Gait Parameters in Parkinson's Patient Reflect Changes in Subthalamic LFPs

by

Milan A. Greuter

to obtain the degree of Master of Science
at the Delft University of Technology,
to be defended publicly on Friday 11 July, 2025 at 13:00 PM.

Student number:	4672593	
Project duration:	September 2, 2024 – July 11, 2025	
Faculty:	Faculty of Mechanical Engineering	
Thesis committee:	PhD. M. L. van de Ruit ,	TU Delft, supervisor
	MD. PhD. M. Beudel,	Amsterdam UMC, supervisor
	PhD candidate. D. Hubers,	Amsterdam UMC, supervisor
	Prof. dr. F. C. T. van der Helm,	TU Delft, external committee member

TU Delft

Abstract-Purpose: **Parkinson's Disease (PD) is the second most common neurodegenerative disease with a still increasing incidence. The implementation of new medical technology also increases yearly, to achieve better and a more efficient healthcare. One implementation of such a corresponding medical technology is Medtronic's sensing technology, which allows for reading of Local Field Potentials (LFPs). Furthermore, new assessment options are also investigated, with Markerless Motion Tracking (MMT) programs as interesting option for assessment of the Unified Parkinson's Disease Rate Scale (UDPRS). This study aims to investigate correlations between these LFP signals and parameters extracted from MMT programs during gait.**

Methods: **Pose estimation in this study was performed using MMT programs, while simultaneously recording LFP data in PD patients implanted with a Deep Brain Stimulation (DBS) device. LFP activity was filtered to only include beta activity, while this is primarily correlated with motor impairment. Normalisation methods were then applied on pose estimation data for allowance of distance calculation and extraction of the arm-swing parameters: velocity, acceleration and jerk.**

Results: **Results indicate a negative trend between LFP data and among almost all examined parameters. This applies for both trends observed: beta power analysis, as well as the UPDRS analysis. Left hemisphere shows significant correlation for the velocity ($\rho = -0.356, p = 0.046$), acceleration ($\rho = -0.456, p = 0.01$) and jerk ($\rho = -0.465, p = 0.01$). While right hemisphere does not show this significance. Whereas, amplitude calculations even show contrary outcomes.**

Conclusion: **This study shows multiple connections between LFP data and gait parameters. Furthermore, it confirms the importance of arm-swing as indication for gait abnormalities. Finally, these findings suggest the need for more research on other parameters originated from different UPDRS tasks.**

1 Introduction

Currently, PD is the second most common neurodegenerative disease in the world. There is still an increasing growth in the amount of patients diagnosed with PD. [1]Clinically PD is characterized by the primary motor symptoms including: akinesia, bradykinesia, rigidity, postural stability and tremor, and secondary by: gait disturbances, speech problems, micrographia and precision grip impairment. [2,3] Additionally, PD patients can also experience non motoric symptoms, which comprise off: behavioural changes, sleep disturbances, sensory abnormalities, depression, autonomic dysfunction and fatigue, which are harder to quantify. [4, 5]
Assessment of PD symptoms is frequently done with the UPDRS, which consists of the subsets: Mentation, Behaviour, Motor and Mood and Activities of Daily Living. [6] Consequently, this UPDRS has been revised by the Movement Disorder Society and thus PD symptoms are primarily assessed using the Movement Disorder Society - Unified Parkinson's Disease Rate Scale (MDS-UPDRS). [7] Furthermore, an increase in symptoms means an increase in UPDRS score.
To get an objective UPDRS score and more UPDRS scores, collection of video material combined with automatic UPDRS assessment has become more interesting. Consequently, video analysis and movements of patients are tracked through MMT programs. Currently, motion tracking through sensors, for example accelerometers are still the golden standard. However, when comparing MMT techniques with marker based methods, not much difference in study parameters are found. [8] Moreover, when analysing gait, a sub part of the UPDRS, good results are found. This study again compared sensor based techniques with MMT techniques. Results show, high similarity for all; flexion/extension angles, hip adduction/abduction angles and ankle inversion/eversion. [9] This indicates that video material, could provide valuable biomechanical information.
When tracking is captured well and symptoms are also well assessed, symptom management becomes an important part in disease progression of PD. Ini-

tially, medical therapy is given when patients are diagnosed with PD. However, the dose and frequency of this medical therapy increases throughout the years, because of disease progression. Eventually, when patients still experience symptoms even though medication is given, advanced therapies as Deep Brain Stimulation (DBS) are indicated. There are two different DBS treatment options: unilateral or bilateral stimulation. Unilateral has one lead located in the brain, whereas bilateral has two leads located in the brain. Correspondingly, these leads and thus stimulation is either located in the globus pallidus interna (GPI) or subthalamic nucleus (STN). [10] Where, in PD patients the most common lead placement is the STN. While there is more motoric improvement in PD patients implanted with STN leads. [11]

In recent years technological advancements have been made regarding these neurostimulators, the DBS devices. Currently, there are new neurostimulators, which are able to sense brain data. [12] These neurostimulators are able to sense LFP signals directly from the brain. LFPs are generated through multiple mesoscopic and microscopic factors, induced by cells including neurons. Furthermore, these field potentials (FPs) may reflect the dynamics of single cells, or are caused by assembly firing of cells. [13] Nonetheless, these LFP signals reflect a form of brain activity. Correspondingly, multiple studies show a correlation between LFP signals and motor symptoms. Specifically, changes in the beta range frequency (13-30 Hz) and motor symptom severity. [14–16] Therefore, this is the selected region of interest for studies investigating motor impairments in PD patients.

Currently, there are no studies, examining relationships between parameters extracted from MMT programs and LFP data. Therefore, this research aims to investigate how parameters extracted from real time video data correlates with LFP data in PD patients executing gait movement. This eventually could lead to improvement better control of symptoms. When gait parameters decrease during movement for example, a change in DBS settings would be initiated.

2 Methods

2.1 Settings

This is a single center study, where all patients recruited are under general care of neurologists and specialised nurses located at the Amsterdam University Medical Center (UMC) location AMC. The Medische Etische Toetsing Commisie (METC) has granted approval to perform this study. All patients provided written informed consent for participation. Eventually, 7 patients with PD and DBS were included during this research. These 7 patients delivered a total of 32 files available for analysis. The following inclusion criteria were assessed and implemented by a neurologist: 1.Parkinson's disease diagnosis based on the clinical diagnostic criteria of Movement Disorder Society (MDS), 2. In possession of a DBS device, 3. Age of 18 years or older, 4. Understand the Dutch language. Contrary to inclusion criteria, exclusion criteria were also made; 1. Legally incompetent adults, 2. No written informed consent, 3. Previous functional stereotactic neurosurgery, 4. Dementia, 5. Current depression or psychosis.

2.2 Setup

Patients included in this study are implanted with the Medtronic Percept PC dual-channel implantable neurostimulator. This neurostimulator is equipped with two SenSight™ directional leads of varying sizes. [17] During hospital visits and at home patients were to asked record the UPDRS.

In hospital recordings were done with an Apple Iphone 10 or higher. Furthermore, the phone was placed in a tripod for a steady recording. The camera position was positioned in parallel with the gait of the patient. At home recordings were mainly captured with an Apple Iphone 8, but in very few cases with an Apple Iphone 6. Similar, a tripod was given to the patients for steady recordings at home as well. Both phones allow for recordings of approximately 30 frames per second. Recordings captured at home were performed using the Kelvin-Reach-PD app at home. While recordings during

hospital visits performed by researchers were captured with KELVIN-PD^{TM} app. Both are mobile applications which allow for capture of UPDRS tasks. Although, both are similar apps the Kelvin-Reach-PD is more user friendly, because patients need to this app. Nonetheless, the computer-vision system is identical with both apps.

2.3 Protocol

All patients included were tracked during the entire procedure of finding the correct DBS settings, which is approximately 6 months for each patient. Following the DBS operation, patients are invited to the hospital for exploration of initial DBS settings. During this visit patient receive the equipment for filming at home recordings. Throughout this time period, from initial DBS settings (visit 2) and final visit (visit 5), patients were asked to make a weekly video recording of themselves. This video recording consists of a subset from part III of the UPDRS. Accordingly, this subset consisted of; "3.1 & 3.2 Speech and Facial Movement", "3.4 Finger tapping", "3.5 Hand Movements", "3.9 Arising from chair", "3.10 Gait", "3.15 Postural Tremor of Hands". After these videos were recorded patients were also asked to register when they completed these tasks. The system would then save a short window of LFP signals. Also, during this period of finding proper DBS settings the patient has in hospital visits as regular care. After the initial in hospital visit, patients are invited again to the hospital after generally 6-8 week for regular care. Following, these regular care hospital visits patients were evaluated for in study purposes. This occurred two times and those visits were called visit 2.5 and visit 3.5. During those visits, patients were checked on rigidity at those moments and were asked whether there medication changed to the last visit. Additionally, patients were asked if they felt "OFF" or "ON". Where the OFF state primary includes bradykinesia, rest tremor and rigidity. [18] Logically, the ON state characterises itself by the absence of these symptoms. Finally, an additional UPDRS was conducted on video tape in the hospital as well. However, this recording does include all part III items of the UPDRS, instead of a subset. While patients perform the UPDRS, LFP signals are simultaneously captured with Medtronic's sensing technology. During, one specific task, the "Speech" task a "ticking" method was performed, where patients underwent ticking on the neurostimulator. This ticking had to create an artifact to synchronise LFP data with video material. When this artifact was present, synchronisation was possible. All data collected during the in hospital visits and at home are saved in JavaScript Object Notation (JSON) files. These JSON files can be downloaded from tablets containing the DBS app by Medtronic, which connects with the neurostimulator. At first these JSONs contain primarily LFP data. Then these LFP files are uploaded to the Kelvin Cloud, provided by Machine Medicine Technologies. Consequently, Machine Medicine processes these files. Adding in the pose estimation data and the UPDRS score provided by the clinician, as well as the automatic UPDRS labeling.

2.4 Data analysis

2.4.1 Motion Markerless Tracking

This system makes use of the deep learning library OpenPose [19]. This open-source library provides state of the art pose estimation performance. OpenPose used Motion Markerless Tracking (MMT) to extract 25 body and 21 hand key-point coordinates on each frame.

During analysis a peak detection method was used to analyse maxima (peaks) and minima (trough), see Figure 1. These peaks and troughs are used for detection of critical points during movement. For example, when a foot strikes the floor or when it is lifted off at a maximum. It may seem contrary, but normally a peak means not in contact with the floor. However, due to it being the proportional distance between a neck marker and a marker on the left foot. The highest proportional distance between these points means the foot is on the floor, thus giving a peak in the data. Therefore, a trough means the highest point the foot comes off the floor.

Furthermore, to capture which task was performed

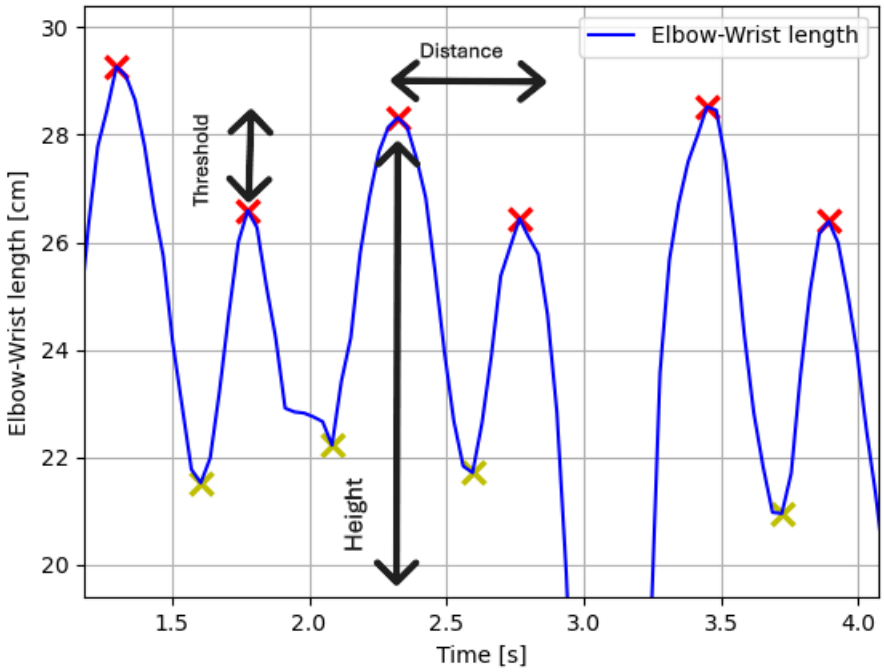

Figure 1: **Peak and trough analysis:** Peaks are visible due to the a combination of the three given parameters: Threshold (relative vertical distance between peaks), Distance (horizontal distance between peaks) and Height (absolute vertical distance between peaks). Troughs are visible due to inversion of the signal and applying the same method. The y-axis shows the distance [cm] between the elbow and wrist, with the x-axis showing time [s].

an automatic labeling occurred. This automatic labeling provided Regions Of Interest (ROIs) in which a patient performed the specific task. Separations within a video were made between the performed task with the left leg and the right leg. However, some tasks did not need this separation and then the automatic labeling in general was used.

2.4.2 Time Series

During performance of all the UPDRS tasks a time serie signal was created, that is able to capture that specific task. Correspondingly, the time serie signals are also automatically cut to match the selected ROIs of that task. Based on these time serie signals, different features were extracted. Multiple signals are defined using the following description as given by Machine Medicine [20]:

- $x_{b(i)}, y_{b(i)}, \mathbf{P}_{b(i)}$ are the x coordinate, y coordinate and 2D positional vector $\begin{pmatrix} x_{b(i)} \\ y_{b(i)} \end{pmatrix}$ of the i^{th} body key point.

2.4.3 Distance calculation

The output of the MMT program are the body key points $\mathrm{x}_{b(i)}$ and $\mathrm{y}_{b(i)}$. Although, it outputs a $\mathrm{x}_{b(i)}$ and $\mathrm{y}_{b(i)}$ processing needs to be done, because these $\mathrm{x}_{b(i)}$ and $\mathrm{y}_{b(i)}$ are pixel coordinates. Therefore, a normalisation method has been applied. This normalisation is necessary, because parameters extracted from the MMT will change based on position of patients. To illustrate, a pixel location can be the same in two different frames, while the position is different between the frames. Then calculations with actual distances would be inaccurate. A normalisation of pixel distance would eliminate this problem. According to this normalisation method the pixel length per frame

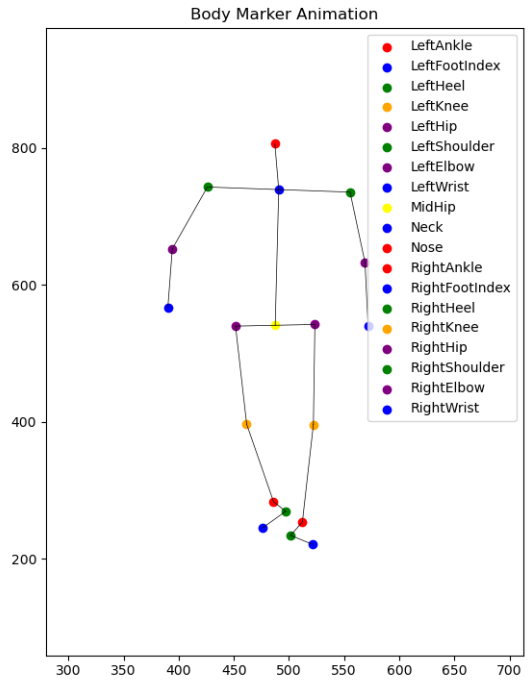

Figure 2: **Pose Extraction Model:** An example of a patient walking towards the camera. Not all points are included in this example, while not each individual hand point is of interest during the gait task.

is calculated based on spine and total length. Due to the spine not being completely straight, first Pythagoras theorem needs to be applied to know the pixel distance of the spine:

$$\textbf{\textit{Pixel Distance}} = \sqrt{(x_{b(i)} - x_{b(j)})^2 - (y_{b(i)} - y_{b(j)})^2}$$

Where i indicates the pixel coordinate of the neck and j the pixel coordinate point of the middle of the hip.

Due to spine length on average being a proportion of body length, indicated by body proportion, calculation of pixel length is possible. [21] Total length is almost always stored in the electronic patient record, while this is commonly measured in general care as part of the vital statistic. Knowledge of both these metrics allows for integration of the following formula in eventually pixel length:

$$\textbf{\textit{Spine Length}} = \textit{Total Length}/\textit{Body Proportion}$$

$$\textbf{\textit{Pixel Length}} = \textit{Spine Length}/\textit{Pixel Distance}$$

This formula outputs the pixel length per frame, which allows for calculation of distances and speeds respectively. However, this normalisation method only applies on each patient individually, but can not be applied between patients.

Additionally, to extract peak and trough coordinates a find peak function from the Scipy Python library was used. This algorithm is able to identify local maxima (peaks), however to find the local minima (troughs) an inverse of the signal was created and then the same algorithm was used . This function requires at least two inputs (three were given), for which the following formula is given:

$$\textbf{\textit{Height}} = median(ny_i) + (std(ny_i)/2)$$

$$\textbf{\textit{Threshold}} = mean(ny_i) - max(ny_i)$$

$$\textbf{\textit{Distance}} = length(ny_i)/12$$

First, the ny_i stands for the normalised y_i, representing a real point instead of a pixel coordinate. In these formulas height indicates the absolute minimal height a peak has to be to be detected. Threshold is defined as the the relative vertical distance to the next peak. The minimal horizontal distance is samples between peaks is described by distance. Figure 1 provides a clear image of all the specific inputs.

2.4.4 Local Field Potentials

Currently, neurostimulators are able to detect LFP signals originated from the STN or the GPI. Medtronic's sensing technology allows for capture of LFP signals. These captured signals were then used for further analysis. Commonly, these signals are presented on a frequency scale ranging from 0 - 125 Hz. Additionally, this total frequency range is

divided into different frequency bands: delta 0 - 4, theta 4 - 7, alpha 8 - 12, beta 13 - 35 and gamma 35 - 250 Hz. [22] PD patients frequently show peaks in the beta range, where almost all patients show at least one peak in this range. [23] Therefore, the ROI will be in this beta range. Due to DBS systems stimulating at a certain frequency, which is frequently at 125 Hz, signal modulation is necessary.

Due to stimulation in high frequency range and the focus on beta activity a low pass filter and a high pass filter was used. For both filters a Butterworth filter was used. First the low pass filter was applied, where a 4^{rd} order Butterworth filter was applied. Due to the focus on beta range, the critical frequencies Wn = [13 - 30 Hz] are determined based on this range.

Initially, LFP data is captured during UPDRS tasks and is automatically plotted against time. From this LFP data the Power Spectral Density (PSD) (Appendix Figure 1A) will be calculated, using Welch averaging. [24] The signal was cut in 4 segments (Nperseg = len(y)/4), because some LFP signals are not that long depended on task. The sample frequency remains 250 Hz. Furthermore, a Hanning window has been applied, to minimise effects of frequency leakage. Finally, because it is a real signal, only positive frequencies are returned. However, the PSD will output onto the whole frequency spectrum. To get an outcome measure for only beta activity, the area under PSD within the frequency range of 13 - 30 Hz was calculated. This outputs the beta power per hemisphere, which is associated with motoric impairment in PD patients. Additionally, while beta power can differ considerably between patients also a normalisation for beta power per patient has been applied. Where beta power during activity was divided by beta power during rest task of that specific patient.

2.4.5 Gait parameter

To score motor impairments the UPDRS is used, this is also the golden standard for assessment of gait. This UPDRS looks at general parameters like bradykinesia to score gait impairment. However, gait can be characterised by many more spatial parameters and temporal parameter, for example stride length and arm-swing. Accordingly, a recent study shows a significant correlation between arm-swing and UPDRS scores. [25] In addition to correlation between arm-swing and UPDRS, this study will try to correlate arm-swing data with LFP data as well. Through analysis of video data combined with MMT extraction, estimates of arm-swing were created. This was done with the calculation of the Pixel Length. The following formula was used to calculate lengths between different body markers:

$$\textbf{\textit{Limb Length}} = \textit{Pixel Length} * \textit{Pixel Distance}$$

This formula was used to calculate the length between the elbow and the wrist, which are the most prominent parts involved in the arm swing.

Furthermore, to calculate speeds of important body markers the difference between either $x_{b(i)}$ or $y_{b(i)}$ coordinates per frame were calculated. Additionally, a moving average filter was used, due to high variability of body key points from frame to frame. A simple moving average filter was made, and then used with a window size of 3 frames. This relatively small window size was chosen, because the task size of gait is highly variable between patients. Thus, some patients have arrays that are not long enough to average over a larger size without creating more bias. This moving average filter allows for better observation of trends within the data. From this task analysis three parameters will be available for further examination. These compose of velocity, acceleration and jerk. Furthermore, for all these variables a mean will be calculated.

As with beta power, preferably one estimated measure will be present for arm-swing for allowance of correlation calculations. This estimated measure will be a smoothness factor. In addition to jerk as being a smoothness factor for movement. Fourier transforms will be performed on the velocity of the arm swings. With this Fourier transform the power of the movement will be calculated. Where

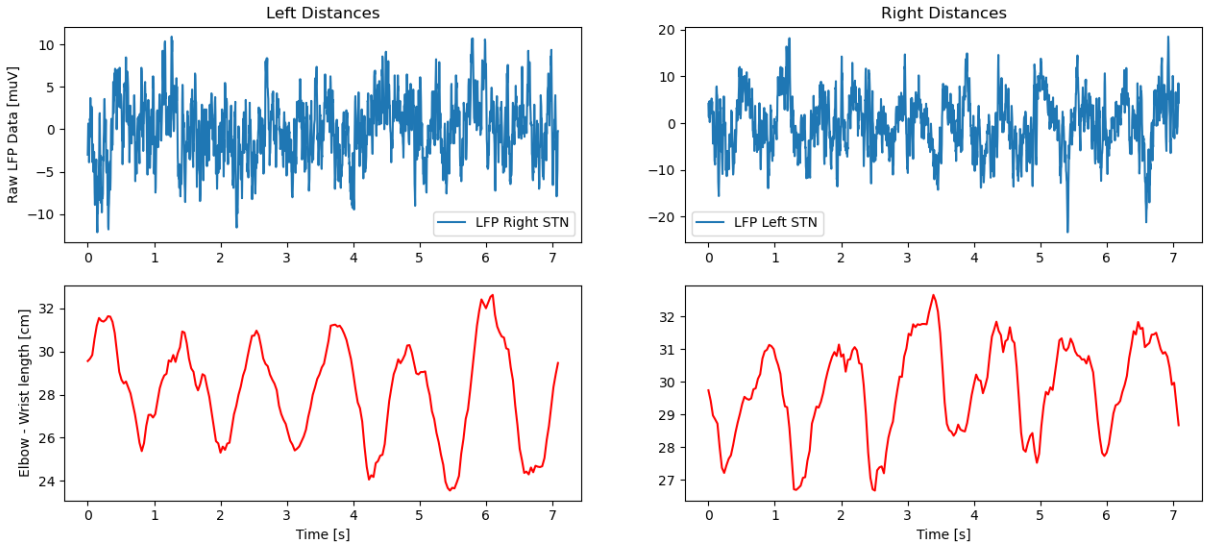

Figure 3: **LFP and arm-swing data during UPDRS Task:** Top: Raw left STN LFP data of a PD patient during Gait towards camera with on the y-axis LFP amplitude [muV]. Bottom: difference in distance [cm] between elbow and wrist marker, where distance between the elbow and wrist is on the y-axis and on the x-axis time [s].

movements with high smoothness will have high powers in the lower frequencies. While, sudden changes in movement will have more power in the higher frequencies.

2.5 Statistical Analysis

All statistical analysis are performed using Pycharm (Python version 3.13). Spearman's test was used for correlation of data, including correlation coefficient ρ and p values. P values > 0.05 were considered significant. Cross correlation was also performed to check whether movement artifact was based on neural delay, values were presented as correlation coefficient and max lag. Adjustments were made to correlate LFP data with gait data. Therefore, interpolation of data was applied, because Spearman and cross correlation does not allow for correlations between different size arrays. Correlations between multiple parameters have been done. First, LFP data was correlated with movement to check whether movement artifact was present. Second, all parameters extracted from the gait were correlated with beta power as well as normalised beta power. In order to see whether gait impairments are present in LFP data. Moreover, amplitude correlations with beta power were made, in order to check differences between amplitudes connected with beta power. A smoothness factor of the Fourier transform of velocity was correlated with beta power. To see whether smoother movements are present when beta power changes. Finally, UPDRS scores were correlated with the gait parameters, beta power and normalised beta power. As additional check, whether gait parameters have high influence on UPDRS scores.

3 Results

3.1 Sub Second Synchronisation

During most calculations only beta power is analysed, in association with parameters originating from gait. However, in some patients it is also possible to examine whether movement artifact is present in the LFP data. To analyse this a "sub second synchronisation" is necessary. This sub second synchronisation was made possible due to creating an artifact. This artifact had to be present in LFP data to synchronise it with available video data.

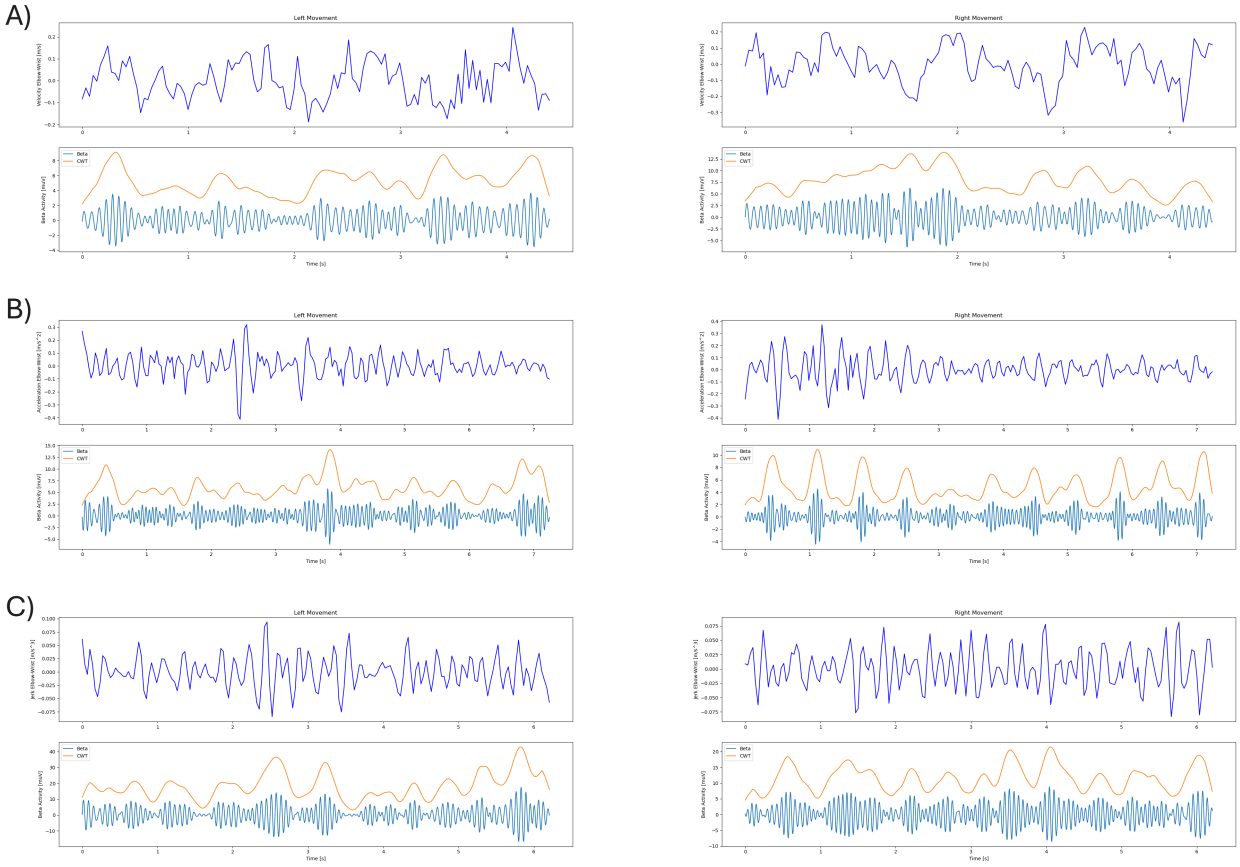

Figure 4: **Beta Activity during UPDRS gait task: A)** Top: Velocity of the left and right arm-swing (combined marker points elbow and wrist) defined by the difference in positions between different frames, where the y-axis indicates the velocity [m/s]. Bottom: Beta activity of the right and left STN of a PD patient UPDRS Score 0, during gait towards camera with on the y-axis the beta activity amplitude [muV] and on the x-axis time [s]. **B)** Top: Acceleration [m/s^2] of the left and right arm-swing. Bottom: Beta activity of the left and right STN of a PD patient with UPDRS Score 1. **C)** Top: Jerk [m/s^3] of the left and right arm-swing. Bottom: Beta activity of the left and right STN of a PD patient with UPDRS Score 2.

Processing needed to be done to detect these artifacts and to detect whether this artifact was present enough for sub second synchronisation. Only then correlation of LFP data with movement data was possible.

Figure 3 shows the velocity of the arm swing and the corresponding LFP data of a patient walking towards the camera with an UPDRS score of 0. In the second part of the figure the same task is performed, only the different hemisphere and arm are made visible. To see whether movement artifact was present in the LFP, correlations between the movement and the LFP data was made. Average results for both hemispheres indicate no movement artifacts were present in the data($\rho_l = -0.0235, p_l = 0.509$) & ($\rho_r = 0.0303, p_r = 0.429$). However, individual correlations do show significant values in one of the hemispheres. Only one visit shows significance in both hemisphere during one visit, thus meaning movement artifact. Furthermore, cross correlation for these visits have been performed. With no visit showing movement artifact caused by physiological neural conduction of the brain nerves to the muscles. Data with movement artifact from this one visit is excluded for further analysis. An overview of individual correlations and cross correlations can be found in Appendix Table 1A and Appendix Table 2A respectively.

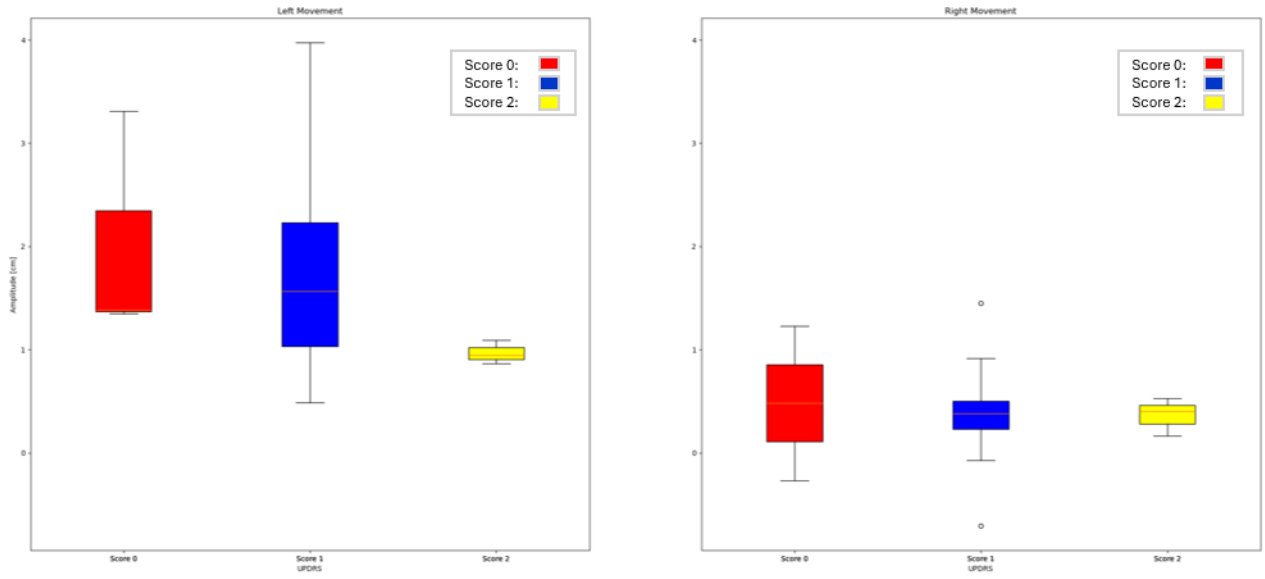

Figure 5: **Amplitude Boxplots of different UPDRS Scores:** Left: Boxplots of all the different UPDRS scores, with on the y-axis the difference in amplitude [cm] of the left arm-swing. The x-axis shows the different scores. With score 0 indicated with red, score 1 indicated with blue and score 2 with yellow. Right: Identical description only observed for right movement.

3.2 Gait Parameters

3.2.1 Distance Derivatives

The arm-swing was examined with multiple parameters, starting with the velocity parameter. While this data contains gait, data of both hemispheres and both body parts will be analysed. Figure 4A shows an example of velocity during the gait task, while walking towards the camera. This patient had an UPDRS score of 0. Additionally, at the bottom of figure 4A a visualisation of the beta activity over the associated task is shown. Analysis of beta power with velocity in both hemispheres, show for the right hemisphere a low correlation with beta power ($\rho = -0.133, p = 0.475$). However, the other hemisphere does show significant correlation ($\rho = -0.403, p = 0.024$).

The derivative of velocity was then taken to see whether acceleration also shows correlation with beta power. Figure 4B illustrates acceleration of the arm-swing of a patient performing the gait task, while the beta activity is shown simultaneously. This patient had an UPDRS score of 1. Similar, as with velocity, acceleration of arm-swing decreases as beta power increases. Again, the left hemisphere however shows a highly negative correlation ($\rho = -0.510, p = 0.003$).

Table 1: Table with Spearman's correlation coefficients between Beta Power and Gait Parameters.

	Beta Power			
	Left Movement		Right Movement	
	ρ	p value	ρ	p value
Velocity	-0.133	0.475	-0.403	0.024
Acceleration	-0.122	0.514	-0.510	0.003
Jerk	-0.248	0.178	-0.518	0.003

Finally, figure 4C shows the jerk of a patient performing the gait task, with beta activity at the bottom. Furthermore, this patient had an UPDRS score of 2. The same trend is observed for jerk where the left hemisphere shows the highest negative correlation. So, the most significant result is seen in the left hemisphere regarding the jerk ($\rho = -0.518, p = 0.003$). An overview of all values is provided in Table 1.

After normalising the beta power the values regarding the right hemisphere does not become significant. However, right hemisphere p values show a

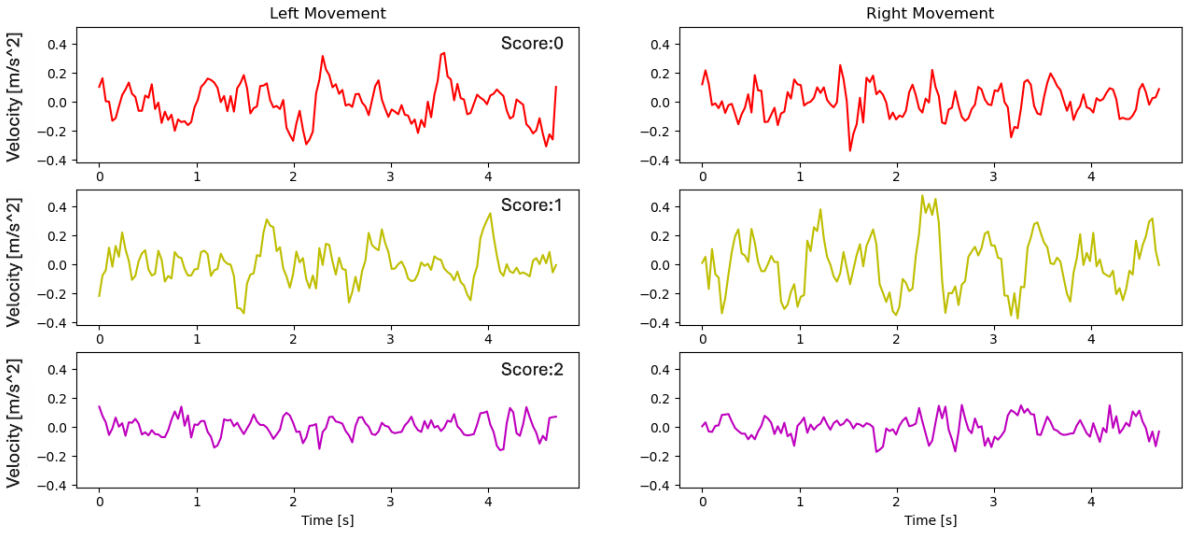

Figure 6: **All present UPDRS scores:** Velocity of the left and right arm-swing of all the combined marker points (elbow and wrist) defined by the difference in position between different frames. Where the y-axis indicates the velocity [m/s] and the x-axis time [s]

Table 2: Table with Spearman's correlation coefficients between Normalised Beta Power and Gait Parameters.

	Normalised Beta Power			
	Left Movement		Right Movement	
	ρ	p value	ρ	p value
Velocity	-0.219	0.237	-0.394	0.028
Acceleration	-0.177	0.342	-0.457	0.010
Jerk	-0.315	0.085	-0.450	0.011

Table 3: Table with Spearman's correlation coefficients between Amplitude Differences, Beta Power and Normalised Beta Power.

	Amplitude Difference			
	Left Movement		Right Movement	
	ρ	p value	ρ	p value
Beta Power	-0.137	0.486	0.251	0.197
Normalised Beta Power	-0.173	0.379	0.414	0.028

relatively high decrease. Despite an increase in all p values for the left hemisphere, influence from the normalisation is minimal. As seen in Table 2, only a small increase in correlation is observed. Nonetheless, left hemisphere p values are still highly significant.

3.2.2 Amplitude calculation

With use of the find peaks function (See Figure 1), amplitudes where found and calculated. Figure 5 shows boxplots for both hemispheres with the differences in arm swing amplitudes between the various UPDRS scores. Out of all the calculated peaks and troughs a mean amplitude for both left and right were calculated. This was both based on the normalised distance between the elbow and the wrist (representing the arm-swing). Both hemispheres do not show a very strong correlation, in addition to being opposite. Respectively, the right hemisphere shows the more reasonable relationship, compared to the left one. Normalised beta power shows for the right hemisphere still a negative, but stronger correlation. Whereas, the left hemisphere shows a significant positive correlation ($\rho = 0.414, p = 0.028$). Table 3 shows an overview of all statistics.

3.2.3 Smoothness factor

When Fourier transforming the velocity into frequency content, the power will be divided over all frequencies. If a lot of power is present in the

Table 4: Table with Spearman's correlation coefficients between Smoothness Factor, Beta Power and Normalised Beta Power.

	Smoothness			
	Left Movement		Right Movement	
	ρ	p value	ρ	p value
Beta Power	-0.278	0.153	-0.274	0.158
Normalised Beta Power	-0.460	0.013	-0.145	0.461

higher frequencies, sudden movements are present. Due to this velocity being a real signal only positive frequencies are considered in this analysis, because the signal is conjugate symmetric. Both hemispheres do give negative correlation as well, however again no significant results. Right hemisphere show very similar results compared with left hemisphere. After normalisation the same negative trend is observed. With right hemisphere p values becoming significant ($\rho = -0.460, p = 0.013$), while left hemisphere p values decrease even further, as shown in Table 4.

3.3 UPDRS

UPDRS scores are the golden standard when assessing symptom severity. Therefore, comparison are made between the gait parameters and this golden standard the UPDRS. Figure 6 shows the velocity of the arm-swing of three different patients while performing the gait task of the UDPRS. As with beta power, correlations between both hemispheres and all three derivatives are made. Not all values are significant with the UPDRS. Yet, all show the same trend and are almost significant. Right hemisphere gives the lowest correlation compared to the left ($\rho_{vel} = -0.445, p_{vel} = 0.029$) with only one significant result for velocity. However, beta power as well as normalised hemisphere show the highest correlation for right hemisphere. Similarly, the left hemisphere also shows a negative trend, but one that is stronger($\rho_{vel} = -0.530, p_{vel} = 0.008$), ($\rho_{acc} = -0.470, p_{acc} = 0.021$) & ($\rho_{jerk} = -0.517, p_{jerk} = 0.010$). With all gait parameters showing significant correlations. All remaining statistics are presented in Table 3.

Table 5: Table with Spearman's correlation coefficients between UPDRS, Gait Parameters Beta Power and Normalised Beta Power.

	UPDRS			
	Left movement		Right movement	
	ρ	p value	ρ	p value
Velocity	-0.445	0.029	-0.530	0.008
Acceleration	-0.289	0.171	-0.470	0.021
Jerk	-0.289	0.171	-0.518	0.010
Beta Power	0.494	0.014	0.193	0.367
Normalised Beta Power	0.361	0.083	0.205	0.337

4 Discussion

In this study, relationships between STN LFP data and real time video data of PD patients is investigated. A relationship between the two was observed, only one hemisphere showed a compelling result. All gait parameters from the right hemisphere do not show significance, except for the normalised beta power in smoothness which also shows significance. However, a negative correlation is seen in all parameters. By contrast, results from the left hemisphere do present as impactfull. This could be caused by the low amount of data present in this study, which sequentially causes higher p-values. Thus, this does mean that a strong relationship is present between the left hemisphere and the gait parameters. Frequently, PD patients have a irregular gait pattern. [26] One possible explanation for the results in the left hemisphere is hand domination. Most people are right handed [27], so it is reasonable to assume posture dis balance will sway to the dominant side. Therefore, creating less swing at the right side of the body. Changes in beta power do occur in the contralateral side of the body, possibly explaining the observed results. [28]

Amplitudes were calculated based on the find peaks function. However, in some patients very high peaks or very high troughs were found in the data. These could be present due to failure of MMT programs tracking properly, creating unrealistic datapoints. Which then could cause biased results for the gait parameters, and thus also biased correlations. It is difficult to solve this problem, while filling in these values based on previous pattern seems

a plausible option. However, this will also create unrealistic results, because the pattern in some cases is not smooth and this algorithm will try to create smooth patterns. Therefore, results will again become biased. Additionally, in some patients the MMT program was not able to track any points, possibly because of the disappearance of points behind other body parts. Meaning, missing data and again creating biased data. Therefore, this analysis could also give contrary results, with one giving a positive correlation and the other hemisphere giving a negative correlation. Furthermore, normalising the data means removing outliers in the data, which contributes to the amplitudes correlations to be stronger. However, the above mentioned bias still exists. Additionally, movement artifact undetected can still cause the value to become significant.

In addition to jerk an extra smoothing factor was examined, this is based on how power is divided in the frequency spectrum. This method has been used by Chidean et al,. and shows to work properly. Although, patients were not diagnosed with PD, gait was assessed using this method. [29] Similarly, the amount of data for this analysis is on the low side even lower than for other analysis. The observed trend tends to also having relationship with beta power. Where smoother movements indicate a better arm-swing and therefore lower beta power. However, after normalisation one becomes significant, while the other decreases in p value. Possibly, as a result of the aforementioned removing of outliers.

Comparisons between UPDRS and the gait parameters are made, while it serves as control on whether these parameters also correlate with the golden standard. Neurologists determine gait UPDRS score based on numerous factors, including: postural instability, insufficient stride length and reduced or absent arm-swing. [25, 30] This was done to determine whether this parameter could be one of the key elements in assessment of gait abnormalities. Results indicate that arm-swing is one of those high contributing elements. Although, not every parameter has the same impact, all parameters are almost or are significant. Despite the amount of data present in this study. An additional check between beta power and UPDRS was also made. This is consistent with previous research. As higher beta peaks are frequently observed in higher UPDRS scores. [31]

When capturing LFP data, there is a possibility data is contaminated with artifact. Two different types of artifact are occasionally present in LFP data: ECG artifact and movement artifact. [14] Movement artifact will be present as very high peak in LFP data, while ECG artifact presents as a rhythmic pattern with preliminary peaks that exceed the normal LFP patterns. In addition to visual inspection of movement artifact, correlations between raw LFP data and arm-swing data were done. Contrary results were found were one indicate a positive correlation, the other hemisphere shows a negative correlation. Furthermore, both values are relatively small. Based on this general result, it seems that there is no general correlation between the arm-swing and raw LFP data. This implies that no peak in LFP data originated from movements during the gait. However, when looking at individual relationships, it is seen that some patients do have movement artifact present. In most cases, this occurs in only one hemisphere. Therefore, no exclusion of these patients have been performed. Only one patient showed correlation for both hemispheres and is therefore excluded for further analysis. Likewise, the data is visually checked for ECG artifacts, where no apparent ECG artifacts were present. However, some ECG artifacts can still be present that have gone unnoticed. Currently, there are multiple studies that introduced methods to find and filter these ECG artifacts. [14, 32, 33] Applying these method to this study would improve quality. Therefore, it is recommended that during future studies this filtering should be applied.

Also, this study includes PD patients. Presence of symptoms are commonly described as ”ON” or ”OFF”. [34, 35] Although patients were asked before every visit they categorised themselves as either ON or OFF, during data analysis no distinction was made between those patients. In addition to applying a ECG filter, future research should include patient states as well. Preferably, increase sample

size, while examining other parameters from other UPDRS tasks. Finally, it could be interesting to assess whether other frequency bands have similar relationships with gait parameters.

5 Conclusion

In this study STN LFP data of PD patients implanted with a DBS device and gait parameters have been assessed. Results suggest definitive connections between beta power and arm-swing parameters. Although, not all parameters show significance a negative trend is observed for almost all parameters. Additionally, it confirms the importance of arm-swing assessment, when evaluating gait severity. This study also suggests that more parameters from different tasks could potentially correlate with LFP data. This could be explored in future research. In the far future, some parameters could potentially be used as input for adaptive DBS. A change in parameters captured by video data would then initiate a change DBS settings. So, patients are less affected by negative symptoms regarding PD.

6 Acknowledgements

The author wants to thank the supervisors: Mark van de Ruit, Martijn Beudel and Deborah Hubers, for the supervision and reviewing results. Futhermore, also thanks to everyone from the department of neurology, who aided during the process. General thanks to the Amsterdam UMC for allowance of a project at the institution and for the TU Delft for permission of the project.

References

[1] Daphne G M Zwartjes, Tjitske Heida, Jeroen P P Van Vugt, Jan A G Geelen, and Peter H Veltink. Ambulatory monitoring of activities and motor symptoms in Parkinsons disease. *IEEE Transactions on Biomedical Engineering*, 57(11):2778 – 2786, 2010.

[2] Ahmed A. Moustafa, Srinivasa Chakravarthy, Joseph R. Phillips, Ankur Gupta, Szabolcs Keri, Bertalan Polner, Michael J. Frank, and Marjan Jahanshahi. Motor symptoms in Parkinson's disease: A unified framework, 9 2016.

[3] Andrew J. Lees, John Hardy, and Tamas Revesz. Parkinson's disease, 2009.

[4] Ronald F. Pfeiffer. Non-motor symptoms in Parkinson's disease. *Parkinsonism and Related Disorders*, 22:S119–S122, 1 2016.

[5] Ariane Park and Mark Stacy. Non-motor symptoms in Parkinson's disease. In *Journal of Neurology*, volume 256, 8 2009.

[6] Christopher C. Goetz. The Unified Parkinson's Disease Rating Scale (UPDRS): Status and recommendations, 7 2003.

[7] Christopher G. Goetz and et al. Movement Disorder Society-Sponsored Revision of the Unified Parkinson's Disease Rating Scale (MDS-UPDRS): Scale presentation and clinimetric testing results. *Movement Disorders*, 23(15):2129–2170, 11 2008.

[8] Nobuyasu Nakano, Tetsuro Sakura, Kazuhiro Ueda, Leon Omura, Arata Kimura, Yoichi Iino, Senshi Fukashiro, and Shinsuke Yoshioka. Evaluation of 3D Markerless Motion Capture Accuracy Using OpenPose With Multiple Video Cameras. *Frontiers in Sports and Active Living*, 2, 5 2020.

[9] Martin Sandau, Henrik Koblauch, Thomas B. Moeslund, Henrik Aanæs, Tine Alkjær, and Erik B. Simonsen. Markerless motion capture can provide reliable 3D gait kinematics in the sagittal and frontal plane. *Medical Engineering and Physics*, 36(9):1168–1175, 2014.

[10] Melissa J. Armstrong and Michael S. Okun. Diagnosis and Treatment of Parkinson Disease: A Review, 2 2020.

[11] The New Eng land Jour nal of Medicine DEEP-BRAIN STIMULATION OF THE SUBTHALAMIC NUCLEUS OR THE PARS INTERNA OF THE GLOBUS PALLIDUS IN PARKINSON'S DISEASE A BSTRACT Background Increased neuronal activity in the sub. Technical report, 2001.

[12] Bart E.K.S. Swinnen, Arthur W. Buijink, Dan Piña-Fuentes, Rob M.A. de Bie, and Martijn Beudel. Diving into the subcortex: The potential of chronic subcortical sensing for unravelling basal ganglia function and optimization of deep brain stimulation. *NeuroImage*, 254, 7 2022.

[13] Oscar Herreras. Local field potentials: Myths and misunderstandings. *Frontiers in Neural Circuits*, 10(DEC), 12 2016.

[14] M. J. Stam, B. C.M. van Wijk, P. Sharma, M. Beudel, D. A. Piña-Fuentes, R. M.A. de Bie, P. R. Schuurman, W. J. Neumann, and A. W.G. Buijink. A comparison of methods to suppress electrocardiographic artifacts in local field potential recordings. *Clinical Neurophysiology*, 146:147–161, 2 2023.

[15] Martijn Beudel, Ashwini Oswal, Ashwani Jha, Thomas Foltynie, Ludvic Zrinzo, Marwan Hariz, Patricia Limousin, and Vladimir Litvak. Oscillatory Beta Power Correlates With Akinesia-Rigidity in the Parkinsonian Subthalamic Nucleus, 1 2017.

[16] Lucia K. Feldmann, Wolf Julian Neumann, Patricia Krause, Roxanne Lofredi, Gerd Helge Schneider, and Andrea A. Kühn. Subthalamic beta band suppression reflects effective neuromodulation in chronic recordings. *European Journal of Neurology*, 28(7):2372–2377, 7 2021.

[17] Medtronic, Percept™ PC Neurostimulator with BrainSense™ Technology.

[18] Kelvin L. Chou, Mark Stacy, Tanya Simuni, Janis Miyasaki, Wolfgang H. Oertel, Kapil Sethi, Hubert H. Fernandez, and Fabrizio Stocchi. The spectrum of "off" in Parkinson's disease: What have we learned over 40 years?, 6 2018.

[19] Zhe Cao, Gines Hidalgo, Tomas Simon, Shih-En Wei, and Yaser Sheikh. OpenPose: Realtime Multi-Person 2D Pose Estimation using Part Affinity Fields. 12 2018.

[20] Gareth Morinan, Yuriy Dushin, Grzegorz Sarapata, Samuel Rupprechter, Yuwei Peng, Christine Girges, Maricel Salazar, Catherine Milabo, Krista Sibley, Thomas Foltynie, Ioana Cociasu, Lucia Ricciardi, Fahd Baig, Francesca Morgante, Louise-Ann Leyland, Rimona S Weil, and ee Gilron. Computer vision quantification of whole-body Parkinsonian bradykinesia using a large multi-site population. Technical report.

[21] Christoph Heidt, ; Thomas Angst, Philippe Büchler, ; Carol-Claudius Hasler, ; And, and Daniel Studer. Traditional T1-S1 Measurement of the Spinal Length on X-ray Images Does Not Correlate With the True Length of the Spine. Technical Report 5, 2022.

[22] Zixiao Yin, Guanyu Zhu, Baotian Zhao, Yutong Bai, Yin Jiang, Wolf Julian Neumann, Andrea A. Kühn, and Jianguo Zhang. Local field potentials in Parkinson's disease: A frequency-based review, 7 2021.

[23] Natasha Darcy, Roxanne Lofredi, Bassam Al-Fatly, Wolf Julian Neumann, Julius Hübl, Christof Brücke, Patricia Krause, Gerd Helge Schneider, and Andrea Kühn. Spectral and spatial distribution of subthalamic beta peak activity in Parkinson's disease patients. *Experimental Neurology*, 356, 10 2022.

[24] Peter D Welch. The Use of Fast Fourier Transform for the Estimation of Power Spectra: A Method Based on Time Aver. aging Over Short, Modified Periodograms Ik(fn) =-I A h (%) [a k. Technical Report 2, 1967.

[25] S Rupprechter, G Morinan, Y Peng, T Foltynie, K Sibley, R S Weil, L A Leyland, F Baig, F Morgante, R Gilron, R Wilt, P Starr, R A Hauser, and J O'Keeffe. A Clinically Interpretable Computer-Vision Based Method for Quantifying Gait in Parkinson's Disease. *Sensors (Basel)*, 21(16), 2021.

[26] Fay B. Horak and Martina Mancini. Objective biomarkers of balance and gait for Parkinson's disease using body-worn sensors, 9 2013.

[27] Marietta Papadatou-Pastou, Eleni Ntolka, Judith Schmitz, Maryanne Martin, Marcus R. Munafò, Sebastian Ocklenburg, and Silvia Paracchini. Human handedness: A meta-analysis. *Psychological Bulletin*, 146(6):481–524, 6 2020.

[28] Adrian G. Fischer, Roland Nigbur, Tilmann A. Klein, Claudia Danielmeier, and Markus Ullsperger. Cortical beta power reflects decision dynamics and uncovers multiple facets of post-error adaptation. *Nature Communications*, 9(1), 12 2018.

[29] Mihaela I. Chidean, Óscar Barquero-Pérez, Rebeca Goya-Esteban, Alberto Sánchez Sixto, Blanca de la Cruz Torres, Jose Naranjo Orellana, Elena Sarabia Cachadiña, and Antonio J. Caamaño. Full band spectra analysis of gait acceleration signals for peripheral arterial disease patients. *Frontiers in Physiology*, 9(AUG), 8 2018.

[30] Jeffrey M. Hausdorff. Gait dynamics in Parkinson's disease: Common and distinct behavior among stride length, gait variability, and fractal-like scaling. *Chaos*, 19(2), 2009.

[31] Wolf Julian Neumann, Franziska Staub-Bartelt, Andreas Horn, Julia Schanda, Gerd Helge Schneider, Peter Brown, and Andrea A. Kühn. Long term correlation of subthalamic beta band activity with motor impairment in patients with Parkinson's disease. *Clinical Neurophysiology*, 128(11):2286–2291, 11 2017.

[32] Yue Chen, Bozhi Ma, Hongwei Hao, and Luming Li. Removal of Electrocardiogram Artifacts From Local Field Potentials Recorded by Sensing-Enabled Neurostimulator. *Frontiers in Neuroscience*, 15, 4 2021.

[33] Jiayuan He, Botao Xiong, Qigang Ran, Tao Zhang, Wei Wang, Wei Zhang, and Ning Jiang. Variation Minimization Based Electrocardiogram Artifacts Removal for Local Field Potentials from Neurostimulator. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, 32:94–101, 2024.

[34] C D Marsden and J D Parkes. "ON-OFF" EFFECTS IN PATIENTS WITH PARKINSON'S DISEASE ON CHRONIC LEVODOPA THERAPY Summary Fluctuations in performance in patients. Technical report.

[35] R J Hardie, A J Lees, and G M Stern. ON-OFF FLUCTUATIONS IN PARKINSON'S DISEASE A CLINICAL AND NEUROPHARMACOLOGICAL STUDY 1. Technical report, 1984.

7 Appendix

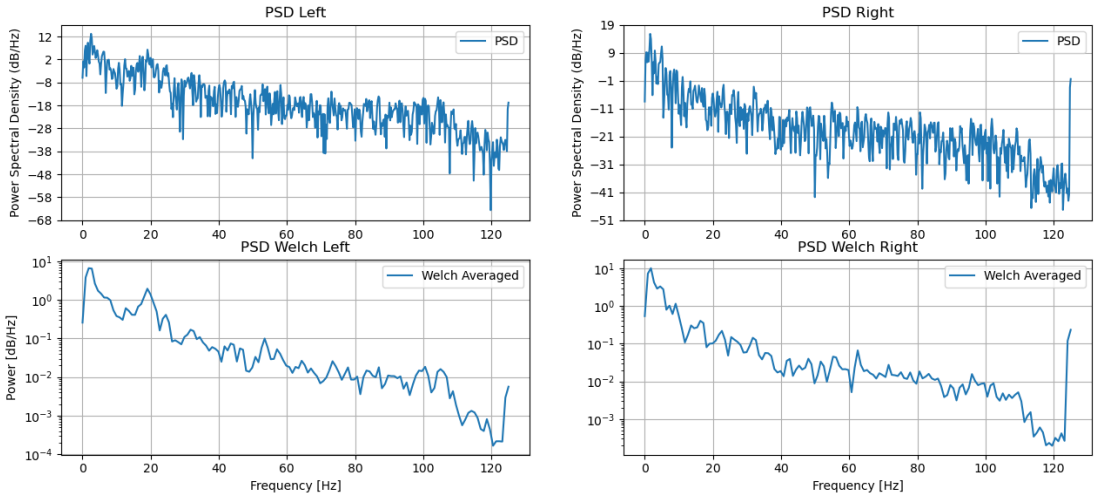

Figure 1A: **Power Spectral Density:** Top: Raw PSD from a Visits LFP signal during the gait task. On the y-axis the power [dB/Hz] is displayed, while the x-axis displays frequency [Hz]. Bottom: Welch averaged PSD of the same Visit (Nperseg = len(y)/4, window = Hanning, Wn = [13-30]).

Table 1A: Table with Spearman's correlation coefficients between Arm Swing and raw LFP data, from multiple visits of multiple patients.

	Left Movement		Right Movement	
	Correlation	P- value	Correlation	P-value
Visit 1	-0.106	0.127	0.016	0.815
Visit 2	-0.043	0.602	-0.011	0.888
Visit 3	-0.058	0.436	0.087	0.240
Visit 4	0.155	0.023	0.049	0.472
Visit 5	0.013	0.873	-0.009	0.914
Visit 6	0.176	0.029	-0.173	0.031
Visit 7	0.126	0.065	-0.020	0.764
Visit 8	0.044	0.620	-0.102	0.255
Visit 9	-0.018	0.819	-0.047	0.562
Visit 10	0.036	0.583	-0.019	0.778
Visit 11	-0.072	0.362	-0.105	0.185
Visit 12	0.229	0.001	0.096	0.253
Visit 13	-0.136	0.080	-0.002	0.978
Visit 14	0.127	0.141	-0.280	0.001
Visit 15	0.002	0.980	0.113	0.152
Visit 16	0.024	0.696	0.032	0.607
Visit 17	0.014	0.851	-0.023	0.760
Total n = 17	Avg corr = 0.030	Avg p-value = 0.127	Avg corr = -0.023	Avg p-value = 0.509

Table 2A: Table with cross correlation coefficients between Arm Swing and raw LFP data, from multiple visits of multiple patients.

	Left Movement		Right Movement	
	Max Cross Correlation	Max Lag [s]	Max Cross Correlation	Max Lag [s]
Visit 1	0.039	1.14	0.042	3.79
Visit 2	0.058	3.47	0.045	1.25
Visit 3	0.061	0.248	0.051	-0.11
Visit 4	0.070	3.05	0.049	2.21
Visit 5	0.064	3.91	0.065	3.05
Visit 6	0.072	0.384	0.053	1.66
Visit 7	0.060	-0.368	0.037	3.17
Visit 8	0.059	1.36	0.085	1.94
Visit 9	0.056	1.44	0.074	4.19
Visit 10	0.039	5.06	0.050	3.61
Visit 11	0.054	4.43	0.060	4.64
Visit 12	0.071	0.40	0.048	3.19
Visit 13	0.052	5.32	0.057	1.00
Visit 14	0.055	3.82	0.048	4.04
Visit 15	NaN	-0.66	NaN	-0.66
Visit 16	NaN	-1.05	NaN	-1.05
Visit 17	NaN	-0.70	NaN	-0.70