Rehabilitation robots for the diagnosis and assessment of disabilities

Capstone Report

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Abstract:

Lately, the use of robots in rehabilitation is widely accepted by clinics and therapists worldwide. Robots are being used for passive and active training to treat disabilities through physical therapy of patients with paralyzed or impaired movements due to strokes and other similar medical problems [1], [2]. However, due to number of problems such as lack quantifiable feedback, variance of training protocols and their efficacy between institutions and therapists[3], the observation of variation in biomechanical and bio signal parameters became vital. The main aim of the study is to use rehabilitation robots as a tool for two purposes, one of them being the treatment of disorders and disabilities, and the other being conducting pathophysiology and diagnosing the cause of disabilities. The main objective is to diagnosis Cerebral Palsy with the gait analysis and gait phase detection using Machine Learning algorithms.

Contents

Preface

This project plays important role in rehabilitaion process used for patients with neurophysical disorders. It also contributes to the development of diagnosis process based on measurements of muscle activations.
I would like to express gratitude to my supervisor professor Prashant Jamwal who gave me an opportunity to work on such interesting project. Also, I would like to thank professor Muhammad Tahir Akhtar for giving the opportunity to work in his laboratory during my second year of studies and establishing my interest in biomedical signal processing. I am grateful for the children's and their parents' agreement in participating in the experiments. I also would like to thank members of Robotics and Artificial Intelligence Lab, Amna Riaz Khawaja and Dilnoza Karibzhanova, for helping me to expand my background knowledge in biomechanics and medicine. Thank to NU Library for providing large number of articles and publication with free access.

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Chapter 1

Introduction

According to statistics, about 800000 Americans have a stroke each year, and the total cost of medical treatment in the United States is estimated to be 34 billion dollars per year[4]. The usage of robots for rehabilitation purposes became a normal situation in hospitals, which is obvious as it solves many problems related to the treatment and rehabilitation of patients: inadequate number of doctors per patient in a populated city, difficulties in the treatment of aged patients, cost and duration of the rehabilitation, keeping following up the treatment process [5]. All of the problems may be solved with the usage of robots as they help to optimize processes and keep consistency in the treatment process. However, rehabilitation robots tend to be used in more traditional methods of rehabilitation rather than novel methods [6]. For example, in the article named "Design and Control of a Diagnosis and treatment aimed robotic platform for Wrist and forearm rehabilitation: DIAGNOBOT", robots DIAGNOBOT was used for passive, isotonic, vario-resistive and isometric exercises, where data of flexion–extension, ulnar–radial deviation movements for the wrist and pronation–supination movement for the forearm were taken [6], and after the training doctor could get and interpret the result for further treatment of patients. New rehabilitation method with the usage robots was proposed in the article "Research on a New Rehabilitation Robot for Balance Disorders", where end robot is used for rehabilitation of balance disorders [7]. The advantages of such robot compared to exoskeletons are stated to be more cost efficient and more compatible design. The robot's body comprises a 9-degree-of-freedom (DOF) redundant series-parallel hybrid motion platform, and each motion platform set consists of a 6-DOF vestibular parallel device and a 3-DOF proprioception parallel device. This design allows DOF decoupling and rapid response, presenting a novel structural approach for the design of proprioceptive and vestibular simulation platforms [7]. However, it is uncommon to use such robots for the assessment of disabilities, which could play an important role at the stage of diagnosis of patients by optimizing the process and giving precise

results.
In addition, in rehabilitation procedures, co-adapting interaction approaches with a behavior prediction power through data-driven models are needed for a quick and complete restoration of lost functions [8]. However, as robotic devices interface with humans, quantifying the interaction and its intended outcomes while maintaining the desired physiological movement is still a research challenge [9]. To address the issue the usage of Machine Learning for data analysis is becoming more widespread. For example, the article "A Systematic Review of Gait Analysis in the Context of Multimodal Sensing Fusion and AI" gives comprehensive overview of 66 studies, 40 of which utilized multiple gait analysis modalities without using Machine Learning for the extraction of gait features, and 26 of which employed multimodal fusion sensors with AI algorithms for gait data analysis [10]. According to the results, integrating data from various sensors enhances the quality of gait analysis and efficiency of Machine Learning algorithms, and EMG signals are stated to be particularly advantageous in fusion data analysis [10]. The best accuracy results among Machine Learning algorithms are achieved with the use of RNN, LSTM, Random Forest and SVM algorithms.

Nevertheless, recent studies suggest the novel approach with Stacked Weighted Random Forest (SWRF) algorithm for pattern recognition using sEMG data was proposed to improve generalizability of WRF and solve the issue of imbalanced performance in standard random forests (RF) [11]. The algorithm is performed with RF being base learner and WRF serving as the meta-leaning layer algorithm [11]. According to the results of study SWRF achieves an average classification accuracy of 89.06%, outperforming RF, WRF, long short-term memory (LSTM), and support vector machine (SVM) algorithms [11]. Although the studies show high accuracy result, in the integration of the algorithms to the robotics design maximizing the number of repeated movements and generating a correct physiological movement trajectory are the two most important factors in task-specific rehabilitation. However, only a few studies are available on how muscles are engaged in such interventions. One of the examples could be usage Intelligent Rehabilitation Assessment Method (IRAM) for evaluating stroke patients' rehabilitation progress using sensor data from a lower limb exoskeleton robot, where parameters of the patient and sensor data are collected and gait feature model was constructed to infer the patient's walking gait parameters based on exoskeleton sensor data [12]. The rehabilitation assessment model was then trained using a combination of feature parameters, gait parameters, and human-machine interaction parameters (joint torque) through a machine-learning based algorithm [12]. Experimental results demonstrate a prediction accuracy of 85.19% for 6MWD and 92.66% for FMA-LE values [12].
Another novel method used in rehabilitation in the walking on non-steady and non-flat surfaces. For example, the article "Deep Learning-Based Identification

Algorithm for Transitions Between Walking Environments Using Electromyography Signals Only" conducted experiment measuring muscle activations of rectus femoris, vastus medialis and lateralis, semitendinosus, biceps femoris, tibialis anterior, soleus, medial and lateral gastrocnemius, flexor hallucis longus, and extensor digitorum longus, in 27 subjects during walking on different terrains such as flat ground, upstairs, downstairs, uphill, downhill, and during transitions between these surfaces [13]. AAN model was used to construct the model, using the entire EMG profile during the stance phase as input, and achieving high accuracy of 95.4% [13].

Chapter 2

Background

The next arising question is about how to perform an assessment of disabilities. There are many studies related to the topic, for example, in the article “Voice Analysis for Neurological Disorder Recognition - A Systematic Review and Perspective on Emerging Trends" provides a comprehensive overview of the use of voice analysis for the recognition of neurological disorder [14]. The study discusses various neurological disorders such as Parkinson’s disease, Alzheimer’s disease, multiple sclerosis, and stroke, and uses voice analysis for neurological disorder recognition with the use of machine learning algorithms such as Support vector machines, decision trees, and neural networks [14]. However, such implementation could be not realizable in our country’s clinics. Thus, another way of assessment and diagnosis could be implemented during gait training.
For example, in the article “Toward an Integrated Intervention and Assessment of Robot-Based Rehabilitation”, the authors made the data analysis and interpretation which involves analyzing the collected data using such as machine learning algorithms and statistical analysis to evaluate the effectiveness of the intervention [4]. In the article, they applied RMS-filtered sEMG response and completed correlation analysis on biceps brachii (BB), triceps lateral (TL), and triceps long (TLo) muscles, and as the result, they found that the analysis could be used as main parameter during training [4]. However, apart from that, disabilities also affect lower limb muscles and rehabilitation usually includes training on that part of the body. For example, during the management of Parkinson’s disease various non-pharmacological interventions, such as physical therapy, occupational therapy, and lifestyle modifications are used [15]. So, the study also aims to the usage of rehabilitation robots for lower limbs training, and one of the main concerns would be gait training.
In the article “Robotic Exoskeleton Gait Training in Stroke: An Electromyography-Based Evaluation” Three gait performance indexes Gait Metric (GM), Burst Duration Similarity Index (BDSI) and agonist-antagonist coherence function were ex-

tracted from patients' sEMG signals of lower limbs before and at the end of the treatment [16]. In particular, GM and BDSI were used to analyze muscular activation during gait in terms of amplitude and timing [16]. At the end, the authors highlight the need for further research to establish standardized protocols and guidelines for EMG-based evaluations of robotic exoskeleton gait training, and to determine the long-term effects of such interventions on gait recovery and functional outcomes in stroke patients [16].
One of the ways to implement gait training is to check energetic passivity and track muscular activation similar to the article. The study shown in the article "Energetic Passivity of the Human Ankle Joint" used techniques such as motion analysis, force plate measurements, and muscle electromyography (EMG) to investigate the mechanical behavior of the ankle joint during different phases of gait [17]. It also suggests that mimicking the energetic passivity of the human ankle joint in these devices may enhance their performance and effectiveness in assisting or augmenting human locomotion [17]. Going back to the topic of Parkinson's Disease, in the article "Adaptation of Stability during Perturbed Walking in Parkinson's Disease" perturbations were induced using a lateral platform translation to challenge balance control during walking [18]. The study utilized motion capture and force plate measurements to assess gait parameters such as step length, step width, and other measures related to stability [18]. The results of the study showed that individuals with PD had difficulty adapting their stability during perturbed walking compared to healthy controls, and authors altered gait parameters such as decreased step length and increased step width, indicating compromised stability control during walking when faced with perturbations [18]. In general, in the topic of rehabilitation, there is the least focus on the lower limb muscles. So, the aim would be to perform rehabilitation by checking energetic passivity and assessing disabilities using Machine Learning Algorithms.
The other way to implement gait training could be classification of gait phases. The paper written by H. T. Vu et al. gives an overview not only to algorithms used for gait phase detection, but also to sensor types and number of detectable phases [19]. The article gives an overview to prior work written from 2010 till 2020. The work concludes that the most effective method to detect stance and swing phases is force sensors, but they have disadvantages of durability and high price [19]. The usage of EMG measurements is stated to be not efficient due to the external facts such as movement of electrodes, etc.[19], because of that the paper report only two article with the usage of the EMG signals. Both of them are outdated, but have high performance. The first one was written by He Huang et al., in 2017, in which HC and TO phases were detected with algorithms combining AAN and LDA classifiers [20]. The accuracy reported to be 85.7%. The second one was written by M. Liu, F. Zhang, and H. Huang in 2017 and has better accuracy of 95% [21]. The used algorithm was Support Vector Machine (SVMs), and it has detected five gait phases

[21]. The usage of SVM algorithm is quite common. For example, article named "Support Vector Machine For Recognition Of Cucumber Leaf Diseases" discusses high accuracy and specificity in identifying various diseases, and the advantages of using the algorithm such as its ability to handle high-dimensional data, its robustness to noise and outliers, and its generalization capability [22]. One of the most recent paper that used EMG measurements was written by N. Nazmi, M. A. Abdul Rahman, S.-I. Yamamoto, and S. A. Ahmad who used Levenberg-Marquart and scaled conjugate gradient algorithms to detect swing and stance phases, while EMG measurement were taken from tibialis anterior (TA), gastrocnemius medialis (mGas) muscles [23]. The ANN model was fed by five time-domain features (RMS, SD, MAV, IEMG, WL) to the model with three layers with 10 tan sigmoid neurons [23]. The accuracy resulted to be 87.4% [23], the paper was published in 2019. Other work with the usage of sEMG signal was written by D. M. Stramel, A. Prado, S. H. Roy, H. Kim, and S. K. Agrawal, where the signals were recorded from left and right gluteus medius (GM) muscles, but except from that the authors also have recorded mTPAD (cable-driven parallel device) Baseline and Moment conditions [24]. The paper's focus was on effect of timed frontal plane pelvic moments where the DeepSole system, which is pair of instrumented insoles and ML algorithm was used [24]. The description of the DeepSole system was found in another work of the authors A. Prado, K. Kwei, N. Vanegas-Arroyave, and S. K. Agrawal named "Continuous Identification of Freezing of Gait in Parkinson's Patients Using Artificial Neural Networks and Instrumented Shoes" where AAN model, which uses signals from instrumented footwear is used to predict if subject is having freezing episode common for Parkinson's disease [25]. The accuracy resulted to be 99.5% [25]. The DeepSole system collects signals from 12 channels: 3 pressure signals, 3 linear accelerations, 3 angular velocities, and 3 Euler angles [25]. The authors have evaluated spatial characteristics, temporal characteristics of gait and balance parameters [25]. The Neural Network design was made of 2D CNN to encode-decode signals and RNN to learn temporal relations [25].

Chapter 3

Methodology

3.1 Methods and Procedure of Data Collection

Data was collected from 3 healthy subjects and 3 children with Cerebral Palsy. The inclusion criteria were children with Cerebral Palsy aged between 12-14 years old, and who are in Levels I & IV of GMFCS, cognitively intact, can report pain. Height should be between 160-195 cm, shoes size should be 38 and upper limbs should be able to handle a walker.
Clinical trials were carried out in the Rehabilitation Room in the Athletic Center and in the laboratory in block S4. The data was collected using Ultium Portable lab equipment, including 3D motion capture system, electromyography sensors and smart insoles.

3.2 Methods and Procedure of Data Analysis

The electrodes were lower limb muscles. The 3D motion capture systems was used to measure joint angles, linear acceleration, etc. The force data from smart insoles was used for identifying gait parameters. The obtained EMG data was pre-processed and used for gait phase detection.

3.3 Ethical Issues

All of the participants have signed agreement on participation in the experiment. The obtained data will be used only during the research and participants are guaranteed to have the measurements kept only in research frame. All experiments are being conducted in accordance with relevant guidelines and regulations. The experimental protocol was reviewed and approved by the Nazarbayev University Institutional Research Ethics Committee (NU-IREC).

Chapter 4

Results and Discussions

4.1 Results

During the project, I learned how to use the software OpenSim to perform a 3D model of a person and analyze different groups of muscles with the normal gait and gait of a person with disabilities. During the study, I completed three tutorials on musculoskeletal modeling, tendon surgery, inverse kinematics, and inverse dynamics. For example, I simulated normal and crouch gait with the following 3D models (see Figure 4.1):

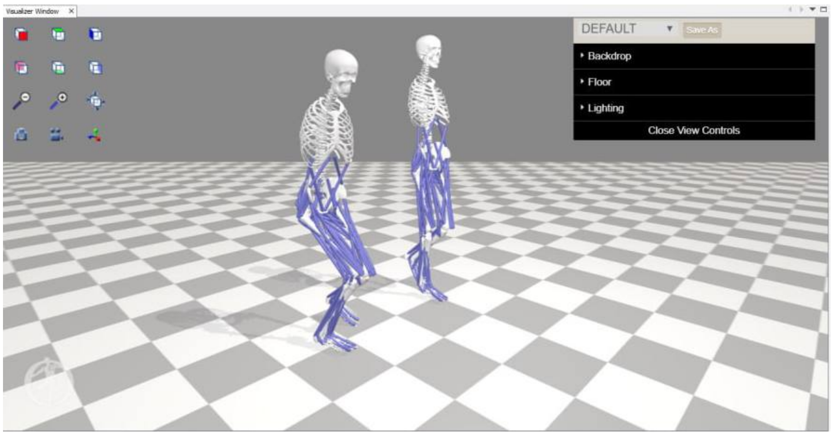

Figure 4.1: Normal and crouch gait in OpenSim

I also learned how to use kinematics tool and dynamics tools in OpenSim. In the tools, a difference between the values of experimental and model markers is found.
The points could be seen in the 3D model in Figure 4.2:

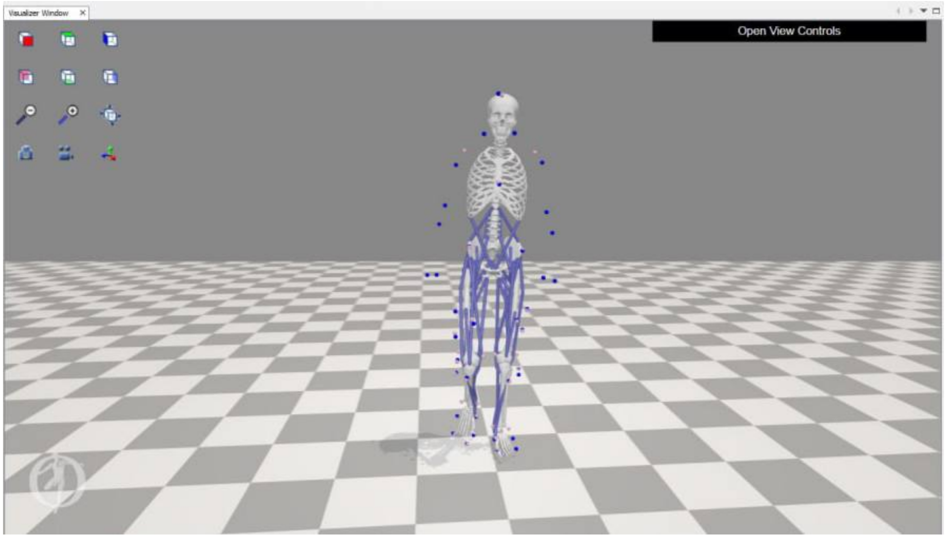

Figure 4.2: 3D model with kinematics and dynamics tools

Firstly, the data taken from healthy subjects was analyzed. Two Unsupervised Machine Learning algorithms were used for gait phase detection.
The first one is k-means clustering algorithm, which was used to divide unlabeled EMG data into clusters. The features were selected based on the work [23]: RMS, MAV, iEMG, WL. The set of muscles were Medial Gastro, Biceps Femoris, Tibialis Anterior and Vastus Lateralis.

	Column	RMS	MAV	iEMG	WL
0	Time	73.126969	63.329750	1.604269e+07	1.266595e+02
1	Force LT	478.702908	367.082784	9.298941e+07	8.431575e+04
2	Force RT	496.590174	380.150036	9.629961e+07	8.945471e+04
3	BICEPS FEM. LT	36.397916	17.268255	4.374394e+06	1.552386e+06
4	BICEPS FEM. RT	45.775259	21.912541	5.550885e+06	2.015147e+06
5	VLO LT	20.150564	9.924693	2.514123e+06	9.772962e+05
6	VLO RT	49.888024	29.037947	7.355893e+06	2.053020e+06
7	TIB.ANT. LT	27.925733	14.423173	3.653678e+06	1.418660e+06
8	TIB.ANT. RT	34.688564	18.314369	4.639396e+06	1.896965e+06
9	MED. GASTRO LT	67.803227	39.503771	1.000710e+07	4.043134e+06
10	MED. GASTRO RT	41.485347	20.917947	5.298934e+06	2.323772e+06

Figure 4.3: Values of selected features for each muscle (healthy patient)

The principle work of k-means algorithm is grouping data set into different clusters based on the value of k. So, the main hyper parameter is k, and the main problem was identifying the right value for k. The elbow method was used for this purpose. As can be seen from Figure 4.4, the best values for k are in range from

1 to 4. Since, the aim is to distinguish at least two phases, the next aim was to identify suitable value between k=2 and k=3.

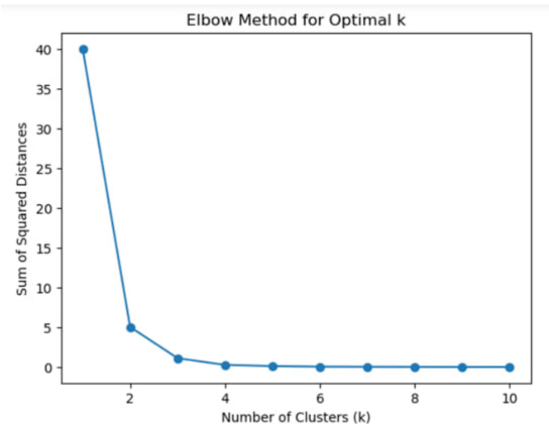

Figure 4.4: Elbow method for k-means algorithm

In order to identify the right value two methods of assessment were used. The first one is the pair plots of all features. The pair plots for k=2 can be seen in Figure 4.5, and for k=3 in Figure 4.6:

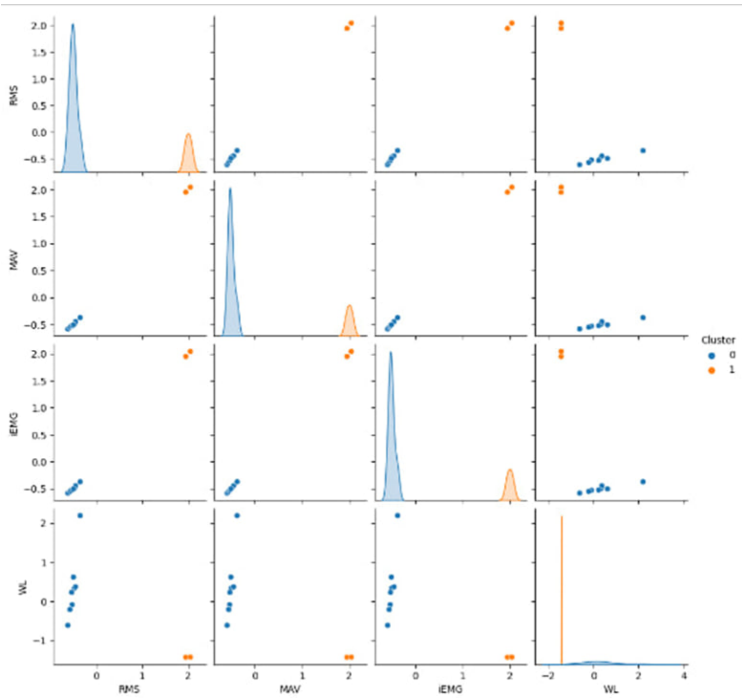

Figure 4.5: Pair plots of all features when k=2

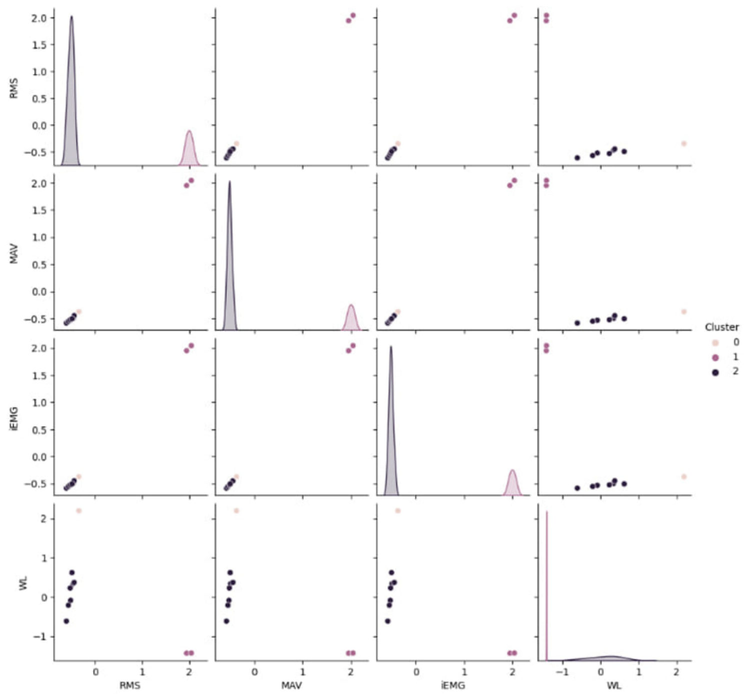

Figure 4.6: Pair plots of all features when k=3

Another type of assessment was Silhouette Score, which ranges from 0 to 1, where 0 meaning that the clusters are not distinguished and 1 meaning that the clusters are perfectly distinguished. So, for k=2 the Silhouette Score was 0.84, and for k=3 the score was 0.719.
Also, DBSCAN algorithm was used to verify the choice of k value. The algorithm also has its own hyperparameters, namely eps and min-samples. In order to assess different combinations of the hyperparameters 2D PCA plot that shows the group according to the density distribution of the points was constructed:

After that, the Silhouette Scores for all of the combinations of hyperparameters was plotted:

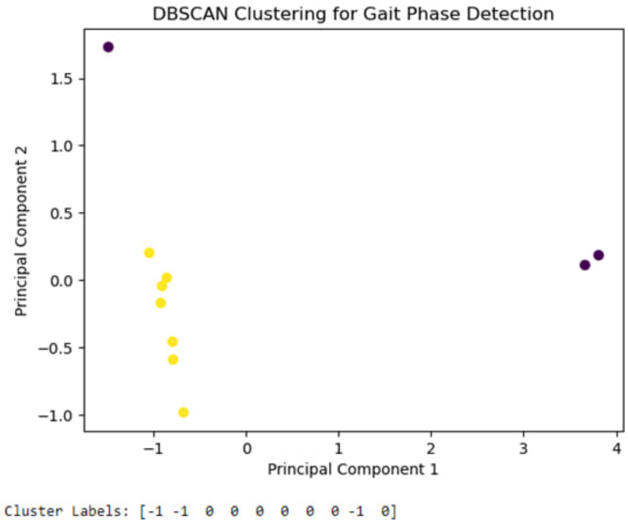

Figure 4.7: 2D PCA plot for min-samples=3 and eps=0.5

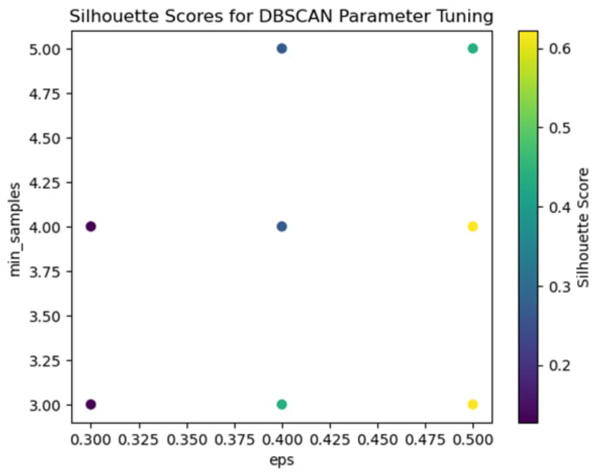

Figure 4.8: 2D PCA plot for min-samples=3 and eps=0.5

Next task was to perform the same procedure for the data of CP patients. Firstly, the EMG data needed to be pre-processed. The data from pelvis muscles was analyzed for three subjects: AT-17, AR-17 and AB-16. Also, the EMG data from lower limb muscles was analyzed for another subject (Anvar). The data from pelvis muscles included data from Gluteus Maximus and Gluteus Medius muscles, while the data from lower limb muscles included data from Medial Gastro, Lateral Gastro and Biceps Femorus muscles. The FIR and Butterworth filters were implemented in the MATLAB.
The results for the subjects AB-16, AT-17 and AR-17 can be seen in Figures 4.9, 4.10

and 4.11 respectively. The EMG data from lower muscles also was pre-processed in similar manner, which can be seen from Figures 4.12:

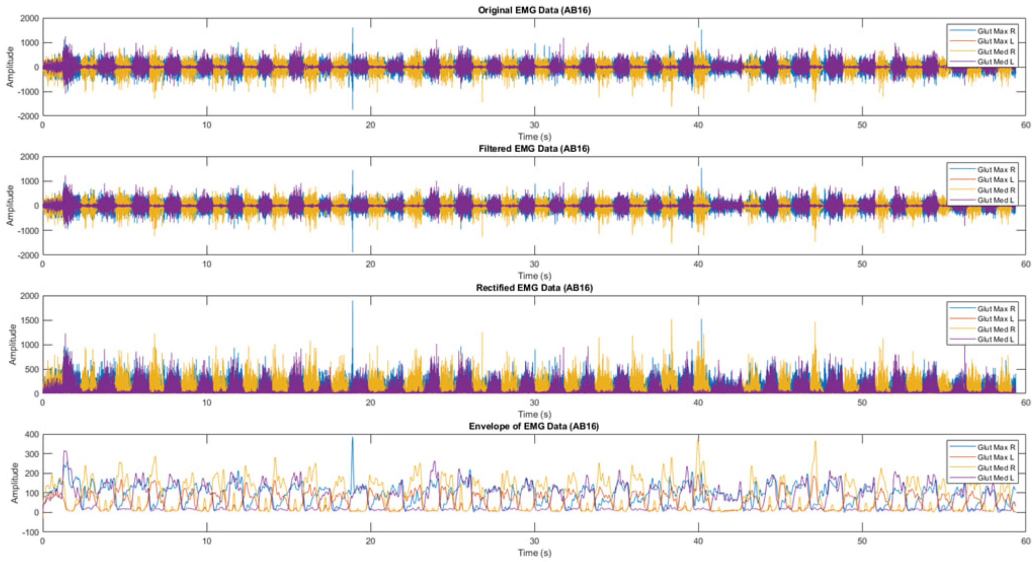

Figure 4.9: Original, filtered, rectified and envelope of EMG data of AB16

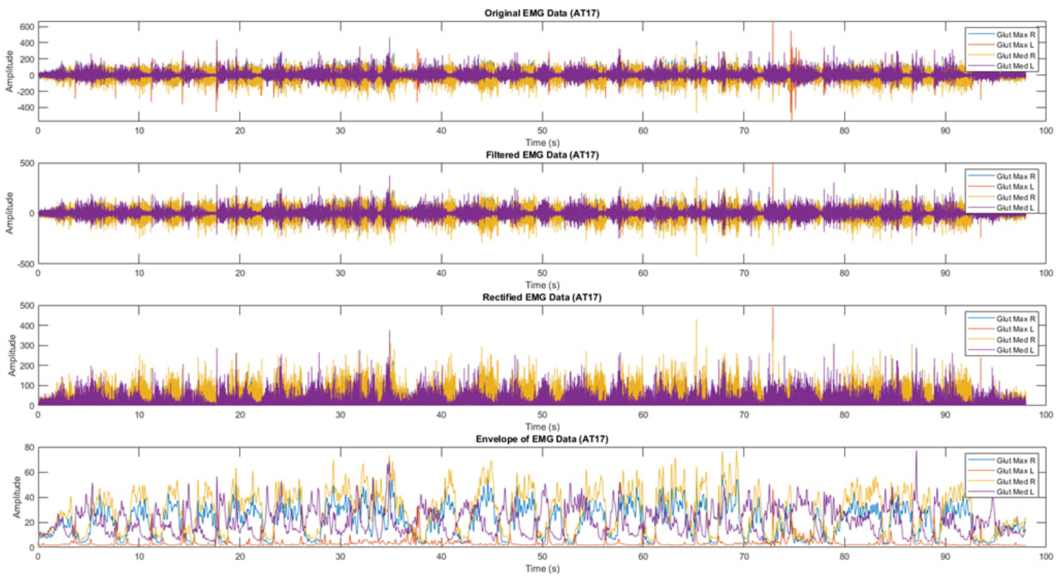

Figure 4.10: Original, filtered, rectified and envelope of EMG data of AT17

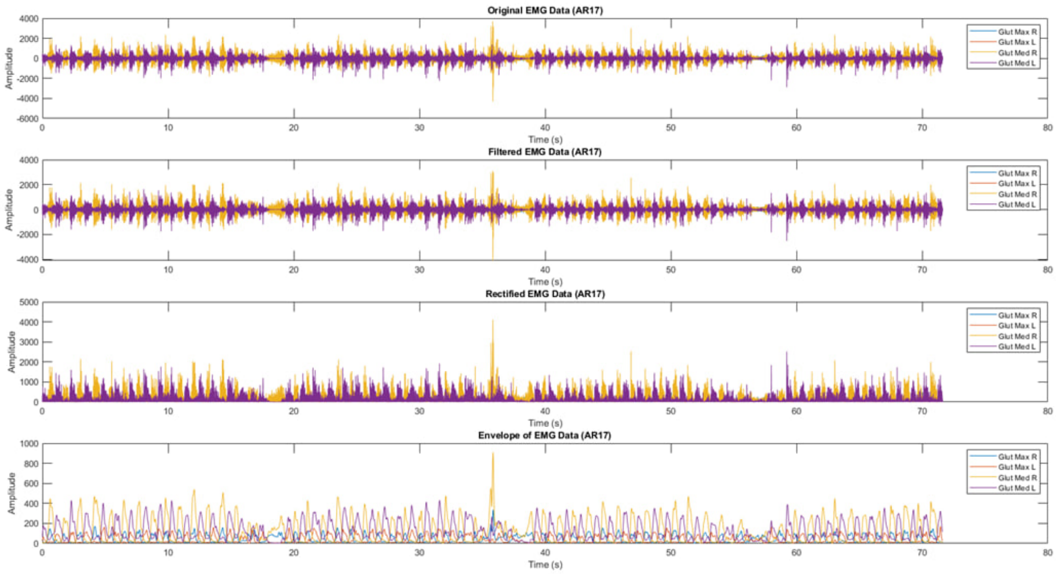

Figure 4.11: Original, filtered, rectified and envelope of EMG data of AR17

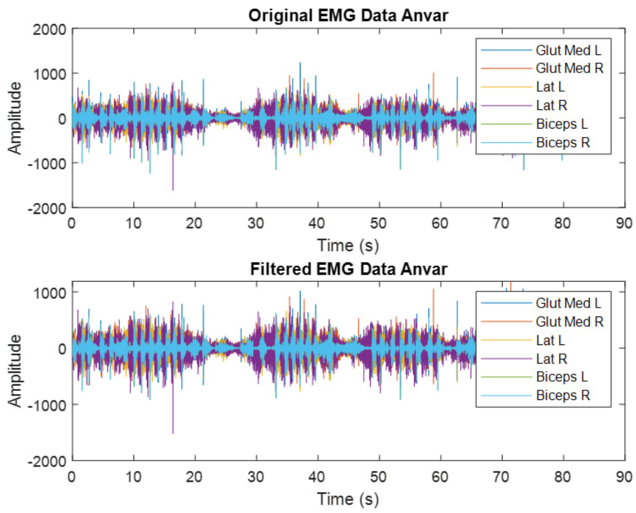

Figure 4.12: Original, filtered, rectified and envelope of EMG data from lower muscles

Then, the filtered EMG data was used with k-means algorithm. The same assessment tools were used for this case. So, the pair plots of the features were plotted when k=2 (Figure 4.13) and k=3 (Figure 4.14) for subject AT17. Also, the Silhouette Score was sued to assess the results. For k=2 the score was equal to 0.72, and for k=3 the score was 0.65.

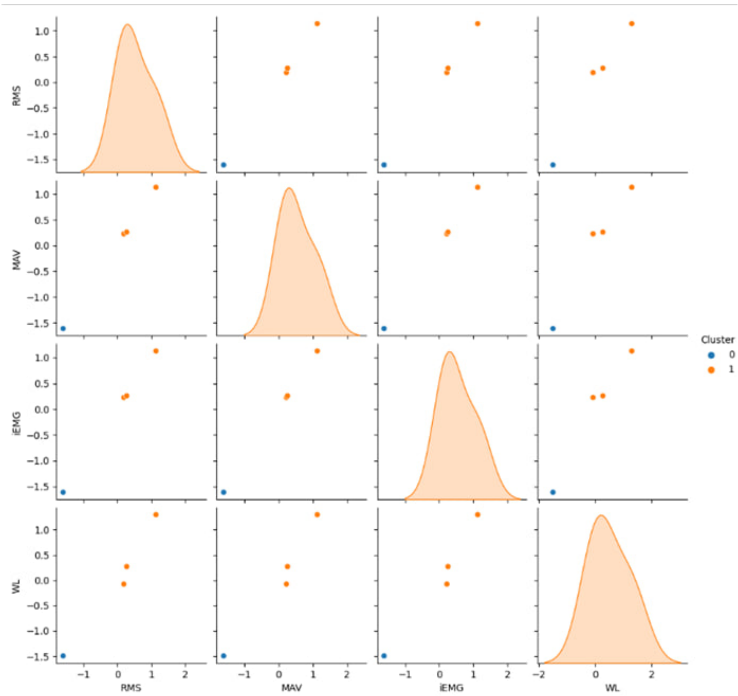

Figure 4.13: Pair plots of features when k=2 for AT17

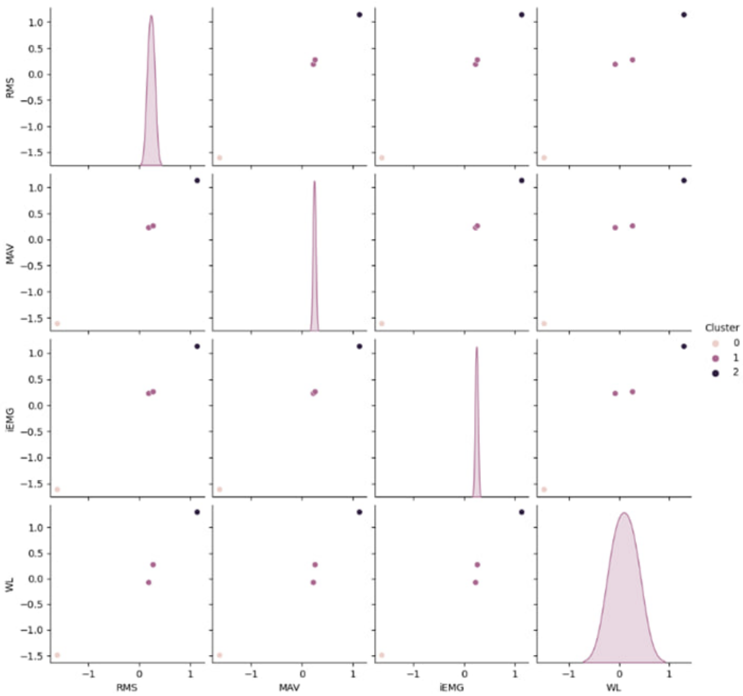

Figure 4.14: Pair plots of features when k=3 for AT17

Another tools for the diagnosis of Cerebral Palsy was gait analysis. So, the force data from smart insoles was analyzed, and the gait parameters can be concluded in Table 4.1:

Table 4.1: Spatial-Temporal Parameters

Subject ID	AB-16	AT-17	AR-17
Stride length (m)	0	0.06	0.03
Velocity (m/s)	0.055	0.833	0.055
Cadence (steps/min)	74	43	100

Also, the force data was plotted against the time as can be seen from Figure 4.15 (for subject AT17), Figure 4.16 (for subject AR17) and Figure 4.17 (for subject AB16). The means and standard deviations of the force data was also identified for each subject as can be seen in Table 4.2:

Table 4.2: Mean and std dev values of force data for each subject

Subject ID	$m_{(F(RT))}$	$m_{(F(LT))}$	$\sigma_{(F(RT))}$	$\sigma_{(F(LT))}$
AR17	215.8782	201.518	184.1051	160.4168
AT17	874.2692	1053.3134	490.796	906.911
AB16	814.477	1502.7267	549.1771	1385.1097

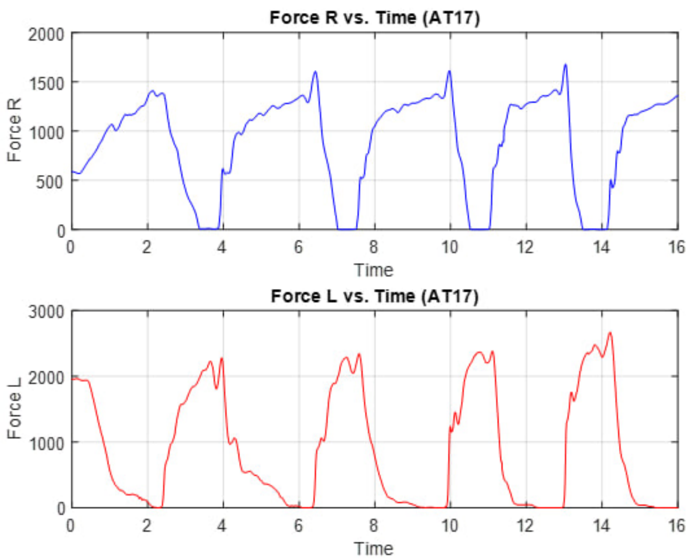

Figure 4.15: Force vs time for one gait cycle (AT17)

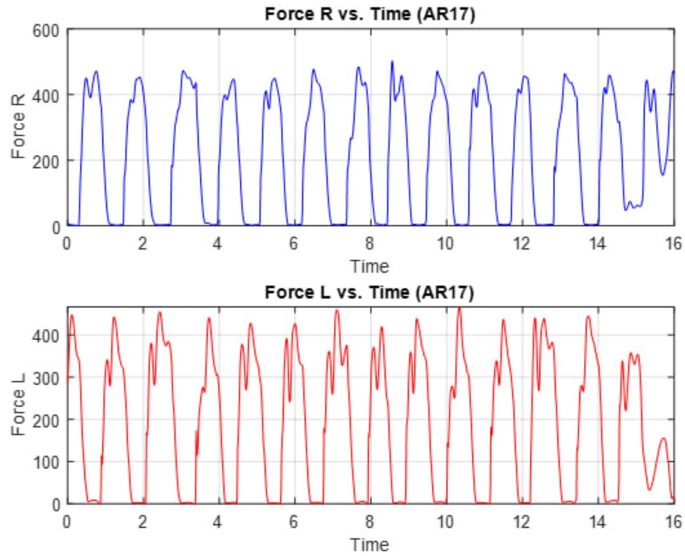

Figure 4.16: Force vs time for one gait cycle (AR17)

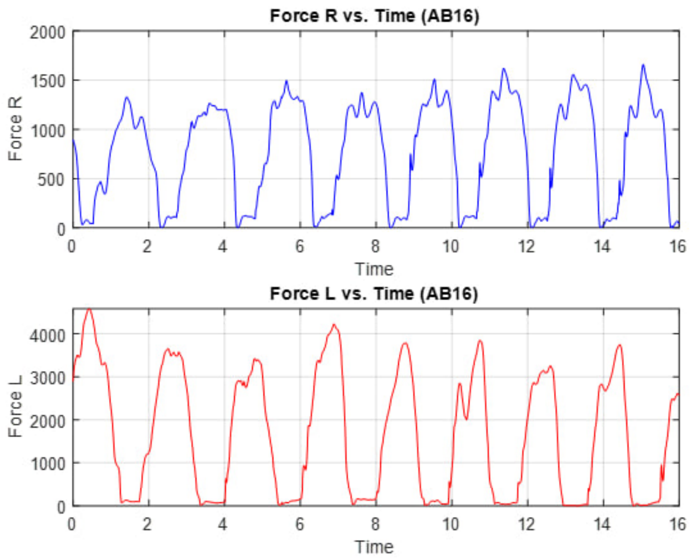

Figure 4.17: Force vs time for one gait cycle (AB16)

4.2 Discussions

During the completion of the Inverse Kinematic and Dynamics tutorial I learned that OpenSim finds the “best match” between experimental error and model marker by solving the weighted least squares optimization problem in order to minimize marker error. So, I have calculated the problem using the following equation and compared the results with simulation in the Inverse Kinematics tool:
$\min_q \left[\sum_{i\in \text{ markers}} w_i \left\|\mathbf{x}_i^{\text{exp}} - \mathbf{x}_i(\mathbf{q})\right\|^2\right]$
The results ended up being the same:

total squared error = 0.0135755

marker error: RMS = 0.0209265

max = 0.079239 (R.Acromium)

So, from the analysis with k-means algorithm it can be concluded that the right value for k is either 2 or 3. Looking into the Figure 4.6 and particularly into the graph of iEMG vs RMS, it is obvious that k-means algorithm struggles to distinguish the clusters in some cases. So, from the analysis with these two assessment tools, it is obvious that k=2 would be better option.
However, to remove human factor from the choice of hyperparameter, it was decided to use DBSCAN algorithm that divides data set into different groups based on density of location of data points. So, after testing different combinations of eps and min-samples, it was concluded that the best values for eps would be between 0.3 and 0.5 and for the min-samples between 3 and 5. From Figure 4.8 it can be seen that min-samples and eps values was appropriate. So, it can be concluded that the k=2 is suitable value.
talking about the gait analysis, it can be seen Table 4.1 that the values are relatively small. Comparing them to the values from [26] work, which investigates norms in spatial temporal parameters for the individuals in the age group from 14 to 21, the results should have the following values:
Stride length (m): 1.34 ± 0.16
Velocity (m/s): 1.28 ± 0.15
Cadence (steps/min): 115.35 ± 8.18
The values are significantly smaller compared to these norms, and it also can be verified from force vs time graphs (Figures 4.15,4.16 and 4.17) where the values fluctuates significantly in one gait cycle.
All of the results confirms that the children indeed have Cerebral Palsy.

Chapter 5

Conclusion

This work presented two ways to make an assessment for diagnosis of Cerebral Palsy: gait analysis and gait phase detection. The gait phase detection was implemented with the use of k-means and DBSCAN algorithms. The k-means clustering algorithm was showing good results both with the data of healthy subject the data of CP patients when k=2. It is also was proved that the results was smaller for the case when k=3. In order to verify the choice of k value, DBSCAN algorithm was used. The analysis with DSBCAN algorithm shows that the optimal value should be 2. However, one of the clusters in the results from 2D PCA plot can be interpreted as noise cluster, so it can better option to choose k=3 despite low Silhouette Score according to the results from DSBCAN algorithm.
In addition, the gait analysis with spatial-temporal parameters and force vs time plots was implemented as another assessment tool. The spatial-temporal parameters were compared to the norms for the age group from 14 to 21 years, and the force graphs were assessed to consistency in one gait cycle.
The project could developed further by using labeled EMG data and more advanced Supervised Machine Learning algorithms. However, the main limitation of the project is unavailability of EMG data in open access, which means that the Supervised Machine Learning cannot be used in that case. The project can be developed further by verifying the results using analysis of force data from smart insoles as well as developing Deep Learning algorithm for EMG data labeling.

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Appendix A

Appendix A name