Freezing of gait detection in Parkinson's disease via multimodal analysis of EEG and accelerometer signals

Ying Wang, Floris Beuving, Jorik Nonnekes, Mike X Cohen, Xi Long, Ronald M. Aarts and Richard van Wezel

Abstract— **Parkinson's disease (PD) patients with freezing of gait (FOG) can suddenly lose their forward moving ability leading to unexpected falls. To overcome FOG and avoid the falls, a real-time accurate FOG detection or prediction system is desirable to trigger on-demand cues. In this study, we designed and implemented an in-place movement experiment for PD patients to provoke FOG and meanwhile acquired multimodal physiological signals, such as electroencephalography (EEG) and accelerometer signals. A multimodal model using brain activity from EEG and motion data from accelerometers was developed to improve FOG detection performance. In the detection of over 700 FOG episodes observed in the experiments, the multimodal model achieved 0.211 measured by Matthews Correlation Coefficient (MCC) compared with the single-modal models (0.127 or 0.139).**

Clinical Relevance— **This is the first study to use multimodal: EEG and accelerometer signal analysis in FOG detection, and an improvement was achieved.**

I. Introduction

Freezing of gait (FOG) is a clinical symptom mostly observed in the advanced stages of Parkinson's disease (PD) patients. FOG is described as "the feeling that the feet are glued to the floor" [1]. The sudden loss of forward moving ability increases the fall risks, and the unexpected falls may cause serious injury such as a bone fracture or a head injury [2]. External rhythmic cues, such as visual cues (seeing multiple lines), and auditory cues (hearing rhythmic beeps), have been found effective in overcoming FOG [3]. However, the continuous presence of the cues may reduce effectiveness and disturb normal social activity [4]. A real-time FOG detection or prediction system is therefore necessary in order to know when FOG occurs and to trigger the on-demand cues [4].

Models for FOG detection and prediction have been developed. Many studies used three-dimensional (3D) gyroscopes and/or 3D accelerometers (ACC) to describe body motion and detect clinical characteristics of PD patients such as trembling. Motion sensors are typically placed on the lower body, and motion features are calculated. The most commonly used feature is the freeze index (FI), which is defined as a power spectrum ratio between the FOG frequency band (3-8 Hz) and the locomotion band (0.5-3 Hz) [5], [6]. With the use of FI, a study achieved a sensitivity of 73% and a specificity of 82% in online detecting FOG onsets using a 0.5-second signal segmented sliding window [6]. However, variable performances of models using motion features exist because of highly heterogeneous clinical symptoms in PD patients.

Given that PD is a neurodegenerative disease, a group of researchers investigated electroencephalography (EEG) signals reflecting brain activity to detect and predict FOG [7], [8]. They used the spatial, spectral, and temporal features of the EEG signals in predicting the transition from normal walking to FOG. Their best performance was 87% sensitivity and 53% specificity [8]. Unfortunately, their FOG detection and prediction model was trained and tested on manually selected data: 400 seconds were extracted from individual groups (normal walking, transition and FOG). Because FOG is rarely observed compared to normal movement, the imbalance-class problem in real-time detecting and predicting FOG has not been solved by their research.

The accuracy and generalizability of real-time FOG detection or prediction systems still needs to be improved. Previous studies analyzed physiological signals from the individual modes: motion features of motion sensors on the body or brain activity measured by EEG. By merging the information from different modes, multimodal signal analysis can enhance the mode communication and improve model performance. For example, the performance of heart beat detection was improved via multimodal signal analysis merging the data from electrocardiogram (ECG), pulmonary arterial pressure, central venous pressure, etc. [9]. However, no previous study has investigated multimodal signal processing for FOG detection and prediction.

This study applied an experiment to acquire a FOG dataset and explored FOG detection via combining the information of motion sensors and brain activity. The objective of the study is to investigate whether using multimodal signal analysis can improve the performance of FOG detection.

II. Method

A. Study design

This is an explorative study to investigate FOG detection via multimodal signal analysis. This study included two phases: acquiring multimodal physiological and clinical data via experiments and developing a FOG detection system. In the data acquirement phase, we applied an in-place-movement experiment for PD patients to provoke FOG, and acquired multimodal physiological signals such as EEG and ACC

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signals during the experiment. In the data analysis phase, we preprocessed the EEG and ACC signals, extracted and merged their features for the FOG detection.

B. Experimental design

The research protocol was reviewed and ethically approved by the Dutch committee on research involving human subjects (Arnhem-Nijmegen region). Seventeen subjects with idiopathic PD and experiencing daily FOG attended the experiment. All subjects were examined at an off-medication state before the experiments, which indicates $\geqslant 12$ hours after the last dose of dopaminergic medication. Subjects that were not able to walk independently were excluded. Each session in the experiment included three conditions: stepping in place, half turning at a self-selected speed, and half turning at a rapid speed given that stepping in place and turning, especially rapid turning, are effective to provoke FOG [10]–[13]. The subjects performed each condition for two minutes, and each session lasted about six minutes. The subjects were asked to finish maximally five sessions. Two independent raters offline annotated FOG and unexpected movements, such as sudden stops caused by other reasons than FOG, based on videos taped during the experiments. Interrater agreements were measured by percent agreement and Cohen's kappa.

The multimodal signals were simultaneously recorded. Multimodal sensors were applied on the subject body as shown in Figure 1. We used a sixty-channel EEG cap (Figure 2) to acquire brain activity signals, four-channel electrooculography (EOG) to collect eye movement signals, three-lead electrocardiogram (ECG) to measure heartbeat, two pairs of bipolar electromyography (EMG) sensors on the forearms and two ACCs above the metacarpophalangeal joints to collect the muscle activity and the movement of the upper body and investigate possible co-occurring symptoms such as tremors, two ACCs above the knees and the ankles to acquire lower body movements, and two pairs of footswitches on the foot palm to collect foot contact patterns.

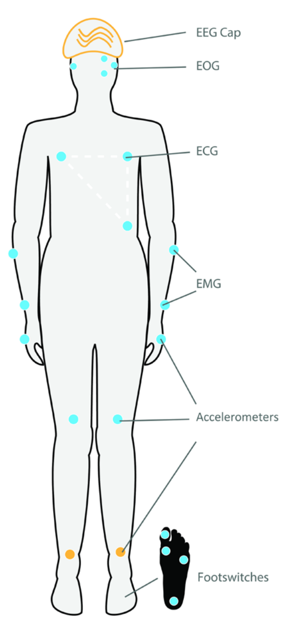

Figure 1 Multimodal sensor placement. The color marks indicate sensors. Only EEG and accelerometers above ankles (marked in orange) were analyzed in this study.

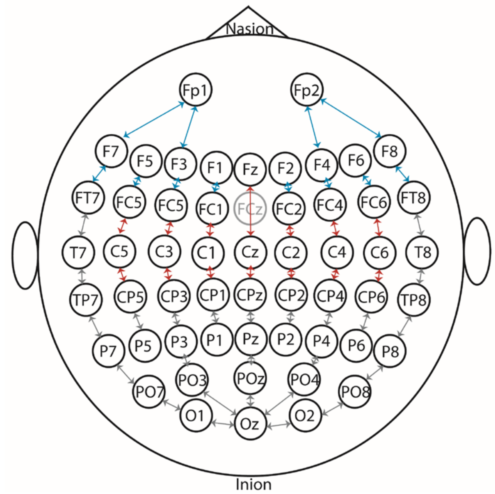

Figure 2 EEG electrode locations of 10-10 system in the study. A longitude montage was marked by the arrows: blue arrows indicate the EEG channels in frontal region and red arrows indicate the channels in central region.

The subjects completed several questionnaires to measure their clinical characteristics. The New Freezing of Gait Questionnaire (NFOGQ) was used as a subjective measure of freezing of gait severity [14]. The Movement Disorders Society - Unified Parkinson's Disease Rating Scale (UPDRS part III) measured the severity of motor symptoms [15]. The Hoehn and Yahr stage, a widely used indicator of Parkinsonian disability and impairment, was additionally rated in UPDRS part III [16], [17]. The mini mental state examination (MMSE) assessed cognitive functioning [18]. The frontal assessment battery (FAB) assessed frontal cognitive function [19].

C. Preprocessing

We presented the analysis of the EEG signals and the lower leg motion signals for FOG detection and not of the other sensors in this paper. The signals were segmented into 50% overlapped 2.56-second epochs for real-time FOG detection. The epochs whose over 50% were annotated as FOG were allocated to the FOG class, the other epochs were in the normal movement (Non-FOG class). The signals were bandpass filtered between 0.5 Hz and 100 Hz and stop-pass filtered around 50 Hz to reduce the effect of direct current offsets, electrical noise and high-frequency muscle activities. Furthermore, the filtered EEG signals were re-referenced according to a longitude montage (Figure 2), and the value differences between each pair (channel) in the montage were calculated.

D. Multimodal features

Commonly used features: FI and the power spectrum of individual EEG channel signals were extracted from the signals of the lower leg ACC and EEG channels, separately. FI was extracted to quantify FOG severity, and its power spectrum ratio was calculated by a wavelet transformation with a Morlet wavelet. The average values of the ratio within each epoch was considered as the motion features. For brain activity features, we calculated the mean of the power spectrum within theta wave bands (4-7 Hz) of each channel in the central and frontal brain areas as the brain activity features given that a previous study found a significant increase of theta wave band power in the "Fz-Cz" channel [7].

To investigate whether multimodal signal analysis can improve the performance of FOG detection, we built three models: a multimodal model with both the motion and brain activity features, and two single-modal models where the motion and the brain activity features were separately included.

E. Classification and validation

In the multimodal and single-modal models, the epochs were classified as FOG or Non-FOG using a RUSBoost classifier, which is broadly used in solving an imbalance-class problem [20]. The classifiers were trained and tested within subjects via a five-fold cross validation. The performance of each model was measured by sensitivity, specificity, precision and Matthews Correlation Coefficient (MCC), and the average performance of the five-fold data fragments were reported in this study. We denoted terms: true positive events, true negative events, false positive events, and false positive events by TP, TN, FP, and FN, individually. The sensitivity ($\frac{TP}{TP+FN}$) and the specificity ($\frac{TN}{TN+FP}$) evaluate models in positive (FOG) and negative (Non-FOG) classes, respectively. The precision ($\frac{TP}{TP+FP}$) considers both the TP and FP instances. MCC is a measure calculating the correlation between true values (epochs annotated as FOG or Non-FOG) and detected values (epochs classified as FOG or Non-FOG). The MCC is expressed by the formula: $\frac{TP\times TN-FP\times FN}{\sqrt{(TP+FP)(TP+FN)(TN+FP)(TN+FN)}}$ and ranged from '-1' indicating a strong negative correlation to '1' indicating a strong positive correlation. The value '0' of MCC means no correlation between the true and detected values. We used the MCC value as a performance comparison measure between the multimodal model and the single-modal model.

III. Results

A. Dataset

In total, fifteen subjects were included. Two of the seventeen subjects were excluded because they were barely able to walk independently or keep balance unassisted. The average age of the subjects was 70 years with a standard deviation (SD) of 11.5 years. The average PD disease duration was 10 years with a SD of 4.7 years. The scores of the questionnaires were: 19.1 ± 4.4 for NFOGQ, 35.8 ± 8.6 for UPDRS part III, 2.3 ± 0.6 for Hoehn and Yahr stage, 28.5 ± 1.7 for MMSE, and 16.9 ± 1.5 for FAB.

In total, 711 FOG events were agreed by the raters in around 7-hour long experiment recordings. 49% of FOG events were observed in the rapid turning condition, 29% of FOG were in normal turning, and 22% of FOG were in stepping in place. The duration of the FOG episodes was relatively variable from around 1 second to 2 minutes. The average duration of FOG was 7.3 seconds with a standard deviation of 13.97 seconds. The percent-agreement between the two raters was ca. 92%, and the Cohen's kappa value was 0.78, indicating a substantial interrater agreement according to the interpretation by Landis and Koch [21].

B. FOG detection performance

The median MCC of the multimodal model of subjects was 0.211 higher than the single-modal model using the motion features (0.139) and the brain activity features (0.127). The

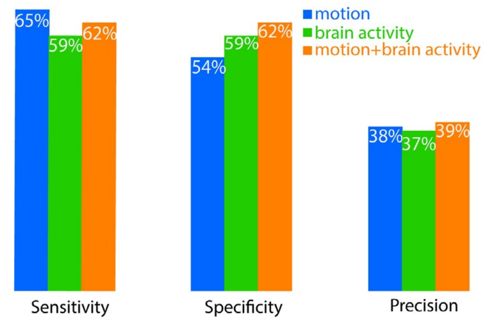

Figure 3 Performances of the models using the motion features and the brain activity features.

median performances: sensitivity, specificity and precision are shown in Figure 3. The multimodal signal model performed better than the other two in aspects of specificity and precision, and the sensitivity of the model using only motion features was higher than the multimodal model.

IV. Discussion

We performed an experiment with PD patients to acquire multimodal data. The motion data measured by the two ACCs placed above the ankles and the brain activity data measured by EEG electrodes in the central and frontal brain areas were analyzed for the FOG detection. In this paper, we presented the preliminary results.

Via the in-place movement experiment, over 700 FOG episodes were evoked from 15 subjects, and most of them were provoked by the turning conditions, especially the rapid turning condition (49%). These findings are consistent with earlier suggested effectiveness of provoking FOG [12], [22]–[24]. The duration of the FOG episodes in our dataset was variable (7.3 ±13.97 seconds). This variety could be explained by the heterogeneity of the subjects in age, disease years, the severity of FOG and general motor symptoms.

The multimodal model performed better than the other two single-modal models measured by the scalar metric MCC. This finding indicates that the multimodal model could improve the performance of FOG detection by merging information originated from the frontal and central brain areas and the lower body of PD patients. However, the MCC values were generally small in all the multimodal (MCC = 0.211) and single-modal modes (MCC =0.127 or 0.139). These MCC values indicate that the correlations between the true FOG instances and the model detected FOG instances are not strong. In future work, we will additionally use precision-recall curves (PR curves) and a statistical metric such as Bayesian information criterion (BIC) in comparing models.

For the single-modal models, the model using the motion data showed a sensitivity of 65% and a specificity of 54% which are lower than the previous results [6]. One possible explanation could be that we detected FOG in epochs rather than events and used a different duration window to segment the signals. Besides, the different subject demography and the variable FOG duration, distribution and provoking conditions could also lead to the differences. In our future work, FOG should be detected and predicted in events and a proper duration window for the real-time FOG detection should be investigated to improve the single-model performance.

However, for the brain activity feature, the performance of our model cannot be compared with the results of prior research [8] because it avoided the practical imbalance-class problem. In following studies, the changes of brain activity in other areas (such as parietal and occipital lobes) besides the frontal and central areas should be further investigated for FOG detection.

For the multimodal model, the performance was probably limited by the performance of the single-modal models. Except for improving the single-modal performances, other modalities such as eye movements, heart rate activity, and foot patterns could be considered in future multimodal model approaches to enhance FOG detection performance. Furthermore, the selection of multiple modes and sensors could be based on investigating the potential FOG mechanisms to ensure the model generalizability. Our future work will explore the changes of the multimodal signals around FOG and investigate their mechanisms.

V. Conclusion

A FOG detection system using multimodal signal analysis was developed in this study. Over 700 FOG were provoked during the in-placement movement experiment, and the multimodal signals, EEG, EOG, ECG, EMG, and motion data, were simultaneously collected. In this paper, we presented the preliminary results of FOG detection using a multimodal model (combing the motion and brain activity features). We found that the multimodal model performed better than the single-modal models, but the model still needs improvements. In future work, we will focus on selecting modalities based on the investigation of FOG mechanisms and merging more modal signals into the model, and improving the single-modal model performances.

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