Prediction of dopaminergic response in Parkinson‘s Disease patients using surface Electromyography

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# Abstract

Parkinsons disease (PD) is a chronic neurodegenerative disorder affecting XXX% of the population and being responsible for XXX% of total costs spent in the healthcare system. Symptom fluctuation and dependency on expert evaluation makes tracking the disease course and therapeutic effects challenging. Using shallow learning techniques and surface EMG we present a simple, cheap and unobstrusive method for the assessment of motor symptoms in PD. Our method shows a good correlation with the UPDRS assessment, the current gold standard. In contrast to the UPDRS it does not depend on expert evaluation and thus is easily applicable anytime at point of care.

### Key words:

Idiopathic Parkinson syndrome, wearables, surface electromyography, Regression, Machine Learning, levodopa, UPDRS

# Abbreviations

EDC – *Musculus extensor digitorum communis*

FDS – *Musculus flexor digitorum superficialis*

EMG – Electromyography

IMU – Inertial measurement unit

iPS – idiopathic Parkinson Syndrome

UPDRS – Unified Parkinson’s Disease Rating Scale

# Introduction

Parkinson’s disease (PD) is a neurodegenerative disorder in which affected subjects develop bradykinesia with additional rigidity, tremor or a combination thereof (Postuma et al. 2015) A pronounced asymmetry, relatively slow progress and response to dopaminergic medication indicate idiopathic Parkinson's syndrome while lack of any of these are suggestive for atypical syndromes. Especially significant levodopa response is of paramount importance, as it allows the possibility of adequate therapies.

Extrapyramidal motor symptoms in PD result from dopaminergic depletion of neurons within the *Substantia nigra.* Consecutive dysregulation of interactions between basal ganglia and cortical areas determine disease progression fundamentally (Poewe et al. 2017). Motor affection is thereby highly individual and requires regular clinical assessment for satisfactory medical or invasive treatment. Yet, pharmacokinetics and drug interactions may hamper objective and long-lasting assessments (Nutt et al. 2008). Moreover, strong fluctuations of dopaminergic treatment particularly at later disease stages may impede finding the right dosages of medication (Quelle?). Phases with good ("ON") and poor mobility ("OFF") may then alternate within a very short amount of time, which is perceived as highly disturbing and often results in complicated medication schedules (Stocchi et al. 2008). Precise temporal assessment of bradykinesia or tremor during the disease course would facilitate tailored therapies.

The severity of PD is usually quantified with the Unified Parkinson's Disease Rating Scale (UPDRS), especially the motor examination part (mUPDRS). Yet its application only provides a snapshot of the symptoms and may thus be insufficient and misleading, especially for patients suffering from fluctuations. Besides, the assessment is resource-intensive and guided training seems to be necessary to achaive a good interrater-reliability (Goetz et al. 2004). Patient diaries, on the other hand, allow for quick and regular assessments at low expenses but at the cost of subjective assessments and the problem of anosognosia of PD-symptoms (Maier et al. 2017). Modern sensors and mobile technologies are gaining importance for continuous determination of symptom severity with objective results.

The establishment of smart phones and watches has facilitated recording continous movement profiles. Commercially available devices usually already contain an accelerometer and a gyroscope, so that data collection is fairly easy and unobstrusive. Great efforts are being undertaken to use these wearables in healthy subjects but also in PD-patients (for reviews see Rovini et al. 2017 and Kleinholdermann et al. 2019). In the remaining article, we present an approach to measure PD-patients’ changes in motor disability via wireless surface EMGs (sEMG) after levodopa intake. We postulate that prediction of UPDRS values and therefore easily applicable monitoring of motor affection and therapeutic effects is possible using sEMG. For this purpose PD-patients were recorded in the OFF- and ON-condition during a tapping task. Different regression models were applied and then tested for the ability to predict clinical changes in motor symptoms.

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# Methods

The study was approved by the local Ethics committee and carried out in accordance with the Declaration of Helsinki. All patients had given their written informed consent prior to participating.

### Patients and clinical evaluation

In total, 47 PD-patients according to recent diagnostic criteria (Postuma et al. 2015) were recruited from in- and outpatient services of a tertiary care hospital. One patient was excluded from the analysis due to ? (40\_MKH). Motor symptom burden ranged from mild to severe (for demographics and clinical details see Table 1). The aim of the study was to analyse interindividual differences between OFF and ON states, that is when medication was washed out and after levodopa intake, respectively. Motor affection was assessed in both conditions by two experienced raters with the MDS-UPDRS (Unified Parkinson’s Disease Rating Scale, Goetz et al. 2008) using video recordings.

### Experimental setup

Participants were seated in an armchair with backrest. The motor paradigm consisted of a simple tapping task, i.e. subjects were asked to tap with the index finger of the more affected side on a table as quickly as possible. The task was started by a signal on a notebook screen at a distance of approximately 60 cm with a countdown of 3 secs. The tapping interval lasted 5 secs following the display of a green cross. After 18 repetitions in the OFF-condition, patients were asked to take 100-200mg Levodopa in a soluble formulation (approximately 1.5 times the morning dose) and the test was repeated 60-90 minutes later (termed hereafter the ON-condition). For the OFF-condition subjects were asked to discontinue dopaminergic medication for at least 12 hours

All data was recorded by using a commercially available armband (Myo Gesture armband, Thalmic Myo Labs), which records eight concentrically arranged sEMGs along with kinetographic data. For this study only the sEMG was analysed. The armband recorded eight different channels, of which only three were related to active superficial muscles during tapping – M. extensor digitorum communis (EDC) and M. flexor digitorum superficialis (FDS). Hence, only channels 4, 5 and 8 were selected for further analysis. The armband was placed 3 cm distal from the elbow with contact four (marked by an LED) on the tendon of the *M. extensor digitorum communis* (EDC, for a schematic see Figure 1). Data was sampled at 200 Hz using the included software development kit (SDK) in combination with custom Matlab scripts (Mathworks).

### Pre-processing and feature extraction

Data was extracted and cut into epochs of 8 secs. Thereafter, visual inspection ensured that no artifacts were present and that activity corresponded to the tapping task. Consequently, data was high-pass filtered with a cutoff frequency of 10 Hz (Butterworth filter of 3rd order) and an adaptive notch-filter at 50 Hz to reduce main grid interference. From preprocessed sEMG signals (see below), data features were extracted. A moving window of 100 samples (~500 ms) and steps of 250 ms was used during the above calculations. All feature analyses are developed from works of Kaczmarek et al. (2019).

### EMG feature sets

Three distinct features sets were used: a) Hudgins’s (Hudgins et al. 1993), b) Du’s (Du et al. 2010) and c) root mean square (RMS) of sEMG data. This choice represents some of the most frequent features currently used for EMG classification [Hakonen et al. 2015, Phinyomark et al. 2012]. Hudgins’ feature vector consists of the Mean Absolute Value (MAV), Zero Crossings (ZC), Waveform Length (WL) and Slope Sign Change (SSC). Former studies have proven a high insensitivity to window size and computational complexity is rather low [Oskoei et al. 2008]. Du’s feature set comprises integrated Electromyogram (iEMG), sEMG variance (VAR), WL, ZC, SSC and Willison Amplitude (WAMP). It has been reported to perform more accurate than Hudgins’ set [Phinyomark et al. 2012]. Even though Hudgins’ and Du’s sets are computed in the time domain, they represent amplitude, frequency, and complexity of the signal [Hakonen et al. 2015]. Formulae of the metrics can be found in the supplementary material.

Updrs prediction

The main goal of this study was the prediction of mUPDRS values using sEMG features and shallow machine learning techniques. four different learning algorithms were compared: a) linear regression, b) random forest regression, c) support vector machine regression (SVR) with a polynomial kernel function and k-nearest neighbours regression (kNN). Also we used different time windows from the available trial data with lenghts ranging between 1 and 7 seconds in order to test for the necessary amount of data for forecasting mUPDRS values. Analyses were conducted using the statistical software environment R. Data of a total of 1364 trials were split into a learning set with 90% of the data and an unseen prediction set with 10%. Hyperparameters were tuned using a “grid search” to minimise mean squared error using the *caret* package and a 10 times repeated 10fold cross validation procedure was applied.

# Results

## Clinical data

In total 46 patients (10 female) at an age of 61.1 ± 9.6 years suffering from iPS for 6.6 ± 4.1 years and with a mean Hoehn and Yahr stage of 2.8 ±1.3 were included. Without medication, subjects had on average 46.0 ± 22.6 points on the mUPDRS and levodopa equivalence dose (LEDD) was 731.6 ± 561 mg (Tomlinson et al. 2010). Clinical details are displayed in Table 1.

Table 1: Demographics and clinical data

|  |  |
| --- | --- |
| *N* | *40* |
| Gender' | 10 female |
| Age [in years] | 61.18 ± 9.61 |
| Levodopa equivalent dose [in mg] | 731.6 ± 561.5 |
| Hoehn & Yahr stage | 2.8 ± 1.3 |
| Disease duration [in yrs] | 6.6. ± 4.1 |
| UPDRS OFF | 46.00 ± 22.57 |
| UPDRS ON | 35.53 ± 20.26 |

### Feature regression

Figure 1 displays the correlation between all features used in the study. As a metric for the regression performance we calculated the correlation between predicted and true mUPDRS values. (see Figure 2.). Random forest regression showed the best predictive performance on mUPDRS values followed by knn regression. Linear regression was associated with the lowest correlations between true and predicted mUPDRS values. The best random forest model showed a correlation of .76. Grid search returned for the number of variables available for splitting tree nodes (mtry) a value of 24, and as a split rule extratrees were used. The best performance was achieved using the longest sampling intervall (7s). However longer data acquisition intervals could be associated with an even better regression performance.

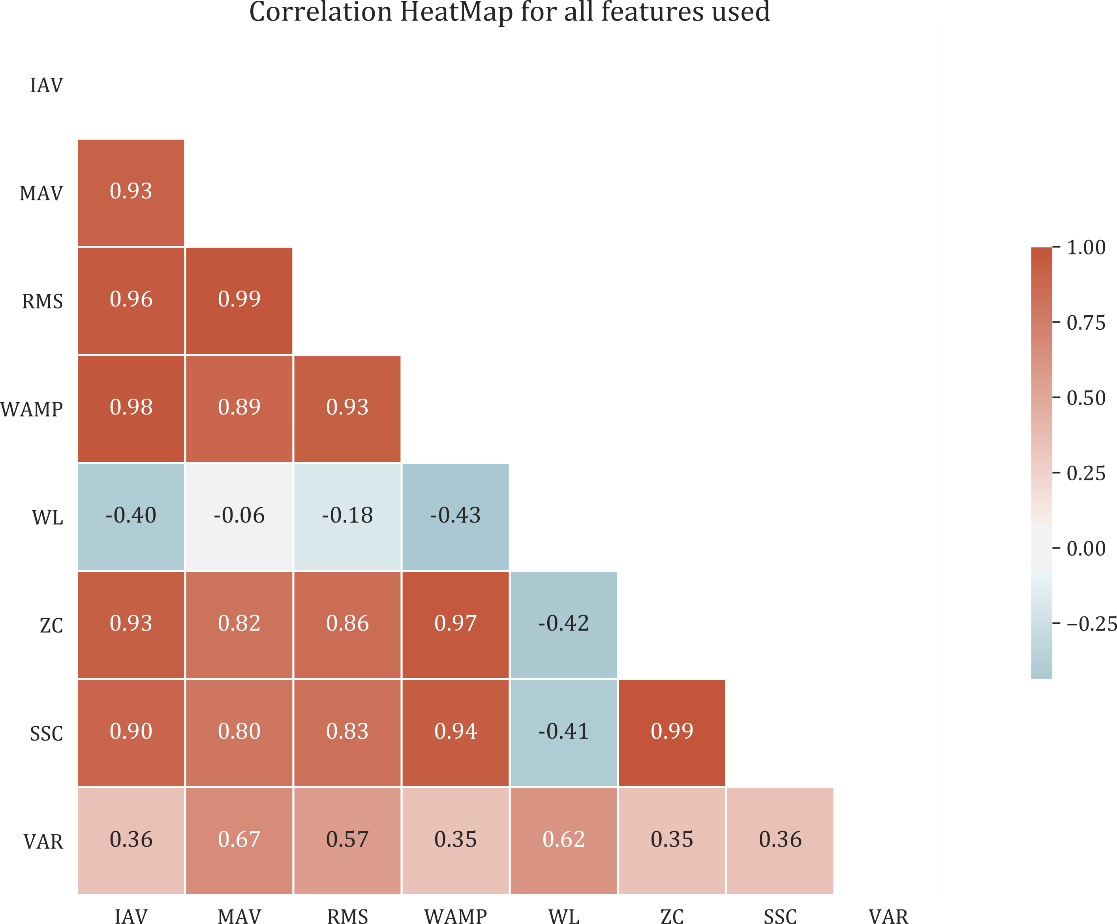
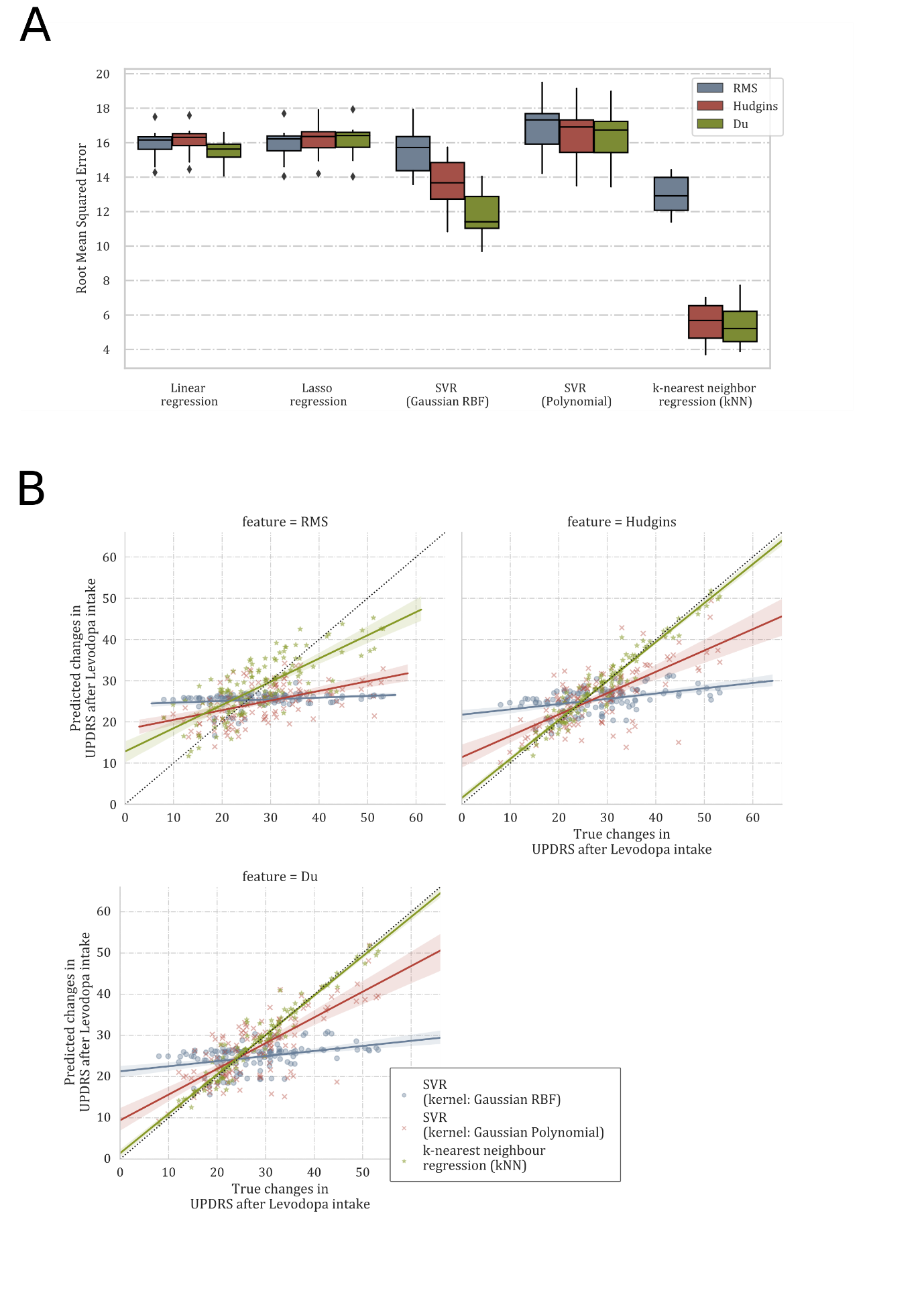


Figure 1: Correlation between the extracted features for iPS patients during tapping task. There was moderate to high correlation between the features at all conditions.



# Discussion

We show that features derived from sEMG signals during a tapping task can be used to predict mUPDRS values. By subjecting these features to different regression techniques, we were able to show a correlation between sEMG activity and mUPDRS scores. For that purpose, ‘shallow learning’ techniques were applied using cross-validation and grid search techniques.

A growing body of evidence supports the usefulness of mobile sensors for patients with parkinson syndromes. Machine learning approaches have been used for diagnosing PD (). Nevertheless, to date there is no consensus about the best marker neither for diagnostic purposes nor for tracking the diseases course. Surface EMG may be one possibility, which has also been shown to successfully discriminate PD-patients form healthy control subjects (Jia et al. 2014, Eskofier et al. 2016, Djurić-Jovičić et al. 2016). To our knowledge this work shows for the first time that clinical ratings of PD-patients are correlated with sEMG features, demonstrating its suitability for tracking therapeutic effects. One may thus think of non-invasive mobile sEMG recordings as a source of information for treatment success and need for therapy adaptation (Rissanen et al. 2015). Besides the possibility for physicians to provide tailored therapies, it may additionally be a good opportunity for caregivers to reduce side-effects and lower hospitalisation rates (Quelle??). Despite these promising results with sEMG as a marker measurng therapeutic success, questions about practicability and possible alterantives need to be addressed first.

Surface EMGs constitute easy applicable and non-invasive recordings of muscle activity. There are however a series of possible problems that require consideration when used in patients. First, unlike kinetography, the correct and reliable placement of sensors is of paramount importance for comparability. One solution may be the use of smart clothes (Niazmand et al. 2011) and also easy wearable gloves may be of special interest (Rovini et al. 2017). Moreover, very little research has been conducted as to which features are particularly interesting. One may therefore object that the choice of standard features (Phinyomark et al. 2012) as used in our study may not be generally valid for different PD-subtypes. In that sense, stronger emphasis on separating tremordominant vs. bradykinetic-rigid symptoms may help in future studies to enhance generalisability. Despite the excellent prediction of changes in UPDRS with our method, it remains, thirdly, to be elucidated whether tasks closer to everyday-life may be useful, as well. In this context, Block et al. showed the possibility of classifying ON and OFF phases and predicting falls based on walking in PD-patients (Block et al. ??). Another aspect worth considering is the fact, that possibly lighter and more commonly available sensors, e.g. measuring kinetographic data may be a feasible alternative. Possibly, remote collection of several symptoms with a set of sensors may provide a comprehensive picture of the disease (Lipsmeier et al. ??) However, the best combination of sensor measurements and the application to everyday life is still the subject of research [35].

Apart from long-term applications of sensor based therapeutic adjustments , one useful short-term scenario could be the adjustments of Deep Brain Stimulation (DBS) parameter settings. With this invasive procedure, patients suffering from PD receive electrodes implanted in specific brain areas such as the subthalamic nucleus (STN) where high-frequency current pulses mitigate motor-symptoms within a short delay. Yet, the identification of the most efficient parameters is resource-intensive and may be seriously compromised when subjects require time-consuming testing of parameter sets. In clinical practise, the usefulness of our approach awaits further confirmation but may indeed help to ascertain the set of most useful settings, especially when combined with modern imaging techniques (Quelle?). Of course, only a subset of the clinical testing is included, so that practicability remains to be elucidated.

In summary, we have identified surface EMG features and their use along with regression techniques to predict PD-patients’ decrease in motor disability after levodopa intake. Validation of this regression model was done on an independent set of subjects. This precludes the possibility that these results are due to overfitting and corroborates the use of our results for predicting motor disability with commercially available sEMG recordings. Hence, we lend considerable support to the notion that peripheral sensor data may be used for tailored therapies in Parkinson’s Disease in a future.

# Tables and Figures:

**Table** 2**:** General demographics for iPS patients

**Figure 1:**

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### Documentation of authors’ roles:

Urs Kleinholdermann participated in the conception and organization of the research project, the programming of the motor paradigms, the data assessment and data analysis, the conception and execution of the statistical analysis and the writing and critical review of the manuscript.

Max Wullstein participated in the organization and execution of the research project, the data assessment and data analysis, the execution of the statistical analysis and the writing of the manuscript.

David J. Pedrosa participated in the conception, organization and execution of the research project, the programming of the motor paradigms, the data assessment and data analysis, the conception and execution of the statistical analysis and the writing and critical review of the manuscript. Moreover, he had full access to all of the data in the study and takes responsibility for the integrity of the data and the accuracy of the data analysis.

### Conflict of Interest statement/Financial disclosure:

U.K. reports no conflicts of interest

M.W. reports no conflicts of interest

D.J.P. reports no conflicts of interest

Apart from the above, the authors report no financial conflict of interest and do not have to disclose any commercial considerations, such as an equity interest, patent rights, or corporate affiliation, including consultantships, for any product or process mentioned in the submission.

# References

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Supplementary Material

### Definition of the features used throughout this paper:

* The integrated amplitude (IAV) of the sEMG expressed as summation of its absolute values’ amplitude:
* Mean absolute value (MAV) as an average of absolute values of the signal in a specific segment:
* Root Mean Squared (RMS), which can be defined as:
* Variance (VAR) of the sEMG as a metric for power, which may be defined as:
* Variance (VAR) of the sEMG as a metric for power, which may be defined as:
* Variance (WL) of the sEMG as a metric for power, which may be defined as: