Processing and synchronization of biomechanical data from wearable sensors from Parkinson's disease patients at home for detection of Freezing of gait

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Introduction

Parkinson's disease (PD) is a neurodegenerative disease which results in problems with motor control and can manifest in different forms. It is caused by cell death in the substantia nigra which is part of the basal ganglia and is responsible for triggering the initiation of voluntary movements [1]. Examples of the symptoms are freezing of gait (FOG), bradykinesia (slow movement), shuffling, tremors and postural instability. However PD does not only result in problems in motor control, it can also cause autonomic dysfunction, impair vision or cause mental issues such as depression or anxiety. This paper will focus mainly on FOG. [2] FOG consists of episodes where the patient cannot move and can happen when initiating a movement but is also possible when nearing obstacles, narrow spaces or when turning around [3]. Different treatments for FOG already exist such as Levodopa which decreases the frequency of freezing episodes [4]. However another form of treatment exists called external cueing which tries to initiate movement after a FOG episode by using auditory, visual or somatosensory cues. Examples of visual cues are lasers pointed at the floor or specific patterns. An example of an auditory cue is a metronome and a somatosensory cue could be vibrating insoles. The mechanisms of external cueing are not yet known but it helps PD patients to initiate movement again in case of a FOG episode. In order to effectively use cueing as a treatment it is necessary to be able to accurately detect or even predict FOG so that the cues can be applied at the correct moment. [5]

Research about detection of FOG in PD patients has already been conducted in the past using different methods. For example Mazilu et al (2012) [6] have used Machine Learning while Delval et al (2010) [7] used Fourier transforms. These studies have succeeded in detecting FOG but are often conducted with a low sample size and in a clinical environment [8]. The gait analysis can be split into two types: qualitative and quantitative. Qualitative methods consist of scales such as the mini-BESTest [9] and MDS-UPDRS [10] to get an indication of the severity of PD and also the patient's quality of life. The mini-BESTest contains various tasks such as standing on one leg or walking while turning their heads, MDS-UPDRS contains similar tasks, but also a questionnaire. Quantitative methods use sensors to analyze the gait and detect FOG episodes. The quantitative methods can be split into laboratory based gait analysis and non laboratory based gait analysis. The former can use video and motion capture to detect FOG while the latter can only use wearable sensors such as Inertial Measurement Units (IMU), smartwatches and/or insoles. One of the downsides of laboratory based gait analysis is that the environment influences the frequency and intensity of FOG episodes. Many patients have more FOG episodes while at home than in a laboratory [11]. This is likely due to distractions or because they are paying less attention to walking while at home. This is where non laboratory based gait analysis is better because it uses small wearable sensors which allows the researchers to gather data while the patient is at home over a longer period of time. This does come with the downside that the researchers do not know what is actually happening and can only look at the data afterwards. [12]

Research about detection of FOG in PD patients has also been conducted on the University of Twente by J. Delgado-Terán. The goal of this research is to detect FOG in order to provide care using external cueing. For this research data was recorded on campus and at home. This paper reports the processing and synchronization of the home data using Python so that it can be used for analysis in future research.

Methods

In the research conducted by J. Delgado-Terán 22 patients were equipped with an IMU (Movisens), smartwatch (Empatica), phone (Android) and insoles (Moticon), see Figure 1 for the exact locations. These sensors measure the gait using accelerometers, gyroscopes and angular rate sensors but can also measure the temperature, skin conductance and heart rate. The patients were instructed to do various tasks which they would also do at home such as making breakfast, brushing teeth, making their bed but also tasks from the mini-BESTest and MDS-UPDRS. These tests were conducted in a dedicated test environment on the campus of University of Twente but the patients also had to take the sensors home for a week in order to gather more data. The sensors would have to be turned on when they woke up, synchronized according to protocol and would be turned off when going to sleep.
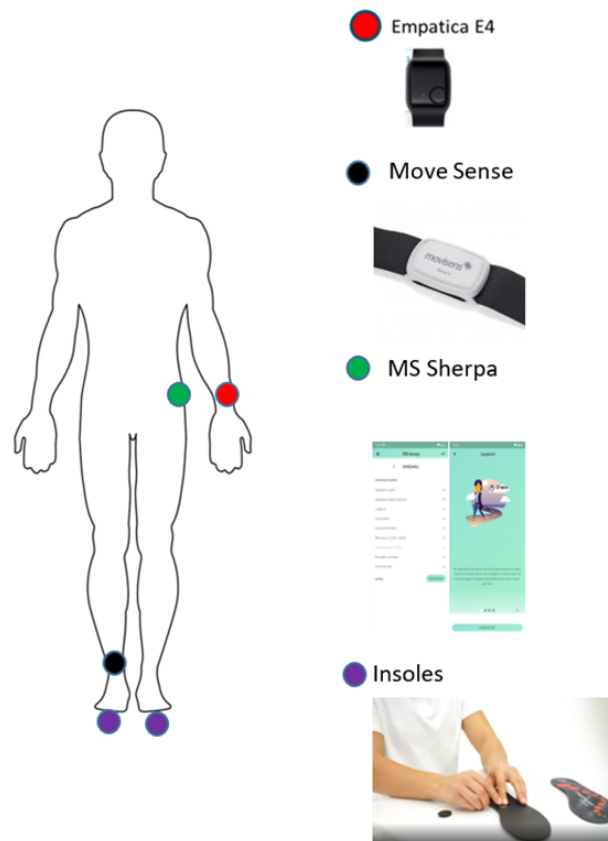

Figure 1: Location of the sensors for the at home measurements

In order to be able to analyse the data a number of pre-processing steps have to be performed, see also Figure 2 for the pipeline:

- The original data is stored in CSV files but this was converted to the H5 format by J. Delgado-Terán. The H5 files are more efficient and can handle the big the datasets with more ease than CSV files. The original structure of the data in the H5 files is that each file contains all data from one sensor for the entire week. This data must first be separated and sorted so that each file contains the data of all sensors for one day only, this will make analysis later on easier because then only one file has to be loaded to get the minimum required data.

- All data is raw unfiltered data. The data must be filtered in order to get rid of disturbances such as noise from the power grid or the static gain while preserving data about the activity of the patients.

- All sensors used in this study have a different sampling frequency. The data must be resampled in order to synchronize.

- The patients start each day by putting all sensors in a case which they have to rotate according to a specific protocol. This allows the sensors to be synchronized later on, because all sensors contain an accelerometer. Many exceptions here are possible because sometimes patients did not follow the protocol strictly or forgot to turn on a sensor. These must be dealt with accordingly in order to still gain information from the data. The reason why synchronized data is important is because it allows the data from different sensors to be combined to determine what exactly was happening during a FOG episode. This helps finding relations between the different physiological features during a FOG episode.

- The final step is to counter sensor time drift. Sensor time drift refers to two sensors slowly drifting out of synchronization due to differences in consistency of timing between samples. This error will build up over time after which synchronization must be performed again. This drift is significant enough to do the synchronization again at least once a day. However the rotation is only performed at the start of the day. This means that a different way of synchronization must be found.
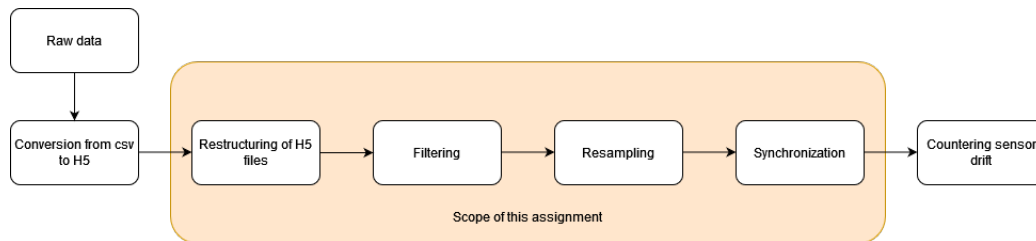

Figure 2: Processing pipeline

Sorting and separation

The data in the H5 files contained all data from one sensor of one patient. This means that one file contained all the data for a recording of one week for one sensor. This was separated so that each H5 file contains all the data for one day for one patient. This new structure means that one file contains multiple datasets, one for each sensor. This separation was done to make the analysis in the future easier. The separation of data had a few challenges. Some datasets did not contain unix timestamps for each sample but only a start time. This start time was not always present in the dataset and sometimes had to be fetched from a different file. Then this start time had to be extrapolated with the sampling frequency in order to connect a timestamp to each sample. Another problem was the file format. The original data was stored in CSV but then converted

to H5 by J. Delgado-Terán because it can better handle the big datasets. However H5 files can only store one datatype, in this case a float. This means that the conversion of unix to datetime object cannot be stored and also data from the Moticon about whether the sample belonged to the left or right insole was lost. The solution to the datetime problem was to only store the day in the H5 file and for the Moticon to convert left and right data to 0 and 1 before converting to H5. After this was done the filtering could begin.

Filtering

The first step in processing is filtering. It is important to note that each different measurement needs its own filter. For example the Empatica's blood volume pulse (BVP) has a different characteristic frequency than walking so a filter for walking could suppress the useful data of a BVP measurement. Literature research was done in order to find out what filters were used in previous studies, see Table 1, third column for references. The cutoff frequencies, type of filter and order were noted and used as starting point for the filters. The power spectral density (PSD) was then used to verify the effect of the filters and tune them accordingly based on the characteristic frequencies of the measurement. The resulting filters can be seen in Table 1.
For all accelerometers, gyroscopes and angular rate sensors it was decided to use one filter design for simplification. This filter must filter out the constant gain, mainly gravity, while also filtering out high frequency noise. For this filter it is important that the characteristic frequencies of human movement (0.5-3Hz) and PD symptoms (3-8Hz) remained [13]. The BVP depends on the heart rate so the frequencies of interest will be within the range of a human heart rate. For the Empatica heart rate a Kalman filter [14] was considered, because it can accurately estimate and predict the actual value, but the data itself was already accurate so a filter was not needed and designing a Kalman filter involves creating a model of the system which is out of the scope of the assignment. Another filter that was considered is the Savitzky-Golay filter [15] but did not provide better data than a low pass filter. The same applies to the Empatica and Moticon temperature. In order to still filter the Empatica and Moticon temperature a low pass filter was used instead. A low pass filter was not applied to the Empatica heart rate due to the low sampling frequency of 1 Hz. All applied filters are zero-lag because of the reduced delay compared to non zero-lag filters [16]. This is necessary because the timing of the movement of PD patients is important for future analysis.

Sensor	Position	Filter	Sampling frequency (Hz)
Android accelerometer	Pelvis	0.5 Hz high-pass Butterworth 4th order & 10 Hz low-pass Butterworth 4th order [17], [18] [19]	100
Android Gyroscope	Pelvis	0.5 Hz high-pass Butterworth 4th order & 10 Hz low-pass Butterworth 4th order [20]	100
Empatica accelerometer	Wrist	0.5 Hz high-pass Butterworth 4th order & 10 Hz low-pass Butterworth 4th order [21]	32
Empatica BVP	Wrist	0.5 Hz high-pass Chebyshev 2 4th order & 5 Hz low-pass Chebyshev 2 4th order [22]	64
Empatica EDA	Wrist	1 Hz low-pass Butterworth 4th order [23], [24]	4
Empatica temperature	Wrist	1 Hz low-pass Butterworth 4th order	4
Moticon accelerometer	Feet	0.5 Hz high-pass Butterworth 4th order & 10 Hz low-pass Butterworth 4th order [13]	50/100 [1]
Moticon centre of pressure	Feet	15Hz low-pass Butterworth 2nd order [25]	50/100
Moticon angular rate	Feet	0.5 Hz high-pass Butterworth 4th order & 10 Hz low-pass Butterworth 4th order [13]	50/100
Moticon total force	Feet	15 Hz low-pass butterworth 2nd order [26]	50/100
Moticon temperature	Feet	1 Hz low-pass Butterworth 4th order	50/100
Movisens accelerometer	Ankle	0.5 Hz high-pass Butterworth 4th order & 10 Hz low-pass Butterworth 4th order [13]	64
Movisens angular rate	Ankle	0.5 Hz high-pass Butterworth 4th order & 10 Hz low-pass Butterworth 4th order [13]	64

Table 1: Table with filter designs and sampling frequency for all sensors including location

Resampling

Not all sensors are turned on at the same time and also do not have the exact same internal clock. Therefore all sensors need to be synchronized in order to be able to relate the data to each other, an exception for this are the Moticon and Android since these were connected to each other during the recordings. A possible method for synchronization is the cross correlation function which is capable of finding the correlation between two sensors as a function of time delay [27]. However cross correlation requires all signals to have the same sampling frequency which is not the case as can be seen in Table 1. All signals have been resampled to 32Hz. The highest cutoff frequency for the low pass filters is 15Hz which means that according to the Nyquist-Shannon sampling theorem [28] a minimum sampling frequency of 30Hz is needed in order to prevent

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[01]This sensor can measure at 50Hz and 100Hz. So not all recordings from the moticon have the same sampling frequency.

aliasing. The reason why 32Hz was chosen and not 30Hz is because 32 is the lowest sampling frequency of the gait related sensors, i.e. the Empatica accelerometer. The reason why upsampling to a higher frequency was not chosen is because upsampling generates data and does not give much additional information due to the Nyquist-Shannon sampling theorem.

Synchronization

In order to make the synchronization afterwards possible all patients were instructed to follow a specific protocol when they turn on the sensors. For this they had to put all sensors in a case and then rotate it in a specific manner. Since all sensors contain an accelerometer they should show a high correlation during this rotation. The cross correlation function returns the time delay which is then used to offset the corresponding signal. Performing another cross correlation after the offset should show maximum correlation at a delay of zero if done correctly. A few problems arise from this however due to the fact that it is unknown what is actually happening in the patient's homes. Possible problems are that the patient forgot to turn on a sensor, forgot to do the rotation or that a sensor has ran out of battery. Due to the amount of exceptions it has been decided to first manually look for patterns and then, if possible, automatize the synchronization.
Each accelerometer has an axis that will always show gravity since gravity is constant. During the rotation the patients must rotate the sensors which means that for a short period of time the gravity will go from positive to negative and then back to positive (or the other way around depending on the initial orientation). This also means that for another axis the gravity will show up shortly. This pattern was used to synchronize the sensors. In order to do this the high pass filter was not included when filtering because this removes the gravity and will be done after the synchronization. If the rotation is manually found the cross correlation function was applied to precisely find the delay. Before the cross correlation is performed a window must be created manually to isolate the rotation. The window should have the form of rectangular function and should only cover the rotation so the length of this window will vary depending on the time it took to rotate the sensors. This window can then be cross correlated across the entirety of the signal of the other sensors. The reason why cross correlating two entire signals is not possible is because the signals only have a high correlation for a few seconds.

Sensor time drift

Solving sensor time drift is out of the scope of the assignment but sensor time drift was identified and quantified. A possible solution is to look at the activity. Since the sensor time drift is usually in the order of seconds all signals should still be somewhat synchronized even after time drift has occurred. By looking at when activity starts and stops it is possible to synchronize again. This however is out of the scope of this assignment.

Results

Sorting and separation

The result of the file separation was that for each patient approximately seven new H5 files were created with each file containing the data of all the sensors of the corresponding day. However for many patients more than seven files were created. This is because the code first generates empty H5 files based on the amount of different days encountered in the first file which is the Android accelerometer. The android accelerometer (and sometimes other sensors) are usually turned on for a short while after the measurements to change the settings which causes the accelerometer to record data for a few minutes. This sometimes happens for more than one day which can cause more than ten files to be created.

Filtering

In the raw and filtered data it is visible that the high frequencies are filtered out but also the constant gain if applicable, see Figure 3. It is also visible that the original power is almost constant after 0.5Hz. This does not only apply to the android accelerometer but also other sensors such as the Moticon and Empatica accelerometer. For the generation of these graphs the high pass filter for the accelerometers was left in in order to show the effect of the final filter in one graph.
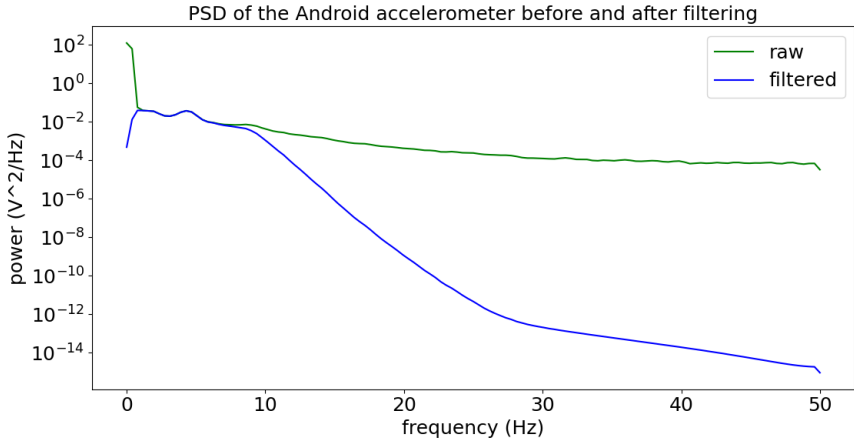

Figure 3: PSD of the android accelerometer before and after filtering. The used filter is a 0.5Hz high pass 4th order Butterworth filter and a 10Hz low pass 4th order Butterworth filter.

Synchronization

The pattern of the rotation in the Android accelerometer for day 2 for PD008 (patient number 8) is visible in Figure 4a. A similar pattern on the same day for the same patient was found for the Movisens and Empatica, see Figure 4b and 4c. Both sensors show a similar pattern for about 20 seconds. It is also worth noting the difference in when the patterns are visible. For the Android it was after 9.5 hours while for the Empatica and Movisens 1 minute and 2.5 hours respectively. These patterns were not only visible for PD008 but also for PD034 and PD044. However for the PD008 Moticon this pattern was not found. This means that another method must be used in order to still synchronize all the sensors. During the recordings the Moticon is connected to the Android which means that these are already synchronized however the original data shows that the sensors were left on at night. The Android kept recording while sleeping but the Moticon stopped recording and continued at 10:30 AM. This information was used to offset the Android data so that these sensors are synchronized again.
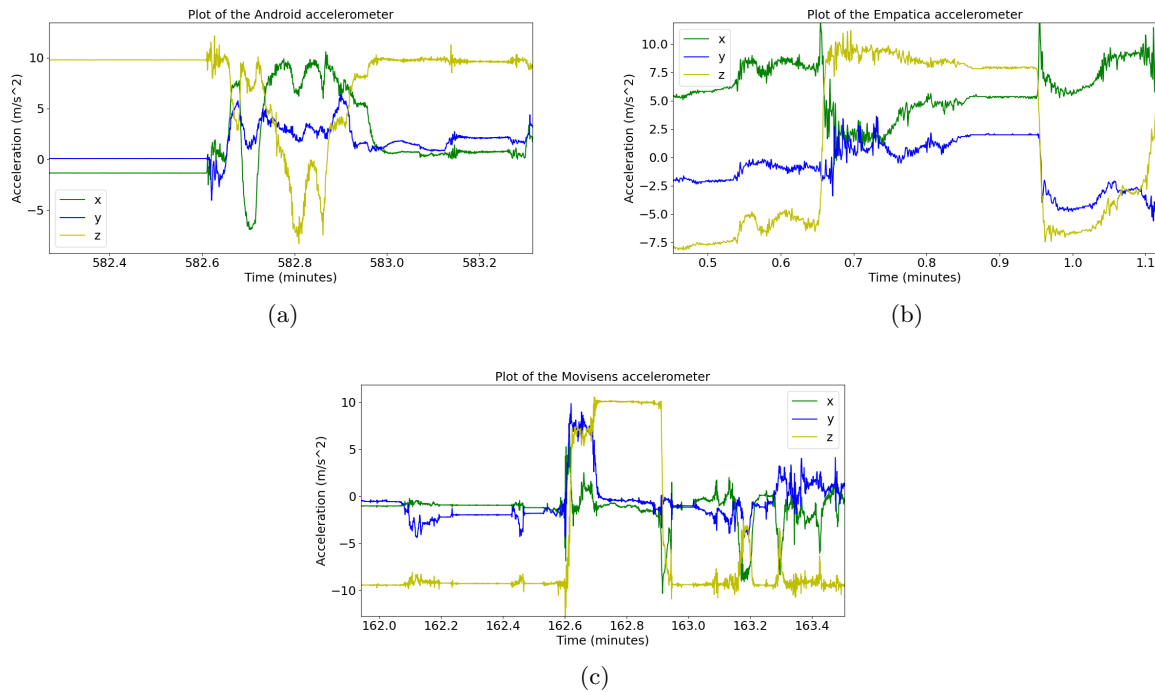

(a)

(b)

(c)

Figure 4: Rotation in the PD008 day 2 Android, Empatica and Movisens.

The cross correlation was also plotted to confirm the similarities between the patterns and to find the exact delay. The cross correlation for the Empatica and Movisens for PD008 day 2 shows high correlation around a delay of approximately 2.5 hours, see Figure 5a. The cross correlation between the Android and Empatica and also Android and Movisens was also calculated. This resulted in a less clear maximum correlation, see Figure 5b.

For PD008 day 2 an attempt was also made to find the degree of sensor time drift for day 2. For this the sensor drift of the Movisens and Moticon was analyzed because they are located near each other so the data is similar. The Moticon was not rotated so it was synchronized by looking at a unique part at the start of the signal which appeared in both signals and another unique part later in the signal (red and blue box in Figure 6 respectively). The difference in delay was 113 seconds after 3 hours.
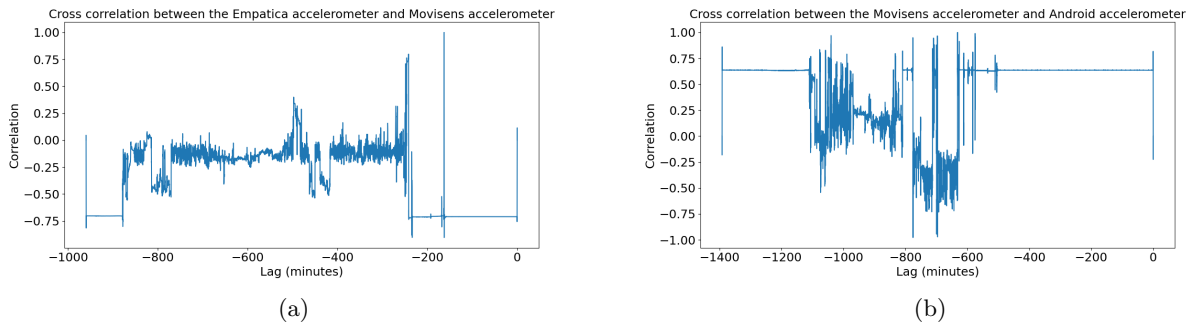
Figure 5: a) Cross correlation between the Empatica and Movisens accelerometer. For this a window for the empatica was used to isolate the rotation. This window was then cross correlated against the Movisens accelerometer. The maximum correlation is found at approximately 2.5 hours delay. b) Cross correlation between the Movisens and Android accelerometer. A window was applied on the Movisens to isolate the rotation. This graph does not show a clear maximum correlation.
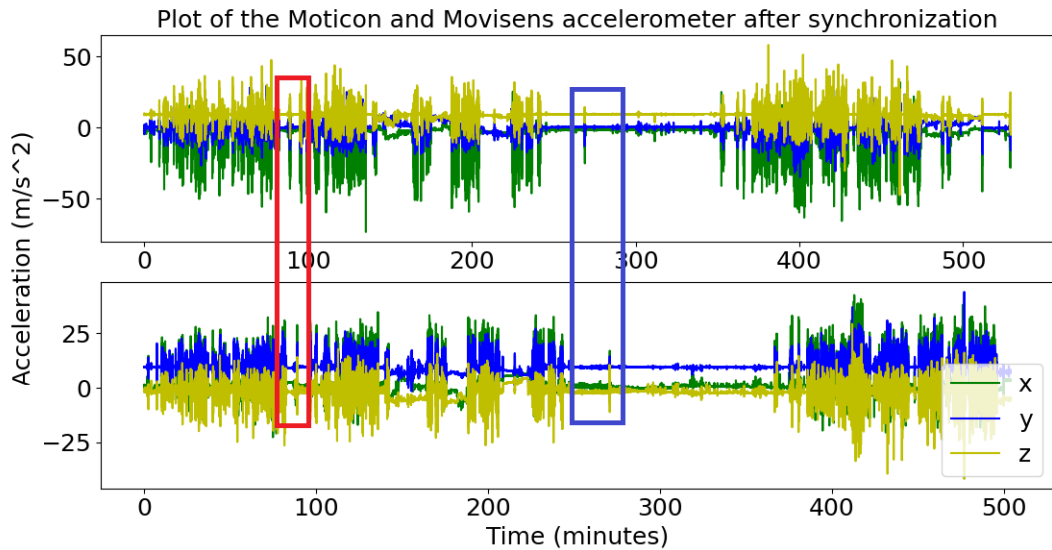

Figure 6: Moticon and Movisens for PD008 day 2 after synchronization. The difference in delay between the red and blue box is 113 seconds after 3 hours.

9

For PD044 day 10 the rotation was found for all sensors, see Figure 7. All sensors were rotated 3 times consecutively for a total amount of time of 15 seconds. For the Empatica the rotation was visible after 8 minutes, Android after 9 hours, Moticon after 1 minute and Movisens after 11 hours.
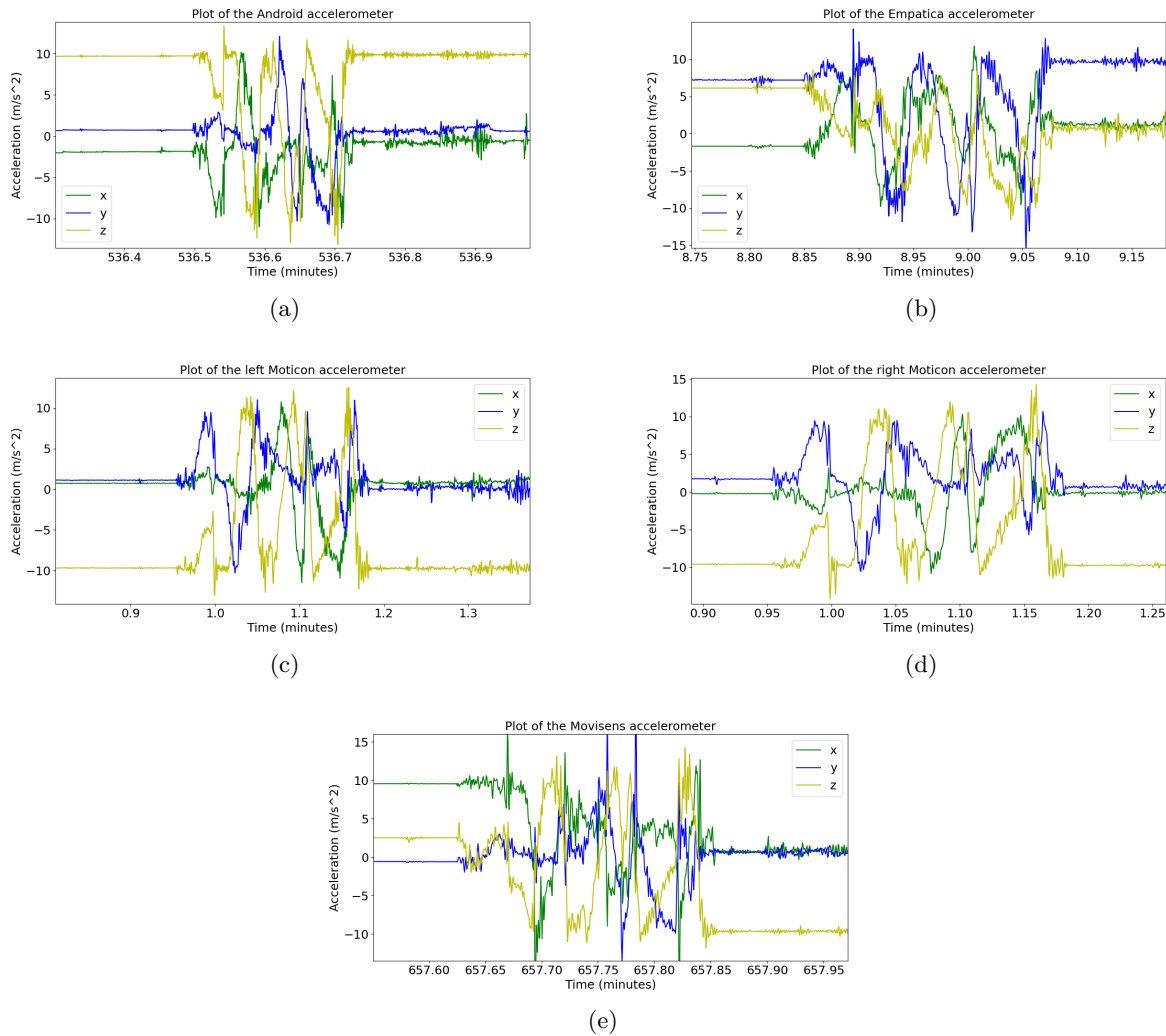

(a)

(b)

(c)

(d)

(e)

Figure 7: Rotation in the PD044 day 10 Empatica, Android, Movisens, right Moticon and left Moticon.

The cross correlation between the Android and Moticon and also Android and Empatica was also calculated, see Figure 8. The cross correlation for the Android and Moticon show a clear peak at the expected delay of 140 minutes while the android and empatica show multiple peaks. The same phenomenon was observed for PD008 where cross correlations with the Android resulted in multiple peaks.

Finally for PD044 the sensor time drift between the Moticon and Movisens was also quantified by looking at the difference in delay between the part highlighted in red and blue, see Figure 9. In this case the difference in delay was 2.8 seconds after 2.5 hours.
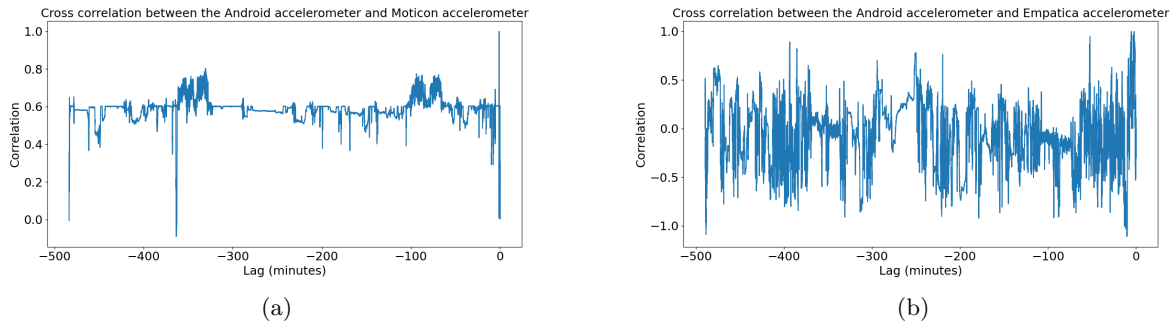
Figure 8: Cross correlation between the Android Moticon and Android Empatica. The delay between the Android and Moticon is 1 minute and between Android and Empatica is 2 hours. The Android and Moticon show one clear maximum correlation while the Android and Empatica show multiple peaks.
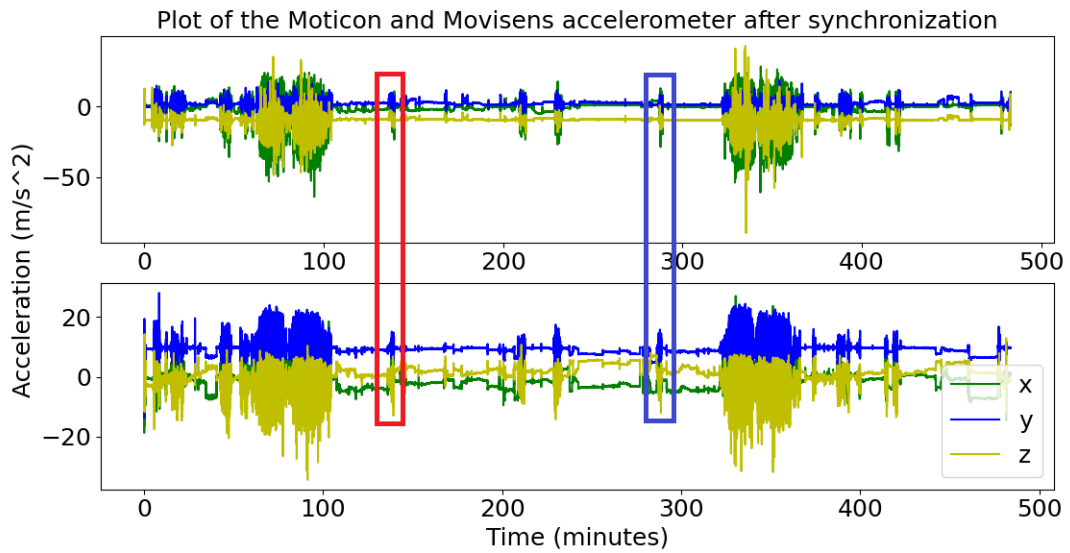

Figure 9: Moticon and Movisens for PD044 day 10 after synchronization. The difference in delay between the red and blue box is 2.8 seconds after 2.5 hours.

Discussion

The new file structure is easier to work with than the old structure. With the new structure only one H5 file must be loaded in order to obtain the data needed for synchronization and in the future detection of FOG. In order to remove the abundant H5 files it is important that the original data only contains data from the actual measurements and not from turning the sensors on for a short while afterwards in order to change settings or prepare them for the next patient. This means that only the data from the recording from the patient's homes remain so that the new H5 files only contain data from the actual measurements. One downside of the new file structure however is that unix time stamps are lost. The H5 files can only hold one data type which means that a conversion from unix time to a datetime object cannot be stored. In order to still separate the data only the day was stored. This means that is not possible to look at the time of certain events. A possible way to solve this is to add a column to each dataset after conversion which contains the unix time. Finally for some recordings the time in the sensors was off by a few days or even years. This means that during sorting the data is not aligned anymore which renders the data useless because you cannot combine the data from different sensors.

The PSD's show that the filters work as intended though the effectiveness is debatable. The PSD's of the raw signals are relatively flat which is not expected. The flat power was also visible when computing the PSD for shorter moments of activity. The same pattern remained when plotting PSD's of 15 minutes, 1 hour and 3 hours of activity so it was not caused by an over representation of inactivity. This was visible for multiple patients. This could imply that some filtering has been done by the sensors itself before the data was recorded.

For the synchronization for PD008 the moment of rotation is visible in the Android, Empatica and Movisens, but not the Moticon. The same patterns of rotation was also found in the data for PD034 and PD044. Not all sensors show an axis with a value of $\pm 10 m/s^2$ for gravity however. For example the x-axis of the Android accelerometer for PD008 often has a constant value of $-5m/s^2$ which is not the value for gravity but is also not likely caused by activity because the value is constant. This is most likely caused by the orientation of the sensor so that none of the axes are aligned with gravity. The rotation in the Android accelerometer for this specific example for PD008 is also not as obvious as for the Empatica and Movisens. This makes the synchronization harder but still possible. Looking at the length of the rotation as an extra verification is effective because for all three signals the rotation takes about 20 seconds. The cross correlation for the Empatica and Moticon also confirms the synchronization because it shows maximum correlation at the expected delay. However the cross correlation between the Movisens and Android does not show a clear maximum correlation. This is expected because it is visible that the rotation in the Android accelerometer does not have the shape of a rectangle function which the Empatica and Movisens have. This could be due to a difference in accuracy between the sensors or another possible explanation for this is that the sensors started rotating internally while the case was being rotated. This makes it hard to say with certainty that the signals are now synchronized because it is unknown what was actually happening at the moment of rotation. And even though the Moticon was not rotated it is possible to synchronize it due to it being connected to the Android. Meanwhile for PD044 the rotation was visible in all sensors so this data was easier to synchronize. It is also important to calculate the cross correlation as a verification for the found rotations. If a patient does the rotation but later does it again because he/she forgot to turn on a sensor then two or more rotations can be found in the signal. Synchronizing all sensors on the first rotation will not result in synchronized data so by calculating the cross correlation it is possible to find the additional rotations. This also adds

to the point that the cross correlation is not a foolproof method for synchronization. If multiple rotations are performed then the cross correlation will show high correlation multiple times, but the patient may also rotate a sensor an additional time when attaching it to the corresponding body part which will show up as a high correlation too. All these exceptions make it hard to automatize this process so each day for each patient should be synchronized manually.

The calculated sensor time drift for PD008 of 113 seconds after 3 hours is significant and more than expected. This is most likely not only caused by the sample timing but mainly by a faulty sensor. If a sensor stops recording for some time then the samples afterwards will be concatenated. This basically means that some amount of time is cut out. In order to counter this it is possible to first identify this during pre-processing and then either interpolate the data or replace it with zeroes depending on the size of the gap. However for PD044 a sensor time drift of 2.8 seconds was found after 2.5 hours which means that the data loss does not happen every time. Due to time constraints it was not possible to quantify this drift for all patients so it is unknown whether data loss is usual or not.

Conclusion

The processed data allows for gait analysis for detection of FOG due to the possibility of synchronization however a lot can be done in order to make the data better. First of all the rotation protocol executed by the patients must be revised. Currently the patients are instructed to perform only one rotation but this can during analysis easily be confused with patients rotating the sensors while putting it in the right location. A better protocol would be to instruct the patients to do multiple consecutive rotations. This will generate a more unique pattern which will make synchronization easier.

The sensors sometimes do not report the correct date and time, this will cause the data to be misaligned when sorting on day. In order to solve this it is of great importance that if this happens the dates are corrected before compiling from CSV to H5. It is also important to leave out data which does not belong to the measurements before compiling to reduce the amount of abundant files after restructuring.

Finally it is important to make sure that the data is not missing any samples by first detecting when data loss occurs and then resolving it by either interpolation or filling with zeroes. This will reduce the observed sensor time drift. However countering sensor time drift itself is something that should still be done for future research. Another thing that was not done but should be done in future research is artifact detection. In the current data it is possible that sometimes abnormally high values occur such as an acceleration of $100m/s^2$. This is physically almost impossible and therefore most likely an artifact. This should be detected, removed and interpolated. Due to all the exceptions that can occur when trying to synchronize the sensors it is hard to automatize this process. For now it is better manually synchronize each day by looking at what was likely happening in order to make the right decisions about synchronization.

This processed and synchronized data brings future research closer to detection of FOG by allowing researchers to analyze the gait using various methods such as Machine Learning models. By being able to detect and predict FOG episodes external cueing can be used as an effective treatment for PD patients which will improve their quality of life.

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