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ABSTRACT

This masters thesis describes the development of signal processing and pattern recognition in monitoring Parkinson's disease. It involves the development of a signal process algorithm and passing it into a pattern recognition algorithm also. These algorithms are used to determine , predict and make a conclusion on the study of parkinson's disease. We get to understand the nature of how the parkinson's disease is in humans.

CHAPTER 1

INTRODUCTION

1.4 What is Parkinson's Disease?

Parkinson's disease is a chronic neurodegenerative movement disorder that is common amongst the elderly to which there is no cure. This disease is from a common progressive damage to the nerves around the brain area. These nerves are responsible for movement and muscle control. The nerves that are damaged are used to produce a neurotransmitter which is called dopamine. The cause of the disease is still not very clear, but researchers believe that it may be due to accelerated aging, radical, environmental toxins and etc. The development of the disease is slow with time, muscle rigidity and trembling arms and legs etc. In Parkinson's disease, the nerve cells in the part of the brain that produces dopamine depreciates, this causes a reduction in the amount of the available dopamine. The chemical in the synapse that breaks down the dopamine continues to decrease what little dopamine that is left. The overall effect is a lot of loss in dopamine in the brain.

The symptoms vary from different patients some of these include drooling, illegible handwriting, rhythmical movement of fingers, excessive sweating, dementia, cognitive problems, stiffness of the muscles, slow movement, eyelids vibrate, blinking of the eyes frequently, depressions and mental functioning decreases with time etc.

As of now there is no cure, but there is great improvement on the drug therapy. The most common drug is SINEMET®, which includes both levodopa and carbidopa. These convert the dopamine in the brain. Others are pramipexole, ropinirole, bromocriptine, selegiline. In Levodopa, the drug is converted to dopamine. The drug may be administered alone, or in combination with carbidopa which holds back the enzyme that accounts for the levodopa ruins. The levodopa or levodopa-carbidopa therapy is limited after two years of treatment or thereby. treatment strategies have been developed to delay the progression of Parkinson's disease, or alternative methods to treatment.

Physical therapy is also needed to strengthen the muscles. When the patient doesn't respond to the drug and physical therapy a surgery is done. This therapy is the deep brain stimulation. There is also speech therapy.

Studies are made on the enhancement of levodopa and the improvement on the symptoms of Parkinson's disease through dietary changes. This is about the protein intake both at dinner and at breakfast & lunch. The consumption of lot of broad beans helps to escalate the action of levodopa and this may lead to an excessive dose of levodopa. And also the patients are recommended to have fibre supplement, coffee and caffeine. Nutritional supplements are also recommended whereby there is an intake of vitamin E, vitamin C, vitamin B.

The side effects are with the central nervous system, and include, light-headedness, dizziness and hallucinations. nausea and vomiting etc.

1.2 Technology Used

During the experiment, a series of data was collected using two activity meters --

- 1). Actigraph – an existing and product validation .The Actigraph is an electronic device that records the level of activity.
- 2). Medclock – a new prototype device which is still under development. This is a remembrance medication for parkinson’s patients.

The activity meters mentioned above are both accelerometers which are useful in detecting the shaking movements and other abnormal motion dynamics. The medclock has sensors that measures pulse rate, skin temperature etc.

The series of data were recorded every five mins from(2003-08-17 10:16:57] to [2003-08-17 19:38:39]). The data recorded were the Pulse rate of a patient, Resistance, ShakeEnergy, skin temperature, Shake Quotient, AccdataX, AccdataY.

It is a continuous recording of the data.

1.5 How Signals and Pattern recognitions are identified in Parkinson’s disease?

A Signal Process is meant to determine the the extent of the disease and identify the unhappiness and happiness of the patient. And also how the signals are used to undergo in the treatment stages of the patient. The Signals show a great deal about the patients Pulse , Resistance, Shake Energy etc. The signals are continuous. We notice the high amplitudes and noises, these are able to represent a sequence which are used in making predictions.

The pattern recognitions using the neural network approach would be able to distinguish, differentiate, divide the data into different groups and each groups has it’s own representation.

CHAPTER 2

PROBLEM DESCRIPTION AND LITERATURE REVIEW

2.1 Problem Description: To be able to develop a signal processing and pattern recognition algorithms for the data collected during an experiment concerning the dosage of medicine of patients with Parkinson's disease. During the experiment data will be collected using the two activity meters – Actigraph and Medclock devices And also to analyse the data and determine the functionality it offers. To also predict statistically with the data given to analyse the Parkinson's disease in humans.

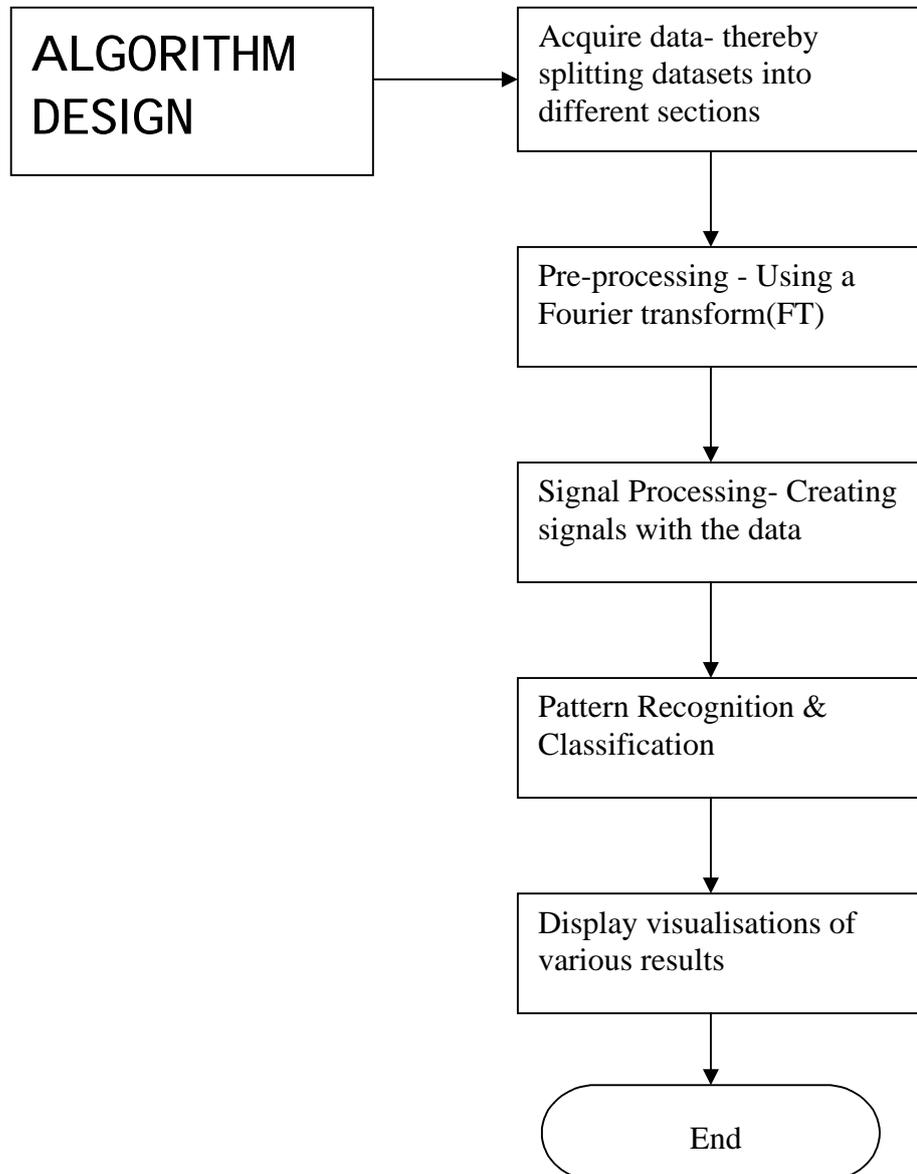
The review of this thesis will include the aim, which is developing signal and using neuro – fuzzy systems to create pattern recognition.

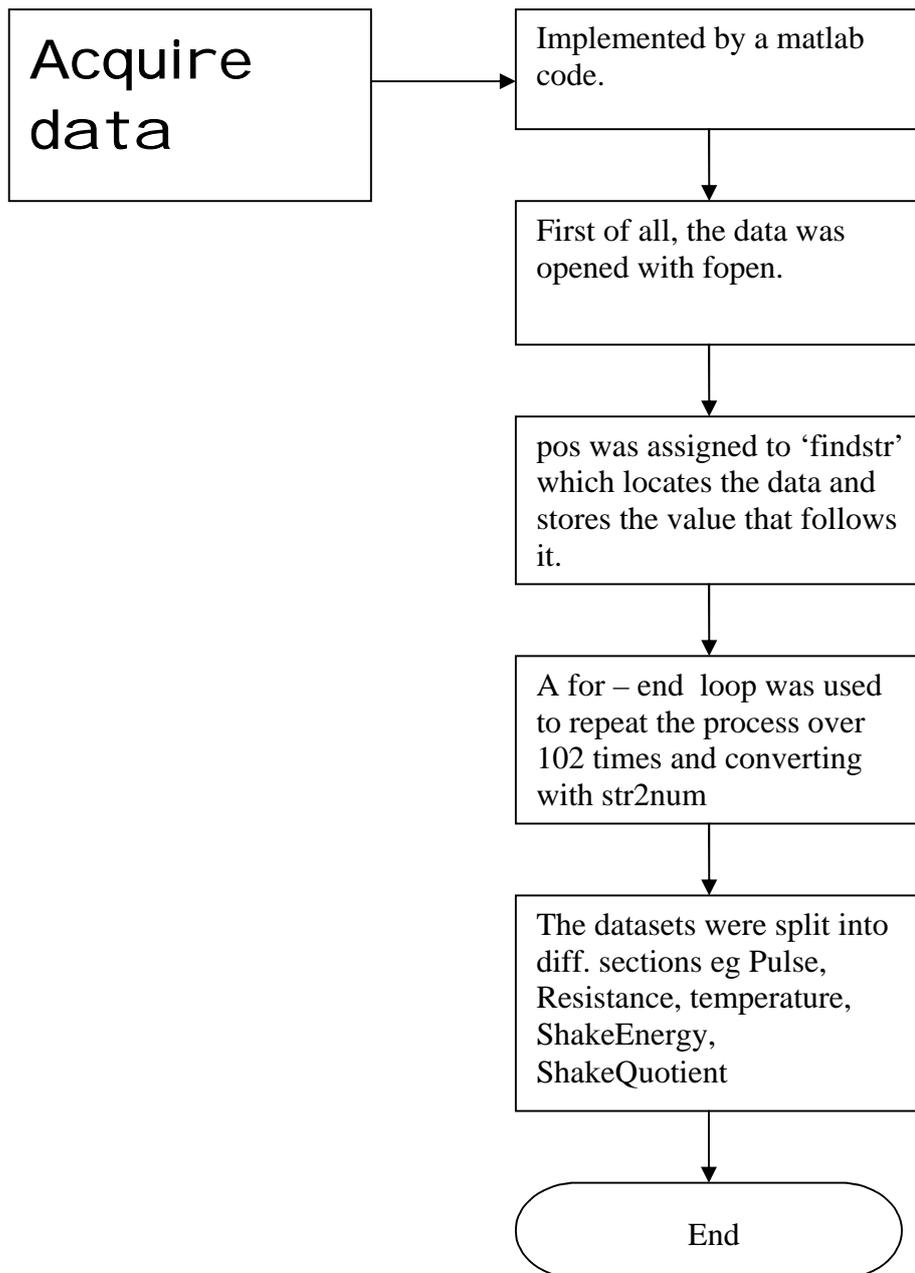
And also the introduction, in this we write about the definition, symptoms and medication used in a patient with Parkinson's disease, generally we write about the background of Parkinson's disease. We also write about the Technology used, how the measurement of data took place, what equipment that was used and how it all went.

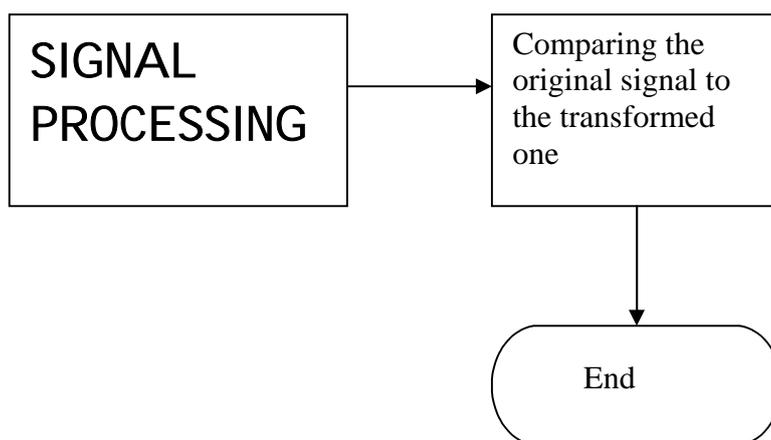
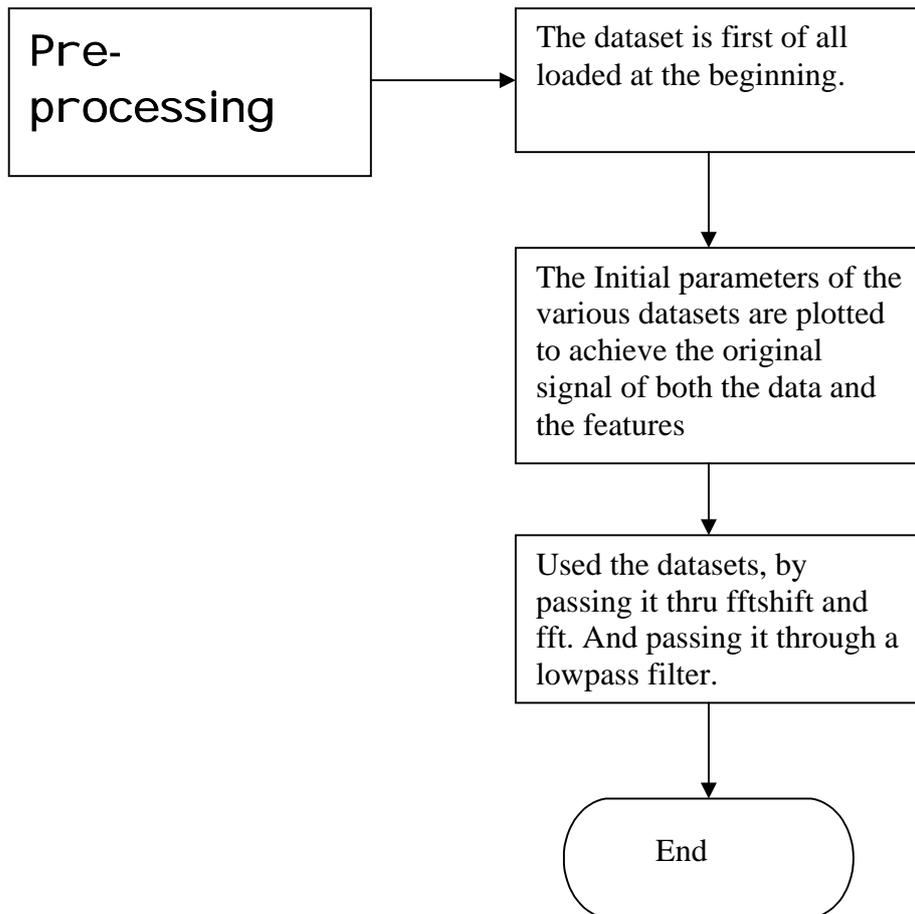
The experimental design consists of the algorithm design. The algorithm design is a series of step by step approach design algorithm. This involves the splitting of data sets into various sections and passing it through a fourier transform to create signals. Also making comparisons of theses signals. The Pattern Recognition undergoes a dimension reduction with various technique e.g PCA, SOM, etc. This involves the scaling input and output data, selecting an structure for the ANN design, the training process, representing outputs, intersecting data, classifying the output, results from simulated network. Display visualisations of various results

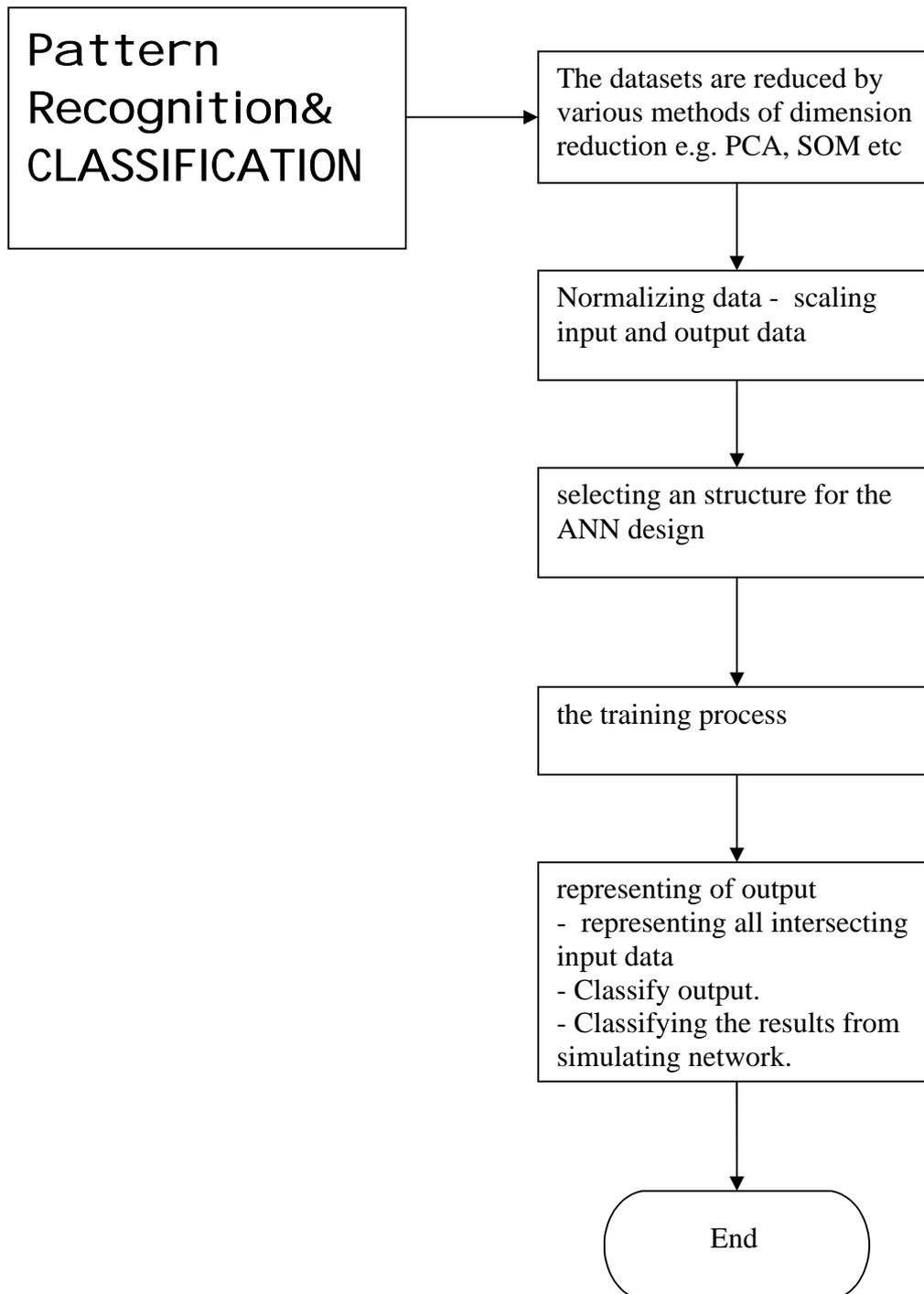
It also includes Testing , Analyzing, Hypothesis , Predictions and conclusions.

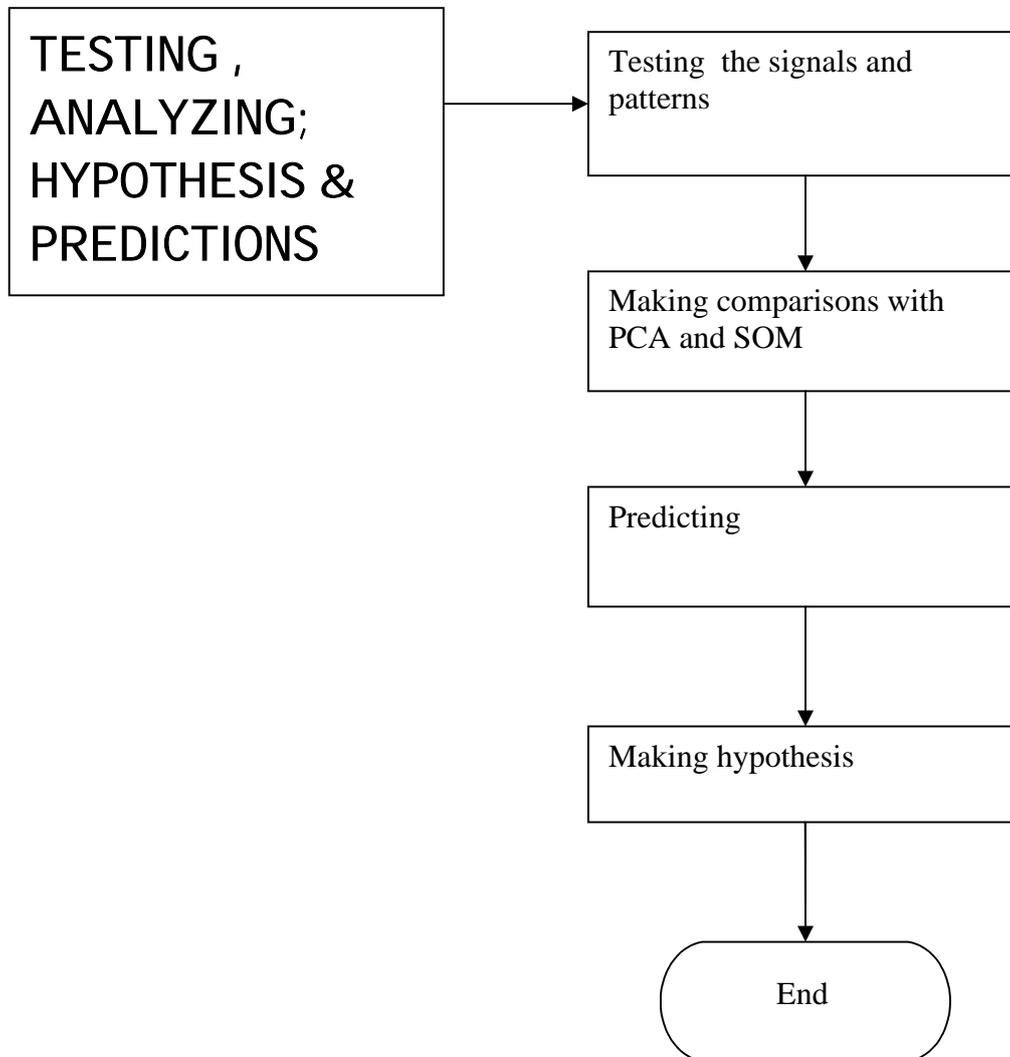
The steps taken in the algorithm design is given as follows;











With these algorithms design, we will be able to solve problems relating to how the patient is to be treated. Determine the dose in the medication. And most of all determine the happiness and the unhappiness of the patient with the medication used.

CHAPTER 3

PROJECT GOAL

3.1 AIM: To develop a signal processing and pattern recognition algorithms for the data collected during an experiment concerning the dosage of medicine of patients with Parkinson's disease. Creating a signal processing using an FFT and also using a neural network approach to create a pattern recognition.

CHAPTER 4

IMPLEMENTATION

4.1 EXPERIMENTAL DESIGN

4.1.1 ALGORITHM DESIGN

In the experimental design, these where we conduct various experiment , results algorithm design and the test are carried out. After the experimental design a statistical hypothesis is achieved.

The steps taken in the algorithm design is given as follows;

- to split the datasets into different sections as features
- to create a signal processing with the sets of data
- to use the signals produced to create a pattern recognition to monitoring the patients with Parkinson's disease.

The split data are then used to create signals. Theses signals of the features are either low or high in Pulse, Resistance, ShakeEnergy, ShakeQuotient, Temperature is constant. In creating the signals, original features were plotted. The Fast Fourier Transform of each feature e.g. Pulse was swapped by the left and right haves of the fast fourier transform of Pulse. So was the case with the rest features. This shifts the zero-frequency component to the centre of a spectrum. This then passed though a lowpass filter and also with the various frequencies, the lowpass filter creates low frequencies in the signal and stops the higher frequency from emerging , plotting the both the fourier transform of each feature but also when passed through a low pass filter and thus, a signal is produced in this process. The same goes to the rest features. There is also the comparing of the original signal with the fourier transformed which is also plotted. To implement this, Z was assigned to the inverse of The Fast Fourier Transform of the real data AX and AY. A subplot was used to plot and make comparisons.

In the algorithm design, a model is designed to hypothesise the class of models and sense the data in order to eliminate noise. And the it is later pre-processed, Signals are pre-processed and segmented. These signals are used to determine, observe, predict and hypothesize. The data used to earlier was voluminous and the next stage was to reduce the data so as to ease the experiment. Two methods were used The Principal Component Analysis and the Self Organising Maps. Both were also used for classification also.

Due to the complex nature of the data, a neural network is needed to be able to identify patterns from the original data that created the signals. There is need for it to be reduced into a reduced form. The Principal Component Analysis was used and aimed at minimizing the data loss in variance of the original data while maximizing the reduction in its dimension.

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The steps for taking a neural network involves the following:

- formulate and conceptualise the inputs and the outputs that were used.
- Gathering the data
- Create the neural network model
- Train the network
- Access, Explore and Analyse the trained network

The sets of input and output to form the neural network is given below:

Traindata: This structured array contained data for traindata.P and traindata.T where traindata.P contained actual training data and traindata.T contained the output data.

Valdata: This structured array contained data for validation purpose for the neural network. This structured array had valdata.P and valdata.T where valdata.P contained actual training data and valdata.T contained the output data.

Testdata: This structured array contained data for testing purpose of neural network. This structured array had testdata.P and testdata.T where testdata.P contained actual training data and testdata.T contained the output data.

The initial data for processing to the neural network was pre-processed in a dynamic way. In Preprocessing, the data was set to pass through the normalisation. The mean and standard deviation features of the data for normalization was chosen. In order to remove any abnormalities (if any) so that the data is appropriate for giving it to the neural network, the scaling of data was introduced in this process.

The datasets were which consists on Pulse, Temperature, Resistance, Shake Energy, Shake Quotient, AccDataX and AccDataY. The features are the Pulse, Temperature, Resistance, Shake Energy, Shake Quotient, while the AccDataX and AccDataY are the real data achieved from these inputs. The data that was provided from the recordings of a patient with Parkinson's disease was voluminous and also had all the features included in it.

To start with the algorithm design, the first thing to do is to split the data into different sections. A matlab program was used to split the features and also the accelerated data X and Y. The various features were Pulse, Resistance, Temperature, ShakeEnergy, ShakeQuotient. The AccdataX and AccdataY is the accelerated data for X and Y. The splitting of the data was implemented by a matlab code, data was opened from the text file(dataold.txt). Read the formatted data from the text file. Assigned a position to locate each string before that dataset records e.g /Pulse[32], the string was found by using 'findstr' in matlab and picked the data 32 and stored it in another file. I did the same with the rest features in the textfile. a loop was created to be able to store each value one after the other using a FOR-loop in matlab.

The next step was to create a signal from the data that was split from the textfile(data). A matlab code was written to be able to perform this operation. The

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data was first of all loaded the texfiles that was split at the beginning of the program, I generated the original signal by plotting each data as it was in the split textfile. each of the data was passed through a fast fourier transform, to make it a continuous transform an fftshift was used and fft and also passed it through a low pass filter and subplotted the results. A lowpass filter Z was assigned to the inverse fft(fftshift) and generated a subplot that was able to compare the original signals of AccDataX and AccDataY to the Z lowpass filter. This compares the imaginary part of the inverse fourier transform to the AccDataX and AccDataY. The reasons for passing it through a lowpass filter is to be able to separate individual signals, eliminate noise, and detect the presence of certain signals for prediction.

The third step was to pass the signals and various data through a neural network. The data is further reduced and transformed by a process called dimension reduction and classification using the Principal Component Analysis, Self Organising Maps.

In this stage we design a neural network approach as follows:

The actual process for designing a neural network for some purpose is very sensitive In our problem, classification problem we will consider this steps:

- a- **Normalizing data:** scaling input and output data, This is the process of applying pre-processing techniques to the raw data to prepare it for input into a neural network. When data has been pre-processed, the input will be kept in an appropriate range and then it can be applied correctly to a specific transfer function. The data is scaled into the range used by the input neurons in the neural network. This stage is important so as to be able to obtain a simple data from the complex data.

- b- **Selecting an structure for the ANN design :** this method contain a lot of parameter and condition and we will adjust just this things:
 - Number of layers.
 - Number of nodes in each layer.
 - Transfer function for each layer: which maybe one of logsig, tansig, purelin,hardlim functions or others for the input and hidden layer and linear transfer function-(purelin) for the output layer..

- c- **The training process :** we will try to train in different initial values for data. There is a division of the input , output training sets, there is the pulling out of the input training data and also the output training data into sets which are used in these processes. And also the features are divided into min and max. Network performance is different between with and without validation set. Training set will influence greatly the final performance of the network; therefore, we should extract the outliers in the training set and put those in test set after pre-processing to provide a more reliable training processess.

- d- **Representing of output :**
 - a. All intersecting input data cases must be represented.
 - b. Classify output.
 - c. Classifying the results from simulating network.

e- Verify results: to decide which step need repeating with other values.

Principal Component Analysis was used reduce dimensions of input data by projecting it onto the subspace and spanning the eigenvectors belonging to the largest eigenvalues of the covariance matrix of data set. So According to the largest 3 eigenvalues(the rest eigenvalues are zeros) of the covariance matrix we will create matrix with the 3 eigenvectors Corresponding to these eigenvalues of covariance matrix when they ordered by descending way then we will make projection to the data set (7 features dimension) on the subspace spanned by these eigenvectors to get a new data set with just 3 dimensions and train the network to see which result's we will get. Then we will repeat the same process but this time with just the tow largest eigenvalues. Principal component analysis (PCA) is also known as a mathematical approach in transforming a number of correlated variables into a number of uncorrelated variables usually from a larger set of numbers to a smaller sets and theses are called principal components. The first principal component defines the variability of the data, and other principal components are used for the remaining variability. Besides reducing the dimension, the principal component analysis is also taking notes of the variables that are both meaningful or not.

The Principal Component Analysis is also a statistical tool. It represents a statistics of variables by calculating the mean and the covariance matrix of the data used. The components of the covariance matrix are representing the co variances between the random variable components of the data used to compute the mean. The variance of a component shows the flow of the component values surrounding the mean value. The calculation of the mean and the covariance matrix is estimated by the mean and the covariance matrix. The calculation is an orthogonal basis is by finding its eigenvalues and eigenvectors. The eigenvectors gets the value of eigenvalues in descending order.

A scatter plot for the first two principal components analysis shows that there are two distinct regions. The process is filtered to remove most data with low variance or low information. These data would have appeared in the middle of the scatter plot. The scatter diagrams are used - to identify the phases on the most important components. The Principal Component Analysis chooses linear combinations of the components of the data sets. These components itemize the most variance in the data.

Another technique for dimension reduction is the Self Organising Maps (SOM). A Self Organising Maps is a way of reducing dimensions by producing a map of usually 2 or 3 dimensions which can plot the similarities of the data by grouping similar data items together such that a certain topological property in input data is shown as a reflection on the outputs unit's weights. A Self Organising Maps has two characteristics

- a. reduce dimensions and
- b. displaying similarities.

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Since performance of Self Organising Maps (SOM) is controlled by many parameters we will try to adjust these parameters as matlab can offer help for us in this task to get the best performance:

- 1- number of dimensions
- 2- number of points used in map
- 3- epochs needed
- 4- similarity measures
- 5- neighborhood function

In the early 1980's, Professor Teuvo Kohonen invented the Self-organizing maps (SOMs) by reducing the dimensions of data through the use of self-organizing neural networks. The SOMs reduces the dimensions by creating a map of usually about one or two dimensions that plot the similarities of the data by grouping similar data items together. The SOM consists of a couple of neural processing elements that are called units. These units are assigned to weights that are n-dimensional vector. The weight vectors have the same dimension as the input patterns. The training process of self-organizing maps is described as the input pattern presented and weight vector adaptation. Each training iteration starts with the random selection of one input pattern.

This input pattern is presented to the self-organizing map and each unit determines its activation. The Self-organizing feature maps (SOM) classifies the input vectors according to how they are grouped in the input. They competitive layers in the neighbouring neurons in the self-organizing map differ from the learning to remember the neighbouring sections of the input. It therefore learns about the distribution and topology of the input vectors that have been trained. The neurons in the layer of an SOM are grouped in such a position according to a topology function. The functions e.g gridtop, hextop or randtop can arrange the neurons in a grid, hexagonal, or random topology. Distances between neurons are calculated from their position with a distance function. These include the four distance functions, dist, boxdist, linkdist and mandist.

A self-organizing map learns to categorize input vectors. It also learns on how to distribute the dataset of input vectors. more neurons are allocated to the Feature maps to recognize parts of the inputs where input vectors occurs, while a fewer neurons is allocated to parts of the input space where few input vectors occur.

To create a network, the Self Organising maps algorithm begins with the initialisation of the network where the weights from input dataset. The present input is inputted at the second step taking note of the input node at that time. Thirdly, the distances are also calculated or computed between the input and the output node. At the fourth step, there is a selection of the minimum distance from the third step where the output design node is at it's minimal peak. The fifth step is about the updating of the weights, new weights are introduced. The sixth step is repeated through step two.

I choose to create a network having input vectors with two elements that fall in the range min to max values of datasets. Further suppose that we want to have neurons in a 10-by-10 network.

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The various training vectors are seen as spots around the perimeter of this figure. The midpoint is initialized with 'newsom'. The Learning in a self-organizing map appears within one vector by the time, regardless of whether the network is directly trained or if it's adaptively trained.

The weights of the winning neuron, and the other neurons in its neighbourhood, are gathered close to the input vector at each stage of learning with the self-organizing map. The weights of neurons in its neighbourhood are adjusted to the proportion of half the learning rate. A learning rate and the distance of the neighbourhood are used to establish the neurons are on the winning list in the neighbourhood. These are determined by two phases namely the Ordering Phase and the Tuning Phase

In the Order, the neighbourhood area begins with the maximum distance between the two neurons, and reduces it to the second phase neighbourhood distance. The learning rate begins at the order phase learning rate and reduces until it gets to the second phase learning rate. As the neighbourhood area and learning rate reduces over this phase, the neurons of the network categorically order themselves as input space with the same properties in which they are ordered physically.

In the tuning stage, the neighbourhood area remains at the tuning neighbourhood area. The learning rate continues to reduce very slowly from the tuning phase learning rate. The small neighbourhood and slowly reducing learning rate tunes the network, and keeps the ordering learning in the first phase stable. The number of epochs for the tuning part of training is usually larger than the number of steps in the ordering phase, the reason being that the tuning phase usually takes much longer.

CHAPTER 5

5.1 RESULTS AND VISUALISATIONS

5.1.1 Signals

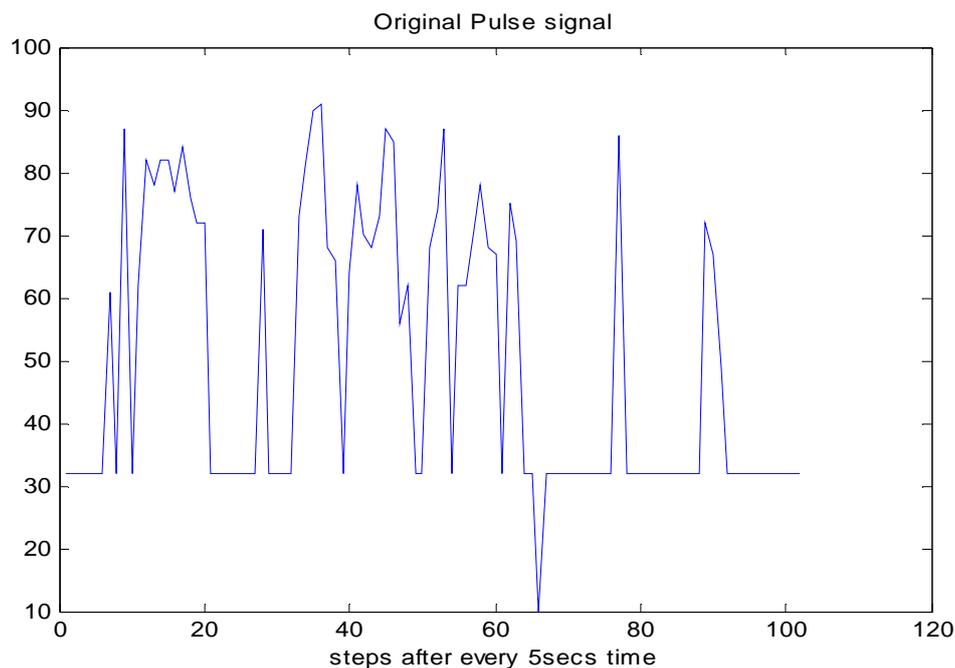


Figure 1: the original signal of feature 1(Pulse)

In Figure 1 pulse rate of the patient was constant with 32 which is considered as very low. It increases to 61 which is also considered as low at 10:44:25 and later falls back to 32 after another five minutes (10:49). In another five minutes, there was a tremendous increase to 84. This is considered as a normal pulse rate. After another five minutes it falls again to 32. it is increased up to 87 and moves to 76. Both are normal pulse rate after every other five minutes. As you can see there is a great fluctuation from low to high and also floors at 32 with two missing value.

The normal Pulse rate of a normal human being is 80 – 120. Any reading below 80 is considered as low pulse rate and any above 120 is considered as high pulse rate. The patient never had a high pulse rate. It had both normal and low pulse rate. The normal pulse rate was achieved 13 times.

The time at which the Pulse rates were normal is as follows:

- 2003-08-17 10:59:25: Pulse rate was 87(normal)
- 2003-08-17 11:14:26: Pulse rate was 82(normal)
- 2003-08-17 11:24:26: Pulse rate was 82(normal)

- 2003-08-17 11:29:26: Pulse rate was 82(normal)
- 2003-08-17 11:39:26: Pulse rate was 84(normal)
- 2003-08-17 13:29:29: Pulse rate was 81(normal)
- 2003-08-17 13:34:29: Pulse rate was 90(normal)
- 2003-08-17 13:39:29: Pulse rate was 91(normal)
- 2003-08-17 14:19:30: Pulse rate was 87(normal)
- 2003-08-17 14:24:30: Pulse rate was 85(normal)
- 2003-08-17 15:04:31: Pulse rate was 87(normal)
- 2003-08-17 16:04:32: Pulse rate was 109(normal)
- 2003-08-17 17:59:35: Pulse rate was 86(normal)

The recordings above showed that the periods when the patient was happy. While the rest of the pulse rate of the patient at other times between [2003-08-17 10:16:57] to [2003-08-17 19:38:39] besides the time listed above remained low. The temperature was constant at all the recordings.

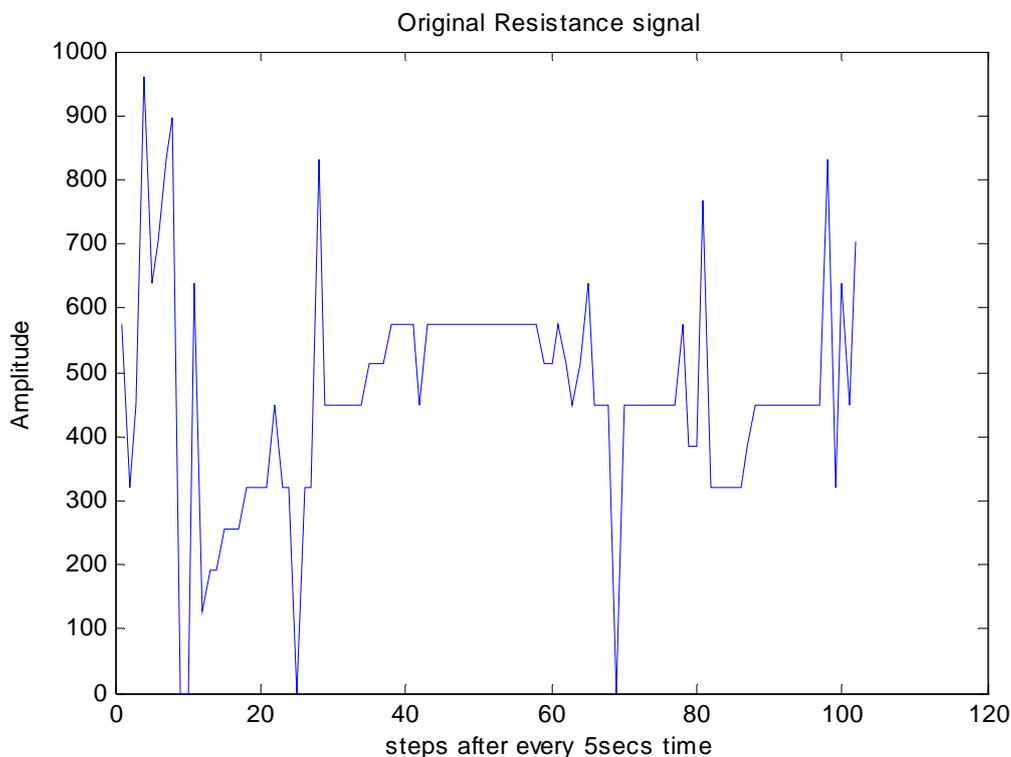


Figure 2: the original signal of feature 2(Resistance)

In Figure 2 we have the various fluctuations of signals from resistance. It has six missing values. You would step like signal above. I compare it with the Pulse rate of a normal Person. When the Pulse rate was 87 at 2003-08-17 10:59:25, the temperature was 960. The resistance was at its minimal (0). In 2003-08-17 11:14:26 Pulse rate was 82(normal), with the temperature still constant at 960. The resistance was increased a little by 128 times by the first normal recordings. At 2003-08-17 11:24:26 Pulse rate was 82(normal), the temperature remained constant with 960. The resistance was 192. At 2003-08-17 11:29:26 Pulse rate was 82(normal) with resistance as 256 and constant temperature was 960. At 2003-08-17 13:29:29 Pulse rate was 81(normal), has a constant temperature at 960 with the resistance at 448. At 2003-08-17 13:34:29

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Pulse rate was 90(normal), with the temperature remaining constant with 960. The resistance was 512. At 2003-08-17 13:39:29 Pulse rate was 91(normal) with constant temperature at 960, the Resistance was 512. At 2003-08-17 14:19:30: Pulse rate was 87(normal) with constant temperature at 960, the resistance was 576. At 2003-08-17 14:24:30 Pulse rate was 85(normal) with constant temperature at 960, the resistance was 576. At 2003-08-17 15:04:31 Pulse rate was 87(normal) with the constant temperature at 960, the resistance was 576. At 2003-08-17 16:04:32 Pulse rate was 109(normal) with constant temperature of 960, the resistance was 448. At 2003-08-17 17:59:35 Pulse rate was 86(normal) with constant temperature at 960. the resistance was 448,

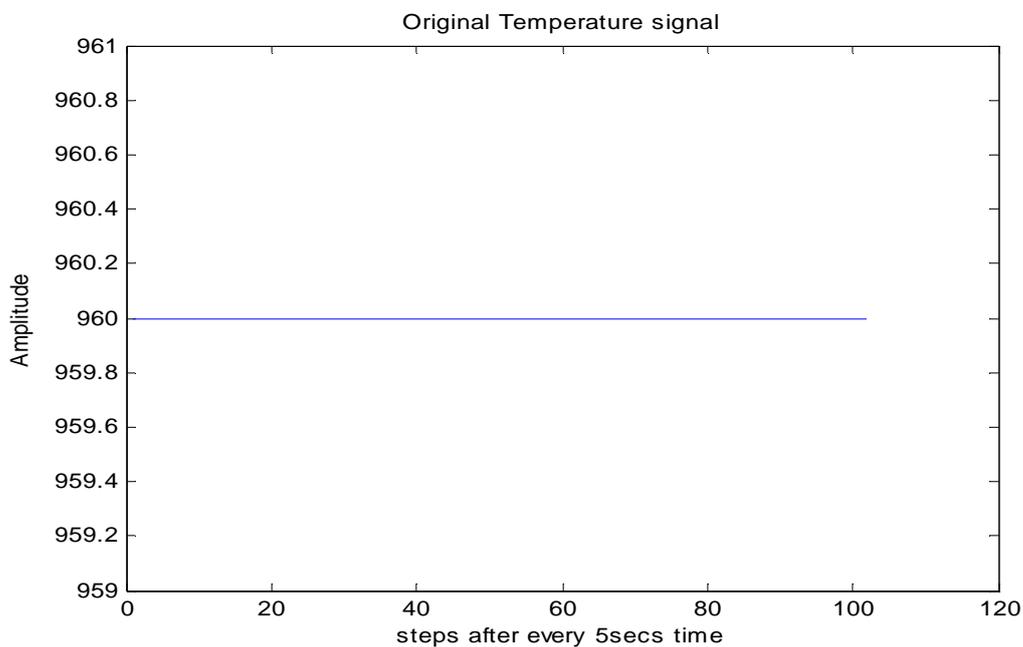


Figure 3: the original signal of feature 3(Temperature)

Constant temperature at all times

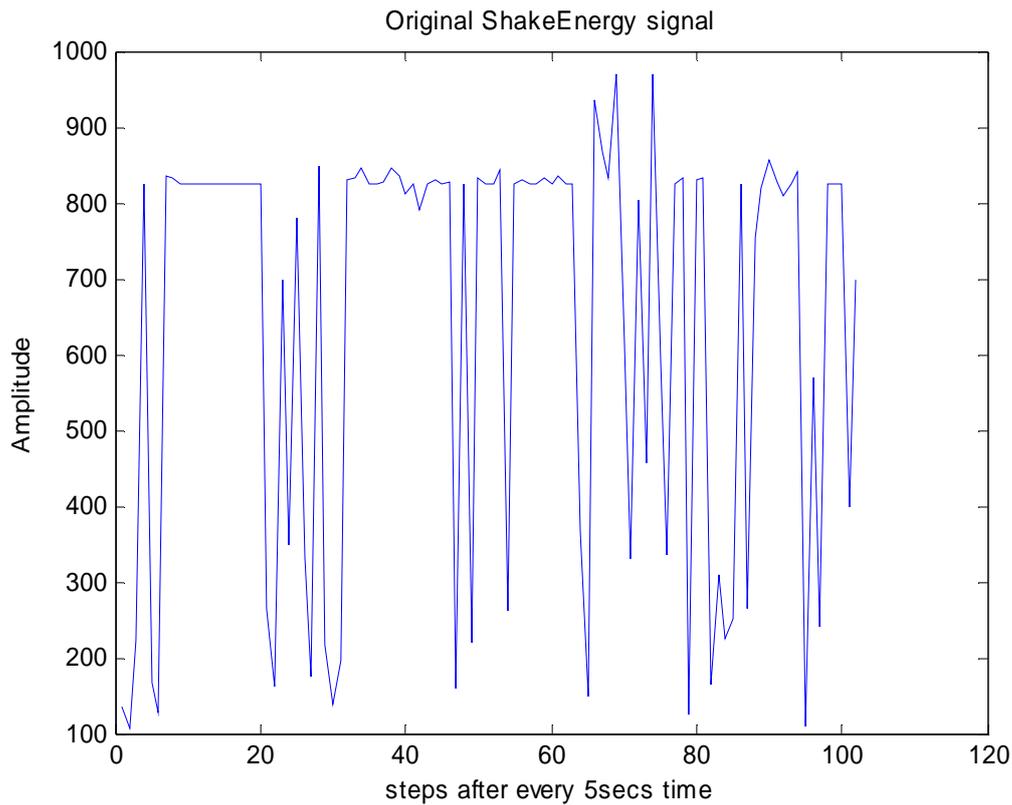


Figure 4: the original signal of feature 4(ShakeEnergy)

The ShakeEnergy and ShakeQuotient was 8251 and 15 respectively. The ShakeEnergy was decreased to 8248 at the second time while the ShakeQuotient was also decreased to 2. The ShakeQuotient remained constant at 2 while the ShakEnergy was increased to 8258 at the third time. The ShakeEnergy was decreased to 8249 and the ShakeQuotient was increased to 4 at the fourth time. The ShakEnergy was decreased to 8246 and the ShakeQuotient was decreased to 2 at the fifth time. The ShakeEnergy and the ShakeQuotient both increases to 8476 and 5 respectively at the sixth time. The ShakeQuotient was increased to 36 at the seventh time while there was a decline on the ShakeEnergy to 8250. The ShakeEnergy was increased to 8258 and the ShakeQuotient was declined to 2 on the 8th time. Both the ShakeEnergy and the ShakeQuotient were increased to 8261 and 4 respectively on the 9th time, it was also increased again on the tenth time 8283 and 22 respectively on the 10th time. There was a very sharp decrease on ShakeEnergy to 844 while the ShakeQuotient decreased to 3. on the 11th time. The eleventh time showed a drastic increase on both the ShakeEnergy and the ShakeQuotient by 9351 & 8864 respectively. The ShakeEnergy was decreased to 8247 and the ShakeQuotient was increased to 4 on the 12th time.

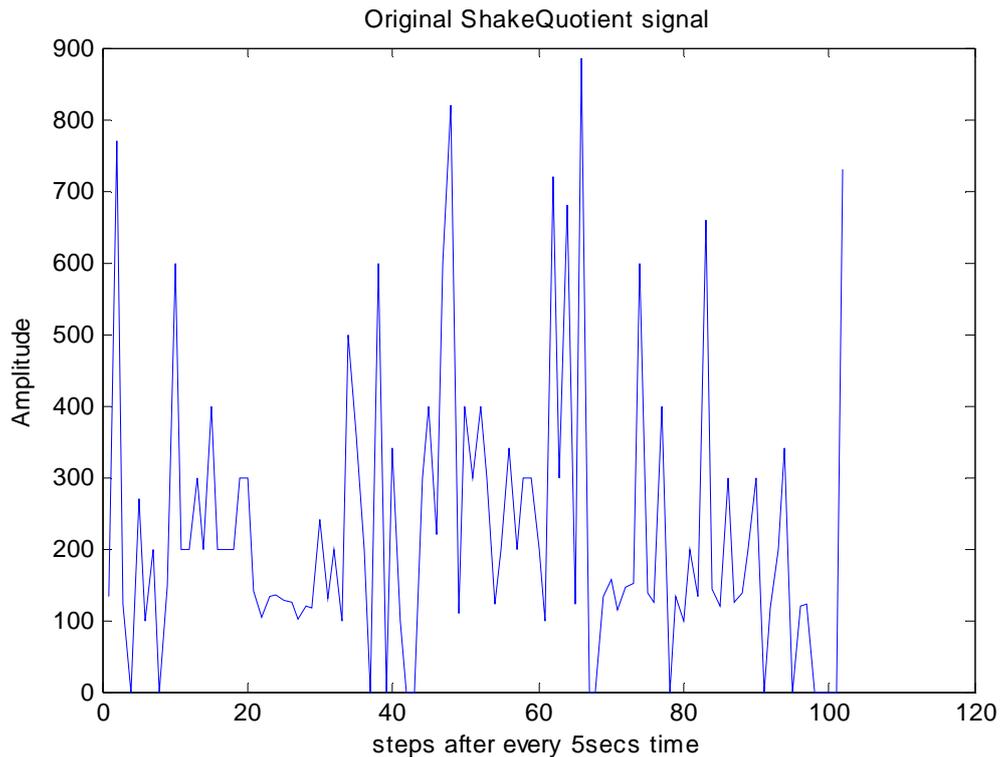


Figure 5: the original signal of feature 5(ShakeQuotient)

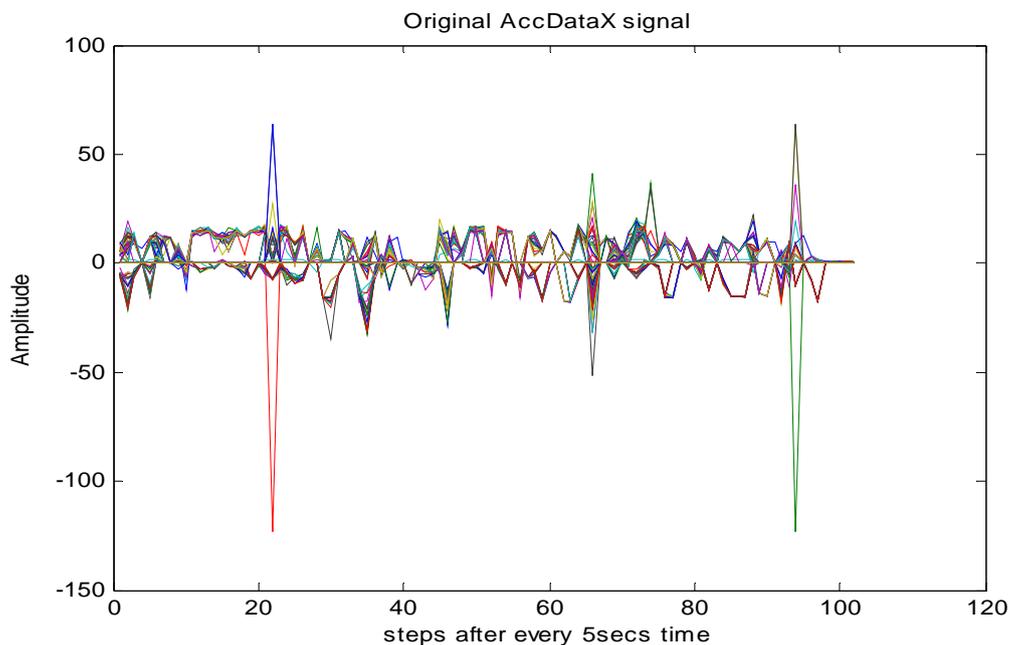


Figure 6: the original signal of (AccDataX)

The AccdataX signals shows the at the 22nd step when the time was 2003-08-17 12:00:09, the amplitude was the highest. At this time there was no noise. It was the best time at which the result was achieved. We also have the 96th time which also has the best time. The amplitude was also higher. The time was 2003-08-17 19:36:37. There is also a slight increase in amplitude at 68th time. It is not much, it also has high

amplitude. The time is 2003-08-17 17:14:37. In AccdataX the highest of the amplitudes were about 55 to -125 in amplitude.

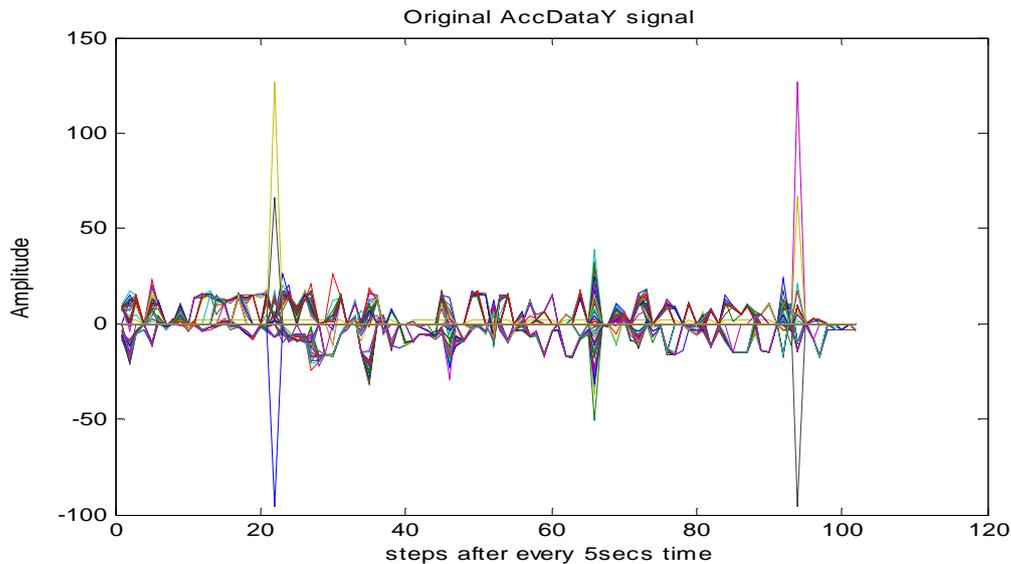


Figure 7: the original signal of (AccDataY)

The AccdataY signals shows the at the 22nd step when the time was 2003-08-17 12:00:09, the amplitude was the highest. At this time there was no noise. It was the best time at which the result was achieved. We also have the 96th time which also has the best time. The amplitude was also higher. The time was 2003-08-17 19:36:37. There is also a slight increase in amplitude at 68th time. It is not much, it's also has high amplitude. The time is 2003-08-17 17:14:37. In AccdataY the highest of the amplitudes were about 125 to -98 in amplitude.

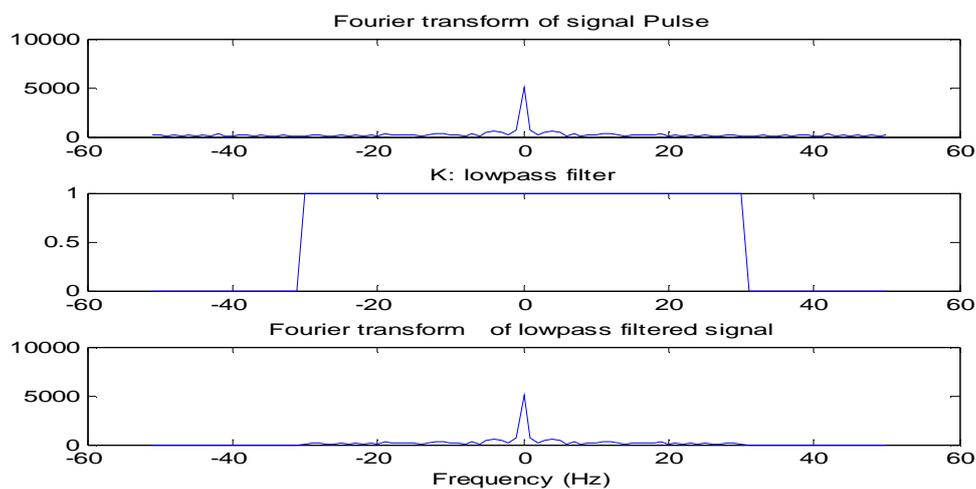


Figure 8: the fourier transform signal of Pulse, k:lowpass filter, ft transform of lowpass filter

The data of each feature were passed through a transform. The Fourier transform of a Pulse signal had a bandwidth of 50 to -50. The height of the transform was 5000. This was passed through a low pass filter. The low pass filter of the Pulse signal was also passed through a low pass filter. There were slight similarities and differences in the transform. In the transform the imaginary part has a bandwidth of 30 to -30. There is a

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similarity in the heights and differences in the bandwidth. The Resistance, temperature, ShakeEnergy, ShakeQuotient signals were all passed through a low pass filter all had the same similarities and differences as in Pulse signal The diagrams are Fig 9,10, 11, 12 respectively.

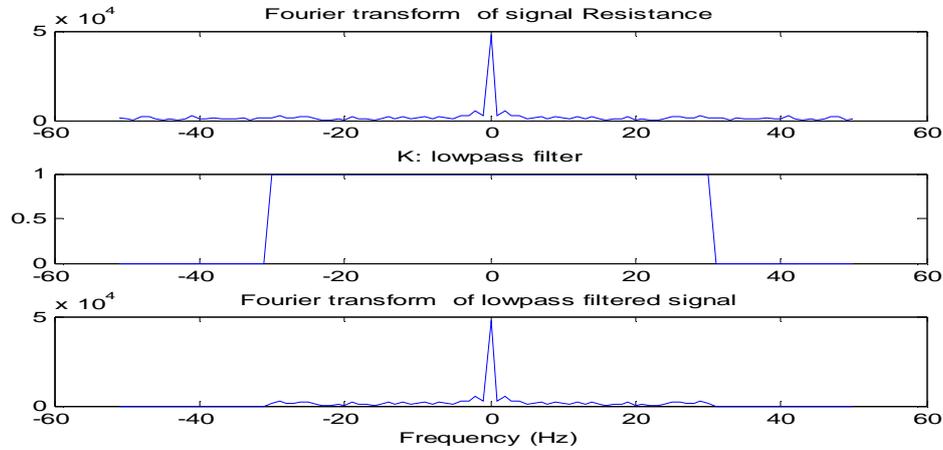


Figure 9: the fourier transform signal of Resistance, k:lowpass filter, ft transform of lowpass filter

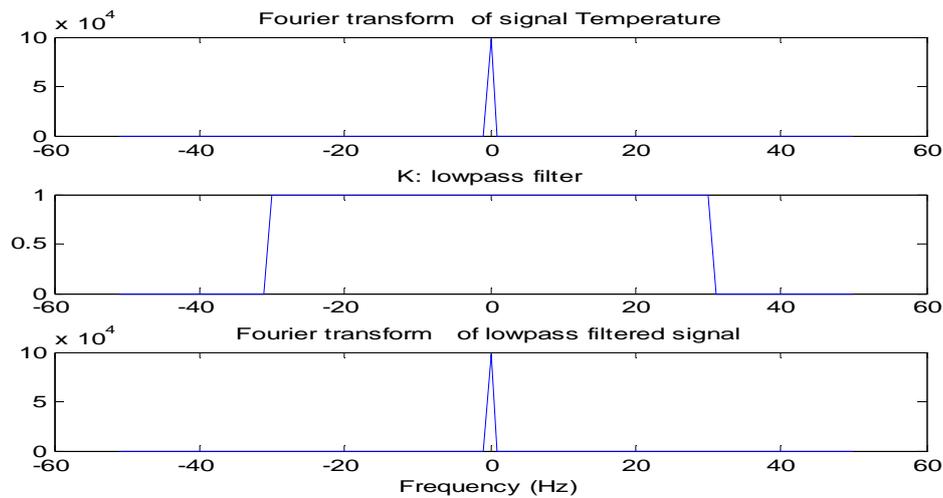


Figure 10: the fourier transform signal of Temperature, k:lowpass filter, ft transform of lowpass filter

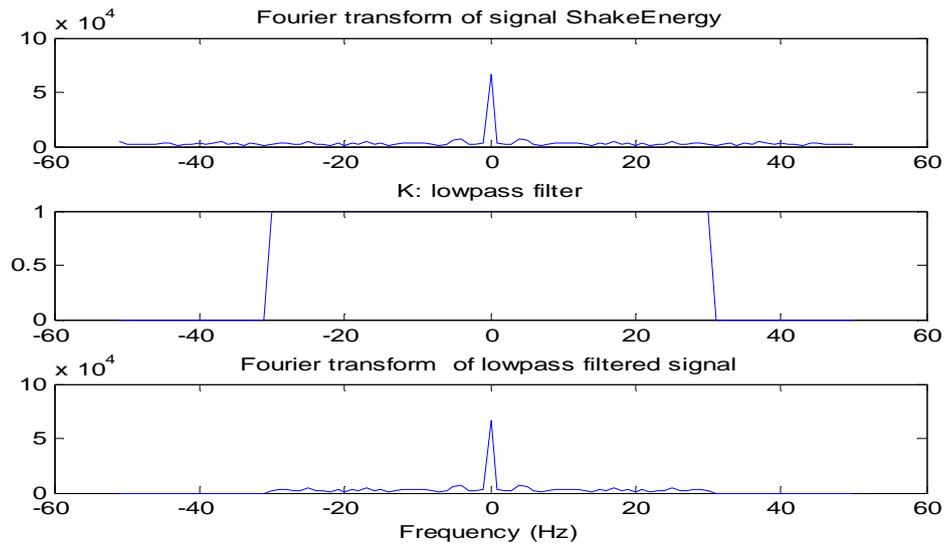


Figure 11: the fourier transform signal of ShakeEnergy, k:lowpass filter, ft transform of lowpass filter

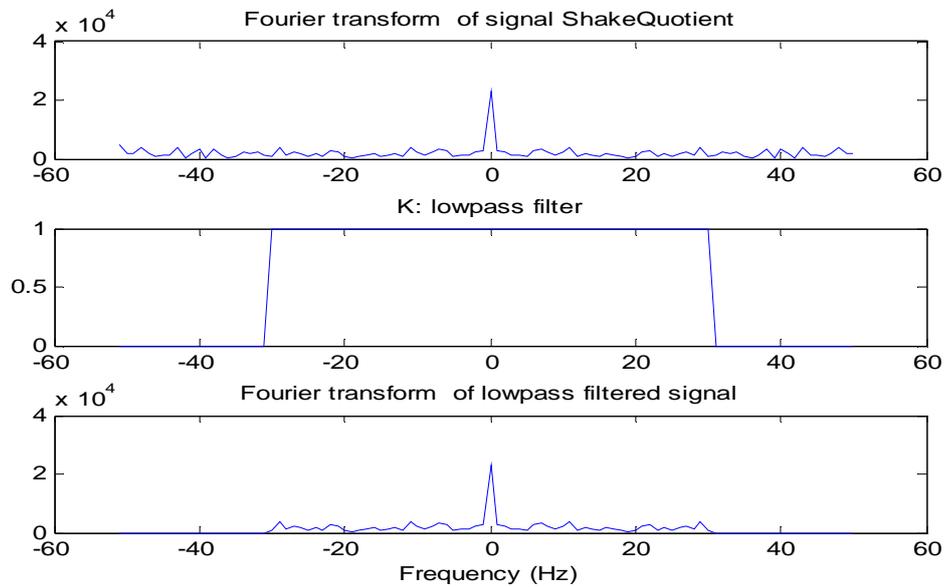


Figure 12: the fourier transform signal of Shakequotient, k:lowpass filter, ft transform of lowpass filter

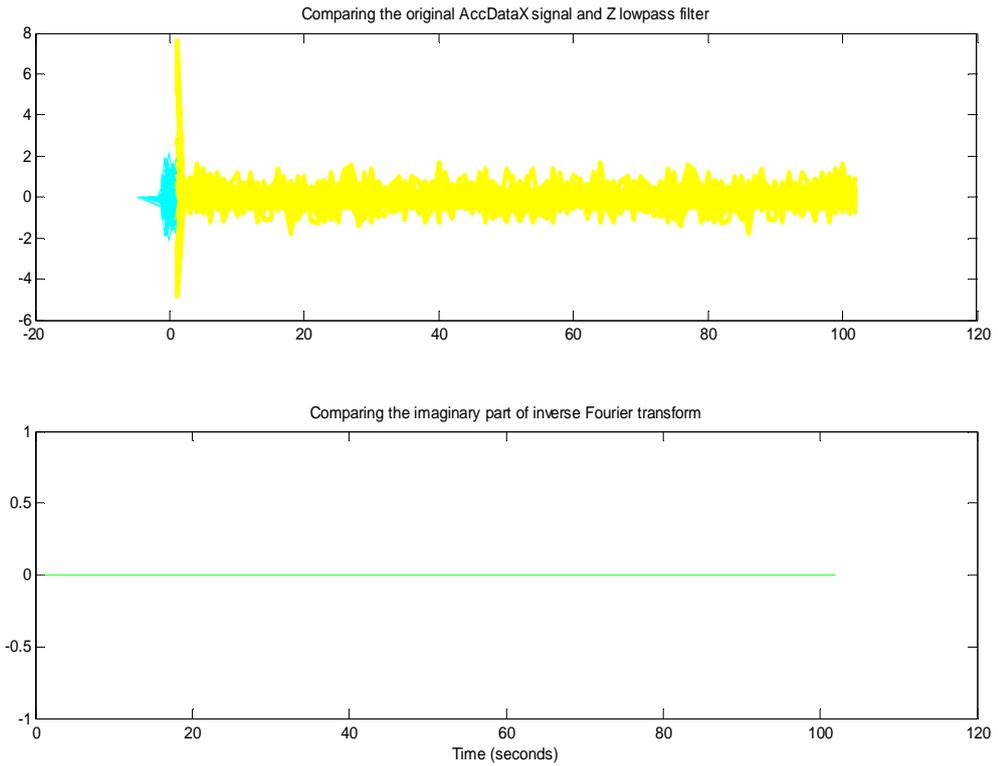


Figure 13: Comparison of AccDataX and Z pass filter

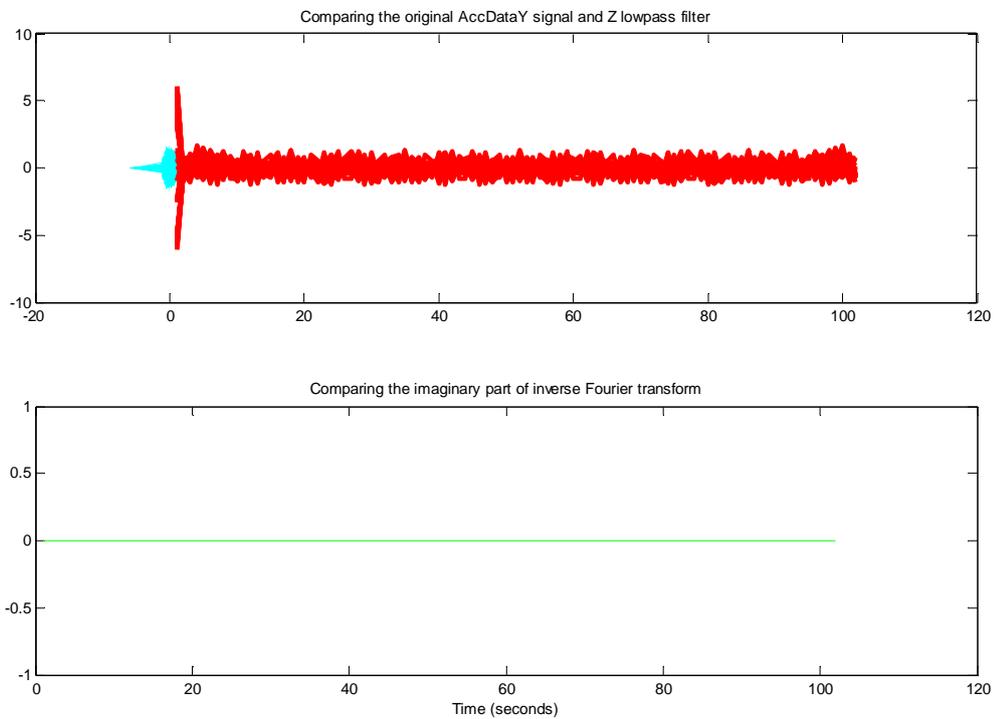


Figure 14: Comparison of AccDataY signal and Z pass filter

In figure 13 and 14, the AccdataX and AccdataY into a transform ranging from 50 to -50. The AccdataX heights on to 800 and the AccdataY heights up to 600. The AccdataX and AccdataY was also passed through a low pass filter which didn't yield any result. There was a lot of noise.

When I compare the original signals of AccdataX, there was a lot of noises. The amplitude at 8 to -5, this was at its highest. At the step i predicted that it was it's best result achieved by the patient. The time was also at 2003-08-17 10:21:25. I also compared the imaginary part from the fourier transfer I got no results. It was 0.

The comparison of the AccdataY, also had a lot of noises. The amplitude was at 6 to -6. which at it's highest was also predicted to be the best result achieved by the patient at 2003-08-17 10:21:25. 0 result was achieved when comparing the imaginary part to the fourier transform.

5.1.2 Pattern Recognition

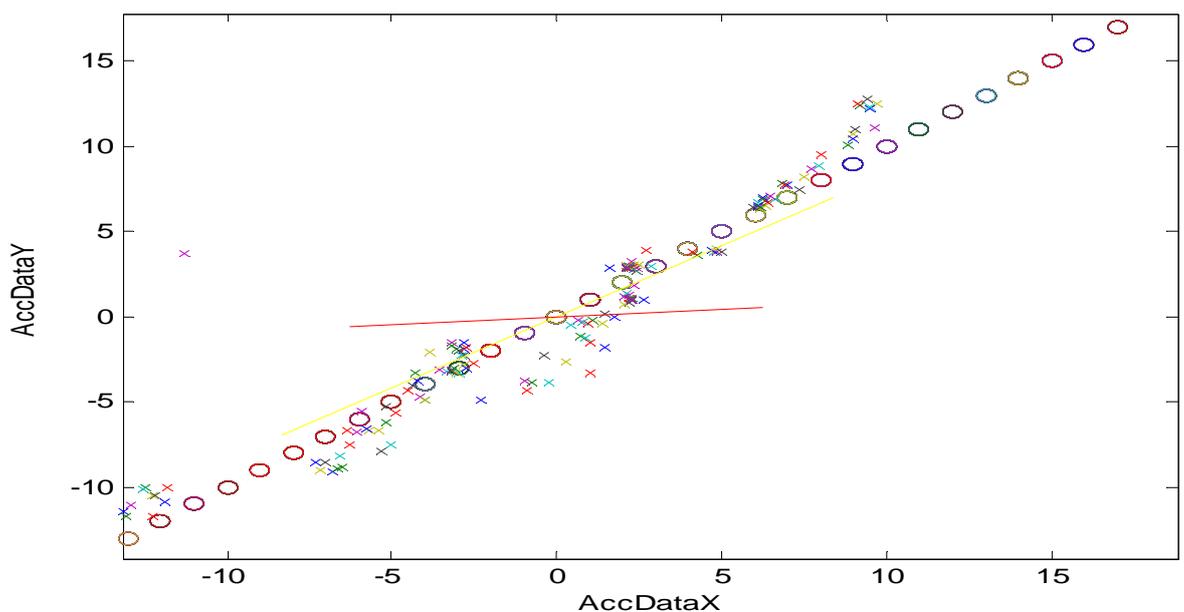


Fig 15

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In fig 15 plots of the data point. The 'o' is the original data and the '*' is the transformed data. The yellow line is the first pn(principal component) and the red is the second one. The two principal components were able to separate the unhappy and happy patients. The point at which the two pn meets it is when the patient becomes happy and strong, from 0 to 15 upward, patients with a smile.. The data downward from 0 to -10, the patient is at its worse, without a smile.

During training I also achieved the following results below:

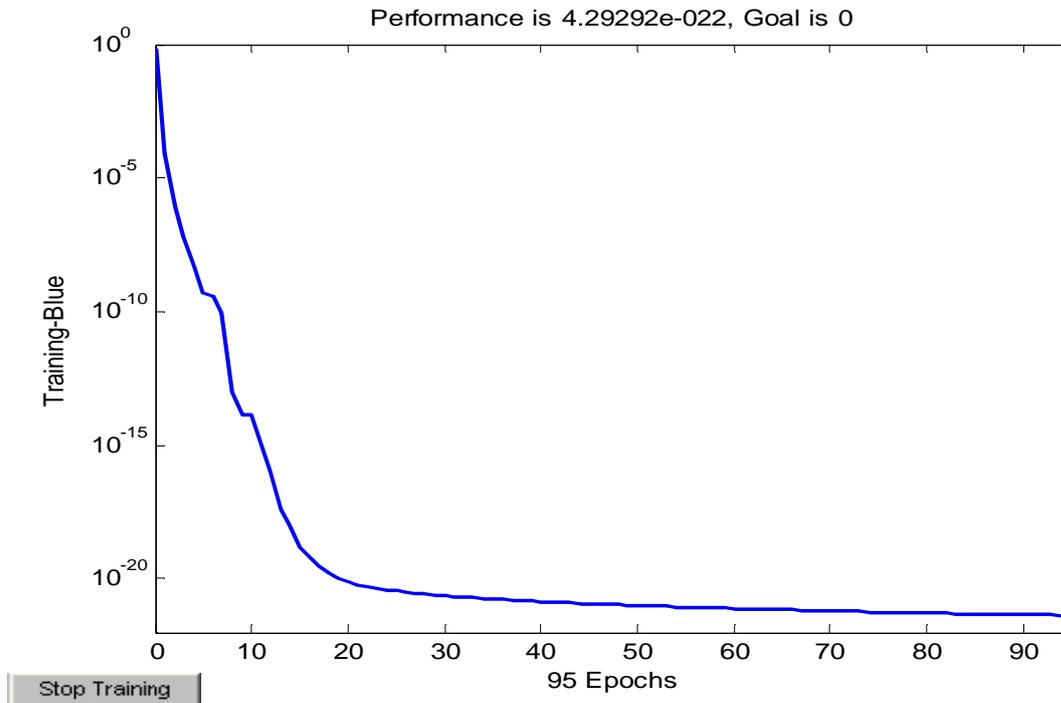


fig 16 the training results

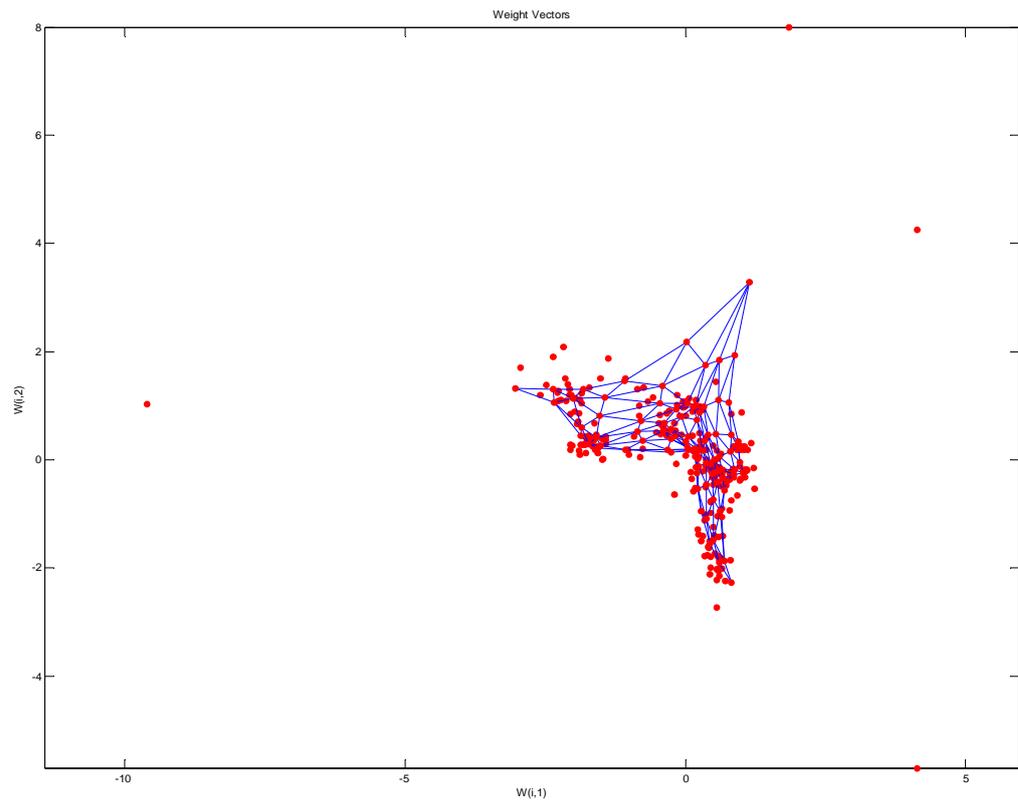


Fig 17 Self Organising maps with 100 epoch

There is a great difference with the self organising maps with 50 epochs and 100 epochs. The results of the SOM with 100epoch is give below as follows;

TRAINR, Epoch 0/100
TRAINR, Epoch 25/100
TRAINR, Epoch 50/100
TRAINR, Epoch 75/100
TRAINR, Epoch 100/100
TRAINR, Maximum epoch reached.

CHAPTER 6

6.1 ANALYSIS: This involves analyzing, testing and observing and also making a hypothesis.

6.1.1 Signals: - I observe that when the patient had a normal pulse rate, with constant temperature at 960. The pulse rate declined after the first normal pulse rate from 87 to 82. It was constant the third and fourth times of the normal pulse rate with 82. At the fifth normal pulse rate it increases by 84 and decline on the sixth to 81. 90 became the 7th and 8th normal pulse rate was 91 which declines again to the 9th and 10th at 87 and 85 respectively. It is increased again at 87 on the 11th, increased again at 109 on the 12th time of the normal pulse rate. The 13th declined to 86. The pulse rate fluctuates but as it fluctuates between 80 – 120. it is still referred to as the normal pulse rate.

The resistance also started from 0 at the first and increased to 128 at the second time, it increased again at the third and fourth to 192 to 256 respectively. Remained constant with 256 at the fifth time. It increased to 448 on the 6th time. It was constant with 512 at the 7th and 8th times. It increases to 576 on the 9th times and remained constant with it till it gets to the 11th times. It decline to 448 on the 12th time. The resistance was increased from the start and was constant at some stages and declined at the very end of the normal pulse rate.

The ShakeEnergy and ShakeQuotient was 8251 and 15 respectively. The ShakeEnergy was decreased to 8248 at the second time while the ShakeQuotient was also decreased to 2. The ShakeQuotient remained constant at 2 while the ShakEnergy was increased to 8258 at the third time. The ShakeEnergy was decreased to 8249 and the ShakeQuotient was increased to 4 at the fourth time. The ShakEnergy was decreased to 8246 and the ShakeQuotient was decreased to 2 at the fifth time. The ShakeEnergy and the ShakeQuotient both increases to 8476 and 5 respectively at the sixth time. The ShakeQuotient was increased to 36 at the seventh time while there was a decline on the ShakeEnergy to 8250. The ShakeEnergy was increased to 8258 and the ShakeQuotient was declined to 2 on the 8th time. Both the ShakeEnergy and the ShakeQuotient were increased to 8261 and 4 respectively on the 9th time, it was also increased again on the tenth time 8283 and 22 respectively on the 10th time. There was a very sharp decrease on ShakeEnergy to 844 while the ShakeQuotient decreased to 3. on the 11th time. The eleventh time showed a drastic increase on both the ShakeEnergy and the ShakeQuotient by 9351 & 8864 respectively. The ShakeEnergy was decreased to 8247 and the ShakeQuotient was increased to 4 on the 12th time.

This is represented in the bar chart and diagrams below:

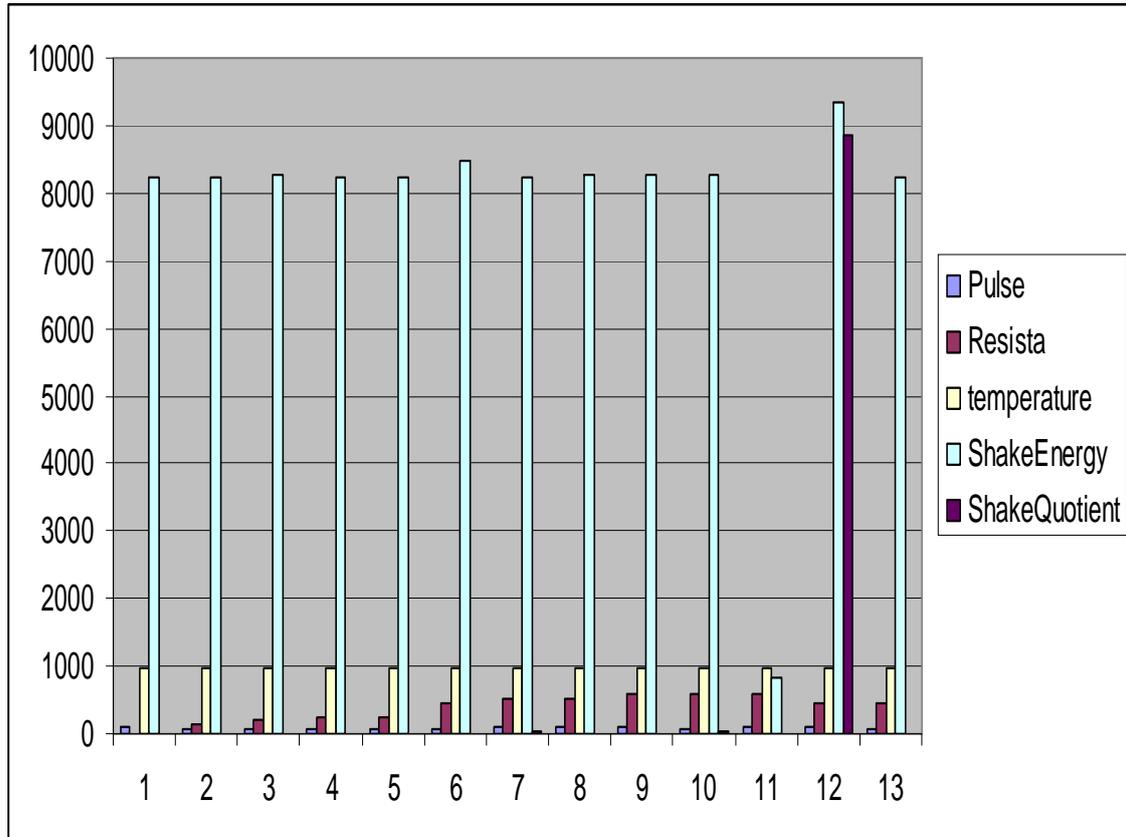


Fig 18: bar chart on features used to generate the set of data.

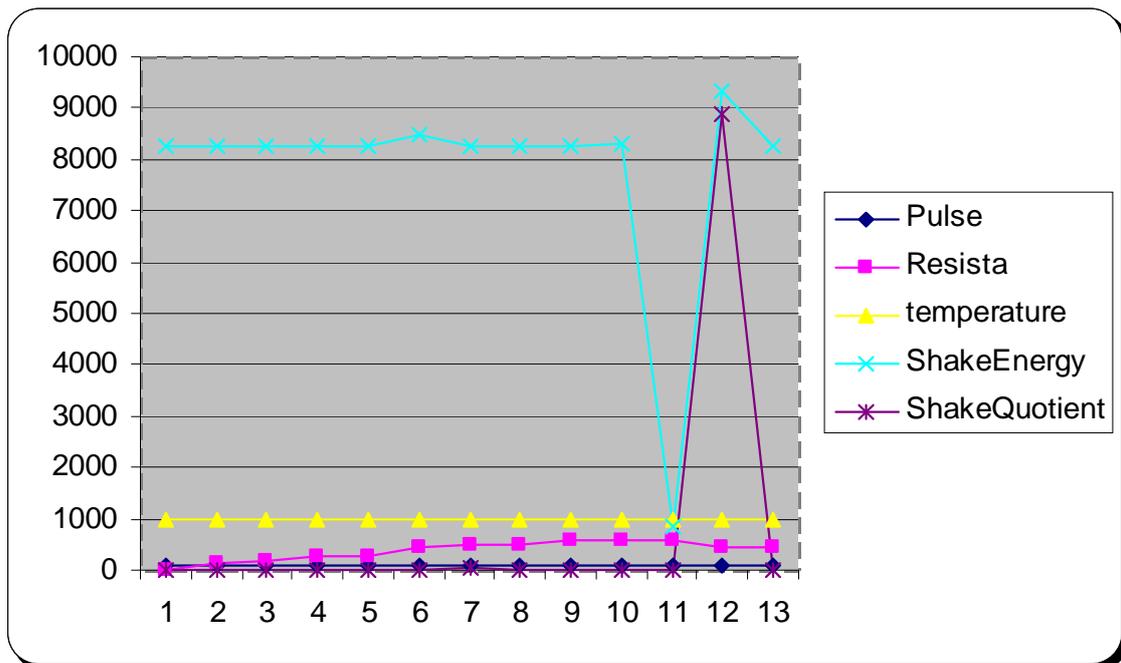


Fig 19: Plotting of the bar chart above.

The diagrams above shows the fluctuations of the features. There was a decrease in Pulse from the first time up to the second time. The Pulse remained constant up to the 4th time. It was later increased to the 5th time and decrease on the 6th time and increased to the 8th time and decrease up to the ninth to tenth time. It is increased from the 11th to the 12th and decreased the 13th time.

The ShakeEnergy was at the highest with a tremendous drop to 844 at the 11th time and also an enormous increase up above 9000. It was increasing and decreasing above 8000.

The resistance increases from the first to the fourth and then remains constant from 4th till 5th and the increases again to 7th and goes constant with the 7th to 8th times. It increases with 8th and goes constant up till the 9th and there is a decrease to the 10th time and it remains constant to the 12th time. There also the fluctuations from low to high in the ShakeQuotient. The temperature remains constant.

The AccdataX signals shows the at the 22nd step when the time was 2003-08-17 12:00:09, the amplitude was the highest. At this time there was no noise. It was the best time at which the result was achieved. We also have the 96th time which also has the best time. The amplitude was also higher. The time was 2003-08-17 19:36:37. There is also a slight increase in amplitude at 68th time. It is not much, it's also has high amplitude. The time is 2003-08-17 17:14:37. In AccdataX the highest of the amplitudes were about 55 to -125 in amplitude. The AccdataY signals shows the at the 22nd step when the time was 2003-08-17 12:00:09, the amplitude was the highest. At this time there was no noise. It was the best time at which the result was achieved. We also have the 96th time which also has the best time. The amplitude was also higher. The time was 2003-08-17 19:36:37. There is also a slight increase in amplitude at 68th time. It is not much, it's also has high amplitude. The time is 2003-08-17 17:14:37. In AccdataY the highest of the amplitudes were about 125 to -98 in amplitude.

The data of each feature were passed through a transform. The Fourier transform of a Pulse signal had a bandwidth of 50 to -50. The height of the transform was 5000. This was passed through a low pass filter. The low pass filter of the Pulse signal was also passed through a low pass filter. There were slight similarities and differences in the transform. In the transform the imaginary part has a bandwidth of 30 to -30. There is a similarity in the heights and differences in the bandwidth. The Resistance, temperature, ShakeEnergy, ShakeQuotient signals were all passed through a low pass all had the same similarities and differences as in Pulse signal.

The AccdataX and AccdataY into a transform ranging from 50 to -50. The AccdataX heights on to 800 and the AccdataY heights up to 600. The AccdataX and AccdataY was also passed though a low pass filter which didn't yield any result.

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When I compare the original signals of AccdataX , there was a lot of noises. The amplitude at 8 to -5, this was at its highest. At the step i predicted that it was it's best result achieved by the patient. The time was also at 2003-08-17 10:21:25. I also compared the imaginary part from the fourier transfer I got no results. It was 0.

The comparison of the AccdataY, also had a lot of noises. The amplitude was at 6 to -6. which at it's highest was also predicted to be the best result achieved by the patient at 2003-08-17 10:21:25. 0 result was achieved when comparing the imaginary part to the fourier transform.

6.1.2Pattern Recognition:

The data is sparsely spread around to produced various patterns

In fig 15 plots of the data point. The 'o' is the original data and the '*' is the transformed data. The yellow line is the first pn(principal component) and the red is the second one. The two principal components were able to separate the unhappy and happy patients. The point at which the two pn meets it is when the patient becomes happy and strong, from 0 to 15 upward, patients with a smile.. The data downward from 0 to -10, the patient is at its worse, without a smile.

During training in fig 16, the results was achieved with a performance of 4.29292 when the goal was 0 with 95 epochs.

These are the training results achieved at different times

TRAINLM, Epoch 0/100, MSE 1.3627/0, Gradient 1577.37/1e-010
TRAINLM, Epoch 25/100, MSE 9.93111e-017/0, Gradient 1.25809e-007/1e-010
TRAINLM, Epoch 50/100, MSE 6.43447e-017/0, Gradient 4.44947e-008/1e-010
TRAINLM, Epoch 75/100, MSE 1.38347e-017/0, Gradient 1.30326e-007/1e-010
TRAINLM, Epoch 100/100, MSE 6.80246e-018/0, Gradient 2.52021e-008/1e-010
TRAINLM, Maximum epoch reached.

TRAINLM, Epoch 0/100, MSE 0.265123/0, Gradient 683.664/1e-010
TRAINLM, Epoch 25/100, MSE 1.19345e-018/0, Gradient 1.93989e-007/1e-010
TRAINLM, Epoch 50/100, MSE 2.67284e-019/0, Gradient 8.31455e-009/1e-010
TRAINLM, Epoch 75/100, MSE 1.40799e-019/0, Gradient 2.052e-009/1e-010
TRAINLM, Epoch 100/100, MSE 3.5863e-020/0, Gradient 1.0294e-008/1e-010
TRAINLM, Maximum epoch reached.

Fig 17 shows the self organising mappings.

There is a great difference with the self organising maps with 50 epochs and 100 epochs. The results of the SOM with 100epoch is give below as follows;

TRAINR, Epoch 0/100
TRAINR, Epoch 25/100
TRAINR, Epoch 50/100
TRAINR, Epoch 75/100
TRAINR, Epoch 100/100

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TRAINR, Maximum epoch reached.
TRAINR, Epoch 0/50
TRAINR, Epoch 25/50
TRAINR, Epoch 50/50
TRAINR, Maximum epoch reached.

CHAPTER 7

7.1 CONCLUSION:

The data was able to determine the extent on how a Parkinson's disease. The data was very voluminous. The signals were able to trace the happiness and unhappiness of the patient. The pattern recognition was also a very efficient algorithm which was used to determine the large data to show the similarities and differences.

The various observations were noticed

- There is a slight overlap of data in the normalisation process.
- The performance of the neural network was not at it's best. I was able to obtain 95%.
- The performance of the neural network depends on the training data.
- The performance also depended on the number of epochs.

The PCA model analyzes the components of the data features while the SOM draws the Organisation map, are used to reduce the data features. PCA is easy to implement while the SOM is very hard to implement. PCA has better performance when compared to the SOM. PCA has a low time complexity while the SOM has higher order time complexity. The dimension reduction in SOM depends on the Organisation maps dimensions of data features and the number of epochs taken.

While in PCA the reduction of data features depends on the variance component.

APPENDIX

```
fid =fopen('dataold.txt');
dataold= fscanf(fid,'%c');
%k=1;
%for i=1:length(dataold);
    %dataold(i:i+6)
    %findstr(dataold,'\Pulse')
    pos=findstr(dataold,'\Pulse');
    Pulse=zeros(1,102);

    for i=1:102%pos(1):pos(length(pos))

        Pulse(1,i)=str2num(dataold(pos(i)+7:pos(i)+8))
        %B=ifft(Pulse);
        save Pulse.txt

    end

pos1=findstr(dataold,'\Resistance');
Resistance=zeros(1,102);

for i=1:102%pos(1):pos(length(pos))

    Resistance(1,i)=str2num(dataold(pos1(i)+12:pos1(i)+14))

    save Resistance

end

pos2=findstr(dataold,'\Temperature');
Temp=zeros(1,102);

for i=1:102%pos(1):pos(length(pos))

    Temp(1,i)=str2num(dataold(pos2(i)+13:pos2(i)+15))
    save Temp
%

end
%
```

```
pos3=findstr(dataold,'\ShakeEnergy');
SE=zeros(1,102);
```

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```
for i=1:102%pos(1):pos(length(pos))

    SE(1,i)=str2num(dataold(pos3(i)+13:pos3(i)+15))
    save SE
end

%
pos4=findstr(dataold,'\ShakeQuotient');
SQ=zeros(1,102);

for i=1:102%pos(1):pos(length(pos))

    SQ(1,i)=str2num(dataold(pos4(i)+15:pos4(i)+17))
    save SQ
end
fclose(fid);

%*****
%*****

%Clear all variables from memory
clear;%
%% Generate a random signal
%
load H:\project\Pulse
load H:\project\Resistance
load H:\project\Temp
load H:\project\SE
load H:\project\SQ
load H:\project\AX
load H:\project\AY
%-----
%-----
% plot Parameters
%-----
%-----
figure(1); plot(Pulse); title('Original Pulse signal');
xlabel('steps after every 5secs time')

figure(2); plot(Resistance); title('Original Resistance signal');
xlabel('steps after every 5secs time')
ylabel('Amplitude')

figure(3); plot(Temp); title('Original Temperature signal');
xlabel('steps after every 5secs time')
ylabel('Amplitude')

figure(4); plot(SE); title('Original ShakeEnergy signal');
xlabel('steps after every 5secs time')
ylabel('Amplitude')

figure(5); plot(SQ); title('Original ShakeQuotient signal');
xlabel('steps after every 5secs time')
ylabel('Amplitude')

figure(6); plot(AX); title('Original AccDataX signal');
```

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```
xlabel('steps after every 5secs time')
ylabel('Amplitude')

figure(7); plot(AY); title('Original AccDataY signal');
xlabel('steps after every 5secs time')
ylabel('Amplitude')
%*****
*

%
% %the mouse-click sets a flag for point aquisition
% set(gcf,'windowbuttondownfcn','hit=1;');
%
% %make a control to stop the loop
uicontrol('style','pushbutton',...
    'string','Quit', ...
    'position',[0 0 50 20], ...
    'callback','stopit=1;');

% for Pulse
b = 30; %% Bandwidth of the filter
N= 102 % no. of samples or window sizes
X = fftshift(fft(Pulse));
K = zeros(1,102);
K(round(N/2)+1+[-b:b])=1; %% Lowpass filter
Y = X.* K; %%pass thru a Lowpass signal
F = -round(N/2):(fix(N/2)-1); %% Frequencies in Ft
figure(8);
subplot(3,1,1); plot(F,abs(X)); title('Fourier transform of signal
Pulse');
subplot(3,1,2); plot(F,K); title('K: lowpass filter');
subplot(3,1,3); plot(F,abs(Y)); title('Fourier transform of lowpass
filtered signal');
xlabel('Frequency (Hz)');
%*****

%
% %the mouse-click sets a flag for point aquisition
% set(gcf,'windowbuttondownfcn','hit=1;');
%
% %make a control to stop the loop
uicontrol('style','pushbutton',...
    'string','Quit', ...
    'position',[0 0 50 20], ...
    'callback','stopit=1;');

% for Resistance
b =30; %% Bandwidth of the filter
N= 102% no. of samples or window sizes
X = fftshift(fft(Resistance));
K = zeros(1,102);
K(round(N/2)+1+[-b:b])=1; %% Lowpass filter
Y = X .* K; %% Lowpassed signal
F = -round(N/2):(fix(N/2)-1); %% Frequencies in Ft
figure(9);
subplot(3,1,1); plot(F,abs(X)); title('Fourier transform of signal
Resistance');
```

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```
subplot(3,1,2); plot(F,K); title('K: lowpass filter');
subplot(3,1,3); plot(F,abs(Y)); title('Fourier transform of lowpass
filtered signal');
xlabel('Frequency (Hz)');
%*****
*****

% %the mouse-click sets a flag for point aquisition
% set(gcf,'windowbuttondownfcn','hit=1;');
%
% %make a control to stop the loop
uicontrol('style','pushbutton',...
    'string','Quit', ...
    'position',[0 0 50 20], ...
    'callback','stopit=1;');

% for Temp
b = 30; %% Bandwidth of the filter
N= 102 % no. of samples or window sizes
X = fftshift(fft(Temp));
K = zeros(1,102);
K(round(N/2)+1+[-b:b])=1; %% Lowpass filter
Y = X .* K; %% Lowpassed signal
F = -round(N/2):(fix(N/2)-1); %% Frequencies in Ft
figure(10);
subplot(3,1,1); plot(F,abs(X)); title('Fourier transform of signal
Temperature');
subplot(3,1,2); plot(F,K); title('K: lowpass filter');
subplot(3,1,3); plot(F,abs(Y)); title('Fourier transform of lowpass
filtered signal');
xlabel('Frequency (Hz)');
%*****
*****

%
% %the mouse-click sets a flag for point aquisition
% set(gcf,'windowbuttondownfcn','hit=1;');
%
% %make a control to stop the loop
uicontrol('style','pushbutton',...
    'string','Quit', ...
    'position',[0 0 50 20], ...
    'callback','stopit=1;');

% for ShakeEnergy
b = 30; %% Bandwidth of the filter
N= 102 % no. of samples or window sizes
X = fftshift(fft(SE));
K = zeros(1,102);
K(round(N/2)+1+[-b:b])=1; %% Lowpass filter
Y = X .* K; %% Lowpassed signal
F = -round(N/2):(fix(N/2)-1); %% Frequencies in Ft
figure(11);
subplot(3,1,1); plot(F,abs(X)); title('Fourier transform of signal
ShakeEnergy');
subplot(3,1,2); plot(F,K); title('K: lowpass filter');
subplot(3,1,3); plot(F,abs(Y)); title('Fourier transform of lowpass
filtered signal');
```

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```
xlabel('Frequency (Hz)');
%*****
***

% %the mouse-click sets a flag for point aquisition
% set(gcf,'windowbuttondownfcn','hit=1;');
%
% %make a control to stop the loop
uicontrol('style','pushbutton',...
    'string','Quit', ...
    'position',[0 0 50 20], ...
    'callback','stopit=1;');

% for SQ
b = 30; %% Bandwidth of the filter
N= 102 % no. of samples or window sizes
X = fftshift(fft(SQ));
K = zeros(1,102);
K(round(N/2)+1+[-b:b])=1; %% Lowpass filter
Y = X.* K; %% Lowpassed signal
F = -round(N/2):(fix(N/2)-1); %% Frequencies in Ft
figure(12);
subplot(3,1,1); plot(F,abs(X)); title('Fourier transform of signal
ShakeQuotient');
subplot(3,1,2); plot(F,K); title('K: lowpass filter');
subplot(3,1,3); plot(F,abs(Y)); title('Fourier transform of lowpass
filtered signal');
xlabel('Frequency (Hz)');

%*****

uicontrol('style','pushbutton',...
    'string','Quit', ...
    'position',[0 0 50 20], ...
    'callback','stopit=1;');

b = 30; %% Bandwidth of the filter
N= 102 % no. of samples or window sizes
X = fftshift(fft(AX));
K = zeros(1,102);
K(round(N/2)+1+[-b:b])=1; %% Lowpass filter
%Y =X.* K; %% Lowpassed signal
F = -round(N/2):(fix(N/2)-1); %% Frequencies in Ft
figure(13);
subplot(2,1,1); plot(F,abs(X)); title('Fourier transform of
AccDataX');
subplot(2,1,2); plot(F,K); title('K: lowpass filter');
%subplot(3,1,3); plot(F,abs(Y)); title('Fourier transform of
lowpass filtered signal');
xlabel('Frequency (Hz)');

%*****
*****

b = 30; %% Bandwidth of the filter
```

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```
N= 102 % no. of samples or window sizes
X = fftshift(fft(AY));
K = zeros(1,102);
K(round(N/2)+1+[-b:b])=1; %% Lowpass filter
%Y = X.* K; %% Lowpassed signal
F = -round(N/2):(fix(N/2)-1); %% Frequencies in Ft
figure(14);
subplot(3,1,1); plot(F,abs(X)); title('Fourier transform of
AccDataY');
subplot(3,1,2); plot(F,K); title('K: lowpass filter');
%subplot(3,1,3); plot(F,abs(Y)); title('Fourier transform of
lowpass filtered signal');
xlabel('Frequency (Hz)');

%*****
%
% %the mouse-click sets a flag for point aquisition
% set(gcf,'windowbuttondownfcn','hit=1;');
%
% %make a control to stop the loop
uicontrol('style','pushbutton',...
    'string','Quit', ...
    'position',[0 0 50 20], ...
    'callback','stopit=1;');

%% Return to time domain and look at lowpassed filtered signal
%%
Z = ifft(ifftshift(AX));
figure(15);
subplot(2,1,1); plot(Z,'c');
hold on; plot(real(Z),'y','LineWidth',3); hold off
title('Comparing the original AccDataX signal and Z lowpass filter');
subplot(2,1,2); plot((Z)); plot([1 N],[eps eps],'g'); hold off;
hold on;
hold off;
title('Comparing the imaginary part of inverse Fourier transform');
xlabel('Time (seconds)');

%*****

Z = ifft(ifftshift(AY));
figure(16);
subplot(2,1,1); plot(Z,'c');
hold on; plot(real(Z),'r','LineWidth',3); hold off
title('Comparing the original AccDataY signal and Z lowpass filter');
subplot(2,1,2); plot((Z)); plot([1 N],[eps eps],'g'); hold off;
hold on;
hold off;
title('Comparing the imaginary part of inverse Fourier transform');
xlabel('Time (seconds)');

%*****
*****

load H:\project\AX
load H:\project\AY
```

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```
%this function train network after dimension reduction by principal
componenet analysis PCA
% using the largest tow eigenvalues.
% for i=1:39
%     for j=1:139
%         traindata.P =AX(1:34,1:139);
%     end
% end

% for i=40:75
%     for j=1:139
%         testdata.P =AX(35:68,1:139);
%     end
% end

% for i=78:102
%     for j=1:139
%         valdata.P =AX(69:102,1:139);
%     end
% end

% for i=1:34
%     %for j=1:139
%         traindata.T =AY(1:34,1:139);
%     end
% %end

% for i=35:68
%     %for j=1:139
%         testdata.T =AY(35:68,1:139);
%     end
% %end

% for i=68:102
%     %for j=1:139
%         valdata.T =AY(69:102,1:139);
%     end
% %end

%testdata.P=[AX(52:102)]
inp=[traindata.P,valdata.P,testdata.P];
avg = mean(inp') ;
inp = (inp - (ones(length(inp),1)*avg)');% Apply averages
out = [traindata.T , valdata.T , testdata.T];
out = (out - (ones(length(out),1)*avg)') % Scale output

X=inp';
C=cov(X); %covariavce matrix
[V,D] = eig(C);% produces matrices of eigenvalues (D) and
eigenvectors (V) of covariance matrix C.
i=length(D);
EV=V(i,:);

inp=EV*inp ;%projecting the data set on the eigenvectors
avg = mean(inp'); % Calculate averages for each feature
stand = std(inp') ;% Calculate standard deviation for each feature
```

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```
inp = (inp -
(ones(length(inp),1)*avg)') ./ (ones(length(inp),1)*stand)';
% for i=1:2
%     low(i) = min(inp(i,:));           % minimum for each
feature
%     high(i)= max(inp(i,:)) ;         % maximum for each
feature
% end

low(1) = min(X(1,:));
low(2) = min(X(2,:));
high(1) = max(X(1,:));
high(2) = max(X(2,:));

tr anum = length(traindata.P);
valnum = length(valdata.P);
testnum = length(testdata.P);

traindata.P =inp(:,1:tr anum);
valdata.P= inp(:,tr anum+1:tr anum+valnum);
testdata.P =inp(:,tr anum+valnum+1:length(inp));
traindata.T = out(1:tr anum);
valdata.T = out(tr anum+1:tr anum+valnum);
testdata.T = out(tr anum+valnum+1:length(inp));

if max(max(abs(inp(:,1:tr anum)))) > 3           % Check if feature
value greater than 3 standard deviations from mean
    disp('Outliers exist!');                   % Need to put
outliers in test set
else
    disp('No outliers. ');                     % No problem
end

m=max(max((traindata.P)));                       % getting the
outliers
[i,j]=find(traindata.P==m);

testdata.P=[testdata.P,traindata.P(:,j)];        % putting it
in test set
testdata.T=[testdata.T,traindata.T(:,j)] ;
%testdata.names=[testdata.names;traindata.names(j,:)];
testnum=testnum+1;                               % adding 1
to number of test set
traindata.P=[traindata.P(:,1:j-1),traindata.P(:,j+1:tr anum)]; %
deleting it ftom training set
traindata.T=[traindata.T(1:j-1),traindata.T(j+1:tr anum)];
%traindata.names=[traindata.names(1:j-
1,:);traindata.names(j+1:tr anum,:)];
tr anum=tr anum-1;

net = newff([-123 64],[10 1],{'tansig' 'purelin'});
Y = sim(net,inp);

figure(1)
```

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```
    plot(AX,AY,'o',inp,Y,'*')
    net.trainParam.epochs = 100;
    net = train(net,inp);

%*****
*****

load H:\project\AX
load H:\project\AY

% PCA for AX
[pn,minAX,maxAX] = premmx(p);
[pn,meanAX,stdp] = prestd(AX);%PRESTD Preprocesses the data so that
the mean is 0 and the standard deviation is 1.
[AXtrans transmat]=prepca(pn,0.09);% apply PCA
%AXtrans = AX.T

% PCA for AY
[pn_val,meanAY,stdAY] = prestd(AY);
[AYtrans transmat]=prepca(pn_val,0.09);
%AYtrans= AY.T

x1=AX;
avg=mean(x1')
stand=std(x1')
y1=AX
avgval=mean(y1')
standval=std(y1')

% Load the data to be used
figure(1)
plot(x1, y1, 'o'); % Plot all the data points
xlabel('Feature 1')
ylabel('Feature 2')
%
figure(2)
plot(AXtrans, AYtrans, 'x'); % Plot all the data points
xlabel('Feature 1')
ylabel('Feature 2')

figure(3)
plot(x1, y1, 'o', AXtrans, AYtrans, 'x'); % Plot all the data points
xlabel('AccDataX')
ylabel('AccDataY')

hold on;
plot([-8 8]*pn(1,1),[-8 8]*pn(2,1),'y-');
plot([-6 6]*pn(1,2),[-6 6]*pn(2,2),'r-');
%pause;

% Plot data points
z=AXtrans
u=AYtrans
```

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```
figure(4)
scatter(z(1,:),z(2:,:), 'x');
axis equal;
drawnow;
pause;
% %
% % % Calculate PC's.

% %
% % Draw PC's on the data top
hold on;

plot([-8 8]*pn(1,1),[-8 8]*pn(2,1), 'y-');
plot([-6 6]*pn(1,2),[-6 6]*pn(2,2), 'r-');
pause;
% %
% % % Rotate the data to the PC's
y = (x1'*pn)';
% %
% Plot data.
figure(5);
scatter(u(1,:),u(2,:));
axis equal;
drawnow;
pause;
% %
% % % Calculate PC's, to demonstrate they now lie on the axes.
% %
% %
% draw PC's on top of data.
hold on;
plot([-8 8]*pn(1,1),[-8 8]*pn(2,1), 'y-');
plot([-6 6]*pn(1,2),[-6 6]*pn(2,2), 'r-');
pause;
% %
% we set the 2nd component of y to zero, reducing the dimensionality
to one.
y1(2,:) = 0;

% Transform back to the original data.
x = (y1'*(pn_val))';

% Plot data.
figure(6);
scatter(x(1,:),y(1,:), 'x');
% scatter(x1,y1)
axis equal;
drawnow;
pause;

% Tidy up.
close all;
```

%*****

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```
load H:\project\AX
load H:\project\AY

% PCA for AX
[pn,meanAX,stdp] = prestd(AX);%PRESTD Preprocesses the data so that
the mean is 0 and the standard deviation is 1.
[AXtrans transmat]=prepca(pn,0.09);% apply PCA
%AXtrans = AX.T

% PCA for AY
[pn_val,meanAY,stdAY] = prestd(AY);
[AYtrans transmat]=prepca(pn_val,0.09);
%AYtrans= AY.T

x1=AX;
avg=mean(x1')
stand=std(x1')
y1=AX
avgval=mean(y1')
standval=std(y1')

%this function train network after dimension reduction by principal
componenet analysis PCA
% using the largest tow eigenvalues.
% for i=1:39
%     for j=1:139
%         traindata.P =AX(1:34,1:139);
%     end
% end

% for i=40:75
%     for j=1:139
%         testdata.P =AX(35:68,1:139);
%     end
% end

% for i=78:102
%     for j=1:139
%         valdata.P =AX(69:102,1:139);
%     end
% end

% for i=1:34
%     %for j=1:139
%         traindata.T =AY(1:34,1:139);
%     end
% %end

% for i=35:68
%     %for j=1:139
%         testdata.T =AY(35:68,1:139);
%     end
% %end

% for i=68:102
%     %for j=1:139
%         valdata.T =AY(69:102,1:139);
%     end
```

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```
% %end

inp=[traindata.P,valdata.P,testdata.P];
avg = mean(inp') ;
inp = (inp - (ones(length(inp),1)*avg)');% Apply averages
out = [traindata.T , valdata.T , testdata.T];
out = (out - (ones(length(out),1)*avg)') % Scale output

X=inp';
C=cov(X); %covariavce matrix
[V,D] = eig(C);% produces matrices of eigenvalues (D) and
eigenvectors (V) of covariance matrix C.
i=length(D);
EV=V(i,:);

inp=EV*inp ;%projecting the data set on the eigenvectors
avg = mean(inp'); % Calculate averages for each feature
stand = std(inp') ;% Calculate standard deviation for each feature
inp = (inp -
(ones(length(inp),1)*avg)')./(ones(length(inp),1)*stand)');

Y=out';
c=cov(Y); %covariavce matrix
[v,d] = eig(c);% produces matrices of eigenvalues (D) and
eigenvectors (V) of covariance matrix C.
n=length(d);
ev=V(n,:);

out=ev*out ;%projecting the data set on the eigenvectors
Avg = mean(out'); % Calculate averages for each feature
Stand = std(out') ;% Calculate standard deviation for each feature
out = (out -
(ones(length(out),1)*avg)')./(ones(length(out),1)*stand)');

P = [(inp(1,:)); (out(1,:))];

net = newsom([-4 4; 0 1],[10 10]);
plotsom(net.layers{1}.positions)

% Here the SOM is trained for 50 epochs and the input vectors
are
% plotted with the map which the SOM's weights has formed.
%
net.trainParam.epochs = 50;
net = train(net,P);
plot(P(1,:),P(2:,:),'.r','markersize',20)
hold on
plotsom(net.iw{1,1},net.layers{1}.distances)
hold off
```

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The data sets are as follows:

```
\begin{File}[Note][0]
\end{File}
\begin{File}[HMJ][0]
\begin{HMJ}[2003-08-17 11:45:41][3]
\end{HMJ}
\begin{HMJ}[2003-08-17 12:00:06][4]
\end{HMJ}
\begin{HMJ}[2003-08-17 12:15:01][1]
\end{HMJ}
\begin{HMJ}[2003-08-17 12:54:28][5]
\end{HMJ}
\begin{HMJ}[2003-08-17 15:29:36][1]
\end{HMJ}
\begin{HMJ}[2003-08-17 15:29:40][3]
\end{HMJ}
\begin{HMJ}[2003-08-17 16:00:08][0]
\end{HMJ}
\begin{HMJ}[2003-08-17 18:21:37][0]
\end{HMJ}
\begin{HMJ}[2003-08-17 19:01:47][7]
\end{HMJ}
\begin{HMJ}[2003-08-17 19:37:35][4]
\end{HMJ}
\end{File}
```

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```
\AccDataX[0,1,0,1,1,1,1,1,1,1,0,1,1,1,1,0,1,1,1,1,-15,-15,-15,-15,-16,-  
18,-16,-15,-15,-11,-10,-10,-13,-14,-13,-12,-12,-13,-  
14,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,  
0,0,0]  
\AccDataY[-14,-15,-15,-15,-15,-15,-15,-15,-15,-14,-15,-15,-15,-15,-15,-14,-  
15,-15,-15,-15,-15,-15,-15,2,1,1,0,0,-4,-1,-2,-1,-6,1,2,7,-6,-9,-4,-4,-4,-4,-  
5,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,  
0,0]  
\end{BioData}  
\begin{BioData}[2003-08-17 13:34:29]  
\Pulse[90]  
\Resistance[512]  
\Temperature[960]  
\ShakeEnergy[8250]  
\ShakeQuotient[36]  
\AccDataX[1,-2,-3,-6,-2,0,3,3,4,4,0,5,8,10,12,8,5,0,0,-1,0,-4,-7,-7,-2,4,1,-22,-30,-33,-  
32,-13,-17,-28,-23,-31,-33,-31,-22,-20,-22,-21,-27,-24,-14,-10,2,-1,0,-1,-  
1,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,  
0,0,0,0,0,0]  
\AccDataY[-22,-24,-22,-26,-22,-21,-22,-26,-31,-31,-22,-22,-20,-21,-19,-25,-32,-30,-  
30,-28,-29,-29,-30,-21,-15,-14,2,2,16,5,17,10,13,8,6,1,-1,-  
2,1,2,1,6,2,5,19,12,5,8,11,7,9,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,  
0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0]  
\end{BioData}  
\begin{BioData}[2003-08-17 13:39:29]  
\Pulse[91]  
\Resistance[512]  
\Temperature[960]  
\ShakeEnergy[8258]  
\ShakeQuotient[2]  
\AccDataX[12,12,13,12,12,12,12,13,12,13,11,13,13,13,4,13,13,12,14,12,14,13,14,13,  
12,13,13,-1,-2,-2,-3,-3,-3,-3,-3,-4,-4,-5,-4,-5,-5,-5,-5,-6,-6,-6,-7,-  
6,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,  
0,0,0,0]  
\AccDataY[0,1,1,0,1,0,0,1,1,1,2,3,2,1,-1,0,0,1,1,0,0,0,-1,0,-1,-  
1,2,13,15,14,13,15,13,12,12,14,12,12,13,13,13,12,13,12,12,11,4,14,0,0,0,0,0,0,0,0,  
0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0]  
\end{BioData}  
\begin{BioData}[2003-08-17 13:44:29]  
\Pulse[68]  
\Resistance[512]  
\Temperature[960]  
\ShakeEnergy[8273]  
\ShakeQuotient[0]  
\AccDataX[-5,-5,-5,-5,-5,-5,-6,-3,-4,-4,-5,-3,-3,-5,-3,-5,-4,-5,-3,-6,-2,-5,-3,-4,-4,-4,-  
4,4,4,3,3,3,4,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0]  
\AccDataY[4,4,3,3,4,4,4,4,4,3,4,4,3,4,3,4,3,4,4,3,3,4,4,4,4,2,-3,-4,-5,-3,-4,-  
5,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0]  
\end{BioData}
```

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```
\ShakeEnergy[8243]
\ShakeQuotient[0]
\AccDataX[1,0]
\AccDataY[-3,0]
\end{BioData}
\begin{BioData}[2003-08-17 19:38:08]
\Pulse[32]
\Resistance[320]
\Temperature[960]
\ShakeEnergy[8247]
\ShakeQuotient[0]
\AccDataX[1,1,1,1,1,1,1,0,0,0,0,0,0]
\AccDataY[-3,-3,-3,-2,-3,-3,-3,0,0,0,0,0,0]
\end{BioData}
\begin{BioData}[2003-08-17 19:38:30]
\Pulse[32]
\Resistance[64]
\Temperature[960]
\ShakeEnergy[8248]
\ShakeQuotient[0]
\AccDataX[1,1,1,1,1,1,1,1,0,1,0,1,1,1,0,0,0,0,0,0,0,0,0,0,0,0]
\AccDataY[-3,-3,-3,-3,-3,-3,-3,-3,-3,-3,-3,-3,-3,-3,-3,0,0,0,0,0,0,0,0,0,0,0,0]
\end{BioData}
\begin{BioData}[2003-08-17 19:38:36]
\Pulse[32]
\Resistance[448]
\Temperature[960]
\ShakeEnergy[4]
\ShakeQuotient[0]
\AccDataX[1,1,1,0,0,0]
\AccDataY[-3,-3,-3,0,0,0]
\end{BioData}
\begin{BioData}[2003-08-17 19:38:39]
\Pulse[32]
\Resistance[704]
\Temperature[960]
\ShakeEnergy[7]
\ShakeQuotient[73]
\AccDataX[1,1,1,1,1,1,1,1,1,1,0,0,0,0,0,0,0,0,0,0,0]
\AccDataY[-3,-3,-3,-3,-3,-3,-3,-3,-3,-3,-3,-3,-3,-3,-3,0,0,0,0,0,0,0,0,0,0,0]
\end{BioData}
\end{File}
\begin{File}[MEDInfo][0]
\end{File}
\begin{File}[MEDTimer][0]
\medtime[6][0][1]
\medtime[8][0][2]
\medtime[10][0][2]
\medtime[12][0][1]
```

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```
\medtime[14][0][2]  
\medtime[16][0][2]  
\medtime[18][0][1]  
\medtime[22][0][3]  
\end{MEDTimer}  
\medtime[0][0][0]  
\medtime[6][0][1]  
\medtime[8][0][2]  
\medtime[10][0][2]  
\medtime[12][0][1]  
\medtime[14][0][2]  
\medtime[16][0][2]  
\medtime[18][0][1]  
\medtime[20][0][2]  
\medtime[22][0][3]  
\medtime[0][0][0]  
\end{MEDTimer}  
\end{File}
```

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Reg No: E 3094D

References

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2. Digital Signal processing, A practical Approach: Emmanuel C.
Ifeachor. Barone .W. Jervis
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