INDIAN INSTITUTE OF TECHNOLOGY DELHI

Department of Computer Science and Engineering

REPORT OF THE PROJECT SHORTLISTED UNDER SURA–2014

Project Titled

Artificial Neural Network treatment of EEG Signals for thought-controlled prosthetics

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Introduction

The recent advances in modern brain-imaging techniques have hugely bolstered research in areas of brain sciences and cognitive studies. While they were earlier being used for merely diagnosing brain disorders, they are now being used to generate highly utilitarian bits of data. One such imaging technique is electroencephalography, or EEG, which essentially measures the averaged electrical potential across the human scalp. It is non-invasive, and faster in response compared to techniques like fMRI, which makes it advantageous to be used in real-time itinerant applications, and thus the technique of choice in the present study undertaken in this project.

The motivation behind this project is to develop a computational basis for developing real-time brain controlled actions, such as thought-controlled prosthetic limbs or electronic devices. Whenever we execute, or even think of executing a motor activity, neurons in certain sections of the brain get fired up, which eventually manifests itself into the change in the averaged electrical activity of the region, as recorded by the EEG device. The problem with the so-procured EEG signal is two-fold:

1. The process of acquiring the EEG signal could be very dynamic, simply because the human brain is very dynamic. It could depend on the subject’s mood, state of mind, uncontrolled thoughts, environment disturbances, or even muscular movements of the body itself. This dynamism is often hard to capture using conventional methodologies.
2. Also, the signal is averaged over many neurons, and recorded from over the skull and the scalp, which further attenuates the overall signal quality and adds a lot of noise to it, which masks the actual valuable signal. Thus, the signal-to-noise ratio is poor, and large amounts of data are needed for significant research analysis (Alois Schlögl, 2002).

To these two issues, one could also add the pragmatic problem of achieving real-time control, which would mean that the computations should be able to strike a reasonable balance between the accuracy of prediction and the time it takes to pop the prediction. Most current brain-computer interfaces involving EEG look at aggregate signal parameters, like the “level of concentration” or the “level of meditation” (easily extractable by looking at the frequency of the signal, since low frequency brain signals correspond to drowsiness and vice-versa) to control a device in a binary manner, like in the game *Adventures of Neuroboy* or *Mindball* (Larsen, 2011). To permit for more complicated control, we cannot use such gross parameters.

It is therefore only natural, to turn to nature, to handle problems of dynamism in a system. Artificial Neural Networks (ANNs) have been modelled on the lines of biological neural networks that exist inside the brain. One such network usually consists of an input, a hidden and an output layer of “neurons”. If one were to do, say a clustering or classification task, then the output neurons could represent these classes, while the input neurons could represent the data that needs to be classified. The hidden neurons are, so-to-speak, the “feature extractors”, as they sift out the usable (significant) data from the rest of the data pool. Thus, the network is able to eliminate the noise and recover the actual signal as it passes through it. The network exploits the dynamic nature of data by using the concept of Hebbian Learning, that is, there are certain weights associated with each connection between any two consecutive layers, and these weights keep getting adjusted, (the network, over time, *learns*,) as and when the network keeps getting trained with newer input data, *due to* the differences in the input data sets and corresponding output classification. Once trained, a network can be tested with sample inputs to verify the correctness of the output.

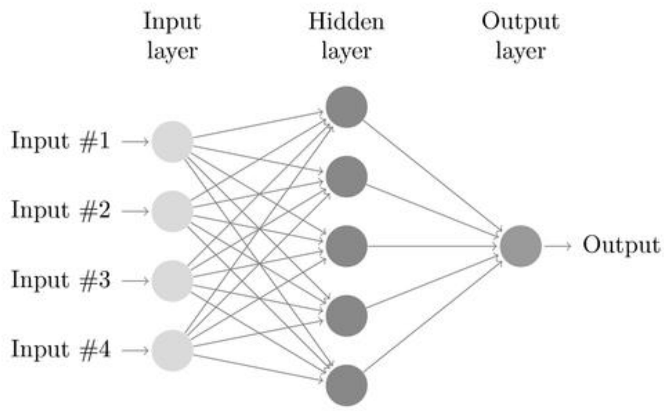

Figure 1. A schematic of an Artificial Neural Network with a single hidden layer

Thus in essence, the problem for this study was reduced to:

1. Devising appropriate experiments for generating relevant (and as far as possible, error-free) data.
2. Establishing a means of converting the raw data into usable data, which can be directly fed into the ANN.
3. Listing out the appropriate motor classifications of the input data, and thus defining the ANN parameters.
4. Training and testing the network and explicating *any* motor action in terms of the chosen motor classifications.

Experiments

The experiments were carried out in the EEG Lab at IDDC, IIT Delhi. Initially, 4 sets of experiments were carried out on a basic 14-channel wireless EEG headset (the one used and developed by Emotiv^{TM}) which had the advantage of allowing marking of events (say the moment the subject jerked his/her arm), but the disadvantage of a low sample rate (128 bits/sec) and dynamic positioning of electrodes in every new sitting. The next 3 sets of experiments were done on a newly purchased 32-channel wired EEG headset (the kind used in hospitals for diagnosing epilepsy and other brain disorders) which had the advantage of a higher sampling rate, but the disadvantage of no provision of event markers (which led to confusion in extracting useful strings of data) and the qualitative/amateur nature of the user controls. Therefore eventually, the data used for further analysis (and as presented in this report) was taken from the former EEG setup, and the Emotiv Test Bench software was used to record and export the data from each of the 14 channels to a .csv file which can then be worked upon in MATLAB.

An EEG machine essentially records the voltage across each electrode in the EEG cap at a given time instant. Individual neurons are electrically charged by the pumping of ions across their membranes. When many neurons in close proximity cause a large push or pull of electrons, it generates a wave of ions across the extracellular milieu, whose effect reaches right till the EEG electrode on the scalp (Tatum, 2008). Clearly, the voltage perceived at the electrode is averaged over multiple neurons. The plasticity of the brain, and the small amplitude of the EEG signal (of the order of µV) means that the recorded signal can be very dynamic and prone to disturbances, which imposes a lot of constraints on the experiment process.

The experiments devised, inspired by the "block formats" used by Porbadnigk et al. (Anne Porbadnigk), were initially supposed to cover 10 different (simple) motor actions, in three formats of

- "jerks", wherein the subject committed the action suddenly, at any random instant of time, separated by random intervals of time.
- "continuous movements", wherein the subject continuously executed the action for the length of the recording.
- "thought-of-the-motor-activity"–format, wherein the subject would merely think of executing the motor activity.

Out of the ten activities, many required lengthy movements that perturbed the setup or at times, even the subject. Also, since the subject executing the “jerk” movements was otherwise completely disjoint from any external stimuli of vision or sensation, somebody else had to mark the jerk event in the recording, which led to creeping in of an undetermined time lapse between the actual event and the event marked in the recording. Thus eventually, after multiple failed attempts at gathering useful unperturbed data, and for the sake of rigour on one particular act, the experiments were limited to the motor action of continuous right arm movement (actual action, plus the thought of the action) and the normal rest condition.

The experiment was carried out with 3 different subjects, and each sitting lasted for 2-3 hours, in a dark noise-free room. After a general relaxation of the mind and body, the subject’s rest state would be recorded (across all 14 channels). Following which the subject would be told to commit the right arm movement for around 30 seconds. Then, the subject would be told to just think about moving the right hand for another 30 seconds. Note that each recording would last between 30 and 60 seconds. Moreover, it may be noted that the data sets used for final analysis in this report were all taken from the same subject, across 2 experiment sittings.

Figure 2. The 32-channel EEG setup used for some experiments of this study

The 14-channel data from each recording (essentially an array of size (128*seconds X 14)) was exported to MATLAB via a .csv file, where it was trimmed to a data recording of 16 seconds (2048X14) before being subjected to actual computational analysis.

Analysis

The raw data received after experiments stands at a high dimensionality of 2048X14. Feeding raw data as the input to a network would not only necessitate a very large network and high computational time complexity, but also cause a poor fitting of the network to the data. Therefore, the data was processed and its dimensionality was reduced before being fed into the network.

The usual range of each signal was observed to lie between 3000 and 5000 units. There could be some values overshooting this range, but they were artefacts (such as muscular ones) which would mean that we must assume for them to be an external noise in the signal, and thus have them curtailed to the boundary case of value equal to 3000/5000. Also, the best way to look at variations in a signal would be in the frequency domain, so that we can quantify the repeated occurrences of certain signal values. Thus, it was decided to convert the raw data into a frequency distribution (which is representative of the probability distribution and thus the Shannon Entropy[1], or the *amount of information*, in the signal). The signal range was divided into 10 bins, and the outliers were curtailed to the extreme bins. Also, the signal was assumed to have been sampled at every one second, that is, each 1-second recording was treated as an individual sample. (This allows for usage of small-duration data in running the network, which would enhance the real-time attribute of the system.)

Since we have 14 channels, and 10 bins corresponding to the frequency distribution of each channel, each input sample is a column vector of size 140 (with distribution across each channel stacked on top of one another). Since we have 16 seconds of raw data, we get 16 such samples corresponding to each experiment set. Furthermore, each sample was used twice for training the network, to allow for twice the total number training samples.

Since we have 3 classifications, we have 3 neurons in the output layer, corresponding to the value 0/1 depending on whether the given input data belongs to that class or not:

- <u>R</u>est – 100
- <u>M</u>ovement – 010
- <u>T</u>hought-of-movement – 001

[1] If X be a random variable (in this case, the value of the signal), then the Shannon Entropy of the random variable is given by $H(x) = -\sum_{i=1}^{n} P(x_i)\log(P(x_i))$

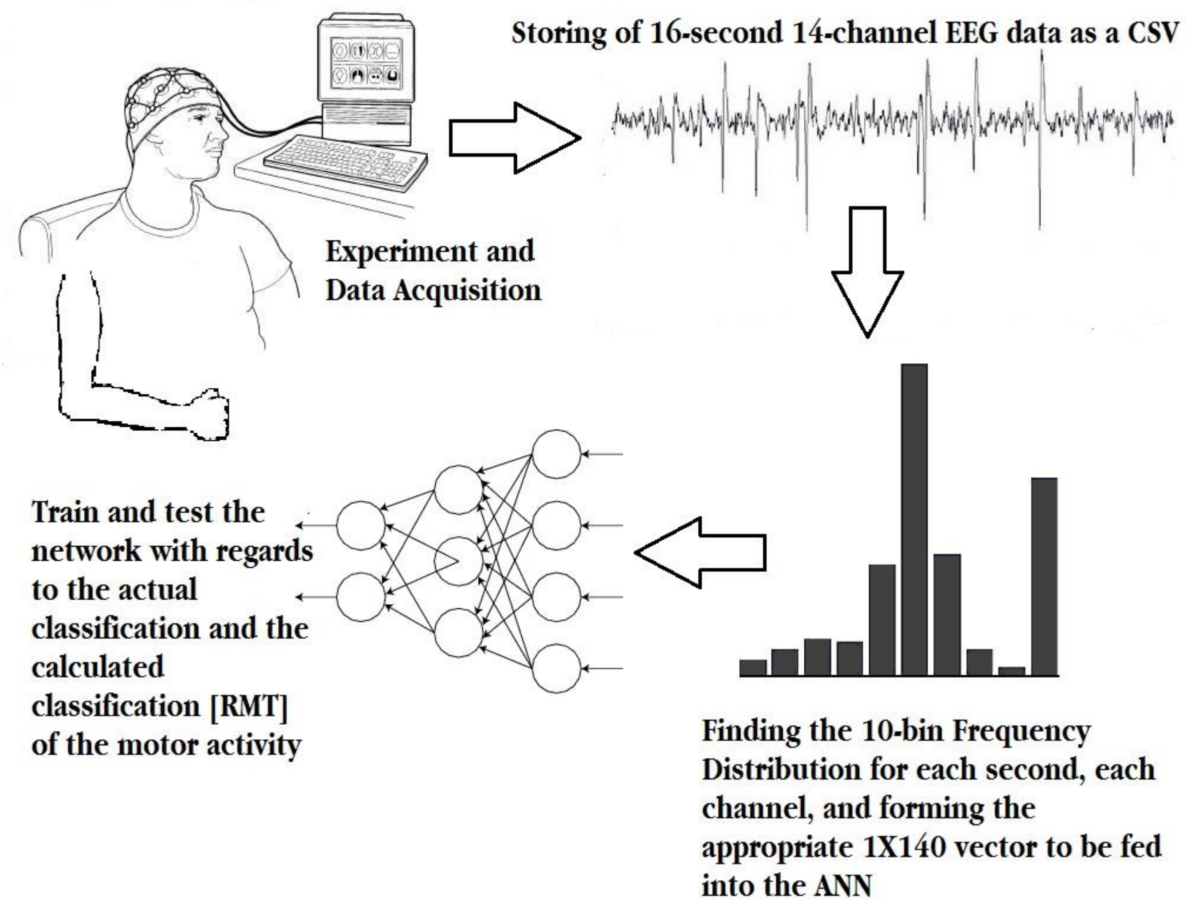

Figure 3. An overview schematic of the experiment and analysis process

Thus the output sample (1X3) for each input sample (1X140) is of the form [RMT]. For the purpose of training the network, we had in all (3*32 =) 96 input-output sample pairs. Clearly, we have 140 input nodes, 3 output nodes. By empirical hit-and-trial (for suitable trade-offs between accuracy and time complexity, and since there are 10 bins for every frequency distribution), the number of nodes in the hidden layer was chosen to be 10 (see figure 4).

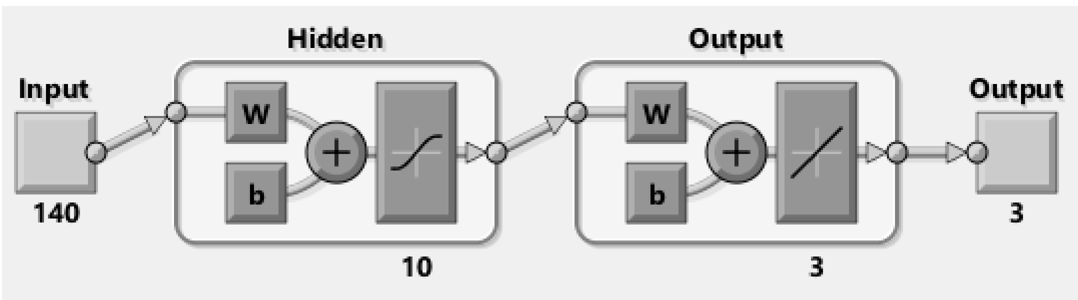

Figure 4. A cartoon of the ANN used in the current analysis

Clearly, as in usual practice, a sigmoidal activation function was used for the hidden layer, while a linear activation function was used for the output layer (Jain, 1996). Out of the 96 samples, 68 samples were randomly chosen for training the network, while 14 each were used for validating and testing it. The backpropogation algorithm is used for training the network and setting the weights. Evidently, as we iterate more and more over the entire network (number of epochs increase), the mean-squared-error in the real versus calculated classification generically keeps on declining, until finally it remains almost constant for the testing/validating samples.

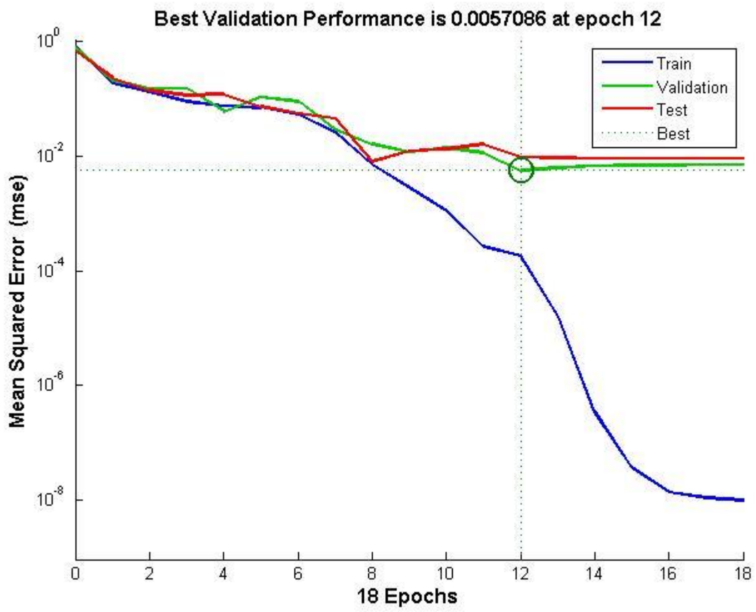

Figure 5. The variation of MSE with the number of epochs

Also, the error values (= actual – calculated) are concentrated around zero and very few sample instances have error values that are much larger than that.

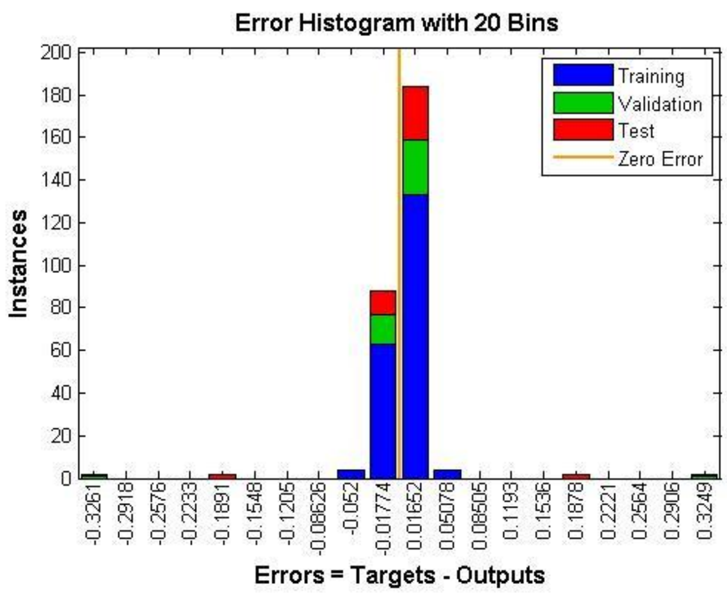

Figure 6. Frequency Distribution of Error Values

Another measure to quantify the correlation between the actual and calculated classifications is to find out the regression values for all sample pairs (the idea being that ideally, the actual and calculated values must be equal, that is, they must lie along the Y=X line). The regression value is a measure of how well our data fits our statistical model, which in this case is the identity function; a value close to 1 is indicative of good-fitting (Draper, 1998). From the regression plots (see figure 7) it is clear that for most sample types, the regression value is close to 1, and the overall regression value is 0.99467, which is again very close to unity. Note that the regression value for all 14 testing samples is quite high as well ($R_{testing}$ = 0.97807).

All of the above measures are indicatory of the successful training of the neural network. Note that each input sample essentially corresponds to 1 second of 14-channel data. To further verify the model, a new 1-second sample of movement class was taken from another experiment sitting of the same subject. The output achieved when this sample was passed to the trained network was

[RMT] = [0.273, 1.0417, 0.1487]

which is a reasonably accurate classification of this task, among the 3 possible classes. Therefore, in effect, we can express any arbitrary EEG signal in a parameterised form, where the parameters are nothing but the output vector [RMT].

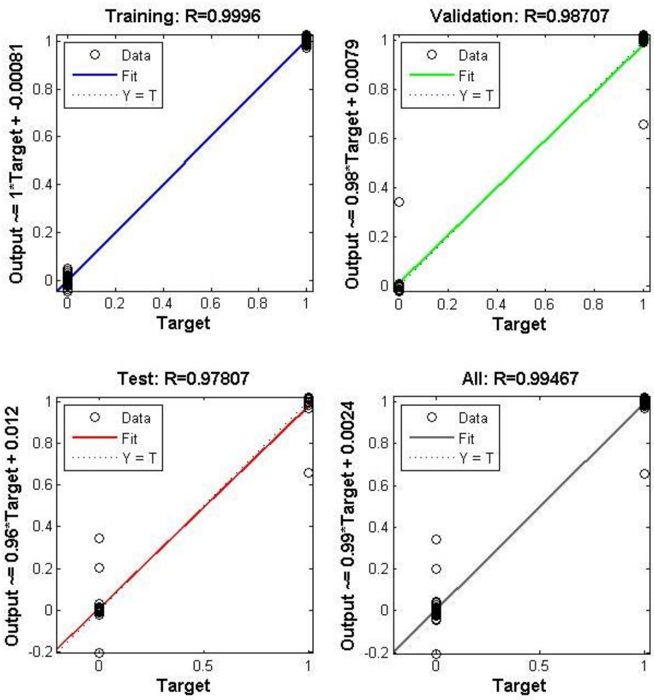

Figure 7. Regression Analysis of the actual (X-axis) versus calculated (Y-axis) classifications

Results

We have emerged successful in:

- Devising a suitable experimental structure and data manipulations for appropriate training of the neural network, while respecting the real-time nature of the study's application.
- Validating the accuracy of the trained neural network via various metrics like error and regression values.
- Developing a method to express any arbitrary EEG signal in terms of a constant number of parameters (which in this case, was 3) and thus appropriately classify them. This means that in essence, every action will be represented by merely 3 dimensions.
- Differentiating thought-of-movement from actual movement (at least in this rudimentary scenario) by successfully classifying the input data for these two situations into two different categories. This could be exploited for creating prosthetic limbs for different *kind* of patients more appropriately.

We have failed in:

- Extending the action set to more number of motor activities, so that even very complicated actions can find an accurate parameterisation among more number of parameters. (The primary reason being the perturbing nature of more complicated actions.)
- Improving the accuracy of training samples by using "jerks" instead of "continuous movements". (The primary reason being inadequacy of available EEG apparatus and the software bench for handling quick event markers.) Note that continuous movement would cause synaptic fatigue of neurons (Kilpatrick, 2010), which makes the data procured henceforth as less accurate and representative than the one obtained from a sudden-movement recording. Also, real-life movements are rarely executed in a continuous fashion.

This project could be extended in the future by:

- Instead of treating the output vector as the parameterisation of an input EEG signal, parameterise these actions on the *probability* of an input vector belonging to a particular class (Torsten Felzer, 2003).

- Using targeted electrodes located at relevant cortex lobes instead of all 14/32 channels, say the ones located just at the motor cortex, for reduced complexity and redundancy of the model, and increased accuracy.
- Long term and rigorous training with vast amounts of data, to check for robustness and consistency of the model in the long run.
- Using other imaging techniques, such as fMRI which offer higher spatial resolution of data. Or directly using electromyography (EMG) for measuring the electrical impulses in the skeletal muscles, which would provide better raw data to our model in the first place.
- Suggesting ways to convert the model from theory to practice, as far as real-life applications are concerned. Say possibility of development of embedded systems, and portable EEG caps for real-time computing.

References

Alois Schlögl, M. S. (2002). *Presence research and EEG.*

Anne Porbadnigk, M. W.-P. (n.d.). *EEG-based Speech Reognition - Impact of Temporal Effects.*

Draper, N. R. (1998). *Applied Regression Analysis.* Wiley-Interscience.

Jain, A. K. (1996). *Artificial Neural Networks: A Tutorial.* IEEE.

Kilpatrick, Z. P. (2010). *Spatially Structured Waves and Oscillations in Neuronal Networks With Synaptic Depression and Adaptation.*

Larsen, E. A. (2011). *Classification of EEG Signals in a Brain-Computer Interface System.*

Tatum, W. O. (2008). *Handbook of EEG Interpretation.* Demos Medical Publishing.

Torsten Felzer, B. F. (2003). Analyzing EEG Signals Using the Probability Estimating Guarded Neural Classifier. *IEEE Transactions on Neural Systems and Rehabilitation Engineering, VOL. 11, NO. 4,*, 361-371.

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