

Inertial Sensor Based Detection of Freezing of Gait for On-Demand Cueing in Parkinson's Disease

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Abstract: Freezing of Gait (FoG) is one of the cardinal symptoms of Parkinson's disease, which arises in the late stages of the disease. It affects the gait cycle and increases the risk of falling. FoG leads to heterogeneous gait cycles, which makes the detection of gait phases and events difficult. In this article, we introduce a new inertial measurement unit-based approach for detecting Parkinsonian gait phases based on the acceleration, velocity, rate of turn and orientation of the foot. Furthermore, we introduce a new gait evaluation measurement, the so-called GaitScore, for distinguishing between normal and FoG-affected motion phases and thus for detecting FoG episodes. Preliminary results show that the extreme values of the pitch angle during a motion phase provide valuable information for the detection of FoG. The proposed method can detect FoG episodes with a sensitivity of 97% and specificity of 87%. The reference data were generated by clinical experts who annotated FoG episodes in video data synchronized with the measurements of the inertial sensors. The detection of FoG in real-time enables on-demand cueing.

Keywords: Biomedical Systems, Inertial Measurement Unit, Rehabilitation, Parkinson's Disease, Freezing of Gait, On-Demand Cueing, Gait Analysis, Detection Algorithms

1. INTRODUCTION

Parkinson's disease (PD) is, after Alzheimer, the second most common neurodegenerative disorder in the world. The major cause of PD is affiliated with a deficiency of dopamine. The dopamine deficiency is due to the degeneration of the dopamine-producing nerve cells in the substantia nigra in the midbrain. Motor-disabling symptoms like rigidity, bradykinesia, slowness, tremor, and Freezing of Gait (FOG) are prominent features in PD. The disease incidence has shown an increasing tendency over the years and has reached 22 per 100,000 person-years for all age groups and up to 529 per 100,000 person-years in the older population over 65 years (Lill and Klein, 2017). The number of patients in the world with PD in 2016 was estimated to be around 6.1 million (Dorsey et al., 2018). Due to the neurodegenerative character of PD, affected patients suffer from a progressive decline in mobility limiting both the quality of life and participation in social activities. Not only patients but also society is affected by the disease, since the costs of treatment place a burden on health economics (Moore et al., 2007; Giladi and Hausdorff, 2006). The development of wearable systems

for non-invasive gait monitoring and therapy might help patients to regain lost mobility and reduce the cost of the disease treatment. In this contribution, we propose new inertial measurement unit (IMU)-based algorithms for online gait assessment and FoG detection in Parkinson's patients.

Freezing of Gait (FoG) is one of the cardinal symptoms of PD and a typical sensomotoric symptom of PD that is observed in the later development of the disease. FoG is defined as an episodic process during which an increased restriction of movement or complete blockage is present despite the intention to move. This process is described by patients as "if the feet were glued to the floor" (Punin et al., 2019). FoG episodes typically last only a few seconds. Longer episodes lasting more than 30 seconds are rare (Schaafsma et al., 2003). The causes of FoG are still unknown, although some scenarios are known to trigger a FoG episode with increased likelihood, such as gait initiation, turning, walking through narrow spaces such as door frames and obstacles. Such scenarios are used in various clinical trials to provoke FoG episodes. A major implication of FoG is the increase in the risk of falls. Falls can lead to physical injuries, fractures, disabilities and significant impairment in the quality of life. It was estimated that falls can lead to death with a 10.6% rate (Kalilani et al., 2016). FoG episodes can be divided into three groups according to the appearance of motor activity. One manifestation

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of FoG episodes can be characterized by small forward movements using small and fast steps (festination). The second manifestation is characterized by shank trembling without forwarding movement and the third by akinesia, i.e. no movement (Bradley et al., 2004)[16, chapter 25, pages: 323 – 336].

In the course of the last years, several wearable sensors-based methods for detecting FoG were proposed. Researches have used different types of sensors and signals: inertial sensors (Moore et al., 2013; Bächlin et al., 2010; Azevedo Coste et al., 2014), force sensors (Hausdorff et al., 2003; Popovic et al., 2010), electroencephalography (EEG) (Handojoseno et al., 2012), and electromyography (EMG) (Nieuwboer et al., 2004). The advantage of inertial sensors lies in the usability. In the case of EMG and EEG, electrodes must be attached to the human body after appropriate skin preparation.

In the present article, we focus on online methods using inertial sensors for the detection of FoG. Moore et al. (2008) proposed a spectral measure, named Freezing Index (FI), for detecting FoG Episodes. FI is defined as the ratio of spectral power of the freeze band (3 – 8 Hz) to the spectral power of the locomotive band (0.5 – 3 Hz). Moore et al. (2008) estimated the FI over a window of 6 s. Inspired by the results of Moore et al., Bächlin et al. (2010) extended the algorithm with an energy threshold to distinguish between standing and walking. They reported that their method detects FoG events with a sensitivity of 73% and specificity of 81.6%. However, they indicated that the detection of FoG events was associated with a time delay of 4.5 s. Azevedo Coste et al. (2014) proposed a different approach for the detection of FoG based on two step parameters: the step length L_n and step frequency C_n . The introduced decision parameter was called the FoG Criterion ($FOGC_n$) and is calculated as follows:

$$FOGC_n = \frac{C_n \cdot L_n}{C_{max} \cdot (L_n + L_{min})}, \quad (1)$$

where C_{max} and L_{min} are the expected maximum step frequency and minimum step length, respectively. A large $FOGC_n$ value indicates a FoG episode. The threshold on which $FOGC_n$ is based must be adjusted individually for each patient, just as it is the case for FI .

In the present article, we propose a new method that exploits the profile of the pitch angle of the foot during every foot motion phase to detect FoG episodes. This facilitates a more responsive (less delayed) on-demand cueing to improve and unfreeze the gait than the approach by Bächlin et al. (2010). The proposed FoG detection algorithm is also simpler and less error-prone than the approach by Azevedo Coste et al. (2014) because no step length calculation from bias-affected accelerations is required. Furthermore, a new algorithm for motion phase detection is proposed that takes the specific characteristics of Parkinsonian gait into account and that exploits the foot's estimated orientation with respect to the ground, the acceleration and its derivative, the rates of turn, and the estimated velocities in forward and sideward walking direction. A fixed parameter set for the algorithm is used for all PD patients in this study. The new methods for FoG and gait phase detection (GPD) are validated on four PD patients and compared to the outcome of the FoG criterion by Azevedo Coste et al. (2014).

2. METHODS

We introduce a new algorithm for gait phase detection based on kinematic measurements of the foot motion. For this purpose, a 6D inertial measurement unit (IMU) is attached to the foot instep (mid-foot) of the most affected leg. It provides real-time measurements of the linear acceleration $a(t) \in \mathbb{R}^3$ and angular velocity $\omega(t) \in \mathbb{R}^3$ of the foot with a sample rate of 200 Hz.

2.1 Online Parkinsonian Gait Phase Detection Algorithm

The algorithm detects three phases of Parkinsonian gait. It distinguishes between a rest phase, an unrest phase and a motion phase, which represents a sub-phase of the unrest phase. Unrest phase and motion phase differ in the amount of movement activity. An effective displacement or orientation change of the foot with respect to the last rest phase takes only place in motion phases. A state \mathcal{Z} is introduced, which enables/disables the search for a new motion phase within a detected unrest phase. The state \mathcal{Z} is required for detecting successive motion phases within a single unrest phase. This occurs for example during festination or non-alternating step sequences. On the transition from rest to unrest phase, the state \mathcal{Z} is always active, meaning the search is enabled.

The first step of the algorithm is to transform the linear acceleration and angular rate from the intrinsic measurement frame of the IMU to an inertial frame of reference. Denote those measurements in *global* coordinates by $a_g(t), \omega_g(t) \in \mathbb{R}^3$, respectively. The transformation uses the orientation quaternion of the IMU, which is estimated using an algorithm described in (Seel and Ruppig, 2017). For each rest phase, the bias of acceleration and angular velocity are estimated and subtracted from the corresponding signals prior to the aforementioned transformation. The bias-free signals are denoted $a_{d,g}(t), \omega_{d,g}(t) \in \mathbb{R}^3$.

Detecting Rest and Unrest Phase The algorithm distinguishes between rest phase and unrest phase. A threshold-based condition \mathcal{A} is used for detecting rest phases. Upper bounds $a_{rest}, \omega_{rest} \in \mathbb{R}_{>0}$ are defined for the Euclidean norm of the linear acceleration and angular rate. If both signals lie below the defined threshold ($(\|a_{d,g}(t)\|_2 - 9.81 \text{ m/s}^2) < a_{rest} \wedge (\|\omega_{d,g}(t)\|_2 < \omega_{rest})$) for at least $n_r \in \mathbb{N}_{>0}$ consecutive samples, a rest phase will be detected. An unrest phase is detected in the same way. If any of both signals exceeds its threshold for at least $n_r \in \mathbb{N}_{>0}$ consecutive samples, an unrest phase will be detected.

Detecting the Start of Motion Phase The motion phase is typically associated with changes of the foot orientation relative to the last rest phase. It has been demonstrated that this foot-to-ground orientation can be measured accurately by foot-worn IMUs (Seel et al., 2015). In the present case, it is determined by decomposing the foot orientation into Euler angles, i.e. yaw, pitch and roll. We use three conditions to mark the beginning of the motion phase.

The first condition \mathcal{B} is linked to the physiological forward movement of the foot. Before the swing phase, the pitch angle of the foot reaches a local maximum. If such a local maximum is observed in the pitch angle $\phi_{pitch} > \phi_p$, then

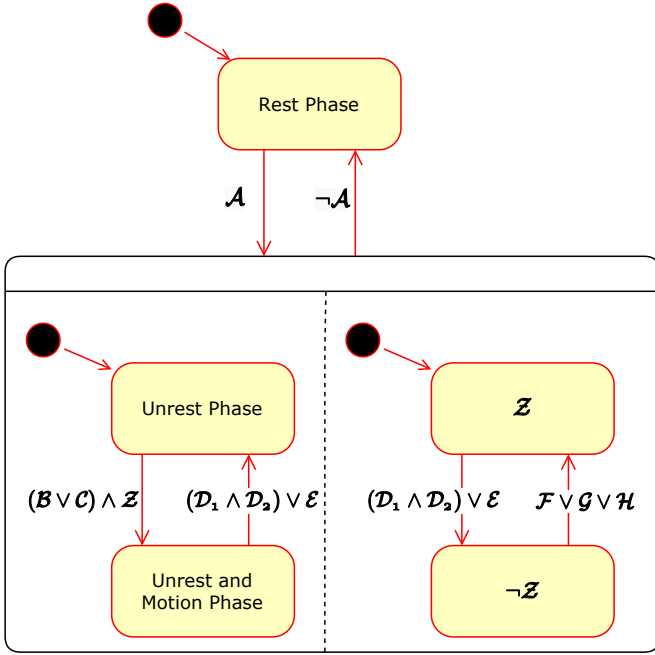


Fig. 1. State diagram of the gait phase detection algorithm. The GPD algorithm consists of two parallel sub-diagrams, actively interacting with each other.

the start of the motion phase is detected. The parameter $\phi_p \in \mathbb{R}$ defines a lower bound for the pitch angle.

The second condition \mathcal{C} exploits the roll angle to detect a motion phase during turning or if the condition \mathcal{B} failed to detect the start of the motion. Similar to the condition \mathcal{B} , the unrest phase and the state \mathcal{Z} must also be fulfilled. Condition \mathcal{C} is fulfilled if a local maximum is found in the roll angle $\phi_{\text{roll}} \in \mathbb{R}$ and a local maximum is found in a signal $a_{d,7}(t) \in \mathbb{R}$. The signal $a_{d,7}(t)$ is obtained by filtering $\|a_{d,g}(t)\|_2$ by means of a moving-average filter with a window width of 7 samples. The filter is used to eliminate less prominent local maxima caused by noise. If both aforementioned maxima are at most $\Delta = 0.25$ s apart and the local maximum of $a_{d,7}(t)$ is greater than a defined threshold $a_s \in \mathbb{R}$ while the pitch angle is negative, then a motion phase is detected.

Detecting the End of Motion Phase The end of the motion phase is defined by the initial contact of the foot with the ground. It is indicated by a sudden increase of $j(t) = \left\| \frac{d(a_{d,g}(t))}{dt} \right\|_2$, which is the jerk norm. However, a large jerk norm may likewise occur at the beginning of the motion phase. Therefore, the initial contact is detected when a specified $t_{\text{mot}} \in \mathbb{R}_{>0}$ has elapsed since the beginning t_0 of the motion phase and the following conditions are valid:

$$\mathcal{D}_1 : j(t_s k) > \alpha \cdot \max_{\tau=[t_0, \dots, t_s(k-1)]} \{j(\tau)\} \quad (2)$$

$$\mathcal{D}_2 : |v_x(t_s k)| < \beta \cdot \max_{\tau=[t_0, \dots, t_s(k-1)]} \{|v_x(\tau)|\} \\ \wedge |v_y(t_s k)| < \beta \cdot \max_{\tau=[t_0, \dots, t_s(k-1)]} \{|v_y(\tau)|\}, \quad (3)$$

where t_s is the sampling period, k is the sampling index, and $\alpha \in \mathbb{R}_{>0}$ is a factor that exploits that the norm of the jerk at the initial contact is larger than at the

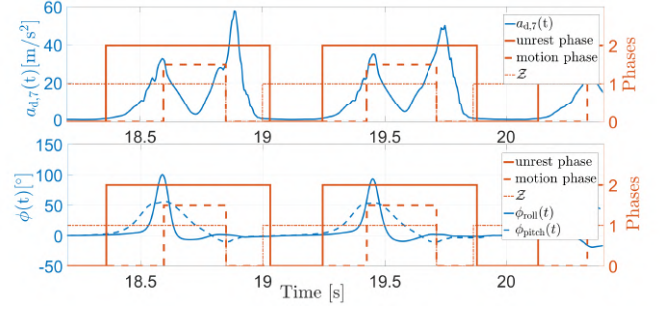


Fig. 2. Example of filtered acceleration norm $a_{d,7}(t)$, pitch $\phi_{\text{pitch}}(t)$ and roll angle $\phi_{\text{roll}}(t)$ and gait phases.

toe detachment. The sub-condition \mathcal{D}_2 exploits that the velocity in the x-y transverse plane (forward and sideward movement) reaches a maximum velocity during the mid-motion phase and then decreases until the end of the motion phase. The parameter $\beta \in \mathbb{R}$ is a factor that determines the threshold as a function of the maximum velocity during the motion phase. This condition was inspired by Seel et al. (2014).

An additional condition \mathcal{E} based on the profile of pitch angle during a motion phase is introduced. The start of the motion phase was characterized by a local maximum in pitch angle. After the toes are detached from the ground, the foot begins to rotate in the opposite direction than before the motion, and it reaches a minimum at the initial contact. If during the motion phase a local minimum in the pitch angle is found, then the initial contact and the end of the motion phase are detected if also two sub-conditions $|\phi_{\text{roll}}| < \phi_r$ and $|\phi_{\text{pitch}}(t)| < \kappa \phi_{\text{pitch,max}}$ hold. The first sub-condition $|\phi_{\text{roll}}| < \phi_r$ demands that the roll angle should have small values at the initial contact. The second sub-condition $|\phi_{\text{pitch}}(t)| < \kappa \phi_{\text{pitch,max}}$ demands that the difference between the local maximum at the beginning of the motion phase and the current local minimum in pitch angle should fall below a certain threshold, which depends on the local maximum $\phi_{\text{pitch,max}}$. The parameter $\kappa \in \mathbb{R}$ is a scaling factor that determines how small the local minimum of the pitch angle should be, to detect the motion phase. The two sub-conditions serve to prevent the algorithm from remaining in a local minimum before the initial contact. At the end of the motion phase, the state \mathcal{Z} is set inactive.

Reactivation of the State \mathcal{Z} As mentioned above, state \mathcal{Z} determines the start of the search for the next motion phase. The state \mathcal{Z} is automatically reactivated when an unrest phase begins and remains active if the beginning of a motion phase is detected within the unrest phase. It is then deactivated at the end of that motion phase. If it remains inactive for a certain time $t_x \in \mathbb{R}_{>0}$ within the unrest phase, i.e. if the motion phase is not followed by a rest phase within t_x , then the following two conditions are validated:

$$\mathcal{F} : |\phi_{\text{pitch}}(t)| < p_1 \wedge |\phi_{\text{roll}}(t)| < p_1 \quad (4)$$

$$\mathcal{G} : \text{var}(\|a(t)\|_2) < p_2 \quad (5)$$

If either of the two conditions is valid for at least $n_r \in \mathbb{Z}$ consecutive samples, then the state \mathcal{Z} is reactivated. The parameters p_1, p_2 are two thresholds, chosen empirically.

The state \mathcal{Z} is also reactivated when the local maximum in the pitch angle is larger than a threshold $\phi_{\text{thres}} \in \mathbb{R}$ (condition \mathcal{H}).

The state diagram of the proposed GPD algorithm with all conditions is shown in Fig. 1.

Fig. 2 shows examples of the measured acceleration norm and the estimated pitch and roll angle profiles during forward movement of a patient together with the detected gait phases and the state \mathcal{Z} . Note that, at 19 s, the state \mathcal{Z} is reactivated because the aforementioned conditions are fulfilled. Fig. 3 shows an example of a series of motion phases, which are not separated by rest phases. It can be observed from the signals that the gait is more affected by the Parkinson's disease than the gait shown in Fig. 2.

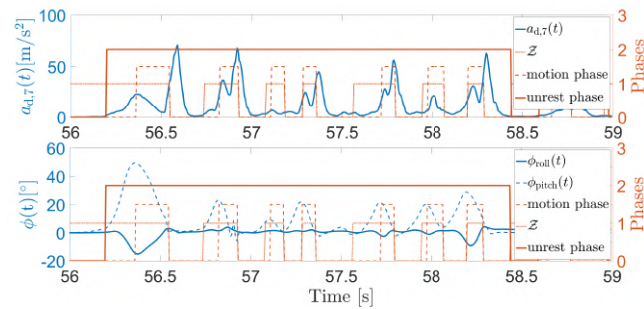


Fig. 3. Example of a series of motion phases with no rest phases in between. The filtered acceleration norm $a_{d,7}(t)$, pitch $\phi_{\text{pitch}}(t)$ and roll angle $\phi_{\text{roll}}(t)$ and gait phases are displayed.

2.2 Real-Time Detection of FoG: GaitScore Ω

In this section, we introduce a new approach for gait evaluation and detection of FoG episodes, called the GaitScore $\Omega \in (0, 1]$. The calculation of the GaitScore exploits the profile of pitch angle during the motion phase to extract the minimum and maximum values in the pitch angle:

$$\Omega = \left| \frac{\phi_{\text{pitch},\min}}{\gamma_{\min}} \right| \cdot \left| \frac{\phi_{\text{pitch},\max}}{\gamma_{\max}} \right| \cdot \lambda \quad (6)$$

$\gamma_{\min}, \gamma_{\max} \in \mathbb{R}$ are reference values, on which the gait is evaluated. They are calculated as

$$\gamma_{\min} = \begin{cases} \zeta_{\min} & \zeta_{\min} < \phi_{\text{pitch},\min} \\ \phi_{\text{pitch},\min} & \text{otherwise} \end{cases} \quad (7)$$

$$\gamma_{\max} = \begin{cases} \zeta_{\max} & \zeta_{\max} > \phi_{\text{pitch},\max} \\ \phi_{\text{pitch},\max} & \text{otherwise} \end{cases} \quad (8)$$

The adjustable parameters $\zeta_{\max}, \zeta_{\min} \in \mathbb{R}$ define minimum thresholds for differentiating between a pathological and healthy step. A GaitScore of one indicates a healthy gait cycle and a GaitScore close to zero a pathological gait (cf. Fig. 4). The GaitScore is also a measure of shuffling. Shuffling gait is characterized by the feet remaining in contact with the ground while moving forward. Thus, the pitch angles do not become negative or at least remain close to zero. This effect is captured by the minimum pitch angle in (6).

The parameter $\lambda \in \mathbb{R}$ describes another weight for the evaluation of the last gait cycle.

$$\lambda = \begin{cases} 1 & \text{for } \text{sgn}(\phi_{\text{pitch},\max}) = -\text{sgn}(\phi_{\text{pitch},\min}) \\ \frac{|\phi_{\text{pitch},\max} - \phi_{\text{pitch},\min}|}{c(|\phi_{\text{pitch},\max}| + |\phi_{\text{pitch},\min}|)} & \text{otherwise} \end{cases} \quad (9)$$

If $\phi_{\text{pitch},\max} > 0$ and $\phi_{\text{pitch},\min} < 0$, then the term has no influence on the GaitScore Ω . If both extreme values have the same sign ($\text{sgn}(\phi_{\text{pitch},\min}) = \text{sgn}(\phi_{\text{pitch},\max})$), then λ becomes < 1 . The term weighs the distance between the two extreme values. The parameter c is a tuning weight used for scaling λ .

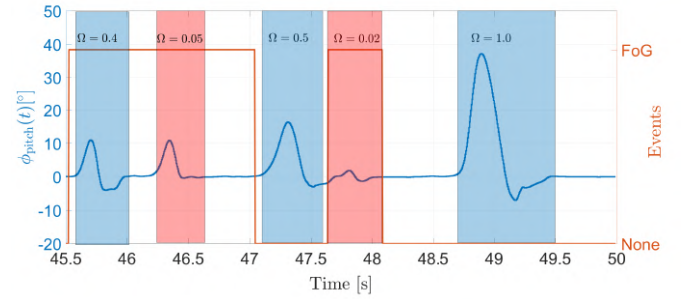


Fig. 4. Example of pitch angle, FoG episodes labelled by a clinical expert (red line) and detected motion phases with the corresponding GaitScore Ω . A motion phase with FoG is detected, when the GaitScore fulfills $\Omega < 0.4$. Blue and red areas indicate motion phases without and with FoG, respectively.

2.3 Dataset

The dataset used for testing the developed algorithm is recorded in a clinical study that is part of the ongoing project Mobil4Park and is being conducted by the Charité Universitätsmedizin Berlin. For the study, idiopathic Parkinson patients who show prominent gait disorders but are able to walk are recruited. For the evaluation of the proposed approach, a preliminary dataset consisting of four patients is used. Large variabilities in the motoric abilities are observed among the patients. The patients are tested mainly in the morning. The test consists of two walking tests. The first test consists of normal walking (distance of 10m length) in a straight line along a hallway, including a 180° turn. This test is repeated three times, and in the last of three trials of the normal walking test patients are asked to perform an additional cognitive task to increase the difficulty of the test: Counting backwards from 100 in steps of seven. The results of the cognitive task are not recorded and evaluated. The second test is a freezing assessment course proposed by Ziegler et al. (2010) to provoke and score FoG. The task consists of standing up from sitting position, turning twice by 360° in each direction within a marked area (40x40 cm), leaving and reentering the room through a narrow door frame and sitting down again. This test is repeated two times. During all tests, the kinematic data of both mid-feet are recorded using IMUs. Only the sensor data of the most affected leg are evaluated in the article.

In addition, the testing sessions are recorded using two cameras. The trials are conducted by two examiners. The FoG episodes are evaluated by two clinical experts based

Table 1. Parameter values used in the gait phase detection algorithm.

Parameter	Value	Parameter	Value
a_{rest}	0.5 m/s ²	α	1.2
w_{rest}	0.11 rad s ⁻¹	β	0.6
Δ	0.25 s	κ	0.8
n_r	10	p_1	0.75 °/s
ϕ_p	1 °	p_2	1.5 m/s ²
ϕ_r	5 °	ϕ_{thres}	15 °
a_s	2 m/s ²	t_{mot}	0.075 s
t_x	0.1 s		

Table 2. Parameter values used in the gait phase detection algorithm.

Parameter	Value
ζ_{min}	-5 °
ζ_{max}	20 °
Threshold for Ω	0.4
c	0.75
Threshold for $FOGC_n$	0.08

on the video data. Start, end and type of the FoG episodes are noted. The experts also count all motion phases for both feet. Lifting the foot and placing it back on the ground without any horizontal translation or rotation of the foot is also counted as motion phase. Such motion occurs typically during the FoG manifestation (shank trembling).

3. RESULTS

In this section, the results of gait phase and FoG detection algorithms are presented. The GPD algorithm is applied to the data set described above. All fixed parameters of the phase detection algorithm are given in Table 1. Comparing the number of IMU-detected motion phases and the number of motion phases counted by the expert, we find that 10% less steps have been detected by the IMU-based algorithm than counted by the expert who inspected the video.

The GaitScore approach was evaluated on data from four patients, including only the two trials of the freezing assessment course per patient (no FoG was observed in the 10m normal walking test). Sensitivity and specificity were used as performance parameters for the evaluation of the approach. The manual FoG annotations (time periods) of the expert are used as ground truth: The evaluation is performed for every detected motion phase. If the beginning of a motion phase lies in an expert-annotated FoG period, then the motion phase is labelled as FoG, otherwise the motion phase is labelled as non-FoG. Sensitivity describes the ratio of correctly detected true FoG motion phases (true positive) to the total number of true FoG motion phases. Specificity defines the ratio of correctly detected non-FoG motion phases (false positive) to the total number of true non-FoG motion phases.

The parameters for the FoG detection algorithm are displayed in the Table 2. A GaitScore threshold of 0.4 was chosen to distinguish between FoG and non-FoG motion phases. A GaitScore Ω below the threshold indicates a FoG motion phase. Table 3 shows the evaluation results. Average sensitivity of 97% and specificity of 84% were achieved using the GaitScore approach. The results of

Table 3. Results of the GaitScore approach and FOGC as comparison.

Patient	Trial	GaitScore Ω		$FOGC_n$	
		Sens.	Spec.	Sens.	Spec.
P1	T1	1.00	0.91	1.00	0.82
	T2	1.00	1.00	1.00	0.82
P2	T1	0.96	0.89	1.00	0.85
	T2	1.00	0.90	1.00	0.71
P3	T1	0.94	0.54	1.00	0.42
	T2	0.87	0.85	1.00	0.74
P4	T1	1.00	0.96	1.00	0.67
	T2	1.00	0.90	1.00	0.63
	Mean	0.97	0.87	1.00	0.71
	Std	0.05	0.14	0.00	0.14

the method proposed by Azevedo Coste et al. (2014) are also shown in the Table 3 and used for comparison. The parameters and the threshold ($FOGC_n > 0.008$) are taken from (Azevedo Coste et al., 2014). This method achieved an average sensitivity of 100% and an average specificity of 71%.

4. DISCUSSION

The evaluation of the GPD is limited as no reference measurement system was available. The true sensitivity of the algorithm might be lower than 90%. A first analysis of the GPD results discloses that most failures were associated with turning movements. The obtained results for the FoG detection still have to be interpreted with caution as non-detected/false-detected motion phases affect the FoG detection. The real sensitivity and specificity could be lower. This applies to both investigated approaches (GaitScore and $FOGC_n$). Both methods, GaitScore and $FOGC_n$, achieved a high sensitivity. The specificity of the $FOGC_n$ method is lower than the specificity of the GaitScore approach. Despite this, it will be incorrect to assume the superiority of the GaitScore method, because by individual tuning of the detection thresholds of the $FOGC_n$ approach a better specificity could be achieved. The latency of the FoG detection is determined by the duration of the motion phases but should in general be much shorter than the latency of 4.5 seconds reported in (Bächlin et al., 2010). Another limitation of the present study is the limited number of patients and experiments.

5. CONCLUSION

In this article, new IMU-based approaches for the detection of Parkinsonian gait phases and FoG were introduced. In contrast to the majority of existing GPD algorithms, we detect rest and motion phases of the foot instead of stance and swing phases of the leg. This approach seems useful in the presence of phenomena like festination and trembling, but it also renders the comparison of our algorithm with other IMU-based real-time GPD algorithms difficult. A fixed parameter set worked well for all patients in this study. The GPD distinguishes rest and motion phases. The latter are classified into FoG and non-FoG based on a novel score that has been derived from the relative change of the foot pitch angle with respect to the previous rest phase. The use of this GaitScore yielded a similar sensitivity and better specificity than an existing criterion based on step

length and cadence (Azevedo Coste et al., 2014). This confirms our hypothesis that the pitch angle provides valuable information for the detection of FoG. The methods introduced by (Moore et al., 2008) and (Azevedo Coste et al., 2014) give valuable information about the gait parameters in Parkinson's patients. A combination of these methods with our approach could further improve FoG detection, but might require an additional IMU at the shank.

Future work will therefore involve larger data sets also containing additional data from reference GPD systems (e.g. insole system for pressure measurement) for a better validation of our algorithms. In addition, we plan to employ the developed methods for on-demand cueing with the aim to reduce FoG episodes with festination, shank trembling and shuffling and to prevent/unfreeze FoG episodes with akinesia.

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