Prediction of Freezing of Gait in Parkinson's From Physiological Wearables: An Exploratory Study

Sinziana Mazilu, Alberto Calatroni, Eran Gazit, Anat Mirelman, Jeffrey M. Hausdorff, and Gerhard Tröster

***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 (SC) data from 11 subjects who experience FoG in daily life, and found statistically significant changes in ECG and SC 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 SC features. We were able to predict 71.3% from 184 FoG with an average of 4.2 s before a freeze episode happened. Our findings enable the possibility of wearable systems, which predict with few seconds before an upcoming FoG from SC, and start external cues to help the user avoid the gait freeze.**

***Index Terms*—Body-fixed sensors, electrocardiography (ECG), freezing of gait (FoG), Parkinson's disease (PD), prediction, skin conductance (SC), wearables.**

I. Introduction

PARKINSON'S disease (PD) is a neurodegenerative disease with a worldwide prevalence estimated at 16.1 million people [1] 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 [2]. FoG is a "brief, episodic absence, or marked reduction of forward progression of the feet despite the intention to walk" [3]. It is typically sudden and transient, lasting usually from a few seconds up to few minutes [3], during which the motor system is blocked. FoG is a severe problem, since it is associated with falls [4], anxiety, loss of mobility, mortality [5], and has substantial clinical and social consequences which decrease the quality of life [6], [7]. Hence, it is important to build systems that can help reducing FoG incidence.

FoG does not respond well to pharmaceutical treatment. Nevertheless, clinical studies [8]–[10] 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 [11], [12] can detect FoG and deliver a rhythmical cue upon its detection. While such systems are already beneficial in shortening the freeze duration [12], [13], they cannot help the user to avoid FoG, since they need at least some hundreds of milliseconds to react to the existent episode [11], [12]. 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 that was not exploited until now is that mental conditions might play an important role in the pathogenesis of FoG [14]. Factors such as stress and anxiety are linked to and likely contribute to FoG occurrence [6], [15]. These factors have a measurable influence on physiological signals like heart activity or skin conductance (SC), modalities which have been used in previous research to reflect the emotional state, stress, and anxiety in daily life [16], [17].

We, therefore, make a step further and study whether physiological data such as electrocardiogram (ECG) or SC show specific variations before FoG. We hypothesize that changes in the ECG and SC might occur during and just before FoG as a reflection of the emotional and cognitive state of the patient, factors associated with provoking FoG [6]. Such changes could potentially also help in predicting FoG.

Our study has also a practical motivation: Commonplace wearable technologies such as wristwatches or wristbands that collect heart rate (HR) or electrodermal activity information in real time enable the possibility of unobtrusively and continuously monitoring the user in daily-life settings. We envision systems that 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 SC *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?

Manuscript received April 6, 2015; revised July 2, 2015; accepted July 28, 2015. Date of publication August 5, 2015; date of current version November 3, 2015.

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Digital Object Identifier 10.1109/JBHI.2015.2465134

To answer them, we make the following contributions:
(a) We collect ECG and SC from 11 subjects in a laboratory setting, where 184 FoG episodes are identified.
(b) We analyze the variations of specific features extracted from ECG and SC for periods of data *just before*, during, and *just after* FoG events, compared to normal walking events, for each subject.
(c) We propose a method for predicting gait-freeze events using SC features and multivariate Gaussians.

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

The remainder of the paper is structured as follows. In Section II, we survey the state-of-the-art regarding detection and attempts of *prediction* of FoG and summarize how ECG and SC data have been used to detect the emotional state. Section III details the collected dataset. In Sections IV and V, we describe our data-driven study and findings regarding FoG prediction from physiological sensors. In Section VI, we present a vision of a wearable assistant for predicting FoG episodes. We conclude our work in Section VII.

II. 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 FoG 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.

A. FoG and Wearable Systems

Many research studies have described methods for detecting FoG in real time using wearables [7], [11]–[13], [18]–[24]. Most of them focus on the gait properties captured with inertial sensors such accelerometers and/or gyroscopes mounted on-body [11]–[13], [18]–[20], [24], extended with electroencephalography (EEG) [21] and electromyography [22]. 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.* [25] attempted to capture changes in gait characteristics a few seconds before FoG from accelerometers mounted on the subject's ankle from DAPHnet dataset [13], 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 [11]–[13]. However, the findings from [25] 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.

B. FoG and Brain Activity

Handojoseno *et al.* [26]–[28] 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 *et al.* [29] 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 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: ECG and SC.

C. 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 [14]: stressful situations, anxiety, depression, cognitive challenging situations, or fatigue have been associated with gait freeze, and might be a contributing factor [6], [15], [30].

In a recent study, Maidan *et al.* [31] found correlations between the HR variations during FoG, compared with periods of walking before or just after the episode. Moreover, HR 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" [31]. 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 s were considered, and data were analyzed only few seconds before or just after the FoG.

We take the idea in [31] forward and test whether there are significant correlations in changes of physiological status captured by ECG and SC just before or during FoG, compared with all the rest of walking events, such as straight line walking, turns, and gait initiation. Different from [31], we focus on all the FoG episodes, independent of their subtype.

D. Physiological Data for Mental State Recognition

Stress, fear, or other emotions could be detected from electrodermal activity or from ECG changes, in real-life scenarios: Wearable ECG sensors are used in monitoring the stress arousal in the wild [16], [32], for recognition of sleep apnea [33], and for real-time detection of cardiovascular diseases such as

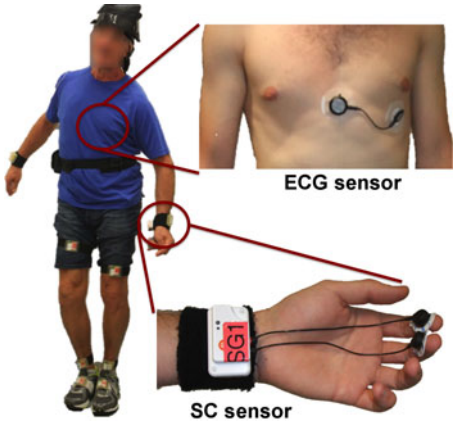

Fig. 1. Subject wearing the system used for the data collection, with a focus on the ECG and SC sensor systems. The ECG sensor is attached on the chest, using two electrodes. SC data are collected using finger electrodes attached on the index and middle fingers, and a wristband on which the Shimmer sensor is attached using Velcro stripes.

arrhythmia [34]. Similarly, wearable electrodermal activity sensors are useful in recognizing stress or other emotions [35], and for daily-life monitoring of bipolar disorder [17]. Schumm *et al.* [36] show that fight-or-flight reflex, which relates to fear, can be sensed using galvanic skin response (GSR) information, despite moderate levels of physical activities. We use ECG and SC to evaluate the correlations between FoG and the changes in these sensor signals in order to predict FoG.

III. Dataset

To study whether ECG or SC are useful for predicting FoG, we collected the CuPiD multimodal dataset. The CuPiD dataset contains sensing data collected from subjects with PD who performed different walking protocols in a laboratory setting designed to provoke FoG. The customized system contains nine IMUs attached on different parts of the body, a near-infrared spectroscopy sensor, an ECG sensor, and an SC sensor. In this study, 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 $N_{\text{ECG}} = 512$ Hz. For SC information, we used a Shimmer sensor,[2] with synchronized 3-D acceleration and GSR modules. Shimmer samples both GSR and acceleration data at $N_{\text{GSR}} = 51.2$ Hz. In Fig. 1, we show the two sensors and their on-body placement.

A. Protocol Description

Building on previous work [37], [38], 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* [38] 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 five times a figure eight shape in a 3-m 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 m, turns, and walks again on the opposite direction, all this for five times. The task takes approximately 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.
4) *Circles:* The subject walks in circles, with random 180° and 360° turns, when asked by the clinicians, for a period of 3 min.
5) *The hospital tour* is a real-life session that includes approximately 10 min 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 s. We refer to these as *baseline sessions*, as data from these sessions are used as reference for the physiological data. Apart from them, we include also other types of nonwalking 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 h, which includes the walking sessions, along with the baselines, nonwalking sessions, and rest periods; the walking tasks sum around 25–30 min from the protocol.

B. 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 ms. A first clinician went over all videos and marked the FoG episodes. All events on which the first clinician was

[1] www.camntech.com
[2] www.shimmer-research.com

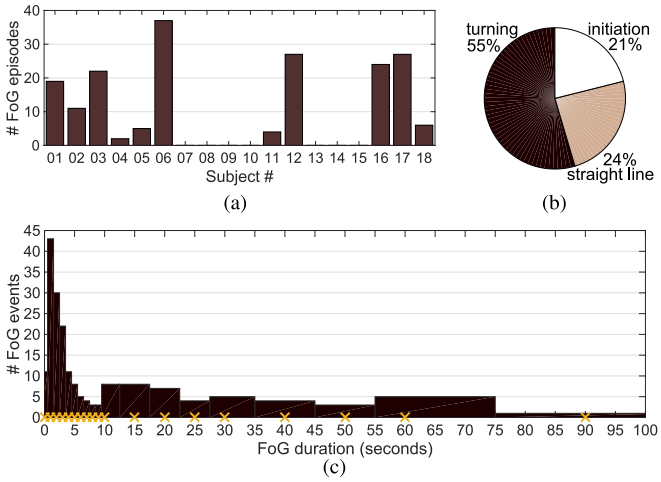

Fig. 2. FoG statistics. (a) FoG events distribution across subjects, (b) distribution of FoG subtypes, and (c) FoG-duration distribution.

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 SC 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.

C. 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 comorbidities, 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 HR that is controlled by a pacemaker would not reflect FoG; hence, we did not collect data for this subject.

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 [39]. 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

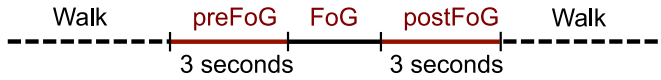

Fig. 3. Categories assigned to the data: FoG represents the ground truth labels as set by the clinicians. preFoG and postFoG are artificially set to observe whether there are specific changes just before FoG, compare with walking. The *Walk* category contains the rest of the walking and gait events in the session.

diverse scores for the PD and FoG severity: UPDRS scores between 25 and 56 (average: 41.7, std: 10.2), and FOG-Q [40] between 4 and 30 (average: 19.7, std: 7.1), being representative for II-IV Hoehn & Yahr disease severity [41]. 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 [42] are the following: a total of 184 FoG episodes were identified, with a duration between 0.12 and 98.88 s (average: 8.84 s, std: 14.87 s). FoGs are not equally distributed among the patients, as shown in Fig. 2(a): seven did not experience any FoG, four had between two and six FoGs and the other seven experienced more than ten episodes. In Fig. 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 Fig. 2(c), approximately 65% of FoG episodes having a duration between $[0, 5]$ s. 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 [43].

IV. Changes in Physiological Data for FoG Prediction: An Exploratory Analysis

A. 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 SC have 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 four categories, as in Fig. 3: 1) FoG represents data during the FoG; 2) preFoG is the data from the T_{preFoG} period; 3) postFoG is 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 $T_{\mathrm{preFoG}} = T_{\mathrm{postFoG}} = 3$ s. These values are chosen *a priori* as in [31]. The ECG or SC properties might change with

TABLE I
FEATURES EXTRACTED FROM ECG SIGNAL

#	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

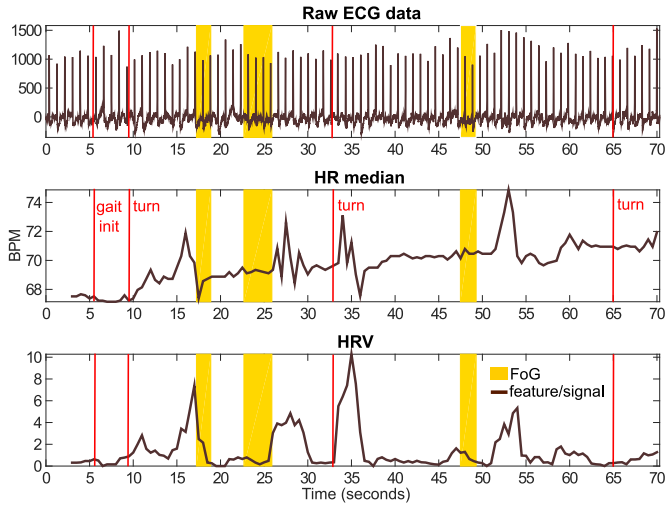

Fig. 4. Sequence of ECG raw signal, together with the extracted median of HR and HRV. The sequence contains three FoG episodes, straight line walking, and events such turns and gait initiation. Both HR and HRV increase within 3 s before the first FoG episode, or in the 5-s interval just after the second 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.

less than or more than 3 s 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 four categories. Different from, and in extension to the work from [31], 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 [13], [18], [25]. We set the window size to $N_{\text{window}} = 3$ s, and the window-overlapping step to $N_{\text{step}} = 0.5$ s. We choose a 3-s processing window to map on TpreFoG, and TpostFoG, as a tradeoff 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

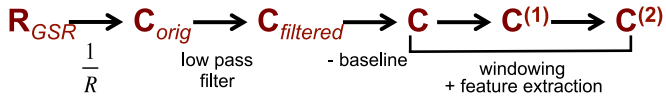

Fig. 5. SC data-processing framework: from the original R_{GSR} collected from Shimmer, we obtain C, $C^{(1)}$, and $C^{(2)}$ signals, on which we apply windowing and feature extraction techniques.

TABLE II
FEATURES EXTRACTED FROM SC AND ITS DERIVATIVES

#	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

about the data processing and extracted features for each of the two sensor modalities.

1) 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 [44]. We then compute the instantaneous HR values in the window as

$$\text{HR} = \frac{60 \times \text{SamplingRate}_{\text{ECG}}}{\text{RR}}. \quad (1)$$

We extract the mean and median of HR vector and the heart rate variability (HRV) as defined previously in [31]. In addition to the HR features, we extract frequency-based features from the raw ECG [44], such as the power on different spectra. A summary with all the ECG features and their description is contained in Table I.

Fig. 4 contains an example of raw ECG signal, together with HR_{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.

2) SC Data Processing: In Fig. 5, we present the steps for processing the SC data: Before extracting the features, we first 1) transform the galvanic skin resistance signal obtained from the Shimmer sensor into conductance data. SC (C_{orig}) is the inverse of the skin resistance: $C_{\text{orig}} = \frac{1}{R_{\text{GSR}}}$. We then follow the same processing steps for SC as in previous work [45], [46]: 2) we first apply on the C_{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 C_{filtered}, we extract its baseline. We refer to the resultant signal as C. 3) From C, we then extract its first derivate $C^{(1)}$, and its second derivative $C^{(2)}$, by following the same procedure as in [45] and [46]. Using the sliding window

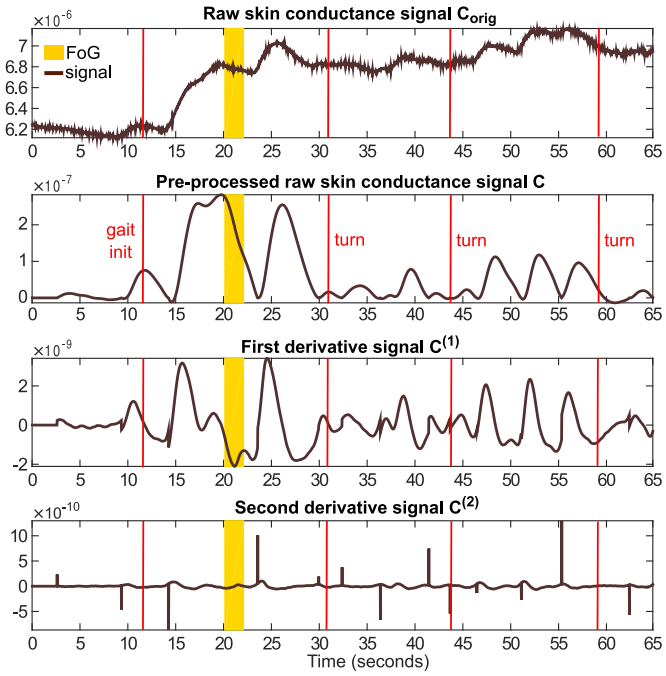

Fig. 6. Sequence of straight line walking with turns, containing am FoG episode, captured in the raw SC, C, $C^{(1)}$, and $C^{(2)}$ signals. There are specific changes just before FoG, different from the signals' changes during other walking events (turns, gait initiation).

procedure, 4) we extract the following eight features for each of the resultant signals C, $C^{(1)}$, and $C^{(2)}$ as described in Table II. In total, we obtain 24 features from each window (eight for each signal: C, $C^{(1)}$, $C^{(2)}$).

In Fig. 6, we show an example of raw SC 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 SC variations corresponding to other walking events such as gait initiation or turns.

B. Informative Features and Statistics

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

1) One-Way Analysis of Variance: We use ANOVA [47] in MATLAB to assess the p-value for each of the features from ECG or SC data, with respect with the four categories. Prior to using ANOVA, we checked the normality assumption for each ECG or SC 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 threshold set to 0.001. A feature that has the p-value ≤ 0.001 shows that the information from at least two of the four categories of data is statistically different, although the features selected will not be necessarily useful in predicting FoG.

TABLE III
ECG-BASED FEATURES WHICH HAVE THE p-VALUE ≤ 0.001 FROM ANOVA TEST, FOR EACH SUBJECT

#	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	$Power_{HF}$

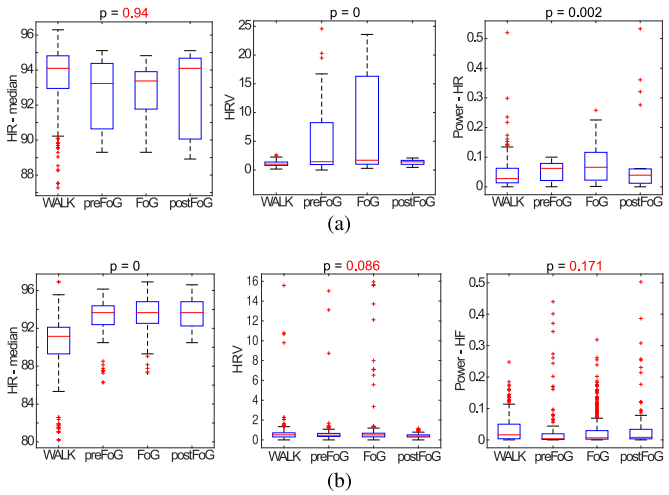

Fig. 7. Boxplot representation for HR_{median}, HRV, and $Power_{HF}$ features, in case of two subjects with different ECG trends related to the four categories: In case of S05, HRV and $Power_{HF}$ increase during preFoG and FoG compared to Walk. In the case of S06, HR increases significantly during preFoG, FoG, and postFoG periods, and $Power_{HF}$ decreases during preFog.

2) Mutual Information: MI [48] is another measure we use to check whether there is a link between the observations from a feature related to the four categories of data, i.e., preFoG, *FoG*, postFoG, and *Walk*. MI is usually used for feature selection [48], but here we apply MI for feature ranking, to explore which of the features capture differences between the four categories.

C. ECG Features

Table III 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 three 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

TABLE IV
SC-BASED FEATURES WHICH HAVE THE p-VALUE ≤ 0.01 RESULTED FROM ANOVA1 TEST, FOR EACH SUBJECT*

#	Subj.	C	$C^{(1)}$	$C^{(2)}$
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

*The text-bolded features represent the top five occurred ones across all subjects.

this subject, there are no significant changes ECG with respect to the four categories of data.

Similarly, the top MI scores were obtained by HR (mean, median), 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-s 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 four 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 Fig. 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 [see Fig. 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.* [31], 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 (see Fig. 2(b) in Section III), compared with the dataset from Maidan *et al.* [31], which includes only FoG during turns. However, different from [31], 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, which could lead or be a cause for the upcoming freeze event. In this case, ECG could be used to predict FoG.

D. SC Features

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

Table IV lists the features that 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 SC features, which imply significant variations on the four categories, suggesting that the SC 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-derivative features. In case of S05, no SC-based features passed the ANOVA test, suggesting that for this patient, the SC does not capture any significant changes during preFoG, FoG, or postFoG, compared with the rest of walking.

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 Fig. 8, we present the variations of some six 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.

Fig. 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 second-derivative signal, during preFoG, compared with Walk. The first four features increase also for FoG and postFoG periods, compared with the Walk. Changes in the SC suggest that there is an increase in the SC 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.

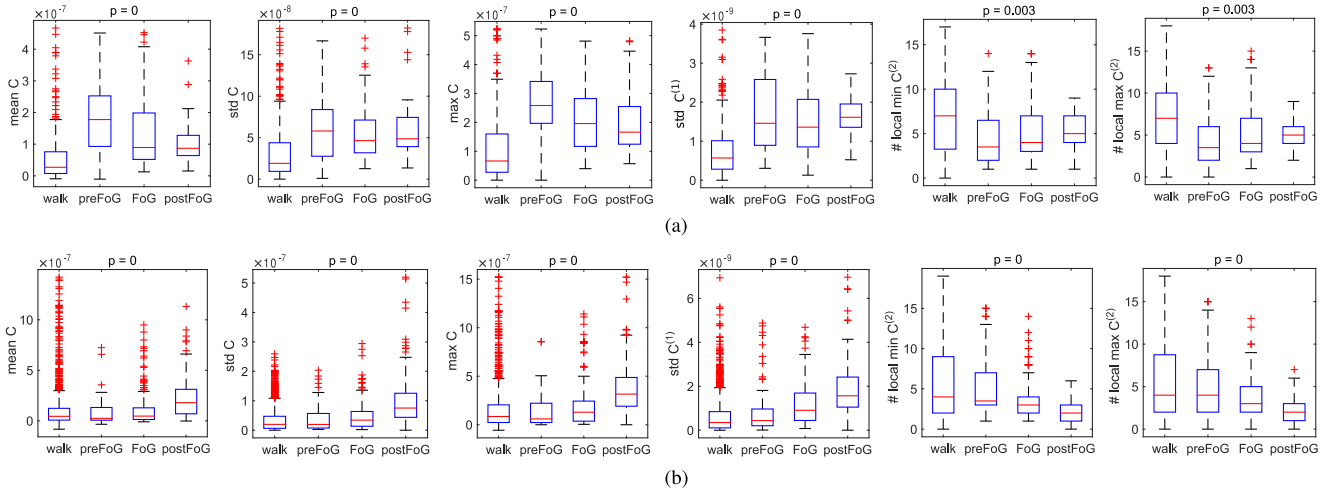

Fig. 8. Boxplot representations for SC-based features—mean, std, and max of C, std of $C^{(1)}$, and # local minima, and # local maxima from $C^{(2)}$—in case of two subjects with different trends during preFoG and FoG: For S18, there is a significant increase in the first four features during preFoG 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 four features just after FoG.

On the other side, for S17 [see Fig. 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 SC 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 four categories of data. This is due to the *a priori* durations of preFoG and postFoG periods, which are set both to 3 s 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 SC data capture 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 SC 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 SC is person-specific.

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

SC might incorporate noise generated from touching the electrodes. As mentioned earlier in Section III, 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.

V. 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 SC, 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 SC data is specific for each person. Following the previous findings, in this section, we answer the second research question: 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) [49]. MGD was successfully used for anomaly detection with image data [50]. Moreover, MGD allows for multiple and different time-series fusion, being suitable for our different features from ECG or SC, which capture themselves various changes in the data. We build a FoG prediction model for each of the 11 subjects, as ECG and SC data changes and reactions are specific for each person.

A. FoG-Prediction Model

We consider the vector of features for each subject S, as vector-valued random variable $X = [X_1, X_2, \ldots, X_k]^T$, where the k columns represent the features, resulted either from ECG signal, or from SC 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 semidefinite covariance matrix. We compute the MGD, or the probability density function p as

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

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 $\text{Label}_{\text{anomaly}}$, with decisions for each line in X, as

$$\text{Label}_{\text{anomaly}} = p(x;\mu,\Sigma) \leq \text{TH} \tag{3}$$

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 are labeled with the anomaly events. Thus, there are available ground truth labels for periods before FoG, FoG, and after FoG. But in our case, ground truth 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 s. 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 ground truth 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.

B. 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) SC.

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 $\text{Label}_{\text{anomaly}}$ outputs continuously that there is an anomaly in the data with at most 8 s *before* a FoG episode. The false positive (FP) events are the number of false FoG predictions, i.e., the method predicts a FoG, when none happens. Additionally, we compute the average prediction time $T_{\text{prediction}}$ 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.

C. Results

1) Prediction of FoG From ECG data: We were 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 with 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.

2) Prediction of FoG From SC data: Table V presents the FoG-prediction performances for each of the subjects' datasets, when using features from SC. Data from SC are 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 s before the freeze event. Moreover, the prediction rate comes with a relatively low number of false predictions (71 false alarms across approximately 2 h 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 SC signal during walking to predict FoG episodes in real time. There might be a subject specific pattern in the SC signal, which happens before the FoG, which is accurate enough to distinguish between the other walking patterns, given the low number of false alarms.

TABLE V
FOG-PREDICTION PERFORMANCES

#	Subject	#TP / # total (%)	#FP	Avg. pred. time (s)
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

Two types of reactions: The specific variations in SC 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 [14]. However, as suggested also in the previous section, SC 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 SC features. In the previous section, we observed that there are two types of reactions in the SC: In the first one, SC 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 SC increases only toward the end of FoG, or after the event. Sometimes, the SC does not capture any reaction even after FoG. Subjects such as S01, S05, S06, and S17 are included in this category. For these datasets, the number of FoG predictions comes 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 four 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 SC 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 SC captured as a result of a FoG could be used to predict the next FoG.

However, even for this reaction type, the SC 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 SC data seconds before the actual FoG event (average of 4.2 s, min 1.5 s, and max 6.3 s), for the successfully predicted events. This finding suggests, as also stated in [31], 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 s, 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 s, 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 SC 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 (see Fig. 2(c) from Section III), while more than 71% from the total FoG were successfully predicted. This suggests that the changes in SC 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 [25]. Moreover, different from ECG, SC data are 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 SC data are not only before FoG, but also during and just after FoG, as also shown in Section IV. Thus, in case if the FoG is not predicted, then it can be detected, either with the same anomaly-detection algorithm and SC data, or with previous methods based on ankle-mounted accelerometers [12].

VI. 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 toward a real-time FoG-prediction system based on SC 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 an SC wearable sensor. There are commercial wrist mounted sensors, such as wrist bracelets, which sense SC-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 SC 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 [12], which will help the subject improve the gait and maybe overcome the FoG.

A main conclusion of our study is that the reactions in SC 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 SC 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 [12], 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 telemedicine system, for long-term monitoring of patient's gait.

VII. Conclusion

We propose the use of new sensor modalities to continuously monitor the gait anomalies in PD, in particular FoG episodes. We suggest that FoG can be predicted before it happens by means of physiological data, namely ECG and SC.

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 SC information. We created patient-specific models by fitting MGDs on data from each subject. The anomaly-based models allowed to predict 71.3% of all 184 FoG episodes, on average 4.2 s 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 SC 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 PD.

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.

ACKNOWLEDGMENT

The authors would like to thank I. Maidan for support with data collection, and D. Roggen for his valuable advice.

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