

Gait analysis of spinal cord injured patients

BIOENG - 404 : Analysis and modeling of locomotion

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Introduction

The goal of this project is to characterize and compare the gait of spinal cord injured and healthy subjects. The dataset used for this project contains the kinematic and EMG data that were gathered from a healthy subject during the visit at the CHUV as well as data gathered from experiments with a spinal cord injured subject. It includes positional coordinates of markers that were attached to the hip, knee, ankle and foot of the subject, along with unfiltered EMG signals of different muscles. Since each experiment used slightly different positioning of the markers and EMG sensors, the intersection of the experiments was used which resulted in the following measurements.

Hip marker	LHIP	RHIP
Knee marker	LKNE	RKNE
Ankle marker	LANK	RANK
Toe marker	LTOE	RTOE

iliopsoas	LII	RII
Rectus femoris	LRF	RRF
Vastus lateralis	LVlat	RVlat
Tibialis anterioris	LTA	RTA
Semitendinosus	LST	RST
Medial gastrocnemius	LGM	RGM
Soleus	LSol	RSol

Two healthy subjects had to perform 3 different experimental setups, which gives 6 sets of data. Both subjects walk on a treadmill. During the first experiment they perform a walking task on a treadmill at a constant speed of 2km/h. The second one the treadmill speed went from 2km/h to 3km/h. Then, during the third one the treadmill was inclined and the subjects had to walk from a speed of 3km/h to 4km/h.

Then, a participant with spinal cord injury was asked to walk on a treadmill without and with Epidural Electrical Stimulation (EES) under different speeds. First, without EES at a steady speed at 1km/h, then with EES from 0.8km/h until 1km/h and finally with EES from 0.8km/h until 2km/h.

With this data we would first perform detection of gait events in order to divide the data in gait cycles and characterize each gait cycle by different kinematic and EMG parameters. These parameters would then be used to perform PCA in order to compare different experimental setups.

1. Gait event detection

1.1 Visual gait event detection

From the visual gait event detection, one could easily deduce the gait events on healthy subjects data by looking at the knee angle behavior.

However, it is less easy visually to detect the gait events on the data of injured patients.

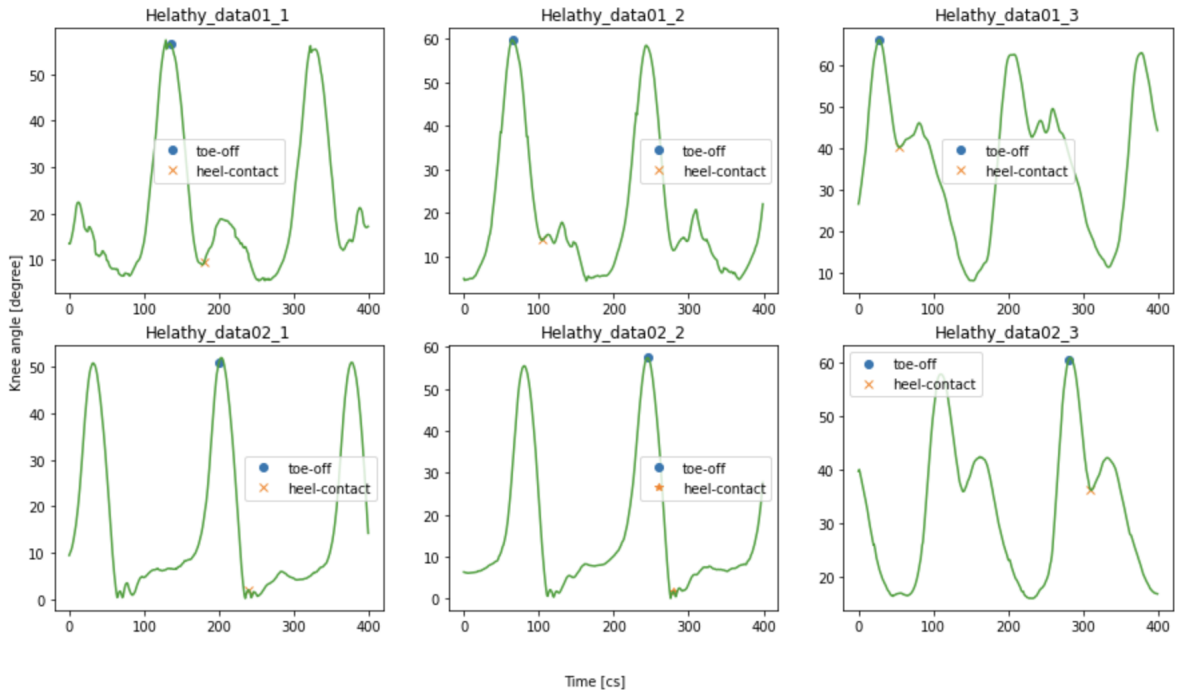


Figure x. Visual detection of some gait events on healthy data

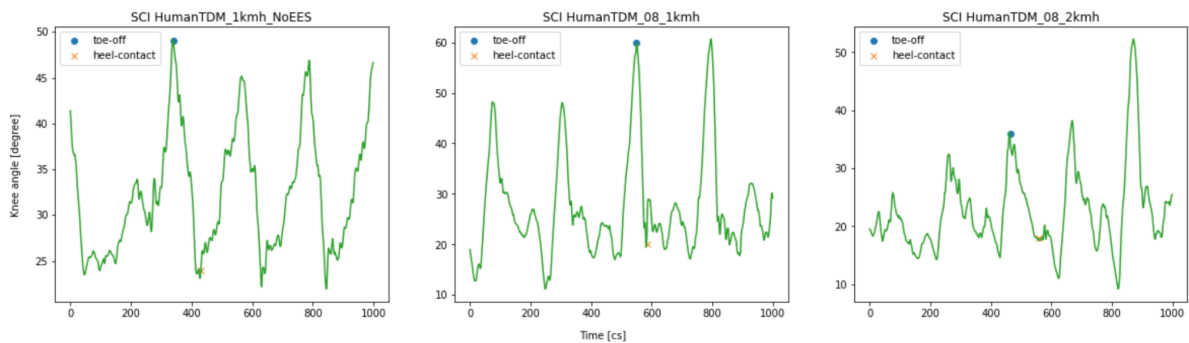


Figure x. Visual detection of some gait events on SCI data

1.2 Automated gait event detection algorithm

Another method that was also used to automatically detect the gait events, was the vertical position of the toe marker. The toe seems to be at the highest position during the heel strike and at the lowest during the foot off. Therefore a peak detection algorithm in python (scipy) was used to detect the corresponding peaks and valleys. This algorithm works especially well for the inclined values since the position of the toe is much higher at the initial contact and much lower at the toe off due to the inclination of the platform.

However for the experiments with spinal cord injured subjects the aforementioned method does not work that well since the subject mostly walks on his toes and therefore on the initial

contact the toe is not at the highest but the lowest position. As a result the gait events were determined by finding the peaks (of vertical positions) and their width at a relative height of 0.85. The interpolated positions of left and right intersection points of a horizontal line at the mentioned evaluation height correspond to the toe off and the initial contact respectively.

Before using the scipy's peak detection algorithm the data was first filtered using a fourth order lowpass filter with 5 Hz cutoff frequency. Subsequently the data was interpolated using fifth order univariate spline with a smoothing factor of 1 for data from healthy subjects and 100 data from injured subjects. Additionally, the following peak detection parameters were used. The detected gait events were thereafter used to define the gait cycle as the interval between 2 subsequent toe offs.

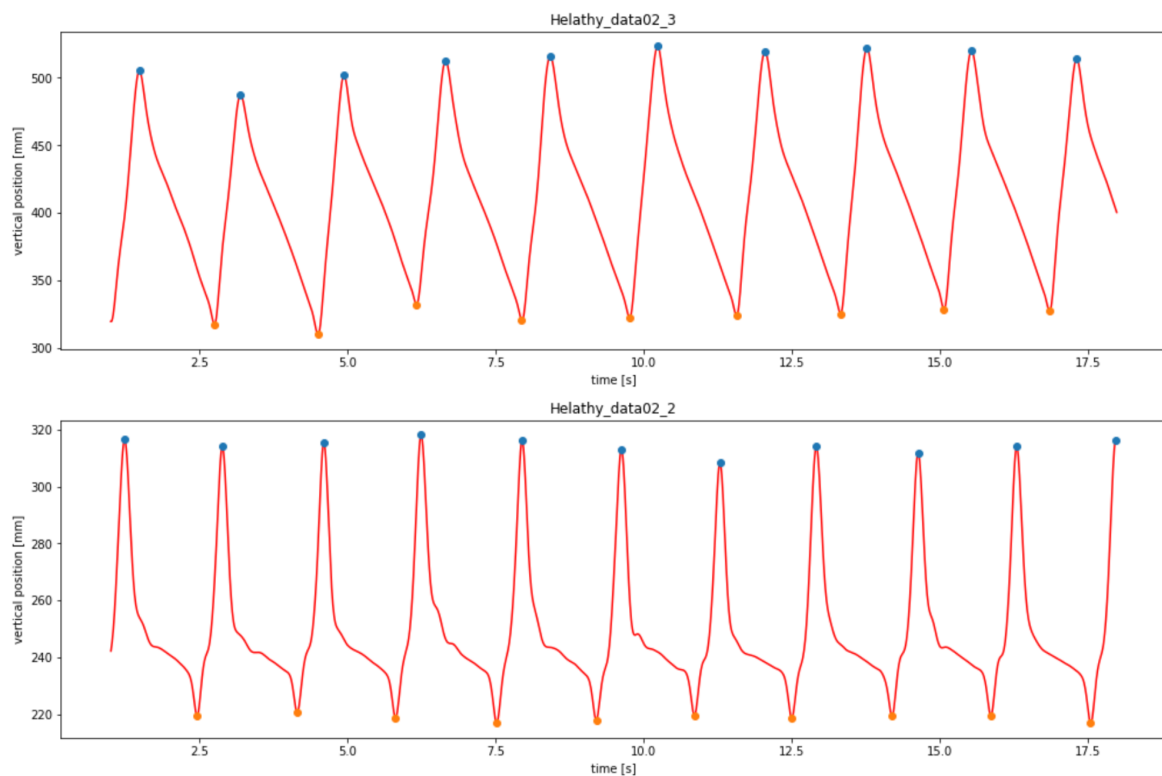


Figure 1: Automatic gait detection visualization of healthy gait (1.) inclined platform (2.) normal platform. Blue dots represent initial contact whereas orange dots represent toe offs.

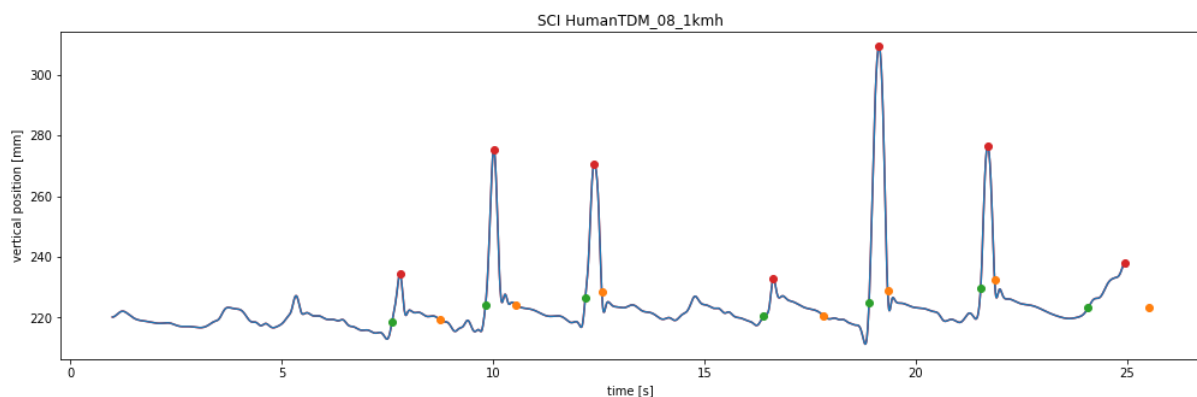


Figure 2: Automatic gait detection visualization of injured gait. Green dots represent toe offs whereas orange dots represent initial contact.

By inspecting the video it has been noticed that both the visual as well as the automatic gait detection methods are quite accurate however an exact comparison and accuracy of both methods would be more difficult since now force plates were involved in the experiments.

2. Gait and EMG parameters

2.1 Gait parameters

By looking at the video it has been noticed that the gait of spinal cord injured subjects would include lots of walking on toes. Furthermore the range of movement in spinal cord injured joints were quite limited which is why min and max values of hip, ankle, and knee joint angle were taken as parameters. This would not only help to characterize injured labeled gait but also healthy gait on the inclined platform. What has also been noticed, are the foot tremors of the injured subjects during the swing phase. With that, the variance of the foot (ankle angle) as well as the max ankle angular velocity might be useful parameters for characterizing the gaits. Additionally the gait of injured subjects seem to be more hasty which is why swing and stance duration were included as parameters too.

2.2 EMG parameters

EMG preprocessing

Before defining the EMG parameters one should preprocessing them to transform the raw data into a format that is more suitable for further analysis such as features extraction to create EMG parameters for the PCA. First, a bandpass filter was done to remove artifacts associated with drift due to movement or sweating and any DC offset. Then, we rectify the signal to identify the overall strength of the muscle contraction output, so that we get the shape of the EMG signal. Finally, we lowpass filter the rectified EMG to get the linear envelope. [1]

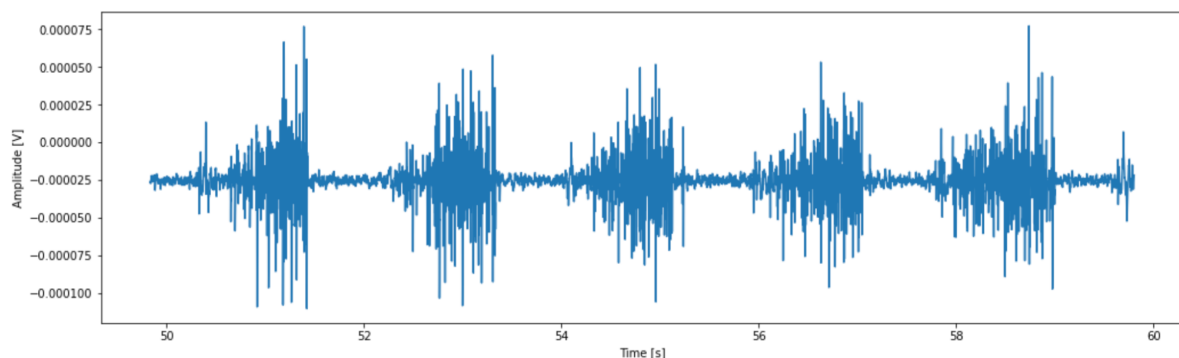


Figure 1. Part of raw EMG data of the soleus from a healthy patient walking at 1km/h

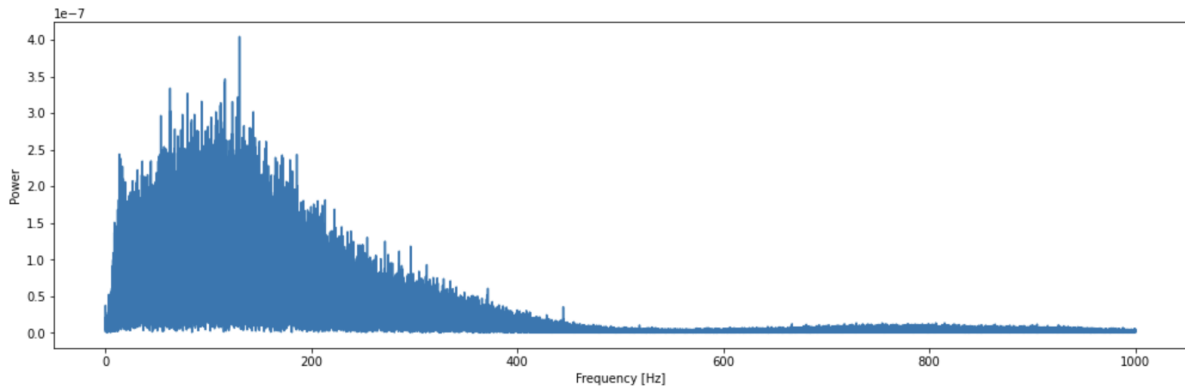


Figure 2. Power spectrum of the raw EMG data of the soleus from a healthy patient walking at 1km/h

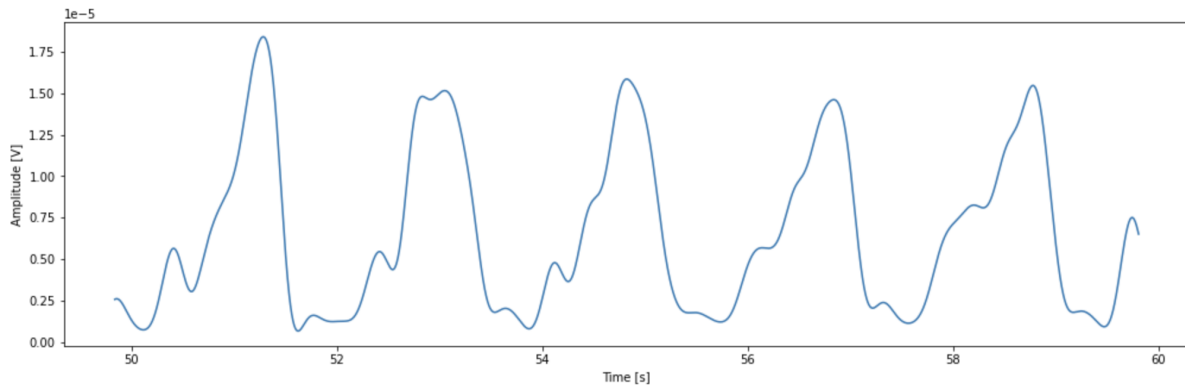


Figure 3. Part of the filtered EMG data of the soleus from a healthy patient walking at 1km/h

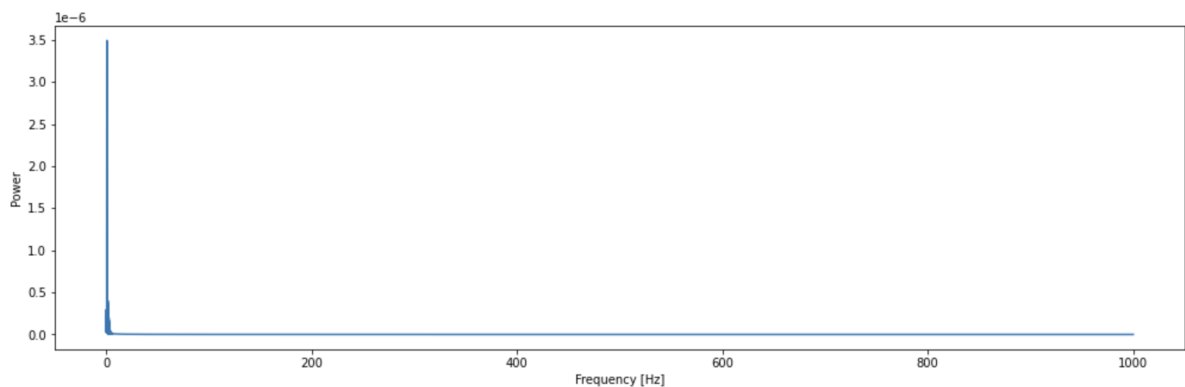


Figure 4. Power spectrum of the filtered EMG data of the soleus from a healthy patient walking at 1km/h

EMG parameters selection

From the SCI videos, we noticed the patient was able to include more plantarflexion and hip flexion in its gait with EES, in comparison without EES. From these observations we decided to focus on the muscles involved in the plantarflexion, soleus (extensor) and tibialis anterior (flexor), and the muscles involved in hip flexion, iliopsoas (flexor) and semitendinosus (extensor).

Then, the spinal cord injured patient was experiencing some tremor in his feet during the swing phase without EES. This means the muscles are rapidly contracting and relaxing. Thus we decided to compute the number of burst onsets and ends of the 4 muscles as EMG parameters. The Figure 5 below shows the detected burst onsets of the soleus muscle of a healthy subject. Additionally since some experiments also included inclined platforms and different walking speeds, we decided to take the mean amplitude of the muscles to analyze the amplitudes of contraction of the muscles during these different experimental setups.

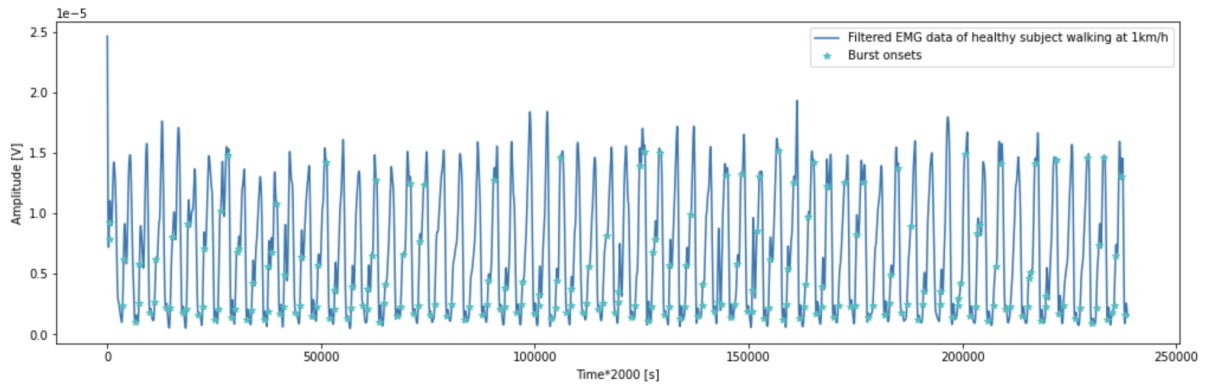


Figure 5. Filtered EMG data with the associated burst onsets

3. PCA results

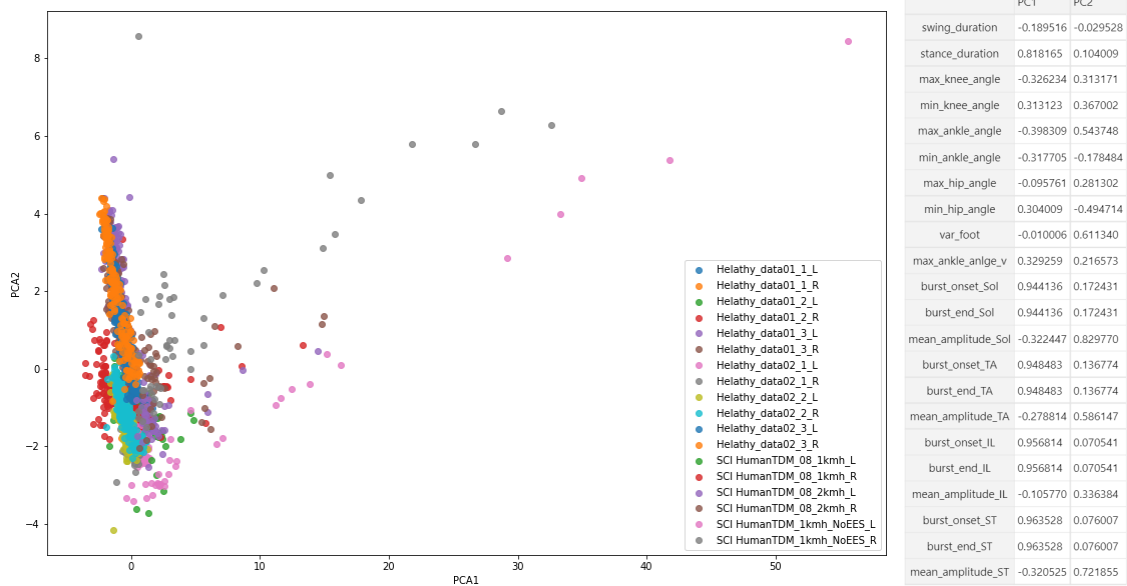


Figure 6. PCA with all labeled data (PCA1: 0.41, PCA2: 0.14) + correlation matrix

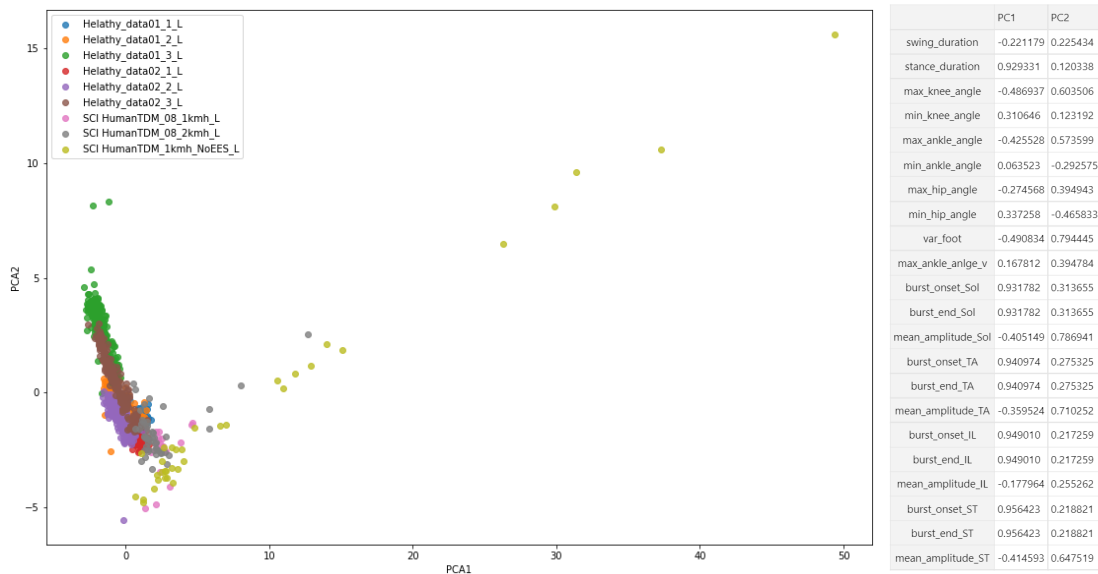


Figure 7. PCA with left foot gait cycles (PCA1: 0.43, PCA2: 0.19) + correlation matrix

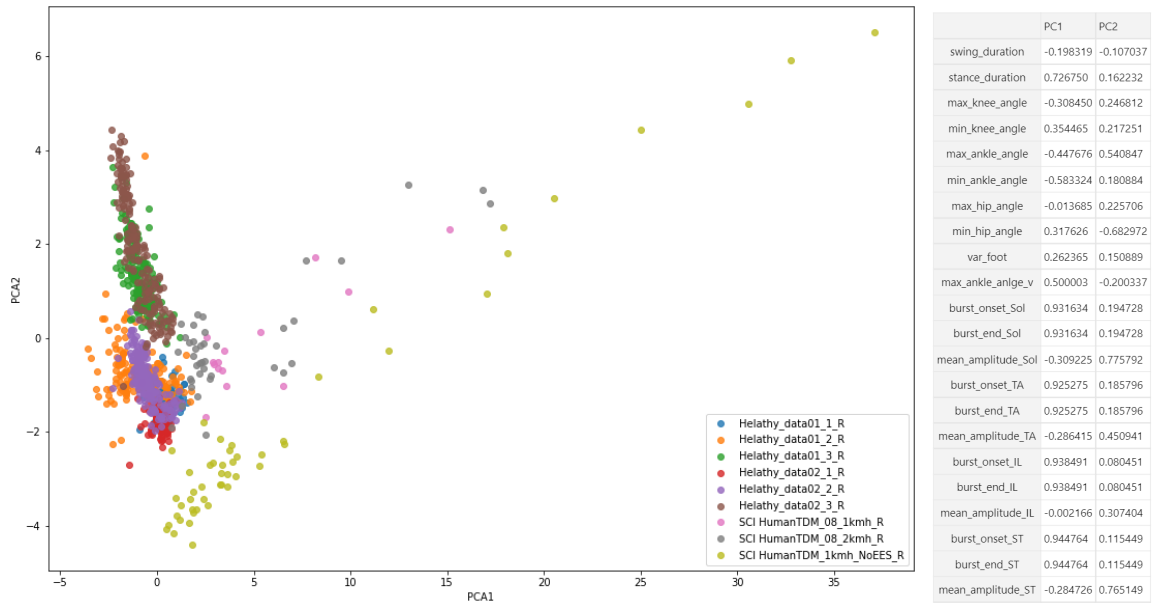


Figure 8. PCA with left foot gait cycles (PCA1: 0.41, PCA2: 0.12) + correlation matrix

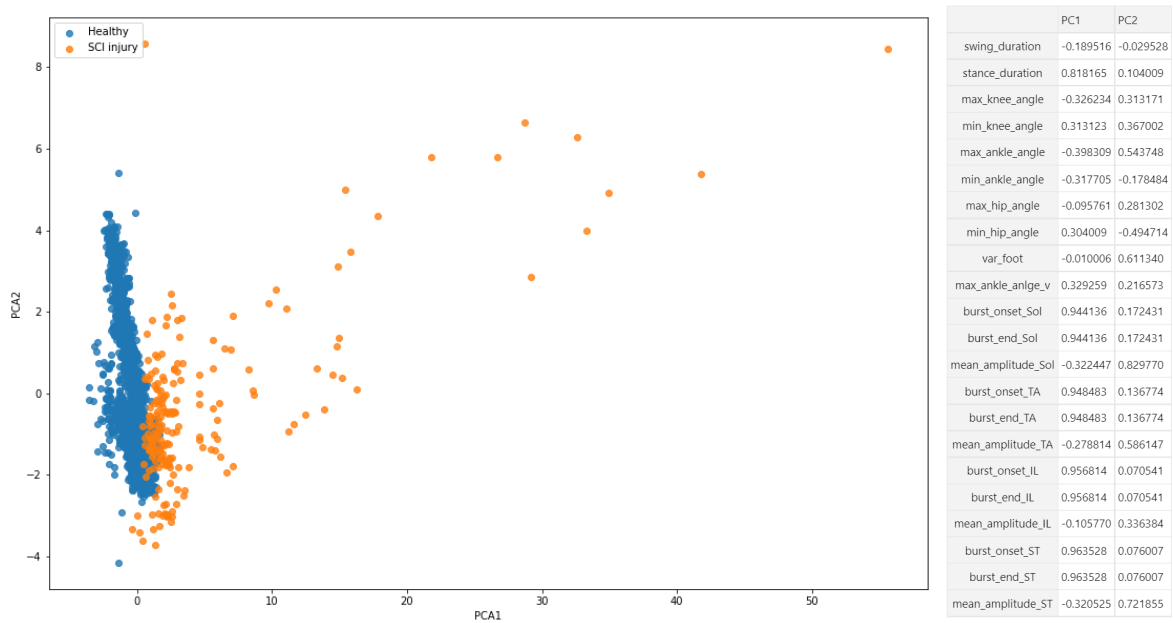


Figure 9. PCA of healthy and injured labeled data (PCA1: 0.41, PCA2: 0.14) + correlation matrix

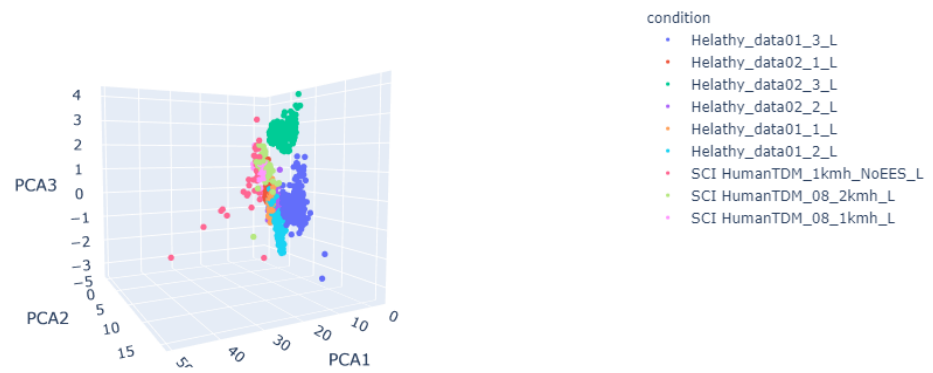


Figure 10. PCA 3D wit left foot gait cycles

(Check jupyter notebook for more information on the interactive 3D plots :

<https://datalore.jetbrains.com/notebook/gvyDqamQsAm24AvVvqxjFh/YvKtRDQErIsnoR3lc1e0Ya/>)

4. Analysis and discussion

The first thing to notice in our PCA is that data points gathered from injured subjects especially the ones with no epidural electrical stimulation clearly seem to be more dispersed than data points from healthy subjects (Figure 9), indicating what has already been observed in the video, namely the irregular nature of the (unstimulated) spinal cord injury gait. Additionally the injured labeled data points seem to lean more to the right on the first principal component. So the healthy gait cluster seems to be quite distinguished from the unhealthy labeled one, since the first principal component accounts for most of the variance in the data (41-43%).

By looking at Figure 7 and 8 (and also at their corresponding 3 plots) it can also be noticed that the data points from the inclined plane seem to be also quite distinguishable from the rest of the gait cycles. However, no significant difference seems to be observable between left and right foot.

Concerning the parameters used for the PCA, what immediately catches the eye are the high correlation (> 0.9) of the burst onsets and ends with the first principal component, indicating a high efficiency when it comes to characterizing and differentiating spinal cord injured gait cycles. Parameters such as max hip angle, mean amplitude of iliopsoas and the swing duration seem to have quite weak correlations with the first three principal components suggesting low performance when it comes to gait characterization. The rest of the parameters seem acceptable, having at least a moderate correlation with one of the principal components.

Another prominent thing to notice is the unbalanced nature of the data. The number of data points for each type of experiment is not really equal. Moreover there are much more data points for healthy gait than for unhealthy gait. So to improve the PCA it might be a good idea to increase the walk time of SCI experiments until enough gaits have been detected (possibly by using force plaits which might be also more accurate and simpler for detecting gait events).

5. References

1. Winter, D. A., & Winter, D. A. (1990). *Biomechanics and motor control of human movement*. New York: Wiley. p. 271