Engineers Meet Clinicians: Augmented Parkinson's Disease Patients to Gather Information for Gait Rehabilitation

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ABSTRACT

Many people with Parkinson's disease suffer from freezing of gait, a debilitating temporary inability to pursue walking. Rehabilitation with wearable technology is promising. State of the art approaches face difficulties in providing the needed bio-feedback with a sufficient low-latency and high accuracy, as they rely solely on the crude analysis of movement patterns allowed by commercial motion sensors. Yet the medical literature hints at more sophisticated approaches. In this work we present our first step to address this with a rich multimodal approach combining physical and physiological sensors. We present the experimental recordings including 35 motion and 3 physiological sensors we conducted on 18 patients, collecting 23 hours of data. We provide best practices to ensure a robust data collection that considers real requirements for real world patients. To this end we show evidence from a user questionnaire that the system is low-invasive and that a multimodal view can leverage cross modal correlations for detection or even prediction of gait freeze episodes.

Author Keywords

Wearable system, Data collection, Parkinson's disease

ACM Classification Keywords

H.5.2 Information Interfaces and Presentation: Miscellaneous

1. INTRODUCTION

Freezing of gait (FoG) is an incapacitating problem in Parkinson's disease (PD) characterized by a motor block and the inability to continue or to start walking [12]. Fall incidences and social consequences are related to FoG, which is often resistant to pharmacological treatment [2].

Rhythmic auditory stimulation (RAS) was introduced as an assistive tool for FoG [5]. RAS consist in a rhythmic ticking sound produced upon detection of a FoG episode with motion sensors. Preliminary evidence showed benefits to pursue or regain stable gait [1]. However, the detection latency (tenth's of seconds at best [1, 7]) does not allow the suppression of the entire FoG episode. Our target is to investigate FoG data in more depth, and so to advance towards preemtive RAS and to avoid the freeze episode in its entirety.

Wearable FoG-detection assistants are based on unimodal approaches with hand selected motion characteristics only [1]. Consequently, public datasets on FoG [1] are limited to a single modality, i.e., acceleration, which proved to contain limited characteristics to *predict* FoGs. Furthermore most systems are developed on rather simplistic in-the-lab activities [10, 11], e.g., walking on a treadmill. That leads to potential lack of robustness in daily life, as often in-the-lab settings are not similar with the daily life ones. We argue that a multimodal view on the FoG will allow minimizing the FoG-detection and even to predict the FoG events.

Nutt et al. [12] assert that it is difficult to characterize FoG to allow preemptive measures, but provide an overview of clinical observations during and before FoG events. Other studies [9] indicate that several aspects such as situation or physiological aspects relate to gait freeze.

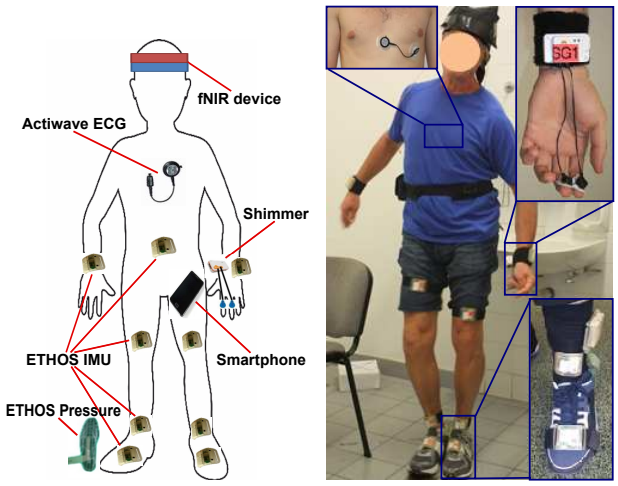

Figure 1. (a) The 5 sensor systems and on-body locations, (b) PD patient wearing the system.

We follow this directions and build a multimodal wearable system to capture FoGs in PD patients (Sec 2). We consider multiple characteristics found in clinical literature and we take a holistic view to describe the FoG phenomenon in best detail, using a multitude of observable evidence ranging from locomotion, over inertial movement to the physiological/mental state. We collect data from real patients that execute a wide span of natural activities (Sec 3) and show preliminary evidence that a multimodal approach may help to predict FoGs (Sec 4). To our knowledge, such a complete data set does not exist and will be a valuable asset for the activity recognition research as well as for medical engineering. Since experiments are conducted with real PD patients we pay special attention towards the robustness of the data acquisition. We minimize the impact of the wearable system on the patient, while probing for as much observation as possible (Sec 4.2). Finally, we conclude our work, provide recommendations for a data collection from real patients, and outline future work (Sec 5).

2. WEARABLE SENSING SYSTEM

From literature findings we know that FoG is not only expressed in motion patterns from on-body accelerometers, but also from in-sole pressure, ECG, EMG or EEG [10, 6, 9, 3]. Such modalities have been studied before. However, each study focuses on a single sensing modality. We want to identify further sensor modalities and investigate multimodal support that not only improve FoG detection, but allow prediction as well. In the following we will describe the sensor system and the data management enabling best robustness for the data collection.

2.1 Sensing Modalities

Following medical observations we acquire different types of data which allow us to study the clinical observations. We incorporate the following sensing modalities:

IMU Literature shows evidence that in straight walking, stride frequency increases and stride length decreases short before onset of FOG in contrast to voluntary stopping [12, 11]. Inertial sensing at both legs and possibly on other body locations, e.g. a sensing smart phone in the pocket, are used to capture these characteristics.

Foot pressure Similar to FOG detection based on accelerometers, frequency analysis has been used to detect FOG periods from foot pressure sensors [2, 6].

ECG Maidan et al. [9] measured heart rate, a marker of activation of the autonomic nervous system before, during, and after FOG periods. During FOG periods a significantly increased heart rate could be observed.

GSR Similar to heart rate, GSR could indicate psychological or physiological arousal.

fNIR fNIR uses near infra-red light to measure concentration of oxygenated and de-oxygenated hemoglobin. We seek to observe changes in the fNIR signal prior to FOG episodes.

We deployed 5 on-body sensor systems[1]. Each system comprises a subset of sensors including a total of 9 IMUs, 1 IMU with pressure sensor, 1 EDA sensor, 1 ECG sensor, 1 smartphone, and 1 fNIR sensor attached on 13 different body location (see Table 1 and Figure 1). We obtained a complex and heterogeneous setup, which requires special data managmenet care (see Sec 2.2). For the experimental study with real Parkinson' disease patients we need to reduce the system intrusiveness as much as possible. Based on trials with healthy subjects, we refined the system until we obtained satisfying feedback. To measure feedback of PD patients on the wearable system, we performed a user questionnaire.

2.2 Data management

Each of the 5 systems have different management software, and commercial systems such as Actiwave or fNIR have proprietary management software which hampered the development of a single synchronized data collection system. In order to prevent data loss and to save battery consumption, we stored data locally on each sensor and synchronized different sensor streams offline. The only exception was the fNIR system which transmited the data via Bluetooth, thus allowing real-time activity labeling. Next, we give details about the issues experienced during or after the data collection, and how we solve them.

[1]Sensor system - a set of similar nodes, that form a sensor network, and have the same software for data acquisition.
[2]www.shimmer-research.com
[3]www.camntech.com
[4]www.samsung.com/global/microsite/galaxys2
[5]www.artinis.com/product/portalite

Table 1. Sensor Systems

Sensor System	Sensing Type	Location
ETHOS IMU[4]	3-D accelerometer, 3-D gyroscope, 3-D magnetometer	wrist, lower back, thigh, ankle, foot
Shimmer[2]	3-D accelerometer, GSR	wrist
Actiwave[3]	3-D accelerometer, 1-D ECG	chest
Samsung Galaxy S2[4]	3-D accelerometer, 3-D gyroscope	pocket
ETHOS Pressure	3-D acceleration, 3-D gyroscope, 3-D magnetometer, pressure	foot
PortaLite[5]	fNIR	head

Synchronization. We synchronized the data from all the 5 sensor systems to allow accurate extraction of information regarding the PD gait anomalies. Four out of five sensor systems stored data locally (ETHOS, smartphone, Actiwave, Shimmer). Given different sampling rates, we used the acceleration signals to record synchronization patterns both at beginning and at the end of the recordings. To this end, the sensors were fixed on a single pad, and observable synchronization patterns were performed (e.g., change 3 times the acceleration from y-axis from 0 to 1g, followed by hitting the pad on a surface for 3 times). We used a stopwatch activated in parallel to the video recordings to annotate the start time of the fNIR system, for later synchronization between its data and the gait events.

Data loss. Local storage for 4 out of 5 sensor systems prevented data loss. However, for ETHOS, we experienced internal time-drift. Also, for fNIR device there was no loss since the sampling rate that was used is 5Hz leading to a slow transmission rate. In addition the receiving laptop was placed close to the sensor allowing good data reception.

3. SCENARIO DESCRIPTION

Based on clinical literature [13, 14], we designed a set of scenarios with different types of motor activities that patients were asked to perform. We chose activities shown to cause FoG above average (e.g., turnings, passing narrow corridors) and activities that reassemble standard movements experienced in daily life, e.g., in a home setting. Between the trial sessions, the protocol included resting periods, or sessions in which patients were asked to complete questionnaires. In the following, we describe each of the protocol session:

Ziegler [14] It is clinically designed for PD with FoG and includes two 360 degrees turns, one 180 degrees turn, and passing through a narrow passage. The Ziegler session was performed (a) *simple*, (b) *while carrying a glass of water*, and (c) *carrying a glass of water and counting given a formula*. The (b) and (c) sessions seek to observe if the FoG events are related to the cognitive load.

Figure eight Consisted in performing 5 times the figure eight shape in a 3-meter area. Figure eight was performed (a) *simple* and (b) by *counting given a formula*.

Straight line walking with turns The subject needed to complete 20 m of straight line walking, turn, and walk again on the opposite direction. The session was performed simple,

Table 2. Protocol Steps

Protocol session	Time (min)
Base	0.5
Ziegler (simple)	2
Ziegler (carrying a glass of water)	2
Ziegler (counting and carrying a glass)	2
Base	0.5
UPDRS Protocol	10
Figure 8 simple	2
Figure 8 with cognitive load	2
Base	0.5
FoG Questionnaire	5
Straight line walking	1.5
Debrief	3
Straight line walking & narrow corridor	1.5
Base	0.5
Sitting & Cognitive load	1
Circles + Base	3 + 0.5
Standing & Cognitive load	1
Hospital tour + Final Base	10 + 0.5

sometimes in addition with a cognitive load task, and by passing a narrow corridor during the straight line.

Circles The subject walked in circle, with random 180 and 360 degrees turnings, when asked by the clinicians.

Hospital tour A real-life session that included random walking through the hospital's crowded hall with involuntary stops, turns, changes of direction, using the elevator, and walking in narrow spaces.

Base sessions Between the sessions from above, subjects were asked to sit and relax for periods of 30-60s. Data from these sessions is used as a base for physiological data such as ECG or GSR, and to recalibrate IMUs that potentially displaced during the activities. Other types of baselines included sitting with cognitive load, standing with cognitive load, completing questionnaires and debriefing sessions.

3.1 Experimental Protocol

First the patient was examined by a clinician that decided whether the patient is capable of performing the protocol. Meanwhile, engineers prepared the sensor systems. Because of different data acquisition systems, the synchronization patterns were performed before placing the sensors on the patient. Next the sensors were attached to the patient, who was asked to perform the clinical protocol. Details about the complete and ordered protocol sessions, with their estimated duration, are given in Table 2. Not all the patients could perform the entire protocol. In between the protocol sessions or if required, patients were resting. After the patients performed the protocol, sensors were de-attached, and another set of synchronization patterns were performed.

3.2 Data annotation

Our target is to predict and detect the gait freeze episodes in Parkinson's disease. Accurate annotation is therefore critical to this goal. We also keep track of the high-level context (e.g., protocol session type) and the low-level context (e.g., type of movement: start walking, turning) to investigate correlations with freezing episodes. In total we labeled the data on three levels: *(1) high-level context*, *(2) low-level context*, and *(3) freezing of gait labels*, that are synchronized with the data streams from the sensors. For fine grained annotation we deployed two video systems to record the patient's activity during the protocol: (1) a mobile HDR camera, and (2) a fish-eye camera. After the recordings, two clinicians labeled offline the video samples. Most accuracy is required for FOG labels, which was performed on the level of a video frame (40ms). To link the labels to the data streams, we labeled also the sensor synchronization sessions.

4. RESULTS

The experiments took place in an hospital setting during a 3 weeks period. We recruited 18 Parkinson's disease patients with history in freezing of gait, with age between 49 and 89 years (average: 68.9 years, std: 10.2 years), with disease duration between 2 and 18 years (average: 8.8 years, std: 4.6 years). Three of the patients could not perform the entire protocol, due to the disease severity. Overall 23 hours of data was collected.

180 FoG episodes were labeled by 2 physiotherapists, with a duration between 0.12 sec and 98.88 sec (average: 9.06 sec, std: 15 sec). FoGs are not equally distributed among the patients: 7 did not experience any FoG, 4 had between 2 and 6 FoGs and the rest of 7 experienced more than 10 FoG. The average FoG durations, FoG characteristics and gait performances varied strongly across patients. This gives a hint that we need an adaptive and patient-dependent solution for the FoG-prediction/detection system. The duration of all FoG episodes summed 27.18 minutes (so 1.96% of the whole data) and 64% of them are between $[0, 5]$ sec, thus making difficult to spot the FoG events in a real-life setting.

4.1 Visual Data Inspection

Figure 2 shows an example of multimodal sensor data with 3 labeled FoG episodes.

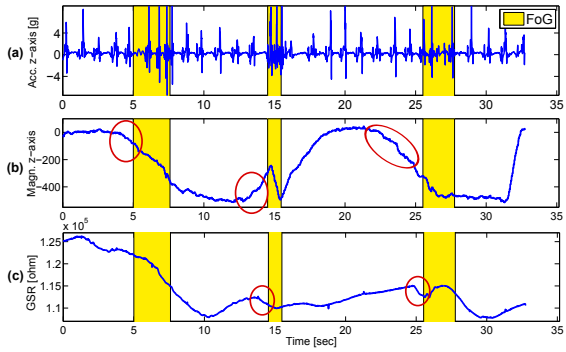

Figure 2. Multimodal data with FoG episodes: (a) Right ankle acceleration (b) Back magnetometer (c) Hand GSR

By visually inspecting the data we observe that the acceleration patterns during the first two FoG episodes are different from the rest of the gait signal. The onset of the second FoG episode can be detected from acceleration. The first FoG can be observed also from the acceleration, but it is hard to detect its onset. The third FoG is not visible in the acceleration signal. From the magnetometer signal at the back we observe that prior to each FoG episode a change in the orientation (red circles) – the patient was turning prior to the FoG events. Furthermore, if we analyze the GSR data, even if noisy, we observe that before the second and the third FoG, there is a decrease in skin resistance. The same pattern happens also prior to the first FoG, even if not that visible. Our hypothesis is that by augmenting the information from accelerometer with information from other sensing modalities such as magnetometer (e.g., turns) or physiological data such as GSR, we will be able to achieve a reduction of detection latency of the FoGs, or even to predict FoG.

4.2 User questionnaire

During the system design we emphasized on the system's wearability, as it was the key to collect all the complex data without affecting the patient's motor performances. Subsequently to an experimental protocol, patients were asked to complete a questionnaire concerning various subjects including the wearability of sensors.

We designed a qualitative questionnaire based on [8] that we tailored to our scenario. We asked healthy users and patients to rate on a scale from 1 (low) to 5 (high) the following statements: *(1) Attachment*: I can feel the device on my body. *(2) Harm*: The device is causing me some harm. *(3) Change*: I feel strange wearing the device. *(4) Movement*: The device effects the way I move.

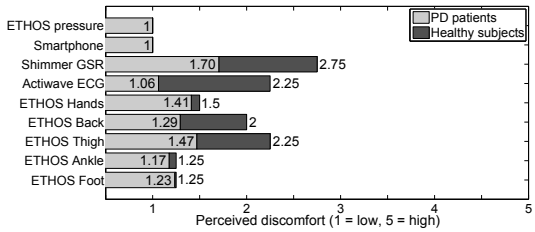

Figure 3. Sensor wearability average grades for all PD patients (light gray) and healthy subjects (dark grey)

Figure 3 depicts the average grades for all the sensor systems and body locations. In case of the PD patients the average values are low, showing that the users were feeling comfortable wearing the sensors, and the system did not affect their motor performances. Even the intuitively less comfortable Shimmer GSR sensor obtained a good wearability score. The pressure insole, ECG sensor and the smartphone obtained the best scores in terms of wearability, followed by ankle, foot and back attachments. Patients often answered that they actually forgot that they are wearing these devices. As expected, the healthy subjects gave higher discomfort grades for all the sensor attachments (except the smartphone). They tested the system before its refinement, on which their grades and input contributed in increasing its wearability. It is also in line with prior studies that patients suffering from a clinical condition are more likely to accept assistive systems, with the promise to improve their lifes.

5. CONCLUSION

We designed a multimodal sensor system and collected data from Parkinson's disease patients within a complex experimental protocol. Motivated by medical literature we incorporated 7 sensor modalities from 13 on-body sensor systems totaling a number of 38 sensors. In total we collected 23 h of 18 patient's activity. Our experiments show preliminary evidence that a multimodal view can help in reducing detection latency by considering lower level context (e.g. turning) and physiological data. From our experience with recording real patient data, we conclude with lessons learned and best practices to ensure robustness of data acquisition and experiment design to minimize the burden on the patient:

Local storage reduces the risk of data loss and maximizes battery life instead of wireless communication.

Intermediate reference signals help to recalibrate sensors displacement and reduce the risk of corrupted data.

Compact Experimental Protocol. While the base sessions were used for the patients to rest, we used these sessions to recalibrate IMUs, for synchronization patterns, or for letting subjects fill out questionnaires. The session were also used as baseline for the physiological baseline. This allowed us to minimize the duration of the experiment.

Wearability robustness. Our experiments showed that ECG sensors are highly sensitive for long term wearing and get easily loose. Similarly GSR sensors lacked robustness, as patients tend to touch the electrodes and consequently corrupt the signal.

Further research will investigate automatic detection and prediction of FoG events using a multimodal approach and higher contextual aspects such as localization, environmental changes, or activity.

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