

## Objectives

- **Proof-of-concept study to describe the relevant methodological and data processing steps for accelerometry and gyroscopic recordings from a wrist-worn sensor band**
- **To characterize and understand the processing complexity when handling large amounts of sensor data captured from Parkinson's patients in daily-life activities**

## Medical Background

- Brady-hypokinesia and dyskinesia characterize the motor syndrome of Parkinson's disease (PD)
- Motor fluctuations with alterations of the motor state are the hallmark of the later disease stages of patients with PD
- Currently, the motor state is evaluated by a rater or the patient, which regularly leads to biased assessments
- Ideally, the motor state should be detected by an objective assessment in free-living situations with high temporal resolution
- To date, such an objective detection of the motor state has been validated

## Technical Background

- Many commercial mobile devices, such as smartphones or wristbands, carry motion sensors for accelerometric, gyroscopic, or magnetometric recordings
- These sensors are worn imperceptibly over long time periods
- The data from the sensors can be used to assess physiological and disordered movement
- The large set of data and the complexity of the data processing pose numerous challenges to data validity, among which are noisy data, technical artefacts, variations of sensor position, or interference by voluntary activity

## Methods

- We obtained approval from the ethics committee of the TU Munich (Az. 234/16 S)
- We recorded data from 30 patients with PD and from 8 healthy controls (HC)

### PD patients

• Age [years]	67 ± 10
• Hoehn & Yahr stage	2 (2:2)
• Disease duration [yrs]	11 ± 5
• MoCA [points]	26 ± 3

- Patients were continuously clinically evaluated during the time they wore the band by a certified rater
- Clinical ratings included severity of brady-hypokinesia (MDS-UPDRS) and dyskinesia (AIMS)
- The rater co-registered any activity the patients were performing
- Sensor raw sensor data was recorded using a Microsoft band 2 (MS, Redmont, WA, USA) with a sampling frequency of an approx. 62.5 Hz that records a 3D-accelerometry and a 3D-gyroscopy signal. Other sensor data from the band were not investigated.
- Sensor orientation of the band as detailed in the Microsoft Band SDK documentation

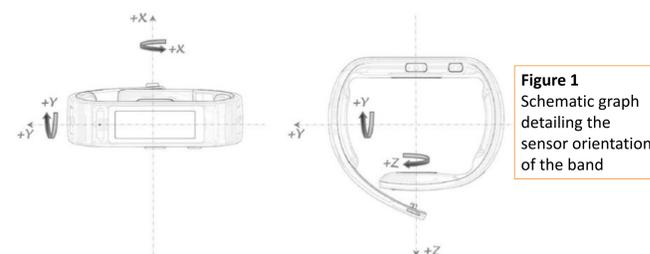


Figure 1  
Schematic graph detailing the sensor orientation of the band

- For further band details visit the Microsoft website (see References)
- Data was transferred to a smartphone using the Bluetooth interface, and analyzed off-line
- Ultimately, the data was used for motor state detection using machine learning techniques such as recurrent and convoluted neuronal nets  
 → Pfister et al. Poster 1354

## Results

### Obstacles related to technical issues

1. Sampling artifacts
2. Gyroscope integration drift & Acc noise
3. Position variation of the band placement

### Obstacles related to clinical issues

1. Generation of clinical labels
2. High inter-subject variability of activity labels

#### • Obstacle 1 – Sampling artifact

We found gaps in the raw data that probably resulted from lapses in the Bluetooth connection. We solved this issue by resampling the data at a frequency of 100 Hz.

#### • Obstacle 2 – Gyroscope integration drift & Acc noise

The gyroscopic data were smoothed with a band-pass filter (1 - 12 Hz) to remove the drift following integration as well as high frequency noise

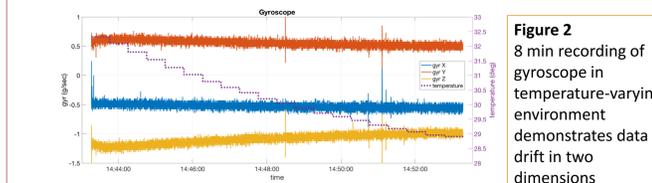


Figure 2  
8 min recording of gyroscope in temperature-varying environment demonstrates data drift in two dimensions

#### • Obstacle 3 – Band position variation

Depending on the mounting orientation of the wristband device, i.e. lateral or medial and bottom up or down, the captured signals are different. This is caused by the two sensors' functioning, which is to measure the gravity vector motion and acceleration, respectively. As in the internal device coordinate frame the gravity points in different directions (depending on the mounting orientation), the signals consequently appear different, even when describing the same movement.

#### • Obstacle 4 – Generation of clinical labels

Labelling clinical data is time consuming and prone to bias and individual error. New large-scale labelling approaches are required and need to be invented to answer to this need.

#### • Obstacle 5 – Activity labels

We learned that we needed to reduce the number of activity labels to a small amount of clinical meaningful activities, such as walking, sitting, standing, in order to gather enough samples for the neuronal nets to classify clinically meaningful categories

## Discussion

- We demonstrate the feasibility of using a low-cost sensor device for the detection of motor signals from the wrist of healthy controls and patients with Parkinson's disease
- A significant number of relevant technical issues needed to be addressed before the data could be meaningfully interpreted, and generalized to larger patient populations
- These preprocessing steps include re-sampling of data in case of sampling errors, and filtering of the data
- The position of the band, and thus the sensors, creates further variation of the data, and increases both intra- and inter-subject variability
- Involuntary motor activity integrates with voluntary motor activity. To validate the sensor data with clinical labels both motor activities have to be recorded with meaningful labels

## Conclusions

- **Specific steps of data processing are required for the meaningful interpretation of sensor data from e-health devices**
- **3D sensor data depend of the mounting position of the band, so variant positions systematically influence the data**
- **Despite of the reported obstacles, analysis of body worn sensor data opens a realistic pathway to objectively describe the motor symptoms of people with Parkinson's disease**

## References

- Pfister et al. (2016) Time for change – closing the loop in Parkinson's Disease. Basal Ganglia
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