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Communication

Predicting the Onset of Freezing of Gait Using EEG Dynamics

Alka Rachel John [1,*], Zehong Cao [2], Hsiang-Ting Chen [3], Kaylena Ehgoetz Martens [4], Matthew Georgiades [5], Moran Gilat [6], Hung T. Nguyen [7], Simon J. G. Lewis [5] and Chin-Teng Lin [1]

1 Australian Artificial Intelligence Institute, Faculty of Engineering and Information Technology, University of Technology Sydney, Ultimo, Sydney 2007, Australia
2 STEM, Mawson Lakes Campus, University of South Australia, Adelaide 5001, Australia
3 School of Computer Science, University of Adelaide, Adelaide 5005, Australia
4 Department of Kinesiology, University of Waterloo, Waterloo, ON N2L 3G1, Canada
5 Parkinson's Disease Research Clinic, Brain and Mind Centre, University of Sydney, Sydney 2006, Australia
6 Department of Rehabilitation Sciences, KU Leuven, 3000 Leuven, Belgium
7 Faculty of Science, Engineering and Technology, Swinburne University of Technology, Hawthorn 3122, Australia
* Correspondence: alkarachel.john@student.uts.edu.au

Abstract: Freezing of gait (FOG) severely incapacitates the mobility of patients with advanced Parkinson's disease (PD). An accurate prediction of the onset of FOG could improve the quality of life for PD patients. However, it is imperative to distinguish the possibility of the onset of FOG from that of voluntary stopping. Our previous work demonstrated the neurological differences between the transition to FOG and voluntary stopping using electroencephalogram (EEG) signals. We employed a timed up-and-go (TUG) task to elicit FOG in PD patients. Some of these TUG tasks had an additional voluntary stopping component, where participants stopped walking based on verbal instruction to "stop". The performance of the convolutional neural network (CNN) in identifying the transition to FOG from normal walking and the transition to voluntary stopping was explored. To the best of our knowledge, this work is the first study to propose a deep learning method to distinguish the transition to FOG from the transition to voluntary stop in PD patients. The models, trained on the EEG data from 17 PD patients who manifested FOG episodes, considering a short two-second transition window for FOG occurrence or voluntary stopping, achieved close to 75% classification accuracy in distinguishing transition to FOG from the transition to voluntary stopping or normal walking. Our results represent an important step toward advanced EEG-based cueing systems for smart FOG intervention, excluding the potential confounding of voluntary stopping.

Keywords: freezing of gait; Parkinson's disease; voluntary stopping; convolutional neural network; EEGNet; Shallow ConvNet; Deep ConvNet

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1. Introduction

Freezing of gait (FOG) is a gait impairment resulting from neurodegeneration in advanced Parkinson's disease (PD) patients. Nieuwboer and Giladi [1] defined FOG as the "inability to deal with concurrent cognitive, limbic and motor inputs, causing an interruption of locomotion". This episodic gait difficulty causes the patients to suddenly experience the feeling that their feet are "stuck to the ground" [2] while walking or initiating gait. This increases the risk of falling, negatively affecting the patient's quality of life.

FOG can be triggered by simple activities such as gait initiation, walking through a doorway, encountering obstacles in the pathway, or even performing a dual-task while walking [3,4]. Therefore, accurate and timely detection of FOG can significantly enhance the quality of life for PD patients. An automatic prediction of FOG can provide neurologists with relevant indicators about the condition and its evolution [5]. Furthermore, freezing episodes can be mitigated or prevented with external intervention, such as visual or auditory cues, activated by predicting the onset of FOG.

FOG detection is still a widely researched topic, with attempts made by several combinations of devices and algorithms. The first automatic detection of FOG was proposed by Moore et al. [6] using frequency-based features from accelerometer signals. This work was extended to improve the detection accuracy and developed as a FOG monitoring system with smartphones and wearable accelerometers [7]. Accelerometers [8,9], gyroscopes [8] and inertial data [10,11] have been employed for automatic FOG detection [9].

Several researchers attempted the early detection of FOG as it benefits intervention strategies. Handojoseno et al. [12] detected the onset of FOG based on EEG wavelet energy and entropy features. The onset of FOG was also detected by a sensor placed on the lower limb of the patient [13]. Electrocardiogram and skin conductance were used to predict the onset of FOG [14].

An efficient FOG detection system should not only be able to predict the onset of FOG, but it should also be able to distinguish involuntary stopping from the transition to voluntary stopping. The potential of brain dynamics in discerning the onset of freezing in PD patients has already been established [12]. However, earlier researchers relied on a 5 s window to discern the transition to freezing from normal walking [15,16].

Recently, we discovered that EEG signatures for transition to FOG are distinct from the intention to stop [17]. We observed an increase in the delta, theta, and beta power at the central region during the transition to freezing compared to normal walking. The transition to voluntary stopping was observed to show increased EEG power at the frontal, central, parietal, and occipital regions compared to the transition to FOG. Accurate detection of the transition to FOG from potential confounding transitions to voluntary stopping and normal walking is still challenging because of the complexity of designing handcrafted features.

In order to determine the differences in brain activity during the transition to freezing and the transition to stopping, we employed the classical timed up-and-go (TUG) task [18] in our experiment. The TUG protocol involves the participants starting from a sitting position to standing before walking towards an identified point and then turning back there to return to the starting position. This sequence of steps followed in the TUG protocol elicits freezing episodes, particularly when performed in that order [19]. In order to incorporate the transition to stopping in our experiment, we included TUG trials with voluntary stop conditions. In the TUG trials with voluntary stop, the participants were verbally instructed to "stop". We contrasted the brain dynamics of the patients while walking normally, transitioning to freezing, transitioning to voluntary stopping, and during freezing episodes and voluntarily stopping. Discerning the brain dynamics during the transition to freezing from normal walking or the transition to voluntary stopping could pave the way towards improved therapeutics that accurately predict the possibility of freezing while excluding potentially confounding voluntary stopping instances.

Our aim is to perform automatic feature learning and distinguish between normal gait, transition to FOG, and transition to voluntary stopping. Deep learning (DL) methods are feature learning methods that are not constrained by the engineering ability of handcrafted features or the complexity of the data representation. ConvNets are a type of feed-forward deep neural network, which typically combines convolutional layers with traditional dense layers to reduce the number of weights composing the model. The proposed system eliminates the need to extract features and feature selection manually. We evaluated three classical convolutional neural network (CNN) models: EEGNet [20], Shallow ConvNet [21], and Deep ConvNet [21] to detect FOG.

2. Materials and Methods

2.1. Subjects

Seventeen patients from the Parkinson's Disease Research Clinic at the Brain and Mind Centre, University of Sydney, participated in this study. The University of Sydney Ethics Committee provided ethics approval for this experiment (HREC approval number: 2014/255). All participants for the study were chosen based on the score for the third item on the self-reported FOG questionnaire and assessment of a clinical specialist. The mean

age of the participants was 64 ± 7.25 years, and none had any depression or dementia, as assessed by neurologist Simon J. G. Lewis using the DSM-IV criteria. Furthermore, the participants had a Mini-Mental State Examination (MMSE) score ≥ 24 and fulfilled the UK Parkinson's Disease Society Brain Bank (UKPDSBB) criteria [15,17]. Furthermore, these participants had a varying severity and frequency of freezing and, when in their practically defined off period, having withdrawn PD medications overnight, had an MDS Unified Parkinson's Disease Rating Scale III stage of 40.10 ± 12.21 and a Hoehn and Yahr stage of 2.34 ± 0.73.

2.2. Experimental Design

The patients were in their off state, having had no medications for at least 12 h when they participated in this study. They performed the TUG task, starting with the participants seated. The participants were instructed to stand up and walk towards a target location in a large corridor. The target location was marked on the floor using a box with dimensions of 0.6 m × 0.6 m, positioned 6 m away from the starting position to allow for multiple FOG episodes. The participants were instructed to turn within the marked box. In the TUG tasks, the participants were asked to perform either a 180° or a 540° turn. Turning within a box elicits freezing episodes in PD patients. The researcher initially demonstrated the task and the direction to turn within the box, and the participants followed the researcher's example. The experiment was video recorded and reviewed by two clinical researchers to identify freezing episodes.

As described in [17], we considered two variants of the TUG task: the classical TUG task and the TUG task with a voluntary stopping element. As shown in Figure 1A, the classical TUG task was employed as it elicits freezing in PD patients [19]. We considered two seconds immediately preceding the freezing episode as the transition to freezing. The period of two seconds before this transition period was regarded as normal walking.

In the TUG tasks with the voluntary stopping element (Figure 1B), the researcher guided the participant in the voluntary stopping by providing verbal instructions such as "stop" and "walk". In these TUG trials, the target box was located 10 m away from the starting position. The box was located 10 m from the starting position in these TUG tasks so as to prevent participants from anticipating exactly when they might receive the instruction to stop walking. Furthermore, verbal instructions to stop walking were generally provided to the participants while they were walking back to the chair after turning inside the box. The participants were required to stop as soon as they heard the researcher say "stop", and they resumed walking when the researcher said "walk", usually in 5–10 s. We defined two seconds when the researcher said "stop" and the participants were preparing to stop walking as the transition to voluntary stop. We also considered two seconds before the "stop" instruction as normal walking. The participants were randomly asked to perform a standard TUG task or TUG task with voluntary stopping to avoid any habituation effects.

Even though we strived to have an equal number of normal walking, transition to FOG, and voluntary stopping, this was not accomplished. The well-being of the patients was given the top priority, and we stopped the experiment for any PD patients who expressed difficulty in continuing with the experiment. Hence, we could not collect an equal number of trials for normal walking, transitions to FOG, or voluntary stopping. Table 1 shows the number of normal walking trials, the number of transitions to FOG, and the transitions to voluntary stopping for each participant.

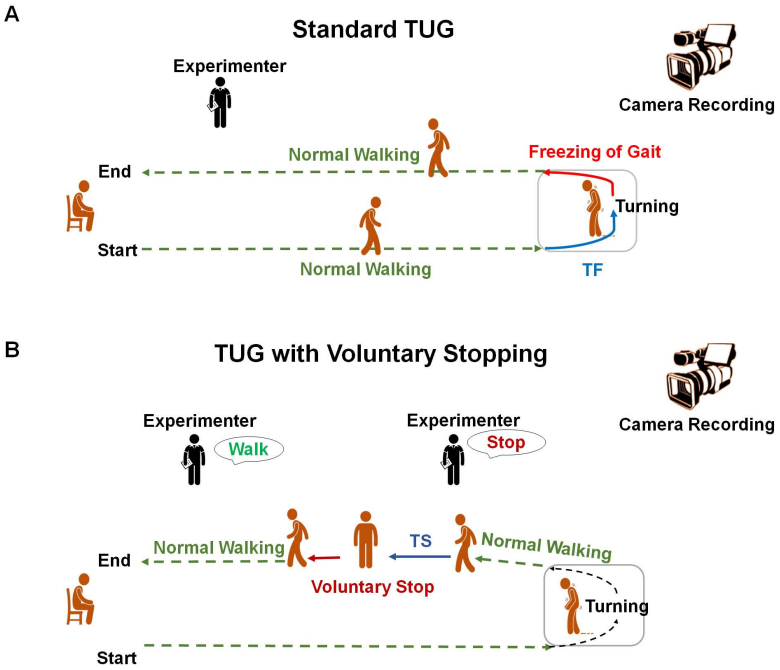

Figure 1. Experimental paradigm of (**A**) standard TUG task. (**B**) TUG task with verbal instructions to "stop" and "walk" to facilitate voluntary stopping. TF denotes the transition to FOG, and TS denotes the transition to voluntary stopping.

Table 1. Participant-based count of normal walking, transition to FOG, and transition to voluntary stopping.

Subject No.	No. of Normal Walking Epochs	No. of Transition to FOG Epochs	No. of Transition Voluntary Stopping Epochs
1	11	8	3
2	12	8	4
3	1	1	0
4	33	33	0
5	5	2	3
6	8	5	3
7	7	1	6
8	15	11	4
9	8	8	0
10	23	23	0
11	5	0	5
12	30	24	6
13	3	0	3
14	15	15	0
15	33	26	7
16	7	1	6
17	17	12	5

2.3. Equipment

The EEG data were collected from the participants using a 32-channel BioSemi Active-Two system (Biosemi Systems, Amsterdam, The Netherlands). The placement of the electrodes was per the International 10–20 system. The patient's skin was prepared by washing with 70% isopropyl alcohol, and data were recorded at a 500 Hz sampling rate. The clinical researchers used ELAN tagging software [22] to tag the precise time of each freezing episode, and the events' information was later imported to EEG manually.

2.4. EEG Processing

The EEGLAB toolbox [23] was used for processing EEG data, as shown in Figure 2. The raw EEG was band-pass filtered between 1 and 30-Hz to eliminate low- and high-frequency noises. The line noise was removed with the pop_cleanline function in EEGLAB. Further, channels with at least three seconds of flatlines were corrected with clean_flatlines functions, and all channels were cleaned with clean_channels. There were 3 ± 0.5 channels removed on average, and these channels were interpolated. Afterwards, normal walking, transition to FOG, and transition to voluntary stopping trials were extracted to provide input to the deep learning models.

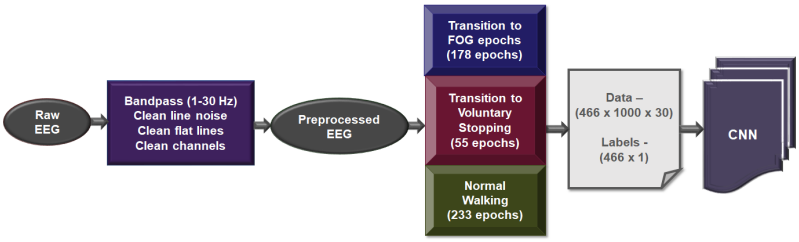

Figure 2. EEG preprocessing and feature extraction for DL models.

In this study, a total of 178 trials of transition to FOG episodes, 55 transitions to voluntary stopping, and 233 trials of normal walking were extracted from the continuous EEG data of 17 subjects. These transitions to FOG were extracted from both standard TUG and TUG tasks for voluntary stopping based on the occurrence of FOG episodes, and each trial was 2 seconds in length. These data were reformatted to a matrix with the shape number of trials $\times$ time points $\times$ number of channels format ($466 \times 1000 \times 30$) before providing it to the DL models.

We also performed two-class classifications with the transitions to FOG and the transition to voluntary stopping. This matrix was with the shape number of trials $\times$ time points $\times$ number of channels format ($233 \times 1000 \times 30$) before providing to the DL models.

We performed a grid search to select the optimal hyperparameters for the three CNN models: EEGNet, Shallow ConvNet, and Deep ConvNet. The data were shuffled and randomly divided into three separate sets, the training (60%), validation (20%), and testing sets (20%). The performances of these models were obtained by 5-fold cross-validation. We also performed leave-one-subject-out cross-validation to evaluate the performance of these models.

3. Results and Discussion

Classification Performance

For two-class classification, all models achieved acceptable performances with high sensitivity and specificity, as shown in Table 2. Leave-one-subject-out (LOSO) classification results for the transition to FOG vs. transition to voluntary stopping are shown in Table 3. The undesirable coh-kappa values might be due to the unbalanced classes. Further, all models achieve acceptable performance for three-class classification with high sensitivity and specificity, as shown in Table 4. LOSO classification results for the three-class problem are shown in Table 5.

Our models were trained with a relatively small dataset with an unbalanced number of trials in the three classes, which might have adversely affected the performance of these data-hungry models. Deep ConvNet performed better than EEGNet or Shallow ConvNet because of its greater depth, while EEGNet and Shallow ConvNet might have been more susceptible to noise from the raw EEG data, as they are compact and shallower, degrading the features and resulting in poorer performance.

In earlier works, the period of four seconds prior to freezing was considered as the transition to freezing [15]; however, we considered a shorter window for the transition to freezing [17]. This shorter transition period might have more clinical practicality as brain

dynamics dynamically change within a short period. Therefore, by employing a sliding window of two seconds, our results demonstrate that we might be able to identify the transition to freezing from normal walking or the transition to voluntary or intentional stopping. Further, we considered the raw EEG data with minimal data processing to allow for real-time prediction of the onset of FOG. However, employing sophisticated advancements in EEG analysis methods might further improve classification accuracies.

We employed CNN models to detect the transition to FOG or the onset of FOG from the potential confounding intention to stop and normal walking conditions. The distinct brain dynamics during the transitions to FOG and voluntary stopping episodes were exploited in a system design. These classification models are valuable in developing compensatory systems that preserve and advance alternate neural pathways to assist gait in PD patients. Therefore, with an accurate and reliable prediction of freezing, cueing strategies to redirect attention or prompt movement can help alleviate gait impairment in PD patients [24].

Further, the advances in wearable technology have made it possible to deliver a comfortable cueing system for PD patients [25,26]. However, despite the development of several FOG prediction models [14–16], accurately and reliably detecting the onset of freezing remains an open challenge. It is also crucial to avoid the confounding transitions to voluntarily stopping or normal walking to ensure a robust prediction of freezing onset.

Our findings demonstrated the potential of EEG data in distinguishing FOG onset from normal gait or initiation of voluntary stopping. Our results will pave the way toward therapeutic prediction and mitigation of freezing in PD patients. Further, these results aid and promote investigations of intentional stopping during gait, as a reliable prediction of intention could be valuable for motor rehabilitation.

Table 2. Five-fold classification performance for transition to FOG vs. transition to voluntary stopping.

Model	Accuracy	F1-Score	Coh-Kappa	Sensitivity	Specificity
EEGNet	88.09 ± 4.25%	80.09 ± 4.62%	68.30 ± 2.50%	94.42 ± 4.65%	96.21 ± 3.52%
Shallow ConvNet	89.9 ± 2.31%	89.21 ± 3.94%	70.11 ± 3.91%	96.49 ± 2.97%	94.36 ± 3.60%
Deep ConvNet	92.28 ± 2.70%	93.02 ± 2.03%	72.94 ± 2.27%	96.89 ± 2.04%	96.91 ± 2.09%

Table 3. LOSO classification performance for transition to FOG vs. transition to voluntary stopping.

Model	Accuracy	F1-Score	Coh-Kappa	Sensitivity	Specificity
EEGNet	87.28 ± 5.89%	87.61 ± 5.53%	69.19 ± 4.37%	84.89 ± 5.72%	84.16 ± 4.71%
Shallow ConvNet	87.92 ± 4.3%	82.16 ± 3.02%	71.14 ± 4.84%	86.23 ± 3.71%	85.55 ± 4.62%
Deep ConvNet	87.83 ± 5.35%	84.81 ± 5.86%	70.6 ± 5%	86.37 ± 3.31%	84.72 ± 2.49%

Table 4. Five-fold classification performance for transition to FOG vs. transition to voluntary stopping vs. normal walking.

Model	Accuracy	F1-Score	Coh-Kappa	Sensitivity	Specificity
EEGNet	71.92 ± 5.64%	69.49 ± 5.38%	52.57 ± 4.63%	87.8 ± 5.90%	84.02 ± 4.06%
Shallow ConvNet	73.68 ± 3.87%	73.53 ± 3.76%	57.14 ± 4.53%	89.28 ± 4.59%	86.2 ± 3.37%
Deep ConvNet	75.43 ± 1.48%	72.52 ± 1.44%	58.11 ± 1.64%	92.85 ± 1.70%	75.86 ± 1.75%

Table 5. LOSO Classification performance for transition to FOG vs. transition to voluntary stopping vs. normal walking.

Model	Accuracy	F1-Score	Coh-Kappa	Sensitivity	Specificity
EEGNet	70.85 ± 3.25%	70.79 ± 3.86%	52.54 ± 5.89%	83.83 ± 5.65%	82.80 ± 4.13%
Shallow ConvNet	73.45 ± 3.69%	72.84 ± 3.61%	54.43 ± 4.92%	88.91 ± 5.08%	86.34 ± 5.62%
Deep ConvNet	74.65 ± 4.19%	71.54 ± 4.7%	57.52 ± 3.42%	91.18 ± 5.04%	74.46 ± 4.79%

4. Conclusions

In this study, we investigated the application of CNN to an end-to-end classification of transitions to FOG, voluntary stopping, and normal walking. The model automatically learns the discriminative features for classifying normal walking, transitions to FOG, and voluntary stop. Furthermore, the convolutional neural network approach removed the need for feature extraction and selection. This research is the first of its kind, and the reported classification model could pave the way to detecting the onset of FOG precisely and effectively. As the transitions to FOG can be accurately distinguished from the transition to voluntary stopping with just a two-second window, this could enable appropriate interventions (e.g., cueing) to help the patient avoid freezing. Further, a larger dataset can improve the performance of the models, and future studies should investigate the real-time FOG detection performance. This work will expedite the development of future therapeutic interventions that can reliably predict freezing episodes in PD patients. Future interventions for FOG must diligently eliminate all false positives from the confounding voluntary stopping.

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Informed Consent Statement: Informed consent was obtained from all subjects involved in the study.

Data Availability Statement: The data will be made available upon reasonable request to the corresponding author.

Conflicts of Interest: The authors declare no conflict of interest.

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