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Fast track article

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.

1. Introduction

Parkinson's disease (PD) is a neurological degenerative disorder with a worldwide prevalence of 16.1 million people [1]. 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 [2] and described as a sudden incapacity to walk or move the lower limbs. With FoG lasting from few seconds up to 1–2 min [3], it carries the danger of falling, the main cause of mortality in Parkinson's disease [4,5].

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 [6] suggest that rhythmic

☆ The current contribution extends the findings from Mazilu S. et al. Gait, Wrist and Sensors: Detecting Freezing of Gait in Parkinson's Disease from Wrist Movement. Workshop on Sensing Systems and Applications Using Wrist Worn Smart Devices, IEEE International Conference on Pervasive Computing and Communications (PERCOM), 2015.

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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 [7], 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 s, 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 [8,9] 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 [10], in particular for people with motor deficits. Moreover, stigmatization is a barrier in accepting the wearable systems [11], 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 [12,8,13]. But during walking, humans move their arms in tandem with their lower limbs [14]. 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 [15].
(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 [16].
(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 2), and present the dataset used in our investigation (Section 3). In Section 4 we propose, describe and quantify new statistical and frequency features extracted from IMU to characterize freezing of gait. Section 5 details our findings on the use of wrist movements to detect FoG. In Section 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 7.

The current work is based and extends on our previous contribution [17]. 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), and compare and discuss the upper limb versus lower limb information regarding recognition performances and wearability (Section 6). Moreover, we complete the discussion over the FoG-detection performances using wrist-attached inertial measurement units (Section 5).

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 [13,18,8,9,19,20,12,21]. 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) [12]. Other features involve entropy [13], time-domain and statistical features such as mean, standard deviation, and variance. However, all the FoG detection approaches except [13] require that the sensors are attached to the lower limbs, in order to analyze the gait properties. Tripoliti et al. [13] uses data from wrist sensors, but only in combination with data coming from sensors mounted on lower limbs. Cole and colleagues [20] 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 [22]. However, first evidences that *freezing* in Parkinson's disease is present also in the upper limb are given in [23,24], where frequency analysis of wrist movements showed early occurrences of manual motor blocks in PD. Moreover, Vercruysse et al. [25] 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. [26] 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 [14,27,28], creeping, and swimming [29]. Changes in coordination of arm and leg movements are used to identify differences in walking patterns or in the walking speed [30]. The upper limb movement dysfunction, for example the arm constraint, causes slowness in walk due to atypical coordination between upper and lower body movement [31]. 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. [32] 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 [33] 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. [34] 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 [11,35].

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 [36], to recognize human activities [37,38], self-harming activities [39], social gestures [40], and to recognize human emotions such as stress [41] or sleep patterns [42].

3. Dataset

To analyze the correlation of the upper limb motion with freezing of gait, we use the inertial measurements from the CuPiD dataset [15]. The CuPiD dataset contains multimodal sensor information collected 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 [43], 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 Fig. 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

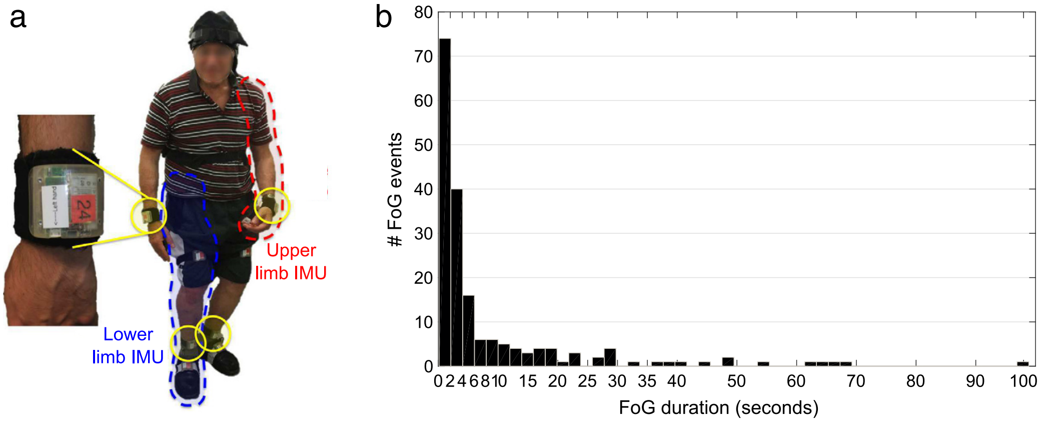


Fig. 1. (a) Subject wearing the system used in the dataset collection, with a focus on the IMUs attached on the wrists and on the ankles. (b) Histogram representing the distribution of FoG duration in the dataset.

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 [44]. 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 s and 98.8 s (average: 8.84 s, standard deviation: 14.87 s). 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.

As observed in Fig. 1(b) most of the FoG episodes are short, with approx. 38% of all events are ≤ 2 s, and 73% of them are ≤ 5 s. 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. Wrist movements during freezing of gait

The majority of studies which target FoG detection from motion look into leg movements [45,8,21,18,16], or lower back changes [21,13]. This approach is intuitive, as the anomaly itself happens at the lower limbs level. However, in Fig. 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.

4.1. 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* [12,21,13,16], 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 1 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 $W = 3$ s, with a window-overlapping step of $S = 0.25$ s. The 3 s 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 ≤ 5 s, while we aim to detect the onset of FoG, as soon as it starts. Prior to feature extraction, we compute the magnitude

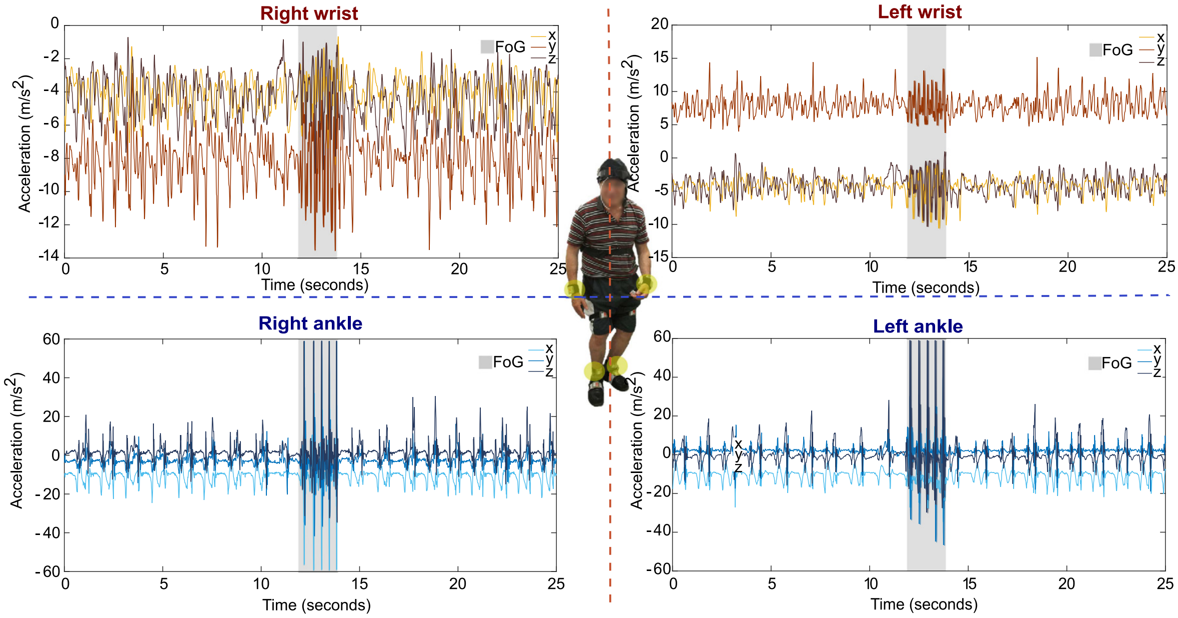


Fig. 2. A walking sequence with a FoG episode, as captured by the accelerometers mounted on different limbs. Ankle acceleration a distinguishable pattern on both right and left legs during FoG. In this particular case, we choose an example of a freezing characterized by strong trembling of the legs. 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.

Table 1
Features extracted from wrist mounted IMUs to describe FoG episodes.

#	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	$Power_{[0,1]\text{ Hz}}, \dots, Power_{[15,16]\text{ Hz}}$	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 [12])
22	$Power_{[5,8]\text{ Hz}}$	Power on [5, 8] Hz band from acceleration which is included in the so-called *freeze* band introduced in [12]
23	$Power_{[9,12]\text{ Hz}}$	Power on [9, 12] Hz band from acceleration magnitude
24	$Power_{[13,16]\text{ Hz}}$	Power on [13, 16] Hz band from acceleration 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 Fig. 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 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.

4.1.1. *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 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) [46] 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 [46], but here we use MI for feature ranking, to explore which of the features

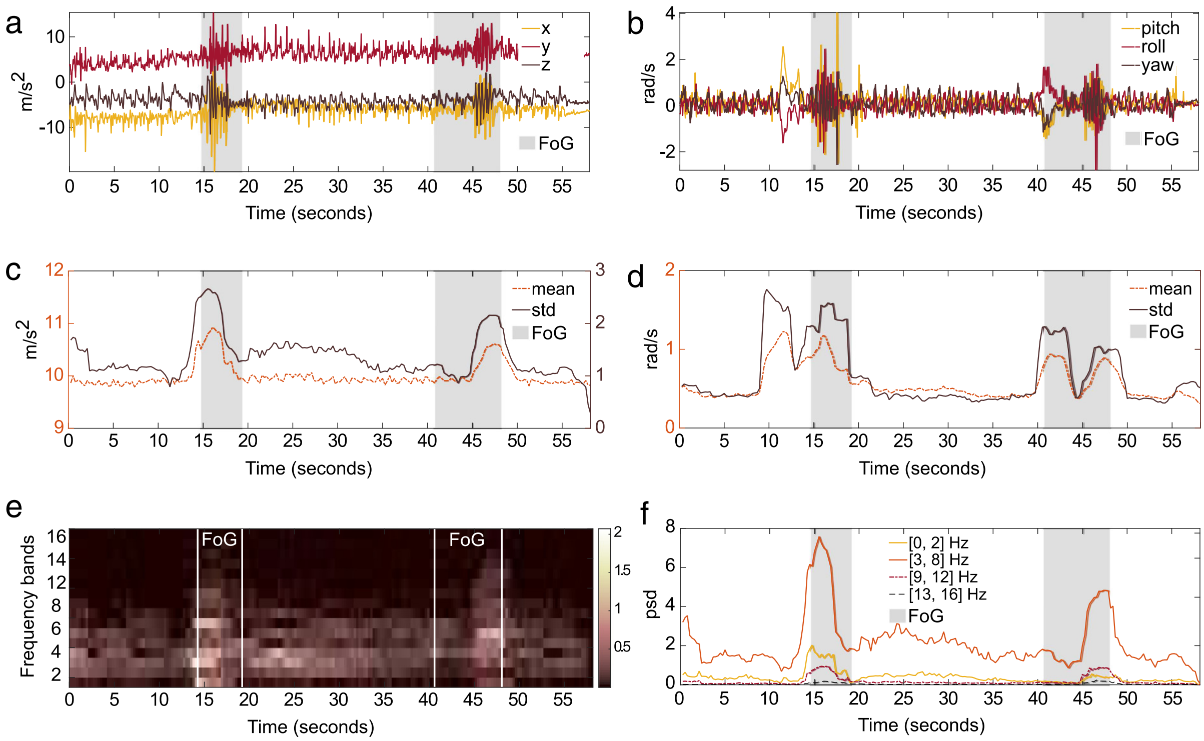


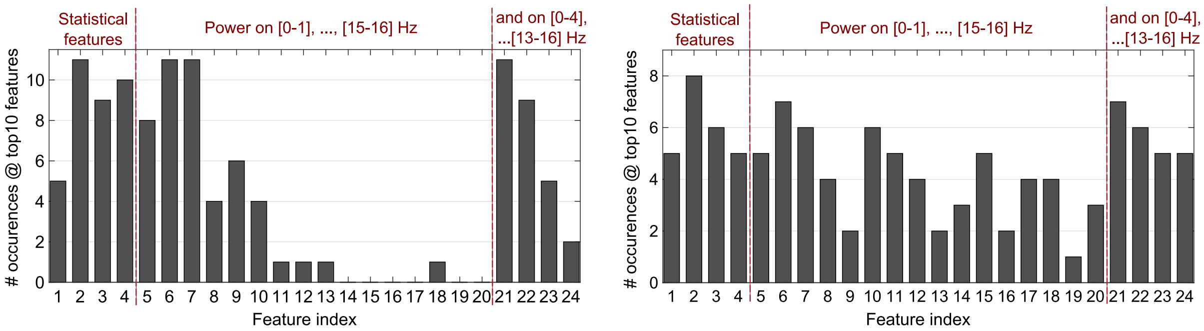
Fig. 3. An example of approx. 60 s of wrist motion data, which contains two FoG episodes during walking in straight line with turns from subject S06, expressed in different ways: (a) Raw acceleration data, (b) Raw gyroscope data, (c) Mean and standard deviation acceleration features, (d) Mean and standard 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.

better captures differences between the 2 categories. Additional to feature ranking, we use One-way Analysis of Variance (ANOVA) [47] 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.

Fig. 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 (Fig. 4(a)) or R values (Fig. 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 Walk and FoG classes, as ranked with MI and R.

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 Fig. 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, 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



(a) Features ordered by MI scores.

(b) Features ordered by R scores.

Fig. 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.

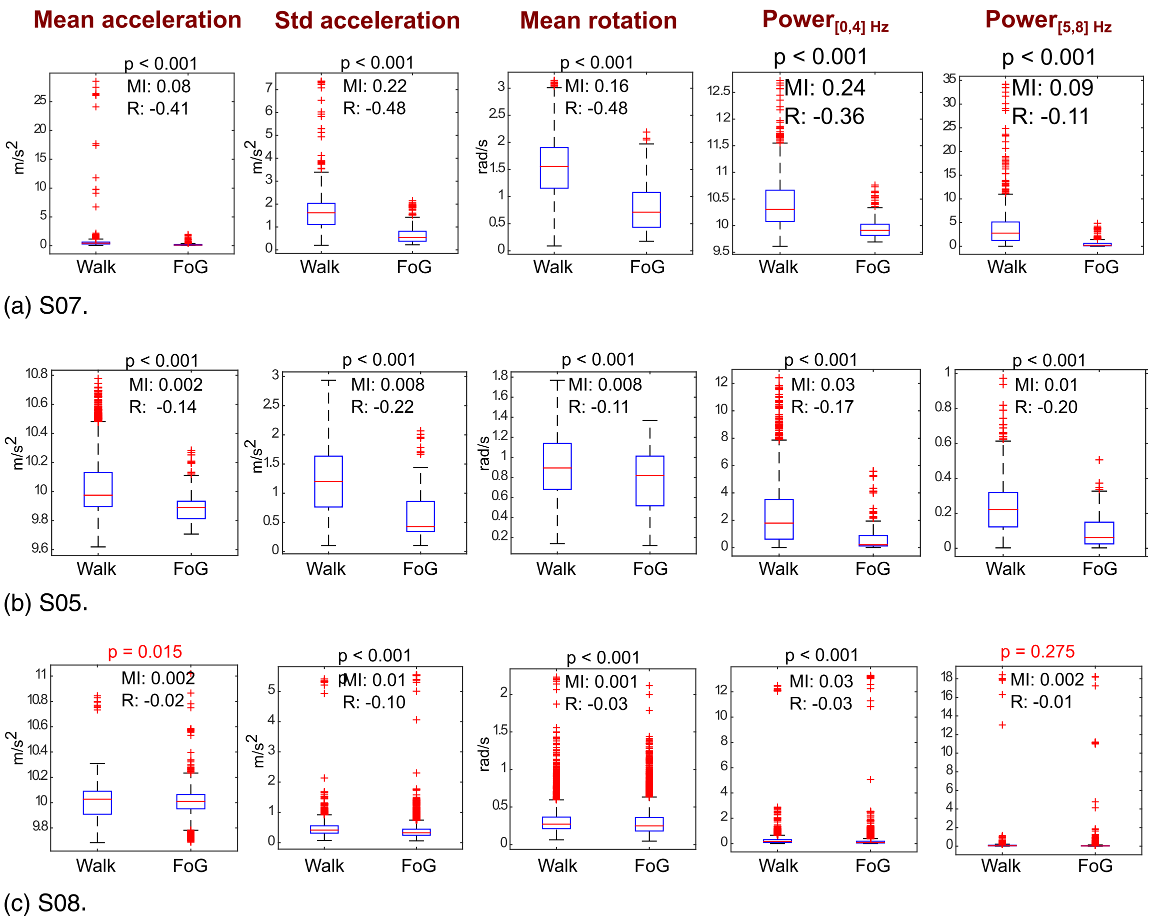


Fig. 5. Boxplots with the variation of top 5 most informative features for all 11 datasets (mean and std of acceleration, mean of gyroscope, power on [0, 4] Hz, and on [5, 8] Hz respectively) in case of three subjects: S07, S05, and S08. For the first two, the 5 features have different ranges for Walk 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.

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.

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 [16]. We choose this as the FoG recognition chain obtained robust FoG detection performances both in offline validation on CuPiD dataset and real-time settings [16], when using information from ankle motion.

The FoG-detection framework is the following: Raw wrist IMU readings are separated into windows of 3 s with overlapping step of 0.25 s, from which features are extracted, as detailed in previous Section 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 [48], to automatically distinguish between FoG and the rest of data.

Different from our previous work in [17], and following the findings from Section 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.

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.

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 [21], 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 [16] start a rhythmic cueing upon first time prediction of the FoG event, which continues up to 8 s 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.

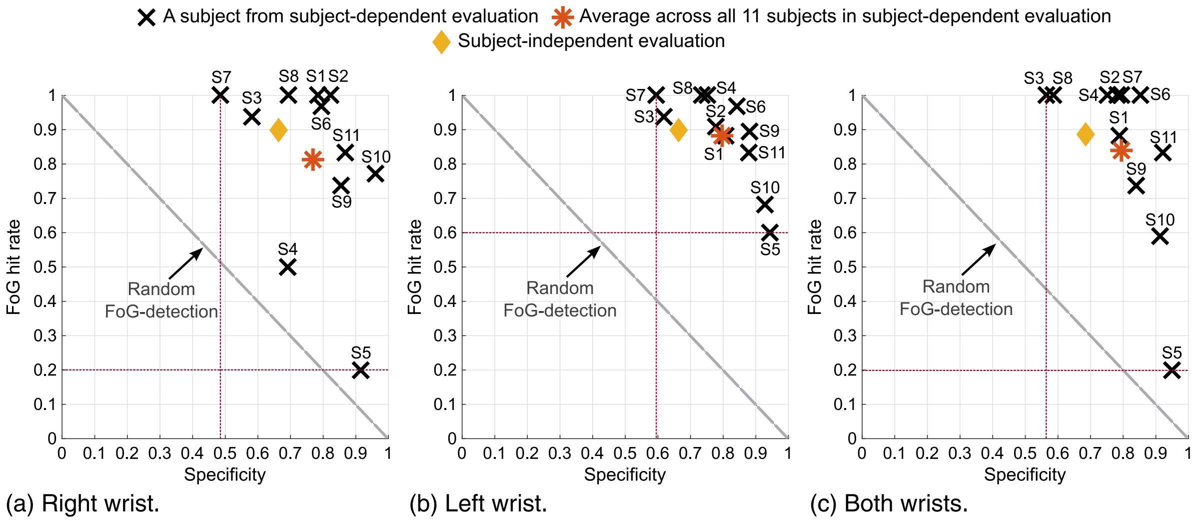


Fig. 6. Scatter plots reporting FoG-detection performances for three different scenarios: when using information from (a) right wrist, (b) left wrist, and (c) both wrists. Each scatter plot reports the FoG hit-rate against the specificity for each of the 11 individual datasets, the average across them 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.

Table 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.

Subject	# FoG	# False positives events			Averaged Latency (seconds)		
		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

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 $N = 3$ s, 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.

Fig. 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 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.

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 Fig. 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 the freezing at the gait level.

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 — 185 across all subjects.

FoG recognition latency. The average FoG-detection latency varies between 1 s (for right wrist data) up to 1.37 s (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 s, 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 [5]. 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.

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 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 s 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, 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.

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 [12,8,21,20,13,19]. From all, the ankle showed to be the most informative position to describe and detect gait freeze [21,16]. 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 [16], we apply the same steps and the same parameter values to evaluate the ankle information: a window of $W = 3$ s, with a window-overlapping step of $S = 0.25$ s. We employ C4.5 detection models as used in [16] and in the current work. In case of using ankle data, we extract from each window of acceleration magnitudes the following features as in [16]: (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 [12] as the ratio between the power on the *freeze band* and the power on the *locomotion band*.

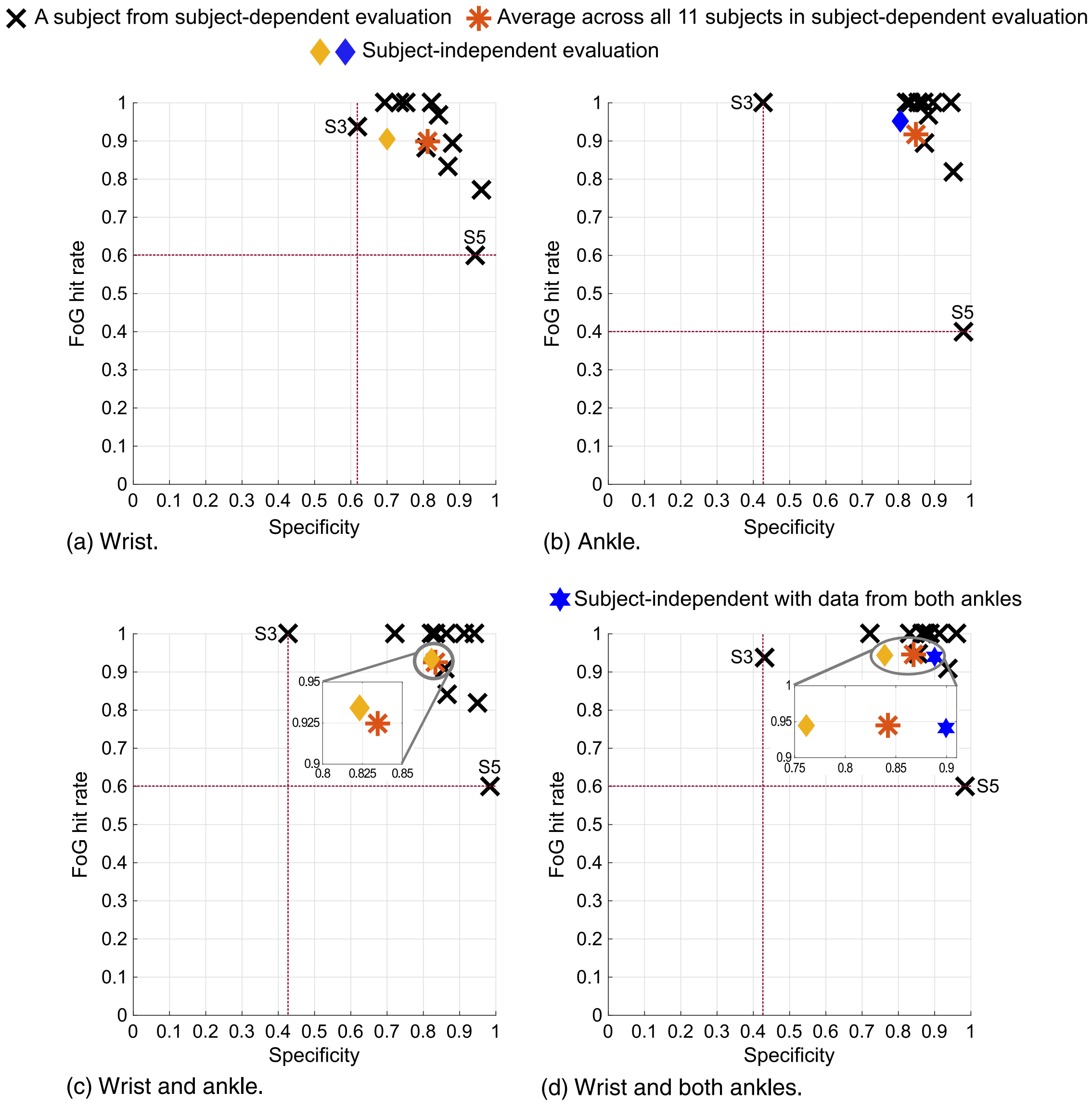


Fig. 7. Scatter plots reporting FoG-detection performances for four different scenarios: when using information from (a) wrist, (b) ankle, (c) wrist and ankle, and (d) wrist and both ankles. Each scatter plot reports the FoG hit-rate against the specificity for each of the 11 individual datasets, the 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. In a subject-dependent setting, the average performances when using wrist are similar with those obtained by the ankle. However, there are differences for each subject. The addition of wrist to ankle data does not come with better performances and even harms the FoG-detection as in case of (d) scenario.

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 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 5, for each of the data combinations.

Fig. 7 and Table 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. 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.

Table 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.

Subject	# False positives				Latency (seconds)			
	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

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.

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 (Fig. 7(a) and (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 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 s in case of ankle to 1.15 s 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 Fig. 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.

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 Fig. 7(c) and (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 Fig. 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.

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.

Table 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.

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

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 s in duration. The under-represented FoG class has an impact on 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 [33], 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 min. 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 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 [3]. The walking task is a combination between transversal limb coordination [14], thus an explanation why the left wrist is most informative in case of our dataset.

Mahabier et al. [32] 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.

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 [34]. 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.

6.5. A wrist wearable prototype for real-time FoG-detection

In a previous work we proposed GaitAssist [16], 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 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 [16], 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 5 and 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 s, the last 3 s 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 s from the last time when the system detected a FoG event.

Different from the experiments in Sections 5 and 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 [49]. 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 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.

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 [34].

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

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

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.

The analyses 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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