DEEP LEARNING IN OBJECTIVE CLASSIFICATION OF MOVEMENT OF PATIENTS WITH PARKINSON'S DISEASE USING LARGE-SCALE FREE-LIVING SENSOR DATA

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Objectives

- **Proof-of-concept study to classify movement of people with Parkinson's Disease (PD) recorded with a wrist-worn motion sensor in free-living situations**
- **Using Deep Learning (LSTM/CNN) for the development of an objective measure to quantify the PD motor state**

Background

- Brady-hypokinesia and dyskineasia characterize movement in people with PD (PwP)
- Motor fluctuations are the hallmark of later PD stages
- Currently, the motor state is evaluated by a rater or the patient opening numerous paths to biased assessments
- Ideally, the motor state could be detected using an objective assessment in free-living situations with sufficient temporal resolution
- Deep learning has so far only be applied to data retrieved from PwP in test-based controlled setups, e.g. task-based
- To date, no objective detection of the motor state has been validated
- Commercially available mobile devices, such as smartphones or wristbands, carry motion sensors and can be imperceptibly worn over long time periods

Challenges in working with PD motion data

- **Noisy Labels** (due to symptom changes within given rating time intervals)
- **High-Inter-Subject Variability**
- **Motion Interference** (due to voluntary motion)
- **Noisy Motion Data** (due to limited sensor quality)

Table 1 – PwP cohort

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

Methods

- We obtained approval from the ethics committee of the TU Munich (Az. 234/16 S)
- We recruited 30 patients (see table 1) with PD and 8 age-matched healthy controls (HC)
- Patients were continuously clinically evaluated during the time they wore the sensor by a certified rater, which were >230 hours of recordings
- Clinical ratings included severity of brady-hypokinesia (MDS-UPDRS III.14) and dyskinesia (mAIMS)
- Sensor raw data (3D Acc, 3D Gyro) was recorded using a Microsoft band 2 (MS, Redmont, WA, USA) with a sampling frequency of 62.5 Hz running the STM LSM6DS2 Accelerometer / Gyroscope module
- Data was transferred to a storage device using a Bluetooth 4.1 interface, and analyzed off-line
- Data Augmentation methods as described in Um et al. were introduced for preprocessing

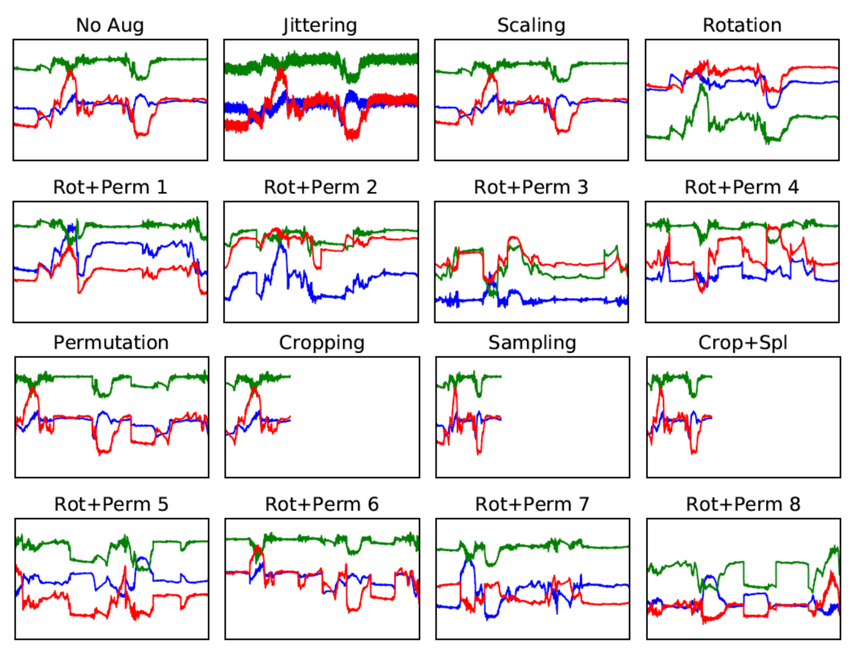


Figure 1: Various data augmentations that are used in the experiments: jittering, scaling, cropping, sampling, rotating, permutating data signals. The second and fourth rows show several examples generated by the combination of rotation and permutation.

- Data analysis included the use of various deep learning methods (CNN/LSTM), *see Fig. 2*

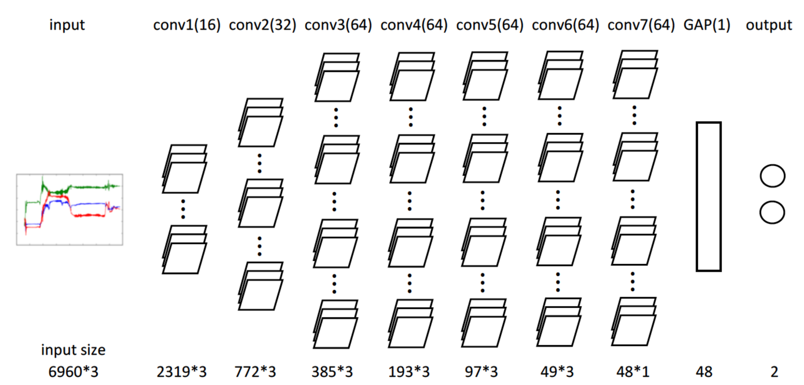


Figure 2: Architecture of a 7-layer CNN with a global average pooling (GAP) layer at the end is used for the experiments.

- On a second poster we describe details of the preprocessing methodology and the data process → **Pichler et al. Poster 1355**

Results

- **Difficult raw data patterns** & their classification

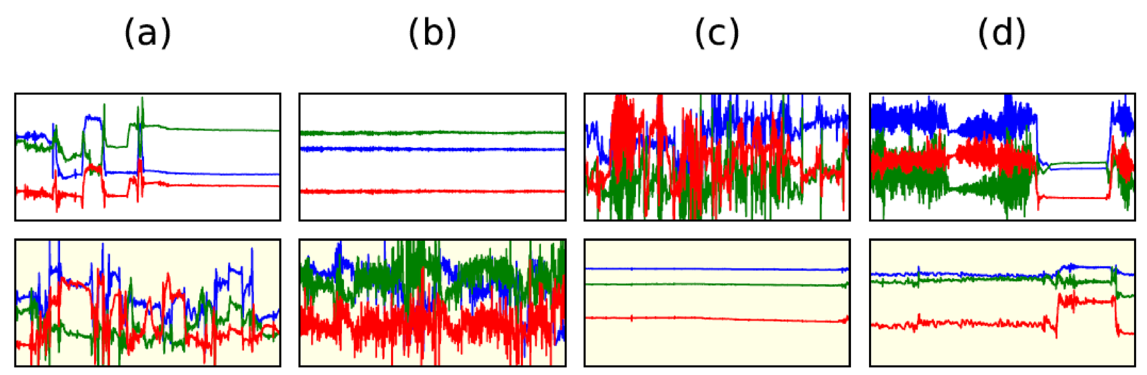
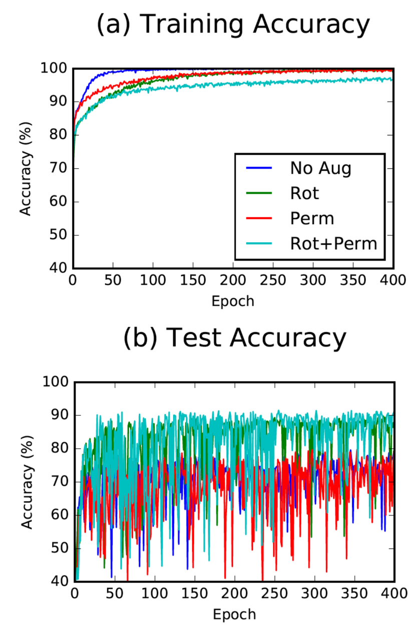


Figure 3: Examples of bradykinesia (white) and dyskinesia (yellow) data in a 1 min window. (a) and (b) show stereotype examples of bradykinesia and dyskinesia while (c) and (d) show the opposite patterns. The blue, red, green represent X, Y, Z signals from the accelerometer, respectively.

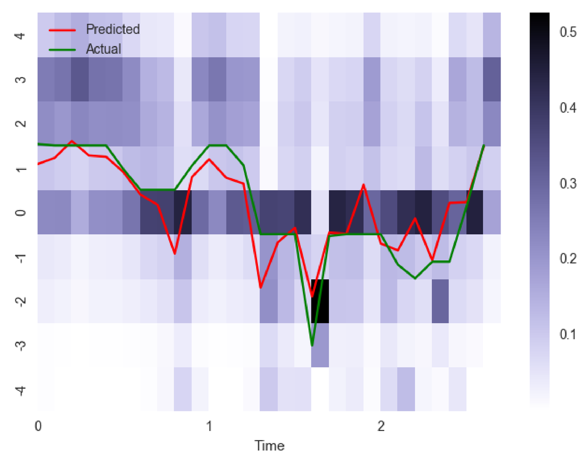
- Use of **Data Augmentation** boosts accuracy for **Two-Class-Classification** (OFF/DYS) – **F1 score up to 92%**



(400 epoch)	Train	Test			
	Top	Top Aug	Top	Med	Std
No Aug	100.0	76.7	76.7	74.8	0.023
Jitter (0.01)	100.0	76.7	76.5	75.7	0.024
Jitter (0.05)	100.0	73.3	73.3	72.1	0.024
Jitter (0.1)	100.0	65.8	67.3	64.7	0.038
Scale (0.05)	100.0	81.2	80.9	78.9	0.024
Scale (0.1)	100.0	81.2	81.2	79.4	0.034
Scale (0.2)	100.0	81.4	81.2	80.2	0.029
Crop	97.0	79.1	71.9	68.9	0.023
Sample	99.2	75.6	72.6	72.4	0.026
Crop+Sample	98.6	81.9	76.8	70.3	0.070
Rotation	99.9	**88.6**	**88.6**	**87.3**	0.023
Permutation	99.3	79.5	78.7	74.5	0.023
Rot+Perm	97.0	**92.0**	**91.2**	**90.6**	0.039
Rt+Pm+Sc	95.7	**92.0**	**91.1**	**90.6**	0.032
Rt+Pm+Cr+Sp	92.7	89.4	88.3	86.8	0.069

Figure 4a (left): Training curves for No Aug, Rot, Perm, and Rot+Perm. The curve of Rot+Perm shows a good generalization performance by a regularization effect.
Figure 4b (right): The results of PD motor state classification with various data augmentation methods

- **Generalization for Nine-Class-Classification** (GMS-9) using MDS-UPDRS III.14 (Level of Global Spontaneous Movement Loss) and mAIMS II.5 (Severity of Dyskinesia in affected hand) as mapping – **F1 score >60%**



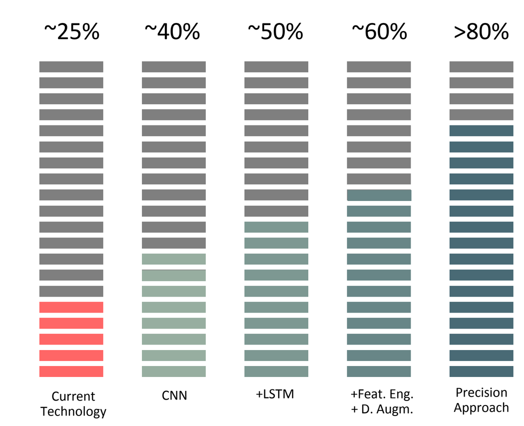


Figure 5 (left): GSM-9 – Motor fluctuations of one patient over 3 hours – comparison between predicted label (using a multilayer CNN+LSTM) vs. clinical label by certified rater (nine-class-classif.)
Figure 6 (right): The results of PD motor state classification with various deep learning methods

- High inter-subject variability is a bottleneck for generalization
- Precision Approach: Individual models using a pretrained generalized model boost accuracy

Discussion

- Sensor data from low-cost devices are effective to detect the motor signals from healthy controls and people with Parkinson's disease
- Relevant technical issues have to be addressed before the data can be analyzed
- Deep Learning proves to be a powerful instrument to classify motion data
- The temporal and manifestation resolution of the achieved classification is unprecedented.
- Generalization can be a hard task: Individual Calibration will be key (Precision Approach)

Conclusions

- **We describe a novel approach for the objective classification of the PD motor state, the core characteristic of the disease, using Deep Learning and a low-cost commercially available sensor device**
- **This method is not limited to a controlled test setup, but can be applied in free-living situations and thus potentially allows for full seamless integration of the IoT technology into the daily lives of patients**
- **The precision and temporal resolution of the measurements is unprecedented, and could be used for numerous clinical indications**
- **Individual models will enable more accurate monitoring of the PD motor state**

Literature

- Kubota et al. (2016) Machine learning for large-scale wearable sensor data in PD. MDJ
- Shoaib et al. (2016) Complex human activity recognition using smartphone and wrist-worn motion sensors. SENSORS
- Sanchez-Ferro et al. (2016) New technologies for the assessment of Parkinson's. MDJ
- Del Din et al. (2016) Free-living monitoring of Parkinson's disease: lessons from the field. MDJ
- Sama et al. (2012) Dyskinesia and motor state detection in PD. IEEE EMBC
- Um et al. (2017) Data Augmentation of Wearable Sensor Data for Parkinson's Disease Monitoring using Convolutional Neural Networks