EEG Signal Classification by Feed Forward Neural Network

ECE 501NN – Neural and Adaptive Systems

Project Report

April 2006

By:
Amin Fazel

I. Introduction to Brain Computer Interface

The goal of brain computer interface (BCI) research is to provide a person with a new communication channel that accepts commands directly from the brain without requiring physical movements. Classification of electroencephalogram (EEG) is an important part of EEG-based brain computer interface.

Several attempts have been made to build an EEG-based BCI system. The most important parts of these systems consist of two procedures: feature extraction and classifier. For feature extraction, adaptive auto regressive model, Hjorth parameters, power spectrum and principle component features have been widely employed [6]. Various classifiers were also used. These include linear discriminant analysis (LDA) [2], artificial neural networks (ANN) [1], linear dynamical systems and recently hidden Markov model (HMM) [6].

In brain signal and in fact many other signals it is very seldom that we have the precise model for the process under the test. The systems used are very complex and our understanding of the underlying mechanism is so limited, that some hypothesis that are not always true, must be made in order to get the model. In many cases the benefits of having a model are so great, that is usually beneficial to assume inaccurate assumptions.

In this report, we use feed forward neural network to model the raw data of slow cortical potential (SCP) with some preprocessing to remove artifacts. This approach avoids the need of expert knowledge for extracting suitable features. The proposed method is tested on data set Ia of BCI Competition 2003 and promising results are obtained. Our results strongly support the feasibility of this approach.

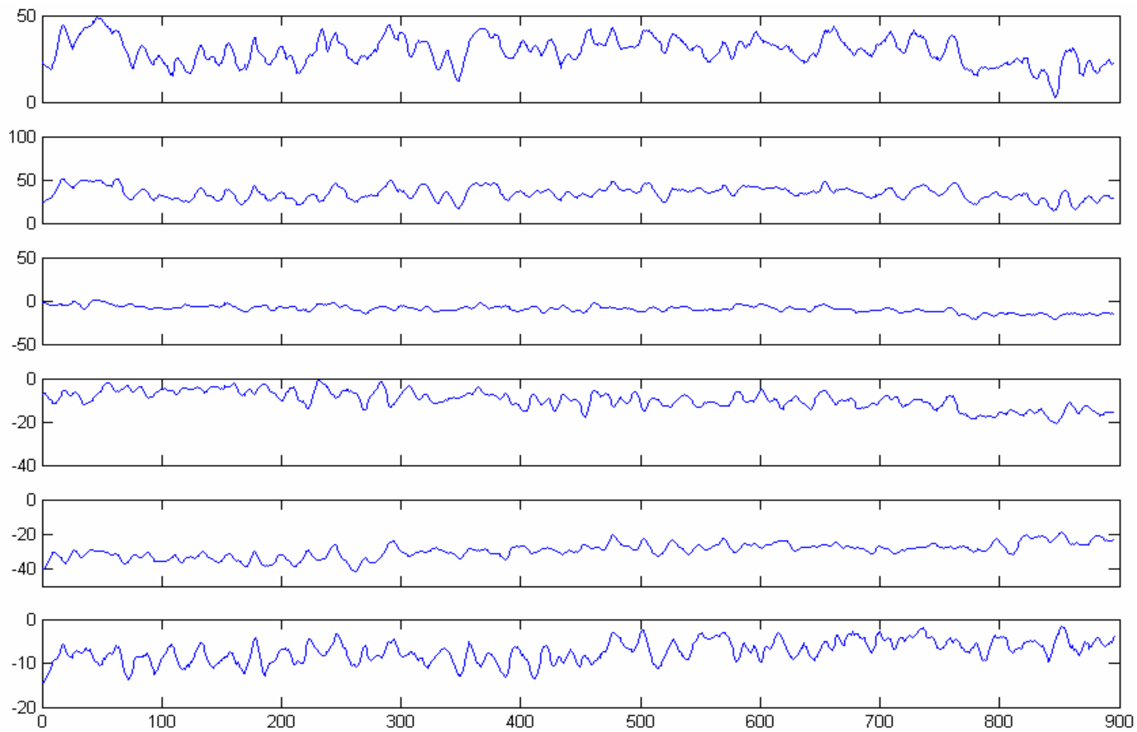
The organization of this report is as follows. Section II describes the data and the task. Section III presents our feature extraction method. Section IV describes the neural network that was used as an EEG classifier in this project. Finally, section V gives the results of this project.

II. Data Acquisition and Task

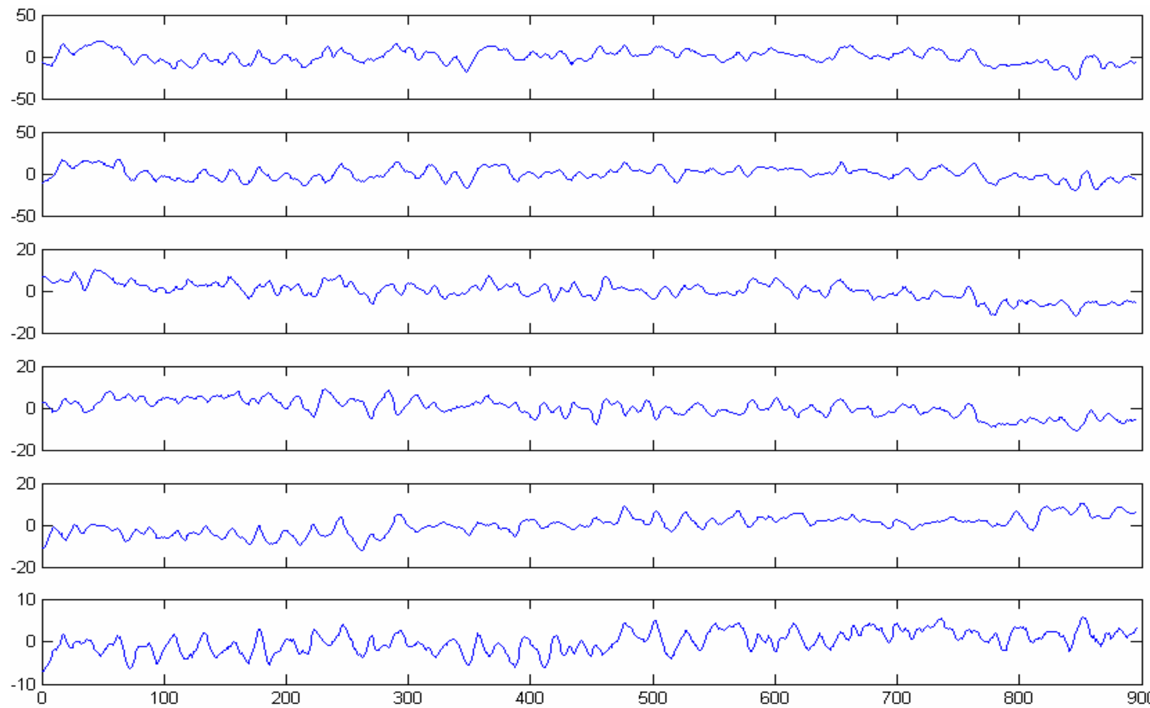
The data set were collected from a single healthy subject at the University of Tuebingen, Germany [2]. This data were acquired by six EEG electrodes. These six EEG channels were sampled at 256Hz. Trials consisted of three phases: a 1-s rest phase, a 1.5-s cue presentation phase, and a 3.5-s feedback phase. At the beginning of the 1.5-s cue-presentation phase, a visual target indicator appeared either at the top, instructing the subject to strive for cortical Negativity, defined below, or bottom, cortical Positivity, of the screen. The target remained visible during the subsequent 3.5-s feedback phase, during which a cursor appeared, whose vertical position indicated the current level of cortical negativity being generated by the subject. The subjects were asked to move a cursor up or down on a computer screen, while their SCPs were recorded. The subjects received visual feedback of their SCPs which were corrected for vertical eye movement. The trials were separated into a train set of 268 trials and a 293 trials test set, which both of them contained EEG data from only the feedback phase of each trials.

III. Signal Preprocessing and Linear Predictive Coding (LPC) Features

A direct current offset in a SCP is typically an artifact of the recording process. Due to the DC in the data, we use mean subtraction method to remove this effect. In this method the mean of whole time domain data in a trail subtracted from each sample in that trail.

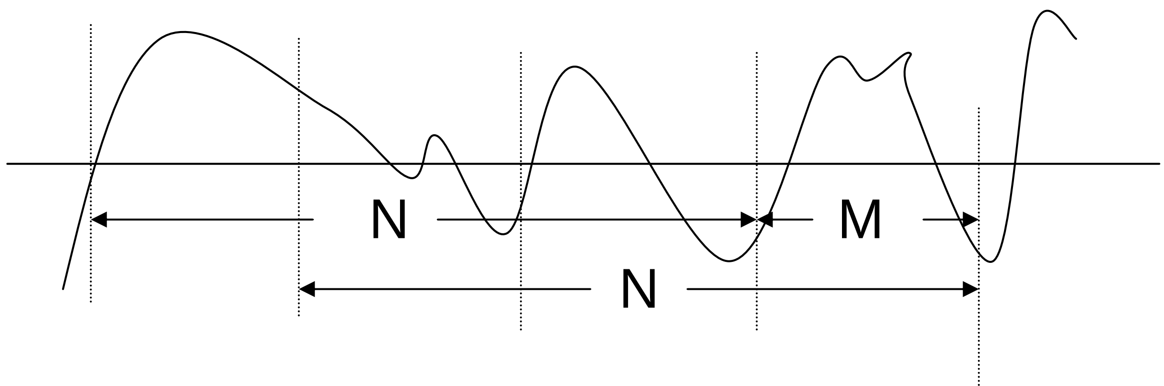


EEG signal for 6 channels of first trial



Mean subtraction EEG signal for 6 channels of first trial

In [4], it is reported that multivariate autoregressive (AR) parameters are effective to represent the features of the EEG patterns for mental imagery tasks. In this project, rather than the direct exploitation of AR parameters, we use the LPC [5] with a sliding window for the feature extraction, which is well-known technique for speech applications. This strategy is based upon the analytical fact that the AR parameters vary dramatically even between the respective EEG patterns of the same imagery task and thus the direct use of the AR coefficients is considered not suitable for our imagery tasks. This situation is similar to the case of the speech recognition tasks where the speech signals are highly non-stationary.



Framing of EEG signal

Linear Predictive Coding (LPC) provides low-dimension representation of signal at one frame. This method is also analytically tractable.

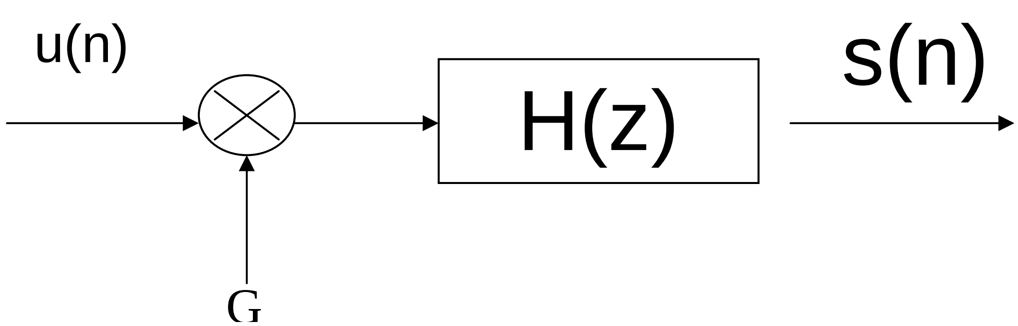
LPC models signal as approximate linear combination of previous p samples:

$$s(n) \approx a_1 s(n-1) + a_2 s(n-2) + \cdots + a_p s(n-p)$$

Where a_1, a_2… a_p are constant for each frame of signal.

One can also see the LPC coefficients as a filter:

$$s(n) = \sum_{k=1}^{p} a_k s(n-k) + Gu(n).$$



Representation of LPC coefficients as a filter

Given a window of signal samples, the first p+1 terms of the autocorrelation sequence are calculated from

$$r_i = \sum_{j=1}^{N-i} s_j s_{j+i}$$

where i = 0,..,p.

The filter coefficients are then computed recursively using a set of auxiliary coefficients k_i which can be interpreted as the reflection coefficients and the prediction error E which is initially equal to r_0.

Let $\{k_j^{(i-1)}\}$ and $\{a_j^{(i-1)}\}$ be the reflection and filter coefficients for a filter of order i-1, then a filter of order i can be calculated in three steps.

Firstly, a new set of reflection coefficients are calculated

$k_j^i = k_j^{i-1}$ for j = 1,…, i-1 and

$$k_i^{(i)} = \frac{\left\{ ri + \sum_{j=1}^{i-1} a_j^{(i-1)} r_{i-1} \right\}}{E^{(i-1)}}$$

Secondly, E is updated

$$E^{(i)} = (1 - k_i^{(i)} k_i^{(i)}) E^{(i-1)}$$

Finally, new filter coefficients are computed

$a_j^{(i)} = a_j^{(i-1)} - k_i^{(i)} a_{i-j}^{(i-1)}$ for j = 1,…,i-1 and

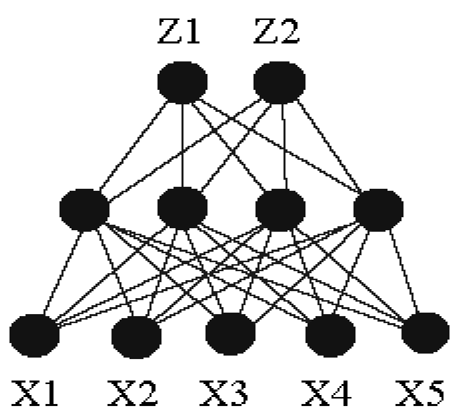
$$a_i^{(i)} = -k_i^{(i)}$$

This process is repeated from i=1 through to the required filter order i=p.

Block diagram of feature extraction

IV. Neural Network Classifier

Feed forward neural networks (FNNs) are composed of layers of neurons, in which the input layer of neurons are connected to the output layer of neurons.



A general feed forward neural network

Multilayer feed forward networks are universal approximators (Hornik 1989). Hornik writes: "...standard multilayer feed forward networks with as few as one hidden layer unit arbitrary squashing functions are capable of approximating any Borel measurable function from one finite dimensional space to another to any desired degree of accuracy, provided sufficiently many hidden units are available. In this sense, multilayer feed forward networks are a class of universal approximators." Kreinovich (1991) proved that neural networks are universal approximators even if the requirement of squashing function is replaced by more realistic requirement of smooth nonlinear activation functions. However, in practice, things are not so simple. There are cases where two hidden layers are even necessary or worthwhile - it depends on the learning algorithm and the over-all purpose of the ANN.

In feed forward architectures, the activations of the input units are set and then propagated through the network until the values of the output units are determined. The network acts as a vector-valued function taking one vector on the input and returning another vector on the output.

Feed forward networks may have a single layer of weights, where the inputs are directly connected to the outputs, or multiple layers with intervening sets of hidden units. Neural networks use hidden units to create internal representations of the input patterns. In fact, it has been shown that given enough hidden units it is possible to approximate arbitrarily closely almost any function with a simple feed foward network. This result has encouraged people to use neural networks to solve many kinds of problems.

Each neuron receives a signal from the neurons in the previous layer, and each of those signals is multiplied by a separate weight value. The weighted inputs are summed, and passed through a limiting function which scales the output to a fixed range of values. The output of the limiter is then broadcast to all of the neurons in the next layer. So, to use the network to solve a problem, we apply the input values to the inputs of the first layer, allow the signals to propagate through the network, and read the output values.

As we have 13 frames for each of 6 channels and each frame has 12 LPC features, so we used a 936X268 matrix as an input matrix. Based on our input data and also the task which wants to classify between two classes, a feed forward neural network with 936 neurons in input layer and one neuron in output layer was used. This feed forward neural network has 3 layers, one as input, one as output and one as the hidden layer.

V. Results

Table 1 summarizes the classification results of the above feed forward neural network method with various neurons in hidden layer. The table is also shown the impact of using 10 percent validation data set. As we know use of validation data set suffers from less amount of training data set and as we have not enough training data set, we got the worse results with the use of validation data set.

TABLE I
Performance

Feature(s)	Classifier	Number of neurons in HL	Test Set (% Mean)	Test Set (% Best)
12 order LPC	FFNN without validation	10	80.22	82.46
12 order LPC	FFNN with validation	10	63.43	72.39
12 order LPC	FFNN with validation	40	62.62	66.42
12 order LPC	FFNN with validation	100	65.42	76.87
12 order LPC	FFNN without validation	100	79.17	80.22
12 order LPC	FFNN with validation	500	64.99	67.91

References

[1] Ernst Haselsteiner and Gert Pfurtscheller, “Using time dependent neural networks for EEG classification,” IEEE Transactions on Rehabilitation Engineering, vol. 8, no. 4, pp. 457--463, December 2000.

[2] Mensh, B.D.; Werfel, J.; Seung, H.S., “ BCI competition 2003-data set Ia: combining gamma-band power with slow cortical potentials to improve single-trial classification of electroencephalographic signals,” IEEE Trans. Biomed. Eng., vol. 51, pp. 1052 – 1056, June 2004.

[3] B. Blankertz, K.-R. Mueller, G. Curio, T. M. Vaughan, G. Schalk, J. R. Wolpaw, A. Schloegl, C. Neuper, G. Pfurtscheller, T. Hinterberger, M. Schroeder, and N. Birbaumer, “The BCI Competition 2003,” IEEE Trans. Biomed. Eng., vol. 51, pp. 1044–1051, June 2004.

[4] C. W. Anderson, E. A. Stolz, and S. Shamsunder, “Multivariate autoregressive models for classification of spontaneous electroencephalographic signals during mental tasks,” IEEE Trans. Biomed. Eng., vol. 45, no. 3, pp. 277-286, Mar. 1998.

[5] L. Rabiner and B-H. Juang, Fundamentals of speech recognition, Prentice Hall: New Jersey, 1993.

[6] Shi Zhong and Joydeep Ghosh. “HMMs and coupled HMMs for multi-channel EEG classification” In Proc. IEEE Int. Joint Conf. on Neural Networks, vol. 2, pp. 1154-1159, Honolulu, Hawaii. May 2002.