Master Research Proposal Nr: .

Topic: Detection of Freezing of Gait Events in Parkinson's Disease Patients Using Foot-Worn IMUs

Freezing of gait (FoG) is a brief and involuntary interruption of gait, typically lasting only a few seconds. It affects people with Parkinson's disease (PD) and related disorders, occurs most often during turning, gait initiation, navigating tight spaces, or under stress or distraction, and can often be alleviated by focused attention or external cues [1]. FoG is episodic and unpredictable, making it greatly under-reported by patients, frequently missed in the clinic, and so far remains one of the most abrasive symptoms of PD as well as a major cause of falls [2].

Clinicians currently rely on patient diaries or questionnaires, but these subjective tools suffer from recall bias and low sensitivity to changes in FoG frequency or severity [3]. Continuous cues (auditory, visual, or proprioceptive) can reduce FoG. Yet, its effectiveness wanes with habituation, while personalized on-demand cues triggered by real-time FoG detection have proven to be more effective in both laboratory and daily settings [3]. Automated monitoring is therefore essential, but patients themselves often do not notice every freeze, and brief clinical examinations rarely capture these events [4].

Inertial measurements units (IMUs) provide a non-invasive, low-cost way to record gait continuously. Data mining and signal processing of time series from IMU reveals the presence and severity of Parkinsonian motor deficits [5]. ML approaches examine these sensor data, enabling the semi automated extraction of hidden patterns such as tapping, shuffling, and freezing [3].

Recent advances in detecting FoG episodes in PD have mainly taken advantage of ML and deep learning (DL) techniques. These include classical ML approaches like random forests and decision trees applied on engineered features, achieving substantial accuracy with multi-IMU setups in controlled environments [4]. More recent methods have shifted towards sophisticated DL architectures that capture both temporal and spatial patterns, such as CNN-GRU hybrids, transformers, and temporal CNNs, resulting in improved detection accuracy and precision, even with fewer IMUs or simplified sensor placements [3, 6, 7, 8]. Studies using hybrid approaches such as CNN-LSTM with frequency-domain inputs have demonstrated promising sensitivity and specificity [9].

While advancements in FoG detection using deep learning and wearable sensors show promise, significant limitations persist in current research. First, a critical limitation is that most existing FoG detection systems demonstrate poor generalization to real-world daily living conditions because studies primarily collect data in the OFF-medication state or fail to specify medication status [5, 4, 3, 10], which creates a fundamental mismatch with patient experiences. This limitation severely restricts the real world applicability of these detection systems, as patients in daily life are usually in their ON-medication state where FoG manifestations may differ significantly from OFF-state presentations [6]. While OFF-state data collection may artificially increase FoG episode frequency for algorithm development purposes [6], the resulting models fail to accurately detect FoG episodes under the medication conditions that patients actually experience in their daily lives, leading to unreliable performance when deployed in real-world settings [10].

Additionally, current FoG detection systems struggle to differentiate between actual freezing episodes and similar movement patterns during regular daily activities, particularly during turning, stopping, or transitional movements [6]. This challenge is especially pronounced in real-world settings where activities are more diverse and unpredictable than in laboratory environments [10]. Finally, sophisticated techniques like transfer learning and patient-specific fine-tuning, which could personalize generalized models and reduce computational complexity, are largely underexplored [7, 6].

In this thesis, we utilize our free-living dataset, which captures natural FoG episodes under normal medication schedules. This dataset enables the development of more practical and reliable detection methods capable of distinguishing true FoG events from similar movement patterns encountered in daily life. Additionally, if time permits, we aim to explore patient-specific fine-tuning to personalize the model and enhance its performance for individual patients.

The dataset used in this thesis consists of long-term monitoring (LTM) recordings captured with two foot-mounted IMUs manufactured by Portabiles HealthCare Technologies (PHCT). Each sensor contains a triaxial accelerometer and a gyroscope. The Data were collected at the Passauer Wolf Rehabilitation Center in Bad Gögging. Participants were asked to wear the sensors every day throughout their stay and to go about their normal, unscripted activities. To date, recordings from nine patients have been processed, with 471 detected freezing episodes, 282 of which have been manually annotated. All labelled episodes have also been categorised by duration. Data collection is still in progress, and the dataset will be expanded as new recordings become available.

This thesis aims to investigate the following objectives:

- Literature Review
  - Conduct a comprehensive review of existing literature and state-of-the-art methodologies related to the detection of FoG using wearable sensors, specifically IMUs.
  - Identify gaps in current research, particularly regarding data collection methods, feature engineering approaches, model architectures, and personalization strategies.
- Data Preparation
  - Assist with the labeling and relabeling of FoG, identifying and separating the high-reliability freezes from the low-reliability ones. According to the protocol, annotations made by clinicians have a higher reliability having been made closer to the event than those made by patients.
  - Explore the characteristics of the signal and identify trending features that appear before and during FoG based on the gait behavior explained in the literature. For this a labeling guideline should be created that explains the characteristics of the events and their representations based on the signal.
- Implementation
  - Create a representative train–test split, addressing the uneven distribution of labeled events across patients to ensure unbiased model training and evaluation. This is required because FoG events are considered rare compared to daily recordings.
  - Train ML models, such as Random Forests and Support Vector Machines, using the features derived from the literature and those identified in the previous step to establish a baseline for benchmarking. These models will be compared with the existing literature.
  - Implement DL models, testing CNN-LSTM networks or transformer-based models to compare them with the ML models.
  - Compare all models based on recall and specificity. In models using windowing methods, the temporal localization error should be measured.
  - Explore various architectural modifications and design refinements to improve the performance of the models based on the defined metrics.
  - If time allows, adapt the generalized models to individual patient data through personalized fine-tuning, aiming to optimize the F1 score and reduce inter-patient variability.
- Documentation and Writing

The thesis must contain a detailed description of all developed and used algorithms as well as a profound result evaluation and discussion. The implemented code has to be documented and provided. Extended research on literature, existing patents, and related work in the corresponding areas has to be performed.

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Literatur

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