas du corps. BM est détecté en temps réel avec des algorithmes d'apprentissage automatique supervisé mises en œuvre dans un système portable. Le taux de succès est de 97% (99 episodes sur 102) à partir de 5 sujets en phase ON dans un environnement de laboratoire, avec 27 fausses alarmes et une latence de détection de 0.5 secondes. Nous proposons d'utiliser des attributs extraites d'une manière non supervisé et des attributs spécifiques pour capturer le BM et la dégénérescence de la marche avant BM à partir des mouvements des membres inférieurs. En outre, nous montrons qu'il y ait des mouvements spécifiques des membres supérieurs en corrélation avec BM. Nous détectons 90% des épisodes de blocage avec une spécificité de 89% à partir des capteurs inertiels attachés au poignet.

Nous introduisons et modélisons la prédiction de BM, et analysons les périodes de quelques secondes avant le blocage, à partir de la détérioration de la marche et des changements dans les informations physiologiques à l'aide de capteurs portables inertiels et physiologiques. Nous avons trouvé des changements de la marche spécifiques pour chaque sujet, avec jusqu'à 6 secondes avant BM incorporés dans attributs extraites d'une façon non supervisé de l'accélération du membre inférieur. En outre, les attributs EGC et RGP ont d'importants changements dans la période de 3 secondes avant BM. Ces résultats ont contribué à la prévision d'environ 70% des épisodes de BM avec une latence moyenne de 4,2 secondes avant BM. La prédiction de BM est traitée comme un problème de détection d'anomalies.

Les constatations antérieures sont la base pour l'élaboration d'un assistant portable pour suivi en temps réel de BM. Le système est composé de jusqu'à deux capteurs inertiels attachés sur les chevilles et un téléphone intelligent. Le système déclenche les signaux sonores rythmiques pour une période limitée à quelques secondes après la détection de BM. Le système agit à la fois comme une assistant pour la marche et pour l'entraînement dans l'ambiance quotidienne du sujet.

Les résultats préliminaires d'une étude en laboratoire pendant 1 semaine suivi par un protocole de formation d'une semaine dans les maisons des sujets montrent que l'utilisation du système pour entraînement et activités quotidiennes diminue la durée de BM détecté chaque journée de formation pour 3 sujects sur 5. Par ailleurs, l'analyse montre une diminution régulière du nombre et la durée de BM étecté sur 4 sujets 5, au cours de sessions quotidiennes.

En conclusions nous observons que les capteurs portables sont un outil précieux pour décrire, détecter automatiquement et prévoir les épisodes de blocage de la marche dans la maladie de Parkinson. En outre, les assistants portables pour BM sont prometteurs pour aider dans le traitement de BM avec des exercices de marche et assistance avec des signaux sonores rythmiques.

1

Introduction

1.1. Introduction

It is 2015. We could use the words of G. Leibniz and describe this time as "the best of all possible worlds": Continuous industrialization, development, medical findings, hygiene, and food availability contributed to increasing the duration and quality of life [64]. Only in Switzerland the life expectancy at birth reached an average of 82.3 years in 2014 [1]. Technology advances are a main reason for all these: Computers are used to decode the human brain [3], or map the human genome [27, 114]. Smart devices monitor health parameters [79, 112], diagnose diverse diseases' symptoms [110], or literally keep us alive, such as the cardiac pacemaker.

Yet, there is another side of the coin: population ageing, which comes together with chronic health diseases. From these, disorders such as Alzheimer's or Parkinson's are considered as ones of the 21st century diseases, and even the challenge of the next century [2, 32, 46].

Parkinson's disease (PD) is among the most common neurodegenerative and movement disorders nowadays, with a worldwide prevalence between 7.5 and 16.1 million people [70, 119], and expected to double by 2030 [24]. The average age of diagnosis is 62 years, but there are cases in which subjects are diagnosed with PD before the age of 50 [72]. PD originates from the death of dopamine-generating cells in a specific midbrain region, which affects mainly the motor system. Most of the PD symptoms are related to the loss of the movement automaticity, subjects with PD finding difficult to maintain the movement amplitude, rhythm, posture and balance. Common motor signs of Parkinson's include tremor, uncontrollable movements, slowness of movement, rigidity, and loss of balance [45, 49]. Non-motor symptoms, usually present in the advanced stages of the disease, include depression, sleep disorders, and even dementia [17]. All these contribute to an impaired quality of life and shortened life expectancy [17, 45].

A specific motor symptom usually present in the advanced Parkinson's stages is *Freezing of gait* (FoG) [29, 31, 78]. In Nutt et al. [78] clinicians commonly define it as a "brief, episodic absence or marked reduction of forward progression of the feet despite the intention to walk". During FoG onset, subjects suddenly loose control over their gait, and cannot move their lower limbs, despite their wish to walk or initiate gait. This impromptu incapacity to walk is transient, lasting from few seconds up to few minutes with the disease progress [78, 98]. The pathogenesis of FoG is not known at the moment [78], although a recent study correlated the progression of gait freeze with cognitive impairment and hallucinations, and with the density of cortical Lewy body-containing neurons [116]. Estimated statistics show that between 25% and 81% of subjects with PD develop FoG [29, 31, 44, 61, 116].

There is no specific cause for the gait freeze episodes, yet they can be correlated with gait characteristics such as festination, with the context of walking, for example during turns, crowded spaces, passing narrow corridors, avoiding obstacles [20, 28, 78, 103], and even with reactions to stimuli or situations such as stress, dual-tasking, or being under time pressure [29, 78, 93, 118]. FoG is associated with loss of mobility, and non-motor symptoms such as visual abnormalities, anxiety and depression are more frequent in subjects with gait freeze [78, 93, 118].

There is no cure at the moment for Parkinson's, medication based on dopaminergic stimulation being used to alleviate or temporary release the manifestations as the disease progresses, while training exercises help in improving the motor symptoms [4, 26, 45, 49]. In severe cases, brain surgery and deep brain stimulation [51] are used as a last resort to ameliorate the disorder features. Unlike the other PD motor symptoms, FoG is least responsive and is resistant to pharmacological treatment [100], and it is even associated with longer levodopa treatment [13, 78]. This leads to substantial decrease in the functional independence and quality of life of PD subjects [68, 107, 118]. Moreover, this paroxysmal event is one of the most disturbing in PD [29], being the main cause of falls and mortality in Parkinson's disease [13, 35]. Thus, it is important to find alternative to medicine treatments, to helps subjects coping with FoG in daily-life.

Clinical research suggests that besides positive emotions such as excitement [101], (a) attentional cueing at the proper pace and (b) gait training exercises [6, 12, 26] might precipitate FoG [23, 41, 76, 105], and ameliorate gait features [78].

Auditory or visual rhythmic cues facilitate the continuation of a repetitive movement such as gait. For example, when listening to music, one tends to walk, run or exercise in the tempo imposed by the listened song [25]. In case of subjects with PD, providing a rhythmic external cue such an auditory signal can re-initiate cadence as a pacemaker and might help to quicker overcome a freeze episode [43, 58, 95, 108]. However, the effectiveness of continuously providing rhythmic cueing during walking wears off with time [21, 74, 76, 96]. It is the same as when listening for the same song for longer periods of time: one gets used with the imposed rhythmicity, and after a while treats it like background noise, and stops following the imposed rhythm. For this reason, rhythmic cueing needs to start for a limited period of time, e.g., few seconds, upon the onset of FoG event or when the subject has gait difficulties that might lead to freeze. The temporary lead needs to stop when the subject resumes the rhythmical gait pattern. To start cueing in such critical situations, the subjects' context and gait needs to be continuously monitored, recognized, and the onset of FoG detected in real-time. The detection of a FoG episode translates into discriminating between the gait freeze and other walking events or human activities, which is constrained by being able to characterize and describe FoG.

On the other side, training and rehabilitation exercise therapies for FoG and PD usually take place in the clinics or require medical staff to assist the patient performing exercises. There is an increasing burden of the medical sector, where 78% of the budget is devoted to chronic disease management [9]. With limited resources in terms of personnel and infrastructure, the healthcare is challenged to develop novel self-management solutions, which will both be available to a wide number of people with PD [24], and to be used in the natural environments of the subjects, without the supervision of a caregiver or a clinical specialist.

Wearable technologies have begun to take root in our everyday life. On-body mounted sensors are used to identify in real-time the human context or human activities [54, 55], to supervise the sport skills [10, 52], to detect emotions [85], to monitor general health parameters [79], or to diagnose symptoms and states of diverse diseases such as bipolar disorder [36], cerebral palsy [111], or dementia [79]. Healthcare wearable systems were developed to help subjects to cope with various cardiac, respiratory, motor, mental, and neurodegenerative disorders [5, 16, 34, 60, 79]. Wearable assistants even support motor learning and rehabilitation [14, 56, 80].

Motivated by clinical evidences, we aim to use on-body attached sensors to characterize, detect in real-time, and even predict FoG in Parkinson's disease, and to develop a wearable solution to both assist gait training and give rhythmical cues upon FoG in the natural environments of the users. The target of the thesis is to develop solutions towards the treatment of freezing of gait in Parkinson's disease.

1.2. Related Work

We survey the following groups of studies related to FoG research: (1) clinical studies which attempt an overview of gait freezing phenomenon, (2) research related to description of FoG from wearable sensors, (3) attempts to predict FoG from sensor information, and (4) related research on freezing of gait management and rehabilitation.

1.2.1. Freezing of Gait from Clinical Perspectives

There is a plethora of research attempting to characterize and describe FoG and its causes from the clinical point of view. The reference paper of Nutt et al. [78] survey the characteristics and observations about FoG from the clinical, physiological, and neurological perspectives. FoG can be expressed as trembling in place, shuffling forward, or even complete akinesia [78]. It is not an isolated anomaly in the normal gait pattern, patients which exhibit freeze episodes having an increased variability of step timing, disordered bilateral coordination, and a reduction of the stride length [78].

Iansek et al. [48] postulated that FoG is the consequence of a "sequence effect", i.e., the inability to maintain a predefined movement amplitude and movement timing. Sofuwa and colleagues [102] observe an abnormal timing of tibialis anterior and gastrocnemius muscle activation, that suggests a central deficit in the rhythmic control of gait is fundamental to FoG. From another perspective, Vandenbossche et al. [113] demonstrate that a specific executive impairment, e.g. conflict resolution, can be associated with FoG in PD. This suggests that physiological characteristics that define a freezing episode are actually a result or the manifestation of the freezing. Plotnik et al. [87, 89] show that the impairments in left-right coordination are associated with the presence of FoG, and Yogev and colleagues [120] finds that gait asymmetry is increased in people with PD and FoG. Later in [88, 91], Plotnik and colleagues assess that three gait attributes are associated with FoG: gait rhythmicity, gait asymmetry, and bilateral uncoordination of left-right stepping. These impairments may lead predispose or lead to FoG, when they are altered beyond a certain threshold or exacerbated by another trigger. In a recent and more general study, Plotnik et al. [90] suggest that seemingly independent motor features, i.e., gait rhythm control, gait symmetry, bilateral coordination of gait, dynamic postural control and step scaling, may have mutual interactions which, in certain circumstances, jointly drive to predisposed locomotion system into a gait freezing. That means that more than one gait impairment could be associated with the FoG and that these gait features are linked between each other.

There are clinical evidences that freezing is not only on the gait level, but also is present in the upper limb [8, 125]. Vercruysse et al. [115] present proof that upper limb freezing power spectra are broadened, and Nieuwboer et al. [77] show that freezing episodes in the upper limb are correlated with the FoG severity. However, even if there is evidence of freezing at the level of the arm, wrist or fingers in Parkinson's disease, there are no studies to analyze the correlation between *freezing of gait* synchronized with patterns of the upper limb movement.

1.2.2. Systems and Methods to Describe and Detect FoG

FoG is a motor symptom, thus most of the clinical observations attempt to describe the motor variations prior or during gait freeze. As a result, most of research using wearable sensors focus on capturing the FoG attributes from accelerometers and gyroscopes [11, 19, 22, 50, 69, 73, 83, 84, 97, 109, 123], usually attached on lower body. Moore et al. [69] uses the information regarding the human locomotion range in $[0, 3]$ Hz, and that during FoG, there is an increase in the $[3, 8]$ Hz frequency band. In order to distinguish FoG from normal gait, the authors proposed the Freeze Index (FI), which is the ratio between the FoG and the locomotion bands. Bächlin et al. [11] extend their work, by taking into account also the total power on the $[0, 8]$ Hz acceleration band in order to distinguish FoG from sitting or standing. Pepa and colleagues [84] uses the accelerometer information from smartphones to detect FoG, and expand the Bäechlin approach [11] by taking into account the cadence variability using the power spectrum. Djuric and colleagues [22] use the energy of both accelerometer and gyroscope signals to distinguish between small steps, shuffling, akinesia, and festination. Niazmand et al. [73] introduce specific frequency features extracted from accelerometers, Tripoliti et al. [109] extracts the acceleration's entropy, while in [121, 123] the Power Spectral Density (PSD) information is used to distinguish FoG from other gait events.

Cole et al. [19] extends the information from on-body accelerometers with Electromyography (EMG) to describe FoG, while Saad and colleagues [97] add to accelerometers data from telemeters and goniometers, from which they extract a multitude features such as average, standard deviation, PSD, mean frequency, FI, or kurtosis.

In addition to data which capture the motor variations during gait freeze, the FoG episodes is observed in data from sensors capturing the brain activity such as electroencephalography (EEG) [40], and functional Near-Infrared Spectroscopy (fNIRS) [62], and physiological sensors such as Electrocardiography (ECG) [63].

Besides wearable sensors, Kinect is proposed to track the PD subjects in their homes, and to recognize FoG episodes from the information sent by the device [106].

The methods used to distinguish between FoG and other gait events are based on thresholds [11, 22, 50, 69, 73, 123], supervised machine learning methods [109], dynamic neural networks [19], and fuzzy logic inference [83].

Most of the enumerated systems and methods use specific and expert-based features [11, 19, 22, 50, 69, 73, 109], usually extracted from one single type of sensor information [11, 50, 69, 83, 84]. Expert-based extracted features are limited in containing the FoG attributes, given that gait freeze itself is an unknown phenomenon [78], and represents several syndromes with different underlying mechanisms [78].

We aim for a complete description of FoG from inertial measurement units, by using statistical and time-frequency features used in activity recognition, and unsupervised / deep learning extracted features, which are independent of the expert knowledge. Moreover, the research focused using sensors attached on lower body to capture the motor changes during gait freeze. We pursue to analyze diverse on-body positions to attach inertial measurement units, such as the wrist, in order to detect the freeze episode at the gait level.

1.2.3. Towards Freezing of Gait Prediction

Research focused on using wearable sensors, and developed methods to detect FoG, which gives the opportunity to start a rhythmical cue upon gait freeze, and help subjects to resume walking. Such FoG-aware systems are beneficial in shortening the FoG duration [11], although they cannot help to avoid freeze episodes, since the FoG is detected at best with few hundred milliseconds after its onset [50]. A step further is to predict with few seconds before that there is a risk a FoG might happen, and start preemptive cueing which might help a subject to entirely avoid entering FoG. We call this *FoG prediction.*

There are several clinical observations regarding the gait impairments associated with the period prior to FoG and which might contribute to it [59, 113], such as stride length reduction [18], step festination [48], deterioration in rhythmic control [42, 71] and in step-to-step time variability [42], or the reduction of the cadence [18, 48]. However, there are few research works which attempt to characterize and describe the period prior to FoG from a sensing perspective. The existing works focus on the brain activity and physiological sensors: Handojoseno and colleagues [38, 39] show that EEG power features have specific patterns when transitioning to FoG. In a similar direction, Maidan et al. [62] use the functional Near-Infrared Spectroscopy (fNIRS) to study the changes in the brain frontal lobe in the seconds prior and during FoG. The analysis suggests that there is a distinguishable pattern in the frontal lobe activity just prior to FoG. Clinicians found correlation between FoG pathogenesis and the mental state [28]. In extension to this, Maidan and colleagues [63] use the changes in the ECG signal to show that the heart rate increases in the interval of 3 seconds before FoG. Nevertheless, there are no existent methods to predict FoG from wearable sensing data.

Our aim is to analyze whether there are variations prior to FoG of the gait captured with inertial measurement units, to extend the existing research on physiological sensors, and to develop a solution to predict FoG with few seconds before the onset.

1.2.4. Freezing of Gait Management and Gait Rehabilitation

Wearable sensor systems have been successfully applied in rehabilitation scenarios [80], such as stroke rehabilitation, and back and upper limb rehabilitation. Allen et al. [7] identify 53 relevant trials which show evidence that exercise, motor training and rhythmic cueing strategies delivered individually are beneficial to reduce the severity of freezing [76, 81]. Nevertheless, the training programs were closely supervised by the clinicians, even when the training was taking place in the participants' homes.

The systems and solutions for FoG awareness and FoG detection focus on the sensor technology choices and on the feasibility of FoG-detection offline or in real-time [11, 19, 22, 50, 69, 73]. The final users did not participate in the design process of the systems, as the systems were not developed for unsupervised environments use. The existent solutions did not study the effect of the wearable system on the users' gait, and the interaction with it from a user point of view.

Regarding the usage of such technologies in unsupervised environments, Steele and colleagues [104] show there are issues in accepting the systems in out-of-the-lab environments compared with in-the-lab settings. Social, emotional, and environmental factors play a key role in the adoption and the use of healthcare systems in the home settings [5, 80]. As suggested in [99], the perception of a healthcare technology has a strong impact on the outcome of a treatment.

In this thesis, we include the final users' input in the development of a FoG-aware wearable system for gait training. Moreover, we study the acceptance of the system in the homes of the subjects, and the effects on the gait by training assisted by wearable FoG-detection system.

1.3. Thesis Aims

The thesis aims are organized in two parts, closely related to the use of wearable sensors to study gait anomalies in Parkinson's disease:

(a) Motivated by the fact that FoG is a less known phenomenon, and the FoG pathogenesis is not understood at the moment [78], we aim first to find and describe the freezing of gait attributes in Parkinson's disease, as expressed in the movement of different body-limbs, captured with wearable sensors. Besides FoG, we aim to discover, characterize, and define the body changes with few seconds prior to FoG, from different perspectives, i.e., movement, physiological, with the use of on-body attached sensors. The target of understanding FoG and prior-to-FoG periods is the real-time detection and even prediction of the gait freeze onset, which will be used further for our second objective.

(b) Clinical evidences show that training in the clinics with rhythmical cueing upon FoG might have a positive impact on the gait quality [23, 76]. Therefore, in the second part of the thesis we aim to engineer a real-time FoG detection assistive device, and measure the effect such a device has on the subject's gait when used in the patient's natural environment. Designing and building this device to be easy to use and accepted by the user is a challenging endeavor.

More specifically, in the thesis we address the objectives detailed in the next three subsections:

1.3.1. Characterize and Detect Freezing of Gait with Wearable Sensors

Our first aim is to characterize FoG and detect in real-time the onset of gait blockades from wearable inertial sensors. Past works focused on detecting freezing of gait episodes from on-body attached inertial measurement units with specific defined features [11, 68]. In completion to prior work, we investigate features to describe FoG attributes and propose methods to detect FoG. In particular, we investigate the following aspects:

- Whether the *real-time detection of FoG* can be modeled as a supervised machine learning problem.
- Which features extracted from inertial measurement units are capturing best the gait freezing characteristics.
- Which are the optimal lower-body positions that capture FoG periods.
- Whether upper limb movements are correlated with freezing at the lower limb.

1.3.2. Develop Methods and Features to Predict Gait Freezing

Currently, the *golden rule* to label FoG requires a clinical specialist looking at video recordings of lower limb. However, there is no golden standard to define the prior-to-FoG periods, if any. There are few clinical evidences and hypotheses that freeze episodes are not precipitous, but are a result of a cumulus of factors which predispose to motor blockade condition [42, 75, 90]. Our aim is to observe and characterize prior-to-FoG behaviors in subjects with PD, as observed with different sensor modalities, such as inertial measurement units and physiological wearable sensors. For this, we introduce and define the *automatic prediction of FoG* problem. A further aim is to investigate new sensor-based features to describe prior-to-FoG from different aspects, to propose methods which model and solve the prediction of FoG episodes, and finally to discuss how a system for predicting FoG in real-time should be designed.

1.3.3. Design and Build a Wearable System for Out-of-the-Lab Gait Training

Clinical literature suggests that rhythmical cueing upon FoG onset might have a positive impact on the subject's gait, helping in resuming walking [74]. Moreover, gait training exercises improve the motor function in Parkinson's disease [7]. Our aim is to develop a wearable solution for independent motor training and assistance in out-of-the-lab environments for subjects with FoG. Apart from the engineering challenge to design and build the device and the software, we face a Human Computer Interaction (HCI) problem requiring carefully crafting the system for easy use and better acceptance. We investigate the following aspects:

- How to design and deliver a system for at-home FoG-support and training to both enable FoG-aware real-time cueing and enable the independent use by PD subjects.
- The HCI perspective, user acceptance and subjective experiences of using such a wearable system.
- The effect of using the system on the subject's gait performances, both as a subjective perception and measured effect.

1.4. Thesis Outline

The thesis is structured into eight chapters. Chapter 2 summarizes the main achievements, draws the conclusions, discuss the limitations of the current findings and provides an outlook. Chapters 3 to 8 comprise six scientific peer-reviewed publications, as detailed in Table 1.1. Figure 1.1 illustrates the thesis aims with their corresponding thesis chapters, completed with the link between different contributions.

Chapter 3 targets the detection of freezing of gait with features extracted from lower-limb mounted wearable accelerometers. To this end we model FoG detection as a supervised machine learning problem. We discuss the best statistical- and frequency-based features to describe FoG from lower limb, which is the best lower-body position to sense FoG, and what are the FoG-detection performance of ML models.

Chapter 4 completes the previous chapter by analyzing the upper-limb movements during FoG, their correlation with the freeze in the lower limb, and the feasibility of detecting FoG from wrist-attached inertial measurement units.

Next, Chapter 5 introduces and models the *FoG-prediction* problem, focusing on the extraction of informative features which describe both FoG and the periods prior-to-FoG from ankle-mounted accelerometers. Moreover, it introduces unsupervised feature learning as a method to extract the useful information to characterize FoG and the prior-to-FoG periods of movement. The work in this chapter links and extends the findings from Chapter 3.

In Chapter 6, we study the physiological reaction measured from wearable electrocardiogram and galvanic skin response sensors prior, during and after FoG episodes. We propose specific physiological features to describe the prior-to-FoG episodes, introduces and models the *FoG-prediction* as an anomaly-detection problem, and discusses the possibility of predicting FoG episodes from changes in the physiological information.

Chapter 7 and Chapter 8 detail the experiences in designing and developing a wearable system to support FoG training and assist subjects with gait freezing, in unsupervised out-of-the-lab environments. In Chapter 7 we evaluate the performances and acceptance of the wearable FoG-assistant in a laboratory trial, while in Chapter 8 we present a trial with subjects wearing the system and performing gait-training exercises unsupervised in their homes. The main purpose is to study a preliminary effect of using the system on the subjects' gait.

Chapter	Publication
3	**Online Detection of Freezing of Gait with Smartphones and Machine Learning Techniques**. S. Mazilu, M. Hardegger, Z. Zhu, D. Roggen, G. Tröster, M. Plotnik, and J.M. Hausdorff. 6th International Conference on Pervasive Computing Technologies for Healthcare (PervasiveHealth), pages 123-130, IEEE, 2012.
4	**The Role of Wrist-Mounted Inertial Sensors in Detecting Gait Freeze Episodes in Parkinson's Disease**. S. Mazilu, U. Blanke, A. Calatroni, E. Gazit, J.M. Hausdorff, and G. Tröster. Pervasive and Mobile Computing (PMC), Elsevier, in press, 2016.
5	**Feature Learning for Detection and Prediction of Freezing of Gait in Parkinson's Disease**. S. Mazilu, A. Calatroni, E. Gazit, D. Roggen, J.M. Hausdorff, and G. Tröster. Machine Learning and Data Mining in Pattern Recognition, pages 144-158, Springer, 2013.
6	**Prediction of Freezing of Gait in Parkinson's from Physiological Wearables: An Exploratory Study**. S. Mazilu, A. Calatroni, E. Gazit, A. Mirelman, J.M. Hausdorff, and G. Tröster. IEEE Journal of Biomedical and Health Informatics (J-BHI), 19(6), pages 1843-1854, IEEE, 2015.
7	**GaitAssist: A Daily-Life Support and Training System for Parkinson's Disease Patients with Freezing of Gait**. S. Mazilu, U. Blanke, M. Hardegger, G. Tröster, E. Gazit, and J.M. Hausdorff. Proceedings of the SIGCHI Conference on Human Factors in Computing Systems (CHI), pages 2531-2540, ACM, 2014.
8	**A Wearable Assistant for Gait Training for Parkinson's Patients with Freezing of Gait in Out-of-the-Lab Environments**. S. Mazilu, U. Blanke, M. Dorfman, E. Gazit, A. Mirelman, J.M. Hausdorff, and G. Tröster. ACM Transactions on Interactive Intelligent Systems (TiiS), 5(1), pages 5:1-5:31, ACM, 2015.

Table 1.1: *Publications and the corresponding chapters in the thesis.*

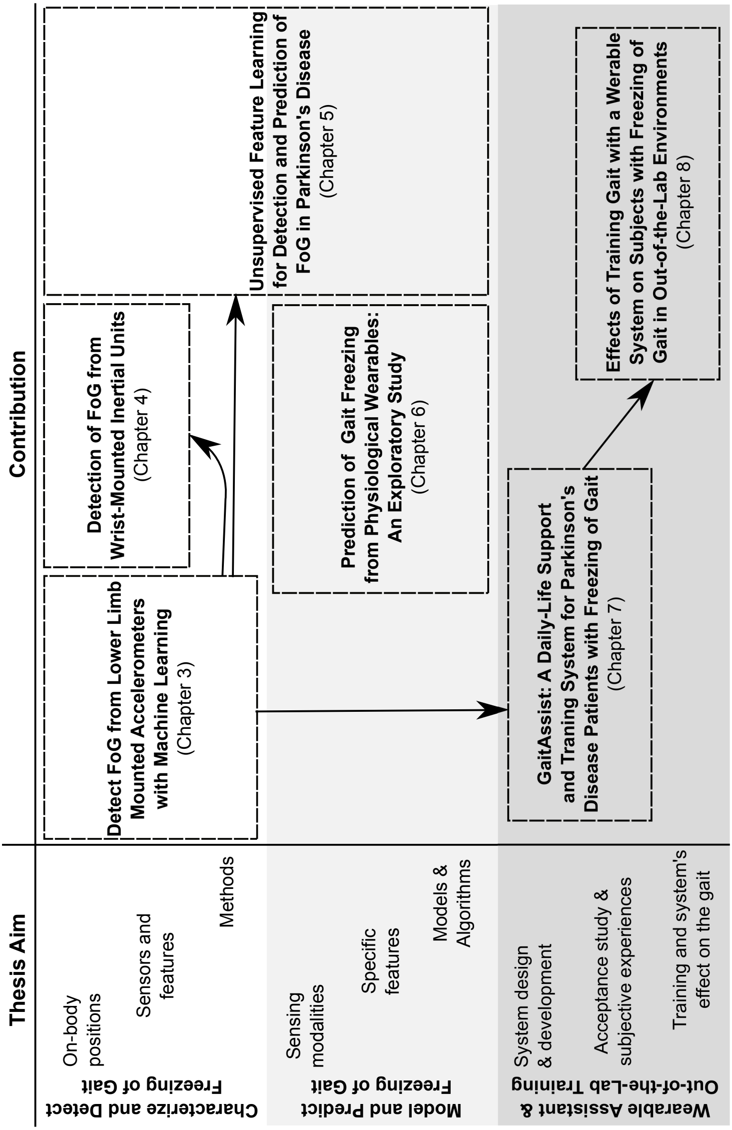


Figure 1.1: *Outline of the thesis chapters, thesis aims, and the relation between contributions.*

1.5. Additional Publications

The following papers have been authored or co-authored in addition to the publications presented in this thesis:

- L. M. Ferster, S. Mazilu and G. Tröster. Gait Parameters Change Prior to Freezing in Parkinson's Disease: A Data-Driven Study with Wearable Inertial Units. In *Proceedings of the 10th International Conference on Body Area Networks (Bodynets)*, ACM, 2015.

- S. Mazilu and G. Tröster. A Study on Using Ambient Sensors from Smartphones for Indoor Location Detection. In *Proceedings of the 12th Workshop on Positioning, Navigation and Communication (WPNC)*, IEEE, 2015.

- S. Mazilu, U. Blanke, and G. Tröster. Gait, Wrist and Sensors: Detecting Freezing of Gait in Parkinson's Disease from Wrist Movement. In *Proceedings of the IEEE International Conference on Pervasive Computing and Communication Workshops (PerCom Workshops)*, pages 579-584, IEEE, 2015.

- L. Palmerini, L. Rocchi, S. Mazilu, E. Gazit, J.M. Hausdorff, L. Chiari. Quantitative analysis of motor patterns preceding freezing of gait in Parkinson's Disease. In *Gait & Posture*, 42, pages 8-9, Elsevier, 2015.

- M. Hardegger, S. Mazilu, and G. Tröster. Continuous Indoor and Outdoor Tracking with a Stand-Alone Wearable System. In *Proceedings of the 12th Workshop on Positioning, Navigation and Communication (WPNC)*, IEEE, 2015.

- S. Mazilu, U. Blanke, M. Hardegger, and G. Tröster. GaitAssist: A Wearable Assistant for Gait Training and Rehabilitation in Parkinson's Disease. In *Proceedings of the IEEE International Conference on Pervasive Computing and Communication Workshops (PerCom Workshops)*, pages 135-137, IEEE, 2014.

- S. Mazilu and G. Tröster. Wearable Technologies: One Step Closer to Gait Rehabilitation in Parkinson's Patients. In *XRDS: Crossroads, The ACM Magazine for Students*, 21(2), pages 48-53, ACM, 2014.

- S. Mazilu, E. Gazit, U. Blanke, D. Roggen, J. M. Hausdorff, and G. Tröster. Engineers Meet Clinicians: Augmenting Parkinson's Disease Patients to Gather Information for Gait Rehabilitation. In *Proceedings of the 4th Augmented Human International Conference (AH)*, pages 124-127, ACM, 2013.

- S. Mazilu, U. Blanke, A. Calatroni, and G. Tröster. Low-Power Ambient Sensing in Smartphones for Continuous Semantic Localization. In *Proceedings of the 4th International Joint Conference on Ambient Intelligence (AmI)*, pages 166-181, Springer, 2013.

- M. Hardegger, S. Mazilu, D. Caraci, F. Hess, D. Roggen, and G. Tröster. ActionSLAM on a Smartphone: At-Home Tracking with a Fully Wearable System. In *Proceedings of the 4th International Conference on Indoor Positioning and Indoor Navigation (IPIN)*, pages 1-8, IEEE, 2013.

- M. Hardegger, D. Roggen, S. Mazilu, and G. Tröster. ActionSLAM: Using Location-Related Actions as Landmarks in Pedestrian SLAM. In *Proceedings of the 3rd International Conference on Indoor Positioning and Indoor Navigation (IPIN)*, pages 1-10, IEEE, 2012.

2

Thesis Summary

In the following, we summarize the main contributions of the dissertation, which are organized according to the thesis aims listed in Section 1.3 and shown in Figure 1.1.

To introduce them, we first present in Section 2.1 the CuPiD multimodal dataset, which acts as a base for the thesis contributions.

Section 2.2 to Section 2.4 describe our main findings: (1) features and methods to describe and detect freezing of gait in Parkinson's disease (Section 2.2), (2) sensor modalities and methods to predict FoG (Section 2.3), and (3) findings regarding gait training in natural environments with a wearable FoG assistant (Section 2.4). Detailed information are presented in the publications contained in Chapter 3 to Chapter 8 and outlined in Table 1.1.

2.1. The CuPiD Multimodal Dataset

Currently, research focuses on understanding FoG from unimodal sensor information obtained from EEG [40], ECG [63], or on-body accelerometers [69] such as in the DAPHnet dataset [11]. Few works take into account other modalities in addition to acceleration, such as rotation data [22, 109], or electromyography [19]. Moreover, FoG is characterized in controlled laboratory setups with subjects instructed to not take the daily medication for PD, i.e., in OFF medication state, such as in DAPHnet dataset [11] and other studies [63, 109].

One of the purposes of this thesis is to build an assistive device that helps users overcome FoG episodes and supports gait-training exercises. Hence, FoG must be accurately detected in realistic settings from patients under their daily Parkinson's disease medication treatment.

To describe gait freezing from different body *reactions* in naturalistic scenarios, with the goal to detect and predict FoG, we collected the CuPiD dataset [65], under the umbrella of the CuPiD EU FP7 Project[1]. We contribute to research with a multimodal wearable system to collect several aspects related to periods before and during FoG [78], i.e., motor observations, physiological features, and cognitive-related aspects. The system was worn by subjects in ON state of medication, asked to perform similar tasks as in a daily-life setting and a real-life walking session.

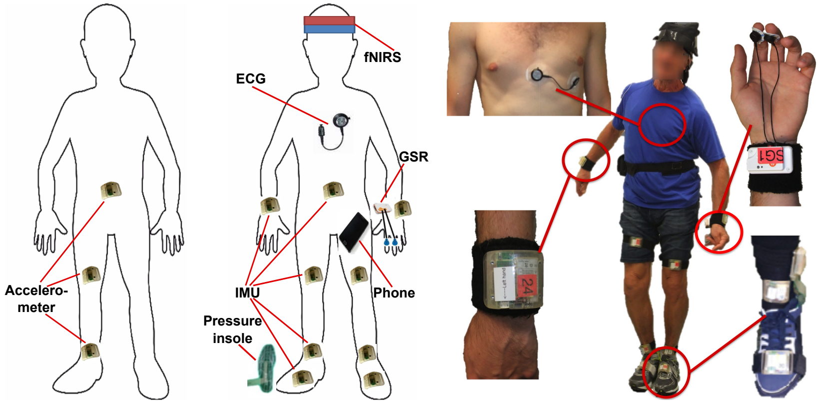
Trial setup. The data collection procedure took place during 3 weeks

[1]CuPiD - Closed-loop system for Personalized and at-home rehabilitation of People with Parkinson's Disease (http://www.cupid-project.eu/)

in September-October 2012 at the Tel-Aviv Sourasky Medical Center in Israel. The Parkinson's disease subjects recruited for this study were cognitively intact, and suffered from self-reported freezing of gait. Prior to trial, participants underwent a complete clinical physical and neurological examination that included the assessment of Parkinson's disease severity.

During the data collection, subjects were asked to perform walking sessions which contain similar tasks as walking in a naturalistic setting, and are also shown to increase the FoG likelihood. Sessions included Ziegler tasks [124], various types of turns, passing narrow corridors, performed with or without an additional cognitive task. In addition to in-the-lab sessions which resemble at-home walking, and different from prior work [11], subjects were asked to perform a real-life walking session, which consisted of approx. 10 minutes of random walking through the hospital's crowded halls with involuntary stops, turns, changes of direction, using the elevator, and passing narrow spaces. During the clinical protocol, all participants were in the ON medication state, i.e., medication was effective or wearing off, in order to obtain similar conditions as in daily-life. The walking sessions were completed by rest sessions and non-walking sessions which included sitting and standing with cognitive load, clinical evaluations, and completing questionnaires. The description is given in Section 6.3 from Chapter 6, page 184.

Sensors. The DAPHnet dataset [11], collected previously by the Wearable Computing Lab ETH, contains data captured from three accelerometers mounted on ankle and thigh of one limb, and lower back, as shown in Figure2.1(a). We extended the DAPHnet system, and collected motor information from 9 Inertial Measurement Units (IMU) attached on 5 positions, i.e., foot, ankle, thigh, wrist, and lower back, on both body limbs. IMU sample 3D acceleration, 3D rotation, and 3D compass information. In addition to the IMU sensors, we acquired foot pressure to study the FoG-related motor aspects, electrocardiogram (ECG) and Galvanic Skin Response (GSR) to capture the FoG physiological features, and functional Near Infrared Spectroscopy (fNIRS) for the FoG-cognitive related aspects. The sensors and their attachment in CuPiD is shown in Figure 2.1(b). All sensor datastreams were synchronized with each other. In parallel with the wearable system, we deployed two video systems, i.e., a mobile HDR camera and a fish-eye camera to record the subject's activities during the in-the-lab protocol, for fine grained annotation of FoG.



(a) (b) (c)

Figure 2.1: *(a) The sensor modalities and their positions in DAPHnet dataset [11], (b) the sensors and their on-body attachment positions in CuPiD system, and (b) a subject wearing the CuPiD system.*

Statistics. 18 subjects participated in the data collection protocol. Their age varied between 49 and 89 years (average: 68.9 years, standard deviation: 10.2 years), and the span of the PD duration was between 2 and 18 (average: 8.8 years, standard deviation: 10.2 years). Participants were representative for II-IV stages of Parkinson's disease severity according to Hoehn & Yahr [45]. From each participant we collected 1-1.5 hours of data, including rest and non-walking sessions.

The dataset contains 184 FoG episodes from 11 out of 18 subjects, with a duration between 0.12 and 98.88 seconds (average: 8.84 seconds, standard deviation: 14.87 seconds). 7 subjects did not encounter any gait freezing during the protocol. The accuracy of FoG labels is at the level of a videoframe, i.e., 40 milliseconds.

Most of FoG events are short, with approx. 65% having a duration ≤ 5 seconds, and are underrepresented with respect to the total amount of data collected, the overall FoG duration summing to approx. 27 minutes. The walking and FoG data are imbalanced, but exhibit the representation of FoG events in an out-of-the-lab daily-life setting, with subjects under PD medication. The majority of FoG occurred during or just after turning (101 out of 184), 38 were related to gait initiation,

Subject	Age (years)	PD duration (years)	FOG-Q score [30]	H & Y score [45]	UPDRS score [94]
S01	89	13	19	4	43
S02	55	14	22	3	38
S03	63	4	30	4	55
S04	68	7	16	3	24
S05	63	5	16	3	54
S06	60	10	27	3	36
S07	73	10	18	3	53
S08	78	8	15	2	31
S09	78	7	17	4	44
S10	77	10	17	4	56
S11	64	5	25	2	38
S12	77	17	32	4	55
S13	62	2	11	2	29
S14	65	18	23	4	41
S15	63	5	4	2	25
S16	81	12	27	3	43
S17	49	3	18	2	44
S18	76	10	16	3	42

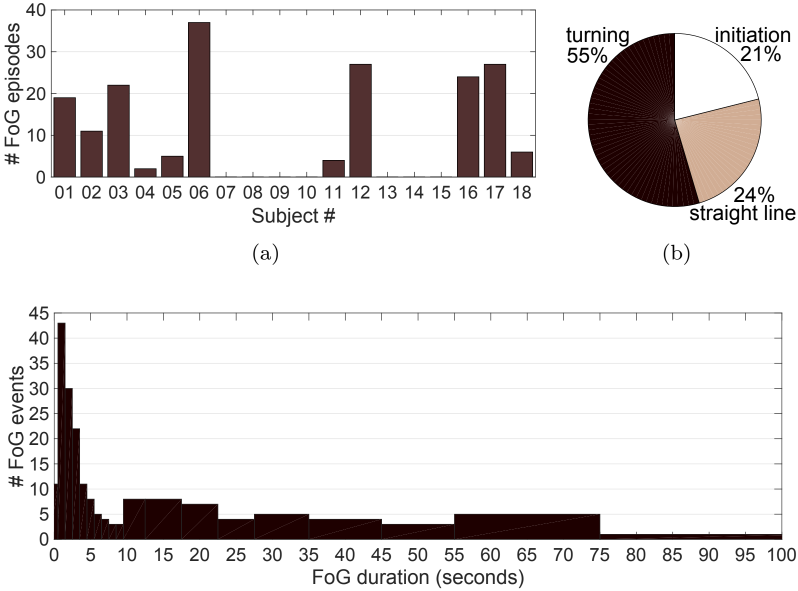
Table 2.1: *The age, disease duration, and clinical scores for each participant in the CuPiD trial.*

and the rest of 45 events happened during walking in straight line. Details about the FoG-related statistics are given in Figure 2.2.

In addition to FoG labels synchronized with the sensing data streams, the dataset contains labels for other walking events such as turns, gait initiation, stop walking, and labels of the protocol sessions.

Novelty and Difference from Other Public Datasets. CuPiD Multimodal Dataset extends the knowledge from prior data collections with the following points:

- *Multimodality.* Different from other data collection setups and FoG-available datasets [11], in CuPiD the FoG is captured from 7 synchronized sensing modalities, with the IMUs attached on both body limbs.
- *Naturalistic conditions.* Prior research focuses on capturing FoG



(a) (b)

(c)

Figure 2.2: *FoG-related statistics: (a) FoG events distribution across subjects, (b) distribution of FoG subtypes, and (c) FoG-duration distribution (Figure 6.2 from Chapter 6, page 188).*

in-the-lab conditions with FoG-provoking tasks [11, 22, 50, 69, 109], and from subjects in OFF medication state [11, 50, 69, 109]. Differently, CuPiD is unique, as it focuses on capturing the FoG characteristics close to real-life scenarios: subjects were in ON medication state, as in their daily-life settings, and the walking protocol tasks are designed to reproduce the walk as in a naturalistic setting. Moreover, the protocol contains a real-life walking task of 10-15 minutes per subject.

- *Labels.* In addition to the FoG labels, CuPiD contains FoG-subtype labels, labels of other walk events such as gait initiation, turns, stops, activity-related labels such as opening the door or sitting/standing, and labels of the different walking protocol sessions. All these 5 types of labels are synchronized with the sensors' data streams.

We use the CuPiD dataset to characterize and detect FoG from inertial measurement units attached on different body positions (Chapter 4), to describe changes in physiological signals during FoG an prior-to-FoG periods, with the goal of predicting FoG (Chapter 6), and use the ankle acceleration to build a model for real-time FoG detection, which is integrated in a wearable FoG training system (Chapter 7 and Chapter 8).

2.2. Characterize and Detect Freezing of Gait with Wearable Sensors

The freezing of gait pathogenesis is unknown [78], with most of clinical and engineering studies focusing on describing FoG from the changes in the lower limb movements [69, 78]. The first aim of the thesis is to characterize FoG from different types of information, i.e., sensors, body positions, and to propose methods to evaluate the quality of such information in relation to FoG detection.

We categorize and present the contributions in three components:

1. Model the real-time *FoG detection* as a supervised machine learning problem.

2. Describe gait freezing properties from on-body attached inertial measurement units.

3. Find the optimal on-body positions to capture FoG.

2.2.1. Model FoG Detection as a Machine Learning Problem

Automatic freezing of gait detection is defined as an accurate differentiation of the FoG event from the rest of walking. Daily-life walking includes various events such as turns, gait initiation, voluntary stops, or simple human activities such as sitting or standing. There are two ways of modeling detection of FoG as a machine learning problem: (1) Model FoG as an anomaly, and use one-class classification or anomaly detection methods to detect it, or (2) model FoG-detection as an activity recognition problem.

FoG can be modeled as a walking anomaly, underrepresented in terms of number of events and duration compared with the rest of general walking activity. FoG is not the only gait abnormality in PD.

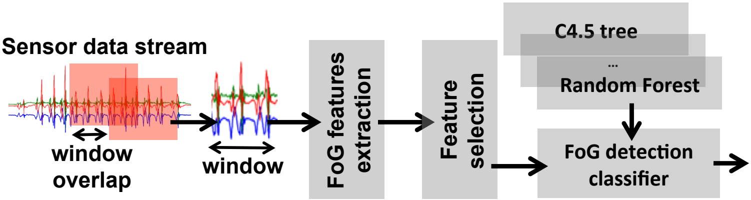


Figure 2.3: *The activity recognition framework used to detect FoG (Figure 8.3 from Chapter 8, page 260).*

Parkinson's disease gait has a multitude of anomalous gait characteristics, e.g., festination and bradykinesia, added to daily-life abnormal walking events, such as missteps or falls. Anomaly-detection methods focus on defining the walking class characteristics, in order to detect its abnormalities. All these make difficult to detect FoG as an anomaly. However, we use anomaly detection models to predict FoG events from physiological sensors, as detailed further in Section 2.3.

FoG Detection as Activity Recognition. We thus model the *FoG detection* as an activity recognition problem [15], solved with supervised machine learning (ML) techniques. The use of supervised ML methods with sensor data is successful in discriminating between diverse types of human activities [15], such as sitting, standing, walking, running, or to detect sudden events such as falls [122]. The groundtruth labels provided by clinicians regarding FoG consist of two categories, i.e., FoG and no-FoG. Thus, we consider sensor information categorized in two classes of activities: *FoG* and *Walk*. *FoG* class represents the sensor data during the FoG episodes as labeled by clinicians. *Walk* is composed mainly from data collected during walking, to which other human activities and gait events are added, such as standing, turns, stops, gait initiation. ML algorithms gives the possibility to automatically learn the *boundaries* between the two classes, thus characterizing FoG from the sensing data given as input.

Framework. To detect FoG we use the activity recognition framework detailed in Figure 2.3: Time-series data streams from sensors are separated into overlapping windows of information. From each window we extract a set of characterizing features to describe FoG. The next optional step is to apply feature selection methods. The resulted vectors of features together with the groundtruth classes are then used to automatically learn a FoG-discriminative model.

Algorithms and Detection Results. To evaluate the feasibility of using supervised ML methods to detect FoG, we apply different evaluation schemes on acceleration data from two FoG datasets, DAPHnet [11] and CuPiD dataset.

Classifier	Sens.	Spec.	F-score	AUC
Näive Bayes (NB)	0.48	0.98	0.73	0.93
C4.5	0.93	0.99	0.95	0.97
kNN3	0.91	0.99	0.96	0.98
Multilayer Perceptron (MLP)	0.77	0.97	0.82	0.95
Random Forest (RF)	0.97	0.99	0.99	0.99
Bayes Network	0.48	0.99	0.77	0.96
AdaBoost with C4.5	0.98	0.99	0.98	0.98
Bagging with C4.5	0.97	0.99	0.97	0.99

Table 2.2: *Average sensivity, specificy, F-score, and AUC values for detecting FoG with various ML algorithms, across the 8 subjects in DAPHnet dataset, in a subject-dependent validation setting with random selection 10-fold cross validation for each subject. The window size in the activity recognition chain is set to 1 second (extension to Table 3.2 from Chapter 3, page 102).*

In Chapter 3 we first evaluate different supervised algorithms, with simple classifiers such Naïve Bayes (NB), Decision Trees (C4.5), k-Nearest Neighbors (kNN), ensembles such as Random Forest (RF), Bayes Networks, Multilayer Perceptron, and meta-methods such as Bootstrap Aggregating (Bagging), and Adaptive Boosting (AdaBoost). We use acceleration data from DAPHnet dataset [11], which contains data from 8 subjects who experienced FoG in a laboratory setting, with sensors attached on the ankle, thigh, and lower back. Table 2.2 contains the performances in terms of sensitivity, specificity, F-score and AUC metrics of detecting FoG with the mentioned ML methods applied on DAPHnet dataset, in a subject-dependent evaluation setting with random-selection 10-fold cross validation. Detection performances vary from a sensitivity of 0.48 in case of probabilistic classifiers, i.e., NB and Bayes Networks, up to 0.97-0.98 in case of ensembles such as RF and AdaBoost. From the simple classifiers, C4.5 trees obtain the best performances, with 0.93 sensitivity for FoG-detection. The specificity is around 0.98-0.99 for all algorithms.

In Table 2.3 we summarize the FoG-detection performance results, when using different evaluation schemes and datasets across the thesis chapters. For all the evaluations, we fixed the supervised ML algorithm to C4.5 decision trees.

Dataset	Sens. (or FoG hit-rate)	Spec.	Evaluation procedure	Chapter
DAPHnet	0.93	0.99	subject dependent; *random selection* 10-fold cross validation	3
DAPHnet	0.77	0.87	subject dependent; 10-fold cross validation	5
DAPHnet	0.66	0.95	subject independent cross validation	3
CuPiD	0.60[2]	0.94	subject independent cross validation	8

Table 2.3: *A summary of FoG-detection performance results, in terms of sensitivity (or FoG event hit rate) and specificity values, using the activity recognition framework with C4.5 classifiers, for different evaluation procedures and datasets.*

By applying C4.5 trees with a random selection 10-fold cross validation on the 8 subjects from DAPHnet, all the FoG events were detected (237 out of 237 events), with 9 false events, using a 31-sample median filter on the classifier output. The performances decrease when not randomizing the cross-validation process, down to 0.77 sensitivity and 0.87 specificity in a subject-dependent scheme on DAPHnet.

On a subject-independent evaluation setting, the FoG-detection average performances reach 0.66 sensitivity, and 0.95 specificity on DAPHnet data. In case of CuPiD, on the patient-independent cross-

[2] FoG hit rate value

validation setting we could detect 60% of FoG events, with 20 false events detected, and a specificity of 0.94 [66].

From the enumerated performance results, one could conclude it is feasible to model detection of FoG as an activity recognition problem with supervised ML methods. However, the performances vary, depending on the used algorithms, on the validation schemes, or on the dataset: User-dependent evaluation settings obtain increased FoG-detection performances, as shown in Table 2.3. Thus, for a robust detection of FoG in out-of-the-lab settings, one needs to define the common FoG features, independent of subject.

In case of subject-independent evaluation, the performances obtained on the CuPiD data are slightly lower in terms of detection sensitivity compared with the ones obtained on DAPHnet. This might be due to the different settings of the data collection. In case of CuPiD, subjects were in ON medication phase during the protocol, while in DAPHnet they were in the OFF medication. Thus, the FoG events in CuPiD are less *intense* than in DAPHnet, while their number is lower: only 184 FoG episodes during approx. 24 hours of data in CuPiD, compared with 237 FoG events across 8 hours of data in DAPHnet. Moreover, the CuPiD protocol tasks were designed to be closer to a naturalistic setting, thus increasing the difficulty of detecting FoG among a diversity of daily-life gait events.

FoG Detection Latency. For a real-time FoG detection setting, besides the detection performances, the *latency* of detecting the gait freeze is important. One needs to start the cueing during the beginning of FoG, in order to help the subject resume walking as soon as possible. The FoG detection latency is defined as the difference between the first time when an algorithm detects the FoG event and its onset.

There are two causes of detection latency in the activity recognition framework we use: (1) the temporal complexity of the classifier's evaluation, and (2) the latency due to the sliding window approach. The detection latency is dependent on the ML model used: For example, a kNN classifier is a *lazy evaluator* [67], while a decision tree has a lower complexity in predicting a class for a new instance [67]. However, the main cause of the FoG detection latency comes from and is dependent on the size of the sliding window used to extract the instance features in the activity recognition framework.

We evaluated the FoG-detection performances and latency with respect to the window size on DAPHnet, as shown in Figure 2.4. There

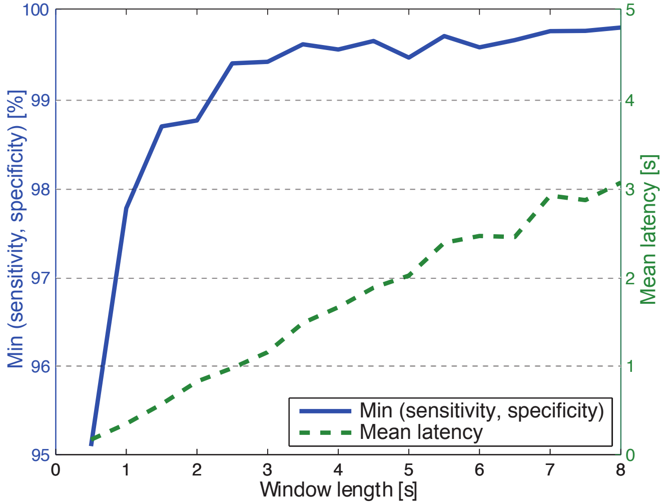


Figure 2.4: *The FoG-detection performances and detection latency, depending on the data window length. The results are obtained with Random Forest classifiers (Figure 3.5 from Chapter 3, page 108).*

is a trade-off for choosing the optimum window size in terms of performances and latency: On DAPHnet dataset, the optimal FoG-detection performances are obtained using a window between 2 and 3 seconds, as shown in Figure 2.4. A further increase of the window size does not significantly improve the FoG recognition, while it increases the latency of detection. Similarly, experiments on CuPiD dataset (Chapters 7 and 8) show that a window size of 2 seconds is optimal in terms of trade-off between FoG recognition and detection latency.

Conclusion and Integration in a Wearable System. Supervised machine learning models are robust to automatically detect and discriminate gait freeze episodes from walking events. Along with an accurate FoG detection, the use of ML to model the FoG detection problem is an objective setting to evaluate of how informative are the features extracted from sensor data in describing FoG. Thus, in the following contributions we employ ML models to evaluate the how useful are the various sensing information or features in defining FoG.

We use the findings in this section in Chapters 7 and 8, where we implement a FoG-detection model based on activity recognition model with ML methods, in a gait-training wearable device. We train C4.5 models on features extracted from sliding data windows of 2 seconds, from the 11 subject datasets with FoG in CuPiD. We use only the CuPiD data for building the FoG-detection models, due to its naturalistic protocol setting. The final functionality evaluation of the system's FoG detection in a laboratory setting with 5 subjects as detailed further in Section 2.4. The wearable system could detect in real-time 0.97 FoG events (99 out of 102) with a detection latency of ≤ 0.5 seconds after the start of a FoG, and a total of 27 false alarms during the laboratory protocol.

2.2.2. Features to Describe FoG from Inertial Sensors

For an accurate detection of FoG, one needs to characterize it and to discover the differences in the sensor data from other walking events. In this section we propose, develop, and quantify features to describe gait freeze as captured from wearable inertial measurement units.

Features. We compute the following types of features, extracted in a sliding-window manner as detailed previously in Figure 2.3: (a) domain-specific features, (b) time-series and statistical features, and (c) unsupervised extracted features. The first two sets rely on supervised extraction of the features, being either domain specific-features such as *Freeze Index* [69], or general activity-recognition features.

(a) Domain-Specific Features. Moore et al. [69] introduced the Freeze Index (FI) to recognize FoG from the rest of the gait events. FI is defined as the ratio between the power on the $[3, 8]$ Hz interval, called the *freeze band*, and the power on $[0, 3]$ Hz, which incorporates the human movement range, and is called the *locomotion band*. Baechlin and colleagues [11] add to the FI a new domain-specific feature – the total power on $[0, 8]$ Hz – to distinguish between FoG and shorts events during walking, such as standing or stops. However, both features are compositions of information extracted from the freeze and locomotion bands. To get a even more detailed idea about the gait changes during FoG, we propose the directly use of the power values on the locomotion band and on freeze band. In Table 2.4 we describe the 4 FoG domain-specific extracted features, and in Figure 2.5 we give an example of how they vary during a FoG episode compared with walking, which includes events such as gait initiation, turns, and stops.

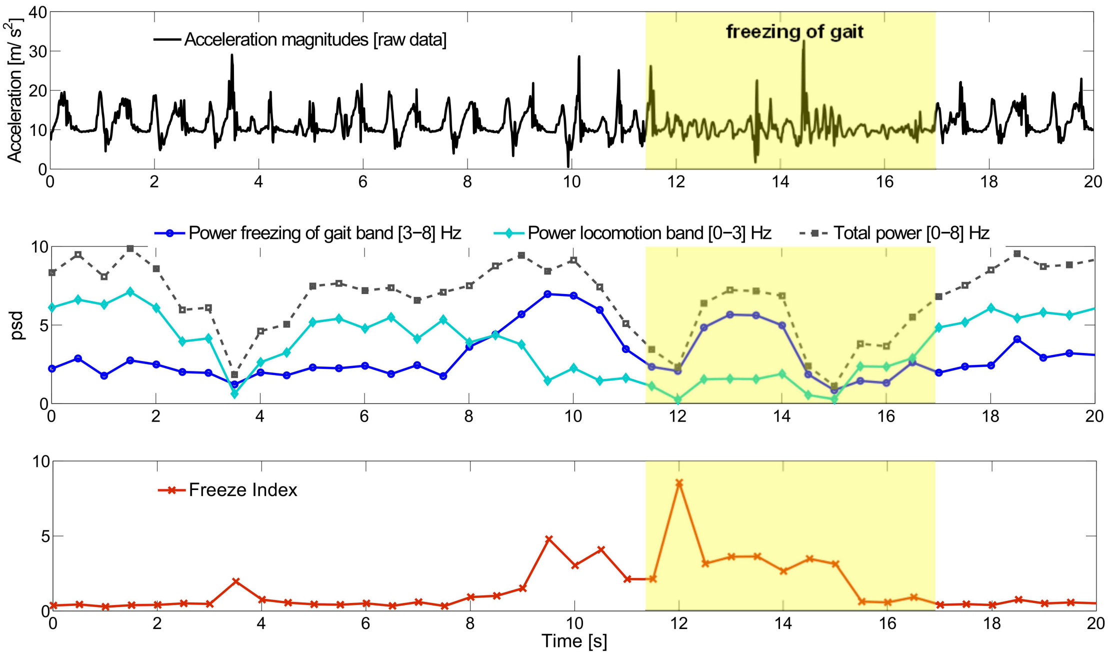


Figure 2.5: *A sequence of 20 seconds of walking with a FoG episode from CuPiD dataset. It shows the acceleration magnitude from an ankle inertial sensor, and the 4 features extracted from the sliding windows: Power on [0, 3] Hz, power on [3, 8] Hz, total power from [0, 8] Hz, and the freeze index (a similar example is contained in Figure 8.4 from Chapter 8, page 262).*

Feature	Description
Freeze Index (FI)	Power of the freeze band [3-8] Hz divided by the power in the locomotor band [0.5-3] Hz as used in the FoG-detection algorithm from [69]
Power Total (PT)	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 [11]
Power on locomotion band (PL)	Power on the [0.5-3] Hz band of the acceleration magnitude signal in the window
Power on freeze band (PF)	Power on the [3-8] Hz band of the acceleration magnitude signal in the window

Table 2.4: *FoG domain-specific features.*

(b) Time Series and Statistical Features. As we model FoG-detection as an activity recognition problem, we extract time series-based features and statistics used in activity recognition to distinguish between human activities [15]. We build a database of 24 activity recognition-related features, which include statistics such as different types of averages, median, min, max, variance, kurtosis, skewness, mode, asymmetry coefficients, zero and mean crossing rates, as well as convoluted features such as the signal of the magnitude vector, the normalized signal of the magnitude vector, the eigenvalues of the dominant directions, entropy, and the averaged acceleration energy. Table 2.5 gives an overview of the extracted features, along with their descriptions.

Axis Features		
No.	**Feature**	**Description**
1,2	Min, Max	Minimum and maximum of the signal
3	Median	Median signal value
4,5	Mean, ArmMean	Average and the harmonic average across the window
6	Root Mean Square (RMS)	Quadratic mean value of the signal
7	GeoMean	Geometric average of the signal
8	Variance	Square of the standard deviation

9	Standard Deviation (STD)	Mean deviation of the signal compared to the average
10	Kurtosis	The degree of peakedness of the sensor signal distribution
11	Skewness	The degree of asymmetry of the sensor signal distribution
12	Mode	The number that appears most often
13	TrimMean	Trimmed mean of the signal in the window
14	Entropy	Measure of the distribution of frequency components
15	Asymmetry coefficient	The first moment of the data in the window divided by STD over the window
16	Range	The difference between the largest and smallest values of the signal
17	Zero Crossing Rate (ZCR)	Total number of times the signal changes from positive to negative or back, normalized by the window length
18	Mean Crossing Rate (MCR)	Total number of times the signal changes from below average to above average, normalized by the window length
	Sensor Features	
No.	**Feature**	**Description**
1	Signal Magnitude Vector (SMV)	Sum of the euclidean norm over the three axes in the window normalized by the window length
2	Normalized Signal Magnitude Area (SMA)	Acceleration magnitude summed over three axes normalized by the window length
3-5	Eigenvalues of Dominant Directions (EVA)	Eigenvalues of the co-variance matrix of the acceleration data along x, y, and z axes
6	Averaged Acceleration Energy (AAE)	Mean value of the energy over three acceleration axes

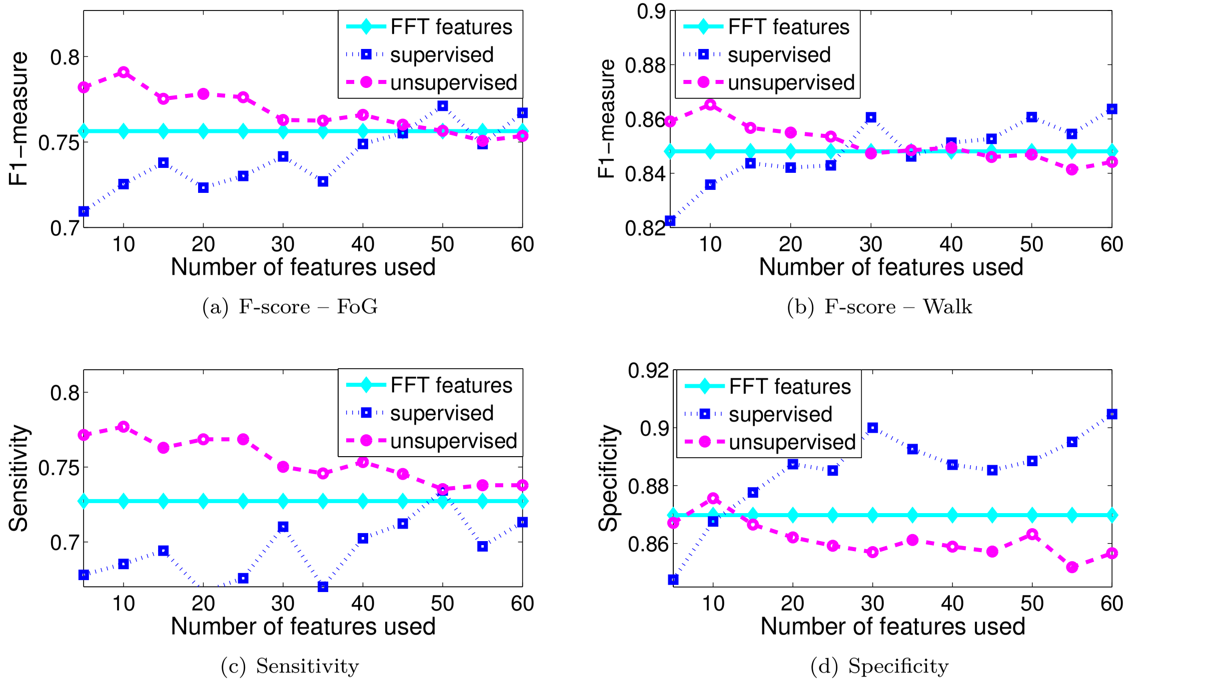
Table 2.5: *Time-series and statistical features and their brief descriptions.*

(c) Unsupervised Extracted Features. There is a lack of physiological understanding of the gait deterioration preceding FOG and during freeze [78], which makes it difficult to propose problem-specific features to describe FoG based on expert knowledge. Automatic (unsupervised) feature extraction has been proposed in the context of human activity recognition based on motion sensors [86]: Instead of using the explicit knowledge to select specific features to describe activities, one can extract the core signal characteristics by means of deep learning methods, namely Principal Component Analysis (PCA) applied directly on the raw acceleration data from the sensors. This allows to uncover meaningful, low-dimensional representations in the motion data without relying on the expert and domain-specific observations between classes. We attempt to model the implicit structure of FoG and Walk categories from unsupervised features extracted by means of PCA applied on raw acceleration data.

Evaluation of Features to Describe FoG. In the following, we evaluate the different proposed features to characterize FoG, with respect to the two FoG-datasets, DAPHnet and CuPiD.

DAPHnet Dataset. In a first experiment (Chapter 3), we compute a subset of 7 statistical and domain-specific features from the three axis of acceleration in DAPHnet: mean, standard deviation, variance, entropy, energy, and the domain-specific features FI [69], and PT [11]. We use Correlation-based Feature Subset Selection [37] as a method to select the most informative features to discriminate between FoG and Walk classes. The selected features, regardless of the sensor location, are two statistical features, mean and standard deviation of the acceleration, along with the two domain-specific features, FI and PT.

Further, we extend the set of extracted features to characterize FoG from ankle-mounted acceleration in DAPHnet (Chapter 5), by taking into account three types of features: (1) In the first set we consider the two domain specific, frequency-based, features introduced in [11, 69], FI and PT. (2) In the second set we compute the time-series features enumerated in Table 2.5. We compute in total 60 features, 18 axis features from Table 2.5 for each of the three axes of the accelerometer, on which we add the 6 extracted sensor features described in Table 2.5. (3) The third set of features represent 60 unsupervised extracted features with PCA applied on the raw 3D acceleration data.



(a) F-score – FoG

(b) F-score – Walk

(c) Sensitivity

(d) Specificity

Figure 2.6: *Average sensitivity, specificity and F-score for detection of FoG when using C4.5 models with different types of extracted features, in a subject-dependent cross-validation with acceleration data from ankle-mounted sensors in DAPHnet (Figure 5.4 from Chapter 5, page 167).*

We compare the three different types of features in terms of FoG-detection performances, by using the activity recognition chain with C4.5 models as evaluation method, and report the average sensitivity, specificity and F-score across all eight subject datasets in a patient-dependent evaluation setting. Before using the 60 time-series features with ML methods, we rank them using Mutual Information (MI).

Figure 2.6 contains the FoG-detection performances, when varying the number of used features, in case of time-series and unsupervised feature sets. The use of unsupervised extracted features obtains the best FoG-detection performances, when using a $\leq$ 30 number of features in the classifiers, followed by the 2 domain-specific FFT features, and then by the time-series features.

CuPiD Dataset. We consider the IMU attached on ankles from CuPiD dataset, and extract two sets of features (Chapter 8): (1) the four domain-specific FFT features, FI, PT, PF, and PL, and the 24 time-series features from Table 2.5. Features were computed from both 3D acceleration and 3D gyroscope data magnitudes. We evaluate the features in terms of FoG-detection performances, with the activity recognition framework and C4.5 classifiers, in a subject-independent evaluation setting. The use of the 4 domain-specific features extracted on the acceleration magnitudes obtain the best FoG recognition rates. Moreover, the addition of activity-recognition features on top of the four FFT features does not improve the FoG-detection performances, although some of them are informative, such as EVA, AAE, average, and variance. The use of features extracted from the gyroscope does not help in recognizing FoG, as rotation data in case of some walking events such as turns is similar as during the FoG.

Conclusion. The unsupervised extracted features obtain the best results in terms of FoG-detection. The unsupervised features are able to capture variations in the data, without the bias of the expert knowledge and without any prior knowledge about the category labels. One explanation is that some of the gait changes during FoG might not *visible* to an expert, thus not captured by the domain-specific features, but can be incorporated with deep learning techniques, i.e., PCA applied directly on the raw sensor data in our case. However, it is difficult to compute such features in real-time, which will lead to an increase of the FoG-detection latency.

The second group of most informative features are the domain-specific, expert-based FFT features, as resulted from the experiments on both DAPHnet and CuPiD, followed by the activity recognition features. The use of general activity recognition-based features obtain the lowest FoG detection rates in our experiments, although some of them are informative, mostly on DAPHnet data. This might be due to the fact that these features are used usually to discriminate between general human activities, e.g., walking, sitting, standing, running, biking, and might not be suitable for gait anomalies such as FoG.

For online FoG-detection models integrated in a wearable system (Chapters 7 and 8), we used the 4 domain-specific frequency features extracted from the CuPiD acceleration data, as a result from the prior experiments on the CuPiD dataset and for the simplicity of computation. Unsupervised-extracted features, although obtain the best detection performances, are difficult to be extracted in real-time, which will contribute to the FoG-detection latency due to the temporal complexity of the extraction method. The addition of other time-series features would not come with a significant detection improvement, while introducing computation latency.

2.2.3. On-Body Sensor Placement for FoG Description

The on-body position from which the movement information is extracted plays an important role to accurately describe FoG, along with the defined features. We study which is the best position to describe FoG from inertial measurement units.

DAPHnet Dataset. In case of DAPHnet, we evaluate the three sensor placements, i.e., ankle, thigh, and lower back, in terms of FoG-detection performances, by using the FoG-detection framework with RF classifiers, in a subject-dependent evaluation setting. The three on-body positions obtained similar FoG-detection performances as shown in Table 2.6. However, the ankle and the lower back obtained the best detection results in terms of accuracy and detection latency.

CuPiD Dataset. In case of the CuPiD, the FoG-detection framework with C4.5 models, in a subject-independent evaluations scheme, from 5 body sensor locations: foot, ankle, thigh, lower back, and wrist. The best performances were achieved by using information from IMU placed at the ankles of the subjects, followed by the lower back position, as shown in Figure 2.7 and detailed in Section 7.4 from Chapter 7.

Acc. Axis	x	y	z	Sensor
Ankle				
Sens	0.92	0.89	0.91	0.98
Spec	0.99	0.98	0.99	0.99
Thigh				
Sens	0.89	0.87	0.88	0.97
Spec	0.98	0.98	0.98	0.99
Lower back				
Sens	0.88	0.83	0.90	0.98
Spec	0.98	0.98	0.99	0.99

Table 2.6: *FoG-detection performances with RF classifiers, in a subject-dependent validation setting, when using acceleration information from the three on-body locations in DAPHnet: ankle, thigh, and lower body (Table 3.4 from Chapter 3, page 107).*

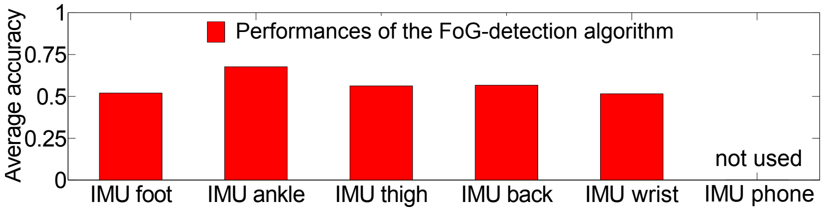


Figure 2.7: *FoG-detection performances with C4.5, in a subject-independent validation setting, for different on-body attachments of the sensors in CuPiD: foot, ankle, thigh, lower back, wrist (Figure 7.4 from Chapter 7, page 229).*

We investigated also the option of detecting FoG from phone's internal inertial sensors, placed on the trouser's pocket. The differences in placement across subjects, added to the loose attachment to the body of the phone, resulted in noisy acceleration data. Hence, it was not possible to detect the typical motions that are characteristic to FoG.

Conclusion. Based on the Fog-detection results on the two datasets, the optimal lower body positions to attach the inertial units in order to describe and detect FoG are the ankles, followed by the lower back. Following the findings from this section, for the real-time Fog-detection system (Chapter 8), we use up to two inertial measurement units attached on the ankles of the system's user.

2.2.4. Characterize FoG from Upper Body Movements

FoG is a motor symptom, and most of the clinical observations attempt to describe the motor variations prior or during gait freeze [78]. As a result, research focused on describing FoG from inertial sensors attached on the lower limbs or lower back [11, 19, 22, 50, 69, 97]. The extracted domain-specific features to describe FoG are modeled from and are specific to sensors attached on these positions [11, 69]. As a result, using features extracted from IMU attached on the wrist obtain lower detection performances when using the FFT features designed specifically for the lower limb, as shown in Figure 2.7.

Wearable wristbands or smartwaches are promising to be integrated in healthcare systems, due to their design, common on-body placement, and high acceptance from the user. We investigate whether FoG can be described from wrist movements. The motivation is that arms are moving in tandem with the lower limbs during walking. For this, we propose, and quantify new features extracted from wrist-attached IMU to characterize FoG. We show that it is feasible to detect FoG from upper limb movements, and discuss the trade-offs of using wrist sensors for FoG detection, compared with sensors attached on lower limbs.

Features. We propose the following frequency-based and statistical features from the wrist movement to describe FoG, as in Table 2.7: the average and standard deviation of acceleration and rotation magnitudes from each window of data, acceleration power on short intervals ranging from [0,1] Hz up to [15,16] Hz, and acceleration power on more sparse frequency intervals such as [0,3] Hz, [3,9] Hz, up to [13,16] Hz.

We rank the extracted features with respect to FoG labels, using Mutual Information [82], Pearson Correlation, and ANOVA [47], on the 11 subjects from CuPiD dataset, in a subject-independent setting. Top ranked features with all three methods, which show most significant changes in the wrist movement during FoG, are the acceleration power on [0, 1] Hz up to [5, 6] Hz, acceleration power on larger intervals ($[0, 2]$, $[3, 8]$ and $[9, 12]$ Hz), and the statistical features from both acceleration and rotation.

#	Feature	Description
		Statistical features
1-2	Mean	The average values over the accelerometer and gyroscope magnitude vectors
3-4	Standard deviation	The standard deviation values over the accelerometer and gyroscope magnitude vectors
		FFT-based features
5-20	$Power_{[0,1]Hz}$, ..., $Power_{[15,16]Hz}$	16 FFT features computed from acceleration magnitude vector, each feature corresponding to the *power* on $[0,1]Hz$, $[1,2]Hz$, ..., $[15,16]Hz$
21	$Power_{[0,2]}Hz$	Power from $[0,2]Hz$ band from acceleration magnitude vector (which includes the band of the human gait as in [69])
22	$Power_{[3,8]Hz}$	Power from $[3,8]Hz$ band from acceleration magnitude vector which is included in the so-called *freeze* band introduced in [69]
23	$Power_{[9,12]Hz}$	Power from $[9,12]Hz$ band from acceleration magnitude vector
24	$Power_{[13,16]Hz}$	Power from $[13,16]Hz$ band from acceleration magnitude vector

Table 2.7: *Features extracted from wrist mounted IMUs to describe FoG episodes from correlated hand movements (Table 8.2 from Chapter 4, page 261).*

Evaluation setting	Wrist	Ankle	Wrist & ankle	Wrist & 2 ankles
Subject-dependent	1.15	0.62	0.85	0.93
Subject-independent	0.81	0.72	0.77	0.93

Table 2.8: *FoG-detection latency in seconds in case of two evaluation settings on the 11 subjects in CuPiD dataset, in case of using IMU data from: (a) one wrist, (b) one ankle, (c) wrist and one ankle, and (d) one wrist and both ankles.*

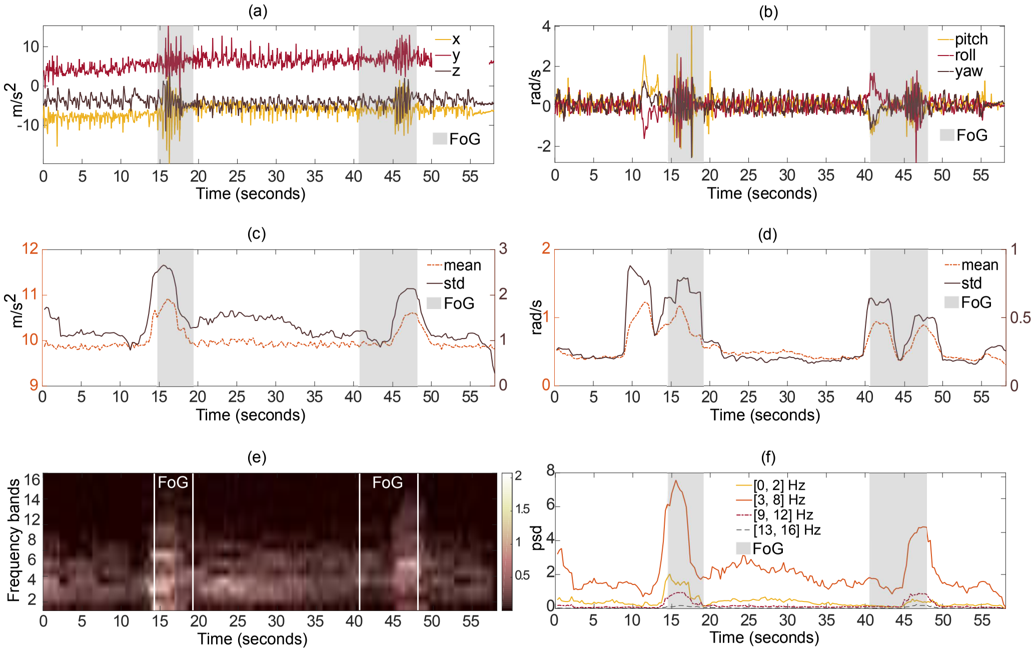


Figure 2.8: *Two FoG episodes during walking in straight line with turns, as captured from a wrist-mounted sensor: (a) Raw acceleration data, (b) Raw rotation data, (c) Mean and standard deviation from acceleration, (d) Mean and standard deviation of rotation, (e) Power on different frequency bands from* $[0, 1]$ *Hz to* $[15, 16]$ *Hz, and (f) Power values on* $[0, 3]$ *Hz,* $[3, 8]$ *Hz,* $[9, 12]$ *Hz, and* $[13, 16]$ *Hz. Raw data and extracted features show distinguishable patterns of the upper limb during FoG (Figure 4.3 from Chapter 4, page 126).*

FoG-Detection Performances. We use the 13 top ranked wrist features extracted from windows of 3 seconds, with the FoG-detection framework as in Figure 2.3, with C4.5 models, in both subject-dependent and subject-independent evaluation schemes, across the 11 subjects in CuPiD. Figure 2.9 presents the FoG-detection performances in the same settings, when using (a) wrist data with the 13 top ranked features, and (b) ankle information with the four domain-specific features, (c) considering data from one wrist and one ankle, and (4) considering both ankles and one wrist IMU. Similarly, Table 2.8 summarizes the FoG-detection averaged latency results for all four cases of sensor information used. We compare wrist features with ankle-extracted features, because the ankle was ranked as the best on-body position to detect FoG in Section 2.2.3.

We can robustly detect gait freeze from wrist movement, with a FoG-hit rate of 0.81 - 0.83, specificity of 0.76 - 0.79, and an averaged FoG-detection latency of 1.15 seconds in a subject-dependent setting, and 0.81 in a subject-independent scheme.

When comparing FoG-detection performances of wrist and ankle positions, the detection results are only slightly decreased when using wrist compared with ankle IMU data, in a subject dependent setting. However, the averaged FoG-detection latency is almost double when using wrist movements, compared with the ankle, as shown in Table 2.8. The difference between the two positions is better shown in the subject-independent setting, where the overall specificity drops by 0.1 and the FoG hit-rate by 0.05 when using wrist-extracted specific features, compared with the ankle features. This comes along with an increase in the FoG-detection latency when using wrist information, as shown in Table 2.8. Moreover, the use of both upper limb and lower limb movements are not helping in improving the FoG-detection, as shown by Figures 2.9(c) and (d).

Conclusion. We show that by extracting specific features from the rotation and acceleration data, wrist mounted sensors are useful and robust to detect freezing at the gait level. The most informative data with respect to FoG correlation comes usually from the opposite upper-body limb of the FoG-preeminent lower-body limb, as FoG it is known to occur more often in the dominant part of the body.

The decrease in specificity, thus an increase in the number of false FoG detections, might be due arm movements which results from human actions or gestures, as the arms are not used only for the syn-

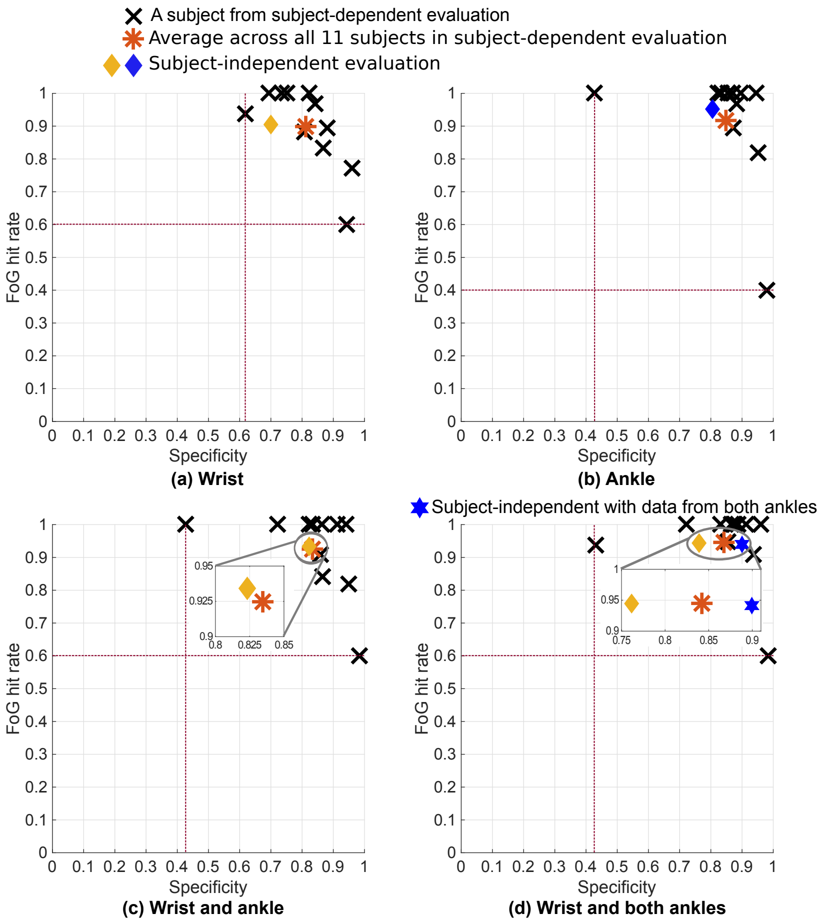


Figure 2.9: *Scatter plots reporting FoG-detection performances for four different scenarios: when using information from (a) wrist, (b) ankle, (c) wrist and ankle, and (d) wrist and both ankles. Each scatter plot reports the FoG hit-rate against the specificity for each of the 11 subjects in CuPiD, the average across them for the subject-dependent evaluation, and the overall values for the subject-independent setting. In case of (d) we add also the hit-rate and specificity of the case when using data from both ankles in a subject-independent setting (Figure 4.7 from Chapter 4, page138).*

chronicity of walking. For example, talking on the phone, waving to someone, or holding something while walking cancels the wrist movement during walking, thus affecting the FoG-detection performances.

Related to the usage of wrist- or/and ankle-attached IMU in a wearable system to detect FoG, there are trade-offs of the FoG-detection performances versus on-body acceptance: Using an ankle mounted sensor comes with a higher detection rate. Also wrist movements are useful to detect freezing at the gait level. Yet, they come at the cost of a higher rate of false detected events compared when using lower limb movements to detect freeze. On the other side, wrist position is the optimal position to wear electronics and to interact with them [92]. Moreover, there are commercially available devices such as smartwatches and wristbands for sports which integrate accelerometers and gyroscopes, and they can be used to provide the wrist movement information to detect FoG.

Moreover, experiments show FoG can be detected from a single inertial sensor (Figure 2.9). The addition of information from multiple sensors does not significantly improve the detection performances.

2.3. Methods and Sensors to Predict Freezing of Gait

Rhythmic auditory stimulation upon FoG might help shortening the duration of such episodes [23, 76]. However, it cannot avoid them altogether due to the FoG-detection latency, which is at the best in the order of hundreds milliseconds [11, 50], as shown in experiments from Section 2.2. *FoG detection* implies that gait freeze needs to take place, the target being an accurate and *fast* detection of the FoG onset. A step further is to predict when a subject is *about* to experience FoG, and enable preemptive rhythmical stimulation which might help avoiding entirely the upcoming gait freeze. We introduce this as the *prediction of FoG* problem. We focus on predicting gait freeze with up to few seconds before it happens.

To predict FoG, we aim to characterize the periods with few seconds prior to gait freeze episode from a multimodal perspective, and propose methods to detect such changes prior to FoG. Both tasks are complex, due to the lack of information whether there are specific patterns prior to FoG from diverse data, and due to the lack of labels, i.e., there is no groundtruth information available whether and when gait transitions towards FoG.

We contribute the following:

1. Characterize the motor changes prior to FoG from on-body accelerometers. We attempt to predict FoG with a three-class activity recognition problem.

2. Study the physiological reactions from wearable Electrocardiography and Skin Conductance Response sensors, and model FoG prediction as an unsupervised anomaly detection problem.

2.3.1. Prediction of FoG from On-Body Accelerometers

The pathological process of FoG is not understood at the moment [48, 78]. Nonetheless, clinical literature surveys several gait anomalies which might contribute to gait freezing and are present in the prior-to-FoG periods, such as stride length reduction [18], step festination [48], deterioration in rhythmic control [18, 42] and in step-to-step time variability [42], and the reduction of the cadence [18, 48]. Motivated by these observations, we study whether there are specific variations in the acceleration from on-body sensors with few seconds prior to FoG episodes, which are different from the information from both FoG and Walk.

FoG Prediction Model. In Section 2.2 we model FoG detection as a two class activity recognition problem. However, in case of FoG prediction we assume that the gait does not enter in FoG state directly from walking. As illustrated in Figure 2.10, we make the hypothesis that there is a transitioning period of few seconds in which the gait degenerates from walking up to the point of FoG. This is represented by a period of duration T_{preFoG} that we refer to as *preFoG* state. Thus, we add to the two categories of data as labeled by clinicians, FoG and Walk, a hypothetical preFoG category.

Following the work on FoG detection from Section 2.2.1, we apply the activity recognition framework from Figure 2.3, page 24 to solve the new 3-category classification problem with supervised ML methods.

Features to Describe PreFoG Patterns in Acceleration. To observe whether there are changes in the gait prior to FoG, we extract from each window of acceleration data the same three types features as in case of FoG-detection problem, following the experimental setting detailed in Section 2.2.2: (1) two FoG domain-specific features, Freeze

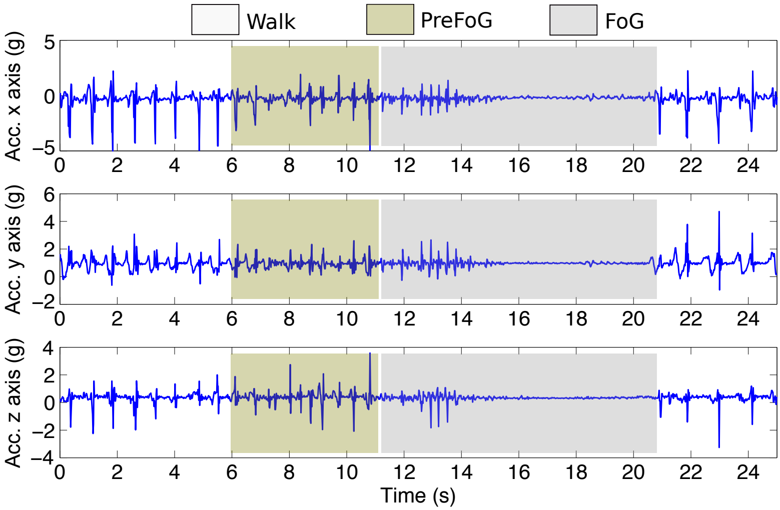
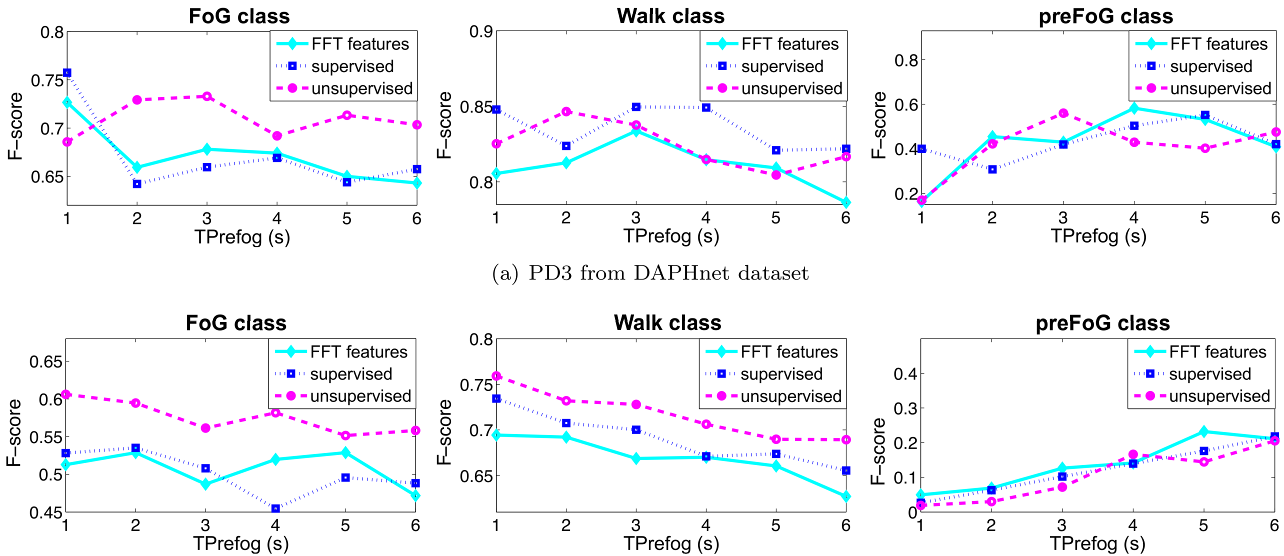


Figure 2.10: *An example of a 3D acceleration signal capturing a straight line walking sequence with a FoG episode. The gait freeze is preceded by a hypothetical preFoG period (Figure 5.2 from Chapter 5, page 161).*

Index [69] and total power on $[0, 8]$ Hz [11], (2) 60 activity recognition features, 18 *axis features* from Table 2.5 page 32, for each axis of the 3D accelerometer, added to 6 sensor features described on the same table, and (3) PCA-based unsupervised extracted features.

Experiments and Results. We test our 3-class FoG-prediction hypothesis on DAPHnet dataset, using the information from the ankle-mounted sensors, motivated that ankle information obtained the best performances in terms of FoG detection. The preFoG class is hypothetical, i.e., there are no groundtruth labels provided by physiotherapists regarding the prior-to-FoG periods, and there is no available knowledge about the T_{preFoG}, if any. Thus, we simulate the preFoG class, by varying the time T_{preFoG} from 1 seconds up to 6 seconds in steps of 1 second, prior to each FoG episode. We report the performances of FoG prediction using C4.5 classifiers, in case of different preFoG duration, in a subject-dependent 10-fold cross validation setting.



(a) PD3 from DAPHnet dataset

(b) PD8 from DAPHnet dataset

Figure 2.11: *F-scores for each of the three classes, FoG, Walk, and preFoG, in case of FoG-prediction modeled as an activity recognition problem, for PD3 and PD8 subjects in DAPHnet. We use C4.5 models, while varying the T_{preFoG} period from 1 second up to 6 seconds prior to gait freeze (Figure 5.8 from Chapter 5, page 172).*

The FoG prediction results are subject specific, following two trends as illustrated in Figure 2.11: *(a)* In case of 4 out of 8 subjects from DAPHnet, such as PD3 for example, the introduction of the preFoG class improves both FoG and Walk F-scores, for a $T_{preFoG} \in [1, 3]$ seconds, when using unsupervised or FoG-domain specific features. The increase in the F-score for all three classes for T_{preFoG} periods ≤ 3 seconds show the preFoG class is different from both Walk and FoG data, leading to the possibility of predicting FoG. *(b)* Differently, for the other half of 8 subjects in DAPHnet, such as PD8, the addition of the preFoG class harms the recognition performances on both FoG and Walk classes. In case of all three types of features extracted, an increase of T_{preFoG} leads to a constant decrease in F-score of Walk class, showing that preFoG and Walk categories share similar data. Therefore, no preFoG specific pattern is present in the acceleration features extracted.

Conclusion. We model the FoG-prediction problem as a 3-class activity recognition and show that for half of subjects in DAPHnet there are subject-dependent motor variations captured from acceleration, with up to 3 seconds prior-to-FoG. These observations led to the prediction of some of the FoG events, e.g., up to 50% of the FoG in case of PD3, as shown in Figure 2.11. However, using a supervised activity recognition solution to predict FoG has drawbacks: In our setting, the T_{preFoG} has a fixed duration for each of the FoG episodes, while the preFoG duration, if any, might be subject- and gait context-dependent. Moreover, the motor deterioration prior to FoG might be related and linked to the FoG context, such as during turns. Hence, the risk that the presumed preFoG category incorporates the signature of the walking event prior to FoG, e.g., turn, and not an actual prior-to-FoG specific pattern.

2.3.2. Prediction of FoG from Physiological Sensors

In previous sections we focused in studying the gait variations captured with inertial measurement units to detect or predict FoG. There are clinical evidences that apparently mental conditions play an important role in the pathogenesis of FoG [28]. Stressful situations, anxiety, depression, fatigue, and cognitive challenging contexts have been associated with and are a contributing factor to freezing of gait [28]. Wearable sensors which capture physiological signals such as Electrocardiography (ECG) or Skin Conductance Response (SCR) have been used to reflect the emotional state, the stress level, and the anxiety in daily-life [53].

Our aim is to use ECG and SCR captured from body-mounted sensors to predict FoG with few seconds prior its onset. We study first whether there are statistically significant changes in the physiological information with few seconds *before*, *during*, or *just after* gait freeze. Further, we model FoG-prediction as an anomaly detection problem without groundtruth labels. We use for our experiments the ECG and SCR data from the 11 subjects from CuPiD.

Changes in Physiological Signals Prior to FoG

Methodology. To observe whether physiological information particularly changes prior to FoG, we analyze the sensor data as following: For each FoG event, we consider a fixed period of 3 seconds just prior to FoG as *preFoG*. Similarly, we set a 3 seconds period after the FoG as *postFoG*. Hence, the sensor data will be slip in four categories as in Figure 2.12: (1) *FoG* represents the data during the gait freeze, (2) *preFoG* is the data gathered with few seconds before the FoG event, (3) *postFoG* the information gathered just after the gait freeze events, and (4) *Walk* represents the rest of the data in the protocol session, which includes events such as turns, gait initiation, and stop walking. We consider all the gait freeze episodes in the CuPiD protocol, independent of duration, or of the walking context associated with them.

Figure 2.12: *The four categories assigned to the sensing information:* FoG *class represents the groundtruth FoG labels as set by the clinicians.* PreFoG *and* postFoG *are composed from the periods of 3 seconds before of just after FoG. The* Walk *category represents the rest of the walking information in the protocol session (Figure 6.3 from Chapter 6, page 190).*

For each sensor, ECG and SCR, we extract specific features in a sliding window manner, with a window size of 3 seconds, and an overlapping step of 0.5 seconds. In case of ECG information, we extract 7 features as detailed in Table 2.9. In case of SCR, we first extract the filtered skin conductance signal C, and then compute its first and

#	Feature	Description
1	HR_{mean}	Mean over the HR values in the window
2	HR_{median}	Median over the HR values in the window
3	HRV	$HRV = \frac{std(HR)*100}{mean(HR)}$
4	$Power_{VLF}$	Power on very-low frequencies (VLF) [0.01, 0.04] Hz of the ECG signal
5	$Power_{LF}$	Power on low frequencies (LF) [0.04, 0.15] Hz of the ECG signal
6	$Power_{HF}$	Power on high frequencies (HF) [0.15, 0.4] Hz of the ECG signal
7	$Ratio_{LF/HF}$	The ratio between the power on LF and HF bands of the ECG

Table 2.9: *Features extracted from ECG signal (Table 6.1 from Chapter 6, page 191).*

#	Feature	Description
1	Mean	The average value over the signal
2	Median	The median over the window
3	Std	The standard deviation value
4	Min	The minimum of the signal
5	Max	The maximum value of the signal
6	Diff	The difference between the maximum and minimum values of the signal
7	# min	The number of local minima in the window data vector
8	# max	The number of local maxima over the same window

Table 2.10: *Features extracted from SCR signals C, $C^{(1)}$, and $C^{(2)}$ (Table 6.2 from Chapter 6, page 193).*

second derivatives, $C^{(1)}$ and $C^{(2)}$, respectively, following the procedure from [117]. For each of the three signals (C, $C^{(1)}$, and $C^{(2)}$), we extract in a sliding-window manner 8 features described in Table 2.10.

For each feature, we employ the (1) One-Way Analysis of Variance (ANOVA), and (2) Mutual Information (MI), to explore whether there are specific and significant changes with respect to the four categories of data, preFoG, FoG, postFoG, and Walk. In case of ANOVA, we set the significance threshold set to $p \leq 0.001$. We report the results obtained in a subject-dependent setting on the 11 subjects from CuPiD.

ECG Features. In case of 3 out of 11 subjects from CuPiD, we were not able to perform the experiments due to the lack of ECG information or the noise in the data. For one subject, none of the ECG features passed the ANOVA significance test. For the rest of 7 subjects, the top ranked features as resulted from both ANOVA and MI are two HR-based statistics, i.e., mean and median, the HRV, and the power on $[0.15, 0.4]$ Hz. A visual example of how HR and HRV changes during a walking session containing FoG is given in Figure 2.13.

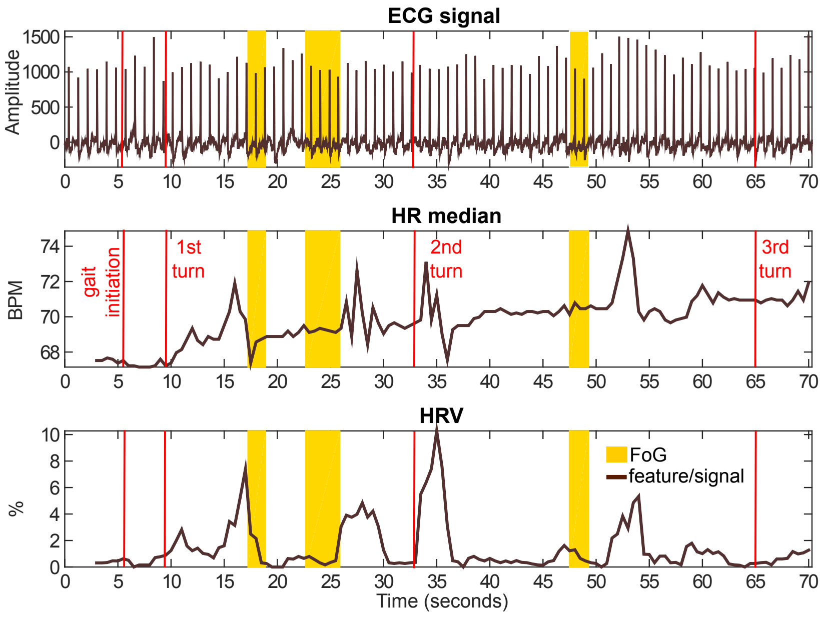
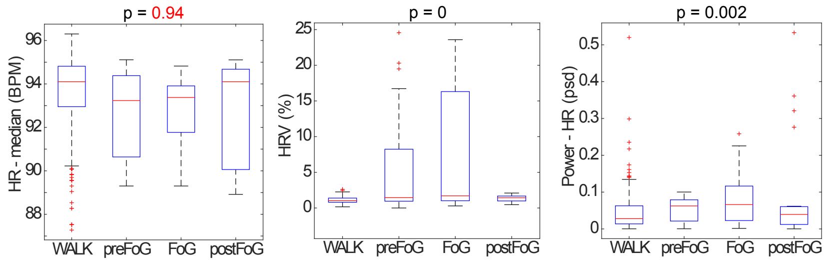
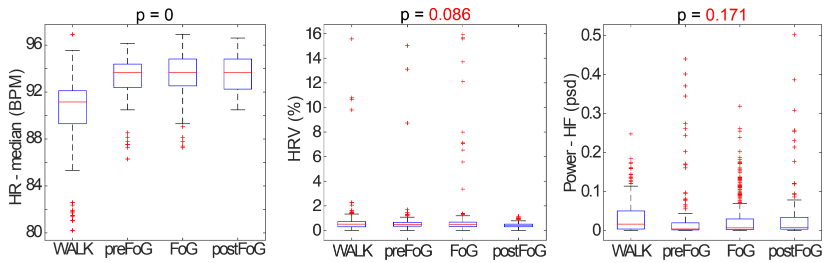


Figure 2.13: *A sequence of ECG signal, together with the extracted HR median and HRV features. The sequence contains three FoG episodes, and walk events such as gait initiation, and turns, with straight line walking in-between. Both HR and HRV increase within 3 seconds before the first FoG episode, and in the 5 seconds interval just after the second and third FoG event. However, HR and HRV also increase during the second turn in the walking sequence (Figure 6.4 from Chapter 6, page 192).*

However, for these 7 subjects the variations in the ECG information with respect to the 4 classes of information, i.e., preFoG, FoG, postFoG, and Walk, are subject dependent. In case of 4 datasets, the HR-based features incorporate changes during preFoG, FoG, or post-FoG compared with Walk, while for 3 datasets, the HRV is informative as resulted from ANOVA and MI. Power on $[0.15, 0.4]$ Hz is selected independently of these two groups. As illustrated in Figure 2.14, S05 represents the first groups, for which the HR captures significant changes and increases in the preFoG periods. S06 is part of the group of subjects for which HRV increases during preFoG and FoG periods. The power on $[0.15, 0.4]$ Hz is independent of the two groups, with subject-dependent trends.



(a) S05



(b) S06

Figure 2.14: *Boxplot representation of the distribution of HR_{median}, HRV, and $Power_{HF}$ features' values, in case of 2 subjects in CuPiD with different ECG trends related to the four categories. In case of S05, HRV and $Power_{HF}$ increase during preFoG and FoG compared to Walk. In the case of S06, HR increases during preFoG, FoG, and postFoG periods, and $Power_{HF}$ decreases during preFog. The p in the graph represents the p-value from ANOVA (Figure 6.7 from Chapter 6, page 196).*

SCR Features. Figure 2.15 illustrates an example of how the skin conductance response and its derivatives vary prior, during and after FoG, compared with the rest of walking.

In case of a single subject dataset from CuPiD, i.e., S05, none of the SCR-based features passed the ANOVA significance test. For the rest of 10 subjects, the top features ranked with ANOVA are mean, median, standard deviation and maximum of the C signal, the standard deviation of $C^{(1)}$, and the minimum and maximum of the $C^{(2)}$ signal. However, the top most informative features as resulted from MI, are the # of local minima and # of local maxima for all the three signals, C, $C^{(1)}$, and $C^{(2)}$.

Similar as in the case of ECG, the top ranked SCR features are subject dependent and moreover have subject-specific patterns. We distinguish two specific trends, as shown also in 6 top ranked features in Figure 2.16: For 7 out of 10 subjects, represented by S18, features significantly change as shown from ANOVA in all three preFoG, FoG, and postFoG classes, compared with Walk. In case of S18, the statistical features from C and $C^{(1)}$ increase starting with the preFoG class, while the # local min and # local max in $C^{(2)}$ decrease starting with the preFoG period. For the rest of 4 subjects, represented by S17, the features change in FoG and postFoG, while the preFoG data is similar with the Walk information.

Predict FoG from Physiological Signals

Previous data analysis shows that both ECG and SCR capture variations in the few seconds period prior to gait freeze, i.e., 3 seconds, during FoG or just after FoG, although the top ranked features with ANOVA and MI are dataset-dependent. This is expected, as each person has a specific reaction to external stimuli, hence information captured with the physiological sensors is subject-related. Based on these findings, we study whether FoG can be predicted with few seconds before, by using the information captured from ECG and SCR sensors.

FoG Prediction Model. We model *FoG prediction* as an anomaly detection problem. We consider the changes in the features just prior to FoG as an anomaly in the signal, together with the actual gait freeze episode. By detecting these variations prior to freeze, we will actually *predict* the forthcoming FoG episode. We use Multivariate Gaussian

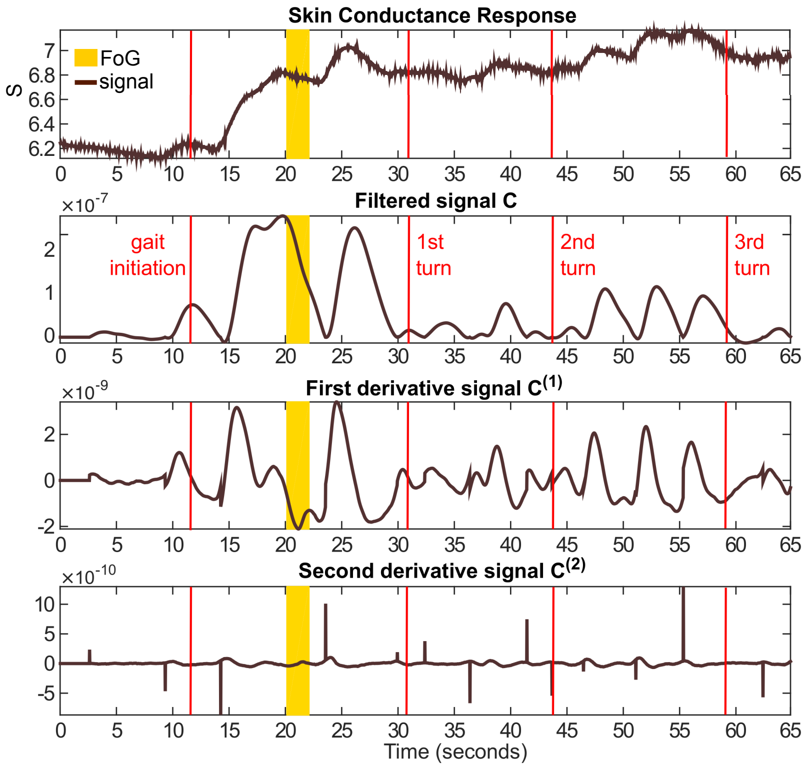
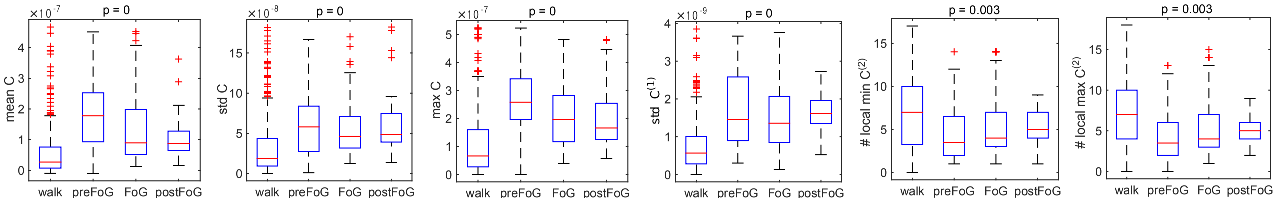
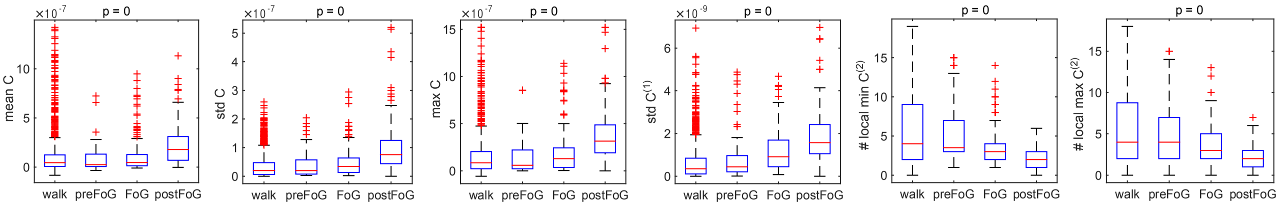


Figure 2.15: *A sequence of straight line walking with turns containing a FoG episode, as captured in the SCR, C, $C^{(1)}$, and $C^{(2)}$ signals. The C and $^{(1)}$ increase with up to 5 seconds prior the FoG, and in the interval of 2-3 seconds just after FoG, which is not visible during turns or gait initiation (Figure 6.6 from Chapter 6, page 194).*

Distribution (MGD) [33] to model and solve the anomaly detection problem. The MGD allows for multiple and different time-series fusion, being suitable for the features extracted from ECG and SCR which capture diverse changes in the data.



(a) S18



(b) S17

Figure 2.16: *Boxplot representations of the distribution of for SCR-based features' values – mean, std and max of C signal, std of $C^{(1)}$ signal, and # local minima, and # local maxima from $C^{(2)}$ signal – for two subjects which represent two groups of reactions during preFoG, FoG, and postFoG. In case of S18, the mean, std, and max of C, and std of $C^{(1)}$ increase during preFoG, FoG, and postFoG compared with the Walk data. For S17, information from preFoG and Walk are similar. However, the mean, std, and max of C, and std of $C^{(1)}$ increase during FoG, and just after FoG. The p in the graph represents the p-value from ANOVA (Figure 6.8 from Chapter 6, page 200).*

We build a MGD model from each sensor modality, ECG or SCR, for each 11 subjects in the CuPiD. The groundtruth labels provided by clinicians are related only to FoG, while *preFoG* is a priori considered, and fixed to a period of 3 seconds. The preFoG anomaly in the physiological data might start before or after this fixed period. Hence, we compute the MGD from the features extracted on the whole amount of sensor data from each subject, and manually set the anomaly-detection thresholds in a subject-dependent manner.

FoG-Prediction Performances. Although the analysis from prior paragraph shows that ECG features change prior to FoG, we were not able to build MGD models to predict FoG using electrocardiography features. An explanation might be that changes in the ECG prior to FoG are not only correlated with the freeze event, but are generated also by the sudden torso movements during turns for example.

Table 2.11 contains the FoG-prediction performances using MGD models, for each of 11 subjects in CuPiD. We report the number of True Positives (TP) as the number of FoG episodes successfully predicted. We consider a FoG predicted if an anomaly is detected with at most 8 seconds *before* a FoG. The number of False Positives (FP) represents the times when a FoG is predicted, but none takes place. Additionally, we report the average prediction time across all successfully predicted FoG, for each subject dataset.

By using subject-dependent MGD models, we are able to predict overall 71% from all FoG (132 out of a total of 184 events), with an average prediction time of approx. 4.2 seconds prior to a gait freeze. The average prediction time between 4-5 seconds prior to a FoG enables the possibility of starting rhythmic auditory stimulation upon prediction, which will help the subject to react to the cue, regain the gait rhythm, and avoid completely the freeze event. The prediction rate comes with overall 71 false alarms across approx. 2 hours of data.

The FoG-prediction results are independent of the of the Parkinson's disease severity, of the freezing of gait subtypes, and of the walking context. The prediction rate is not equal for all subjects in the dataset, and is correlated with the statistical significance of the changes obtained by the SCR features. In the previous section, we show there are two types of reactions captured by SCR data: In the first one, SCR features increase prior to FoG, and they capture a reaction which might provoke FoG, which leads to an increased FoG-prediction rate as in case of S02, S03, S04, S11, S18, and even S12 and S16 datasets, according

#	Subject	#TP / # total (%)	#FP	Avg. pred. time (sec)
1	S01	12 /19 (63.1%)	11	5.7
2	S02	9 /11 (81.8%)	5	6.3
3	S03	21 /22 (95.4%)	6	3.7
4	S04	2 /2 (100%)	1	4
5	S05	2 /4 (50%)	5	5.2
6	S06	23 /37 (62.16%)	8	4.2
7	S11	4 /4 (100%)	1	1.5
8	S12	20 /27 (74%)	6	3.6
9	S16	14 / 24 (58%)	5	3.6
10	S17	16 /28 (57.1%)	18	4.3
11	S18	6 /6 (100%)	1	4.5
	Total	132 /184 (71.3%)	71	4.2

Table 2.11: *The FoG-prediction performances (Table 6.5 from Chapter 6, page 204).*

to the results presented in Table 2.11. In a second type of reaction, the SCR features increase during or just after FoG, hence the prediction comes at a higher rate of false positives as shown in Table 2.11 in case of S01, S05, S06, and S17.

2.4. Gait Training with a Wearable FoG-Assitant

Clinical studies [6, 76, 81] indicate that gait training exercises and rhythmic cueing upon gait freeze might help subjects to exit FoG and resume walking. In previous sections (Sections 2.2 and 2.3), we show evidences that FoG events can be successfully detected in real-time using wearable inertial units, and even predicted by means of physiological signals. The third contribution of this thesis relates to gait training with a wearable FoG assistive device, and targets the following topics:

1. Design and development of a wearable training device for subjects with freezing of gait.

2. Evaluation of subjects' experiences and opinions on the use of such assistant, and the system's functionality both in a laboratory and in a real-life settings.

3. Preliminary validation of system's effect on the gait, from both subjective perception and measured effect with on-body sensors.

2.4.1. The GaitAssist Wearable System

Based on the algorithms and findings presented in Section 2.2, we develop GaitAssist, a wearable system to assist subjects with freezing of gait in unsupervised environments, e.g., in their homes, where clinicians are not actively monitoring the patient. The development of the system lies at the crossroads of human-computer-interaction, machine learning, and clinical intervention, creating a *sense-act-react* loop which targets FoG rehabilitation and training in Parkinson' disease. In the *sense* part, the GaitAssist system captures the motor properties of the gait in real-time. The system then *acts* by giving an auditory cue to the patient, in case of an ongoing FoG event. Finally, the patient *reacts* to the system's cue by trying to resume gait.

System's Components. The system comprises a smartphone and up to two wearable inertial measurement units attached on the subject's ankle, as shown in Figure 2.17. The IMU sample data at 32 Hz and sends it to the phone via Bluetooth. The core of GaitAssist consists in processing the sensor information on the phone in real-time to accurately detect the FoG onset, and start a temporary Rhythmical Auditory Stimulation (RAS) upon FoG detection, which is synchronized with the usual gait cadence of the subject. The detection framework is implemented as an app on the Android platform.

In Chapter 4 we extend the system to detect FoG from wearable inertial units attached on wrist optional to the ankle-mounted ones, while Chapter 6 contains ideas to use GaitAssist components to predict FoG, by integrating the prediction models proposed.

System's Core Modules. Figure 2.18 shows the modules of GaitAssist, and their interconnection. The system aims are (1) to enable daily-life FoG-aware cueing, (2) to support gait training by means of cueing through FoG-provoking exercises, and (3) the long-term monitoring of FoG related events:

1. **FoG Detection** is performed by an activity recognition chain, detailed prior in Section 2.2.1. It consists of C4.5 classifiers trained on the 11 datasets from CuPiD in a subject-independent setting,

Figure 2.17: *GaitAssist setup: (1) up to two wearable sensors attached on the ankles, (2) the sensor attachments, (3) a smartphone with the GaitAssist pre-installed 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 (Figure 8.1 from Chapter 8, page 257).*

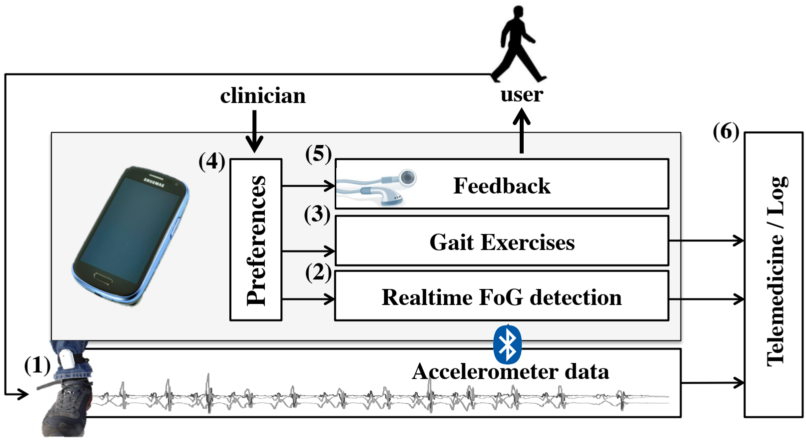


Figure 2.18: *The GaitAssist system with its components and modules: (1) Wearable sensors, (2) FoG-detection module, (3) Motor-training exercises module (4) Preferences module, (5) Auditory feedback, and (6) Logging and telemedicine module.*

with 4 domain-specific frequency features extracted from 3D acceleration magnitudes, and detailed in Section 2.2.2, page 29: The Freeze Index [69], the total power on $[0, 8]$ Hz [11], the power on locomotion band $[0, 3]$ Hz, and the power on freeze band $[3, 8]$ Hz. The attachment of the sensors on the ankle results from the findings detailed previously in Section 2.2.3. Using the ankle acceleration in a subject-independent validation, 110 out of 182 FoG in CuPiD are successfully detected at the cost of 20 false positives and a specificity of 0.94. Ankle position obtained also the highest wearability scores from the PD subjects in the CuPiD during the participatory design sessions, as shown in Figure 7.2(a) from Chapter 7, page 222.

2. The **Training Exercises** are designed by clinicians to encourage patients to practice the use of rhythmical cueing in FoG-aware situations, in order to train the gait. We implement support for two types exercises, gait initiation and turning-based exercises, respectively. Table 2.12 contains a complete exercises' description and the support offered by GaitAssist.

3. **Telemedicine.** The system communicates with a telemedicine server, sending information such as the system settings, the collected sensor data, and the FoG-detection module features and decisions, opening the possibility of long term monitoring of the user's training progress. Also, clinicians can remotely change the exercise and FoG-detection settings via telemedicine.

GaitAssist has two role-depending User Interfaces (UI): The *Patient UI* which consists only of large buttons for each of the gait-training exercises, and the *Clinician UI* which contains options and settings for the exercises and for the FoG-detection models.

#	Exercise	Training type	Exercise description	GaitAssist support and feedback
1	Weight shift standing / stepping	Gait initiation	The user shifts 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 a continuous RAS tone to help users establish the rhythm. In the remaining duration of the exercise it provides RAS upon FoG.
2	Cognitive task	Gait Initiation	The user starts walking when a specific shape, e.g., a green circle, appears on the GaitAssist screen. He needs to make 5 steps or to stop when a red square shape appears, during the exercise time	GaitAssist randomly shows different shapes and colors and it provides RAS upon FoG detection
3	Figure 8 (1)	Turns	The user walks accordingly to the imposed rhythm in a figure 8 shape five times through the right side followed by five times through the left side, continuing this until the exercise end tone	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)	Turns	The same as in the previous exercise	The system starts RAS upon FoG
5	Chairs (1)	Turns	The setting implies that are two chairs facing each other at 3 m apart. The user arises from one chair and walks accordingly to the system's RAS to the other chair, circles it, and returns to the first chair. This repeats until the end exercise tone	Gait Assist provides continuous RAS except during FoG and short periods of time after FoG, e.g., 10 seconds
6	Chairs (2)	Turns	The same as in the previous exercise	GaitAssist starts RAS upon FoG

Table 2.12: *GaitAssist training exercises as designed by clinicians (Table 8.3 from Chapter 8, page 265).*

2.4.2. Validation Studies

To study both the user-acceptance and a potential effect of the system on the user's gait, we performed two validation studies: (1) in a laboratory setting, and (2) in the homes of the participants.

(1) In-the-Lab Validation Study. For the pilot study we recruited 5 subjects suffering from PD and FoG (2 females, and 3 males), with an average age of 75.6 ± 4.7 years, a mean UPDRS [94] motor score of 26.8 ± 18.5 and a mean disease duration of 8.8 ± 3.7 years. Four patients had moderate disease severity (H & Y [45] III) and one had mild disease severity (H &Y II). The FoG severity varied between subjects, with S02 and S05 experiencing FoG even during regular walking, while the others experiencing FoG only during challenging conditions, in particular S01 and S04.

Patients did not have knowledge about the GaitAssist system. They were asked to wear and perform clinical protocols, such as Ziegler [124], figure eight, straight line walking with turns, and turns around a chair, and daily-life walking sessions with GaitAssist, under the supervision of two clinicians and two engineers. On each of the three protocol days subjects were asked to wear GaitAssist and perform the walking tasks during approx. 30 minutes. In the first day, the protocol consisted only of training exercises without cognitive load. On the second protocol day, clinicians added cognitive load tasks during exercises. In the third day, subjects were asked to use the system during a realistic scenario, consisting of recurring walking through hospital crowded hallways, which included involuntary stops, turns, changes of direction, using the elevator, and walking through narrow spaces.

All subjects were under their regular PD medication during the study. The study was video recorded and clinicians labeled the FoG events in the trial, following the same FoG-labeling procedure as in the case of CuPiD, and detailed in Section 2.1.

(2) At-Home Validation Study. For the out-of-the-lab validation, 9 people with PD, from two medical sites in two countries (5 subjects from Israel and 4 subjects from Belgium) participated in the study (mean age: $68.3.8 \pm 10.7$ years; 78% males), mean disease duration of 12.8 ± 8.5 years. 5 participants had mild PD severity (H &Y II), and the rest of 4 had moderate disease severity (H &Y III). 8 out of 9 subjects were under their regular medication treatment for PD and FoG, and did not change their medicines during the study. One subject used medical marijuana.

The protocol consisted of performing (1) gait-training exercises and (2) daily-life activities during three days. Each protocol session in a day lasted approx. 60 minutes.

The subjects were required to setup and use the system without any clinical supervision, just by following an usage manual of GaitAssist, and having the support only of the caregiver or a family member. No experts or clinicians were present in the subjects' homes during the protocol, except in the beginning of the first day, when a clinician explained to the users the system's operation and provided them with the self-use manual. However, the clinician refrained from taking part in the training program. The at-home trial was not video recorded.

2.4.3. System's Acceptance and Feasibility Evaluation

In the following, we detail the functionality results regarding the real-time FoG-detection performances of GaitAssist, and report the participants' acceptance scores regarding the usage of the system in both in-the-lab and out-of-the-lab settings.

GaitAssist Functionality. In case of laboratory validation study, clinicians identified 102 FoG episodes from the 5 subjects. GaitAssist successfully detected in real-time 99 of the events and started rhythmical auditory cueing with a latency of at most 0.5 seconds after the start of a FoG episode. The system detected 27 false alarms in total during the whole study, usually in response to motions that resembled FoG, i.e., step festination, turns with very small steps, or sudden stops.

In case of the at-home study, we were not able to objectively assess the functionality of the system, due to the lack of FoG groundtruth labels because the protocol was not video recorded.

GaitAssist Acceptance and Users' Feedback. During both in-the-lab and at-home studies, participants were asked to fill questionnaires regarding the feasibility of FoG-detection, system operation and comfort. Table 2.13 contains the questions and the average grades on a Likert-scale [57] across all subjects in case of in-the-lab validation study. Table 2.14 present the questions and average Likert- scores across the 9 subjects in two sites for the at-home validation protocol. Besides questionnaires, clinicians had informative interviews with the participants, regarding the usage of GaitAssist.

#	Statement	Mean score
	Feasibility	**4.2**
1	The auditory feedback always turns on when FoG occurs	4.1
2	The auditory feedback always turns off at the end of the FoG event	4.2
	System operation	**3.9**
3	I can use the wearable system independently	3.9
4	Using the system serves as a challenging training for me	3.8
	Comfort	**5**
5	The weight of the earphones does not interfere with the task performance	5.0
6	The auditory feedback is heard well	4.9
7	It is possible to wear the earphones independently	5.0
8	It is possible to take the earphones off independently	5.0
	Subjective opinions	**3.9**
9	In my opinion, the system is suitable for patients with Parkinson's disease	4.5
10	I feel safe when using the system	4.4
11	In my opinion, the feedback provided by the system can reduce the number of FoG events	2.6
12	In my opinion, the feedback provided by the system can reduce the duration of freezing events	4.3
13	I feel that the system may contribute to my independence	3.7

Table 2.13: *The feedback questionnaire and mean grades on a Likert scale from 1 to 5, where 5 is the best score, reported by the 5 participants in-the-lab validation study (Table 7.2 from Chapter 7, page 233).*

Overall, participants from both studies were satisfied with wearing GaitAssist and with its performances, stating that the system is a suitable tool to support people with FoG, and giving overall high Likert-scores regarding the system operation (3.9 and 4 out of a maximum of 5), comfort (4.9 and 4 out of 5), and questions regarding the feasiblity of using GaitAssist for gait training and life quality (3.9 out of 5). The Likert-scores are similar for both in-the-lab and at-home studies,

#	Statement	Site1 Mean	Site2 Mean	Overall Mean
	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
	Comfort	**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
	Subjective opinions	**3.6**	**3.8**	**3.8**
11	I think GaitAssist is simple to use	3.6	3.2	3.4
12	In my opinion, GaitAssist is suitable for people with Parkinson's disease	3.6	4.2	3.9
13	The manual is clear and simple to understand	4.2	4	4.1

Table 2.14: *Satisfaction questionnaire – statements and average scores on a scale from 1 to 5, where 5 is the best score, for participants in Site 1 (Israel), Site 2 (Belgium), and overall average across all 9 participants from at-home validation study (Table 8.5 from Chapter 8, page 278).*

except for the comfort-related questionnaire in case of at-home, which decreases with approx. one on the Likert-scale from 4.9 of in-the-lab study. This is related to the different protocol settings: While in-the-lab the subjects were asked to only wear the system and to perform the gait-training exercises supervised by a therapist, in theier homes participants were asked to setup, mount on-body, and wear the system while performing the protocol without any clinical supervision. How-

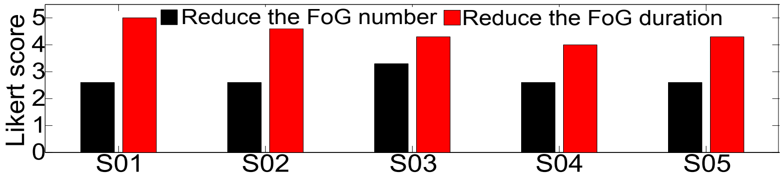


Figure 2.19: *The grades given for each of the 5 participants in the laboratory protocol on a Likert score from 1 to 5 on two statements, where 5 represents the maximum of agreement with the statement: (a) GaitAssist helps in reducing the FoG incidence, and (b) They system helps in reducing the FoG duration (Figure 7.7 from Chapter 7, page 234).*

ever, even in this realistic setting, GaitAssist obtained 4 out of 5 on a Likert-scale, regarding the comfort of use and wearability.

2.4.4. Impact on the Gait: Subjective Perception vs. Measured Effect

Previous analysis shows that GaitAssist was well received by its users, who stated it increases their confidence during walking, and that is suitable for PD subjects with FoG. We study whether the subjective perception correlated with a measured effect on the gait during training with GaitAssist. In the following, we analyze (a) a real-time reaction to the cueing during the walking sessions in the first in-the-lab validation, and regarding (b) a preliminary short-term impact on the gait during different training days during the at-home study.

(a) Reaction to Real-Time Cueing upon FoG. In the laboratory validation (Chapter 7), all 5 participants stated that GaitAssist supports them during FoG. Figure 2.19 shows their subjective perception with respect to whether the cueing upon gait freeze helps in reducing the number of FoG events, and reduce their duration. Answers on a Likert-scale show that the system supports in decreasing the FoG duration, while not helping in decreasing the FoG number.

To validate the subjective analysis, we measured FoG duration statistics during each individual walking task of the 3-day in-the-lab protocol, for each subject, from the groundtruth labels provided by clinicians. We compare the FoG average duration of the first half of each walking task, with the average duration in the second half, to

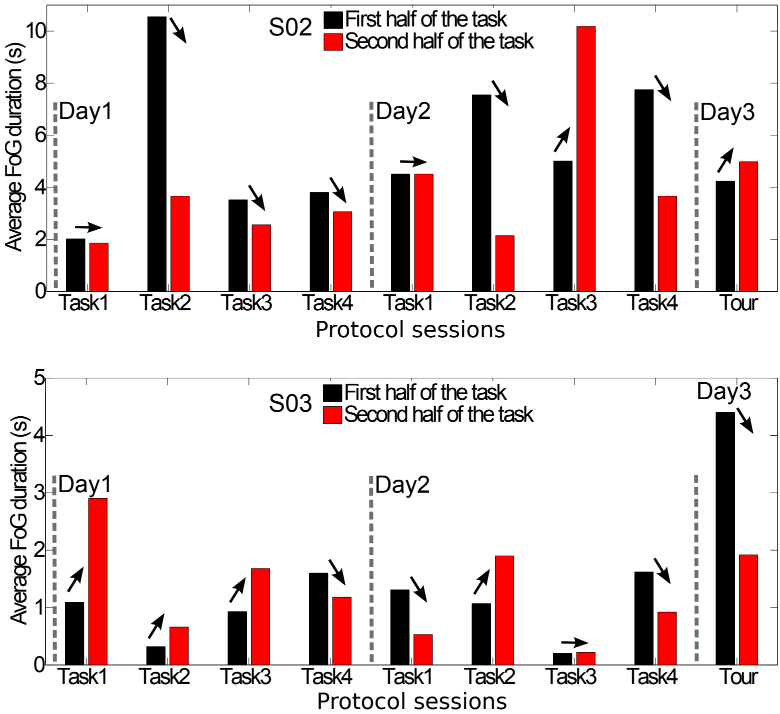


Figure 2.20: *A comparison of the average FoG-duration for the first half and the second half of each walking task in the 3 protocol days, for subjects S02 and S03 in the laboratory trial (Figure 7.8 from Chapter 7, page 237).*

observe whether the user learns to react to the system's rhythmic cueing, and can use the RAS to resume walking. Figure 2.20 contains the reported FoG averages per each session in case of two subjects, S02 and S03, from the 5 participants in-the-lab protocol. For the other 3 the number of FoG were not sufficient to perform the analysis. In case of S02, the FoG duration decreases in the second half of the training session, compared with the FoG duration of the first half, in 7 out of the 9 tasks. It suggests that S02 learns how to follow the RAS, thus the use of GaitAssist might help in decreasing the FoG duration. The decrease in 7 out of 9 protocol tasks of the FoG duration correlates with the subjective score given by S02 related FoG duration decrease statement in Figure 2.19. In case of S03, only for 5 out of 9 protocol tasks, the FoG duration decreases during the second half of the task, although the subject subjectively reported that the FoG duration decreased with using GaitAssist, as shown in Figure 2.19.

The subjective scores and objective FoG-duration driven statistics on the two subjects suggest a positive real-time reaction to the GaitAssist rhythmic auditory stimulation, leading to a decrease in the FoG duration while using the system, but not a decrease in the FoG number.

(b) Preliminary Short-Term Impact on the Gait. In the following, we study how the FoG duration and FoG number changes with respect to the gait-training protocol in the homes of the subjects (Chapter 8). We analyze the data from inertial wearable sensors of GaitAssist, collected during the 1 week trial from the 5 participants from Israel. The subjects followed the same walking protocol during the 3 days of the study. We investigate whether there are any trends in the number and duration of detected FoG while advancing in the trial days, in two different settings: (1) while using the system for gait-training exercises, and (2) when using GaitAssist as an assistive device during daily-life activities. We compute and compare the following FoG-related statistics: (a) The total number of FoG as detected by GaitAssist, and (b) the FoG duration distribution, in each of the three days, for each of the protocol parts, gait training exercises and daily-life activities.

As the at-home protocol was not video recorded, due to its complex settings and privacy issues, we consider the output of the FoG-detection module from GaitAssist, to compute the FoG-related statistics. The system provides the number of FoG episodes synchronized with the time, and for each FoG event its duration. The system obtained robust performances when tested in-the-lab settings, as shown in Section 2.4.2. Moreover, FoG detection using wearable sensors is used as an objective assessment of the FoG in the clinical practice [69].

Figures 2.21 and 2.22 report the number of FoG detected episodes and their duration distribution for each day of the protocol, in case of the gait-training exercises part. Only for one subject out of 5 – PD4 – the number of detected FoG decreases as the training progresses. For the rest of four subjects there are no consistent changes regarding the variation of FoG number. The FoG-duration distributions show a constant decrease in the FoG median, mean and standard deviation with the progression of training day, in case of 3 out of 5 subjects (PD1,

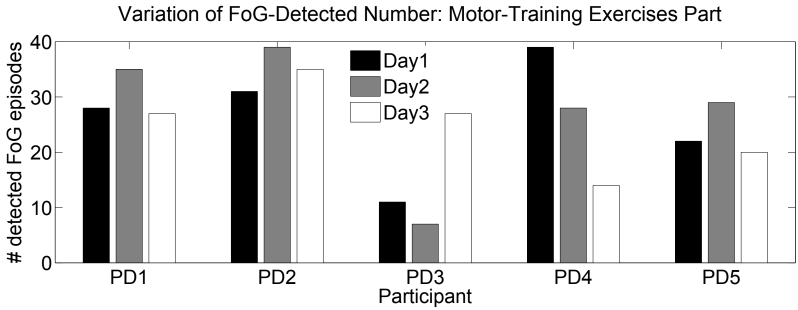


Figure 2.21: *FoG number trends for gait-exercise protocol part, over all three days for each of the 5 participants (Figure 8.9 from Chapter 8, page 285).*

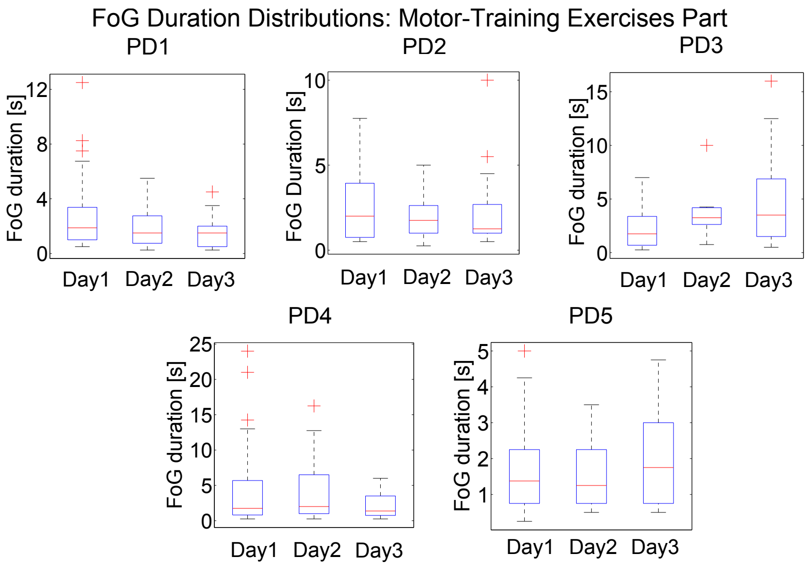


Figure 2.22: *FoG-duration distributions for each of the three training days for each of the 5 participants, during the exercise sessions of the protocol. For PD1, PD2, and PD4 we observe an overall decrease in the detected FoG-duration distributions with the training day. For PD3 and PD5 the detected FoG-duration distributions tend to increase with training (Figure 8.10 from Chapter 8, page 286).*

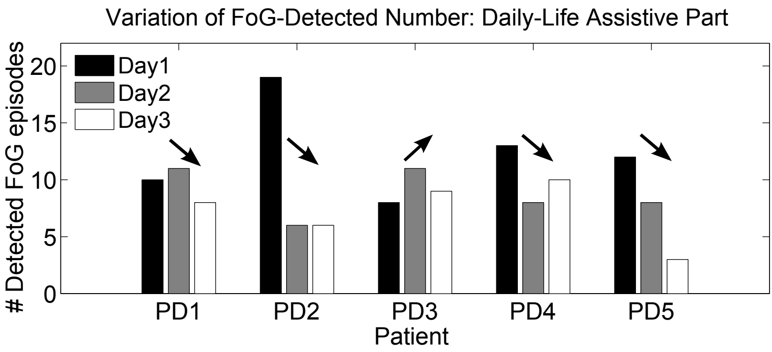


Figure 2.23: *FoG number variation over the three days for the assistive part of the study (Figure 8.11 from Chapter 8, page 288).*

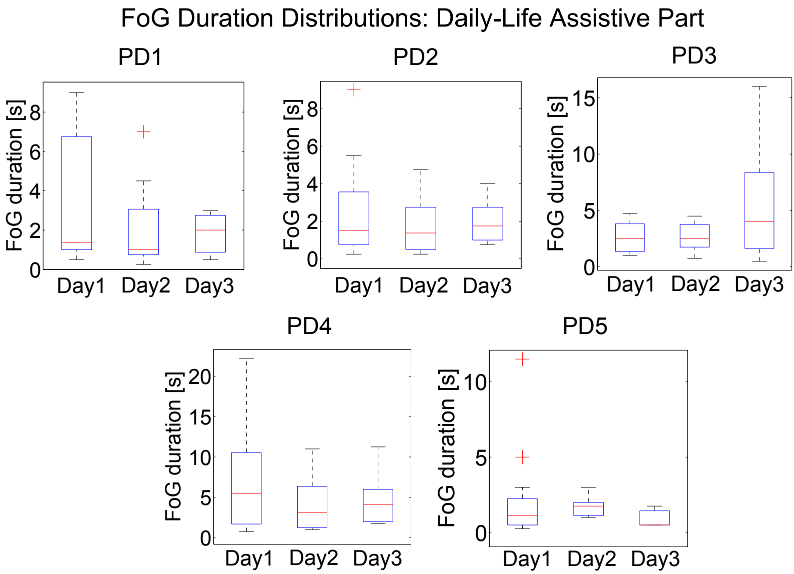


Figure 2.24: *Boxplots of FoG-duration distributions for each of the three training days for each of 5 participants, during the daily-life walking sessions of the protocol. For 4 out of 5 subjects, we observe an overall decrease in the detected FoG-duration distributions with the training day. For PD3 the detected FoG-duration distribution increases with training (Figure 8.12 from Chapter 8, page 289).*

PD2, and PD4). For the other 2 subjects, PD3 and PD5, the median and standard deviation of detected FoG increases with the training day.

Further, Figures 2.23 and 2.24 report the number of detected FoG and their duration distribution for each day of the protocol, in case of the daily-life walking protocol part. In case of 4 out of 5 subjects, except PD3, the number of detected FoG decreases with the protocol day. For the same subjects, the average and standard deviation of FoG duration decrease with the training day. Only for PD3, both FoG number and FoG duration increase with the training using GaitAssist.

Conclusion. GaitAssist's RAS upon FoG might help in decreasing the FoG duration, as resulted from both subjective perspective and data-driven experiments on two subjects in a laboratory setting.

Statistics on FoG number and duration from 5 participants from Israel in the at-home study show that the use of GaitAssist during training exercises has no impact on the FoG detected number, while the FoG duration distribution decreases for three out of 5 subjects. In case of daily-life activities part, for 4 out of 5 subjects both the number and the FoG duration distributions decrease with the protocol day. Both the training and assistive functions of GaitAssist have a positive effect on the gait performances, according to our preliminary analysis. Using the system as a support for daily-life walking tasks had a visible effect in decreasing both FoG number and duration. This might be due to the fact that the gait-training function requires performing complex and FoG-provoking exercises, compared with the usual daily-life walking in the home.

Both the positive feedback from participants and the suggested preliminary short-term positive effect on gait for 4 out of 5 subjects in the at-home study, recommend GaitAssist as a suitable tool to support, or even replace, the motor-training sessions in clinics with an unsupervised gait-training exercises delivered at-home. Besides training support, GaitAssist can be used as an assistive device during daily-life activities in habitual settings.

2.5. Conclusions

We investigate the use of wearable sensors to automatically detect and predict freezing of gait in Parkinson's disease, and develop a wearable assistant for the treatment of FoG and gait training in naturalistic conditions. We draw the following conclusions from the achieved contributions summarized in Sections 2.1 to 2.4:

- We collect a FoG multimodal sensing dataset in naturalistic settings, from subjects in ON medication state. The multitude of wearable sensors are a rich information resource for getting deeper insights on the unknown gait-freeze phenomenon [78].

- Activity recognition framework and supervised machine learning methods are robust to perform automatic real-time detection of freezing of gait, from sensors capturing the human movement. By using ML methods with acceleration data, we could detect FoG with 0.93 sensitivity and 0.99 specificity in a subject-dependent validation in a laboratory setting (DAPHnet dataset), and 60% of FoG events detected with 0.94 specificity in a subject-independent validation in a naturalistic setting (CuPiD dataset). The most accurate movements to express and automatically detect FoG, independent of the validation setting or dataset, are captured by sensors mounted on the ankles.

- We characterize freezing at the gait level from upper limb movements, and automatically detect FoG with C4.5 models and data from inertial measurement units mounted on the wrist from CuPiD dataset, with 0.89 FoG hit-rate and 0.81 specificity, in a subject-dependent evaluation setting.

- We propose, investigate and evaluate diverse features to extract from on-body acceleration to capture common FoG characteristics, independent of subject: (1) domain-specific, expert-based knowledge features, (2) time-series and statistical features, and (3) unsupervised extracted features. The top informative features to automatically detect FoG are the unsupervised extracted information, followed closely by the FoG domain specific features. The gait characteristics during FoG might not be *visible* to an expert eye, while they can be discovered via deep-learning feature extraction methods.

- We define and model the *prediction of freezing of gait* problem using information from on-body attached sensors. In a first analysis, we study the gait deterioration with up to 6 seconds prior to FoG from lower-body acceleration. By modeling FoG prediction as a 3-class activity-recognition model, FoG can be predicted with a 0.40 F-measure, in a subject-dependent validation setting on DAPHnet dataset. Although for some subjects in DAPHnet, the prediction rate increases up to 0.60 in F-measure, the main conclusion is that the current proposed features to detect FoG from movement information are not sufficient to predict it, at least in the case of DAPHnet data.

- We analyze the physiological changes captured with on-body mounted ECG and SCR sensors. Experiments show specific signatures of the ECG- and SCR-based features, in the window with 3 seconds prior to FoG. We model FoG prediction as an anomaly detection problem, and by using Multivariate Gaussian Models with SCR-based features we are able to predict 71% of FoG in CuPiD dataset, with an average prediction time of 4.2 seconds prior to a FoG.

- We develop GaitAssist, a wearable assistant for gait training and automatic real-time detection of FoG from on-body inertial units. In an in-the-lab feasibility study with 5 subjects, the system could detect in real-time 99 out of a total of 102 FoG episodes, with a detection latency ≤ 0.5 seconds, and 27 false events. The system received high acceptance grades on a Likert-score from a total of 14 subjects wearing the system in a laboratory setting or in their homes.

- Preliminary evidences from a laboratory study with 5 subjects show that subjects might learn to respond in real-time to the rhythmical cueing given upon FoG detection. Moreover, initial results from 5 subjects in real-life at-home protocol show that in case of using the system as an assistant during daily-life walking, for 4 out 5 subjects both number and duration of detected FoG decrease across the protocol days. In case of using using the system as support for gait training exercises, the duration of detected FoG decrease with the training day, for 3 out of 5 subjects. The preliminary analysis recommends GaitAssist as a suitable tool to support the treatment of FoG in Parkinson's disease with gait training methods.

2.6. Limitations

We demonstrate the successful employment of wearable sensors to automatically detect and predict FoG, and the use of a wearable system to support gait-training and FoG treatment in naturalistic settings. Nonetheless, we identify the following limitations of our findings:

- **Detection of FoG.** Although feasible, the FoG-detection implemented in the GaitAssist system leaves room for improvement. The current approach does not take into account the changes in the walking during the day related to the medication state, and it is not adaptive to each user gait particularities. The training data for the FoG detection classifiers were collected in a laboratory setting, even if naturalistic, where not all the gait events during daily-life were taken into account. As a result, some false detected events are due to the lack of some activities in the training data, such as sit-to-stand, or stand-to-sit. However, the issue can be solved easily, by collecting a larger amounts of training data containing diverse gait events. Moreover, FoG detection from wrist movements is feasible if the subject uses the upper limbs only for the gait synchronicity. Activities such as carrying a glass of water, or using the phone, and hand gestures harm the FoG recognition from upper limb movements.

- **Prediction of FoG.** In case of modeling FoG prediction as an anomaly in the physiological information such as ECG and GSR, there might be other factors, different from FoG, which generate anomalies in physiological data. Subjects in our analysis did not suffer from heart of mental diseases that could affect the study. Heart disorders symptoms could cause a sudden increase in the heart rate and heart rate variability, and mental disorders symptoms could affect the skin conductance response. Moreover, the transition from one human activity to another, such as walking to running, or biking, or sudden movements can affect the physiological signal. These real-life factors might harm the FoG-prediction performances.

- **Wearable FoG-assistant.** Although the ankle-attached sensors were well accepted by subjects, and received high acceptance grades, patients overall expressed their preference for another on-body position to wear the wearable, e.g., near the pocket, or on the wrist. Moreover, the running time of the system's components (up to max. 4 hours, and average 2 hours) limits the use of GaitAssist as a whole-day assistant, making it more suitable for as a support for gait-training exercises, and as a tool to assess FoG in both clinical and naturalistic settings.

- **Effect on the gait.** In-the-lab and at-home user studies report positive trends in terms of decreasing the FoG duration and even number when using the wearable FoG assistant. However, the drawn conclusions are preliminary, not statistically significant, and act only as a suggestion, due to the narrow number of subjects analyzed in both studies (5 patients in-the-lab study, and 5 subjects in the at-home study). Moreover, both feasibility studies targeted a short-term training with the system, i.e., three sessions over 1 week. Thus, there are no evidences of a long-term impact of the use of a wearable FoG assistant over the gait.

2.7. Outlook

In the following, we present some directions which extend the findings presented in this thesis:

- **Adaptability.** To build detection and prediction models, and even to evaluate them, we used limited amounts of FoG-related data, captured in naturalistic in-the-lab settings. To make detection and prediction more robust, and specific to each subject gait or even subject context, one can use sensor data collected during the usage of the FoG assistant. Real-time collected data is not labeled with groundtruth information. Semi-supervised, unsupervised and adaptive learning methods deal with the lack of labels. By using the collected data from sensors, one could update or re-build the FoG detection or prediction models to adapt in real-time to a new user, new context or to changes in the gait or in the physiological state.

- **Multimodality and context.** In this thesis we focus on detection and prediction of FoG from a variety of sensor information, yet used alone. One could monitor diverse observations related to FoG together, i.e., gait parameters degeneration from inertial sensors, physiological changes from ECG or SCR, and brain activity with fNIRS, to develop models to detect/ predict FoG. Moreover, the human context or the walking context could contribute as a feature in assessing the risk of FoG.

- **Long-term effect on the gait.** Preliminary analysis reports a positive effect on the gait when using the FoG-aware system as both gait training and assistive device, on a limited number of subjects and short period of training, i.e., 3 days across one week. There is a need of a sensor-based data driven analysis to investigate the effect on the gait in a long term clinical study at the patients' home, with a statistically significant number of subjects.

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3

Real-Time Detection of Freezing of Gait with Machine Learning Methods

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Online Detection of Freezing of Gait with Smartphones and Machine Learning Techniques

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Abstract

Freezing of gait (FoG) is a common gait deficit in advanced Parkinson's disease (PD). FoG events are associated with falls, interfere with daily life activities and impair quality of life. FoG is often resistant to pharmacologic treatment; therefore effective non-pharmacologic assistance is needed. We propose a wearable assistant, composed of a smartphone and wearable accelerometers, for online detection of FoG. The system is based on machine learning techniques for automatic detection of FoG episodes. When FoG is detected, the assistant provides rhythmic auditory cueing or vibrotactile feedback that stimulates the patient to resume walking. We tested our solution on more than 8h of recorded lab data from PD patients that experience FoG in daily life. We characterize the system performance on user-dependent and user-independent experiments, with respect to different machine learning algorithms, sensor placement and preprocessing window size. The final system was able to detect FoG events with an average sensitivity and specificity of more than 95%, and mean detection latency of 0.34 seconds in user-dependent settings.

3.1. Introduction

3.1.1. Freezing of Gait in Parkinson's Disease

FoG is a gait impairment common among patients with PD. According to a survey of 6620 PD patients by Macht et al. [18] 47% of the subjects reported regular freezing (28% experienced FoG daily). FoG is associated with falls [3, 17] and has substantial clinical and social consequences [10, 19]. FoG is defined as a "brief, episodic absence or marked reduction of forward progression of the feet despite the intention to walk" [23]. Patients describe FoG as a feeling of having the feet glued to the ground and being temporarily unable to reinitiate gait. Episodes last between a few seconds and up to one minute [29]. While FoG can appear everywhere, it happens most often during turns, before gait initiation, in tight quarters such as doorways and in stressful situations [6, 10, 30]. Treatment of PD patients with Levodopa reduces the FoG frequency during the ON state of medication, but like most gait deficits in PD patients, FoG is often resistant to pharmacological treatment [3].

A common non-pharmacological therapy for FoG is rhythmical auditory cueing [13]. In recent years, the option of using rhythmic auditory stimulation (RAS), e.g. with a metronome that provides a rhythmic ticking sound has gained support. RAS supports the patient to return to a more normal gait pattern. Unfortunately, the effectiveness of RAS wears off with time, so permanent cueing is not advised [7, 22, 28]. For this reason, context-aware cueing systems are proposed where the auditory signal only starts in response to the occurrence of FoG. Patient interviews in a preliminary study by Bächlin et al. [2] suggest that context-aware cueing may help to overcome freezing and re-initiate gait. The challenge in context-aware cueing is to reliably detect FoG episodes online using unobtrusive wearable sensor systems.

3.1.2. Mobile Phones as Wearable Assistants

A context-aware cueing system should be wearable and unobtrusive to the users as they have to wear it during daily-life activities. Recently, smartphones have evolved into a standard equipment in daily life due to their unobtrusive design. In addition, they are relatively cheap and offer high computational power. Therefore, smartphones are an interesting alternative to dedicated hardware in medical applications requiring wearable assistants. Users do not have to buy additional hardware as they often already possess a smartphone. Smartphones were, for example, used as assistants in fitness monitoring [5], heart rate monitoring [1], gait recognition [21], or to promote wellbeing [16]. Another example is the *iPhone* application *iFall* by Sposaro and Tyson [31], which uses the internal acceleration sensor for fall detection. In addition, modern smartphones offer a large number of internal sensors, including accelerometers, gyroscopes and magnetometers. A survey on mobile phone sensing is presented in [15]. To our knowledge, mobile phones have not yet been used in the context of online detection of FoG in PD.

Here, we propose the use of smartphones as a wearable device for FoG detection and perhaps treatment. This has several significant merits: *(1)* Economical – a FoG detection system on a smartphone will be economically beneficial compared to dedicated hardware [2]. *(2)* User friendliness – subjects with PD are typically older adults, a population that usually assimilates new technologies more slowly. However, it may hold that either this or the next generation of elderly people will be sufficiently familiar with smartphone technologies to adapt its use as a wearable assistant. *(3)* Tele-Medicine aspects – one of the future uses of automated detection of FoG provides the treating physician with information on the FoG symptom burden. Having the FoG-detection device built in on a tele-communication platform has obvious advantages with respect to transfer of data from the patient to the clinic. *(4)* Social – a patient will feel more comfortable moving around with a smartphone, rather than a dedicated device that may draw unnecessarly attention from their social environment.

3.1.3. Machine Learning for Analysis of Motion Data

FoG stands out as a typical motion pattern that is visually distinguishable from normal gait and has a unique frequency range. For example, when using wearable devices, motion patterns can be analyzed using acceleration features of body-mounted sensors. If sufficiently discriminative features are used, different motion patterns have different feature-space representations. In simple tasks where a low number of features is discriminative, decision boundaries can be set manually. This however becomes very tedious if the feature space is of high dimensionality.

Machine learning, on the other hand, offers methods for automated setting of decision boundaries, even in higher-dimensional problems. In contrast to manual thresholds, these boundaries are optimal in terms of decision accuracy for a set of training data. When sufficient training data is available, machine learning will outperform manual thresholding. Examples for successful application of machine learning methods to acceleration data are particularly abundant in the field of activity recognition [26], where activities such as running, walking or opening a door were detected using machine learning techniques with features computed from motion data. FoG is not an intentional movement but can be seen as a specific activity in the context of activity recognition. Thus, the analytical techniques applied for activity classification may be applicable to FoG detection.

3.1.4. Contributions

The goals of this work are *(1)* to improve the FoG-detection performance by using machine learning techniques and *(2)* to deploy the final system on a smartphone as an unobtrusive and inexpensive wearable assistant.

To reach this goal, we performed the following steps:

- We evaluated several machine learning algorithms on a real FoG dataset [2] in terms of FoG-detection accuracy and FoG-detection latency (the delay between a FoG start and its detection by the system).

- We performed experiments to optimize the FoG-detection accuracy and latency with respect to sensor placement and sensory-data window size. As a result of this optimization we propose a combination of machine learning algorithm, sensor location and window size that will achieve favorable results in terms of performance and detection latency, while considering the system's wearability and minimizing computational costs.

- Based on the previous evaluation steps, we built a system for online FoG detection using a smartphone and wearable sensors. The resulting Android application uses external accelerometers for FoG detection, but could easily be extended to use the internal smartphone sensors instead. The system provides auditory feedback whenever FoG is detected.

3.2. Related Work

Han and colleagues [12] made a first attempt to detect FoG episodes in PD patients by monitoring body acceleration using a 3-axis accelerometer. Freezing appearances were detected offline, by analyzing the differences in the recorded signals between freezing and normal gait. Moore et al. [20] analyzed offline accelerometer data from the left shank collected in a study with 11 PD patients. They observed high frequency components in the 3–8Hz band of the leg movement during FoG episodes that were not apparent in normal gait or volitional standing. Their algorithm obtained up to 89% accuracy and sensitivity for FoG detection. Delval and collegues [8] collected data from PD patients wearing goniometers, monitored while walking on a treadmill. They obtained a sensitivity of 75 – 83% and specificity above 95% for FoG detection by analyzing the frequency representation of knee joint signals. However, in all of these studies the FoG detection was done offline, so it is not actively helping the PD patients.

Bächlin et al. [2] developed a system for online FoG detection based on the algorithm of Moore [20]. The system contained three 3-axial accelerometers and a wearable computer. It was able to detect FoG episodes in user-dependent settings with a sensitivity of 88.6%, a specificity of 92.4% and a maximum latency of 2s. Whenever FoG was detected, the system provided a metronome ticking sound as feedback to the patient. The FoG-detection results were promising, but there is space for improvement. Also, manual adjustment of algorithm parameters was necessary to achieve optimal results. With machine learning, a patient-specific FoG-detection model can be built automatically and without need for manual parameter optimization.

Another online FoG-detection system based on the algorithm by Moore was presented by Jovanov et al. [14]. Using a 3-axis accelerometer and a wearable computer they detected FoG with an average latency of 332ms and maximum latency of 580ms. However, they do not provide information regarding the detection accuracy.

That machine learning techniques are helpful when analyzing motor fluctuations of PD patients was shown by Bonato et al. [4] and Patel et al. [25]. However, to the best of our knowledge, no one applied machine learning to the problem of FoG detection so far.

3.3. System Overview

In this section we present our system for online detection of FoG episodes (Figure 4.1(a)). First, we describe the hardware components and explain how data from sensors is collected and processed in real-time. In the second part, we describe the online FoG-detection application that runs on top of our wearable system.

3.3.1. Mobile Platform

The proposed wearable assistant is composed of: *(1)* up to three external sensors, which could easily be replaced with the internal sensing platform of the mobile phone and *(2)* a smartphone as the wearable computer.

Similar to [2] we make use of the NTMotion:AccGyro sensors described in [27]. From the available sensor data, we utilize the wirelessly transmitted 3-dimensional acceleration data. The physical dimensions of the sensor node are 25 x 44 x 17 mm^3 and the weight is approximately 22g. On-board is a 300mAh Li-ion battery that lasts 6 hours per charge. Although the sensors are capable of sampling at up to 256Hz, we set the sampling rate to 64Hz for the purposes of this work, to match the FoG dataset sampling rate.

Figure 3.1: *The FoG-detection system.*

In contrast to the dedicated hardware in [2], we utilize the Nexus One smartphone as a wearable computer. Specifically, we implemented an application on top of the Android platform that acts as the hub of the system. In addition to gathering internal accelerometer readings, our application communicates with multiple NTMotion sensors simultaneously via Bluetooth. We ported an existing sensor reading acquisition software – Java Bluetooth Gateway[1] – for the Android platform. As a modular component, the sensor communication and packet parsing functionalities were implemented separately as a helper class which sends acceleration readings to our Android application. Together with the data of the phone's internal accelerometer, these readings are piped into a queue for window-based classification.

The contents of the queue are read at fixed time intervals (e.g. 1s) for pre-processing of the raw acceleration data. The stream is segmented into windows. Features are computed for each window and sensor axis. For this work, we compute 4 time-domain features (mean, variance, standard deviation and entropy), the signal energy and the two features proposed in [2] and [20] for FoG detection. See Table 5.1 for further details.

[1] http://code.google.com/p/javabtgateway/

Feature	Description
Mean	The DC component (average value) of the signal in the window
Standard Deviation	Mean deviation of the signal compared to the average in the window
Variance	The square of the standard deviation
Entropy	Measure of the distribution of frequency components
Energy	Sum of the squared discrete FFT-component magnitudes of the signal, divided by the window length for normalization
Freeze Index	Power of the freeze band (3–8Hz) divided by the power in the locomotor band (0.5–3Hz) as used in the FoG-detection algorithm from [20]
Power	The sum of the power in the freeze and locomotion band – this feature was used by Bächlin et al. to distinguish volitional standing from FoG [2]

Table 3.1: *Extracted features with symbols and brief descriptions.*

3.3.2. Online FoG Application

The online FoG-detection application has two components (Fiure 3.2): A FoG-detection classifier, built offline on a base station, and the real-time FoG-detection app on the smartphone. The two parts are explained as follows:

- **Offline**: The FoG-detection classifier is trained offline with previously collected data (from the same patient or from different patients). Data for offline training must be labeled, i.e. we need to know for each window whether it is a member of the FoG class or not. As a first (optional) step, we perform a feature selection to choose the most discriminative features for distinguishing FoG from normal gait. For this work, we used Correlation-based Feature Subset Selection as described in [11]. Only the selected features are then used for classifier training with supervised machine learning techniques from the Weka data mining suite [32]. The classifier is serialized and ported to the smartphone using the Weka serialization API. The data structure representing the

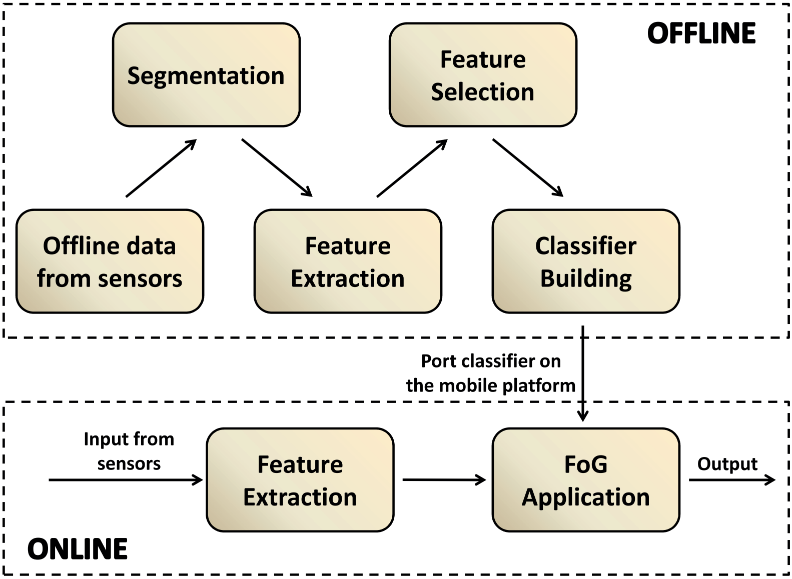

Figure 3.2: *The classification process for the Android online FoG detection application.*

classifier is converted to byte format and stored in a file, which is then copied to the mobile-phone application resources. Since this building and serialization process is performed offline on a computer, there are no additional costs in terms of latency and computational power for the wearable system.

- **Online**: In the online phase of the process, the Android app uses the de-serialized classifier built in the previous step to detect FoG events in real-time from sensor data. We use a modified version of the Weka API for Android[2] to de-serialize and use the classifier. The FoG-detection application calls the sensor communication module to get the last recorded data, pre-processes it to extract the necessary features and passes them to the classifier. When a FoG event is detected, the application provides feedback to the patient. Depending on the patient's preferences and favor-

[2]https://github.com/rjmarsan/Weka-for-Android

able response in terms of gait rehabilitation, this can be an RAS signal (metronome ticking sound) or vibro-tactile feedback (i.e. the smartphone vibrates).

The application respects the patient's privacy by not saving collected sensor data. It is built as an Android service, meaning that the user can start and stop the application anytime. It runs in the background and therefore does not interfere with the use of other applications on the smartphone.

3.4. System Evaluation

3.4.1. Dataset

We tested our system on the DAPHNet dataset [2], the result of a study carried out by the Laboratory for Gait and Neurodynamics, Department of Neurology, Tel Aviv Sourasky Medical Center (TASMC). The DAPHNet dataset contains data collected from 10 PD patients that experienced regular FoG in daily life. Data was recorded using three 3D-acceleration sensors attached to the shank (above the ankle), the thigh (above the knee) and to the lower back of each subject. The sensors recorded at 64Hz and transmitted the acceleration data via a Bluetooth link to a wearable computing system that was located at the lower back of the subjects.

Patients completed two sessions of 10-15 minutes each. Both recording sessions consisted of three walking tasks:

- Walking in a straight line, including 180-degrees turns.
- Random walking in a reception hall space, including a series of initiated stops and 360 degrees turns. Subjects should stop or turn in different directions.
- Simulating activities of daily living (ADL), which included entering and leaving rooms, walking to the kitchen, getting something to drink and returning to the starting room with a cup of water.

Motor performances varied strongly among the participants. While some subjects maintained regular gait during nonfreezing episodes, others walked slowly and very unstable. Overall, 8h and 20 min of data were recorded. To label FoG episodes in the data set, synchronized video recordings were analyzed by physiotherapists. The start of a FoG event was considered when the gait pattern (i.e., alternating left-right stepping) was arrested, and the end of a FoG was defined as the point in time when the pattern was resumed. In total, 237 FoG episodes were identified (23.7±20.7 per patient). The duration of FoG episodes was between 0.5s and 40.5s (7.3±6.7s). 50% of the FoGs lasted for less than 5.4s and 93.2% were shorter than 20s.

3.4.2. Experiments and Evaluation

We evaluated different sensor placements, window lengths and machine learning algorithms in terms of detection accuracy and latency in user-dependent and user-independent experiments.

For supervised machine learning we tested the following algorithms: Random Trees (RT), Random Forests (RF), decision trees and pruned decision trees (C4.5), Naive Bayes (NB), Bayes Nets (BN), k-nearest neighbor with one neighbor (KNN-1) and two neighbors (KNN-2), Multilayer Perceptron (MLP), boosting (AdaBoost) and bagging with pruned C4.5 trees as base classifiers.

The reference for all our evaluations is the video annotation provided by physiotherapists in the DAPHNet dataset. The detection performance is based on window evaluation, i.e. for each window the classifier output is compared to the reference annotation. Windows that are correctly labeled as FoG are counted as *True Positive (TP)*. We define as *False Positives (FP)* the FoG detections in episodes where physiotherapists did not identify FoG. *False Negatives (FN)* are windows where the system failed to detect FoG during FoG episodes in the reference. The remaining windows are correctly labeled as no FoG and are therefore *True Negatives (TN)*.

We measure the *Sensitivity* ($Sens = \frac{TP}{TP+FN}$), which represents the proportion of correctly detected FoG windows to the total of reference FoG windows. The *Specificity* ($Spec = \frac{TN}{TN+FP}$) measures the proportion of correctly detected no-FoG windows to all reference no-FoG windows. Additionally we report *F1-measure* and *area under the curve (AUC)* in the ROC space [9] as performance measures to evaluate our system. The F1-measure takes into account the precision ($Prec = \frac{TP}{TP+FP}$) and recall rate (identical to specificity) for each class (in our case the FoG class and the *null*- or no-FoG class).

Furthermore, we evaluated the algorithms in terms of latency, which is the time delay between the start of a FoG episode in the reference and the start of a detected FoG episode by the application.

	1s window				4s window			
Classifier	**Sens (%)**	**Spec (%)**	**F1 (%)**	**AUC (%)**	**Sens (%)**	**Spec (%)**	**F1 (%)**	**AUC (%)**
Random Forest	**97.7**	**99.7**	**98.3**	**99.8**	**99.54**	**99.9**	**99.7**	**99.9**
C4.5	93.4	99.3	95.9	97.4	98.4	99.8	99	99.3
Näive Bayes	48	98.6	73.6	93	41.8	99.7	71.1	95.3
MLP	77.4	97.2	82.9	95.8	84.9	98.6	91.1	98.4
AdaBoost with C4.5	**98.3**	**99.7**	**98.3**	**99.8**	**99.6**	**99.9**	**99.7**	**99.9**
Bagging with C4.5	97.5	99.5	97.6	99.8	99.4	99.9	99.5	99.9

Table 3.2: *Average Sens, Spec, F1 and AUC for different machine learning algorithms, for 1s windows and for 4s windows.*

3.5. Evaluation Results

3.5.1. User Dependent

In user-dependent experiments, both training and testing data are from the same patient. We performed 10-fold cross validation using feature selection and classification methods enumerated in Subsection 3.4.2 for each patient data from the DAPHNet dataset. We report comparative results on average performance measures on the whole dataset for RF, C4.5, NB, MLP, boosting and bagging methods, in case of window lengths of 1s and 4s. The 4s-window results are presented for comparison with the state-of-the-art FoG detection system in [2], which also uses 4s windows. Best results were obtained with boosting of pruned decision trees and RF. The use of such large windows increases the latency of online FoG detection, therefore we investigated shorter windows as well and report results for window length of 1s. Detection performance was only slightly decreased for 1s windows (98.35% sensitivity and 99.72% specificity for boosting of pruned decision trees).

Compared to [2], that report results of 88.6% sensitivity and 92.4% specificity for patient-dependent experiments with window length of 4s, we obtained better performances with all tested machine learning algorithms, except Naïve Bayes and Bayes Nets. This was expected, as machine learning techniques offer more possibilities to explore the data properties (i.e. computation of more features, selection of most discriminative features, automatic setting of decision boundaries). The results are slightly biased due to the random selection of training and testing data in 10-fold cross-validation, which may lead to selection of subsequent and therefore correlated samples to both subsets. Since FoG episodes of a single user are anyway correlated and have similar feature-space representation, we assume that this bias is small. However we will address the issue in future work.

According to the results presented in Table 3.2 the best performances were obtained by AdaBoost (with pruned C4.5 as base classifier) and Random Forest classifiers. Comparing the ensemble methods, we observed that boosting classifiers obtain slightly better performances than bagging classifiers. However all the ensemble methods tested (boosting, bagging, Random Forests) obtain better results than the single classifiers.

All results were obtained using 10-11 features on average (10.3 features for 1s windows and 11.6 features for 4s windows, selected from the 63 features computed in the pre-processing step). The most discriminative features, regardless of sensor location, were the mean and standard deviation as time-domain features, and the physiological features – freeze index and power computed as in [2].

For all further experiments we selected C4.5 and RF as classification algorithms. Pruned C4.5 was chosen because of its simplicity and still good detection results and RF for its very good detection performances.

3.5.2. Latency Results

As mentioned before, we refer to latency as the time between a FoG episode starts and the time when the system detects it. Here, we only discuss the latency which is inherent to the machine learning algorithm with corresponding window size. We neglect further delays caused by sensor data transmission, pre-processing and feedback generation, assuming that these contributions are small.

Figure 3.3 shows a section of the acceleration signals of Patient 02 with the ground truth annotation (FoG or normal gait) and the FoG-detection results of our system. We observe that the system detects FoG episodes shortly after the FoG event starts.

The system's latency depends on the classification algorithm chosen and on the sampling window length used. Table 3.3 depicts the latency results for patient-dependent experiments with 1s and 4s win-

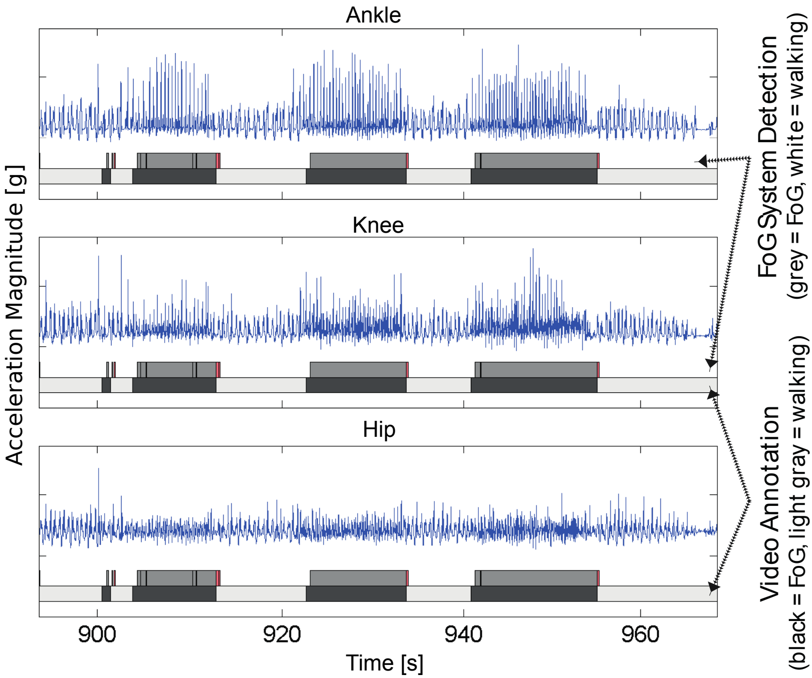

Figure 3.3: *A signal extract from Patient 02 using data from ankle, knee and hip sensors, together with the ground-truth labels and the FoG-detection-system labels.*

dow lengths and two types of classification algorithms: pruned C4.5 and RF. There is a trade-off between performance of the detection algorithm, in terms of sensitivity and specificity, and the detection latency. While RF obtains better performances for FoG detection than C4.5 trees, the detection latency is higher. Figure 3.4 shows that with C4.5 most FoG episodes are detected shortly after their start. For RF classifiers, FoGs are typically detected after approximately half the window length. However, the differences are small and the maximum latency for 1s windows in all experiments was only 0.718s. We further discuss the latency results and the relation to window size in Section 3.6.

Window	Classifier	Mean (s)	Std (s)	Max (s)
1s	C4.5	**0.235**	0.175	**0.578**
	RF	0.346	0.169	0.718
4s	C4.5	**1.085**	0.731	**2.016**
	RF	1.653	0.59	2.047

Table 3.3: *Latency results for patient-dependent experiments.*

3.5.3. User Independent

The online FoG-detection system was also evaluated using leave-one-patient-out cross validation. The classifiers were trained on features selected from $N - 1$ subjects and performance was tested on the remaining subject. We report results for RF classifiers only, because of lack of space. As in the previous set of experiments, we performed feature selection on the data before training the classifiers. Again, mean, standard deviation, freeze index and power were the most frequently selected features. For 1s-window experiments, we report 62.05% sensitivity and 95.15% specificity. For 4s-windows, the results slightly improved – 66.25% sensitivity and 95.38% specificity. In [2], the proposed system obtained 73.1% sensitivity and 81.6% in the same 4s-window-based evaluation. However, the algorithm from [2] allowed for 2s tolerance after the start of a FoG episode, which explains the slightly better sensitivity results.

The comparatively poor results for user-independent FoG detection are a result of the large variability in motor performance, caused by different walking styles among subjects of the DAPHNet study. In this case, training classifiers on general data does not always result in good performances when tested on a specific subject. For some patients the general classifier worked well, e.g. for Patient 09 where window-based sensitivity was 98.19% and specificity 91.17% with 26 out of 27 FoG events detected (mean latency of 0.41s), for others the general classifier failed (e.g. for Patient 01 where sensitivity was 20.53% only). Bächlin et al. approached the problem by dividing the patients in two groups (smooth walkers and intensified stepping walkers) with individually optimized thresholds and thus improved detection results in user-independent experiments [2]. In future, we plan to apply transfer learning techniques [24] to improve the user-independent performance of the system.

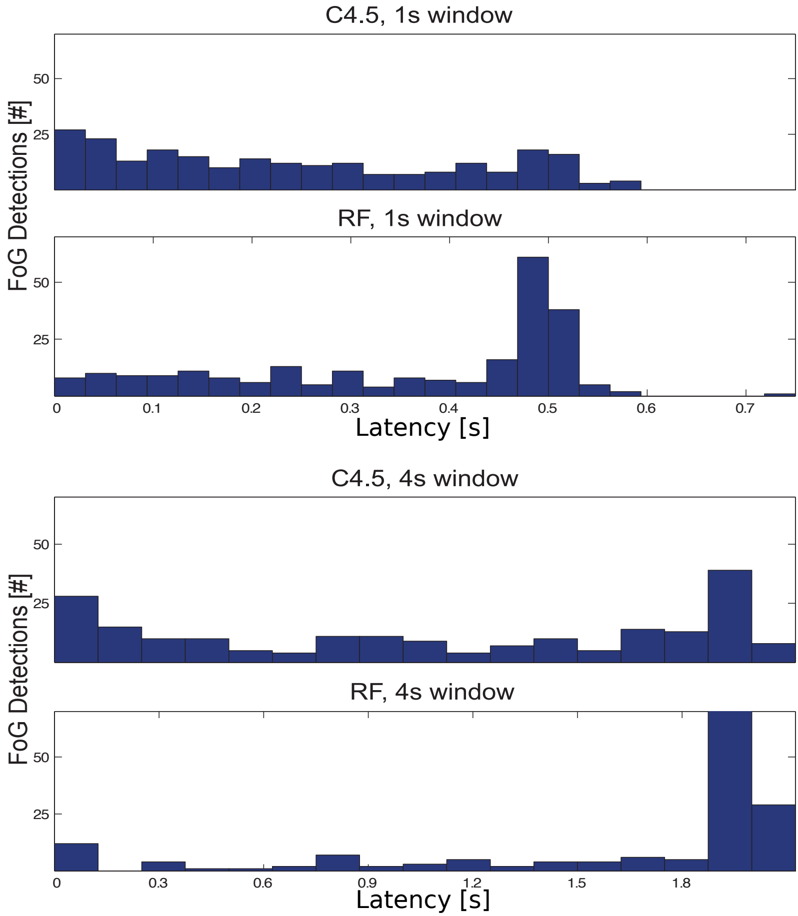

Figure 3.4: *Histogram indicating the correlation of detection latency between the FoG start and the moment of detection.*

3.6. Performance Optimization

3.6.1. Sensor Placement Characterization

In this subsection, we analyze the FoG-detection performance with respect to different sensor placements and orientations. Our goal is to determine the best sensor location taking into account the trade-off be-

Axis	x	y	z	x & y & z
Ankle				
Sens	92.65%	89.18%	91.85%	98.21%
Spec	99.26%	98.84%	99.02%	99.76%
Knee				
Sens	89.36%	87.71%	88.58%	97.94%
Spec	98.86%	98.80%	98.80%	99.73%
Hip				
Sens	88.81%	83.68%	90.77%	98.63%
Spec	98.77%	98.26%	99.02%	99.83%

Table 3.4: *Detection performance vs. sensor placement.*

tween wearability of the system and the detection performance. There are visually obvious differences between the signals from different sensors. For example the signal of the sensor at the hip is more damped than the signal of the sensor at the ankle. Still, the leg motion is visible at both locations (Figure 3.3).

From all 63 features, only a subset of features extracted from a single sensor and a combination of sensor axes was used as input to feature selection and classification for this experiment. Table 3.4 shows results for 12 combinations of three sensor positions (ankle, knee, and hip) and four combinations of the sensor axes (horizontal forward axis x, vertical axis y, horizontal lateral axis z, and features extracted from all the three axes together x *&* y *&* z). Evaluation results in terms of sensitivity and specificity are given for 1s windows in patient-dependent experiments, for C4.5 and RF classifiers. We present and discuss the RF results only, but the observations also apply for C4.5.

As expected, the best results were achieved when using features collected from all three axes of the sensors. When using data from a single sensor, best results in terms of both sensitivity and specificity were obtained for the hip sensor. However, the performances for the three positions did not differ much. Taking into account only a single axis resulted in slightly lower detection performance.

These findings are promising as they indicate that *(1)* a single sensor is sufficient for FoG detection and *(2)* this sensor can be placed at a convenient location for the patient. Even the use of internal sensors of a smartphone placed in the pockets of a patient is possible, making the system even more wearable and patient-friendly.

3.6.2. Performance vs. Window Length Optimization

The latency of the online FoG-detection system is a function of the window length used for feature extraction. We analyzed the potential of window length optimization by plotting *(1)* the FoG-detection performance in terms of minimum between sensitivity and specificity versus window length, and *(2)* the detection latency versus window length. We measured average sensitivity, specificity and latency for C4.5 and RF classifiers in user-dependent settings, for window sizes from 0.5s to 8s, in steps of 0.5s. Further we detail only the results obtained with RF classifier (Figure 3.5), C4.5 results having similar properties.

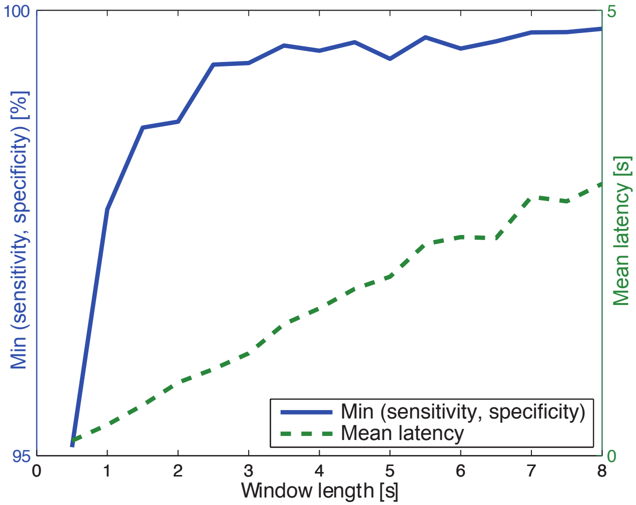

Figure 3.5: *FoG-detection performance and detection latency vs. window length, for RF classifiers.*

When increasing the window up to a maximum length of 3s the detection performance increases. For larger windows, noise in the computation of features is reduced, leading to better discrimination between FoG events and normal gait. For window lengths above 3s the window size has no significant influence on the detection performance. The mean latency of FoG detection increases linearly with the size of the windows. A good trade-off between latency and detection performance is reached for window lengths of 1s.

3.7. Discussion

Following the detailed algorithm evaluation presented in the previous sections, we chose C4.5 and RF classifiers to be used in the smartphone application. Pruned C4.5 classifiers are small, easy and quick to port to the smartphone. Also, they obtain good results in terms of FoG-detection accuracy and latency. On the other hand, RF is more complex, but offers even better FoG-detection performance.

For feature extraction we chose a window size of 1s, which is a satisfying trade-off between detection accuracy and latency. Regarding the system components, experiments showed that a single accelerometer is sufficient for FoG detection and various locations (ankle, knee and hip) result in similar performances. Therefore, the current system uses only a single body-worn acceleration sensor together with the smartphone as the wearable computer. In future, the possibility of replacing external sensors with smartphone sensors will be investigated.

The algorithms presented in this paper worked much better in user-dependent experiments. Patients using this system will therefore need to record a short training set with expert supervision for labeling of FoG episodes. The classifier is then trained offline and without any additional user input.

The system provides RAS or vibro-tactile feedback whenever FoG is detected. To reduce the number of single false positive windows, which would cause a start of cueing even though no FoG is present, we applied a median filter to the raw classifier output. This increases the detection latency, but is necessary to reduce the number of “false alarms". Using a 31-sample median filter, we detected 100% of the 237 FoG episodes in the DAPHNet dataset with only 9 false alarms. For a 15-sample median filter 58 false positive events were found.

3.8. Conclusion

We proposed a system for online FoG detection with wearable accelerometers and a smartphone using machine learning techniques. The system provides feedback to the patients whenever a FoG event is detected. To our knowledge, this is the first time that machine learning algorithms were used to detect FoG episodes online. Our system was capable of detecting all FoG events (237 out of 237 events in the DAPHNet dataset) with an average window-based sensitivity of 98.35% and an average specificity of 99.72%. When comparing directly to the state-of-the-art system for online FoG detection [2], we obtain an average sensitivity of 99.69% and an average specificity of 99.96% compared to 88.6% sensitivity and 92.4% specificity for identical window size. Furthermore we were able to detect all FoG events with a mean latency of 0.34s (and a maximum of only 0.71s).

The analysis of different sensor locations showed promising results in making the system less intrusive and more wearable. The good results obtained with the sensor at the hip open the door to the use of the internal smartphone sensing platform for online FoG detection. Thus a mobile phone might be sufficient for assisting PD patients with FoG.

In the future we plan to build a user-independent FoG-detection algorithm that automatically adapts to the patient's specific gait using domain adaptation algorithms. Also, additional physiological and heuristic features might allow to better distinguish FoG from the many variations of Parkinsonian gait.

3.9. Acknowledgments

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4

Automatic Freezing of Gait Detection from Wrist Movements

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The Role of Wrist-Mounted Inertial Sensors in Detecting Gait Freeze Episodes in Parkinson's Disease
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Abstract

Freezing of gait (FoG) is a motor impairment among patients with advanced Parkinson's disease, associated with falls and negative impact on patient's quality of life. Detecting such freezes allows real-time gait monitoring to reduce the risk of falls. We investigate the correlation between wrist movements and the freezing of the gait in Parkinson's disease, targeting FoG-detection from wrist-worn sensing data. While most of research focuses on placing inertial sensors on lower limb, i.e., foot, ankle, thigh, we focus on the wrist as an alternative placement. Commonly worn accessories at the wrist such as watches or wristbands are more likely to be accepted and easier to be worn by elderly users, especially subjects with motor problems. Experiments on data from 11 subjects with Parkinson's disease and FoG show there are specific features from wrist movements which are related to gait freeze, such the power on different frequency ranges and statistical information from acceleration and rotation data. Moreover, FoG can be detected by using wrist motion and machine learning models with a FoG hit rate of 0.9, and a specificity between 0.66 and 0.8. Compared with the state-of-the-art lower limb information used to detect FoG, the wrist increases the number of false detected events, while preserving the FoG hit-rate and detection latency. This suggests that wrist sensors can be a feasible alternative to the cumbersome placement on the legs.

4.1. Introduction

Parkinson's disease (PD) is a neurological degenerative disorder with a worldwide prevalence of 16.1 million people [27]. PD is expressed by motor anomalies such as rigidity, tremor, reduced movement range and walking difficulties. Freezing of gait (FoG) is a common symptom experienced by more than 70% of patients at a later stage of PD [12] and described as a sudden incapacity to walk or move the lower limbs. With FoG lasting from few seconds up to 1-2 minutes [33], it carries the danger of falling, the main cause of mortality in Parkinson's disease [4, 11].

There is no cure at the moment for PD, medication being used to milden or temporary release the symptoms. Specifically for alleviating the FOG symptom the response to medical treatment is lowest. Clinical findings [9] suggest that rhythmic auditory cues such as metronome sounds help subjects with Parkinson's disease to shorten the gait freeze and to resume walking. However, continuous rhythmical cueing wears off with time [31], as the brain gets used to the sound and learns to ignore the cues. Thus, it is important to start the rhythmic cueing for a limited period of time of $8-10$ seconds, only during a gait freeze or when the subject has gait difficulties that might lead to freeze. Wearable solutions have been proposed to detect the FoG events in real-time [15, 30] and give a temporary rhythmic cue to help subjects resume walking, using data from wearable sensors such as accelerometers. The proposed wearable assistants use on-body motion sensors attached on the lower body of the user, e.g., on thighs, ankles, or even on lower back. This is natural, as the FoG anomaly itself is related to lower limbs. However, the acceptance of such on-body electronics on legs and lower back by elderly subjects is still an issue for human-computer interaction in healthcare due to the weight, bulkiness, and location of on-body sensors [47], in particular for people with motor deficits. Moreover, stigmatization is a barrier in accepting the wearable systems [34], as such technologies are usually visible on-body and can be easily perceived as *different*.

The emerging wrist bands or smartwatches incorporate inertial measurement units (IMU) and are promising to be integrated in healthcare wearable solutions, due to their design, common on-body placement, and radio connectivity with the mobile phones. A FoG wearable assistant using the sensors integrated in wristbands or watches and the personal phone is promising to be accepted by PD patients, given that a large number of population wears such wrist-attached devices in their daily-life.

Research focused on analyzing and detecting FoG from sensors attached on lower body [15, 26, 42]. But during walking, humans move their arms in tandem with their lower limbs [21]. Moreover, humans and in particular Parkinson's disease subjects suffering from FoG tend to not use their arms for other tasks during walking, as they pay attention on their gait and their next step. Thus, information from arms movement can be used for detecting gait freeze.

We investigate whether wrist motions during walking are correlated with freezing of gait, and furthermore, whether wrist-attached wearable sensors can be used to detect FoG episodes. For this, we search whether the wrist movements show typical properties during FoG which are different from the wrist movements during the normal gait. We extend the state of the art in the following three aspects:

(1) We propose, analyze and quantify new features extracted from IMU attached on the wrist to describe FoG. We use the information from the IMU attached on wrist in the CuPiD dataset [24].
(2) We report the performance results and discuss the feasibility of detecting FoG using wrist-attached IMU in both a subject-dependent and -independent evaluation schemes, using the FoG detection framework based on supervised machine learning as in [22].
(3) We compare the information from wrist motion against data from lower limbs to detect FoG. Furthermore, we discuss the trade-offs in terms of FoG detection performances, availability, and acceptance of using wrist or ankle-mounted inertial units to recognize FoG.

In this paper we first survey related studies (Section 4.2), and present the dataset used in our investigation (Section 4.3). In Section 4.4 we propose, describe and quantify new statistical and frequency features extracted from IMU to characterize freezing of gait. Section 4.5 details our findings on the use of wrist movements to detect FoG. In Section 4.6 we compare the use of upper limb versus lower limb data to detect gait freeze episodes, and discuss their trade-offs. We conclude our work in Section 4.7.

The current work is based and extends on our previous contribution [23]. In addition to prior findings, we add two new sets of experiments: We extend prior evidences of the most informative features from wrist movement for FoG-detection (Section 4.4), and compare and discuss the upper limb versus lower limb information regarding recognition performances and wearability (Section 4.6). Moreover, we complete the discussion over the FoG-detection performances using wrist-attached inertial measurement units (Section 4.5).

4.2. Related Work

In the following, we survey the state-of-the-art related to arm movement and freezing of gait, covering four different directions: *(1)* methods and sensors to detect FoG, *(2)* evidences of freezing in the upper limbs and the correlation with FoG severity in Parkinson's disease, *(3)* upper and lower limb coordination and their relation to Parkinsonian gait, and (4) application of wrist attached wearable devices.

Freezing of Gait detection. Several research groups have proposed methods and wearable systems for detection of FoG which require on-body accelerometers or gyroscopes [3, 6, 8, 15, 26, 30, 37, 42]. A standard feature extracted from acceleration signal is the *freezing index*, defined as the ratio between the power contained in the so-called *gait freezing* and *locomotion* frequency bands ($[3, 8]$ Hz and $[0.5, 3]$ Hz respectively) [26]. Other features involve entropy [42], time-domain and statistical features such as mean, standard deviation, and variance. However, all the FoG detection approaches except [42] require that the sensors are attached to the lower limbs, in order to analyze the gait properties. Tripoliti et al. [42] uses data from wrist sensors, but only in combination with data coming from sensors mounted on lower limbs. Cole and colleagues [6] use the electromyography information and acceleration from the forearm to detect whether the subject is upright or not, but for the FoG detection only the lower limb movements are taken into account.

Freezing and the upper limb movements in Parkinson's disease. Arm swing magnitude and upper limb movement asymmetry is used in assessing Parkinson's disease stages in general [18]. However, first evidences that *freezing* in Parkinson's disease is present also in the upper limb are given in [2, 49], where frequency analysis of wrist movements showed early occurrences of manual motor blocks in PD. Moreover, Vercruysse et al. [43] found evidence that upper limb *freezing* power spectra were broadened, with a gradual decrease in the movement amplitude and an increased energy in the gait freezing band. Findings of Nieuwboer et al. [32] show that freezing episodes in the upper limb are correlated with the FoG severity. The authors argue that gait freezing may be also elicited by an upper limb task, showing that bi-manual coordination deteriorates before a freeze of the upper limb. Even if there are evidences of freezing at the level of the arm, wrist and fingers in Parkinson's disease, these works do not study the correlation between *freezing of gait* synchronized with patterns in the upper limb movement. Therefore, we make a first attempt to analyze the arm movements during FoG and compare them with arm movements during walking including straight line walking, turns, or gait initiation, and human activities such as sitting and standing. Our aim is to find specific patterns in the upper limb during FoG episodes.

Upper and lower limbs coordination during gait. Upper limbs play an important role in human gait, early research showing that arm movements serve to maintain equilibrium during walking [19, 21, 46], creeping, and swimming [45]. Changes in coordination of arm and leg movements are used to identify differences in walking patterns or in the walking speed [44]. The upper limb movement dysfunction, for example the arm constraint, causes slowness in walk due to atypical coordination between upper and lower body movement [10]. We follow this observation, and in our experiments we extract features that characterize the arm movement and correlate them with the walking dysfunctions in Parkinson's patients.

Mahabier et al. [29] showed that patients with FoG have an asymmetry of interlimb coordination between the upper and the lower limbs during gait. This coordination deficit is present on both ipsilateral and contralateral arms and legs. Chomiak and colleagues [5] showed that concurrent arm swing-stepping induces limb incoordination and gait start hesitation in Parkinson's disease, which might lead to FoG during gait initiation. We make a step further, and study the interlimb movements during FoG episodes, and compare them with the interlimb features during the rest of walking, standing or sitting.

Wrist-attached wearables and their applications. The wrist is a promising place to attach a wearable sensor, compared with other body parts, such as foot, thigh or ankle. The emerging wearable wristbands or smartwatches which integrate inertial measurement units are easier to be accepted by new users, as their *integration* in the human daily-life was already done, e.g., humans are used to wear watches or jewelry at the wrist. Profita et al. [38] showed that the wrist is the optimal position to wear electronics and to interact with them, from the societal perception point of view. Moreover, wrist placement of electronics and wearables comes to solve issues such as stigmatization, bulkiness of wearable electronics, and privacy [1, 34].

Wrist-worn wearables integrate a plethora of sensing information, such as acceleration, movement angles, skin resistance, heart rate, electromyography, and GPS. These make them useful to monitor physical activities such as running [41], to recognize human activities [17, 40], self-harming activities [20], social gestures [35], and to recognize human emotions such as stress [16] or sleep patterns [28].

4.3. Dataset

To analyze the correlation of the upper limb motion with freezing of gait, we use the inertial measurements from the CuPiD dataset [24]. The CuPiD dataset contains multimodal sensor information collected

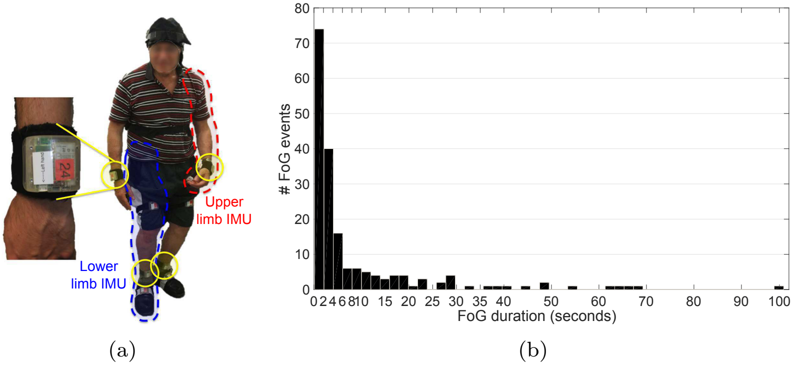


Figure 4.1: *(a) Subject wearing the system used in the dataset collection, with a focus on the IMUs attached on the wrists and on the ankles. (b) Histogram representing the distribution of FoG duration in the dataset.*

from subjects with Parkinson's disease who performed walking sessions designed to provoke FoG in a laboratory setting. The protocol included straight line walking with turns, walking along an eight shape, walking with random turns and changes in direction, the Ziegler protocol [48], all performed with and without cognitive load tasks. Additionally, subjects performed a real-life walking session which consisted in walking randomly along the hospital crowded hallways with voluntary stops, sudden changes of direction, and using the elevator. The protocol was completed with additional non-walking sessions, which required rest periods, sitting, standing, or discussing with clinicians.

Sensor information. We use data from the IMUs attached on both wrists and both ankles of the subjects, as shown in Figure 4.1(a). Wrist-attached IMUs are used to analyze the correlation between upper limbs movements and FoG, whereas ankle data represents the state-of-the-art source of information from the lower limbs to detect FoG episodes. Each IMU samples 3D accelerometer, 3D gyroscope, and 3D magnetometer data at 128 Hz. Sensor data streams are synchronized with video streams of the protocol.

FoG labels and data categories. Two clinicians labeled the freezing of gait episodes and other walking events such as gait initiation, turns and stops, using stopwatch annotations and videos synchronized with the sensor datastream. Labels were updated by also taking into account sensor data visualizations synchronized with videos. Clinicians considered the moment of arrested gait pattern, i.e., stop in alternating left-right stepping, as the start of a FoG, and the instant when the patient resumed a regular gait as the end of FoG.

Data is categorized in two classes: (1) *FoG* – which represents the information gathered during the gait freezing episodes, and (2) *Walk* – which is a heterogeneous class which incorporates all the data during walking events such as straight line walking, turns, gait initiation and voluntary stops, but also data gathered during other human activities such as sitting and standing. During the protocol subjects were asked to behave and perform the sessions as in their usual daily-life behavior. Thus, the walking class includes background activities such as gesturing with the arms when interacting with the clinician. Moreover, a particular walking session, the Ziegler protocol, required the subjects to open a door and during one performance to carry a glass of water. Thus, we attempt to find features from wrist-attached IMUs to distinguish FoG not only from the walking events, but from various human contexts which imply motion of the wrists.

Participants and statistics. In total, 18 subjects with Parkinson's disease and with a history of FoG participated in the study. They were between 49 and 89 years (average: 68.9 years, std: 10.2 years), and had a disease duration between 2 and 18 years (average: 8.8 years, std: 4.6 years). Subjects obtained diverse scores for the PD and FoG severity, being representative for 2-4 Hoehn & Yahr PD staging [13]. Some of the patients could not perform the entire protocol, due to their disease severity.

In total, clinicians labeled 184 FoG episodes from 11 out of 18 subjects, with a duration between 0.12 seconds and 98.8 seconds (average: 8.84 seconds, standard deviation: 14.87 seconds). The rest of 7 subjects did not encounter any gait freezing event during the protocol. We will further refer in the paper to the 11 subject datasets with FoG as S01 to S11. All subjects were in the ON state of medication during the protocol, to have a closer to outside-of-the-lab setting. During the ON state of medication, patients have a more natural gait, and the walking anomalies are not so evident. Thus, the low number of FoG episodes in Cupid, and the fact that some subjects even did not enter FoG during protocol.

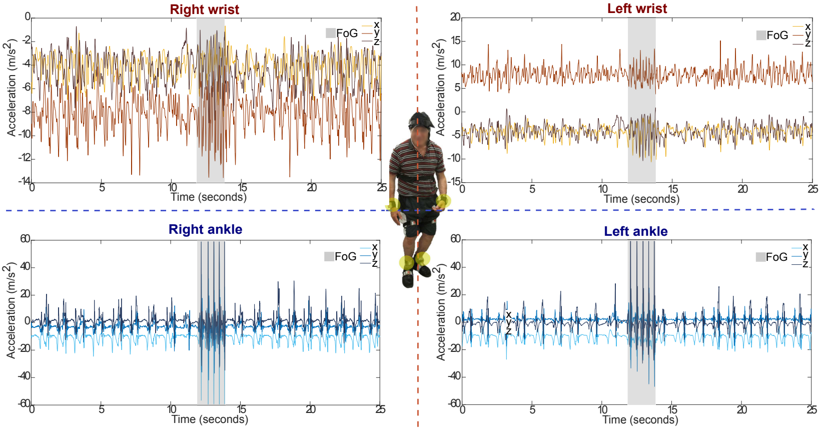


Figure 4.2: *A walking sequence with a FoG episode, as captured by the accelerometers mounted on different limbs. Ankle acceleration a distinguishable pattern on both right and left legs during FoG. In this particular case, we choose an example of a freezing characterized by strong trembling of the legs. Although not as visible as in the case of lower limb movements, wrist acceleration shows some particular patterns during FoG, especially on the left wrist.*

As observed in Figure 4.1(b) most of the FoG episodes are short, with approx. 38% of all events are ≤ 2 seconds, and 73% of them are ≤ 5 seconds. Their evanescent nature increase the difficulty of FoG-detection problem in real-time, as we need to find and extract features which incorporate FoG properties from these modest amounts of IMU representative data. Moreover, the two classes of data, *FoG* and *Walk*, are imbalanced, *FoG* category being underrepresented compared to the rest of walking events.

4.4. Wrist Movements During Freezing of Gait

The majority of studies which target FoG detection from motion look into leg movements [3, 8, 15, 22, 25], or lower back changes [3, 42]. This approach is intuitive, as the anomaly itself happens at the lower limbs level. However, in Figure 4.2 motion of the wrist seem different during FoG: We plot the synchronized acceleration during a walking sequence which contains a FoG episode from all the 4 body limbs. For this example we choose a very particular FoG type, characterized by visible festination steps. Usually, not all the freezing events have such distinguishable characteristics. During FoG, ankle acceleration shows a very particular and distinguishable pattern, compared with the rest of data. Acceleration even saturates, due to the wearable sensor capacity limits. Although not as visible as in the case of the ankles, the wrists accelerations capture patterns during FoG, even if they are different for the right and left limbs.

4.4.1. Wrist Features to Describe FoG

Previous visualization of the raw IMU data suggests that it might be possible to detect the gait freezing by using features of the wrist movement. Having in mind a real-time application for FoG detection with wrist-mounted sensors, we need to extract features from sensing data which describe FoG. Gait-specific features extracted from acceleration data, such as statistical features or FFT-based features such as *freezing index* [3, 22, 26, 42], are used to describe and detect in real-time the gait freezing episodes. However, these features require to have the sensors mounted on the lower body limbs, such as ankles or thighs. The first contribution of this work is to find and analyze new specific features from wrist mounted IMUs, which are related to and describe freezing at the gait level.

In Table 8.2 we list all the features we extract in a sliding-window manner from the wrist accelerometer and gyroscope data. We use a window size of $W = 3$ seconds, with a window-overlapping step of $S = 0.25$ seconds. The 3 seconds window is chosen as a trade-off between extracting the motion during FoG, and the latency of these observations: 73% of FoG events in the dataset are $\leq$ 5 seconds, while we aim to detect the onset of FoG, as soon as it starts. Prior to feature extraction, we compute the magnitude vectors from acceleration and gyroscope data from each window. We extract *statistical features* such as *mean* and *standard deviation* from both acceleration and rotation data, and frequency-based features from the acceleration.

In Figure 4.3, we plot a more detailed example, which contains a sequence of acceleration and rotation data from a wrist mounted IMU, with two freezing of gait episodes. We can visually spot and distinguish the FoG episodes from the wrist movements, without any help from the ankle movements. During walking the wrist movements tend to have a repetitive cyclic pattern, while during FoG we can observe an increase

#	Feature	Description
	Statistical features	
1-2	Mean	The average values over the acceleration and rotation magnitude vectors
3-4	Standard deviation (std)	The standard deviation values over the acceleration and rotation
	Frequency features	
5-20	$Power_{[0,1]Hz}$, ..., $Power_{[15,16]Hz}$	16 Frequency features computed from acceleration magnitude, each feature corresponding to the *power* on $[0,1]$ Hz, $[1,2]$ Hz, ..., $[15,16]$ Hz bands
21	$Power_{[0,4]Hz}$	Power on $[0,4]$ Hz band from acceleration magnitude (which includes the band of the human gait as in [26])
22	$Power_{[5,8]Hz}$	Power on $[5,8]$ Hz band from acceleration which is included in the so-called *freeze* band introduced in [26]
23	$Power_{[9,12]Hz}$	Power on $[9,12]$ Hz band from acceleration magnitude
24	$Power_{[13,16]Hz}$	Power on $[13,16]$ Hz band from acceleration magnitude

Table 4.1: *Features extracted from wrist mounted IMUs to describe FoG episodes.*

in the frequency of movement, suggesting a rapid trembling of the arms. Both mean and standard deviation from acceleration and rotation increase during or just prior to the FoG events compared with the rest of the session, during which acceleration and rotation magnitudes tend to remain constant. In case of frequency-based features, we observe higher values of the power on $[0,1]$ Hz, and on $[8,13]$ Hz during FoG. Similarly, power on $[5,8]$, followed by power on $[0,4]$ Hz and $[9,12]$ Hz increases during FoG compared with the rest of walking events.

Top Descriptive Features and Statistics

To have a deeper understanding of wrist motion during FoG and of which parameters are the most descriptive, we study the correlation

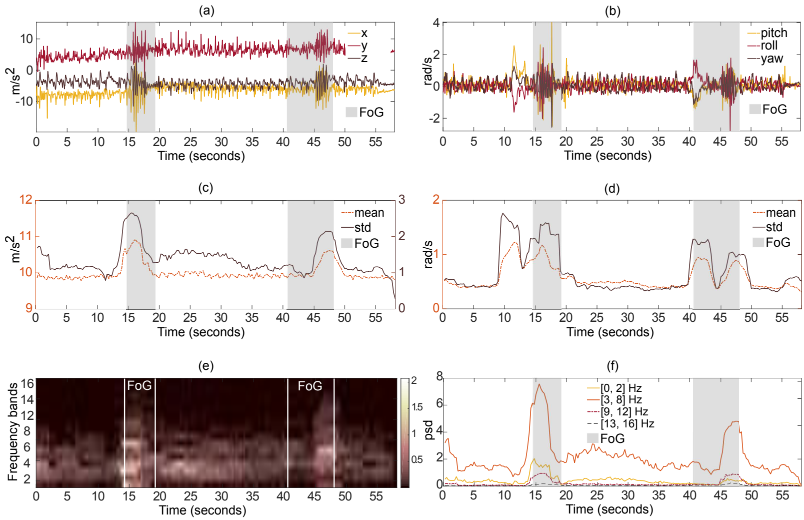


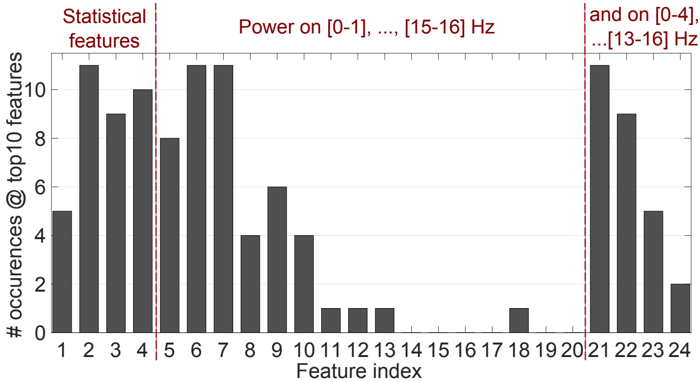
Figure 4.3: *An example of approx. 60 seconds of wrist motion data, which contains two FoG episodes during walking in straight line with turns from subject S06, expressed in different ways: (a) Raw acceleration data, (b) Raw gyroscope data, (c) Mean and standard deviation acceleration features, (d) Mean and standard deviation of rotation information, (e) Power vector on different frequency bands from* $[0, 1]$ *Hz to* $[15, 16]$ *Hz, and (f) Power values on* $[0, 2]$ *Hz,* $[3, 8]$ *Hz,* $[9, 12]$ *Hz, and* $[13, 16]$ *Hz. We observe that raw acceleration and orientation data are different during FoG episodes, and moreover the statistical and frequency features show distinguishable patterns of the upper limb during gait freezing episodes.*

between each of the extracted features and the two categories of data, i.e., *Walk* and *FoG*. We employ three methods to evaluate the similarity between the features' variations and the data categories: (1) mutual information scores, (2) Pearson correlation, and (3) the one-way analysis of variance. We use Mutual Information (MI) [36] and Pearson Correlation (R) to check whether there is a link between the observations from a feature related to *Walk* or *FoG* categories. MI is used for feature selection and data clustering [36], but here we use MI for feature ranking, to explore which of the features better captures differences between the 2 categories. Additional to feature ranking, we use One-way Analysis of Variance (ANOVA) [14] to show whether the variations of a feature across the two classes of movement are statistical relevant. We consider the p threshold set to $p = 0.001$.

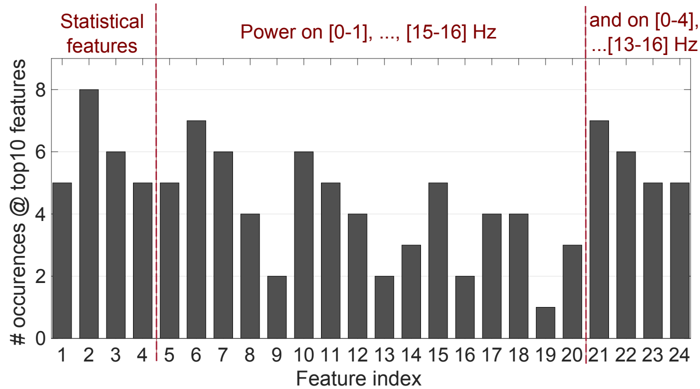
We compute the MI, R, and ANOVA scores for each of the 24 features, in two settings: (a) *patient-dependent*, and (b) *patient-independent*. (a) In case of the patient-dependent setting, we compute the similarity values for each of the 11 patients. We then make an over all ranking of which features occurred most frequently in top 10 in each of the 11 datasets. The top 10 features have the highest values in terms of MI values, or in terms of the absolute R scores. (b) In case of the patient-independent setting we compute the MI, R and ANOVA scores on the data from 11 patients gathered together. Then, we extract the top 10 features ordered by MI values or absolute R scores, respectively.

Figure 4.4 contains the histogram of the number of occurrences in top 10 of each feature across all 11 datasets, in a patient-dependent setting, ordered by MI values (Figure 4.4(a)) or R values (Figure 4.4(b)). In case of MI, the top most informative features across all subjects are the power on the first 6 frequency ranges $[0, 1], ..., [5, 6]$ Hz, along with the power from larger intervals $[0, 4]$ Hz, $[5, 8]$ Hz, and $[9, 12]$ Hz, as well as the statistical features from both acceleration and rotation. According to R values, the top features are more equally distributed in the histogram, yet they are mapping to the ones as in case of MI, with the observation that the power on different intervals such as $[6, 7]$ Hz, $[10, 11]$ Hz, $[12, 13]$ Hz or $[13, 14]$ Hz, and thus the power on $[13, 16]$ Hz can be added to the list of top informative features. Also in case of subject-independent setting, the same features show the highest variations between the corresponding classes.

However, even if the features enumerated before are the top most informative across the 11 subjects, they are not equally useful to describe FoG for each patient, and for some of the subjects they even do not contain any useful information at all. This is quantified by the MI and R values, backed by the ANOVA test. For example, in Figure 4.5 we plot the variations of 5 features selected from the list of most informative ones, as found in the previous paragraph, in case of three different subjects. For S07, all the features tend to have specific ranges for Walk and FoG categories, and this is confirmed by the MI or R values for each of them (except maybe for the power on $[5, 8]$ Hz), differences which are statistically significant ($p < 0.0001$ for all 5 features). In case of S05, the 5 selected features are among the top 10 most informative. Yet, the MI and R values are lower than for S07,



(a) Features ordered by MI scores.



(b) Features ordered by R scores.

Figure 4.4: *Histograms with the number of times each feature appeared in the top 10 features across all 11 patient datasets in a patient-dependent setting. Features are ordered by (a) MI scores, and (b) absolute Pearson correlation values. According to MI, statistical features extracted from both acceleration and rotation are showing the strongest overall variations between Walk and FoG categories. Moreover, the power extracted from the inferior frequency intervals incorporate strong differences between the data categories, along with the power on the* $[0,4]$ *Hz,* $[5,8]$ *Hz, and* $[9,12]$ *Hz frequency bands. In case of the Pearson correlation, the occurrences in top 10 features per patient tend to have an equal distribution. However, the features with most occurrences match the ones identified by MI.*

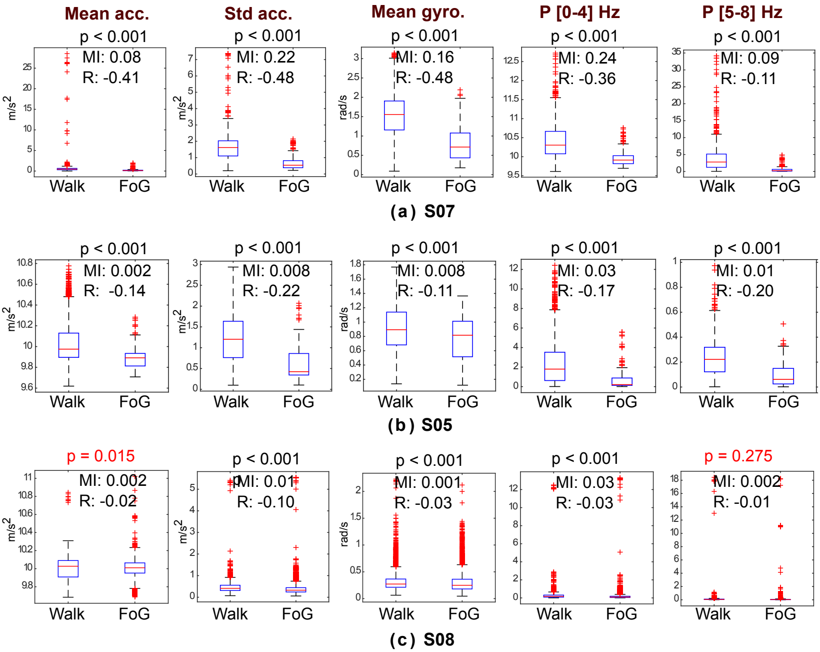


Figure 4.5: *Boxplots with the variation of top 5 most informative features for all 11 datasets (mean and std of acceleration, mean of gyroscope, power on* $[0, 4]$ *Hz, and on* $[5, 8]$ *Hz respectively) in case of three subjects: S07, S05, and S08. For the first two, the 5 features have different ranges for Walk and FoG categories, although they are not equally informative for both S07 and S05. On the other hand for S08, all 5 features, have visible overlaps between the Walk and FoG, as confirmed by the low MI and R values, and by ANOVA* $p > 0.001$*, which suggests their variations are not statistically significant across the two classes.*

suggesting higher overlap between Walk and FoG categories, although still statistically significant. Same as for S07, we can visually observe different ranges across the categories, for the mean and std acceleration, and for the power on $[0, 4]$ Hz and $[5, 8]$ Hz. In contrast with the previous two datasets, for S08 none of the presented features seem to incorporate informative changes between Walk and FoG, as suggested by the low values of MI and R, and moreover ANOVA $p > 0.001$ in case of mean acceleration and power on the $[5, 8]$ Hz.

Different trends in features across subjects. Even when discriminative, feature variations do not follow similar tendencies across different subjects: For example, we observe that in case of S07 and S05 wrist movements tend to decrease in intensity during FoG. On the other hand, in case of S08 the feature values slightly decrease during FoG, compared with the Walk class.

Overall, we observed two distinct trends in the wrist features for subjects in Cupid: (1) The statistical features and the power on ≥ 3 Hz bands increases during FoG, compared with Walk, on 4 out of 11 subjects (S01, S04, and S06). (2) The other pattern is a decrease of the statistical and frequency features overall during FoG, for 5 out of 11 subjects (S02, S05, S07, S09, and S11). In case of S03 and S08, the features do not show a clear increase or decrease during FoG.

We conclude that the most useful information about the wrist movement during FoG is given by the frequency features from acceleration, such as power on $[0, 1]$ Hz, ..., $[5, 6]$ Hz, and on larger intervals such as $[0, 4]$ Hz, $[5, 8]$ Hz, and $[9, 12]$ Hz, completed by the statistical information (average and standard deviation) from acceleration and rotation data. Even if the degree of usefulness is not equal across all 11 subjects, we choose in the following experiments to use these features for evaluating the potential of detecting FoG from wrist motion.

4.5. Automatic Detection of Freezing of Gait from Wrist Motion

To detect FoG episodes from wrist movement, we employ the same FoG-detection chain based on supervised machine learning methods as in [22]. We choose this as the FoG recognition chain obtained robust FoG detection performances both in offline validation on CuPiD dataset and real-time settings [22], when using information from ankle motion.

The FoG-detection framework is the following: Raw wrist IMU readings are separated into windows of 3 seconds with overlapping step of 0.25 seconds, from which features are extracted, as detailed in previous Section 4.4, together with the *FoG* or *Walk* labels set by clinicians. A total of 48 features, 24 features for each wrist, together with the label are added together in a feature vector. Combinations of the feature vectors are then used to train C4.5 classification models [39], to automatically distinguish between FoG and the rest of data.

Different from our previous work in [23], and following the findings from Section 4.4, we further present the FoG-detection results using only the top most informative features across all 11 datasets: power on the 6 frequency ranges from $[0, 1]$ Hz to $[5, 6]$ Hz, power on the three larger frequency intervals $[0, 4]$ Hz, $[5, 8]$ Hz, and $[9, 12]$ Hz, and the 4 statistical features – mean and standard deviation of acceleration and rotation. We evaluate the FoG-recognition performances in three cases: (a) using only right upper limb features, (b) using only left wrist features, and (c) using the features from both right and left limbs.

4.5.1. Evaluation Scheme

Similarly to the previous section, we evaluate the FoG detection performances in two settings: (1) subject-dependent, and (2) subject-independent. (1) For the subject-dependent, we evaluate the wrist movement features for each of the 11 subjects dataset separately. For each subject we consider a *leave-one-FoG-out* cross-validation evaluation scheme: We split the sensing data into sessions which contain in the center a FoG episode, and the remaining of the data in the session is composed from other walking episodes and human activities implying sitting or standing. Each of these sessions is then used as *testing data*, while the classification model is trained on the remaining available sessions. We repeat this procedure for all the sessions in the dataset. (2) In case of subject-independent cross-validation scheme, each subject dataset is considered as testing data, while the rest of subjects datasets are used to train the classification model. We repeat the procedure for all the 11 subjects.

4.5.2. Evaluation Measurements

For both evaluation settings we report the *FoG hit rate*, the number of the *false positive events*, the *specificity*, and the *detection latency*:

- The *hit rate* represents the number of correctly detected FoG events by the classifier, divided by the number of total FoG events. Different from previous work [3], which reports the window-based *sensitivity*, we consider FoG hit-rate a better a more realistic measure to express the FoG-detection performances, as it gives exactly the statistics we are interested in case of a wearable assistant for FoG-detection in real-time, of how accurately the FoG onset is detected, and not how accurate the detection is on a window-to-window comparison on the entire FoG duration. The reason is that such FoG-detection assistants [22] start a rhythmic cueing upon first time prediction of the FoG event, which continues up to 8 seconds after the last time the FoG is detected, in order to help the subjects resume the natural gait.

- The *false positive* events represent how many times the classifier detected a whole FoG event, while the groundtruth labels show no FoG for that period of time.

- For completeness, the *specificity* measures the proportion of correctly detected *Walk* windows to all reference *Walk* class windows, to give a hint over how much from the total amount of non-FoG data is incorrectly detected as FoG.

- In addition to the three classification performances, we considered the *FoG-detection latency* measure, defined as the delay in seconds between the start of a FoG episode as labeled by clinicians, and the first time the event is detected by the recognition algorithm.

Before reporting the *hit-rate* and *number of false positives*, we first pre-process the window-based output of the FoG-detection method: If the difference between two consecutive windows in which the classifier detected FoG is less than the window size $N = 3$ seconds, then the whole period is considered to be part of the same FoG event. Better FoG-detection performances are characterized by higher values of the FoG hit-rate and specificity, together with lower number of false detected events and lower duration of the FoG-detection latency.

Figure 4.6 shows the FoG-hit rate against the specificity for (1) the subject-dependent evaluation (each subject and mean over all 11 subjects) and for the (2) subject-independent setting, for all three cases of data. Table 4.2 reports the number of FoG per subject as labeled by clinicians, the number of false detected FoG events, and the overall detection latency for both subject-dependent and -independent evaluation schemes.

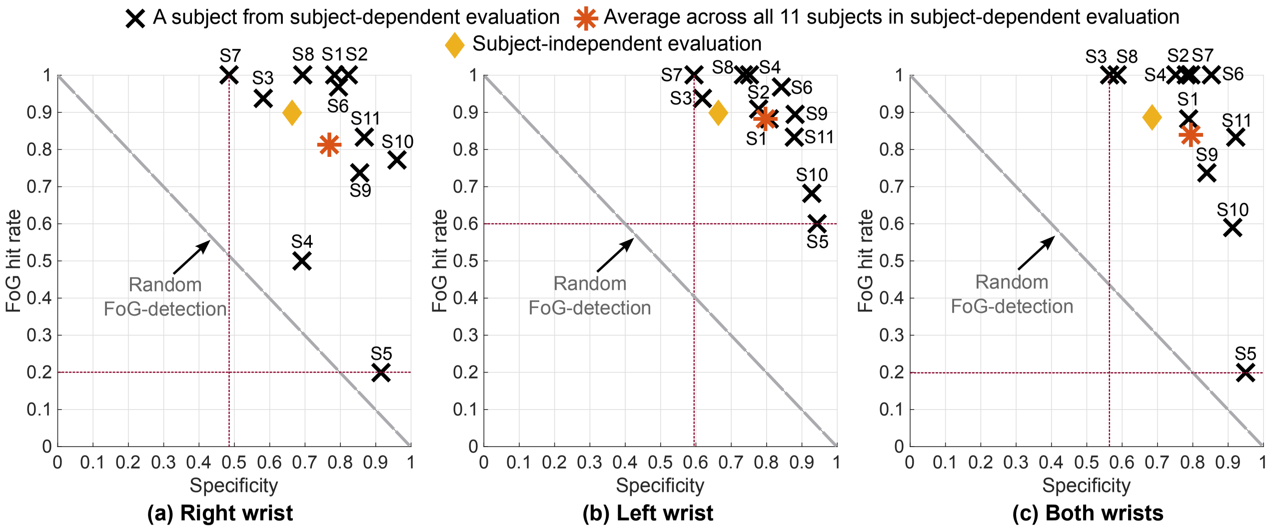


Figure 4.6: *Scatter plots reporting FoG-detection performances for three different scenarios: when using information from (a) right wrist, (b) left wrist, and (c) both wrists. Each scatter plot reports the FoG hit-rate against the specificity for each of the 11 individual datasets, the average across them for the subject-dependent evaluation, and the overall values for the subject-independent setting. We observe that in all three cases, the FoG-detection using wrist information outperforms the random classification. The hit-rate is slightly higher in case of subject-independent evaluation, while the specificity decreases compared with the average recognition of the subject-dependent setting.*

		# False Positives Events			Averaged Latency (seconds)		
Subject	**# FoG**	**Right**	**Left**	**Both**	**Right**	**Left**	**Both**
# Subject-Dependent Cross-Validation							
S01	19	27	20	25	1.13	1.13	1.25
S02	11	14	15	15	1.13	0.62	0.93
S03	22	11	11	12	0.45	0.25	0.90
S04	2	4	0	0	0.5	0.5	3
S05	5	8	8	8	0	2.08	0
S06	37	14	14	17	0.47	0.42	0.38
S07	4	2	1	1	0	3.5	3
S08	27	37	35	24	1	1.08	0.66
S09	24	23	22	21	1.1	0.92	0.76
S10	27	24	32	35	1.73	1.63	1.61
S11	6	7	10	9	3.5	3.2	2.4
Overall	184	171	168	167	1	1.37	1.35
# Subject-Independent Cross-Validation							
Overall	184	218	214	219	1.04	0.80	1.28

Table 4.2: *The total number of FoG from groundtruth labels, the number of false positive events, the average FoG-detection latency across each of 11 subjects, and their overall average, in three cases: (a) when using the right wrist motion, (b) when using left wrist, and (c) information from both wrists. The performance values are reported for both subject-dependent and -independent evaluation settings.*

4.5.3. Subject-Dependent Evaluation

FoG recognition performance. Overall the average hit-rate across all 11 datasets is between 0.81 and 0.83, with an average specificity of 0.76–0.79 across all three scenarios. Moreover, from Figure 4.6 we observe that FoG-detection performances using wrist movement outperform the random FoG-detection results, in case of all individual datasets, suggesting that wrist motion is correlated with FoG.

However, the recognition rates are not linear across the 11 subjects: High FoG detection performances are obtained for datasets S01, S02, S06, S09, and S11, for which more than 75% of FoG episodes are correctly detected, with high specificity > 0.85. On the other end is S05, with low FoG recognition rates (0.2 to 0.6), although the specificity is > 0.9. An explanation is that for this subject the wrist motion during FoG tend to be similar with the motion patterns during other walking and human activities events. The low number of FoG did not seem to affect the FoG-recognition performances, except in case of S05, with only 1 or 3 out of 5 FoG events detected.

All FoG events are recognized in case of 6 subjects (S02–S04, S06–S08) when using information from both wrists. However, the high FoG detection rate comes at the cost of false positives: for 6 out of 11 subjects (S01, S02, S05, S08, S10 and S11) the number of false positives is higher than the number of correctly detected FoG episodes. These suggests that for some subjects, wrist motion during FoG is not specific only to gait freeze. However, overall the total number of false positives across all 11 subjects varies between 167 and 171, being comparable with the total number of FoG events, i.e., 185 across all subjects.

FoG recognition latency. The average FoG-detection latency varies between 1 second (for right wrist data) up to 1.37 seconds (when using information from the left wrist only). This small average latency is promising, given that FoG are short episodes and they need to be detected during their onset, to help the subjects resume walking via auditory rhythmical cueing. More than 73% of freeze events in the CuPiD dataset are longer than 5 seconds, thus the overall detection latency from wrist movements would be sufficient to start in real-time the rhythmical cueing and support subjects to resume walking.

Most informative wrist. The left wrist movement data seems to be the most informative for capturing FoG in the case of the CuPiD dataset: In 8 out of 11 subjects, the best results are obtained using left wrist information, while only for three of them (S02, S03, and S11), the right upper limb movement was most informative. Both specificity and FoG hit-rate are higher than 0.6 in case of the left wrist data, whereas when using right wrist or both wrists information the variation across subjects are higher, with lower recognition limits.

Using data from both wrists does not necessarily come with major improvements over using information from one wrist, as the combination between both right and left data also increases the noise. Thus, it is sufficient to use motion data only from the most informative hand to detect FoG. Most of the people are wearing their watches attached on their left wrist, and clinical evidences show FoG usually starts and is more preeminent in one part of the body [4]. Therefore real-time out-of-the-lab FoG recognition is a promising future application for the inertial measurement units integrated in commercial wrist-attached wearables.

4.5.4. Subject-Independent Evaluation

In case of subject-independent evaluation, the FoG hit-rate is higher with up to 0.03 - 0.07 than the average FoG hit rate of the subject-dependent setting. However, the specificity decreases with 0.04 in case of right wrist and up to 0.11 when using information from both wrists.

We also observe an increase in the total number of false positive events, as shown in Table 4.2, with 46 up to 52 more false events detected, depending on the used information. FoG-detection latency decreases compared with the subject-dependent evaluation, being approx. 0.5 seconds faster when using left wrist information. Same as for subject-dependent cross-validation, the left wrist movements obtain the best detection performances in terms of highest FoG hit-rate, lowest number of false positives and lowest detection latency.

The drop in specificity is expected when using data from different subjects. As suggested in Section 4.4, subjects react differently and tend to have different arm movement patterns during freezing of gait (for 4 of them features increase during FoG, while for 5 of them they decrease). Thus, a subject-independent model comes with an increase in the number of false alarms, due to the subject-specific reactions in the arm motion during gait freezing. However, the increase in the false alarms comes with an increase in the FoG hit-rate in the subject-independent evaluation, and is further associated with and overall decrease in the detection latency, when using data from the left or from both wrists.

4.6. Wrist vs. Ankle Information for FoG Detection

Most of the methods and wearable systems which detect FoG in real-time from inertial measurement units use the lower limbs movement information or the lower back [3, 6, 15, 26, 37, 42]. From all, the ankle showed to be the most informative position to describe and detect gait freeze [3, 22]. In this section we compare the wrist motion with the information captured from the ankles, in order to get the trade-offs of using upper limb information in wearable FoG-assistive technologies. We use the inertial measurement units from both ankles on the same 11 subjects.
As the framework to evaluate the FoG-detection performance from wrist information is similar as the one used in [22], we apply the same steps and the same parameter values to evaluate the ankle information: a window of $W = 3$ seconds, with a window-overlapping step of $S = 0.25$ seconds. We employ C4.5 detection models as used in [22] and in the current work. In case of using ankle data, we extract from each window of acceleration magnitudes the following features as in [22]: (1) the power on the *locomotion band* $[0.5, 3]$ Hz, (2) the power on the *freeze band* $[3, 8]$ Hz, (3) total power on $[0.5 - 8]$ Hz, and the (4) *freeze index* defined in [26] as the ratio between the power on the *freeze band* and the power on the *locomotion band*.

Similar as in the case of upper limb evaluation, we consider three cases of information for detecting FoG from lower limbs: only data from the right lower limb, only data from left lower limb, and information from both ankles. In addition, we use combinations of upper limb and lower limb data to detect FoG: one wrist and one ankle, and one wrist and both ankles.

To evaluate the FoG-detection from combinations of ankle and wrist data, we use the same evaluation schemes as in Section 4.5 for wrist IMU data: (a) subject-dependent cross validation for each of 11 datasets, and (b) subject-independent cross validation for all 11 users. We report the same performance measures as detailed in Section 4.5, for each of the data combinations.

Figure 4.7 and Table 4.3 detail the FoG-detection performances in case of subject-dependent evaluation for the following cases: (a) when using data only from a wrist, (b) when using information only from one ankle, (c) combining the information from (a) wrist and (b) ankle, and (d) combining the information from the wrist in (a) with information from both ankles.

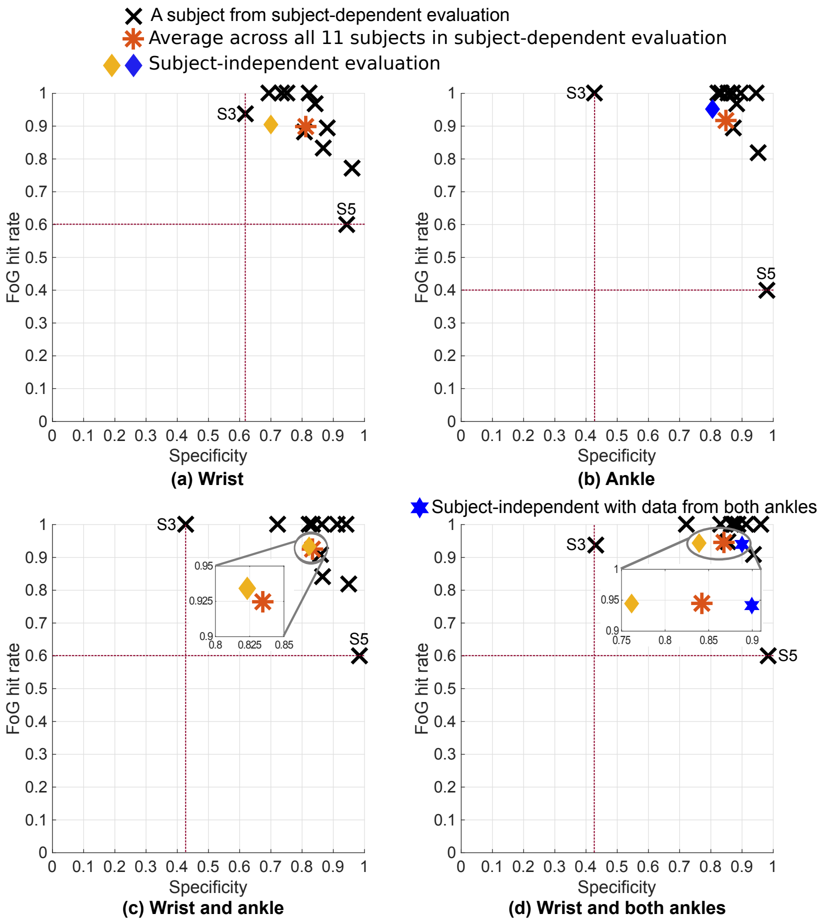


Figure 4.7: *Scatter plots reporting FoG-detection performances for four different scenarios: when using information from (a) wrist, (b) ankle, (c) wrist and ankle, and (d) wrist and both ankles. Each scatter plot reports the FoG hit-rate against the specificity for each of the 11 individual datasets, the average across them for the subject-dependent evaluation, and the overall values for the subject-independent setting. In case of (d) we add also the FoG hit-rate and specificity of the case when using data from both ankles in a subject-independent setting.*

	# False Positives				Latency (seconds)			
Subject	**Wrist**	**Ankle**	**Ankle & Wrist**	**2 Ankles & Wrist**	**Wrist**	**Ankle**	**Ankle & Wrist**	**2 Ankles & Wrist**
# Subject-Dependent Cross-Validation								
S01	20	19	15	17	1.13	0.83	1.22	1
S02	14	8	13	11	1.13	1.04	0.52	1.06
S03	11	2	0	8	0.25	0.31	0.43	0.48
S04	0	3	2	2	0.5	1	3	3
S05	8	6	6	6	2.08	0.87	0.91	0.91
S06	14	14	14	9	0.42	0.17	0.36	0.26
S07	2	0	2	2	0	0	0	0
S08	37	22	26	16	1	0.57	0.55	0.47
S09	22	13	13	15	0.92	0.51	0.65	1.09
S10	24	23	30	24	1.73	0.73	1.11	1.15
S11	7	5	1	2	3.5	0.83	0.66	0.87
Overall	159	115	122	112	1.15	0.62	0.85	0.93
# Subject-Independent Cross-Validation								
Overall	198	158	184	175	0.81	0.72	0.77	0.57

Table 4.3: *The total number of false positives, the FoG-detection latency across each of 11 subjects and their overall average, in four cases: (a) using wrist data, (b) ankle information, (c) wrist and ankle together, and (d) wrist and both ankles together. The performance values are reported for both subject-dependent and -independent evaluation settings.*

For (c) and (d) cases, we fuse the information from wrists and ankles at the feature level: we extract the specific features for each limb, and concatenate them together with the FoG/Walk label into training instances.

Usually FoG is more preeminent in one limb. For the experiments in this section, we report the results of the limb (right or left wrist, or right or left ankle) which obtained the best FoG-detection performances for each subject dataset. The selected limbs in terms of most informative features are given in Table 4.4.

4.6.1. Wrist versus Ankle FoG-Detection

In case of subject-dependent cross validation, wrist-based recognition performances are slightly lower than when using data from one ankle (Figures 4.7(a) and 4.7(b)): On average, the hit-rate is 0.81 for wrist-based compared with 0.84 when using ankle data, and the specificity drops to 0.89 for wrist from 0.91 for ankle. However, we observe that in case of the ankle, there are two outlier datasets: S03, which has a low specificity of 0.42 and a FoG-hit rate of 1, and S05, with a hit-rate of 0.4, but a specificity close to 1. The other 9 subjects cluster their performance measures in the [0.82,1] interval, with six of them obtaining a hit-rate of 1. While when using only wrist data, the S03 and S05 performances are closer to the overall average, but the 11 subjects performances are spread in a larger interval of [0.6, 1].

However, even if the average specificity is similar for both wrist and ankle, the overall number of false positives increases by 40% when using wrist movements, compared with ankle data (from 115 false events in case of ankle data to 159 for wrist), as shown in Table 4.3. The increase in the false positives when using wrist motion might be also because subjects performed different gestures and activities with their arms during the protocol sessions, e.g., gestures during discussions with clinicians, opening doors in the Ziegler session.

There is also a high difference in the overall FoG-detection latency: from 0.6 seconds in case of ankle to 1.15 seconds when using wrist information. The difference between the wrist and ankle data quality is even better shown in the subject-independent setting, as shown in Figure 4.7(a): the overall specificity drops by 0.1 and the hit-rate by 0.05 when using wrist information, in contrast to ankle. This comes along with an increase of the false events, and an increase in the detection latency.

4.6.2. Combination of Wrist and Ankle for FoG-Detection

In case of the subject-dependent cross-validation, combining wrist and ankle information does not come with a major improvement of detection performances, as shown in Figures 4.7(c) and 4.7(d): The addition of wrist information to the ankle helps to increase the FoG-detection for S03 and S05 users, but slightly decreases the performances in case of other subjects. On average, the detection results when using both wrist and ankle data are comparable with when using only ankle information.

When using data from both ankles and one wrist, the average results improve only by 0.03 in specificity, compared with ankle. However, the addition of wrist data slightly increases the number of false positives, and increases the detection latency.

Same trends are observed in the case of subject-independent cross-validation: using wrist and ankle motion together does not improve the overall performances compared to using only one ankle. Moreover, in Figure 4.7(d) we observe that adding wrist and both ankles data together even harms the FoG-detection results, compared to using only data from both ankles: While the hit-rate remains the same around 0.94, the specificity drops by 0.14 units.

4.6.3. Discussion

By using only wrist information, a similar rate of FoG can be detected, but it comes with the cost of a higher number of false alarms, and overall increase in the detection latency, when compared with the ankle-based results.

The addition of wrist information to the ankle data does not improve the overall average performances of FoG-detection, but it helps increasing them for some particular cases of gait: S03 and S12 had difficulties to walk during the protocol, their gait being characterized by a high number of stops, trembling, and small steps. The FoG happened often during walking, in a chain sequence. Both subjects could not complete the whole protocol tasks, FoG and Walk categories in their case being comparable in terms of data amount. For such subjects, the specificity is low when using only ankle information, suggesting that Walk class is often mislabeled as FoG. Thus, in case of such type of walking, wrist motion can come discriminative information between the actual Walk and FoG.

On the other side, S05 had only 5 FoG episodes, and 4 of them 1 second in duration. The under-represented FoG class has an impact on

Limb	**S1**	**S2**	**S3**	**S4**	**S5**	**S6**	**S7**	**S8**	**S9**	**S10**	**S11**
Upper	L	R	L	L	L	L	L	R	L	R	R
Lower	R	L	R	L	R	L	R	L	R	R	L

Table 4.4: *The most informative upper and lower limbs, for each of the 11 subjects. We observe that for 8 out of 11 users the left (L) wrist motion are the most informative for detecting FoG, and for 6 of them the right (R) ankle, contained the most informative data. 8 out of 11 subjects showed a transversal coordination in movements, i.e., opposite lower and upper limbs, to detect FoG.*

the FoG-recognition, with only 2 FoG events being detected from the ankle data. Also in this case, the wrist movement seems to provide discriminative information to detect FoG, which nevertheless comes at the cost of an increased number of false positives. For S05, the use of ankle and wrist together increase the FoG-recognition rate, while preserving the specificity.

Anomalous patterns in wrist movement prior and after FoG. Another possible reason for an increased number of false detected FoG when using wrist-motion information is that in some sessions the anomalous pattern which is present in the arm movement during FoG starts with few seconds before the FoG. On the contrary, in some subjects such as S01, there is no special pattern in the wrist data prior to FoG. However, the motion pattern correlated with FoG continues sometimes few seconds after the subject exits FoG. These two types of *reaction* might cause the increase in the number of false positives when using wrist information, as the classifier tends to detect longer periods of FoG events.

The observed cases when the anomalous patterns in the wrist movement start prior to FoG are in line with the observations of Chomiak and colleagues [5], who showed that arm swing incoordination can induce gait hesitation in PD, which might cause FoG. In these cases, arm movements can be used to help further in prediction of such gait freeze episodes.

In addition, some of the false positives when using the wrist come from the dual-tasking protocol session, in which the subject was asked to perform a walking protocol and carry a glass of water for 1-2 minutes. Performing actions and gestures with the wrist increases the probability of detecting false FoG events.

Evidences of deficits in interlimb coordination during FoG. In Table 4.4 we observe that most informative data to detect FoG is given by the movements of contralateral arms and legs in case of 8 out of 11 subjects. If overall the left wrist movements are most useful (for 8 out of 11 subjects), in case of the lower limb, the opposite right leg gives better information (6 out of 11 subjects). The majority of people are right-sided, which explains why the right leg movements give useful information to detect FoG, as freeze of gait events tend to happen in the most active/dominant limb [33]. The walking task is a combination between transversal limb coordination [21], thus an explanation why the left wrist is most informative in case of our dataset.

Mahabier et al. [29] showed that there is a general deficit between interlimb coordination in the gait patients with FoG, compared with PD subjects without FoG and healthy subjects. We extend these findings by suggesting that there are typical patterns in the movement between contralateral arms and legs during FoG events, compared with the rest of Walk class, for the same subject.

4.6.4. Trade-offs on Integration of Wrist IMU in Wearable Systems for FoG Detection

Having in mind the usage of wrist- or/and ankle-attached IMU in a wearable FoG assistant, there are trade-offs regarding the FoG-detection performance versus system acceptance: Wrist movements are useful to detect freezing at the gait level. Yet, they come at the cost of a higher rate of false events compared when using lower limb movements to detect freeze. On the other side, wrist is the optimal position to wear electronics and to interact with them [38]. Moreover, there are commercially available devices such as smartwatches and wristbands for sports which integrate accelerometers and gyroscopes, and they can be used to provide the wrist movement information to detect FoG. A smartwatch or a wristband can easily pair and send the IMU data to a phone, and a FoG-detection system can be made from available to public devices, which might be already integrated in daily-life of prospective users. Thus, even if it comes at the cost of an increased number of false positives, using the wrist motion has the advantage of established on-body acceptance and of the accessible technology for broad public. Furthermore, if the system can be calibrated for a user by building a specific FoG-detection model, then wrist and ankle movement data report similar performances.

Even if the FoG-detection model yields a higher false positive rate in the subject-independent setting when using wrist motion, it may not be critical in application: In this particular use case less missed FoG events are favored to a high precision (few false positives), as FoG are high-risk events during walking in Parkinson's disease.

However, if the user opts to have fewer false positives, and overall better FoG-prediction performances, he/she can use IMU mounted on the lower limbs. This comes at the cost of having a dedicated system and wearable sensors, and possible issues in the wearability and acceptance of sensors mounted on lower limbs.

Another limitation regarding the usage of wrist-mounted inertial sensors to detect gait anomaly episodes is that users should not perform any actions with their wrist on which the wearable is attached during walking. For example, talking on the phone, or holding something while walking cancels the wrist movement during walking, thus affecting the FoG-detection performances. Daily-life gestures and actions such as waving, or opening a door or a window, might affect too the FoG-detection from the wrist.

We do not recommend a FoG-detection system composed from both wrist commercial IMU and dedicated ankle-mounted sensors, for two main reasons: (1) Using both ankle- and wrist-mounted sensors does not improve FoG-detection, compared with using only ankle-mounted sensors, and (2) Using up to 3 sensors on-body together with a phone decreases the acceptance of the system.

4.6.5. A Wrist Wearable Prototype for Real-Time FoG-Detection

In a previous work we proposed GaitAssist [22], a wearable system using up to two wearable EXEL-S3 IMU[1] attached on the ankles of the user and a smartphone, which detects in real-time the FoG onset and starts a rhythmic auditory cueing to assist the user in resuming walking.

Following the findings from the previous sections, we extend the system to integrate the wrist motion for FoG detection: Instead of having two IMUs on the ankles, the new prototype has the option to attach an IMU on the ankle, and the other to a wrist. The user can choose

[1] www.exelmicroel.com/eng_electronic_medical-wearable-technology-exl-s3_module.html

to attach only the ankle IMU, only the wrist IMU, or both of them. It is at the user choice on which limb to attach the wearables, although from prior experiments in this section it is recommended to attach the sensors on the dominant lower limb and on its opposite wrist. The advantage of placement at the wrist is a potential replacement of the prototypical EXEL-S3 sensor with a commodity smartwatch.

The sensors sample data to a smartphone via a Bluetooth connection. An Android application, similar with and built on top of the GaitAssist app [22], processes the sensor data in real time, with the purpose of detecting FoG. The app implements three subject-independent FoG detection models built using the 11 subjects datasets in CuPiD, following the same recognition framework and specific features prior described in Sections 4.5 and 4.6. The first model uses data only from the ankle, the second FoG-detection model uses information from wrist motion, and the third C4.5 model uses both ankle and wrist data, depending on the option to attach the sensors selected by the user. Once at 0.25 seconds, the last 3 seconds of data window collected from the sensors is used to extract the features specific only for ankle, wrist or both limbs. The feature vector is then fed to the FoG-detection model for classification. If at least 2 out of three consecutive classification outputs belong to the FoG category, the system considers a FoG is detected, and a rhythmic auditory stimulation starts, synchronized with the users' normal gait cadence. This rhythmic sound given as a metronome cue continues up to 8 seconds from the last time when the system detected a FoG event.

Different from the experiments in Sections 4.5 and 4.6, where the sensors' sampling rate is 128 Hz, in the described prototype the sensors sample data at 32 Hz. We chose this as a lower sampling rate equivalates with longer continuous usage of the prototype wearable assistant. The 32 Hz is sufficient to accurately compute all the FoG properties from both ankle and wrist motion, as the computed features use frequency information up to 16 Hz [7]. As the sampling rate in the prototype is different from the sensors' sampling rate in the CuPid dataset, we performed all the FoG-detection experiments detailed in Section 4.5 with CuPiD resampled wrist IMU data at 32 Hz. The FoG detection performances in both subject-dependent and subject-independent settings are comparable in terms of FoG-hit rate, specificity, number of false alarms, and detection latency, showing that a sampling rate decreased from 128 Hz to 32 Hz does not affect capturing the FoG-specific characteristics from the wrist motion.

4.7. Conclusion

We analyzed motion data from wrists of Parkinson's patients to assess whether these reflect freezing of gait episodes. The motivation for focusing on the wrists is that commercially available smartwatches and fitness trackers provide inertial measurement data and are likely to be well accepted by patients, both because they are comfortable and because they do not appear to be a specific device [38].

We conducted our experiments on data from 11 PD subjects with FoG, and we identified features which best correlate with FoG events as opposed to walking events. The selected features consist in power densities in certain spectral bands of the signals, as well as statistical time features (mean and standard deviation) calculated on the magnitude of the acceleration and rate of turn. Using the 13 top informative features, we could achieve FoG-hit rates of 0.85 and 0.9 for respectively subject-dependent and subject-independent classification of FoG versus walking. Furthermore, the specificity reached 0.8 and 0.66 for the subject-dependent and independent case. With these results we can state that a sensor on one wrist is enough for FoG detection. We furthermore observed that the best wrist is in the majority of cases the non-dominant one (usually left for our dataset), since the FoG starts mainly in the dominant leg and gait relates to the opposite wrist.

We also compared the results with the performance of the lower limbs data, which are known as the state-of-the-art to detect FoG in real-time with wearable systems. The use of ankle motion increases the specificity on average with up to 0.2 than when using wrist motions, while the FoG-hit rate and detection latency values are comparable in case of both limbs. We identified trade-offs between using a dedicated ankle-mounted to detect freeze, which lowers the number of false alarms, and a commercial wrist-mounted wearable, which tops in comfort and acceptance. Results suggest as a best practice to design a FoG detection system using by default a sensor mounted on the non-dominant wrist and, optionally, users can decide to use instead an ankle-mounted sensor on the dominant ankle.

Directions for future work would be to deploy the system based on the presented features and algorithms for long-term medical studies, to assess the benefit for the patients in terms of reduction of FoG occurrence. Furthermore, we plan to combine the algorithms with methods to predict FoG few seconds before it happens, to achieve a even more complete system.

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5

Feature Learning for Prediction of Freezing of Gait in Parkinson's Disease

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Abstract

Freezing of gait (FoG) is a common gait impairment among patients with advanced Parkinson's disease. FoG is associated with falls and negatively impact the patient's quality of life. Wearable systems that detect FoG have been developed to help patients resume walking by means of auditory cueing. However, current methods for automated detection are not yet ideal. In this paper, we first compare feature learning approaches based on time-domain and statistical features to unsupervised ones based on principal components analysis. The latter systematically outperforms the former and also the standard in the field - Freezing Index by up to 8.1% in terms of F1-measure for FoG detection. We go a step further by analyzing FoG prediction, i.e., identification of patterns (pre-FoG) occurring before FoG episodes, based only on motion data. Until now this was only attempted using electroencephalography. With respect to the three-class problem (FoG vs. pre-FoG vs. normal locomotion), we show that FoG prediction performance is highly patient-dependent, reaching an F1-measure of 56% in the pre-FoG class for patients who exhibit enough gait degradation before FoG.

5.1. Introduction

Freezing of gait (FoG) is a common gait impairment among patients with Parkinson's disease (PD), defined as a "brief, episodic absence or marked reduction of forward progression of the feet despite the intention to walk" [18]. Patients describe FoG as the feeling of having the feet glued to the ground and being temporarily unable to re-initiate gait. According to a survey of 6620 PD patients, 47% of the subjects reported regular freezing and 28% experienced FoG daily [13]. FoG is associated with falls [12], has substantial clinical and social consequences [6, 15] and is often resistant to pharmacological treatment [2].

Rhythmic auditory stimulation (RAS) was introduced as an assistive tool for FoG treatment [8]. RAS can be applied to produce a rhythmic ticking sound upon detection of a FoG episode, to help the patient resume walking. Wearable systems based on motion sensors have been proposed for the detection and treatment of FoG with auditory stimulation [1, 11]. While RAS upon detection helps to shorten the duration of FoG episodes [1], it cannot avoid them altogether due to the latency of the detection, which is at best on the order of hundreds of milliseconds

[11]. A step further is to predict when a patient is *about to* experience FoG, thus enabling preemptive RAS, with the goal of avoiding the FoG episodes. We call this *FoG prediction* as opposed to *FoG detection*.

There are some known specific properties that differentiate the sensor data during FoG episodes from normal walking (e.g., a large increase in the signal energy in the 3-8Hz frequency band [9, 15]) and the gait of patients with FoG also differs between freezing episodes, compared to patients who do not experience FoG [10]. There are even suggestions of a characteristic change in the gait pattern just prior to the occurrence of a FoG episode; however, currently, there is no way of automatically identifying the prodromal state, when the normal gait pattern is about to transform into FoG.

The lack of physiological understanding of the gait deterioration preceding FoG makes it difficult to come up with a model or with problem-specific features based on expert knowledge. Moreover, walking styles of PD patients differ across subjects (including diverse motor anomalies) [17]. Thus eventual patterns in the data just before a FoG event will also likely be highly subject-specific. Nevertheless, previous work suggests that there is a deterioration of the normal gait before FoG, although this deterioration can be expressed in various ways [17, 18, 19].

In this work, we first formulate the *FoG detection* problem as a two-class classification problem: FoG versus normal locomotion. Similarly, we treat *FoG prediction* problem as a three class classification problem. Beside FoG and normal locomotion, we consider the walking periods before FoG episodes as a third class called *pre-FoG*. We hypothesize that there is a detectable deterioration of gait in this phase which precedes FoG. We assume different durations of the pre-FoG events, since these cannot be labeled by an expert, but can rather only be retrieved through data mining from segments of data preceding FoG events. We focus on the analysis of different feature extraction approaches that lead to a meaningful representation of both the FoG and the new pre-FoG class. The feature extraction approaches that we investigated are the following:

1. Extraction of standard frequency-based features, namely Freezing Index and total energy in the frequency band 0.5-8 Hz. This is the current standard in the field and serves as a baseline [15].

2. Extraction of various *hand-crafted* time-domain and statistical features, which are used in pattern recognition problems involving

motion or human activity recognition.

3. Unsupervised feature learning [20]. This method involves extraction of information from the raw data, without relying on domain specific knowledge, or on the availability of ground truth annotations. We evaluate the use of principal component analysis for extracting a compact representation of the structure of the signals.

The contributions of this work are summarized as follows:

- We go beyond state of the art by explicitly introducing and performing a first step toward FoG prediction, as opposed to mere detection, thereby potentially allowing for the possibility of applying preemptive RAS;
- We compare three methods for feature extraction in the FoG detection and FoG prediction problems and show that unsupervised feature learning outperforms on average standard feature extraction schemes in our real-life dataset;
- We show that removal of pre-FoG sequences from the training data for FoG detection improves classification performance;
- For FoG prediction, we show that, for some patients, gait anomalies associated with the upcoming onset of FoG can be detected, thereby allowing for an early intervention with RAS.

5.2. Related Work

FoG Detection. Several research groups have proposed wearable systems for the detection of FoG episodes [1, 4, 5, 7, 11, 14, 15, 16, 21, 23]. Most sensor setups involve accelerometers and/or gyroscopes [1, 5, 11, 16, 21], extended with electroencephalography (EEG) [7] or electromyography (EMG) [4]. One standard feature which is extracted from the raw signals is the Freezing Index (FI), defined as the ratio between the power contained in the so-called *freezing* and *locomotion* frequency bands (3-8 Hz and 0.5-3 Hz respectively) [1, 11, 15]. This feature is convenient since it requires only FFT-computation. Other feature extraction approaches involve mixed time-frequency features [23] and entropy [21]. In [14], the authors investigated the use of time-domain and statistical features, together with FFT-features. Various classifiers have been used for the two-class classification problem (FoG versus no-FoG), including Decision Trees, Random Trees/Forests, Naive Bayes [21] as well as rule-based classifiers [5] and simple thresholds on the FI [1]. Overall, the different proposed approaches reach detection sensitivities that often exceed 80%, but the detection is performed with at best a latency of a few hundred milliseconds. Handojoseno and colleagues [7] make use of wavelet decomposition to analyze the dynamics of EEG signals during the onset and the freezing periods. Their aim was to achieve an early detection of FoG from brain activity that could, potentially, help patients to avoid an impending FoG episode. To our best knowledge, no attempts have been yet made at tackling the FoG prediction problem using just motion sensors. We therefore perform a first analysis in this direction.

Unsupervised Feature Learning. Automatic (unsupervised) feature extraction has been proposed in the context of human activity recognition based on motion sensors. Plötz et al. [20] argued that instead of using the explicit knowledge to select specific features, one can extract the core signal characteristics by means of principal components analysis. This allows one to uncover meaningful, low-dimensional representations of raw data without relying on domain-specific knowledge. The results on public activity recognition datasets showed that the features learned in this unsupervised manner are more discriminative than state of the art representations based on time- and frequency-domain features. We propose to apply this method for detection and prediction of FoG, since the properties of the FoG and pre-FoG signals are subject-dependent and difficult to model.

5.3. Features for FoG Detection and Prediction

The general process that we adopt for signal processing and classification is depicted in Figure 5.1. The set of operations is standard in pattern recognition problems involving motion data from on-body 3-dimensional accelerometers: sensor signals are sampled and sliced into partially overlapping windows. In each window, features are extracted and the resulting vectors are classified according to a pretrained model. In this work, we empirically set the window length to $1s$ (64 samples) with $0.25s$ of overlap (16 samples). We choose a C4.5 classifier due to its low computational cost when deployed. In this work, we focus on the selection of the appropriate features for detection and prediction of

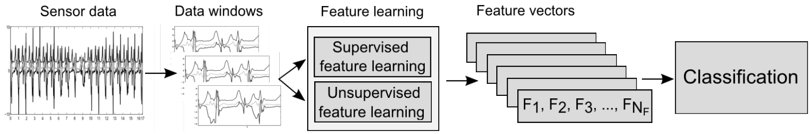


Figure 5.1: *Signal processing and classification for the detection and prediction of FoG.*

FoG, so the optimization of the classifier parameters is out of our scope. In the training phase of the system, we use feature ranking based on Mutual Information (MI) to rank the top discriminant time-based and statistical features [3]. We denote with N_F the number of top-ranked features retained in the classification process.

5.3.1. Feature Extraction Schemes

We choose three groups of features, the first of which has been already used in the context of FoG detection and is used here as a baseline. We call *supervised* the first two feature extraction approaches, since they involve features manually selected due to expert knowledge. The features are computed for each window.

Supervised: Domain-specific Feature Extraction. The first feature group contains the Freezing Index and the sum of energy in the freezing (3-8 Hz) and locomotory (0.5-3 Hz) frequency bands. These features are obtained by computing the FFT, followed by binning, in order to compute the spectral distribution of the energy in the desired bands.

Supervised: Feature Extraction of Time-domain and Statistical Features. The second group of features is often used in activity recognition [22]. Until now, only a small subset of these has been also applied to FoG detection [14]. We list the used features in Table 5.1. We extracted 18 features for each of the three accelerometer axes (x, y, z) and six features using data from all three axes.

Unsupervised Feature Learning. For learning the implicit structure of the data, each data window containing 64 samples for the three accelerometer axes is arranged into a 192-dimensional vector (the first three entries correspond to the first samples from the x, y and z axes, and so on). In the training phase, principal component analysis (PCA) is then applied to the whole training data matrix, obtained by stacking all the 192-dimensional vectors in the training set and disregarding class labels. This yields a projection matrix, which is then used in the testing phase to project the single data frames.

Axis Features

No.	Feature	Description
1,2	Min, Max	Minimum and maximum of the signal
3	Median	Median signal value
4,5	Mean, ArmMean	Average value, and the harmonic average of the signal
6	Root Mean Square (RMS)	Quadratic mean value of the signal
7	GeoMean	Geometric average of the signal
8	Variance	Square of the standard deviation
9	Standard Deviation (STD)	Mean deviation of the signal compared to the average
10	Kurtosis	The degree of peakedness of the sensor signal distribution
11	Skewness	The degree of asymmetry of the sensor signal distribution
12	Mode	The number that appears most often in the signal
13	TrimMean	Trimmed mean of the signal in the window
14	Entropy	Measure of the distribution of frequency components
15	Asymmetry coefficient	The first moment of the data in the window divided by STD over the window
16	Range	The difference between the largest and smallest values of the signal
17	Zero Crossing Rate (ZCR)	Total number of times the signal changes from positive to negative or back, normalized by the window length
18	Mean Crossing Rate (MCR)	Total number of times the signal changes from below average to above average, normalized by the window length

Sensor Features

No.	Feature	Description
55	Signal Magnitude Vector (SMV)	Sum of the euclidean norm over the three axis over the entire window normalized by the window length
56	Normalized Signal Magnitude Area (SMA)	Acceleration magnitude summed over three axes normalized by the window length
57-59	Eigenvalues of Dominant Directions (EVA)	Eigenvalues of the covariance matrix of the acceleration data along x, y, and z axis
60	Averaged Acceleration Energy (AAE)	Mean value of the energy over three acceleration axes

Table 5.1: *Statistical features and their brief descriptions.*

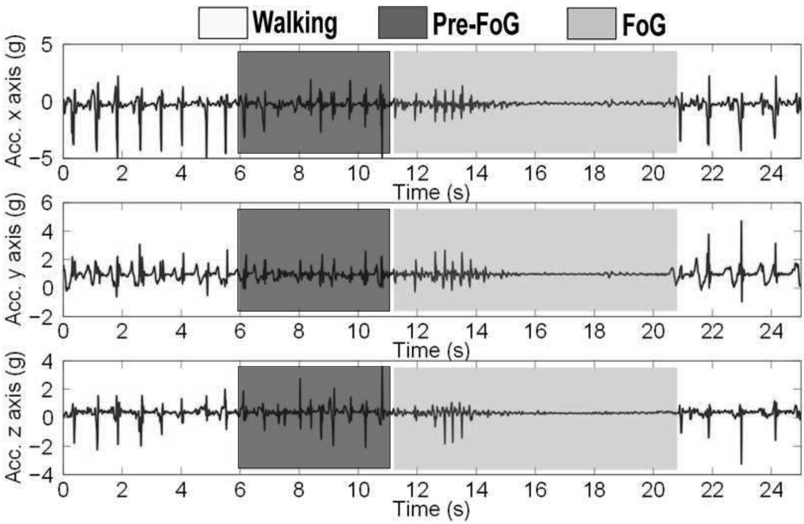


Figure 5.2: *An example of an accelerometer signal, on the three acceleration axes, that captures the motor variations in the gait of a patient with Parkinson's disease. The sequence contains normal gait, a FoG episode, preceded by an assumed pre-FoG period.*

5.3.2. Assumptions About pre-FoG Events: From FoG Detection to Prediction

We assume that the gait cannot enter in the FoG state directly from walking state. Rather, we assume that prior to FoG, there is a gait deterioration that eventually leads to the FoG. This is represented by a transition period of variable duration T_{Prefog} that we refer to as the pre-FoG state. An example of FoG episode, with supposed pre-FoG, is shown in Figure 5.2. The optimal value of T_{Prefog} will be patient-dependent. The identification of segments of pre-FoG data is valuable both for FoG detection and prediction.

Making Detection More Robust. For the detection problem, we set up a two-class classification problem. We name the two classes WALK (which includes instances of normal locomotion, including walking, standing, turning, etc.) and FoG, which represents the freezing episodes. In the training phase, we remove data for a duration of T_{Prefog} before each FoG event contained in the training set. This aims at having a more precise classifier model for the FoG and for the WALK classes.

Towards FoG Prediction. For prediction, we set up a three-class classification problem. Besides the two classes described above (WALK and FoG), we use the segments assumed to be in a pre-FoG state to build the model for the third class.

5.4. Dataset

We validated the proposed approach on the public available DAPH-Net dataset[1] [1], which contains data collected from eight PD patients that experienced regular FoG in daily life. Data were recorded using three 3D accelerometers attached to the shank (above the ankle), the thigh (above the knee) and to the lower back of each subject. For our experiments here we focused on movement data recorded from the ankle, as the data from the other two sensors generally behave similarly. Subjects completed sessions of 20-30 minutes each, consisting of three walking tasks: (1) Walking back and forth in a straight line, including several 180-degrees turns; (2) Random walking with a series of initiated stops and 360 degrees turns; (3) Walking simulating activities of

[1] www.wearable.ethz.ch/resources/Dataset

daily living, which included entering and leaving rooms, walking to the kitchen, getting something to drink, and returning to the initial room.

Motor performances varied strongly among the participants. While some subjects maintained regular gait during nonfreezing episodes, others walked slowly and were very unstable. The DAPHnet dataset contains 237 FoG episodes; the duration of FoG episodes is between 0.5s and 40.5s (7.3±6.7s). 50% of the FoGs lasted for less than 5.4s and 93.2% were shorter than 20s. FoGs were labeled by physiotherapists using synchronized video recordings. The start of a FoG event was defined as the point when the gait pattern (i.e., alternating left-right stepping) was arrested, and the end of a FoG was defined as the point in time when the pattern was resumed.

5.5. Experiments and Evaluation

We performed two sets of experiments using the DAPHnet dataset described in Section 5.4: one for *FoG detection* and one for *FoG prediction*. For FoG-detection we ignored the pre-FoG sequences. For both sets of experiments and for two of the three groups of features introduced in Section 5.3.1, we varied the number of selected features N_F from 5 to 60 in steps of 5. This cannot be done for the domain-specific features, since they are only two - FI and total energy. We further characterized the influence of different choices of the pre-FoG duration on both the two-class and three-class problem, by sweeping the assumed pre-FoG duration in the range $T_{Prefog} \in \{1s, 2s, ..., 11s\}$.

The evaluation was performed on a patient-dependent basis. Since in each patient dataset the WALK class was over-represented compared to the FoG class, we chose to balance the data by having $size(\text{WALK}) = X * size(\text{FoG})$, where $X \in \{1.5, 2, ..., 10\}$. We performed an $N = 10$-fold cross validation, in which the training data contains N-1 parts from the FoG data, N-1 parts from normal locomotion data, and the testing data the rest. The data were split for each fold in such a way as to avoid having time-correlated chunks of the same FoG, WALK, or pre-FoG events in the training and testing data.

We report results in terms of overall patient datasets average sensitivity and average specificity of the FoG class, and F1-measures for FoG, WALK and pre-FoG classes, in a window-to-window comparison.

Top k	x axis	y axis	z axis	sensor
Top 5	variance	–	variance	EVA (2 directions), AAE
Top 10	RMS, variance, range	variance, range	variance	EVA (3 directions), AAE
Top 15	variance, range, RMS, min, STD	variance, range, RMS	variance, range, RMS	EVA (3 directions), AAE
Top 20	max, RMS, variance, STD, min, range	variance, range, RMS, max, min, STD	RMS, variance, range, min	EVA (3 directions), AAE

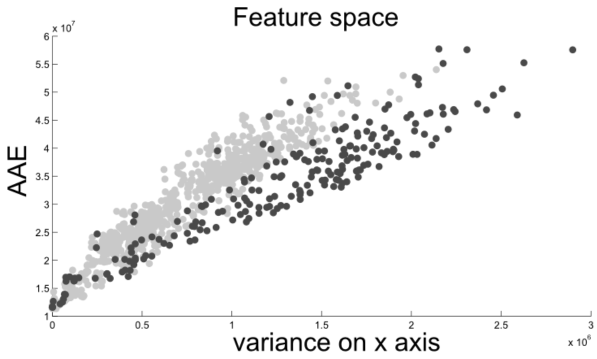
Table 5.2: *Average top ranked features with Mutual Information.*

5.6. Results

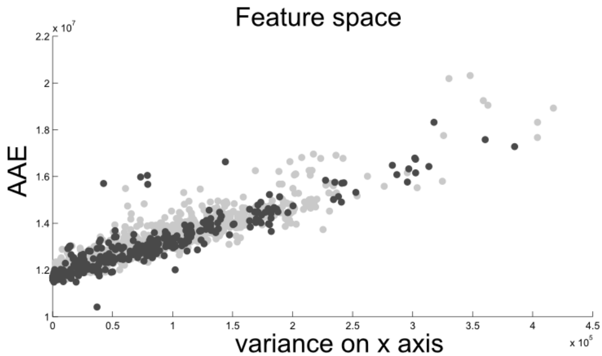
In the following, we analyze the performance of different feature extraction strategies for the FoG-detection and FoG-prediction problems.

5.6.1. Time-Domain and Statistical Features

The top ranked features based on MI for FoG detection are AAE, eigenvalues of dominant directions, range, variance, root mean square, and standard deviation (some features, like standard deviation and variance are of course strictly related). The top ranked features according to their MI are those computed from the entire data window (all axes), followed by those on x-axis. Table 5.2 shows the top k ranked features, for k ranging from 5 to 20. Note that selecting features that are ranked highly by the MI does not automatically guarantee that they are also discriminative enough. Figure 5.3 contains an example of distribution of the top ranked features AAE and variance on x-axis. For some patients these features are enough to distinguish between FoG and WALK – the two classes form two distinct clusters when represented by these two features. Still, this does not work for all the patients. For example, in the case of Patient 8, even if the top ranked features with MI are



(a) Patient 2



(b) Patient 8

Figure 5.3: *AAE vs. variance on x-axis for (a) Patient 2 data and (b) Patient 8 data.*

the same, their discriminative power is lower – FoG is easily confused with WALK, when represented by the same two features.

5.6.2. FoG Detection

We compare the different feature learning approaches in terms of producing discriminative feature sets for distinguishing FoG and normal gait. In Table 5.6.2 the sensitivity, specificity and F1 measures for two feature-extraction methods are depicted as a function of number of features N_F used for classification, for a fixed duration of ignored data

Sensitivity (%)

Features	5	10	15	20	25
Unsupervised	77.15	77.7	76.29	76.86	76.86
Supervised	67.8	68.53	69.42	66.65	67.58

Specificity (%)

Features	5	10	15	20	25
Unsupervised	86.71	87.56	86.65	86.21	85.52
Supervised	84.75	86.76	87.76	88.74	88.52

F1 (FoG)(%)

Features	5	10	15	20	25
Unsupervised	78.2	79.09	77.53	77.62	76.29
Supervised	70.94	72.54	73.79	72.33	73.02

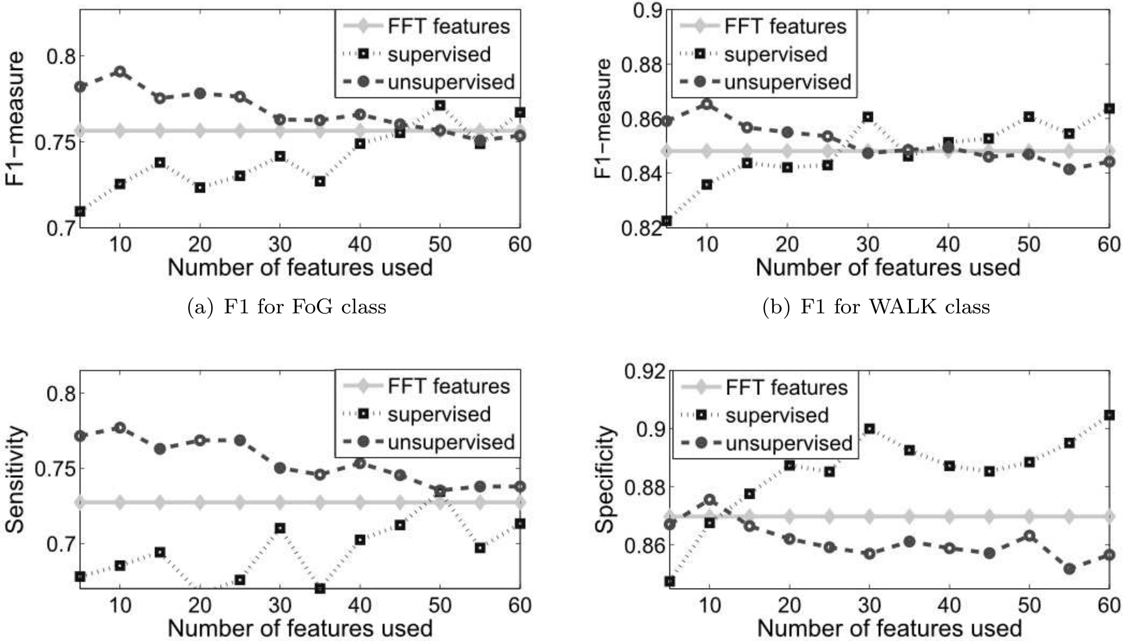
F1 (WALK) (%)

Features	5	10	15	20	25
Unsupervised	85.91	86.53	85.67	85.5	85.35
Supervised	82.25	83.58	84.37	84.21	84.29

Table 5.3: *Average of the sensitivity, specificity and F1-measure for the FoG class for supervised and unsupervised feature extraction methods, in the two-class classification problem. The pre-FoG duration is fixed as* $T_{Prefog} = 3s$.

$T_{Prefog} = 3s$ before each FoG. The classification results are significantly improved when performing unsupervised feature learning compared to the results for the standard feature set, for values of $N_F < 30$. Classification based on PCA features also outperforms the one using FFT-based features, when using small number of PCA features. In Figure 5.4, we observe that for larger values of N_F, the classification performances tend to decrease for unsupervised extracted features. PCA concentrates the variability and the useful information from the raw data in the first features. The usefulness of a feature decreases with its rank. However, our target is to use as few features as possible, as noted above.

In Figure 5.5, we present the classification results with $N_F = 10$ features, when varying the amount of discarded data before each FoG episode in the range $T_{Prefog} \in [1s, 11s]$, in steps of 1s.



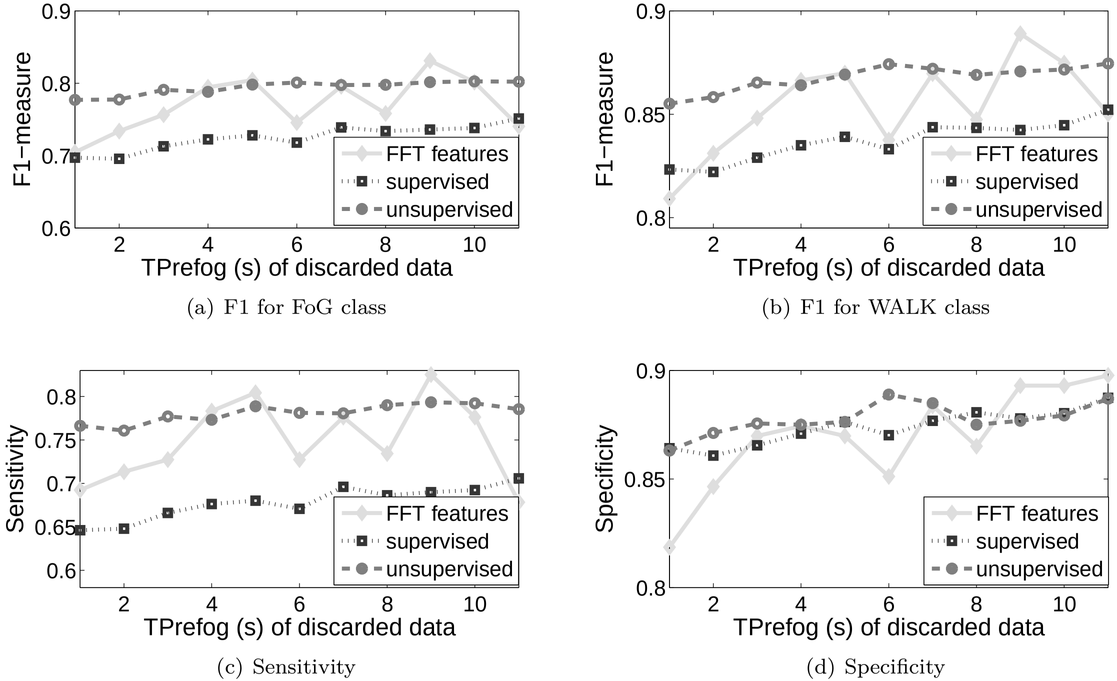
(a) F1 for FoG class

(b) F1 for WALK class

(c) Sensitivity

(d) Specificity

Figure 5.4: *Sensitivity, Specificity and F1 measures for FoG detection when using different values for* N_F *unsupervised and supervised extracted features. The amount of discarded data is fixed to* $T_{Prefog} = 3s$ *before each FoG episode.*



(a) F1 for FoG class

(b) F1 for WALK class

(c) Sensitivity

(d) Specificity

Figure 5.5: *Sensitivity, Specificity and F1-measures for FoG detection when using $N_F = 10$ unsupervised and supervised extracted features. The amount of discarded data varies between $T_{Prefog} = 1s$ and $T_{Prefog} = 11s$.*

We observe that for both supervised and unsupervised features, FoG detection performance increases with the increase of T_{Prefog}, until reaching a plateau value at $T_{Prefog} = 5 - 6s$. This suggests that these discarded portions of data could contain properties that are different both from FoG and normal locomotion. In the next set of experiments, we analyze whether this dataset has specific properties that will lead to prediction of FoG episodes.

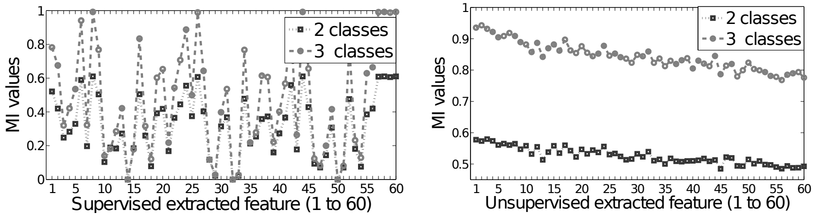
5.6.3. Towards FoG Prediction

In the previous experiments, we observed that discarding T_{Prefog} data preceding each FoG episode improved the FoG detection results for all types of feature extraction. We now present the results for the three-class classification problem, where we use the discarded chunks as examples of the pre-FoG class. As a first step, we analyzed the impact of the addition of this third class to the mutual information between the various features and the classes.

Mutual Information. We compare the mutual information of the features in the FoG-detection and FoG-prediction problems. Figure 5.6 shows an example of MI values computed for both supervised and unsupervised features, on the same Patient 2 dataset, in case of FoG detection and FoG prediction problems. We observe that all MI values improve for top ranked features, when adding the third class. This suggests that the pre-FoG data can indeed be representative.

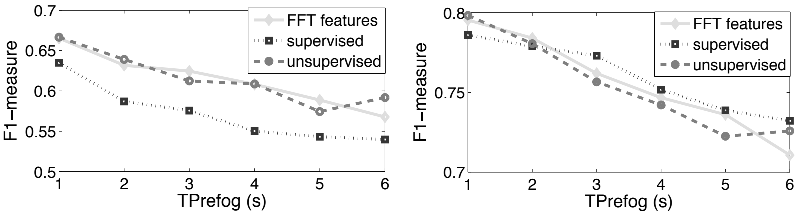
Performance of FoG Prediction. In the next experiments, we set $N_F = 10$, and we varied $T_{pre-FoG}$ from 1s to 6s, in steps of 1s. We stopped at $6s$ because a further increase did not improve the FoG prediction results.

Figure 5.7 shows the variation of F1-measures for all the three classes versus the value of T_{Prefog}. We first observe that, like in the two-class classification problem (FoG detection), the unsupervised features perform better than the supervised ones. Second, the F1-measures for the FoG and WALK classes are smaller than in the two-class problem. This is expected since we are trying to solve a classification task with one extra class – pre-FoG – which is identified using an assumption on its presence and duration, which leads inevitably to a noisy training. Instances of the pre-FoG class will indeed not always be radically different from WALK or FoG instances, which will introduce confusion. Never-

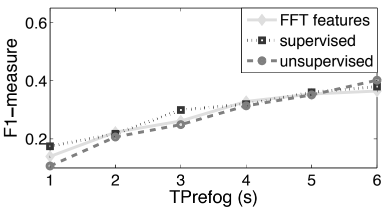


(a) Supervised (b) Unsupervised

Figure 5.6: *MI values for all $N_{total} = 60$ computed features, both with supervised and unsupervised methods, for FoG detection and FoG prediction. $T_{Prefog} = 5s$.*



(a) F1 for FoG class (b) F1 for WALK class



(c) F1 for pre-FoG class

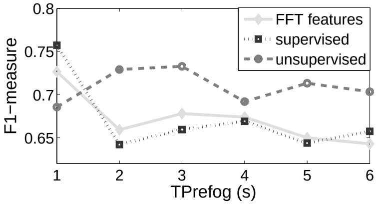
Figure 5.7: *F1-measures for FoG prediction when using $N_F = 10$ unsupervised and supervised extracted features, with $T_{Prefog} \in [1s, 6s]$.*

theless, we identify a trade-off: we can use the unsupervised feature extraction to perform FoG prediction at the expense of performance on detection. Too small values of T_{Prefog} lead to poor results on the F1-measures, because the pre-FoG class is not representative enough. On the contrary, indefinitely increasing T_{Prefog} improves the F1-measure only for this class, but dramatically decreases that of the other classes. This is due to the fact that the pre-FoG and WALK classes become more and more similar.

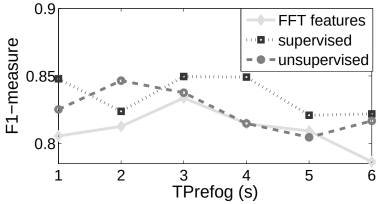
Figure 5.8 displays the F1-measure variations for the datasets of Patient 3 (PD3) and Patient 8 (PD8). In the case of PD3, when using unsupervised extracted features, for T_{Prefog} periods of $2s$ and $3s$, the F1-measures increase for all the classes. The F1-measures for the pre-FoG class are 0.42 for $T_{Prefog} = 2s$ and 0.56 for $T_{Prefog} = 3s$. So there are common patterns in the 2s or 3s before FoG episodes that are distinct from WALK and FoG. The same behavior of F1-measures is observed for supervised extracted features, but with a delay compared to using unsupervised features. For $T_{Prefog} = 1s$ supervised features even outperform the unsupervised ones. The likely reason is that with such short pre-FoG durations, PCA in unable to capture the structure of that class. On the other hand, for PD8, an increase of T_{Prefog} leads to a constant decrease in performance for the detection of the FoG and WALK classes, while having a small increase for pre-FoG (along with a decrease of the WALK F1-measure). That shows that WALK and pre-FoG are similar, thus using two distinct classes just leads to confusion in the classification. So, for this patient, we cannot extract specific patterns that could differentiate pre-FoG from the global WALK class.

5.6.4. Discussion

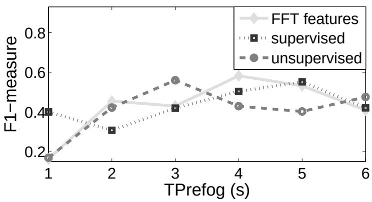
The classification performance for FoG detection is not as high as that reported in other works. We believe this is mainly due to a less optimistic evaluation scheme, where we selected the training and testing data in each fold to avoid having training and testing data chunks coming from the same FoG episodes at once. This should lead to a more realistic estimate of the performance of a real-world deployed system. Furthermore, FoG-prediction performances vary considerably across subjects. We can claim that for some PD patients, like Patient 3, there are patterns, visible in the accelerometer data, that are characteristic of the pre-FoG class, making it different from the normal locomotion class. These patients exhibit a deterioration of the walk just before FoG episodes.



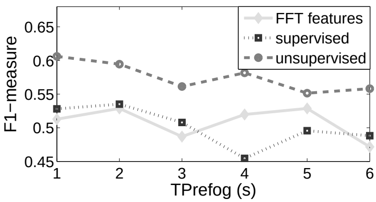
(a) FoG class – PD3



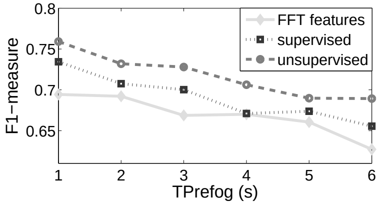
(b) WALK class – PD3



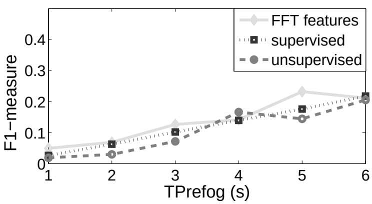
(c) pre-FoG class – PD3



(d) FoG class – PD8



(e) WALK class – PD8



(f) pre-FoG class – PD8

Figure 5.8: *F1-measures for FoG prediction on Patient 3 and Patient 8 data when using $N_F = 10$ unsupervised and supervised extracted features, with $T_{Prefog} \in [1s, 6s]$.*

There are some limitations related to the assumtpions on the pre-FoG class:

- Different nature of the FoG episodes. Some FoG events occur when the subject starts walking, meaning there is no gait before the FoG, so that the gait deterioration that we assume to exist in the pre-FoG phase does not exist, rendering FoG prediction especially challenging for those cases.

- The duration of the pre-FoG class T_{Prefog} is considered to be fixed for each patient. Nevertheless, the pre-FoG pattern duration will probably vary even for different FoG episodes for the same patient. This means that an optimal training set for the pre-FoG class for a single patient might need to contain segments having different values for T_{Prefog}. In order to determine the correct value for each single instance, an approach could involve a direct monitoring of the variation of the features, to detect when they start changing from the normal status to the FoG status.

5.7. Conclusion

In this work, we analyzed the performance of three feature extraction approaches for detecting freezing of gait in patients with Parkinson's disease. Features based on time-domain and statistical features where compared to unsupervised ones based on principal components analysis, while Freezing Index (FI) was used as a baseline reference. We tested the approaches on acceleration data collected at the ankle from patients that experienced FoG in daily-life. Unsupervised feature learning outperformed FI by up to 7.1% and the time-domain and statistical features by up to 8.1% in terms of F1-measure for FoG detection.

We went a step further by analyzing FoG prediction, i.e. identification of patterns (pre-FoG) occurring before FoG episodes, based only on acceleration data. The purpose is to predict FoG so to assist patients in avoiding freezing periods altogether. For this, we assume that walking sequences of a fixed length T_{Prefog} just previous to a FoG episode have different characteristics compared to normal locomotion patterns and to FoG. On the three-class problem (FoG vs. pre-FoG vs. normal locomotion) we obtained results highly patient-dependent, reaching an F1-measure of 56% in the pre-FoG class for one patient. The identification of pre-FoG patterns is also beneficial for the simple FoG detection:

when pre-FoG data are discarded from the training set, performance on FoG detection increases for all the feature extraction methods.

The use of unsupervised features is a promising avenue, since these capture important variations in the data, without the bias of an expert choosing features manually and without any prior knowledge of the class labels. In order to improve the results, other, more complex unsupervised methods for feature learning will be tested (PCA using nonlinear kernels, deep learning). Furthermore, additional unobtrusive sensing modalities could be considered (e.g. gyroscopes). Finally, our assumption on a fixed duration of the pre-FoG class for all FoG events might need to be revised. To this end, methods monitoring directly changes in the extracted features could be beneficial for identifying the actual start of the pre-FoG phases, where present.

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6

Prediction of Freezing of Gait from Physiological Wearable Sensors

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Prediction of Gait Freezing of Gait from Physiological Wearables: An Exploratory Study
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Abstract

Freezing of gait (FoG) is a common gait impairment among patients with advanced Parkinson's disease. FoG is associated with falls and negatively impacts the patient's quality of life. Wearable systems that detect FoG in real time have been developed to help patients resume walking by means of rhythmic cueing. Current methods focus on detection, which require FoG events to happen first, while their prediction opens the road to preemptive cueing, which might help subjects to avoid freeze altogether. We analyzed electrocardiography (ECG) and skin conductance response (SCR) data from 11 subjects who experience FoG in daily-life, and found statistically significant changes in ECG and SCR data just before the FoG episodes, compared to normal walking. Based on these findings, we developed an anomaly-based algorithm for predicting gait freeze from relevant SCR features. We were able to predict 71.3% from 184 FoG with an average of 4.2 seconds before a freeze episode happened. Our findings enable the possibility of wearable systems which predict with few seconds before an upcoming FoG from skin conductance, and start external cues to help the user avoid the gait freeze.

6.1. Introduction

Parkinson's disease (PD) is a neurodegenerative disease with a worldwide prevalence estimated at 16.1 million people [33], and expected to double by 2050. PD is characterized by postural instability, rigidity, reduced movement range, and tremor. According to a survey of 6620 PD patients, 47% of them reported regular freezing of gait (FoG), and 28% on a daily basis [26]. FoG is a "brief, episodic absence or marked reduction of forward progression of the feet despite the intention to walk" [37]. It is typically sudden and transient, lasting usually from a few seconds up to few minutes [37], during which the motor system is blocked. FoG is a severe problem, since it is associated with falls [3], anxiety, loss of mobility, mortality [13], and has substantial clinical and social consequences which decrease the quality of life [32, 48]. Hence, it is important to build systems that can help reducing FoG incidence.

FoG does not respond well to pharmaceutical treatment. Nevertheless, clinical studies [7, 36, 44] suggest that rhythmical cueing synchronized with the gait, like periodic lines projected on the floor or metronome ticking sounds, can help patients to exit the freezing state and resume walking. Wearable systems using body-worn accelerometers [21, 29] can detect FoG and deliver a rhythmical cue upon its detection. While such systems are already beneficial in shortening the freeze duration [2, 29], they cannot help the user to avoid FoG, since they need at least some hundreds of milliseconds to react to the existent episode [21, 29]. A further step is to predict when a subject is about to experience FoG, thus enabling preemptive cueing. We refer to this *FoG prediction*, different from *FoG detection*.

A known aspect which was not exploited until now is that mental conditions might play an important role in the pathogenesis of FoG [8]. Factors such as stress and anxiety are linked to and likely contribute to FoG occurrence [39, 48]. These factors have a measurable influence on physiological signals like heart activity or skin conductance, modalities which have been used in previous research to reflect the emotional state, stress and anxiety in daily-life [22, 25].

We therefore make a step further and study whether physiological data such as Electrocardiogram (ECG) or Skin Conductance Response (SCR) show specific variations before FoG. We hypothesize that changes in the ECG and SCR might occur during and just before FoG as a reflection of the emotional and cognitive state of the patient, factors associated with provoking FoG [48]. Such changes could potentially also help in predicting FoG.

Our study has also a practical motivation: Commonplace wearable technologies such as wristwatches or wristbands which collect heart rate or electro-dermal activity information in real time enable the possibility of unobtrusively and continuously monitoring the user in daily-life settings. We envision systems which recognize in real-time anomalies in the physiological data from such sensors before a gait freeze might occur, and which deliver preemptive rhythmical cueing, with the goal of avoiding FoG altogether.

Our work tackles two research questions:
(1) Are there specific and statistically significant changes in the ECG and/or skin-conductance *before* and during FoG, compared to the rest of walking?
(2) Can we predict that a FoG will happen with few seconds before from physiological data?

To answer them, we make the following contributions:

- We collect ECG and SCr from 11 subjects in a laboratory setting, where 184 FoG episodes are identified.

- We analyze the variations of specific features extracted from ECG and SCR for periods of data *just before*, during, and *just after* FoG events, compared to normal walking events, for each subject.
- We propose a method for predicting gait-freeze events using SCR features and multivariate Gaussians.

To the best of our knowledge, there is no prior work which targets prediction of FoG from patterns in skin conductance, leading to a proposed prediction algorithm.

The remainder of the paper is structured as follows: In Section 6.2, we survey the state-of-the-art regarding detection and attempts of *prediction* of FoG, and summarize how ECG and SCR data have been used to detect the emotional state. Section 6.3 details the collected dataset. In Sections 6.4 and 6.5 we describe our data-driven study and findings regarding FoG prediction from physiological sensors. In Section 6.6 we present a vision of a wearable assistant for predicting FoG episodes. We conclude our work in Section 6.7.

6.2. Related Work

We survey three groups of studies related to FoG research, followed by a review on the use of wearable sensors for mental state recognition:
1) Works on freezing of gait detection through sensor data captured by wearable sensors.
2) Studies on changes in brain activity and FoG prediction.
3) Investigations on potential links between FoG and mental conditions, which lead to visible changes in physiological data.

6.2.1. FoG and Wearable Systems

Many research studies have described methods for detecting FoG in real time using wearables [1, 2, 5, 6, 16, 21, 29, 32, 34, 45, 49]. Most of them focus on the gait properties captured with inertial sensors such accelerometers and/or gyroscopes mounted on-body [1, 2, 6, 21, 29, 34, 45], extended with electroencephalography (EEG) [16], and electromyography (EMG) [5]. However, in this setting FoG needs to take place in order to be detected. A step further is to predict that a FoG might happen, and start a preemptive rhythmical cue which will help the user to avoid altogether the freezing episode.

Mazilu et al. [30] attempted to capture changes in gait characteristics a few seconds before FoG from accelerometers mounted on the subject's ankle from DAPHnet dataset [2], in order to predict FoG. The use of body-fixed inertial measurement units (IMU) is promising, as these sensors are unobtrusive to wear in daily-life and are already integrated in real-time systems that detect FoG [2, 21, 29]. However, the findings from [30] suggest that acceleration, although informative for some of the subjects, is limited in capturing changes in the gait just before FoG episodes, as there are other walking-related events which disturb the signal, such as turns.

6.2.2. FoG and Brain Activity

Handojoseno and colleagues [14, 15, 43] analyzed the dynamics of EEG signals before and during the onset of freezing periods, observing that EEG power features might have specific patterns when transitioning to FoG. Their aim is to achieve an early detection of FoG from brain activity that could help patients to avoid an impending freeze episode.

In a similar direction, Maidan and colleagues [27] evaluate the direct relationship between FoG during turns and frontal lobe activity using functional Near-Infrared Spectroscopy (fNIRS). The changes in brain frontal lobe activation before and during FoG highlight the connections between motor planning, information processing and FoG, suggesting that there might be distinguishable patterns in the frontal lobe activity which happen just before FoG.

However, the continuous, long-term monitoring of brain activity via EEG or fNIRS signals is not possible at the moment in daily-life scenarios. These systems have wearability issues, are expensive, and they are not commercially available. In this study, we search for alternatives to the IMU and sensors which capture the brain activity, in which we can observe distinguishing patterns before a FoG episode: electrocardiography and skin conductance.

6.2.3. FoG Impact on Physiological Data

Clinical studies found that apparently there is a correlation between freezing and stress or anxiety, showing that mental conditions play an important role in the pathogenesis of FoG [8]: Stressful situations, anxiety, depression, cognitive challenging situations, or fatigue have been associated with gait freeze, and might be a contributing factor [39, 46, 48].

In a recent study, Maidan and colleagues [28] found correlations between the heart rate variations during FoG, compared with periods of walking before or just after the episode. Moreover, heart rate also increased just before gait freezing. The hypothesis in the study is that the autonomic nervous system "may be activated during and perhaps just before FoG, reflecting a sympathetic response that exacerbates the risk of FoG or occurs in conjunction with FoG" [28]. The findings suggest that what is described as a sudden, episodic event actually evolves over a relatively long time, i.e., few seconds before the episode. However, only FoG during turns that lasted longer than 3 seconds were considered, and data was analyzed only few seconds before or just after the FoG.

We take the idea in [28] forward, and test whether there are significant correlations in changes of physiological status captured by ECG and SCR just before or during FoG, compared with all the rest of walking events, such as straight line walking, turns, and gait initiation. Different from [28], we focus on all the FoG episodes, independent of their subtype.

6.2.4. Physiological Data for Mental State Recognition

Stress, fear, or other emotions could be detected from electro-dermal activity or from ECG changes, in real-life scenarios: Wearable ECG sensors are used in monitoring the stress arousal in the wild [24, 25], for recognition of sleep apnea [23], and for real-time detection of cardiovascular diseases such as arrhythmia [20]. Similarly, wearable electrodermal activity sensors are useful in recognizing stress or other emotions [42], and for daily-life monitoring of bipolar disorder [22]. Schumm et al. [41] show that fight-or-flight reflex, which relates to fear, can be sensed using galvanic skin response information, despite moderate levels of physical activities. We use ECG and SCR to evaluate the correlations between FoG and the changes in these sensor signals in order to predict FoG.

6.3. Dataset

To study whether ECG or SCR are useful for predicting FoG, we collected the CuPiD multimodal dataset. The CuPiD dataset contains sensing data collected from subjects with Parkinson's disease who performed different walking protocols in a laboratory setting designed to provoke FoG. The customized system contains 9 inertial measurement units (IMU) attached on different parts of the body, a near-infrared spectroscopy sensor, an electrocardiogram sensor, and a skin conductance sensor. In this work, we focus on the information from the last two sensors.

To collect ECG, we used Actiwave[1], which samples synchronized ECG and 3-D acceleration data. The sensor samples ECG data at $N_{ECG} = 512$ Hz. For SCR information we used a Shimmer sensor[2], with synchronized 3D acceleration and galvanic skin response (GSR) modules. Shimmer samples both GSR and acceleration data at $N_{GSR} = 51.2$ Hz. In Figure 6.1 we show the two sensors, and their on-body placement.

6.3.1. Protocol Description

Building on previous work [40, 50], we designed a set of protocol sessions which contain different types of motor activities that subjects were asked to perform in order to provoke FoG. We include activities shown to increase the likelihood of FoG, e.g., turns, passing narrow corridors, and other activities that resemble daily life in a home setting. The protocol contains the following walking tasks, listed in the order in which they were carried out:

(1) The Ziegler protocol [50] is clinically designed to provoke FoG and includes two 360° turns, one 180° turn, and passing through a narrow passage. It takes around 1.5 min and is performed three times: once simple, and two times with cognitive tests. The cognitive tasks consist from (a) carrying a glass of water while walking, and (b) carrying the glass of water while performing serial subtractions.

(2) Figure eight consists in performing 5 times a figure eight shape in a 3-meter area. It is performed for 2 min, twice: once simple, then with a cognitive load task, which requires to perform serial subtractions, or to enumerate words that start with a specific letter.

(3) Straight line walking with turns. The subject walks straight for 20 meters, turns, and walks again on the opposite direction, all this for 5 times. The task takes approx. 1.5 min, and is performed twice: first simple, and then by passing a narrow corridor. Sometimes, straight line walking is performed a third time with a similar cognitive load task as in the case of Figure eight.

[1] www.camntech.com

[2] www.shimmer-research.com

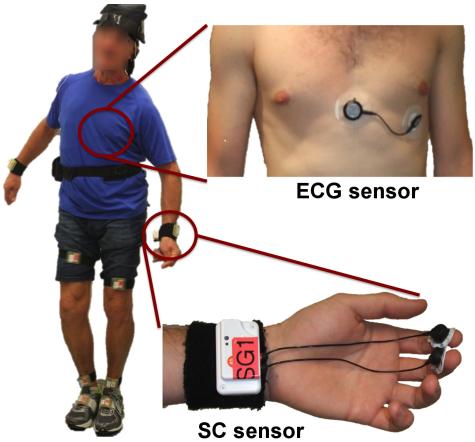


Figure 6.1: *A subject wearing the system used for the data collection, with a focus on the ECG and SCR sensor systems. The ECG sensor is attached on the chest, using two electrodes. SCR data is collected using finger electrodes attached on the index and middle fingers, and a wristband on which the Shimmer sensor is attached using Velcro stripes.*

(4) Circles. The subject walks in circles, with random 180° and 360° turns, when asked by the clinicians, for a period of 3 minutes.
(5) The hospital tour is a real-life session that includes approx. 10 minutes of random walking through the hospital's crowded hall, which includes involuntary stops, turns, changes of direction, using the elevator, and passing narrow spaces.

In between the walking tasks, subjects were asked to sit and relax for periods of 30-60 seconds. We refer to these as *baseline sessions*, as data from these sessions is used as reference for the physiological data. Appart from them, we include also other types of non-walking sessions during the protocol: Completing questionnaires, clinical evaluations, debriefing, and sitting/standing with cognitive load, i.e., performing serial subtractions. When required, the patients were resting in-between the sessions. The whole protocol lasts for around 1-1.5 hours, which includes the walking sessions, along with the baselines, non-walking sessions, and rest periods; the walking tasks sum around 25-30 min from the protocol.

6.3.2. FoG Annotation

For fine grained annotation of FoG events, we deployed two video systems to record the patient's activity during the protocol: (1) a mobile HDR camera, and (2) a fish-eye camera. Offline, two clinicians with expertise in FoG labeled the freezing episodes and other walking events, such as start walking or turns. They used stopwatch annotations and the videos, which were later synchronized with the sensors datastream. Clinicians considered the moment of the arrested gait pattern, i.e., stop in alternating left-right stepping, as the start of FoG, and the instant when the patient resumed a regular gait pattern as the end of it. The accuracy of the FoG labels is at the level of a videoframe, i.e., 40 milliseconds. A first clinician went over all videos and marked the FoG episodes. All events on which the first clinician was not sure were transferred to a second expert clinician, who went over them and decided whether they are FoG or not. The same procedure was followed to determine the start/end time of a freezing episode. A problem of the SCR data is the noise resulted when the subject is touching the electrodes. In our dataset, we made sure such noisy events did not take place, i.e., we continuously reminded the subjects not to touch the electrodes. When it happened, clinicians labeled these kind of events from the videos, and we took out from the analysis the signal segments corresponding to such periods.

6.3.3. Participants and Statistics

The study took place at the Tel Aviv Sourasky Medical Center in Israel, was approved by the medical center's Helsinki committee, and all subjects provided informed written consent. We recruited participants who suffer from PD and self-reported FoG, are cognitively intact, and have adequate vision and hearing abilities. We excluded people who suffer from psychiatric co-morbidities, e.g., major depression, or had a history of stroke, traumatic brain injury, brain tumor or other neurological disorders. We did not explicitly screen for heart abnormalities during recruitment. However, during the protocol, we asked each participant if she/he suffers from any heart disorders. Only one participant reported suffering from a heart disease and had a pacemaker. In this case, it is likely that changes in heart rate that is controlled by a pacemaker would not reflect FoG; hence, we did not collect data for this subject.

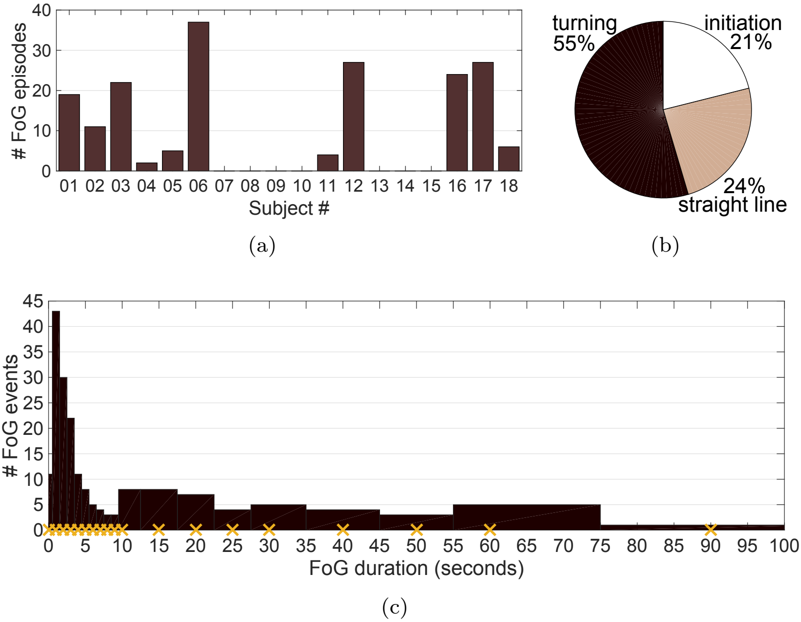


Figure 6.2: *FoG statistics: (a) FoG events distribution across subjects, (b) distribution of FoG subtypes, and (c) FoG-duration distribution.*

Prior to testing, participants underwent a complete clinical physical and neurological examination that included assessment using the Unified Parkinson's Disease Rating Scale test UPDRS-III [10]. During the clinical protocol, all participants were in ON medication state, i.e., medication was effective, in order to obtain similar conditions as in daily life.

In total, 18 subjects participated in the data collection trial. They were between 49 and 89 years of age (average: 68.9 years, std: 10.2 years), and had a disease duration between 2 and 18 years (average: 8.8 years, std: 4.6 years). Subjects obtained diverse scores for the PD and FoG severity: UPDRS scores between 25 and 56 (average: 41.7, std: 10.2), and FOG-Q [9] between 4 and 30 (average: 19.7, std: 7.1), being representative for II-IV Hoehn & Yahr disease severity [18]. Some of the patients could not perform the entire protocol, due to their disease severity.

The updated FoG-related statistics compared with those presented in [31] are: A total of 184 FoG episodes were identified, with a duration between 0.12 sec and 98.88 sec (average: 8.84 sec, std: 14.87 sec). FoGs are not equally distributed among the patients, as shown in Figure 6.2(a): seven did not experience any FoG, four had between 2 and 6 FoG and the other seven experienced more than 10 episodes. In Figure 6.2(b) we illustrate the distribution of the FoG subtypes episodes, related to the walking context: The majority of FoG events occurred during or just after turning (101 out of 184), 38 of them were related to gait initiation, and the rest of 45 occurred during walking in straight line. The average FoG duration, FoG characteristics and gait performance varied across subjects. A histogram with the FoG-duration distribution is given in Figure 6.2(c), approx. 65% of FoG episodes having a duration between $[0, 5]$ sec. The relatively low number of FoG episodes, their distribution across only 11 subjects, and their type might be explained by the fact that subjects were in the ON medication state, which leads to relatively improved gait performance, compared with the OFF medication state. Moreover, FoG is much more difficult to trigger in the clinic than in the home [35].

6.4. Changes in Physiological Data for FoG Prediction

6.4.1. Methodology and Features Extracted

In this first part of our contribution, we aim to answer the first research question: Whether physiological data such as ECG and SCR has different characteristics just before, during, or just after FoG, compared with the rest of walking events.

We analyze physiological data in the following manner: For each of 11 subjects which experienced FoG in our study, and for each walking session in the protocol which contains at least one FoG, we consider the time interval T_{preFoG} before the FoG, as *preFoG* period. Similarly, we consider the time $T_{postFoG}$ just after the FoG episode as the *postFoG* period. Thus, we split the data in 4 categories, as in Figure 6.3: (1) FoG represents data during the FoG, (2) *preFoG* is the data from the T_{preFoG} period, (3) *postFoG* the data from the $T_{postFoG}$, and (4) *Walk* represents the rest of the data in the session, which includes events such as turns, gait initiation, and stop walking.

We set $T_{preFoG} = T_{postFoG} = 3$ seconds. These values are chosen a priori as in [28]. The ECG or SCR properties might change with less

Figure 6.3: *The categories assigned to the data:* FoG *represents the groundtruth labels as set by the clinicians.* PreFoG *and* PostFoG *are artificially set, to observe whether there are specific changes just before FoG, compare with walking. The* Walk *category contains the rest of the walking and gait events in the session.*

than or more than 3 seconds before or after each FoG. However, we fix the pre- and post- FoG periods as a first step only to see whether there are significant changes in the physiological data across the 4 categories. Different from, and in extension to the work from [28], we consider all the FoG episodes in the protocol, independent of duration, or the walking context in which they happen.

From each sensor, we extract features in a sliding-window manner [2, 30, 45]. We set the window size to $N_{window} = 3$ seconds, and the window-overlapping step to $N_{step} = 0.5$ seconds. We choose a 3 seconds processing window to map on TpreFoG, and TpostFoG, as a trade-off between achieving accurate feature estimations from sensing data, and the latency of observing variations prior to or during FoG. Moreover, as FoG is transient and typically short, larger data windows will contain a higher proportion of normal walking, making it more challenging to observe variations prior to freeze. On the contrary, shorter windows might cause poorer estimations of feature values. Next, we give details about the data processing and extracted features for each of the two sensor modalities:

ECG Data Processing

For each window of ECG data, we detect the R peaks, and compute the time between each two consecutive peaks, i.e., the RR intervals [4]. We then compute the instantaneous Heart Rate (HR) values in the window as:

$$HR = \frac{60 \times SamplingRate_{ECG}}{RR} \tag{6.1}$$

We extract the mean and median of HR vector, and the Heart Rate Variability (HRV) as defined previously in [28]. In addition to the heart

#	Feature	Description
1	$\mathrm{HR}_{\mathrm{mean}}$	Mean over the HR values in the window
2	$\mathrm{HR}_{\mathrm{median}}$	Median over the HR values in the window
3	HRV	$HRV = \frac{std(HR)*100}{mean(HR)}$
4	$\mathrm{Power}_{\mathrm{VLF}}$	Power on very-low frequencies (VLF) [0.01, 0.04] Hz of the ECG signal
5	$\mathrm{Power}_{\mathrm{LF}}$	Power on low frequencies (LF) [0.04, 0.15] Hz of the ECG signal
6	$\mathrm{Power}_{\mathrm{HF}}$	Power on high frequencies (HF) [0.15, 0.4] Hz of the ECG signal
7	$\mathrm{Ratio}_{\mathrm{LF/HF}}$	The ratio between the power on LF and HF bands of the ECG

Table 6.1: *Features extracted from ECG signal.*

rate features, we extract frequency-based features from the raw ECG [4], such as the power on different spectra. A summary with all the ECG features and their description is contained in Table 6.1.

Figure 6.4 contains an example of raw ECG signal, together with $\mathrm{HR}_{\mathrm{median}}$ and HRV extracted features, for a walking session which contains three FoG episodes. We observe that HR and HRV increase just before FoG, in the case of the first episode or just after FoG, in case of the last two FoG. However, both features also increase under the same pattern during the second turn.

Skin Conductance Data Processing

In Figure 6.5 we present the steps for processing the SCR data: Before extracting the features, we first (1) transform the galvanic skin resistance signal obtained from the Shimmer sensor into conductance data. Skin conductance ($\mathrm{C}_{\mathrm{orig}}$) is the inverse of the skin resistance: $C_{orig} = \frac{1}{R_{GSR}}$. We then follow the same processing steps for SCR as in previous work [12, 47]: (2) we first apply on the $\mathrm{C}_{\mathrm{orig}}$ a third order low pass filter, non-causal, with a cutoff frequency of 0.9 Hz. We choose this cutoff value empirically, as it showed the most informative changes in the signal prior and during FoG across all subjects. Then from the resulted filtered signal $\mathrm{C}_{\mathrm{filtered}}$ we extract its baseline. We refer to the resultant signal as C. (3) From C we then extract its first derivate $\mathrm{C}^{(1)}$, and its second derivative $\mathrm{C}^{(2)}$, by following the same procedure as in [12, 47]. Using the sliding window procedure, (4) we extract the fol-

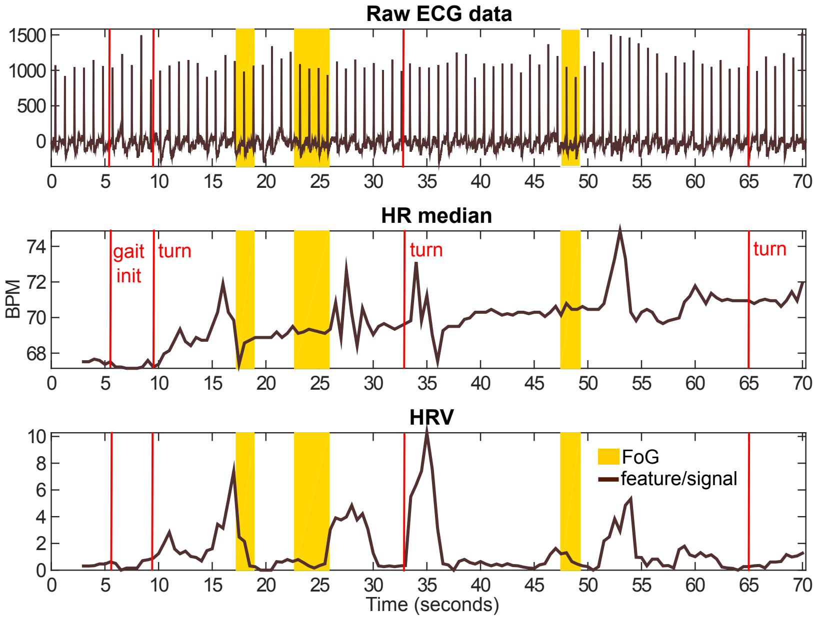


Figure 6.4: *A sequence of ECG raw signal, together with the extracted median of HR and HRV. The sequence contains three FoG episodes, straight line walking, and events such turns and gait initiation. Both HR and HRV increase within 3 seconds before the first FoG episode, or in the 5 seconds interval just after the second and third FoG event. However, these increasing trends are not present only in the vicinity of freeze events, as HR and HRV also increase during the second turn in the walking sequence.*

lowing eight features for each of the resultant signals C, $C^{(1)}$, and $C^{(2)}$ as described in Table 6.2. In total, we obtain 24 features from each window (8 for each signal: C, $C^{(1)}$, $C^{(2)}$).

In Figure 6.6, we show an example of raw SCR data and the resulted C, $C^{(1)}$, $C^{(2)}$ signals, collected during straight line walking with turns. We observe that the C and $C^{(1)}$ increase few seconds before FoG. The same just after the FoG happens. Moreover, these changes are different from the SCR variations corresponding to other walking events such as gait initiation or turns.

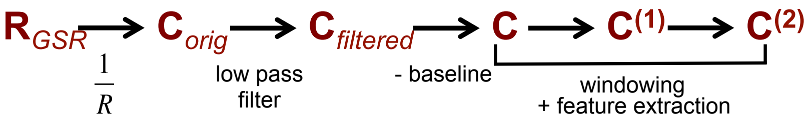


Figure 6.5: *The skin conductance data processing framework: from the original R_{GSR} collected from Shimmer we obtain C, $C^{(1)}$, and $C^{(2)}$ signals, on which we apply windowing and feature extraction techniques.*

#	Feature	Description
1	Mean	The average value over the signal
2	Median	The median over the window
3	Std	The standard deviation value
4	Min	The minimum of the signal
5	Max	The maximum value of the signal
6	Diff	The difference between the maximum and minimum values of the signal
7	# min	The number of local minima in the window data vector
8	# max	The number of local maxima over the same window

Table 6.2: *Features extracted from SCR and its derivatives.*

6.4.2. Informative Features and Statistics

To explore whether there are specific changes in the ECG or SCR during *preFoG* or FoG, compared with *Walk*, we use (1) one-way analysis of variance, and (2) mutual information values for each feature extracted, for each of the 11 subjects.

One-way Analysis of Variance

We use One-way Analysis of Variance (ANOVA) [19] in MATLAB to assess the p-value for each of the features from ECG or SCR data, with respect with the 4 categories. Prior to using ANOVA, we checked the normality assumption for each ECG or SCR feature, for each subject's dataset. Not all the features are perfectly following a normal distribution; however, the MATLAB ANOVA implementation is robust to slight deviations from this assumption. We consider the significance

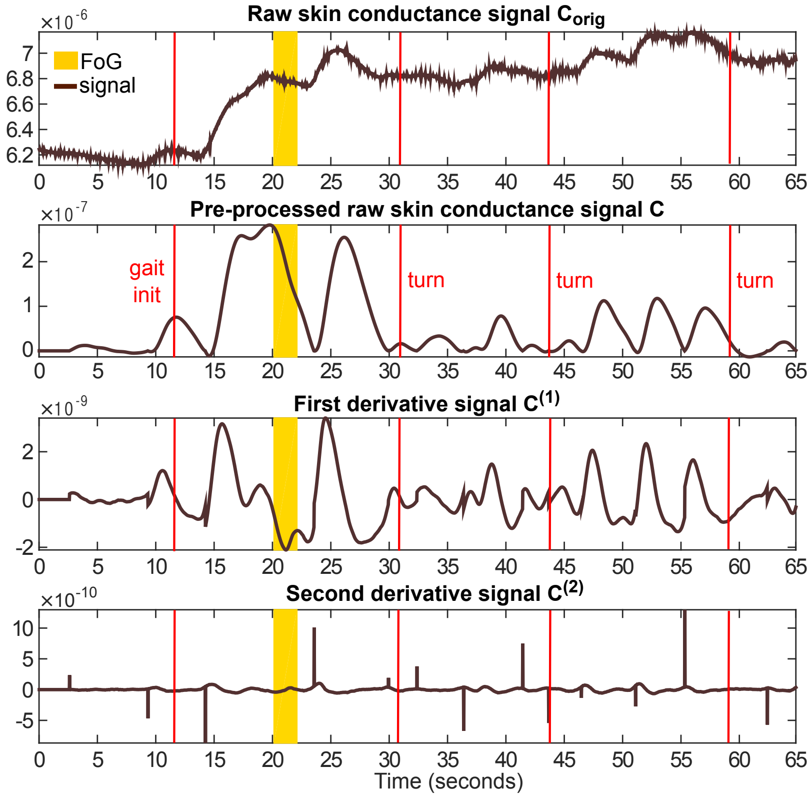


Figure 6.6: *A sequence of straight line walking with turns, containing a FoG episode, captured in the raw SCR, C, $C^{(1)}$, and $C^{(2)}$ signals. There are specific changes just before FoG, different from the signals' changes during other walking events (turns, gait initiation).*

threshold set to 0.001. A feature which has the p-value ≤ 0.001 shows that the information from at least two of the 4 categories of data are statistically different, although the features selected will not be necessarily useful in predicting FoG.

#	Subject	Features
1	S01	HR_{mean}, HR_{median}, HRV
2	S02	HR_{mean}, HR_{median}, $Power_{HF}$
3	S03	*no data available*
4	S04	HRV, $Power_{HF}$
5	S05	HRV
6	S06	HR_{mean}, HR_{median}
7	S11	–
8	S12	*no data available*
9	S16	*no data available*
10	S17	HR_{mean}, HR_{median}
11	S18	$Power_{HF}$

Table 6.3: *ECG-based features which have the p-value* ≤ 0.001 *from ANOVA test, for each subject.*

Mutual Information

Mutual Information (MI) [38] is another measure we use to check whether there is a link between the observations from a feature related to the 4 categories of data, i.e., *preFoG*, *FoG*, *postFoG*, and *Walk*. MI is usually used for feature selection [38], but here we apply MI for feature ranking, to explore which of the features capture differences between the 4 categories.

6.4.3. ECG Features

Table 6.3 presents the features which obtained a $p \leq 0.001$ with ANOVA, for each of the 11 patients. In the case of three subjects (S03, S12, and S16), we were not able to extract the features from the raw ECG, due to the high level of noise in the signal, likely the result of weak attachment of the electrodes to the chest (S03 and S12), or because one subject, S16, had a pacemaker. Results suggest that there are changes in some features which are specific for at least one category of data, when compared with the rest of the 3 categories: Thus either FoG, preFoG, or postFoG has specific changes in some features, when compared with Walk category. For S11 none of the ECG features passed the ANOVA test, suggesting that for this subject, there are no significant changes ECG with respect to the 4 categories of data.

Similarly, the top MI scores were obtained by HR (mean, median),

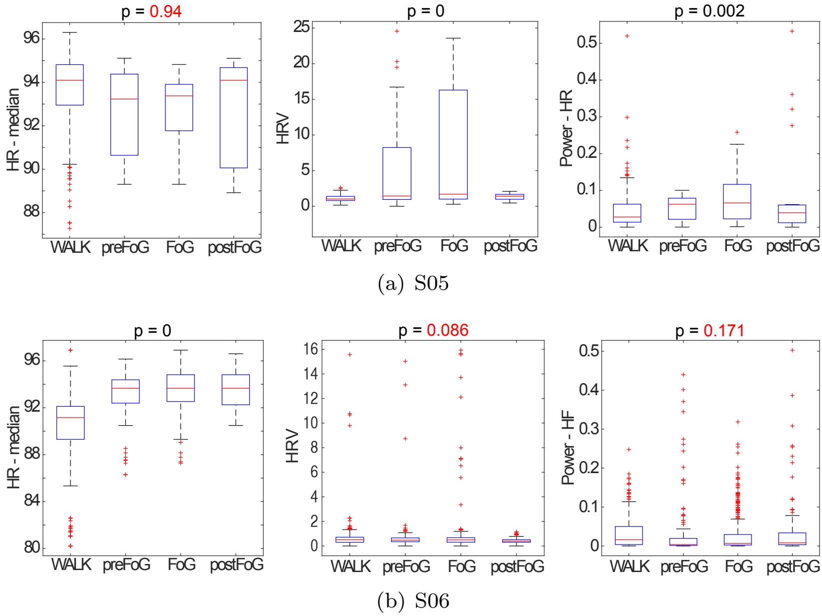


Figure 6.7: *Boxplot representation for HR_{median}, HRV, and $Power_{HF}$ features, in case of 2 subjects with different ECG trends related to the four categories: In case of S05, HRV and $Power_{HF}$ increase during preFoG and FoG compared to Walk. In the case of S06, HR increases significantly during preFoG, FoG, and postFoG periods, and $Power_{HF}$ decreases during preFog.*

HRV and Power_{HF} features, where the HR-based and HRV features obtained top MI scores for all subjects. Power_{HF} is particularly interesting, as data in the processing 3-seconds window may not be large enough for an accurate estimation of the power-based features. Yet, the estimated Power_{HF} captures different trends across the 4 categories.

However, we observe that for some of the subjects the HR values (mean, median) incorporate the significant variations; while for other subjects the HRV varies. Power on HF seems to be independent of these two groups. For example, we plot in Figure 6.7 the $\text{HR}_{\text{median}}$, HRV, and Power_{HF} (features which obtained the best ANOVA p-value and MI scores across all datasets) in case of two subjects which show three different types of ECG behavior. In case of S05, HRV registers a higher variance and has higher values during preFoG and FoG, compared with Walk and postFoG periods. Power_{HF} varies too, and has higher values during PreFoG and FoG; however the values tend to overlap with those of the other two classes. For this particular subject, HRV changes with few seconds before FoG suggests that there is a preFoG specific pattern which can be detected. On the other side, for S06 (Figure 6.7(b)) the relevant changes are captured by the HR (mean, median), while HRV and Power_{HF} do not incorporate any useful information. During preFoG and FoG, and even postFoG the HR increases compared to Walk.

Discussion. Our analysis supports and extends the previous findings from the study of Maidan et al. [28], which show that there are changes in the HR during FoG compared with periods of walking before. Moreover, we generalize these findings: our analysis suggests that there are changes in HR or HRV during all FoG subtypes, compared with the rest of all waking. In our dataset, only 55% of FoG are during turns (Figure 6.2(b) in Section 6.3), compared with the dataset from Maidan et al. [28] which includes only FoG during turns. However, different from [28], these changes do not follow a general trend, but are subject dependent, at least in the case of Cupid dataset.

Due to the diverse FoG subtypes and walking events, results suggest that ECG might capture some physiological changes with few seconds before FoG, that could lead or be a cause for the upcoming freeze event. In this case, ECG could be used to predict FoG.

6.4.4. Skin Conductance Features

We apply the same procedure to the SCR features as in case of ECG, to observe whether some of them capture significant changes in the preFoG and FoG compared with Walk.

Table 6.4 lists the features which obtained a p-value ≤ 0.001 on the ANOVA significance test, for each of the 11 subjects. Different from the ECG, there is a higher fraction of the 24 SCR features which imply significant variations on the 4 categories, suggesting that the skin conductance captures more information related to preFoG, FoG and Walk periods. A higher number of features from C signal passed the ANOVA test overall across the subjects, compared with the first and second derivatives features. In case of S05, no SCR-based features passed the ANOVA test, suggesting that for this patient, the SCR does not capture any significant changes during preFoG, FoG or postFoG.

#	Subj.	C	$\mathbf{C^{(1)}}$	$\mathbf{C^{(2)}}$
1	S01	**mean**, **median**, **std**, min, **max**, diff, # min	mean, median, **std**, min, max, # min, # max	std
2	S02	**mean**, **median**, **std**, **max**	median, **std**, min, max	median
3	S03	**std**, min, # min, # max	**std**, min, max, # min, # max	std, min, max, # min, # max
4	S04	**mean**, **median**, **std**, **max**, diff	mean, median, **std**, min, max, # min, # max	median, std, min, max
5	S05	–	–	–
6	S06	**mean**, **median**, **std**, min, **max**, diff	mean, median, **std**, diff	mean, median, max, # min, # max
7	S11	**mean**, **std**	–	–
8	S12	**mean**, **median**, **std**, min, **max**	**std**, min, max, diff	mean, std, min, max, # min, # max
9	S16	**mean**, **median**, **std**, **max**, diff, # min, # max	# max	–
10	S17	**mean**, **median**, **std**, **max**, diff, # min, # max	mean, median, **std**, min, max, # min, # max	std, min, max, diff, # min, # max
11	S18	**mean**, **median**, **std**, min, **max**	**std**, min, max	std, min, max

Table 6.4: *Skin conductance -based features which have the p-value* ≤ 0.01 *resulted from ANOVA1 test, for each subject. The text-bolded features represent the top 5 occurred ones across all subjects*

The most occurred features across all subjects are the mean, median, std and max of the C signal, and the std feature of the $C^{(1)}$, followed by min and max of the $C^{(1)}$ signal. However, the # of local minima and the # of local maxima features, for all the three types of signals (C, $C^{(1)}$, and $C^{(2)}$) were selected as top features using MI, for all subjects.

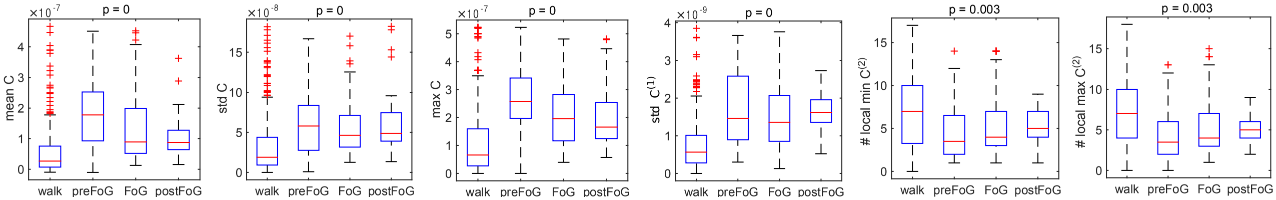
Next, we observe how the top resulted features with both ANOVA and MI change with respect to preFoG, FoG and Walk. In Figure 6.8 we present the variations of some 6 top resulted features from the previous experiment (mean, std, and max from C, std of $C^{(1)}$, and # min and # max from $C^{(2)}$) in boxplot representations, for two subjects.

Figure 6.8(a) shows the changes in case of S18: We observe a significant increase in the mean, std, max of C signal, and std of $C^{(1)}$ during preFoG, compared with the rest of walking. Moreover, there is a significant decrease in the # of local minima and maxima of the 2nd derivative signal, during preFoG, compared with Walk. The first 4 features increase also for FoG and postFoG periods, compared with the Walk. Changes in the SCR suggest that there is an increase in the skin-conductance just before the FoG, which is different from both Walk and FoG categories. Thus, it might be possible to predict FoG, in addition to detect it.

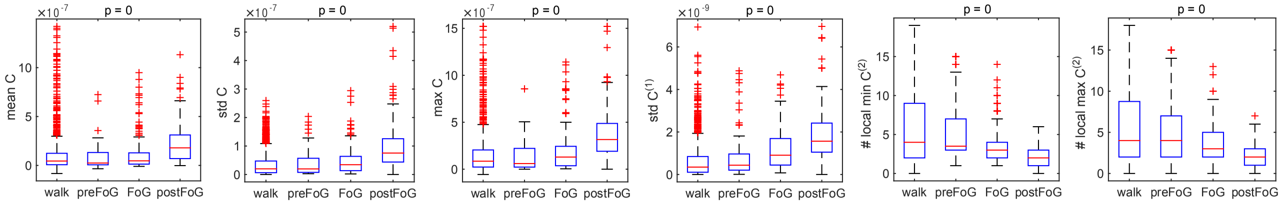
On the other side, for S17 (Figure 6.8(b)) there is a significant variation only just after FoG: The # of local minima and maxima from $C^{(2)}$ decrease, while mean, std, max from C, and std from $C^{(1)}$ increase in postFoG. However, preFoG and Walk values for all the features tend to be similar. This suggests that changes in SCR depict a physiological reaction of the actual FoG, and not its cause.

Similar to ECG, for both subjects we observe a quite high number of outlier values for all the 4 categories of data. This is due to the a priori durations of preFoG and postFoG periods, which are set both to 3 seconds just before and after FoG. However, a preFoG or postFoG behavior can be longer with few more seconds than the fixed set period. Thus, the preFoG, postFoG and Walk share values.

Discussion. We conclude that even if the SCR data captures more statistically relevant information about the preFoG and FoG compared with Walk (suggested also by the high ratio of total features which pass ANOVA), still each subject tends to have a specific reaction, thus significant changes in SCR before FoG are subject-dependent. It is natural, as each person has a specific reaction to external stimuli, thus also the reaction in the captured skin conductance is person-specific.



(a) S18



(b) S17

Figure 6.8: *Boxplot representations for SCR-based features – mean, std and max of C, std of $C^{(1)}$, and # local minima, and # local maxima from $C^{(2)}$ – in case of two subjects with different trends during preFoG and FoG: For S18, there is a significant increase in the first 4 features during preFoG compared with the rest of walking. However, for S17 there are no significant changes in any of the features during preFoG compare to Walk; still, there is a statistically significant increase in the first 4 features just after FoG.*

Moreover, SCR is not prone to the noise from the subject's movements, thus the explanation why skin conductance seem to capture more changes than the ECG data during preFoG and FoG periods.

SCR might incorporate noise generated from touching the electrodes. As mentioned earlier in the Section 6.3, we made sure to avoid such events taking place by continuously reminding subjects not to touch the electrodes. In case it happened, clinicians labeled the events from the videos, and we took out from the analysis the signal segments corresponding to such periods.

6.5. Prediction of FoG Events

In the previous section we found initial evidences that there might be specific changes in the physiological signals, particularly in the skin conductance, just before FoG episodes. These changes are subject-dependent, as each individual has its own way to act to stimuli, and as a result, the physiological answer captured by ECG and SCR data is specific for each person. Following the previous findings, in this section we answer the second research question: Whether we can we predict FoG from physiological signals.

For this, we model *FoG prediction* as an anomaly detection problem. The reasoning behind is that FoG events are themselves *anomalies* during walking, which happen rarely relative to the total walking period. This maps exactly on the definition of the anomaly in a dataset. Furthermore, we consider also changes in the signal during just before FoG as an anomaly in the signal, together with the FoG. By detecting these variations prior to FoG, we actually *predict* the forthcoming freeze episode.

To solve *FoG prediction* problem, we use Multivariate Gaussian Distribution (MGD) [11]. MGD was successfully used for anomaly detection with image data [17]. Moreover, MGD allows for multiple and different time-series fusion, being suitable for our different features from ECG or SCR, which capture themselves various changes in the data. We build a FoG prediction model for each of the 11 subjects, as ECG and SCR data changes and reactions are specific for each person.

6.5.1. FoG-Prediction Model

We consider the vector of features for each subject S, as vector-valued random variable $X = [X_1, X_2, ..., X_k]^T$, where the k columns represent the features, resulted either from ECG signal, or from SCR signal, as detailed in the previous section. We make the hypothesis that values from X are normally distributed. A line in X represents a feature vector, as computed from a window of data. We define $\mu \in \mathbf{R}^k$ as the mean of X, and Σ as its positive semi-definite covariance matrix. We compute the multivariate Gaussian distribution, or the probability density function p as:

$$p(x;\mu,\Sigma) = \frac{1}{(2\pi)^{\frac{k}{2}} \mid \Sigma \mid^{\frac{1}{2}}} exp(-\frac{1}{2}(x-\mu)^T \Sigma^{-1}(x-\mu)) \tag{6.2}$$

Where the resulted $p(x;\mu,\Sigma)$ is a vector with the same length as the matrix of observations (features) X. We then apply on p that resulted from all the data of one subject a threshold based rule: We consider the resultant vector of anomalies $Label_{anomaly}$, with decisions for each line in X, as:

$$Label_{anomaly} = p(x;\mu,\Sigma) \leq TH, \tag{6.3}$$

where TH represents the threshold value.

A cross-validation scheme with training and testing data to automatically model μ and Σ, and select the threshold TH, implies that data is labeled with the anomaly events. Thus, that there are available labels for periods before FoG, FoG and after FoG. But in our case, groundtruth labels provided by clinicians target only the FoG events, while *preFoG* and *postFoG* categories are a priori considered, and fixed to a period of 3 seconds. The preFoG anomaly in the physiological data might start before or after this fixed and artificially set period. As a result, we cannot model the parameters using cross-validation, as there are no groundtruth labels for the anomaly we want to detect, i.e., preFoG. Hence, we compute the μ and Σ on the whole data, and set manually the TH value.

6.5.2. Evaluation

We apply the method detailed above on the data from each of the 11 subjects who experienced FoG, in the case of two types of data: (1) ECG, and (2) skin conductance.

We consider the following performance measures: The number of True Positives (TP) events, defined as the number of successfully predicted FoG from the total number of FoG for a subject dataset. We consider a FoG *detected in advance / predicted* when the $Label_{anomaly}$

outputs continuously that there is an anomaly in the data with at most 8 seconds *before* a FoG episode. The False Positives (FP) event are the number of false FoG predictions, i.e., the method predicts a FoG, when none happens. Additionally, we compute the average prediction time $T_{prediction}$ across the successfully predicted FoG, which shows how much time on average a FoG is predicted, for each subject.

The proposed algorithm detects also FoG, showing whether there is an anomaly during or just after the FoG period. However, we do not present the evaluation results for the FoG-detection, as it is beyond the scope of our work.

6.5.3. Results

Prediction of FoG from ECG data

Our algorithm was not able to build a FoG-prediction model from ECG data. Even if the analysis from the previous section suggested that ECG might be useful in predicting FoG, it seems that the variations of the features were not containing enough information to build the anomaly model.

One explanation is that changes in the ECG features might not be only correlated to FoG, but could come also from the noise captured by the ECG from the sudden movement of the body during different walking events, i.e., the torso movement during turns.

Prediction of FoG from SCR data

Table 6.5 presents the FoG-prediction performances for each of the subjects' datasets, when using features from SCR. Data from SCR is informative enough to predict 71.3% of FoG episodes (overall 132 out of 184 events) across the 11 subjects, with an average prediction time of 4.2 seconds before the freeze event. Moreover, the prediction rate comes with a relatively low number of false predictions (71 false alarms across approx. 2 hours of data). The selected thresholds TH for each subject data are chosen to be slightly in the favor of increasing the number of FoG detected, while keeping a low number of false positives. These results suggest that it is feasible to use changes in the skin conductance signal during walking to predict FoG episodes in real-time. There might be a subject specific pattern in the SCR signal which happens before the FoG, which is accurate enough to distinguish between the other walking patterns, given the low number of false alarms.

#	**Subject**	**#TP / # total (%)**	**#FP**	**Avg. pred. time (sec)**
1	S01	12 /19 (63.1%)	11	5.7
2	S02	9 /11 (81.8%)	5	6.3
3	S03	21 /22 (95.4%)	6	3.7
4	S04	2 /2 (100%)	1	4
5	S05	2 /4 (50%)	5	5.2
6	S06	23 /37 (62.16%)	8	4.2
7	S11	4 /4 (100%)	1	1.5
8	S12	20 /27 (74%)	6	3.6
9	S16	14 / 24 (58%)	5	3.6
10	S17	16 /28 (57.1%)	18	4.3
11	S18	6 /6 (100%)	1	4.5
	Total	132 /184 (71.3%)	71	4.2

Table 6.5: *The FoG-prediction performances.*

Two types of reactions. The specific variations in SCR prior to FoG episodes are a result of the body's reaction to stimuli, which are likely a factor that leads to FoG, as hypothesized in [8]. However, as suggested also in the previous section, SCR is not equally informative for all the subjects. The prediction results across the subjects are strongly correlated with the statistical significance of the changes obtained by the SCR features. In the previous section, we observed that there are two types of reactions in the SCR: In the first one, SCR features increased before FoG, thus we could capture changes in the physiological signal that might provoke FoG, making possible FoG prediction. Subjects such as S02, S03, S04, S11, S18, and even S12 and S16 seem to have this kind of behavior. This is suggested by the high number of FoG predicted (up to 100% for S04, S11, and S18), at a cost of a relatively low number of false positives.

On the other side, a second type of reaction is that SCR increases only towards the end of FoG, or after the event. Sometimes the SCR does not capture any reaction even after FoG. Subjects such as S01, S05, S06, S17 are included in this category. For these datasets, the number of FoG predictions come at a high number of false positives, when compared to the total number of FoG events to be predicted. For example, in case of S05, there are 4 events to predict, but predicting two of them comes at the cost of 5 additional false alarms. This suggests that the reaction of the sympathetic nervous system captured by SCR data might be an answer to the actual FoG. For some subjects here, sometimes the prediction of a FoG might be actually the late detection of a reaction caused by a previous FoG: For example, in case of S06 or S17, in some walking sessions, the FoG events were happening in a chain reaction, with few seconds between them. In this case, the changes in the SCR captured as a result of a FoG could be used to predict the next FoG.

However, even for this reaction type, the SCR changes are useful, as the future FoG events might be the result of the answer to the first FoG, i.e., stress or anxiety due to FoG. In this case, a preemptive cueing for overcoming FoG would be helpful to stop the FoG reaction chain.

FoG prediction time. For all subjects, we observe that the algorithm detected an anomalous trend in SCR data seconds before the actual FoG event (average of 4.2 seconds, min 1.5 seconds, and max 6.3 seconds), for the successfully predicted events. This finding suggests, as also stated in [28], that what was supposed to be a sudden, episodic freezing event actually evolves over a relatively long time, i.e., few seconds. Moreover, this prediction time, i.e., 4-5 seconds, enables the idea of giving rhythmic cueing to prevent the patient from entering the eventual freeze episode: starting a rhythmic auditory stimulation few seconds before gives time to the subject to react to the cue, and follow the imposed rhythm, which would help regain the gait rhythmicity and avoid the FoG. A lower prediction time, e.g., ≤ 1 second, would not be useful, as the subject will not have time to react to cueing.

Correlation with PD scores. We were not able to find any correlation between the FoG-prediction performances, and the PD disease duration, FoG-Q score, Hoehn & Yahr score of UPDRS-III score for each subject. This suggests that the reactions captured in the skin conductance are not related to PD disease stage, but are related to how the sympathetic nervous system reacts to psychological arousal. This reaction is independent of disease severity, at least as captured using conventional measures, and appears to be specific to how each subject reacts to stress or anxiety.

Prediction and FoG subtypes. Only 55% of FoG happened during turns (Figure 6.2(c) from Section 6.3), while more than 71% from the total FoG were successfully predicted. This suggests that the changes in

SCR prior to FoG are only capturing reactions to stimuli which cause FoG, and are independent of the FoG subtypes or walking context. As a result, it is possible to predict even FoG during gait initiation. As a comparison, with accelerometers FoG during gait initiation cannot be detected, as there are no prior information about the gait [30]. Moreover, different from ECG, SCR data is not prone to noise coming from the movement type, such as sudden body movements during turns or start walking.

Prediction versus detection. Our method also detects FoG (during and just after the event detection), on top of the prediction. This is due to the general framework of the algorithm for anomaly detection. In our case anomalous changes in the SCR data are not only before FoG, but also during and just after FoG, as also shown in Section 6.4. Thus, in case if the FoG is not predicted, then it can be detected, either with the same anomaly-detection algorithm and SCR data, or with previous methods based on ankle-mounted accelerometers [29].

6.6. A Vision of a Wearable System To Predict FoG in Real-Time

The high-rate prediction of FoG and the quite low number of false positives are promising towards a real-time FoG-prediction system based on skin conductance data, which will act like a personal assistant for overcoming FoG in real-life settings, such as the users' homes.

We envision a system composed from a smartphone as a wearable computer, which receives data in real-time from a SCR wearable sensor. There are commercial wrist mounted sensors, such as wrist bracelets, which sense skin conductance-related data, such as GSR. The wrist-worn bracelet sensors do not need additional finger electrodes, thus there will not be any noise in the SCR from touching the sensor.

In our present work, we predict the FoG episodes, but our study is done offline. However, our algorithm could be implemented and adapted on a smartphone, which receives and analyzes the sensor data in real-time. Once the algorithm detects an anomaly, thus predicting that a FoG might happen in the next few seconds, the system will start a preemptive rhythmic auditory cue similar as in [29], which will help the subject improve the gait and maybe overcome the FoG.

A main conclusion of our study is that the reactions in SCR before FoG are subject-specific, thus the algorithm thresholds need to be set dependent on each subject data variations. In case of the FoG-prediction assistant, the algorithm threshold can be set during the first setup of the system. Before using the system, the patients need in any case to undergo a clinical evaluation, and test the system for the first time in a lab setting. The SCR data gathered during this consult and the clinician's gait-related observations will be used to set a user-personalized threshold for the prediction algorithm.

The system can have an additional wearable accelerometer sensor as in [29], so that in case a FoG is not predicted, the system at least can detect and start cueing upon FoG. Moreover, sensing data and the algorithm decision output collected during system's usage can be also sent to a tele-medicine system, for long-term monitoring of patient's gait.

6.7. Conclusion

We propose the use of new sensors to continuously monitor the gait anomalies in Parkinson's disease, in particular FoG episodes. More specifically, we suggest that FoG can be predicted before it happens by means of physiological data, namely electrocardiography and skin conductance.

In a first stage, we show through a statistical analysis that there are physiological features exhibiting significant changes across different phases that patients go through, i.e., walking, right before FoG, during FoG and after FoG. However, features incorporating the useful information are subject-dependent, as each of them react differently to stimuli. Subsequently, we deployed an anomaly-based algorithm to predict FoG and skin conductance information. We created patient-specific models by fitting Multivariate Gaussian distributions on data from each subject. The anomaly-based models allowed to predict 71.3% of all 184 FoG episodes, on average 4.2 seconds before a FoG occurred.

Our findings also enable technologies for a real-life system that could help subjects to avoid FoG episodes altogether, by starting rhythmical cueing in real time when users are have a high risk of having a FoG episode. A practical system would consist of a bracelet measuring skin conductance to predict FoG, an optional ankle-mounted accelerometer to enhance FoG detection, and a smartphone for real-time data processing. Such systems offer the possibility of continuous gait monitoring and management in out-of-the-lab settings, and could act like gait-assistants, which help the users to avoid the FoG episodes and maintain the gait. In addition to reducing the FoG incidence, the system would contribute to increasing the quality of life in Parkinson's disease.

Future work should analyze the effect of FoG-prediction and the start of rhythmical cueing during such situations on the gait performance in PD, both on short-term and long-term periods.

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7

GaitAssist: A Training System for Parkinson's Patients with Freezing of Gait

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GaitAssist: A Daily-Life Support and Training System for Parkinson's Disease Patients with Freezing of Gait
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Abstract

Patients with Parkinson's disease often experience freezing of gait, which bears a high risk of falling, a prevalent cause for morbidity and mortality. In this work we present GaitAssist, a wearable system for freezing of gait support in daily life. The system provides real-time auditory cueing after the onset of freezing episodes. Furthermore, GaitAssist implements training exercises to learn how to handle freezing situations. GaitAssist is the result of a design process where we considered the input of engineers, clinicians and 18 Parkinson's disease patients, in order to find an optimal trade-off between system wearability and performance. We tested the final system in a user study with 5 additional patients. They reported a reduction in the freezing of gait duration as a result of the auditory stimulation provided, and that they feel the system enhanced their confidence during walking.

7.1. Introduction

Parkinson's disease (PD) is a degenerative neurological disorder characterized by postural instability, rigidity, reduced movement range, and tremor. Worldwide prevalence is estimated between 4 and 16.1 million people [24]. Current treatment is mainly pharmacological and focuses on relief of motor symptoms. Medication has significant positive effects on some of the motor symptoms; however, other symptoms are not very responsive to anti-parkinsonian medications. Many of these are related to one key deficit – the loss of the automaticity of movement. This loss implies that patients find it difficult to maintain movement amplitude, rhythm, and postural tone without consciously attending to it.

A particular problem of PD patients is Freezing of Gait (FoG). FoG is a transient episode, lasting less than a minute, in which gait is halted [26] and the patient feels that her/his feet are glued to the ground. When the patient overcomes the motor block, walking can be performed relatively smoothly. The FoG phenomenon is common in PD, with approximately 70% of the patients developing FoG during the disease progress [13]. FoG often occurs in situations that involve special attention, e.g., turning, while passing narrow corridors, at gait initiation, or in cognitively demanding situations such as in dual-tasking. In the later disease stages, FoG can also occur spontaneously, even in open runway spaces. FoG does not only drastically increase the risk for falls and fall-related injuries [6], but also has a strong impact on the social life of affected patients [22].

Clinical studies show that attentional strategies such as external rhythmical cueing through visual or auditory stimulation, e.g., floor-projected lines or metronome ticking sounds, have beneficial effects on gait in PD in general [34], and in particular in case of FoG [9]. However, as the effect of this stimulation wears off with time, continuous cueing for PD patients in daily life is not advised. Instead, the cueing support should only be provided in critical situations or during FoG episodes. We use the term *FoG support system* for a system that uses body-worn sensors for FoG-aware cueing in daily life. We furthermore assume that strategies to make use of the stimulation can be learned and improved by patients.

In this work, we present the development, design and evaluation of GaitAssist, a wearable system to support PD patients with FoG. More specifically, GaitAssist aims at assisting patients in unsupervised environments, e.g., at home, where clinicians are not actively monitoring the patient. Our work lies at the crossroads of human-computer-interaction, machine learning, and clinical intervention, creating a *sense-act-react* loop targeting FoG rehabilitation in Parkinson's disease. In the *sense* part, the GaitAssist system captures the motor properties of the gait in real-time. The system then *acts* by giving an auditory cue to the patient, in case of an ongoing FoG event. Finally, the patient *reacts* to the system's cue by trying to resume gait.

GaitAssist is the result of a participatory design effort that took into account input from engineers, patients and clinicians. The contributions of our work are as follows:
(1) In a first step, we assess technical and usability requirements for the design and development of a fully wearable FoG support system. For this purpose, we arranged an exploratory data recording session with 18 PD patients and performed interviews with clinicians, engineers, and patients.
(2) Secondly, we present the resulting prototype system *GaitAssist*, an unobtrusive and robust daily-life system for reducing FoG. Besides operating as a wearable assistant, GaitAssist provides support for a set of FoG-training exercises defined by clinicians.
(3) Finally, we present the results of a preliminary evaluation of GaitAssist. For this purpose, 5 PD patients that did not participate in the design-phase used the system in controlled lab sessions, as well as in a real-life session. A final survey shows the patients' high satisfaction

and a subjective trust in the system. Furthermore, preliminary results indicate a decrease of FoG duration during the study.

7.2. Related Research

In previous work, both auditory and visual cueing have been tested as modalities for decreasing FoG severity [3, 12]. However, these studies rely on continuous cueing, and as shown in [25] the effect of continuous stimulation wears off with time. To mitigate this effect, other systems only provide the cue upon detection of FoG. These FoG-aware support systems use small trembling motions in the 3-8 Hz band that are present during freeze episodes for detection of FoG [15, 23]. They use wearable motion sensors to detect this trembling and activate rhythmic auditory stimulation immediately when the power in the 3-8 Hz band exceeds a threshold. Bächlin et al. [4] present experiences in the development of a system for real-time FoG detection in lab settings, using wearable accelerometers. The focus of the paper is on the technical feasibility for detecting FoG in real-time, and not on the wearable technology choices or the interaction of the patient with the system. In our work, we are going further and aim at the development of a wearable assistant that patients can use in daily life without requiring any support. For this, we are taking into account the input from both clinicians and patients to build the system, and we study how it influences the user's gait. Methods to detect in real-time FoG episodes based on machine learning algorithms are presented in [20, 36]. In this paper, we follow up on the findings from our previous research and use the same methods as in [20] to detect FoG.

While auditory cueing is beneficial for reducing FoG duration [9, 25], the gait training effect on FoG severity with a wearable system was not investigated yet. Literature indicates that PD patients can improve motor functions thanks to performing rehabilitation exercises [35]. Espay et al. [10] present a visual gait training system tested by 13 PD patients. The study showed that there was a significant improvement of gait parameters after daily training with the system for 30min at home. We therefore develop our wearable FoG-assistant to also support gait training exercises in home settings.

As suggested in [32], the perception of a rehabilitation technology by the patient has a strong impact on the outcome of a treatment. While the previously listed papers investigated the technical and medical feasibility of FoG support and rehabilitation in PD, they did not

study the acceptance of such assistants by patients. In this work, we also addressed the user acceptance of a PD gait support system, an often not considered aspect in the development of healthcare systems [5]. The following issues regarding wearable systems for support and rehabilitation are known from literature:
(1) Obtrusiveness: The weight, bulkiness, number and location of sensors attached to the body decide on how comfortable a sensor setup is [21, 27]. In particular for people with motor deficits, the sensor attachment is also critical [38]: Sensors may be mounted with Velcro straps, belts, integrated into cloths or glued to the skin. In general, measurements are more reliable if sensors are fixed tightly to the body.
(2) Stigmatization: As indicated by [28], body-worn technologies that are visible to other people may lead to a feeling of stigmatization. This is a particular problem for sensor setups that are worn permanently, e.g., for monitoring or daily-life support as in our work.
(3) Feedback: [5, 11] report that patients require regular feedback from the system, even if there is no medical reason for this. Feedback is necessary to assure the user of the system functionality and increase his trust in the system.
(4) Further issues that came up in the design of wearable sensor networks for healthcare are related to privacy, security, reliability and battery lifetime [2].

In practice, there is always a trade-off between these user-acceptance issues and the technical feasibility. As shown in [20], multiple sensors would lead to better FoG detection rates but at the same time, this increases the systems obtrusiveness. [33] indicates that the expectations regarding user acceptance by researchers and caregivers do not always agree with the actual perception by patients. Therefore, Uzor et al. [37] recommend involving users as passive participants at all stages of design process: They organized workshops during which elderly people could discuss past experiences with fall rehabilitation, play prototype games and outline own ideas. The inputs lead to improvements in later game versions. In a related example, Alankus et al. [1] showed that customization of games leads to a better patient-experience in stroke rehabilitation. These works proof that patients can provide valuable information on how to improve system features, and that they are able to develop own ideas and suggestions. These findings directly influenced the development methodology applied for GaitAssist: Given that PD patients are the final GaitAssist users, they can best decide on the system obtrusiveness they are willing to accept for optimal FoG support.

Furthermore, they know when and where they experience FoG, and what strategies help to overcome the episodes. For all these reasons, and due to the success of other user-centered rehabilitation technologies, e.g., [7, 18, 37], we decided to adapt the user-participatory design principles for the development of GaitAssist.

A recent survey [28] concludes with the notion that wearable sensor systems have been successfully applied in various rehabilitation scenarios, e.g., back and upper limb, stroke rehabilitation. For this reason we also investigate possible training effects of GaitAssist.

7.3. Research Questions

To build a wearable FoG-support system that can be successfully deployed in unsupervised settings, we base our work on the following questions:

1. How should a wearable assistant for at-home FoG support and training be designed to both enable robust FoG-aware cueing, and be unobtrusive and well accepted by PD patients?

2. What are the patients' experiences and opinions on the use of the resulting wearable system, and how does the system influence the patients' gait? What are the patients' reaction on the system feedback?

7.4. Technology

GaitAssist provides real-time cueing feedback to the PD patients whenever FoG occurs. We based our system on Inertial Motion Units (IMUs) and a smartphone as wearable computing platform. The smartphone processes data received from the sensors and triggers an audio feedback upon FoG detection. The system also provides support for gait-training exercises for FoG designed by the clinicians, and logs the number of FoG events and their duration. In the following, we discuss the design and development of the GaitAssist system, a collaborative effort between engineers and clinicians, taking into account the feedback received from healthy subjects and PD patients with FoG.

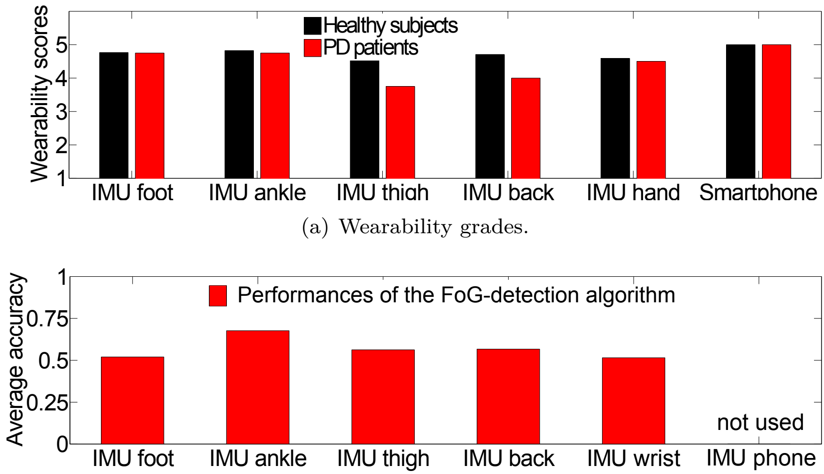
Figure 7.1: *The pre-study system, used by healthy users and PD patients, in order to collect knowledge of how to build the GaitAssist system.*

7.4.1. System Design

Previous studies [18, 20, 23] showed that on-body inertial sensors capture body-movements specific for FoG episodes. Critical for the system's performance is the number and placement of the body-worn sensors. To find a trade-off between technological requirements, i.e., achieving a high FoG-detection accuracy, while maintaining a low obtrusiveness to the patient, we performed participatory design sessions with clinicians, engineers and patients, as well as a data recording that involved 18 PD patients with FoG.

We recruited patients according to the following inclusion and exclusion criteria: patients with PD were included if they are (1) cognitively intact, (2) suffer from self-reported FoG, (3) have adequate vision and hearing abilities, and (4) live with a caregiver or a relative. Patients were excluded from the study if they (1) suffer from psychiatric co-morbidities, e.g., major depression, or (2) have a history of stroke, traumatic brain injury, brain tumor or other neurological disorders.

In the data recording session, we deployed a system with nine wear-



(a) Wearability grades.

(b) FoG detection performance.

Figure 7.2: *Wearability grades versus FoG-detection performance for different on-body sensor positions in the pre-study.*

able IMUs attached to the feet, ankles, thighs, hands and the back of the patients, and a smartphone placed in the trouser pocket (Figure 7.1). We used the same setup previously described in [19] where technical details about the sensors setup and overall flow of the experiment can be found. We chose these sensor placements after reviewing previous related studies [4, 14, 36], and based on discussions with clinicians. The pre-study was video recorded and synchronized with the sensing data [19]. We first tested the setup with 5 healthy subjects (2 females and 3 males with ages between 26 and 31 years), and then with a second group of 18 PD patients experiencing FoG (4 females and 14 males, aged between 49 and 89 years, with disease durations between 2 and 18 years). Both groups performed various gait exercises with the sensors attached. Each of the participants wore the system continuously for approximately 2 hours.

We define as a *FoG label* the period of time when the patient experiences FoG. The FoG labels were obtained from clinicians' annotations using stopwatch and videos, and later synchronized with the sensor datastream. Clinicians considered the moment of arrested gait pattern, i.e., stop in alternating left-right stepping, as start of a FoG episode, and the instant when the patient resumed a regular gait pattern as end. In total, clinicians coded 182 FoG episodes throughout the recording, with durations between 0.2s and 98.8s.

We evaluated the sensor positions in terms of obtrusiveness with questionnaires, as suggested in [17], and semi-structured interviews. We asked both healthy users and patients to rate the following statements on a scale from 1 (lowest score) to 5 (highest score): *(1) Attachment*: I can feel the device on my body, *(2) Harm*: The device is causing me some harm, *(3) Change*: I feel strange wearing the device, and *(4) Movement*: The device affects the way I move.

Figure 7.2(a) depicts the average wearability grades for all the sensor positions on the body. The users generally felt comfortable wearing the sensors, and the attachments did not affect their motor performance. Patients had a lower acceptance for certain on-body attachments, i.e., in particular the thigh position was rated low. These low scores are not only related to the age, but more with the motor problems associated with PD – for people with PD it is complicated to wear on-body accessories in daily life. Nevertheless, the *foot, ankle* and *smartphone* positions obtained similar scores from PD patients and healthy subjects. Patients often answered that they actually forgot that they were wearing these devices. The smartphone, the ankle and foot IMUs received the best scores.

We additionally organized discussions with the 18 patients, in which they could express their opinion regarding the GaitAssist system. Discussions were based on three main questions:

1. At which locations would you prefer to have the sensors attached, if you would use a wearable system for FoG support and training in home settings?

2. Would you put a smartphone in your pocket, if this helps to avoid or shorten FoG episodes?

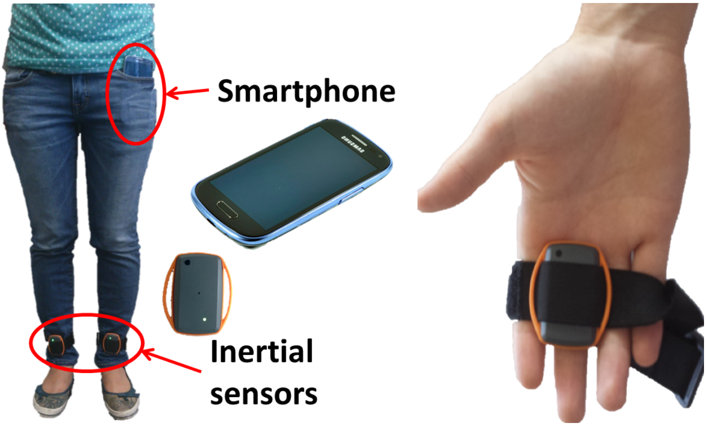
3. If yes, for how long would you be willing to wear it?

Patients chose the ankle as the best position to wear the sensors (5 patients), followed by foot (4), thigh (2), hand (2) and back (1). For 4 patients, the attachment location did not matter. All the patients answered positively regarding the possibility of using a smartphone as a wearable assistant. 16 patients would wear the system all day, while 2 of them prefer to wear it only for 2-3h, during periods of increased movement. Additional discussions with two clinicians and the PD patients gave us the following important social insights, related to the age and gender of the PD patients: *(1)* One patient said that he prefers the sensors to be below the trousers and therefore invisible to others. He associated the attachment with a surveillance system. *(2)* A female patient mentioned that she would wear the sensors only as a bracelet, for social reasons – she did not want to be seen with electronics attached to her lower body. This corresponds to the findings in other studies with wearable systems, e.g., [21, 27, 28]. Thus, for the GaitAssist wearable system, we needed to make sure that the IMU shape and attachment are not only comfortable, but also that they do not induce social exclusion feelings to the patients.

Furthermore, engineers analyzed the data collected from the 18 PD patients to identify the best IMU positions for FoG detection. We modeled detection as a machine learning problem [20], where the input is the sensing data from the IMUs. The FoG-detection chain is detailed further in the next subsection. The same detection algorithm was applied to sensor data from each of the 5 body positions. We evaluated the detection performance using average accuracy as measure, i.e., the output of the algorithm was compared against the ground-truth FoG annotations given by clinicians from videos. Results are plotted in Figure 7.2(b). The best performance was achieved with ankle-mounted IMUs. We also investigated the option of detecting FoG from the smartphones internal sensor data. However, the differences in placement and the sometimes loose attachment to the body across the participants resulted in noisy acceleration data. As a consequence, it was not possible to detect the typical, small trembling motions that are characteristic for FoG from smartphone sensors. Given that ankle-mounted IMUs performed well in terms of FoG detection and were at the same time well accepted by the patients, we decided to base our system on up to two IMUs attached to the ankle of each leg.

Figure 7.3(a) shows the final GaitAssist setup. It comprises a Samsung Galaxy S3 mini as the wearable computer, and up to two wearable EXEL IMUs[1] that stream 3D acceleration, 3D gyroscope, and 3D magnetometer data at $N_f = 32Hz$ to the smartphone via Bluetooth. The sensors are attached with Velcro stripes as shown in Figure 7.3(b).

[1] www.exelmicroel.com



(a) (b)

Figure 7.3: *GaitAssist system setup and sensor attachments.*

7.4.2. Software

The *GaitAssist* system has two aims: (1) to enable daily-life FoG-aware cueing, and thus to help patients resume gait at the occurrence of FoG, and (2) to support training with the FoG cueing through FoG-provoking exercises. As these two functionalities build upon each other, GaitAssist implements them in a single Android application. Subsequently, we describe the individual blocks of the application in detail.

FoG Detection. The main functionality of GaitAssist is the real-time detection of FoG episodes from the continuous motion data collected by the ankle-worn IMUs. To accurately detect FoG in real-time, we built a user-independent FoG-detection model using data from the 18 PD patients participating in the pre-study. For this purpose, we follow a machine learning approach. Raw 3D acceleration data is segmented in windows of $2s$, with an overlap of $0.25s$. 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 sequence for each window, and then extract features such as FFT-based features tailored to FoG detection [22], mean, standard deviation, and movement amplitude. Extracting features from the acceleration magnitude ensures invariance against orientation changes and sensor displacement during walking. Features are fed into a two-class C4.5 classifier with *FoG* and *normal gait* categories. Feature extraction and classification can be executed efficiently and in real-time on a smartphone, i.e., within at most $6ms$. This allows GaitAssist to run in real-time and leave sufficient resources and battery power for other phone activities. 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. In future we will use new versions of EXEL IMUs, which will hopefully solve the battery issue.

Rhythmic Cueing Feedback. In response to the detection of a FoG event, we provide a cueing signal to the user. Previous studies [25] showed that auditory cueing is the most effective for improving gait in PD patients. We therefore chose to provide *Rhythmic Auditory Stimulation* (RAS) in the form of a metronome ticking sound at the onset of FoG episodes [30]. Clinicians and interviewed patients endorsed the metronome-based cueing. The FoG detection and RAS feedback generation together can be used for day-long FoG support, but are also essential for the training component.

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. The exercises include typical movements which cause FoG and that are often performed in unsupervised environments. The system implements the support for performing these exercises. There are two classes of exercises: (1) gait initiation exercises, e.g., sit-to-stand, and (2) turning exercises, both with the additional option of dual-tasking. The GaitAssist user interface provides support for each of the tasks, such as signals to start and stop an exercise, as well as dual-tasking exercises that are displayed on the screen. Table 7.1 presents a brief review of the exercises supported by GaitAssist. If none of the exercises or additional options is selected, the system is in default FoG-support mode, and will start RAS upon FoG detection.

Training	Task	Description	GaitAssist support
Gait initiation	Forward steps	The user has to step forward in response to a sound, then return to the start position	Beeps to signal that the person should step forward and RAS upon FoG
Gait initiation	Weight shifting	The person has to shift his weight while standing or stepping in place	Signals the beginning and end of the training, optional continuous RAS at the beginning of the exercise, and after this period and RAS upon FoG
Gait initiation	Cognitive load	The person should start walking only when a specific shape, e.g., a red circle, appears on the GaitAssist screen	Randomly shows different shapes and colors, with higher probability for red circles to appear; starts RAS upon FoG
Turning		The user is instructed to perform various turning movements, e.g., circles, figure eight, 180-degrees turns, 360-degrees turns	The system provides cueing upon FoG

Table 7.1: *GaitAssist training exercises as designed by clinicians.*

7.5. Procedure

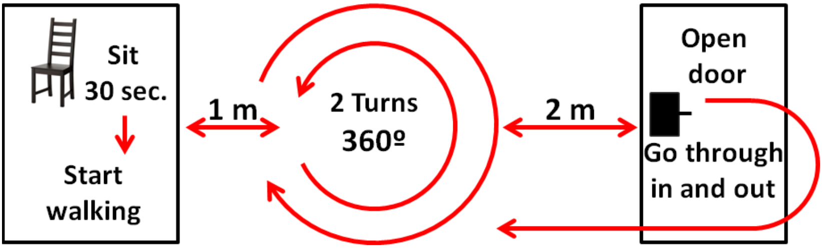
In the first part of the paper we showed how we designed the GaitAssist system together with patients, clinicians, and engineers. To study the efficacy and the user-acceptance of the system, we performed a study with new PD patients that were not involved in the design process. In a 3-day study we *(a)* investigated the effect of training with FoG-aware cueing on FoG duration and frequency, and *(b)* the user acceptance of the wearable assistant. In the first two days, the patients performed gait exercises, following the instructions of a physiotherapist and with GaitAssist providing cueing during FoG episodes. On the third day, the patients used the GaitAssist application in a real-life walking task.

A total of 5 PD patients suffering of FoG participated in this pilot study (2 females, and 3 males, mean age: 75.6 ± 4.7 years). Patients did not have knowledge about the GaitAssist system. We followed the same recruitment criteria as in the pre-study Four patients had moderate disease severity (Hohen and Yahr III) and one had mild disease severity (H&Y II) with a mean UPDRS [29] motor score of 26.8 ± 18.5 and mean disease duration of 8.8 ± 3.7 years. FoG severity varied between subjects with S#2 and S#5 experiencing FoG even during regular walking, and others experiencing FoG only during challenging conditions, in particular S#1 and S#4. This wide inclusion range allowed us to reflect on the potential utility of the system throughout the course of the disease.

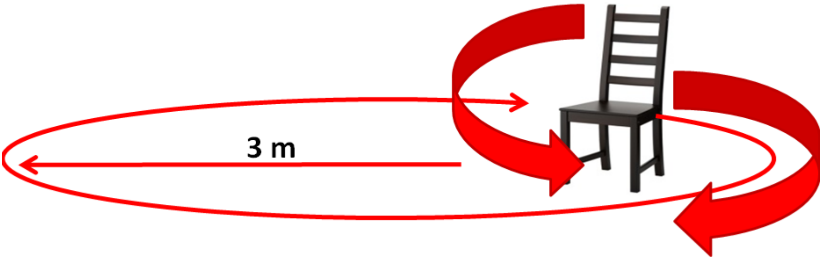
Evaluation Protocol. Participants were invited to come to the hospital on three sessions during different days in one week, with each session lasting approximately 30 minutes. Subsequently, we attached the two IMUs of GaitAssist to the participant's ankle with soft Velcro belts. The application was started in support mode for FoG-aware cueing in daily-life, and the patient was asked to perform FoG-rehabilitation exercises. A clinician supervised the patient while performing the exercises. In the final use-case, the application outlines the same tasks and exercises to the patients as given by the clinician. It will therefore allow the patient to perform the same training routines at home.

The training exercises that the patients performed on the first two days were designed by clinicians, and include FoG-provoking tasks, as known from literature [26, 31]:

1. The Ziegler protocol [39]: This protocol was designed to provoke FoG in PD patients in a clinical setting. It includes two 360-



(a) The Ziegler protocol [39] exercise.



(b) The turn around the chair exercise.

Figure 7.4: *Examples of tasks in the evaluation study.*

degrees turns, one 180-degrees turn, and passing through a narrow passage (Figure 7.4(a)).

2. Figure eight: This task consisted of walking 10 figure eight shapes in a 3 m^2 area.

3. Straight line walking with turns: The patients had to walk on a 10 m straight line, turn, and return.

4. Turn around a chair (Figure 7.4(b)): The patients had to rise from sitting positing, walk 3 m towards a chair, walk in clockwise direction around the chair, then change the direction and circle it in counter-clockwise direction. Finally, patients had to return to the initial position and sit down.

Between the tasks, we included rest periods, and patients were free to ask for a break at any moment of the training.

On the first day, the tasks were executed without cognitive load. During the second day, we increased the task difficulty by adding cog-

Figure 7.5: *The GaitAssist system during assessment with Parkinson's disease patients. From left: sensor location, figure 8 task, Ziegler protocol.*

nitive load through (1) engaging the patients in conversation, (2) letting them execute serial subtractions while walking, and (3) combinations of these distractions. We included them as clinical literature reports that PD patients experience a higher number of FoGs during cognitive load tasks [26]. In the straight-line task, patients had to additionally pass through a narrow corridor, which increases the emotional and perceptual load, and is known to be particularly FoG-provoking. The training program as described above includes tasks that are known to provoke FoG in PD patients, e.g., turns, gait initiation and dual task conditions [31, 39]. We also included activities that often occur in daily life, e.g., rising from a chair, passing through narrow corridors, and are potential hazards for FoG in daily-life settings (Figure 7.5).

After the first two days, patients were familiar with the GaitAssist system. In the third day we asked them to use it in more realistic scenario during a hospital tour including a recurring walking (Figure 7.6). It included roaming the hospital's crowded hallways with involuntary stops to give way to other people, turns, changes of direction, entering cluttered environments such as bookshops, using the elevator, and walking through narrow spaces. In this session, the patients could evaluate the usefulness of the system in a more realistic situation. Synchronized video recordings with the GaitAssist system were taken during the sessions. Clinicians used the same FoG-annotation procedure as in the pre-study [19].

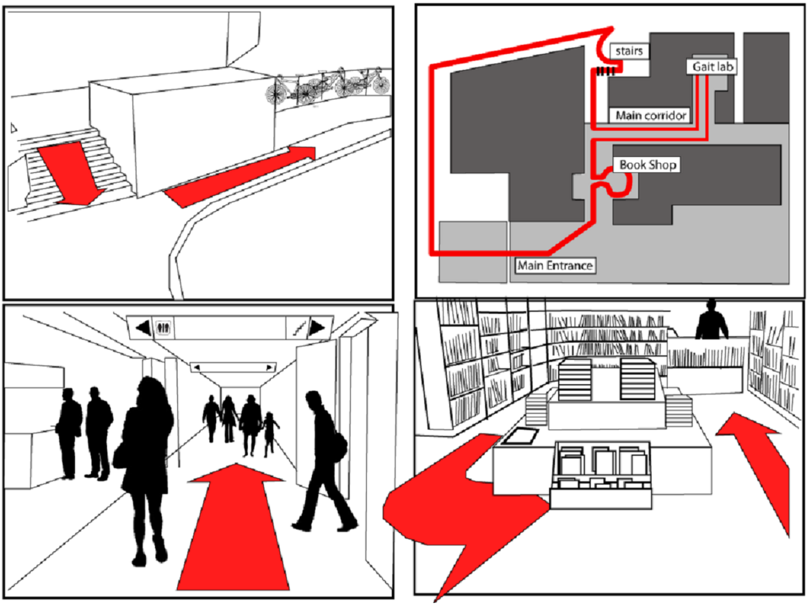


Figure 7.6: *The hospital tour task. A representation of a possible tour including walking in a crowded busy hospital corridor and walking outdoors.*

At the end of each trial day, we asked the patients to complete a feedback questionnaire regarding the system usability, feasibility and comfort (Table 7.2). The structured questionnaire was based on other questionnaires for assessing technology [8], and adapted to the specifics of GaitAssist. Each statement was based on a 5-points Likert-scale. The first part of the questionnaire on usability assessed the participant's experiences with the audio feedback. The feasibility part inquired about the possible use of the GaitAssist system at home, and their motivation to use the system in daily life. In the final part of the questionnaire, we addressed the usage of the system from a technical point of view, and the user-friendliness of the software and sensor setup. Additionally, we performed informal discussions between a clinician and the patient to gather more detailed feedback than in the questionnaire.

7.6. Results

7.6.1. System Functionality

Clinicians used the synchronized videos to identify and annotate 102 FoG events that occurred overall during the validation study. GaitAssist successfully detected 99 FoG episodes and started cueing in response, typically with a latency of $< 0.5s$ after the start of FoG. The 3 missed FoG events were shorter than 0.5 s, and therefore difficult to detect. 27 false alarms occurred in total during the study, meaning that GaitAssist started cueing at moments without a FoG in progress. This was often in response to unusual motions that resembled FoG, for example 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.

The number of false alarms varied for each user, and was dependent on the patient's walking style. For example, S#1 had energetic walking, sometimes even dance-like walk, but sometimes she lost the balance, especially after sudden stops. For her, the false alarms started in response to these sudden stops. S#2 and S#5 had a calm walking style, but they tended to make rapid small steps during turns. For them, GaitAssist sometimes started cueing while they were performing turns. For S#3 and S#4, the RAS started also in response to an abrupt decrease of the step length. While these events are not FoG events as such, they often preceed FoG, and are generally challenging for patients.

7.6.2. Patient and Clinician Feedback

As previously mentioned, the patients filled in a questionnaire at the end of each day. In Table 7.2 we report the mean scores for all participants over the 3 trial days. In general, the patients were highly satisfied with the performance of the system. The average usability score for GaitAssist was 4.2 points (out of 5), the feasibility 3.9 points, and the comfort 4.9 points (out of 5). We subsequently summarize the participants' feedback on the different aspects of the system, i.e. the setting up of the system, wearing it, and performing the training exercises.

#	Statement	Mean score
	Usability	**4.2**
1	The auditory feedback always turns on when FoG occurs	4.1
2	The auditory feedback always turns off at the end of the FoG event	4.2
	Feasibility	**3.9**
3	I can use the wearable system independently	3.9
4	In my opinion, the system is suitable for patients with Parkinson's disease	4.5
5	I feel safe when using the system	4.4
6	In my opinion, the feedback provided by the system can reduce the number of FoG events	2.6
7	In my opinion, the feedback provided by the system can reduce the duration of freezing events	**4.3**
8	I feel that the system may contribute to my independence	3.7
9	Using the system serves as a challenging training for me	3.8
	Comfort	**4.9**
10	The weight of the earphones does not interfere with the task performance	5.0
11	The auditory feedback is heard well	4.9
12	It is possible to wear the earphones independently	5.0
13	It is possible to take the earphones off independently	5.0

Table 7.2: *The feedback questionnaire and mean grades reported by the 5 subjects in the evaluation study.*

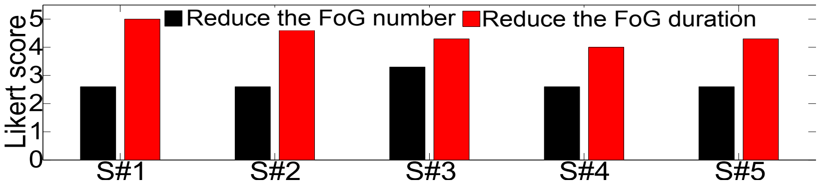


Figure 7.7: *Participants individual feedback for questions #6 and #7.*

Usability and Comfort

Patients reported that they were satisfied with wearing GaitAssist and its performance. They enjoyed using the system and felt that it is reliable and accurate. Sensors did not malfunction and the system was easy to use. Clinicians confirmed that setting up the system could be done within 1-2 minutes, even without supervision. The sensor attachments did not bother the patients during walking, and subjects reported that they often forgot that they were wearing the sensors during the trials. Patients used only one earplug, so that they could hear also the ambient sounds (wearing both earplugs might cause problems in real-life scenarios such as when crossing a street or walking in the city). The audio feedback as played through earphones was perceived as easy to listen to, even in noisy environments. Participants reported that the auditory feedback was always triggered when a long FoG occurred.

Feasibility

All participants felt that they benefited from the GaitAssist support during freezing episodes. Figure 7.7 demonstrates their perception on whether the feedback provided by GaitAssist can reduce the number of freezing events and reduce the duration of FoG episodes. They reported that the FoG duration was shorter compared to their normal experience. They also felt that using the system will probably not decrease the number of FoG. Although RAS was provided in some cases without a FoG in progress, the patients reported that it may have prevented them from experiencing more FoGs.

Informative Feedback

Besides completing the questionnaire, the clinicians had informative interviews with the patients participating in the study after each trial day. During these discussions, patients had the possibility of giving their general opinion about the GaitAssist application. Table 7.3 lists the questions which formed the basis of the interviews. In a first part, we discussed with the patients about the wearability of the on-body system. Then we asked for further feedback about the auditory cueing provided by GaitAssist. We further give details about the feedback that we received from the participants.

Wearability. All the patients were comfortable with wearing sensors attached to the ankle, although they expressed the desire to wear the sensors below the trousers, so that they cannot be seen by other people. This confirms the previous findings from the pre-study with 18 patients. Bending down to attach the sensors to the legs was sometimes difficult, especially when the medication effect wears off. Patients also suggested a simpler attachment with the sensor directly integrated in a Velcro-band or belt strap (similar to sweat bands at the wrist of tennis players). A particular advantage was that the orientation and exact location of the sensors did not influence the application's performance. Regarding the smartphone, reactions varied. Not all of them wore clothes with pockets, and some had to hold the smartphone in the hand during the recording. This was perceived as uncomfortable and dangerous in case of falling. Patients therefore proposed to attach the phone to a special belt or a necklace. It was also suggested to have the possibility of disabling all other functionalities of the phone, as the multitude of smartphone usages may be distracting for the mostly elderly patients suffering from PD. While walking in crowded and noisy environment, the patients suggested they should wear one ear bud only. In that way, they could listen to the RAS and still hear environment sounds.

Auditory Feedback. In the discussion session, patients confirmed that the metronome ticking sound was played at the right time and with low response latency, i.e., less than 0.5-1 seconds, after the beginning of a FoG episode. This corresponds well with our measured latency of less than 0.5s. Patients usually change their walking pattern during the day in response to their medication cycle. An adjustable FoG-detection module could therefore improve the performance of GaitAssist in daily-

Wearability
1. Did you feel the sensors on the legs? Were they comfortable to wear? Would you like to wear them during the home exercises?
2. What is your opinion about using the phone? Is it comfortable to use?
Auditory Feedback
1. Did you feel that ticking sound started when there were gait problems? (e.g., when the FoG occurred, when not feeling sure while walking)
2. Did you have the feeling that the metronome ticking helps in resuming the gait? Improving the gait?
3. Is the metronome ticking too long, or too short?
4. Is the metronome sound annoying for you? Would you prefer other solutions (e.g., music)?
5. Do you think that the whole system will help in improving the gait, resume the gait after FoG events?

Table 7.3: *Questions in the informative discussions session.*

life usage. All patients liked the ticking sound and they did not agree with playing music as an alternative. They stated that it is harder to get the rhythm from songs, and that a tune can get annoying after a short time. Two patients suggested that the RAS should continue for an extended period after the onset of FoG (>30s), as it takes some time for them to pick up the ticking rhythm.

At the end of the questionnaire we asked the users to describe in one phrase their overall experience regarding GaitAssist system. Final statements confirm the appreciation of the tool:
S#1: “I feel like I am not alone. This system is like someone that supports me in my way of walking. I can listen to the rhythm and walk according to the beatings.”
S#2: “I would wear it all day long, as I think it reduces the FoGs duration, but it does not reduce the number of FoGs.”
S#3: “It is a great system. I feel safe, and it might improve the gait pattern and reduce the FoG duration.”
S#4: “It is very useful, as it reduces the FoG duration and reminds me of how to walk.”
S#5: “Very good, I feel that it improves my gait.”

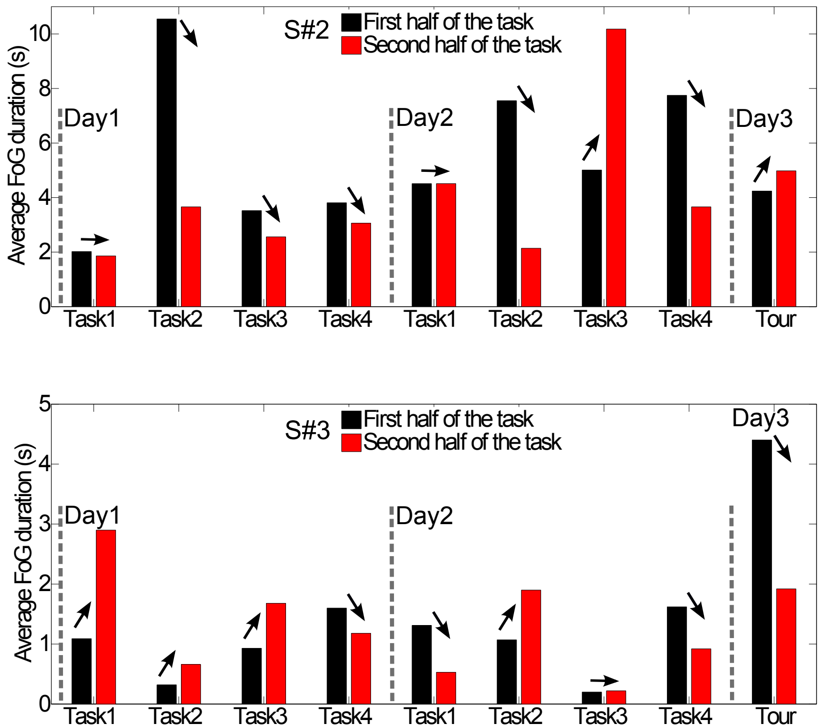


Figure 7.8: *A comparison of the average FoG-duration for the first half and the second half of the tasks, for S#2 and S#3.*

7.6.3. Subjective Perception versus Measured Effect

We checked whether the subjective feeling of the patients corresponds to a quantitative assessment of the FoG duration, i.e., if the system's feedback upon FoG helps the patients to react to it, and thus supports them in resuming walk. For this purpose, we analyzed the FoG durations during each individual task of the three-day study. We compared the average FoG duration in the first half of each task, with the average FoG duration in the second half of the task. The idea behind this correlation is to see if the user learns to react to the feedback received from the system, and can better follow the cues during an exercise.

We show the results of this analysis for S#2 and S#3 in Figure 7.8. Out of all 5 participants in the study, S#2 and S#3 experienced sufficient FoG episodes during the study for evaluating the performances of GaitAssist (S#2 experienced 44 FoG episodes in total, and S#3 41 FoG episodes). For the other subjects, the number of FoG during each task was not sufficient (i.e., during an exercise, the user experienced only one or none FoG).

In case of S#2 (Figure 7.8), there was a significant decrease in FoG duration when comparing the first and second halves of the tasks on the first day. This is in line with the personal feeling of the patient, who stated that she mostly agrees (grade=4) that the system helps her in reducing the FoG duration. During the second day, when dual-task exercises were performed, she stated that she neither agrees nor disagrees (grade=3) with the same statement. The subjective grade is in line with the analysis (only 2 out of 4 sessions had a decrease in FoG duration). However, on the third day, when the patient tested GaitAssist in a real-life setting, she stated that the system helped her (grade=5) even though our technical analysis does not show a decrease in FoG duration throughout the session.

For S#3, the analysis indicates an increase in FoG duration during the first session, although the patient subjectively reported that the FoG duration decreased thanks to GaitAssist (grade=4). On the first day, the patient often stopped doing the exercise when the cueing started, instead of following the rhythm. In the next two days (second session of exercises and real-life session), the patient strongly agreed that the system helped in reducing FoG duration (grade=5), which is in line with the obtained measurements.

7.7. Discussion

Our pilot study confirmed that GaitAssist provides FoG support at the right time, and that this support is perceived as helpful by patients. Furthermore, the decrease in average FoG duration over the three sessions, for subjects S#2 and S#3, suggests that patients react positively to the system's cueing feedback. With this regard, the subjective perception of patients as reported in questionnaires was in line with our measurements.

There are two main outcomes of the pilot, regarding the patient-system interaction: *(1)* only the duration and not the number of FoGs are affected by the FoG support system, and *(2)* what engineers count as false positive (FoG detection during motion difficulty) is actually perceived as helpful by users and clinicians. Patients stated that the feedback in these instances helped them to avoid a potential FoG episode. To conclude, a binocular view on the study, as in [37], confirms that subjective perception by users and measured FoG duration are in line.

As we took into account the feedback of 18 PD patients during the system design phase, GaitAssist was already well-adapted to the patients' needs at the time of the study. Our design procedure was similar to the one described in [37], with discussion sessions and pre-studies during which patients wore a prototype sensor setup. We considered issues regarding obtrusiveness and stigmatization that are common in body-worn systems [28] (small IMUs that can be placed below the trousers, standard smartphone) and, as a result, users did not give any negative feedback regarding this aspect. Overall, we experienced that the involvement of patients and clinicians at an early stage speeds up the design process and leads to a strong acceptance by end users. Nevertheless, the pilot study showed that there is still a need for improvements before widely deploying GaitAssist: simpler attachment of the sensors to the ankles; an attachment for the smartphone in case the person does not have trouser pockets.

The studies described in this paper are preliminary studies, and even though the tasks performed by the patients resemble at-home usage as we imagine it with GaitAssist, they took place in a hospital, with clinicians close-by. We further have to assess the adoption of GaitAssist in daily life and see whether patients are willing to wear GaitAssist outside of the study protocol [16]. For this we plan a clinical study with 40 PD patients in their homes, without any clinical supervision. Patients will use the system as support in gait training exercises, but also as an assistant when walking in unsupervised environments. The target is to analyze whether GaitAssist cueing has a long term effect in the rehabilitation of gait, but also to check the learning curve of the system adoption. Given the positive reactions of all 23 patients that participated in the pilot study and the design phase, we believe that GaitAssist will be well accepted, even outside of clinical settings.

7.8. Conclusions

We introduced GaitAssist, a wearable system for FoG support and training in unsupervised environments. The system consists of up to two ankle-mounted IMUs and a smartphone that collects and processes the sensor data. It reliably provides cueing in the form of a metronome ticking sound after the onset of FoG. In addition, GaitAssist provides exercises that the patients can perform at home for practicing the handling of cueing in FoG-provoking situations. GaitAssist was developed and adapted to the needs of patients through a participatory design process, and well-perceived in terms of wearability and effectiveness in supporting PD patients during daily-life activities. Overall, 23 PD patients with FoG participated in the design and testing of the GaitAssist system. Patients that tested the system reported a reduction in the FoG duration as a result of the auditory stimulation provided, and reported that the system was enhancing their confidence during walking. This must be further investigated in long-term studies with patients using the system at home, without the supervision of clinicians.

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8

Gait Training in Parkinson's Disease in Out-of-the-Lab Environments

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

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.

8.1. 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 [32] and is expected to double by 2030 [12]. 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 which 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 [37]. These unexpected motor blocks severely impinge on the functional independence and health-related quality of life [47]. FoG increases the risk of falls, anxiety, loss of mobility and independence, and mortality [18].

Training and rehabilitation interventions which help in alleviating FoG include group exercise and treadmill training with rhythmic auditory and visual cues [2]. Such rhythmic cues, in form of an external stimulus, have been shown to facilitate the continuation of a repetitive movement such as gait. Providing a rhythmic external cue, for instance as an auditory signal, it can reinitiate neurological rhythm as a pacemaker and thereby helps to quicker overcome a gait freeze episode [22, 25, 48]. However, existing techniques have to be performed in the clinic or require medical staff to assist 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 [12].

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 in detail GaitAssist, a wearable sensing and feedback system that detects the FoG episodes in real-time. The system has two main functions: *(i)* as a gait trainer with personalized exercises, and *(ii)* 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 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 [46]. We see two critical aspects for technology research in Parkinson's disease 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 Parkinson's disease 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 [38]. For instance, FoG is difficult to trigger in the clinics [35], e.g., because of the so-called *white coat syndrome*, when often people experience 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 of validation in the user's natural environments, e.g., at home, or in public areas [4, 24, 30]. We specifically investigate the performance of the proposed system in the habitual environment of the user, where she/he is not supervised and assisted by a technician or clinician [3]. To this end, we formulate the research question:

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

To answer this question, we asked 9 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. Participants also discussed with a clinician at the end of the trial, 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 analyse 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 paper is organized as follows. In Section 8.2, we situate this work into the research landscape. We specifically focus on wearable systems in Parkinson's Disease and acceptance studies of technological artifacts in the healthcare domain. Section 8.3 presents in detail the GaitAssist system and how its components have been implemented. Section 8.4 presents the study design at home, with acceptance results given in Section 8.5 and the data-driven analysis on FoG distributions in Section 8.6. We conclude in Section 8.7 with a summary of the findings.

8.2. Related Work

People with PD can improve motor functions and decrease FoG severity by performing rehabilitation exercises [40, 49]. 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 [2, 11, 36]. Continuous cueing has a positive impact on the gait but wears off over time [34], 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.

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 8.1 contains an overview of the characteristics and evaluation settings of such systems. Most wearable systems involve accelerometers and/or gyroscopes mounted on-body [4, 10, 24, 30, 50] or integrated in garnments [33], extended with electroencephalography (EEG) [20] or electromyography (EMG) [8].

One standard feature which 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., $[3-8]$ Hz and $[0.5-3]$ Hz respectively [4, 24, 31]. This feature is convenient since it requires only FFT-computation. Other feature extraction approaches involve mixed time-frequency features [51] and entropy [50]. In [30], 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%, while the detection is performed with at best 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 the 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 [26], a wearable FoG-assistant for gait training in out-of-the-lab and unsupervised settings, co-designed together with people with PD, clinicians and engineers. GaitAssist uses wearable sensors mounted on-body and machine learning techniques to detect in real-time the FoG episodes. 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 would the system look like 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.

# Ref.	Sensors	Features and methods	Real-time	Dataset characteristics and performances	Experimental setting	Investigation goal
Moore et al. [31]	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. [24]	Accelerometer and gyroscope (either on belt, knee, ankle or shoe) and a wireless headset	Freeze index from [31] and threshold algorithm	Yes	4 experiments of simulated FoG and 1 subject. Detection performance unknown	unknown	System - performance
Djuric-Jovicic et al. [10]	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. [4]	3 accelerometers on ankle, thigh and lower back, and one dedicated wearable computer	Freeze index from [31], 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. [33]	5 accelerometers integrated in a garnment (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. [8]	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. [51]	5 accelerometers integrated in a garment (shanks and belt) with a non-wearable computer as in [33]	Frequency-based features	Yes	8 subjects, 54min of data, 82 FoGs. Performance: 81.7% sensitivity	In the lab with clinical protocol	System - performance
Tripolit[illegible] et al. [50]	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. [30]	3 accelerometers (thigh, ankle, lower back) as in [4]	Statistical and FFT features with supervised machine learning methods	Yes	Dataset from [4]. Performance: 66.2% sensitivity and 95.3% specificity (per data-window basis)	In the lab with clinical protocol	System - performance

Mazilu et al. [**26**] **&** [**29**]	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 $\leq$ 0.5 seconds	In the lab with clinical protocol	System - performance & User - acceptance

Table 8.1: *Related work on wearable systems for FoG-detection.*

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 [35, 38]. Under laboratory conditions they tend to experience increased stress, i.e., white coat syndrome [14], 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 [15]. GaitAssist has been tested in laboratory conditions [26]: Under supervision of clinicians, 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 extend the system impacts gait quality and the user perception in a daily-life setting outside the lab, e.g. at home.

[3] identify 53 relevant trials which show evidence that exercise, motor training and rhythmic cueing strategies delivered individually in out-of-the-lab environments are beneficial for motor training in Parkinson's disease [13], and to reduce the severity of freezing [36, 40]. 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, up 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 setup and to 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 with the real usage scenario. That is, the user buys a commercial wearable assistant and follows independently the gait-therapy protocol guided by a manual only.

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 with in-the-lab settings [46]. Often systems that are highly appreciated in lab conditions have difficulties to be adopted at the user's home environment. Recent studies analyze the implications of using and accepting home-based healthcare systems

[19]. Social, emotional, and environmental factors play a key role in the adoption and the use of healthcare systems in the home settings [1, 39]. As suggested in [44], 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. Also varying technical expertise may lead to differences in perception. Technology artifacts may be even associated with negative effects on their well-being [45]. Experience with patients in managing and accepting the body-worn technology highlight the issue of stigmatization and the need of a constant feedback from the system to the patient [39]. Further issues that came up in the acceptance of healthcare systems are related to privacy, trust, security, reliability and battery lifetime [19]. Thus, in this work we analyze how well is the system accepted in an out-of-the-lab setting, and we investigate potential differences between the perception of the system in the lab vs. at home.

A recent survey [39] 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.

8.3. The Gait-Assist 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 much like from a metronome, for a certain period of time, i.e., 8-10 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 the GaitAssist, including the system components and the communication between them. We describe the FoG detection framework and algorithms, the design of the user interfaces, and we 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 8.1: *GaitAssist system setup: (1) up to two wearable sensors attached on the ankles, (2) the sensor attachments, (3) a smartphone with the GaitAssist pre-installed 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.*

Figure 8.1 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 which 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-body, thus the limitation of the system in connecting up to two IMUs. For this project we choose 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 which 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 a total of 23 people with PD involved in-the-lab settings [26].

[1] www.exelmicroel.com
[2] www.cupid-project.eu

8.3.1. System Architecture

The main functions of GaitAssist are: (A) *training support* for the gait-training exercises, (B) *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 8.2 shows the main modules of 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 32 Hz as a trade-off between IMU's battery power and the amount of data needed to observe changes in the gait properties. As the human movement range is between $[0.5 - 16]$ 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 in real-time the FoG episodes, 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, e.g., exercise completion time, metronome settings, and also 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. *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 is sent periodically to a telemedicine server and can be accessed later by the clinicians.

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

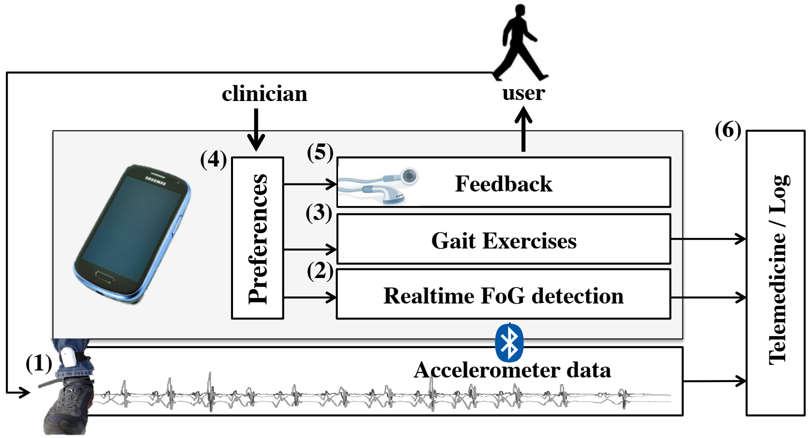


Figure 8.2: *The GaitAssist system with its components and modules: (1) Wearable sensors, (2) FoG-detection module, (3) Motor-training exercises module (4) Preferences module, (5) Auditory feedback, and (6) Logging and telemedicine module.*

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, falling* [6, 7]. A couple of recent studies show that FoG can be accurately detected with machine learning models and wearable sensor's data [30, 50].

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 PD and FoG, a subset of the Cupid dataset [27]. 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

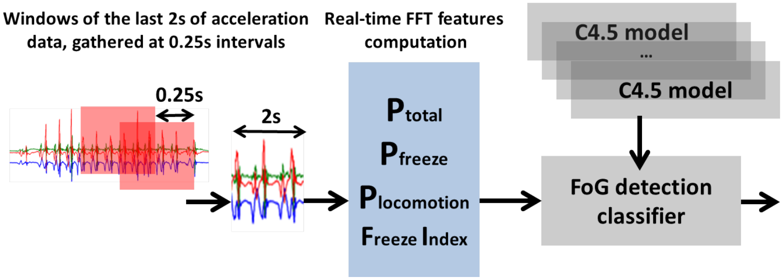


Figure 8.3: *The real-time FoG-detection framework from the GaitAssist system.*

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 [27].

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 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 start of a FoG episode, and the instant when the patient resumed a regular gait pattern as end. We choose the ankle position for the wearable sensors to be attached based on previous studies [4, 30, 50] but also from our prior analysis [26] which show 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 [26] the ankle position received the highest wearability scores to attach on-body sensors.

The FoG-detection machine learning framework. The real-time FoG-detection chain implemented by GaitAssist is presented in Figure 8.3. Raw 3D acceleration data from the Cupid ankle dataset is segmented in windows of 2 s, with an overlap of 0.25 s. 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 8.2 to capture the FoG characteristics compared with the normal gait. The resulted feature vector is fed into a FoG-detection algorithm, which decides in real-time whether the user is in FoG or not.

Feature	Description
Power on locomotion band (PL)	Power on the [0.5-3] Hz band of the acceleration magnitude signal in the window
Power on freeze band (PF)	Power on the [3-8] 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 [4]
Freeze Index (FI)	Power of the freeze band [3-8] Hz divided by the power in the locomotor band [0.5-3] Hz as used in the FoG-detection algorithm from [31]

Table 8.2: *Features extracted from acceleration magnitude vectors.*

As an example, Figure 8.4 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 4 FFT-based features. We observe that *power on freeze band* (PF) and *freeze index* (FI) features increase prior or during the FoG onset compared with the walking periods, while *power on locomotion band* (PL) values decrease before or during FoG. While the PL feature is similar in cases of turning, standing, sudden stops, and FoG, the *total power* (TP) feature 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 the 3D acceleration data from each ankle of the subjects is added together and is split in windows of two seconds. From each window the acceleration magnitude vector is computed, and then the 4-FFT features are extracted. A label from the groundtruth annotations, whether the window time frame is labeled as FoG or normal walking, as 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 a 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.

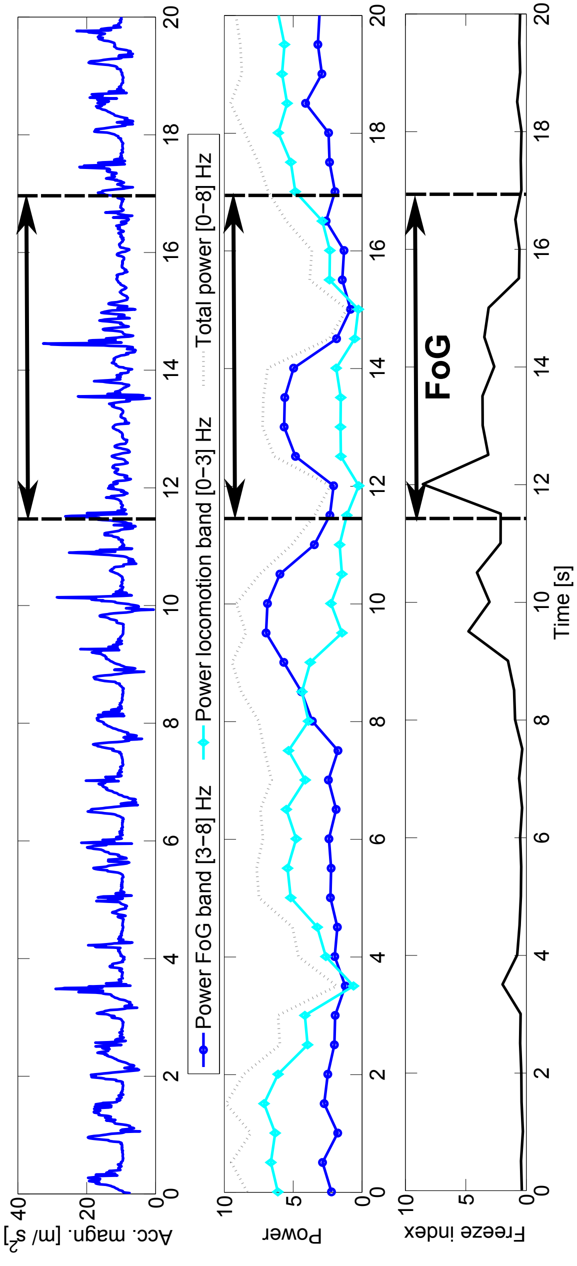


Figure 8.4: *A sequence of 20 seconds of walking, containing a FoG episode. The sequence contains the acceleration magnitudes from IMU raw data, and in the 4 features extracted from the sliding window vectors: Power on FoG band, power on locomotion band, total power between [0.5-8] Hz, and the Freeze Index FI.*

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. Then we 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 groundtruth annotations, at least once the algorithm detects 2 times FoG from 3 consecutive data windows. A false FoG-detection event is considered when the algorithm detects a FoG in the way detailed before, while the groundtruth label shows no FoG for that period of time/data. 110 from 182 FoG in Cupid dataset were successfully detected, with 20 false FoG detections.

We considered also 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 [28, 30]. 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 4 FFT acceleration features.

Rhythmic Cueing Feedback. In response to the detection of a FoG event, we provide a cueing signal to the user. Previous studies [25, 34] 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 [42]. The FoG detection and RAS feedback generation can be used together for day-long FoG support, but are also essential for the training component.

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 [2, 36, 40].

#	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 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, e.g., a green circle, appears on the GaitAssist screen. He needs to make 5 steps and then stop or to 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 accordingly 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 rhythmic auditory stimulation only upon FoG
5	Chairs (1)	Turning	The user is asked to place two chairs facing each other at 3 m apart. The the user needs to arise from one chair and walk accordingly 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	Gait Assist 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

Table 8.3: *GaitAssist training exercises as designed by clinicians.*

Table 8.3 presents a brief review of the exercises supported by GaitAssist. There are two classes of exercises: (1-2) gait initiation exercises, e.g., weight shift while standing or stepping, with the additional option of dual-tasking, and (3-6) turning exercises. Clinicians choose as training these two types of exercises because step initiation and different types of turns, e.g., 180-degree turns or 360-degree turns, are among the main causes which provoke FoG in people with PD [43, 52].

For each of the 6 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 and or analyses 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, in order to support the cognitive load task. Motor training with cognitive load is used to reproduce the natural daily-life condition – usually people don't pay attention to their walk, but do parallel activities, e.g., having a conversation while walking [5].

Exercises 3 and 5 differ from the whole target of the GaitAssist system – to provide rhythmic auditory stimulation upon FoG in FoG-provoking situations. During these exercises the RAS is delivered continuously except in case of FoG and a limited period of time after FoG. The idea behind is that the users are encouraged to follow the rhythm given by the system and to 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 sub-types 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, the BPM settings.

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 which is done by the user. These data is sent to a telemedicine server, and 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 the new data.

The telemedicine service stores the raw data and the output of the FoG-detection classifier, and 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 underlined 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 the 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 the disease progression during longer periods of time. IMU collected data containing 3D accelerometer, 3D gyroscope and 3D magnetometer can be used further for deploying and refining new FoG-detection methods.

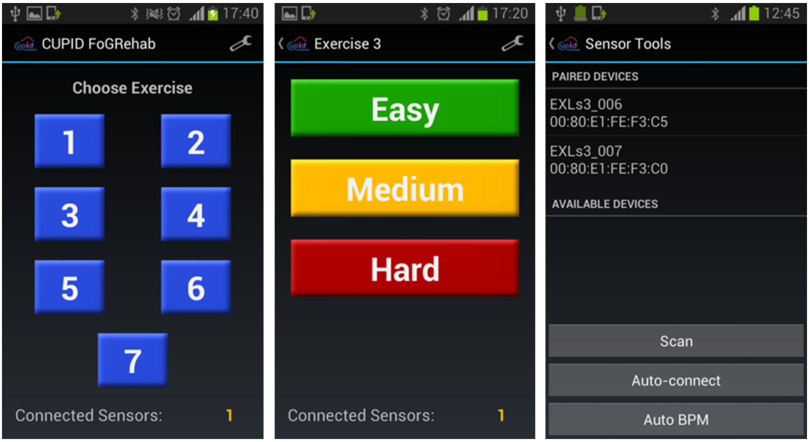
An additional service of the telemedicine is that clinicians can upload a file with new settings for GaitAssist and gait-training exercises to the telemedicine service. During the synchronization between GaitAssist and the telemedicine service, these settings will be updated in the GaitAssist app. This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

8.3.2. User Interface

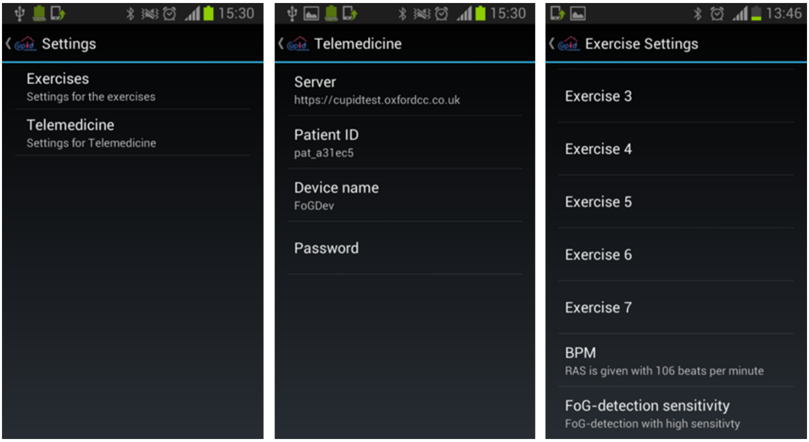
GaitAssist comes with two role depending user interfaces. First, the *patient user interface (UI)*, with simple large buttons for each of the gait training options. This is shown by default, when starting the app. Second, the *clinician user interface* contains all the options and the settings of GaitAssist and training exercises. To enter in the *clinician interface* a user needs to tap for 5 quick times on the screen of the *patient interface*. Figure 8.5 shows screenshot examples of the two user interfaces.

Patient UI

People with PD usually have issues in using the touchscreen of smartphones, when touching the phone's buttons or apps' buttons. To ease



(a) Patient user interface.



(b) Clinician user interface.

Figure 8.5: *The two user interfaces of the GaitAssist app: (a) Patient UI, and (b) Clinician UI.*

the usage of the GaitAssist app, the *patient UI* has in the main tab 7 large buttons, with large text size, corresponding to the 6 motor training exercises (buttons 1-6), and to the gait-assistive option for daily-life activities (button 7), as shown in Figure 8.5(a). For the gait training exercise, in case of pressing each of the buttons 1-6, 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 7 button options. In case of exercise 2, corresponding to gait initiation with cognitive load, in the exercise screen there are different colored shapes which appear randomly during the exercise for a period of 2-3 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, the user needs 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. Also, when the user exits the app, this will send a 'turn off' message to the sensors too. In the *patient UI* there is also a 'Sensor tools' interface, which gives the option to the user 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 the 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 analysis 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 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, in order to help him resume the walking.

Clinician UI

By quick tapping for 5 times in the *patient UI* screen, the app enters in the *clinician UI*, shown in Figure 8.5(b). The UI will change back to *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.

The *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 possibility to the user to update this value, in case she/he thinks the RAS is not synchronized with his 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 ([38], [21]).

In the *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 the data gathered during the GaitAssist usage will be then uploaded to the user's account from the telemedicine service.

8.3.3. 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, also by elderly, 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 of 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

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

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 5 people with PD and FoG to perform a set of walking tasks in the hospital, 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 [26]. The limited number of participants in the preliminary study is a result of the nature of the targeted population, i.e., elderly subjects, with Parkinson's disease and freezing of gait, 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 one week, each session lasting approximately 30 minutes. Each of the 5 participants used the system during gait training exercise and naturalistic walking protocols as following: In the first two 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 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 stopwatch and videos. Clinicians considered the moment of arrested gait pattern, i.e., stop in alternating left-right stepping, as start of a FoG episode, and the instant when the patient resumed a regular gait pattern as end. In total clinicians observed 102 FoG episodes from the 5 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. 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, for example 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 [26]. Discussions of participants with the clinicians and their observations and advices regarding the GaitAssist helped us in improving different system components, i.e., UI, sensor attachments, sensor case, automatically connection of the IMUs with the phone etc. Details about the overall participatory design and development steps are given in [26]. The final system, as presented in this section, integrates all the input received from the patients, clinicians and engineers in the different stages of the system design, deployment, and testing.

8.4. 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 that were not involved in the design or in-the-lab evaluation of GaitAssist.

8.4.1. 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, are cognitively intact, have adequate vision and hearing abilities, live with a caregiver or a family member, and are deemed computer literate by having an email account. We excluded people who suffer from psychiatric co-morbidities, e.g., 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 [17]. Subjects who suffered from FOG were asked to rate their FOG severity using the new FOGQ questionnaire [16].

A total of 9 people with PD, from two medical sites in two countries (5 subjects from Israel and 4 subjects from Belgium) participated in the study (mean age: 68.3.8$\pm$10.7 years; 78% males). Table 8.4 summarizes the participants' characteristics from the two medical sites. Participants

Subject	Gender	Age (years)	PD Duration (years)	FoGQ score [16]	H&Y score [23]	UPDRS score [17]
Site 1	**(Israel)**					
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

Table 8.4: *At-home study: the participants characteristics.*

had moderate (4 participants) or mild (5 participants) PD severity and mean disease duration of 12.8 $\pm$ 8.5 years. All participants were cognitively intact and, except one subject from Site 2, all suffered from FoG based on the FoG questionnaire [16], suggesting severe freezing. 8 out of 9 subjects were under their regular medication treatment for PD and FoG, and did not change their medicines during the study. One subject used only medical marijuana.

The 9 participants are representative for the people with different PD ranges with FoG, were volunteers and expressed motivation to participate in this study. Besides suffering from Parkinson's disease, the participants are elderly people, and even if they are computer literates, they are not early adopters of novel technologies such as wearable devices. Furthermore, users were required to setup the system and to perform the protocol without any clinical assistance or supervision, and in their homes. All these contributed in having a limited number of participants in the study.

8.4.2. Procedure

The training program at home consisted of 3 protocol sessions delivered during 3 different days in one week, as designed by the clinicians. In the first day participants underwent a clinical physical, neurological and cognitive examination and 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 the clinician remained 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 that accompanies the participant every day.

At the beginning of the procedure the user was asked to setup the system on-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 to detach the sensors from the ankle. Each step of the procedure (setup and protocol tasks) was detailed with a short description and pictures in the self-use manual. Figure 8.6 shows the participants during the protocol, operating the GaitAssist system by their own using the provided manual.

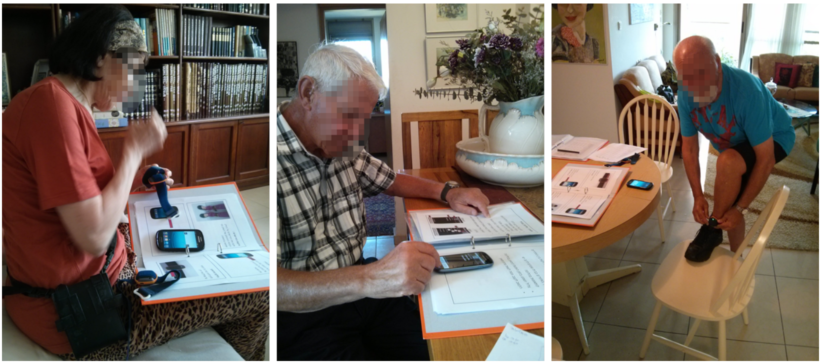
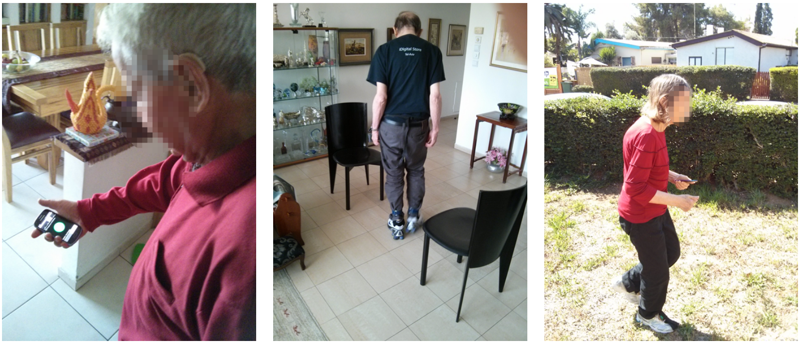


Figure 8.6: *Participants following the user manual and operating the GaitAssist system.*

8.4.3. Protocol

In each of the protocol days the participants used the system around 60 minutes. During each day the participants were asked to perform motor-training exercises and to perform 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: (A) a gait-training exercise part, and (B) a daily-life activities part.

(A) Gait-training exercises. In the first part, the participant was asked to perform motor exercises that have been shown to provoke FoG, e.g., gait initiation, dual task conditions, and turnings [43] (Figures 8.7(a) and 8.7(b)). The suggested motor training exercises are the same as the ones suggested by the clinicians in Section 8.3.1 and implemented in the *patient UI* of GaitAssist (exercise options 1 to 6).



(a) (b) (c)

Figure 8.7: *Users practicing: (a) exercise 2 – step initiation with visual cognitive load, (b) exercise 3 – the figure 8, and (c) free walking in the home environment.*

(B) Daily-life activities. The second part of the protocol included walking during common daily life activities, e.g., rising from chairs, passing through different narrow spaces between furniture, walking around different rooms, walking outdoors (Figure 8.7(c)). This corresponds to the Option no. 7 in the *patient UI* of GaitAssist (Section 8.3.2). The system assists the user by providing gait-synchronized RAS upon FoG or when the user encounters difficulties in walking.

8.5. User's Feedback

At the end of the deployment week, participants were asked to fill a questionnaire regarding the usability and the comfort of GaitAssist system. The structured questionnaire was constructed specifically for the study based on validated questionnaires assessing techniques [9]. 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 relating to the training methodology and the way 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 8.5 we present the mean score over all 9 participants for each statement. In general, participants stated they were highly satisfied with the system and with its potential for use and they enjoyed using it in most of the training sessions. We summarize in the following the relevant feedback and lessons learned for each category.

System Operation. Despite of the high grades given by the participants on the statements regarding system operation (Table 8.5), five of them had difficulties in turning *on* or *off* the sensors. This action required bending and was particularly difficult for participants with tremor, rigidity or fine motor impairments, as common symptoms of PD. In the second and third training sessions though, participants learned how to use the system and it was easier for them to operate it. They even reported improvement in the ability of work with the sensors.

#	Statement	Site1 Avg.	Site2 Avg.	Global Avg.
	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

Table 8.5: *Satisfaction questionnaire – statements and average scores on a scale from 1 to 5, where 5 is the best score, for participants in Site 1 (Israel), Site 2 (Belgium), and overall average across all 9 participants.*

In the first session, participants complained that turning on the mobile phone is 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 on the GaitAssist app icon on the phone's home screen. This action requires fast movement of the index finger or of the thumb. Because of lack of experience with the smartphones and as an effect of the disease, which can make 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 (see Figure 8.8(a)) for the next protocol sessions.

Wearability. Operating the sensors received low wearability scores compared with interaction with the other external modules of the system, e.g., the earphones, which received maximum grades. One explanation is that the earphones were known to the participants, being long-established commercial devices, while wearing sensors is a new concept for the public and especially for elderly people such our participants in the study. Putting on or taking off the sensors and their attachments was a difficult operation since it required bending down. In addition, even if it was not a limitation, they are 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 participants to complete this task (see Figure 8.8(b)).

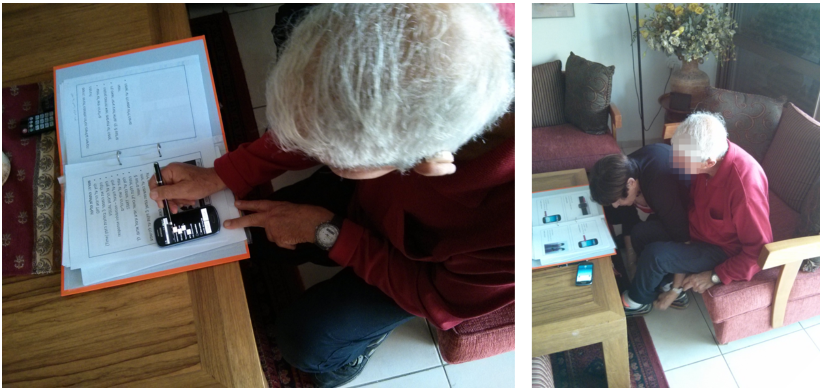
Users were offered earphones for auditory cueing. They successfully managed to introduce the plug of the earphones into the phone's socket. Although they heard the feedback better using the earphones, they preferred not to use them since they could also hear the mobile phone. One of the participants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

Exercise content. This category included 4 questions regarding the training methodology and the way 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 the instructions in the user's manual or they 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 usage manual.

In the case of visual cognitive load exercise, i.e., exercise no. 2, despite of 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 observed in [26] during in-the-lab evaluation, GaitAssist generated erroneous detections and provided RAS also during *sit-to-stand*, *stand-to-sit* situation, 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 the users said that the auditory feedback is well heard from the phone. The phone was held in hand by the participants, or placed in a pouch or in a pocket.

Subjective opinions. The statements in this category refer to all the 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 (3.6 to 4.2 grade out of 5), overall par-



(a) (b)

Figure 8.8: *Using GaitAssist at-home: (a) a participant operating GaitAssist with a stylus pen, and (b) a family member helping the participant to attach the sensors.*

ticipants were satisfied with the system, stating that it is suitable as a gait-training and gait- assistive tool, and has a potential in decreasing FoG severity. Users found the usage manual for GaitAssist clear and comprehensive. One user had difficulties in turning the pages and suggested to add sticky notes in order to easier browse 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, e.g., assistance for sensor placement or typing.

Discussion. GaitAssist received an average of 4 out of 5 as wearability score, i.e., for statements (#5 to #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 the (1) users background – 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 – the users were asked to setup 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 setup the system on-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-#4 and #7-#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 been reported to be intuitive to use. Even the users that did not operate a smartphone before answered to statements #2 and #4 with scores equal or higher than 4. However, using the wearable sensors received low scores in the user's natural environments usage scenarios. Participants in the study reported difficulties in attaching the sensors, and that required help from another person. This is due to the fact that a phone, even if not used as an assistive device, was already present in the daily-life of the participants, hence the low barrier of acceptance. On the other hand, the wearable sensors are 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-lab setting [26]: 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 the *sensor wearability is critical* for the acceptance of the system for home use. The long term goal is to integrate sensing into 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 in average. This still suggests an overall positive opinion towards using the system in their daily-life. Participants expressed their willingness to continue training and using GaitAssist also after the end of the trial, stating that they feel it helps them improving the gait.

There are differences in scores given between the groups of subjects from the two sites, for some statements. The 4 participants in Site 2 are having a mild disease severity compared with the 5 subjects from Site 1. The FoGQ values are overall lower for the participants in Site 2 compared with the participants in Site 1 (please refer to Table 8.4 from

Section 8.4). Moreover, the average age is higher for the group in Site 1 compared with the participants in Site 2, and participants in Site 1 have also overall a more advanced disease severity. This explains why for example, in case of statement #5, the group of subjects in Site 2 gave higher grades than the group from Site 1, when asked how easy is to attach the sensors on body: Participants in Site 2 found 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 are 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 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 side, people suffering from PD and FoG are people having continuous difficulties in walking, feeling constrained during their daily-life activities due to the pervasive nature of FoG, and usually being dependent on a caregiver or member of a family for support on motor activities. Thus explains somewhat why the system was easier accepted by the people in Site 1. As also stated by the participants, people can overpass some limitations of the system, if GaitAssist offers to the user walking assistance and support for motor training. The success in accomplishing the main function of the GaitAssist, i.e., offering rhythmic cueing upon FoG, overcomes the eventual wearability limitations in case of participants in Site 1. Participants stated that *the system helps them in walking better*, this being in line with their main expectation from such an assistive device. On the other side, participants in Site 2, younger on average and with a milder disease severity, tend 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.

8.6. 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* [26], we performed a second experiment: During the one week out-of-the-lab protocol, we collected sensing data from the 5 participants in Site 1. We then performed a data-driven analysis on the FoG distributions over all the three days of the protocol, in order to observe if there are 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 5 participants.

Objective assessment and detection of FoG episodes. The protocol was not video-taped, due to its complex settings and privacy issues, i.e., experiments were executed in the participants' homes, where also other members of their families 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 for each FoG event its duration. The system was shown to provide robust performance when tested in-the-lab settings (please see Section 8.3.3). Moreover, FoG-detection using wearable sensing data is considered a valid objective assessment of the FoG in the clinical practice [31].

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

1. *Total number of detected FoG* in each of the three days for each of the two protocol parts.

2. *FoG duration* statistics for each gait-training or assistive session in three different days.

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

As detailed earlier, GaitAssist system was used by participants in two different settings mapped on the two functions of the system: *(A)* as wearable support for motor-training exercises, and *(B)* 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.

8.6.1. *(A)* Training Exercises Support

(1) Trends in detected number of FoG episodes. Table 8.6 contains details about the numbers of FoG episodes during the gait-exercises protocol, as detected by the GaitAssist. The detection algorithm makes also false detections, i.e., detects a freeze when there is none, thus the computed numbers in the table incorporate false FoG 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 will have fewer FoG episodes than compared with the previous training day, then also GaitAssist will detect fewer FoG compared with the previous day, even if the number of detected FoGs is not the same as the real number of FoG.

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

Table 8.6: *Number of detected FoG episodes by GaitAssist during the gait-training sessions, for each protocol day, and each of the 5 participants.*

Figure 8.9 shows the trends in the detected FoG numbers during the three days of exercise sessions. Except to one subject, we did not find a clear trend in reduction of the number of FoG episodes. Only for patient PD4 we observe a decrease of the number of detected FoG, as the training progresses. A special case is PD3, which due to the disease severity, had difficulties in performing the gait-training exercises during the first two days. The subject performed the training for shorter periods of time than as required, i.e., the total exercise time was approximatively halved from the required daily exercise training. However, in 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 in the third day compared with the first two days of training. However these statistics do not show any consistent effect of GaitAssist on the number of experienced FoG, when performing gait-training exercises.

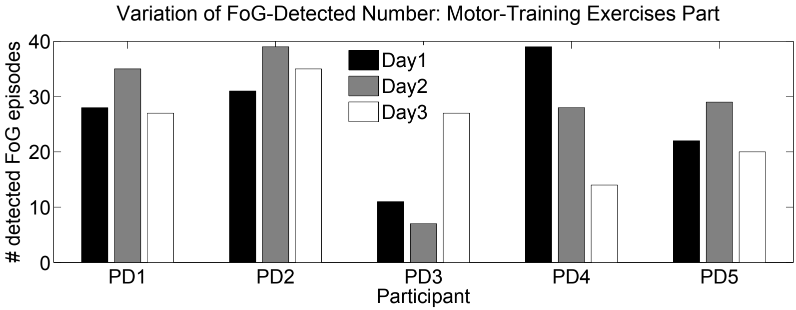


Figure 8.9: *FoG number trends for gait-exercise protocol part, over all three days for each of the 5 participants.*

(2) Trends in detected FoG durations. Figure 8.10 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. Also, in the first day of training the FoG-detection algorithm detected exceptionally long FoG episodes, i.e., $8-12$ seconds for PD1 and $15-25$ seconds for PD4. Until the last day of training there are no such long FoG 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. Also, this decrease of the maximum FoG duration with the training day suggests that the participants might get more and more used with the cueing given by the system, accept it, and learn to respond to it by following the rhythmic pattern to resume gait.

In 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 in the last day of training, which are reaching 10s. This suggests that PD2,

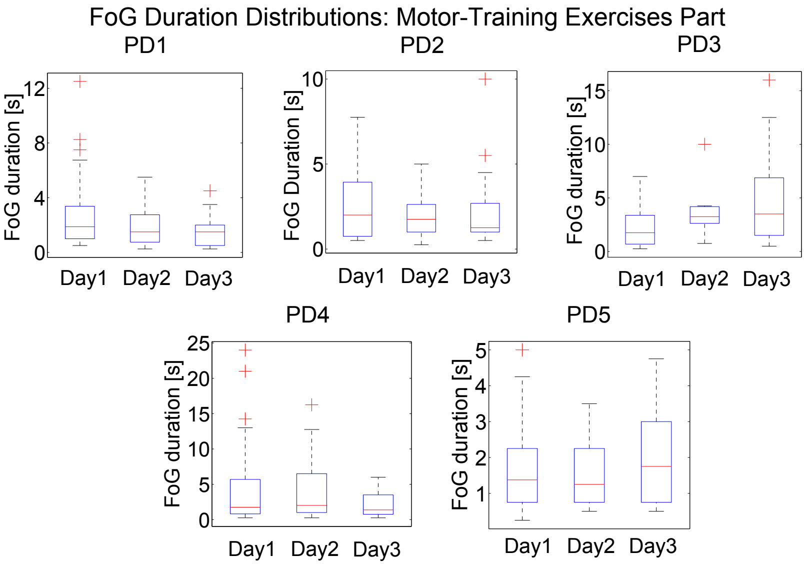


Figure 8.10: *Boxplots of FoG-duration distributions for each of the three training days for each of the 5 participants, during the exercise sessions of the protocol. The boxplot includes the* median *value of FoG durations, the 25th and 75th percentile as* lower hinge *and* uper hinge*, the* H-spread *which is the difference between the 75th and 25th percentile, 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.*

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 rhythmic auditory stimulation started upon FoG, which makes harder to resume walking during FoG. However these two participants had difficulties even in performing all the required exercises, due to the advanced PD motor symptoms.

In summary, for 3 out of 5 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 with assisted by GaitAssist rhythmical cueing, in the users' home environment. For PD5, a slightly negative effect is observed on the FoG duration, while for PD3 the FoG episodes tend to be longer with every training day.

8.6.2. *(B)* Daily-Life Assistive Function

(1) Trends in the number of detected FoG episodes. Table 8.7 contains information about the detected FoG during the daily-life walking protocol part. The detected FoG 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. Also the daily-life walking part of the protocol was shorter in duration than the gait-exercises part.

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

Table 8.7: *Number of detected FoG episodes by GaitAssist during the daily-life walking sessions, for each day and each of the 5 participants.*

Figure 8.11 shows the trends in the FoG numbers during the three days of using GaitAssist as a walking assistant during daily-life activities protocol. For all the participants except PD3 we observe a decrease trend in the number of FoG. The most significant improvements have been measured for PD2 (with a decrease from 19 detected episodes in Day1 down to 6 FoG in Day3) , and for PD5 (from 12 detected episodes in Day1 down to 3 FoG in Day3). Same as before, for PD3 the number of FoG slightly increases during the training days – from 8 FoG in Day1 to 11 FoG in Day2 and 9 FoG events in Day3.

(2) Trends in detected FoG durations. Figure 8.12 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

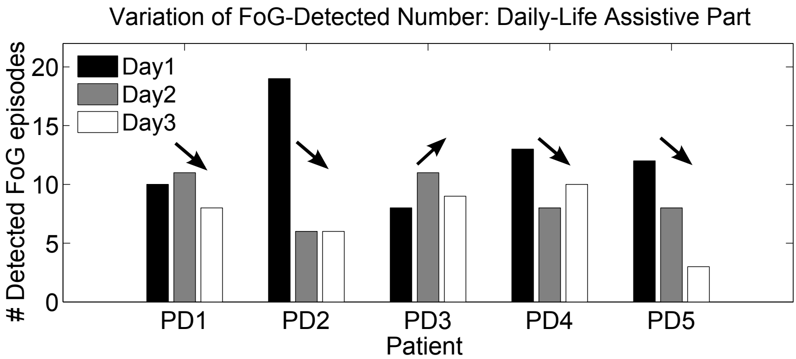


Figure 8.11: *FoG number variation over the three days for the assistive part of the study.*

the distribution (decreasing FoG duration values for the 75th and 91st percentiles) corresponding to shorter detected FoG episodes as the protocol progresses. Also 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 overall decrease 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, the RAS making the exit from FoG more difficult.

8.6.3. Discussion

Overall, the results lean towards a positive effect on the gait of participants when using the wearable training support. 3 out of 5 users, i.e., PD1, PD2, and PD4 responded positively to the gait-training exercises with wearable support cueing, results suggesting a reduction in FoG *duration* with progressing training. In case of PD5, the analysis suggests that he reacted negatively on the 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

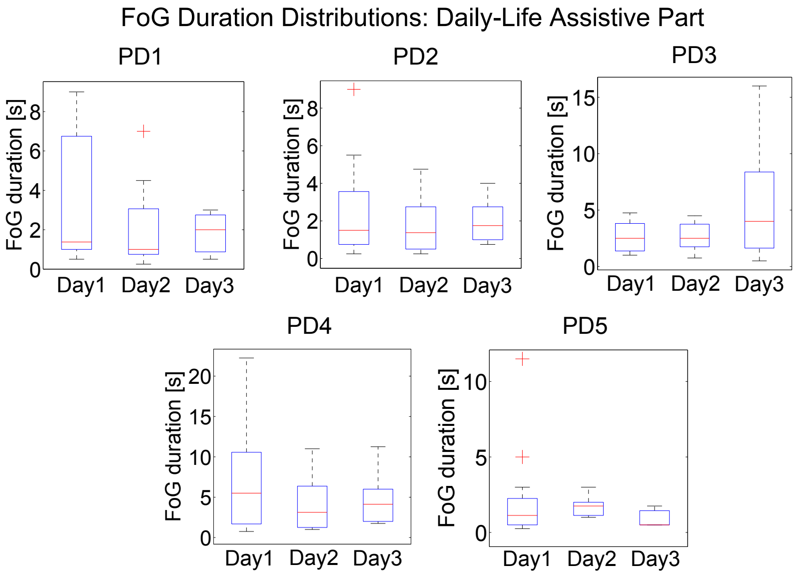


Figure 8.12: *Boxplots of FoG-duration distributions for each of the three training days for each of 5 participants, during the daily-life walking sessions of the protocol. The boxplot includes the* median *value of FoG durations, the 25th and 75th percentile as* lower hinge *and* upper hinge, *the* H-spread *which is the difference between the 75th and 25th percentile, 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.*

FoG. Often it 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., PD1-2, PD4-5, the statistical results show a reduction of the FoG durations when participants used GaitAssist during natural daily life walking, in assistive mode. This suggests that GaitAssist could be suitable to be used by the 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 had troubles also in performing all the protocol sessions, because of the Parkinsonian gait symptoms. This is also in line with previous findings regarding rhythmic auditory stimulation in lab settings, where not all the patients participating in the studies reacted positively on the rhythmic cueing, but some wore bothered by the sound during FoG [25]. Moreover, before the trials clinicians assessed a high score in FOGQ questionnaire (see Table 8.4 from Section 8.4) for PD3 compared with the scores of the other 4 participants, meaning that PD3 has an advanced PD and FoG stage. This suggests that GaitAssist might have a positive impact on the gait for people with PD with low to moderate FOGQ 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 analysed 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 5 participants, thus we cannot generalize if GaitAssist has a positive short-term effect in general in PD. However the data-driven analysis still suggest promising results towards 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 which 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., [41].

8.7. Conclusion

We present a wearable system for motor training and gait assistance for people with PD and freezing of gait. 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 9 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 Parkinson's disease and freezing of gait). Participants deployed and used the system in their homes following a system's user manual, without any clinical help or supervision, during three days in one week – a period similar with 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 towards 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 5 participants in the first site. The analysis of the FoG-number and FoG-duration distributions over the three days of use suggests that three out of five participants might react positively on the independent training exercises with support from the 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 a positive feedback from participants and a 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 an unsupervised gait-training exercises delivered at-home. By supporting existing rehabilitation techniques, people with PD are less burdened by clinical visits and the healthcare sector resources are relieved. Besides motor-training exercises support, 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, and also for monitoring the disease progression during longer periods of time.

GaitAssist is currently a finished system which can be deployed to the masses. Following our short-term findings from the acceptance study and data-driven analysis, clinical researchers are designing a longterm study with 40 PD people to monitor the gait properties during longer periods, i.e., 6 weeks, and to investigate sustained gait improvement when using GaitAssist.

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Glossary

Notation	Description
AAE	Averaged acceleration energy
ANOVA	Analysis of Variance
AUC	Area Under the Curve
C4.5	Decision Tree
CuPiD	The CuPiD Freezing of Gait Dataset (CuPiD EU FP7 Project)
DAPHnet	The DAPHnet Freezing of Gait Dataset (DAPHnet EU Project)
ECG	Electrocardiography
EEG	Electroencephalography
EMG	Electromyography
EVA	Eigenvalues of the dominant acceleration directions
FFT	Fast Fourier transform
FI	Freeze Index
fNIRS	functional Near-Infrared Spectroscopy
FoG	Freezing of Gait
FOG-Q	Freezing of Gait Questionnaire
FP	False Positive
GSR	Galvanic Skin Response
HCI	Human Computer Interaction
HR	Heart Rate
HRV	Heart Rate Variability
H & Y	Hoehn and Yahr scale
IMU	Inertial Measurement Unit
kNN	k-Nearest-Neighbor
MCR	Mean crossing rate

MGD	Multivariate Gaussian Distribution
MI	Mutual Information
ML	Machine Learning
MLP	Multilayer Perceptron
NB	Naïve Bayes
PCA	Principal Component Analysis
PD	Parkinson's Disease
PF	Power on the *Freeze Band* ($[0, 3]Hz$)
PL	Power on the *Locomotion Band* ($[3, 8]Hz$)
PT	Total power on $[0, 8]Hz$ band
RAS	Rhythmical Auditory Stimulation
RF	Random Forest
RMS	Root mean square
RR	Heart Beat-to-Beat Interval
SCR	Skin Conductance Response
Sens	Sensitivity
SMA	Signal magnitude area
SMV	Signal magnitude vector
Spec	Specificity
STD	Standard deviations
TP	True Positive
UI	User Interface
UPDRS	The Unified Parkinson's Disease Rating Scale
ZCR	Zero crossing rate

Curriculum Vitae

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