Gait Identification for an Intelligent Prosthetic Leg

Zunaed Kibria[1] [1]
[1]Electrical and Biomedical Engineering, University of Nevada, Reno, USA
{zkibria}@nevada.unr.edu

Keywords: Control, Intelligent Prosthetic Leg, Gait, Rehabilitation.

Abstract: Design of an actively controlled prosthetic leg is an emerging research area in robotics. When there are changes in walking conditions such as terrain or speed, classical control methods might confront difficulties. An intelligent prosthetic leg will adapt more efficiently to those changes if it is equipped with an online learning control algorithm. To design such controller, the first step is to acquire real-time gait information from the amputee to study walking behaviours of the individual. This paper offers a classification techniques of different gait activities and walking speed based on mainly LSTM and other architectures on gait recognition. Proper classification of gait events will help challenges in terms of rehabilitation engineering.

1 Introduction:

Several reasons such as diabetes, blood circulatory problem, tumor, congenital issue, cancer, trauma etc. can be responsible for amputation (McEwan et al., 2018). The amputation can have undesirable effects on the mental and physical health of a person. As the amputees depend less on their residual limbs, improper choice of prosthetic fit increases the probability of Osteoarthritis, Osteopenia, Osteoporosis, postural changes and most commonly back pain (Roeder, 2008). It has been estimated that by the year 2050, the number of people living in USA with the loss of a limb will be 3.6 million (K et al., 2008). To develop and test any prosthetic limb, it is desired that the prosthetic system will be able to identify user's intended gait fast and efficiently so that the user can able to have smooth locomotion.

The gait cycle can be broken down into two primary phases, the stance and swing phases, which alternate for each lower limb. The stance phase is subdivided into – heel strike, foot flat, mid stance, heel off and toe off phases. The swing phase is subdivided into – initial, mid and terminal swing phases. In this project, we will collect gait angle and foot pressure data from various range of user and then use classification techniques to identify gait subphases irrespective of users' height, weight, age, cadence speed etc.

2 Related Work:

Researchers usually use sensory information systems to measure data from amputees in order to classify different gait patterns and/or detect gait phases. In the initial days, gait analysis was performed based on classical dynamics. Researchers analyze the moment of inertia, center of gravity of a person and analyse the gait asymmetry (Winter, 2009). With the increasing popularity of machine learning, researchers then focused to analyse the gait pattern with neural network techniques. Some researchers used joint angles and the time-distance as features to classify between healthy subjects and amputees (Kohle, 1997). Some researchers detected gait malfunctions of normal subjects using ground reaction force data (Koktas et al., 2006). There has been some neural network based work which analysed collected data from an accelerometer to detect the "stance period", "swing period", and "foot off" of a prosthetic leg (Wolfgang, 2006). Some machine learning techniques used gyroscope and accelerometer data to detect different gait phases of subjects with normal and impaired gaits in several walking conditions (Pappas, 2001). Another identification technique is based on interface force measured between the socket inner wall and the residual limb at the distal end position (Mai, 2011).

There are several vision-based approaches to identify gait and posture of a person. Initially some researchers used view transformation model and frequency domain features to identify gait (Makihara et al., 2006). Then with the help of advanced semantic segmentation algorithms vision-based gait analysis model got improved. With this technique gait recognition from an arbitrary, cluttered complex background was possible (He et al., 2017; Lin et al., 2017). Vision based approaches are mainly based on convolution deep network. In recent years, due to the rapid development of mobile devices, the accelerometer and gyroscope have been

[1] zkibria@nevada.unr.edu

commonly integrated into the smartphones and smartwatches (Le Moing, 2015). With this technique various activities like walking, jogging, climbing stairs were identified. (Hamza issa Abujrida and Emmanuel, 2017). However, these approaches are based on intact person's movement and did not focus on the fact of analysing an amputee patience's gait.

Some of the research works on gait identification are based on Recurrent Neural Network (RNN) architecture and got some promising results. With LSTM technique, researchers were able to make use of unlabelled data for training (Yang Feng and Yuncheng Li and Jiebo, 2016). One approach was based on convolutional energy maps and then adopts to a bidirectional recurrent neural network(Alireza Sepas-Moghaddam and Ali, 2021). There has been work which used RNN technique and inspired by the mechanism of brain sequence processing(Liu, 2016). A very recent memory based RNN approach was successful to detect the pose of a person and translate into the gait. (Liu, 2022).

However, to develop a prosthetic leg control system, it is not enough to be able to detect the gait only. The main concern is to come up with an idea so that detection is fast enough and can be used online to learn the uncertain dynamics of the system. Most of the aforementioned techniques discussed about the detection of gait but falls short to incorporate the detection algorithm with a control algortihm. From control and rehabilitation engineering point of view, a gait detection system needs to adapt with the unintended gait trajectory of the lower lomb joints and help to achieve an amputee near natural locomiton. As a part of the semester project I intend to develop or find out a suitable deep learning based mechanism for gait identification which can be sucsessfuly used for a prostetic leg system and give better performance in terms of control and rehabilitation engineering.

3 Methodology:

3.1 Architecture:

For this project we will classify the gait speed and events based on collected data from several individuals. To generate a proper locomotion trajectory we need to identify the speed of a walking cycle and walking activity such as – walking, climbing stairs, jogging etc. A gait or locomotion cycle be divided into following phases:: Heel strike, Foot flat, Mid stance, Heel-Off, Toe-Off, Mid- Swing, Terminal-Swing. Nominal knee, ankle and foot position angle is given in figure 1.

To begin with we start with human activity recognition dataset in (Kaggle). This dataset is collected from 30 persons (referred as subjects in this dataset), performing different activities with a smartphone to their waists. The data is recorded with the help of sensors (accelerometer and Gyroscope) in that smartphone. This experiment was video recorded to label the data manually.

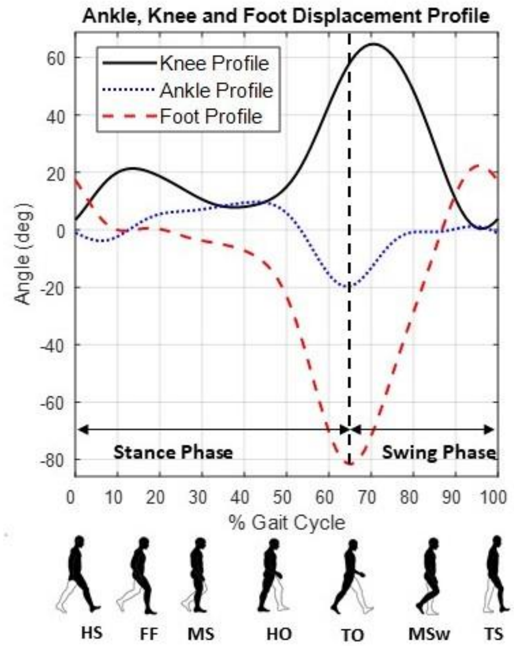

Figure 1 Nominal ankle, knee and foot displacement profiles in different walking phases.

For the activity classification, LSTM network have been used as it works good with timeseries data. The network used for different event classification is given in Figure 2. In the network we used sigmoid activation function, categorical cross-entropy, rms optimizer and 30 epochs.

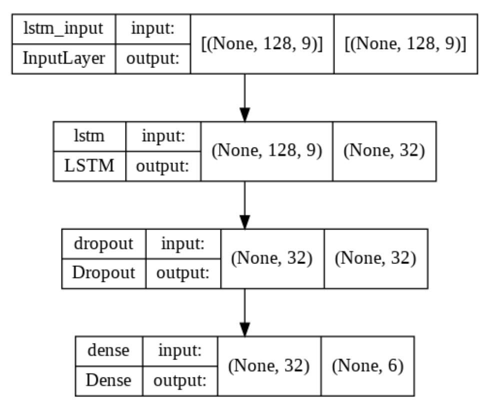

Figure 2 Network Architecture for event classification.

As the end goal of this project is to develop a proper controller for an amputee, that is why not only the activity, also the speed needs to be recognised and classified for the system. To classify the speed several classifier such as SVM, Naïve Bayes, Decision tree, Random Forest, Logistic regression, K neighbour classifier have been used. For speed recognition pressure data have been collected from (Kaggle) where, 21 healthy heel-striking subjects (10 male, 11 female, age: 23.8 yrs ± 3.3 yrs, height: 172.8 cm ± 9.4 cm, weight: 66.6 kg ± 10.9 kg; all values are mean ± standard deviation) without injuries or diseases affecting the musculoskeletal system participated in the study. First, Data has been distributed for 30 subjects and bar plot is given in Figure 3

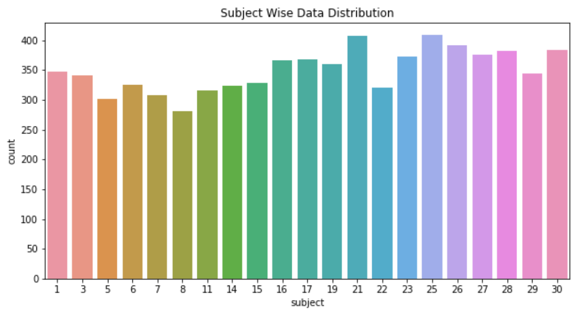

Figure 3 Subject wise data distribution.

To visualize the data for different activity, we have plotted data in terms of activity for a person in Figure 6. Acceleration data is not important for activities like

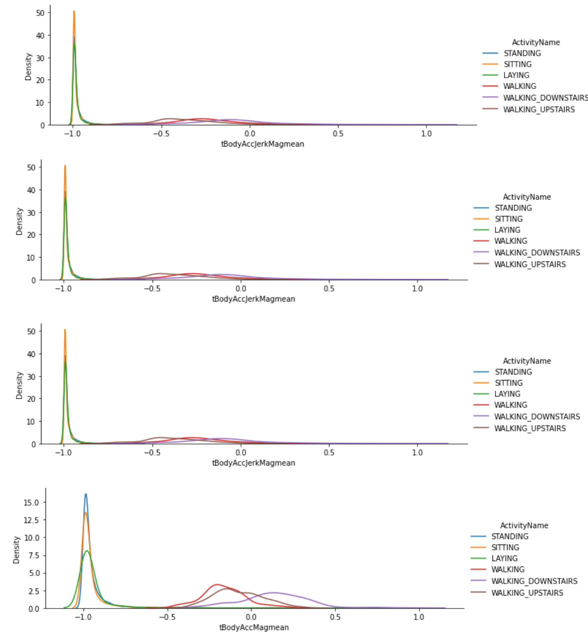

Figure 4 Activity acceleration spectrum

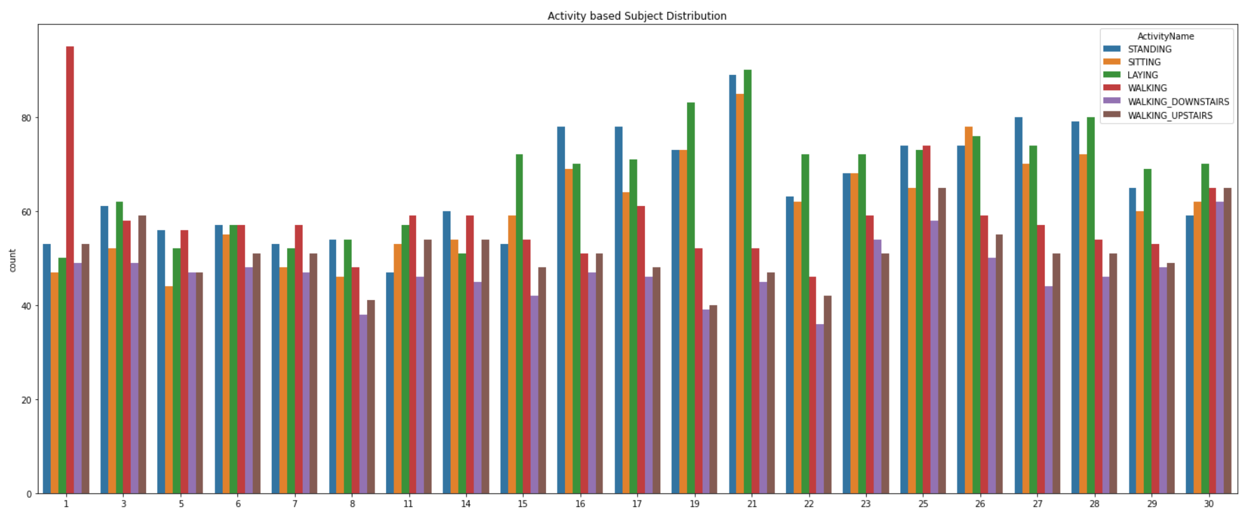

Figure 6 Activity-wise data distribution.

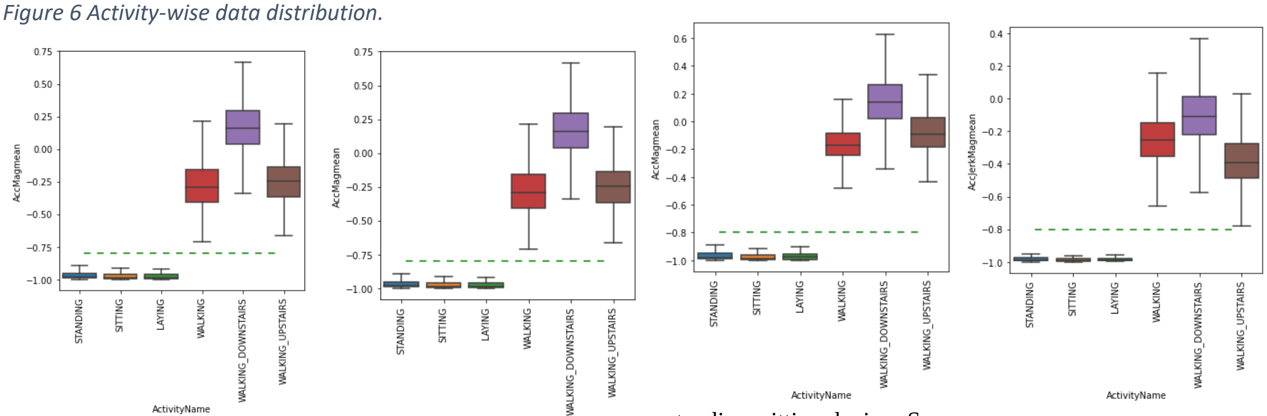

Figure 5 box plot for different activity for different person

standing, sitting, laying. So, we can separate low accelration activity from high acceleation activity from density spectrum and then box

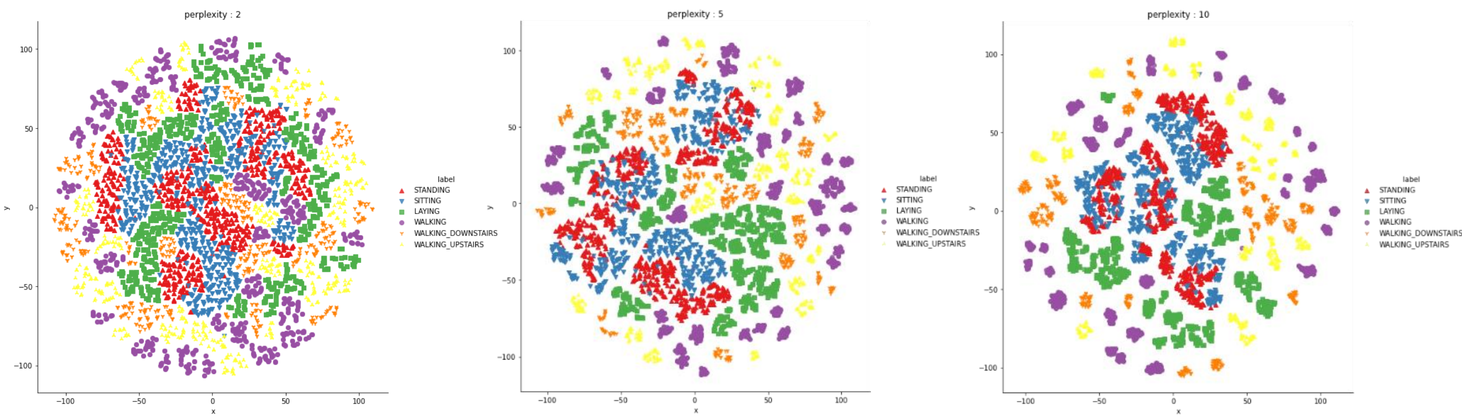

Figure 7: Dimensionality reduction

plotting. Spectrum data and box data are plotted at Figure 5 and Figure 7. To feed the data into classifier, dimensionality of the data from 3 axes has been reduced to 2 axis data T-SNE dimentionality reduction algorithm (Figure 7).

3.2 Results:

To check the performance of the network first we performed the simulation with the mentioned network in section 3.1. In the network there were 50% dropout after the first layer.RMS prop optimiser and sigmoid activation function were used at the outer layer. The network gave a good stable accuracy in 30 epochs in the train set and test set. Around 93% in train set and 90% in test set (Figure 8).

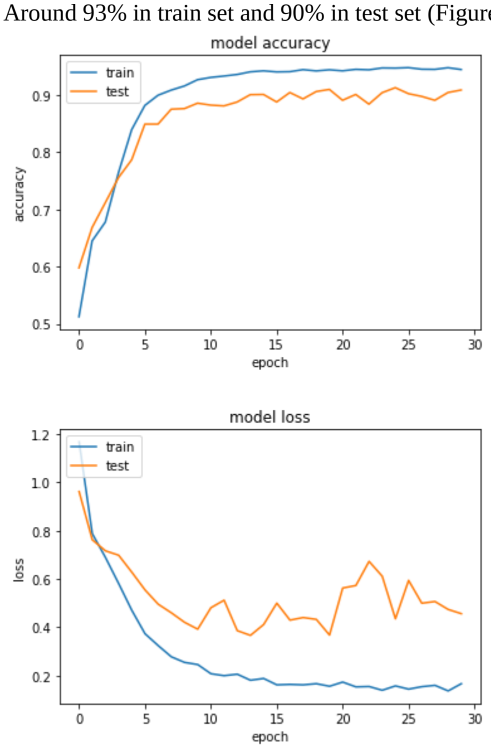

Figure 8: Model accuracy and Loss for first network

After the first approach, optimiser was changed to adam to observe the effect of learning. It was observed that with adam optimser the model accuracy and validation loss were eventually similar but the learning wasn't stable till 20 epochs (Figure 9).

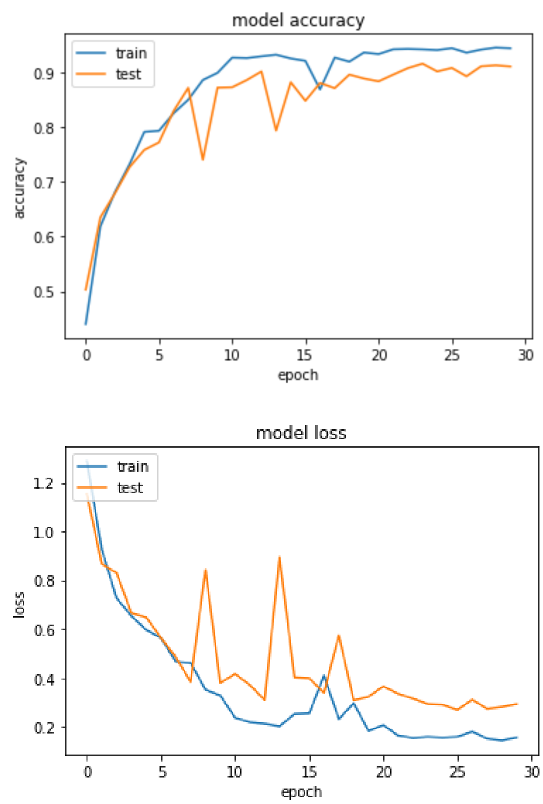

Figure 9: performance of the model with Adam optimizer

In the third approach we removed the drop out layer to observe the performance of the network. Is seems without dropout layer the network takes more epochs to get a stable learning. From Figure 10 it can be seen that it takes more than 30 epoch for the network to make the accuracy curve smoother, especially for testing set (Figure 10).

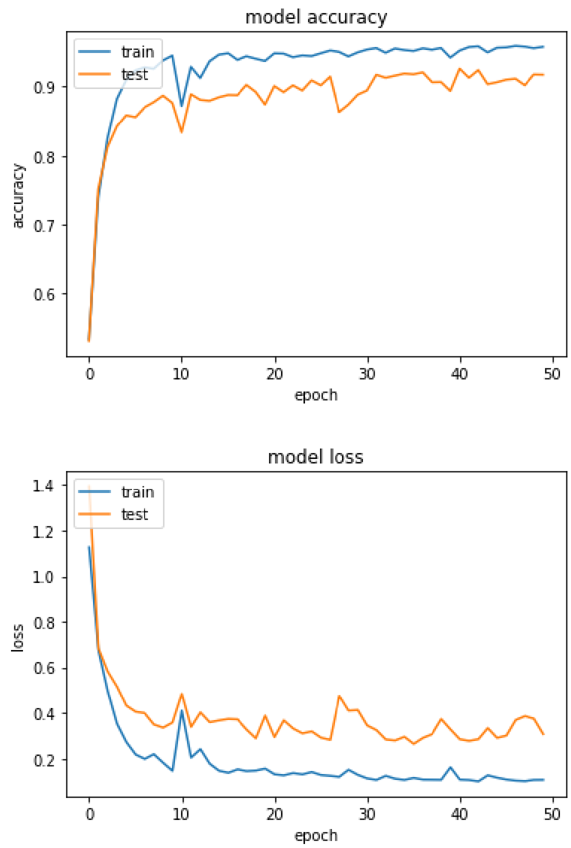

Figure 10: Performance without dropout layer

For three types of network configuration the accuracy for classifying different activity were almost similar.

To classify the activity for walking speed several techniques can be used. For this project we checked the speed classification for a person with SVM, Naïve Bias, Decision Tree, Random Forest, Logistic Regression, K neighbour classifier. The classification resuts have been tabulated in Table 1.

Table 1 : Classification for 0.6ms^{-1} and 0.7ms^{-1} walking speed with different classifier.

SVM	0.9790277777777778
Naive Bayes	0.9383333333333334
Decision tree	0.9965277777777778
Random Forest	1.0
Logistic Regression	0.98625
K neighbour Calssifier (K=3)	0.98625

4 Conclusions and Future Work:

The classification of events and speed can feed into prosthetic leg control system to generate proper angle to the prosthteic leg. In this project report, data classification portion of the system has been investigated using deep learning methode. But to develop a complete robotic system, apart from the input of that system we need to analyse the hardware and its response to the input also. It has been checked with the simulation that the model accuracy is around 90% for classifying the events and mothe than 97% for classifyng the locomotion pace. In future hardware implementation needs to be done with the help of the classifier and check with several amputee patient how well the system is working. Also, a smooth robotics hardware system needs to be developed which should be light and stardy to support the weight of an amputee patient during locomotion.

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