MINOR I REPORT

GAIT ANALYSIS

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We convey our thanks to our supervisor, Dr. Ankit Vidhyarthi of Computer Science and Engineering Department for providing support and guidance throughout the course of this project.

We would also like to thank our parents for supporting us through the journey college and constantly encouraging us to learn more. Their sacrifice in providing this opportunity to learn is gratefully acknowledged.

Janani Pradeep

Ashish Sharma

Harsh Singhal

Objective:
To study, and analyze different gait factors, correlations and effects of speed and inclination with angles at various joints and various other variables.

Introduction:
The main motive to work in this project is to find unseen factors that influence the gait patterns and to analyze the optimum factors to prevent gait related injuries.

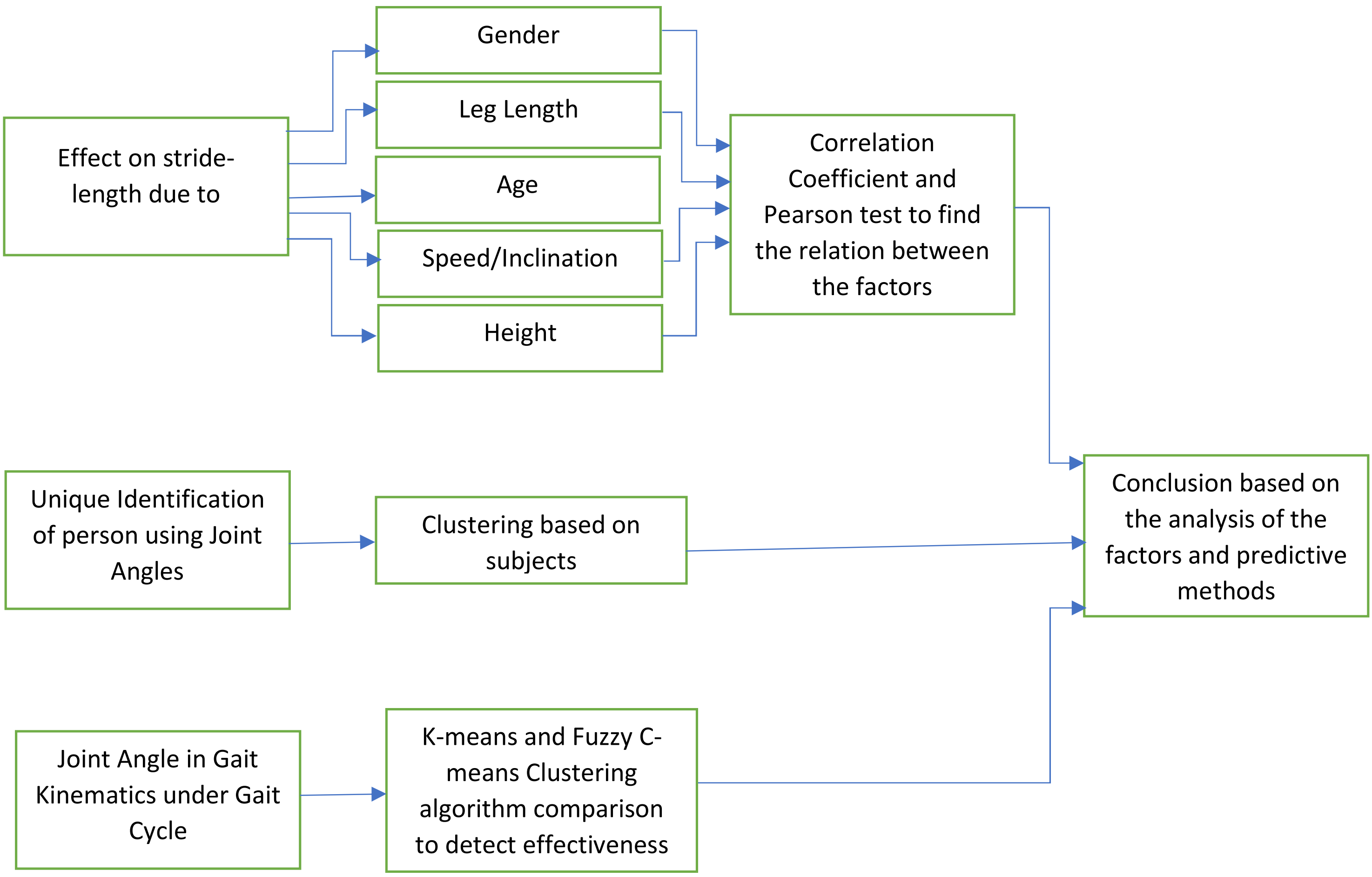
1. Gait has been established as biometrics to recognize people by the way they walk.
2. The study of gait allows diagnoses and intervention strategies to be made for patients suffering from Cerebral palsy and stroke.
3. It also allows creation of effective prosthetic limbs.
4. Gait analysis is used to identify, analyze, and treat individuals with conditions affecting their ability to walk, identify posture-related or movement-related problems in people with injuries, and in sports biomechanics to help athletes run more efficiently

Type of Project: RESEARCH CUM DEVELOPMENT PROJECT
Research Paper Reads:

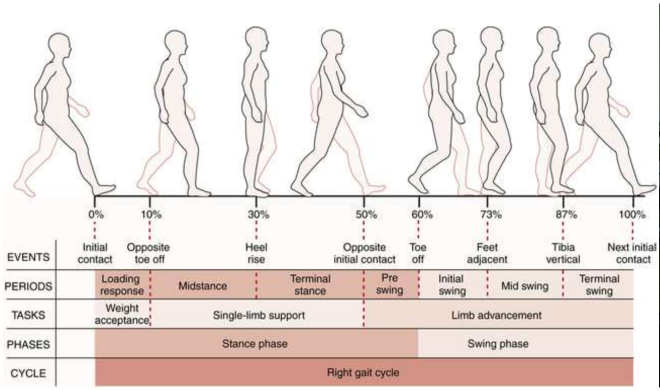
S.No.	Objective	Method Used	Findings	Gaps
1.	The Effect of Inclination and Walking speed on Foot Placement for Slope Walking	A two-way repeated measures ANOVA and t tests to analyze the correlation between the slope, walking speed and step length.	Humans tend to walk more cautiously on downslopes by limiting the step length and tend to change the step length to adjust their walking speed.	In this paper only a few factors affecting the gait cycle were analyzed when many such factors were possible
2.	Human Locomotion Activity and Speed Recognition Using Electromyography Based Features	The RMS and energy feature of EMG were calculated per gait cycle K-means clustering approach to find the Energy-RMS clusters	The energy level of EMG of lower-limb muscle groups remain at the same level for each activity and changes as the activity changes.	K-means clustering approach is a hard clustering and restricts data point to one cluster. But in this case, overlap can be seen.

3.	Modeling the Kinematics of Human Locomotion over Continuously Varying Speeds and Inclines	Basis Modeling method and continuous prediction The Dynamic Plug-in Gait Model was applied to calculate joint angles	Model human locomotion and accurately parameterize the human gait cycle as a function of phase, speed, and incline	No conclusive evidence of gaps found
4.	Inclination angles of the ankle and head relative to the center of mass identify gait deviations post-stroke	Correlation between factors found using p-value function with significance = 0.05	Coordination between the upper and lower body in persons post-stroke and controls evaluating consequences of impairments on gait patterns post-stroke	The section of participants was limited to old-age people with stroke rather than a wide variety of age. So conclusion was restricted to a specific age range
5.	Fuzzy Clustering of Children with Cerebral Palsy Based on Temporal-Distance Gait Parameters	Fuzzy K-means algorithm to cluster children based on Features extracted were stride length and cadence	The normalized stride length can be seen to be an extremely good discriminator between neurologically intact children and children with CP.	No conclusive evidence of gaps found

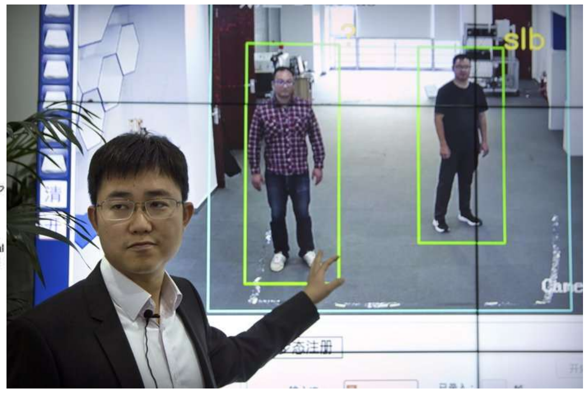
Project Design: Data set - THE EFFECT OF WALKING INCLINE AND SPEED ON HUMAN LEG KINEMATICS, KINETICS, AND EMG



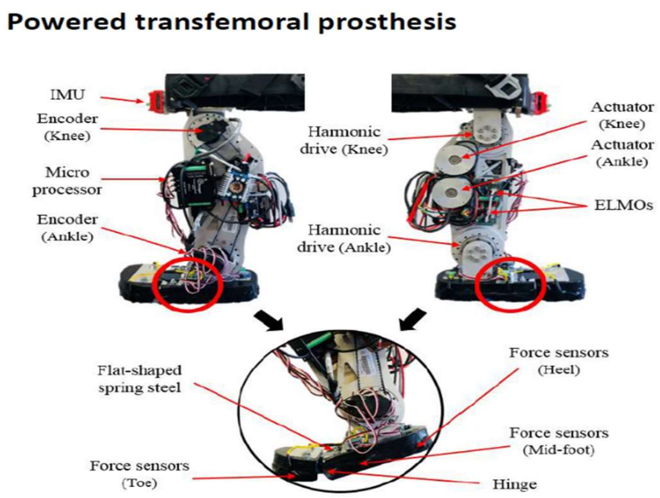
Applications:



(1) Gait Cycle



(2) Person identification by their walk



(3) Limb prosthetics

Methodology:

For the data analysis, Chi square test was used for categorical value and Pearson test for numerical data. Tolerance of 0.005 was considered and correlation and null hypothesis was verified and accordingly the output was derived.

Dynamic time warping (DTW) is an algorithm to measure the similarity between two temporal sequences, which may change in speed. For instance, similarities in walking could be detected using DTW, even if there is variation in the speed of the first person to the second one.

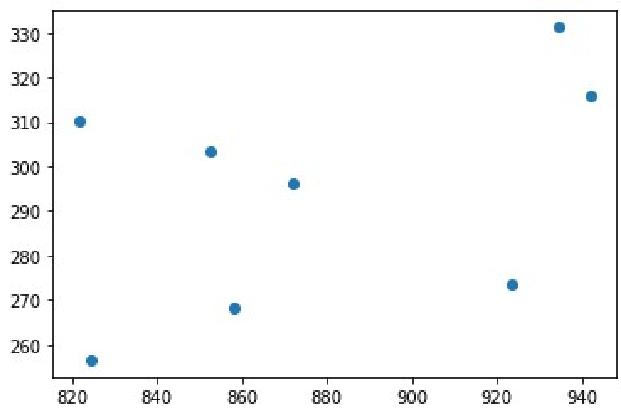
The time complexity of DTW distance function is O(N^2).We have used DTW here because we have worked on time series data, so that proper clustering of series can happen and have also calculated mean of clusters of different variables such as Hip, knee, pelvis, ankle, foot with help of DTW.

Observations & Results:

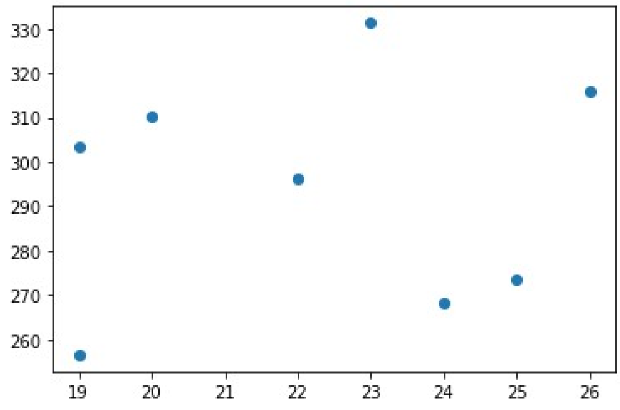
Data Analysis

Gender vs Stride Length:

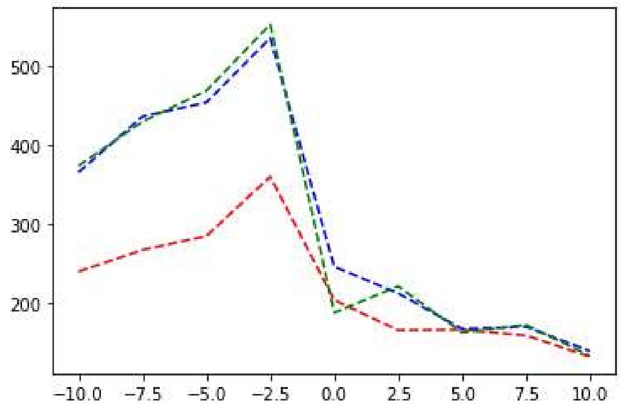
Leg Length vs Stride Length:



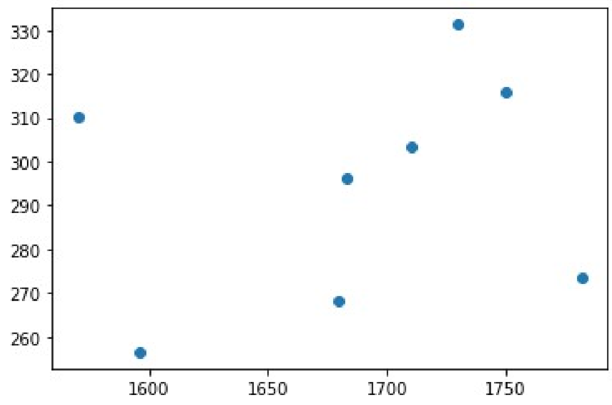
Age vs Stride Length:



Incline vs Stride Length at different Speeds:



Height vs Stride Length:



VS	P VALUE	CORRELATION	NULL HYPOTHESIS
Gender vs Stride Length:	0.987811292	--	Accept
Leg Length vs Stride Length:	4.12E-14	Positive	Reject
Age vs Stride Length:	5.12E-14	Positive	Reject
Incline vs Stride Length at different Speeds:	1.48E-07	Negative	Reject
Height vs Stride Length:	2.79E-17	Positive	Reject

In our analysis, it was shown that:

1. The slope angle and walking speed affected stride length on the sloped surfaces. Humans tend to walk more cautiously on downslopes by limiting the stride length and tend to change the stride length to adjust their walking speed.

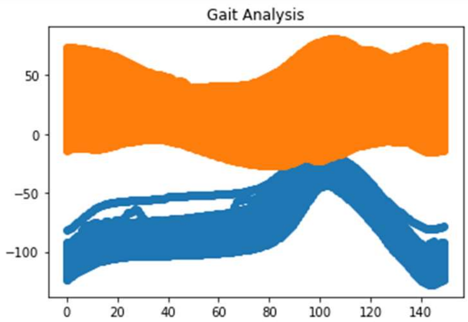
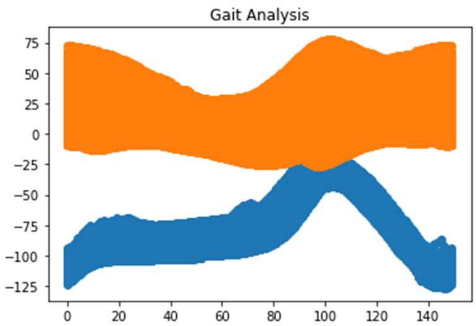
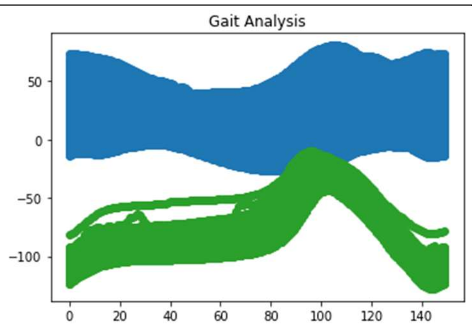
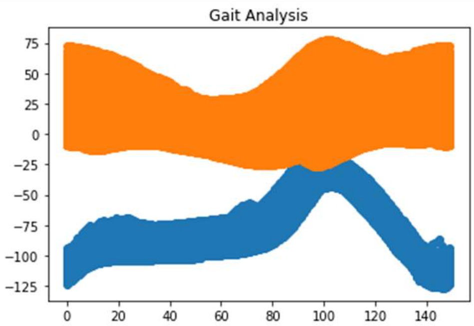
2. In declination, the stride length decreases when the slope becomes steeper for all walking speeds
3. In inclination, the stride length has no significant trend with respect to the slope angle for all walking speeds.
4. The stride tends to increase with the increasing height of the person.
5. Gender has not significant relation with the stride length.
6. Visually, leg length and age do not give a good result, but through calculation, they both return a positive correlation.

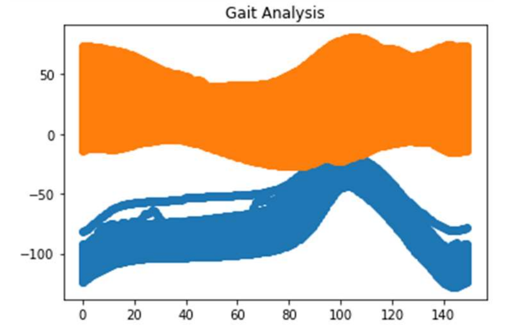
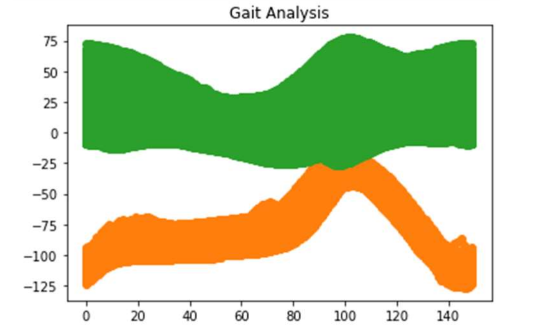
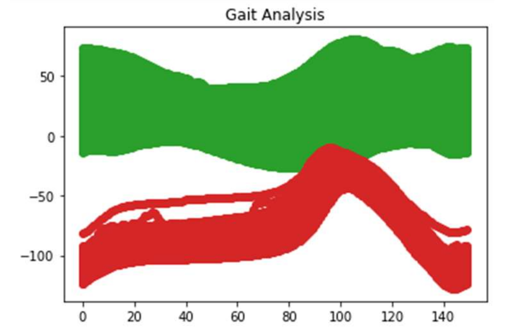
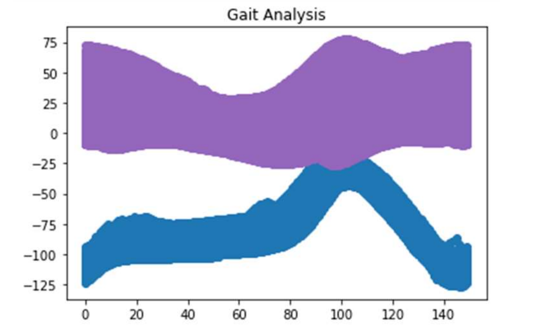
Clustering

Fuzzy C-Means and K-Means algorithm effectiveness measure under various cluster size

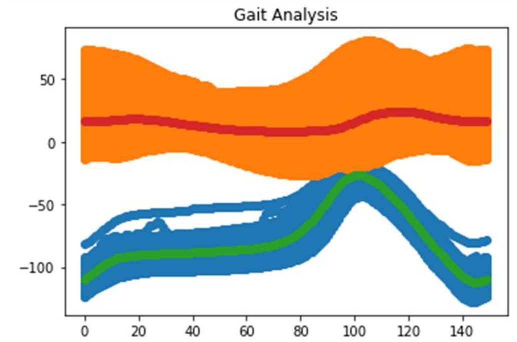
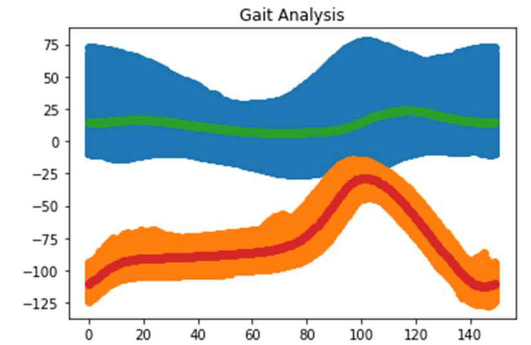
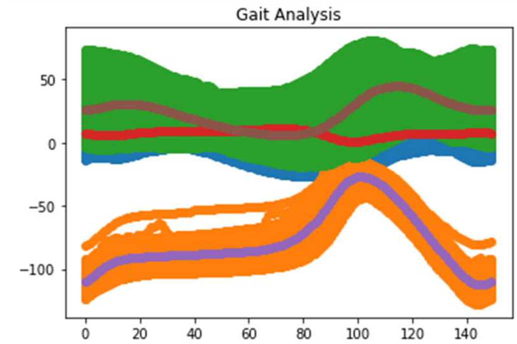
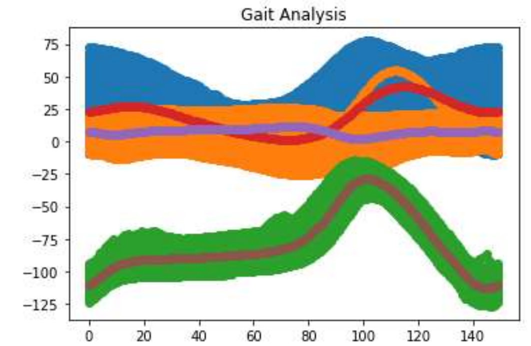
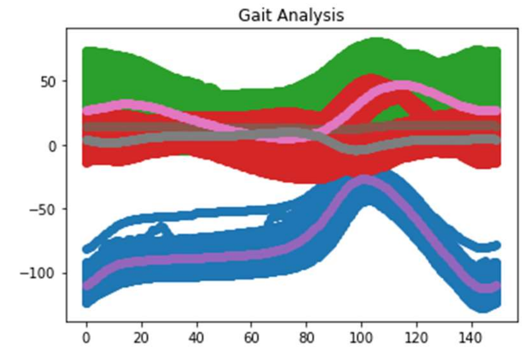
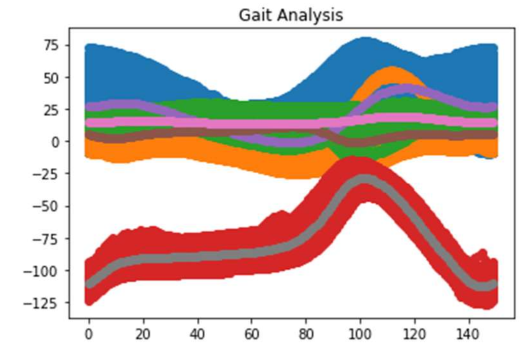
K MEANS (Left)	**2 cluster**	**3 cluster**	**4 cluster**	**5 cluster**
Cluster Purity	0.8	0.6	0.4	0.4
Intracluster Distance	[20.1512, 52.5362]	[52.5362, 502.2201]	[20.1512, 52.5362]	[301.4716, 51.2262]
InterCluster Distance	250.8906788	98.1638773	250.8906788	214.0798235
Silhoute	0.88039371	0.88039371	0.88039371	0.88039371
DB Index	0.289720643	9.478207611	0.289720643	2.122466775
K MEANS (Right)	**2 cluster**	**3 cluster**	**4 cluster**	**5 cluster**
Cluster Purity	0.8	0.6	0.6	0.4
Intracluster Distance	[16.8518, 49.1962]	[16.8518, 49.1962]	[137.5121, 497.9021]	[16.8518, 132.1541]
InterCluster Distance	248.9489834	248.9489834	164.1562831	261.7457479
Silhoute	0.867585855	0.867585855	0.867585855	0.867585855
DB Index	0.265318233	0.265318233	9.244887928	0.476174728
FUZZY C MEANS (Left)	**2 cluster**	**3 cluster**	**4 cluster**	**5 cluster**
Cluster Purity	0.8	0.8	0.7	0.8
Intracluster Distance	[54.0258,318.9783]	[154.0206,54.0862, 250.0191]	[54.0941, 105.8930, 243.6595, 131.3088]	[102.7535, 160.2759, 115.3673, 121.1701, 54.1022]
InterCluster Distance	1165.840295	1614.639804	2005.5554	2444.0002
Silhoute	0.840027749	0.905422683	0.933315779	0.954691575
DB Index	0.178155001	0.47423242	0.103384065	2.122466775
FUZZY C MEANS RIGHT	**2 cluster**	**3 cluster**	**4 cluster**	**5 cluster**
Cluster Purity	0.8	0.8	0.7	0.9
Intracluster Distance	[47.04971, 298.2009]	[46.9979, 139.5616, 249.4814]	[246.2257, 119.1276, 97.5280, 46.9962]	[92.16978, 158.3874, 46.9969, 109.4102, 108.0774]
InterCluster Distance	1159.277504	1584.8194	1965.278346	2394.841617
Silhoute	0.851092316	0.908228796	0.935139225	0.956987492
DB Index	0.171484654	0.118113644	0.068987474	0.617815531

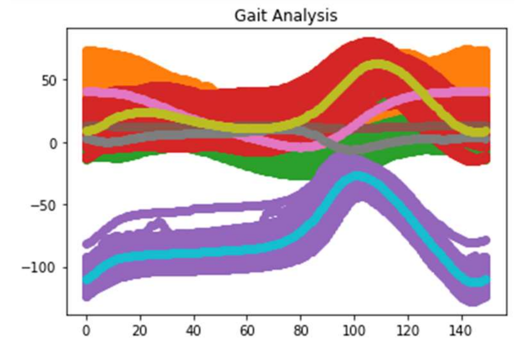
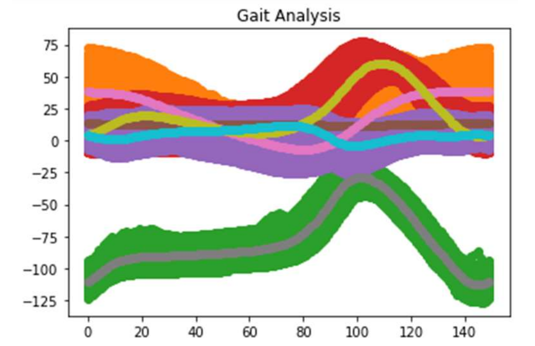
<u>K-MEANS</u>

CLUSTER	**LEFT**	**RIGHT**
2		
3		

4		
5		

<u>FUZZY C-MEANS</u>

CLUSTER	**LEFT**	**RIGHT**
2		
3		
4		

5		

In the clustering comparison chart, it was derived that:

1. Overall, Fuzzy C-Means gave better cluster results than K-Means for both Left and Right leg joint angles.
2. In K-Means,
   a. For left leg, 2 cluster gave best result optimal values of calculated indices.
   b. For right leg, 2 cluster gave best result optimal values of calculated indices.
3. In Fuzzy C-Means,
   a. For left leg, 5 cluster gave best result optimal values of calculated indices.
   b. For right leg, 5 cluster gave best result optimal values of calculated indices.

It can be concluded that there is no major differentiation between the subjects left and right leg and hybrid Fuzzy C-Means clustering fused with K-Means algorithm gave better results when calculated for the continuous time series data.

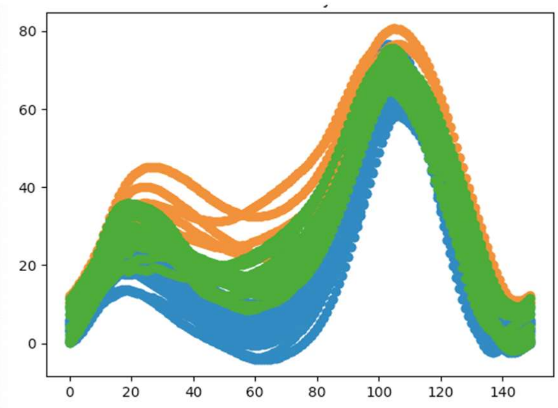
It was also noted that the Joint Angle of foot varied highly than the other five components in the data set. Hence the changes in the foot variable is highly noticeable.

Practical Application

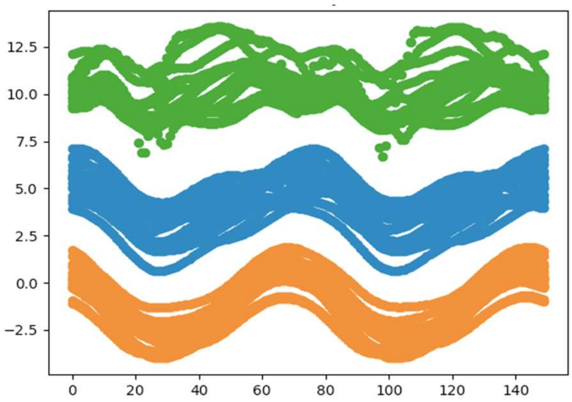
Using the clustering techniques applied, we tried to apply it on a practical aspect.

We wanted to see if we can classify the set of data of joint angles into clusters wherein, each cluster pertains to a single subject. This technique can be used in future to identify the person based on their walking data.

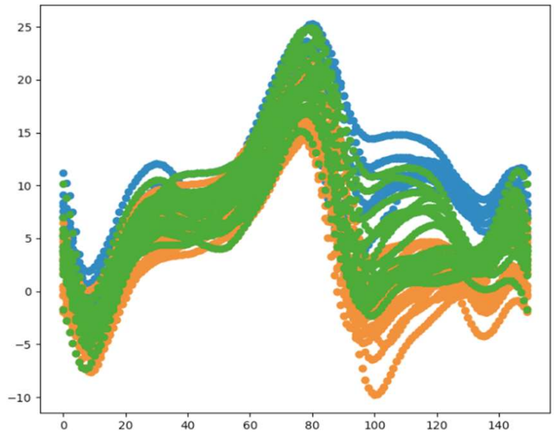
We had the joint angle data of Ankle, Foot, Hip, Knee and Pelvis. Applying the algorithm on each of them individually, we found that using the joint angles of Pelvis in the data of gait-cycles, we were getting the best results that could easily cluster the joint angles differently for all the subjects taken into consideration.



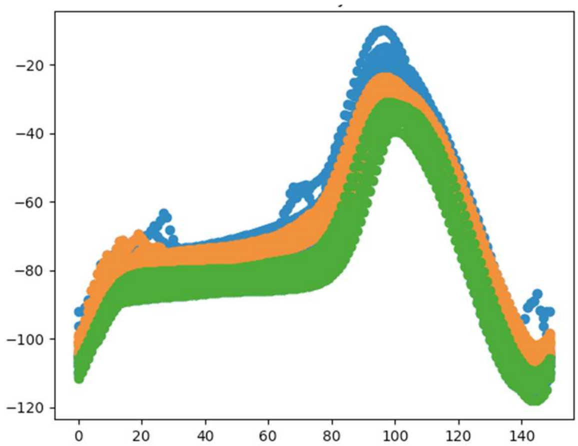
KNEE



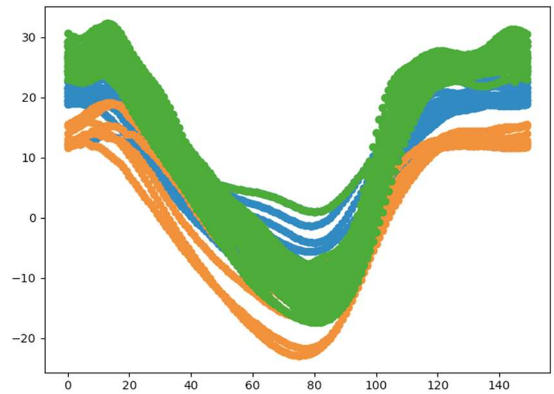
PELVIS



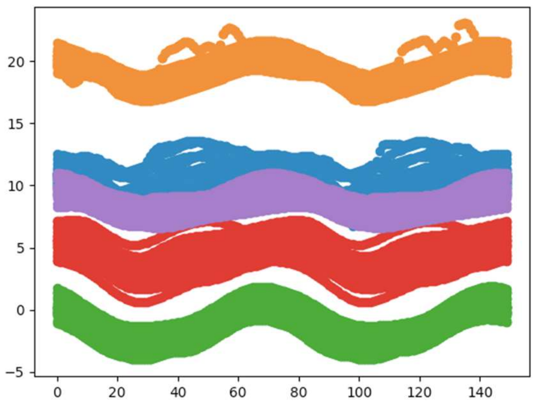
ANKLE



FOOT



FOOT



PELVIS (0.86)

Further, trials were conducted taking the joint angles along X, Y & Z directions and In all three Directions, Pelvis gave the highest Cluster Purity, and cluster purity of 1.0 (100%) was obtained on taking the values in X- Direction. So we moved further on our analysis by increasing the subjects from 3 to 5 and still the Pelvis gave best results.

After this, we tried to increase the number of subjects. The Cluster Purity index reduced from 1.0 to 0.8. Then efforts were made to increase this accuracy and we could reach upto an accuracy of 0.94. But the algorithm took considerable time for the execution.

In future, efforts will be made to increase the efficiency of the Algorithm and reducing the time taken for the cluster classification. Also, we will try and incorporate EMG data for analysis and further studies.

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