KTH Computer Science
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Classification of Electroencephalographic Signals For Brain-Computer Interface

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Abstract

Brain-Computer Interface (BCI) can be used for example to help disabled people to control a computer without the use of mouse or keyboard. The brain signals beta and mu are acquired by electroencephalography (EEG) and shows what parts of the brain that are active not only at the performing of a muscular movement, but also by thinking about it. By analyzing EEG-signals with the methods linear discriminant analysis and artificial neural networks the aim is to explore which of two possible cognitive tasks a subject is performing. In the essay these methods are compared with aspect to correct classifications. In conclusion, when performing binary classification of mu and beta waves, a small multi layer perception is sufficient.

Referat

Klassificering av electroencefalografiska signaler for hjärna-datorgränssnitt

Hjärna-datorgränssnitt (brain-computer interface, BCI) kan användas för att exempelvis hjälpa svårt funktionsnedsatta människor att styra en dator utan att använda mus eller tangentbord. Hjärnsignalerna beta och my erhålls via electroencefalografi (EEG) och visar vilka delar av hjärnan som är aktiva inte bara vid utförandet av muskelrörelser utan även vid tanken därpå. Genom att analysera EEG-signalerna med metoderna linjär diskriminantanalys och artificiellt neuralt nätverk är syftet att undersöka vilken av två möjliga kognitiva uppgifter en försöksperson utför. I uppsatsen jämförs dessa metoder med avseende på korrekta klassificering. Som slutsats kan sägas att vid binär klassifikation av beta- och my-signaler är minsta möjliga flerlagersperceptron tillräcklig.

Contents

Chapter 1

Glossary

- Artificial Neural Network (ANN) - A collection of artificial neurons and the connections between these
- Artificial Neuron - A mathematical function, abstracting a biological neuron
- Beta rhythms or beta signals - An EEG signal of 13-30 Hz measured at the frontal lobe
- Brain-Computer interface (BCI) - A cross-disciplinary research field focusing in manipulating a computer via brain signals
- Electroencephalography (EEG) - A method of measuring brain activity by using the small differences in electrical change that appears when neuron are activated and shut down
- Feedforward Network - An ANN where the connections between the artificial neurons do not form a directed cycle
- Nerve cell - A cell type in the human body specialised in transporting information in the form of weak electrical currents. Synonymous to neuron.
- Neuron - A cell type in the human body specialised in transporting information in the form of weak electrical currents. Synonymous to nerve cell.
- Multi Layer Perceptron (MLP) - A feedforward network with more than one layer
- Mu rhythms or Mu bands - An EEG signal of 8-12 Hz measured near the brains' motor cortex

Chapter 2

Preface

This project was a collaborative work of one student from the School of Computer Science and Communication and one from Medical Informatics and Technology. In this essay, Annika (MI) is mainly responsible for the sections pertaining to the biological nervous system, and Richard (CSC) is mainly responsible for the computational nervous system. Revisions of all sections have been done by both parties.

Chapter 3

Introduction

Brain-Computer Interface (BCI) is a recently emerged field of cross-disciplinary research (1). As suggested by the name, the focus is in manipulating the computer via brain signals, instead of mechanical devices such as keyboards or mice. This would be a breakthrough in computer usage by severely disabled people or people lacking voluntary movement (2, 3). It must be stressed that devices that rely on muscular movement, such as eye-tracking, does not fall under BCI (1). The workflow of a BCI device is as follows: the user performs a cognitive task, the brain signals are recorded, the signals are analysed and classified, and the system reacts, giving feedback to the user. The brain-signals of BCI are mostly often retrieved by the surface electrodes of electroencephalography (EEG) and implanted electrodes (2).

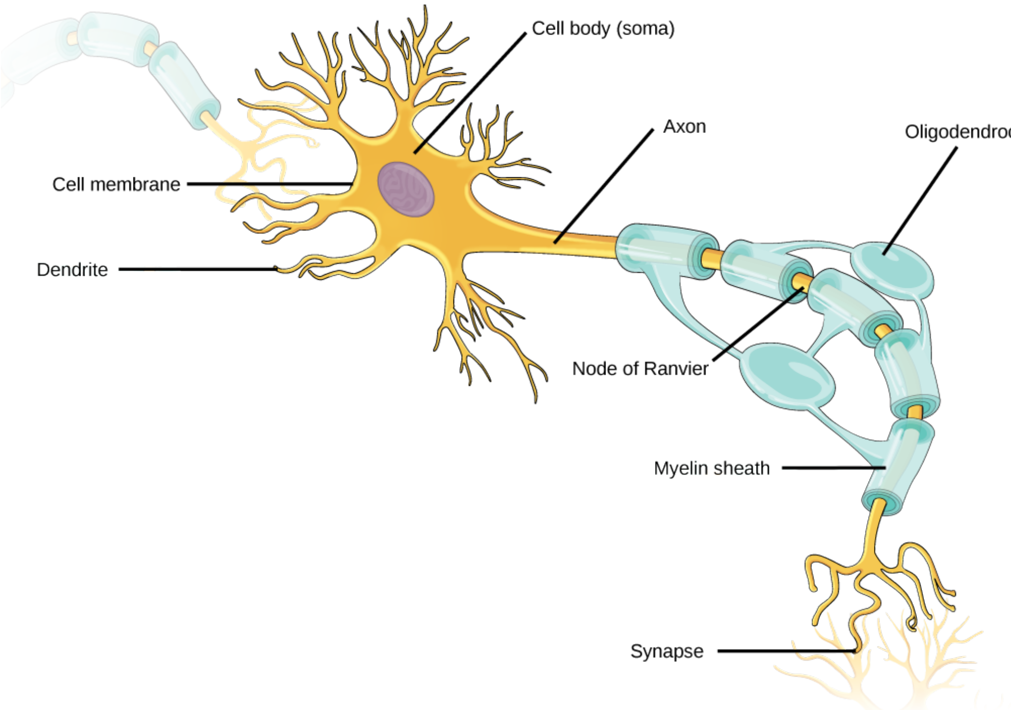
3.1 The nerves and the nervous system

The nerves in the human body are physiologically divided into the central nervous system (CNS) and the peripheral nervous system (PNS). The CNS involves the nerves controlling the brain and the brain stem, while the PNS consists of the remaining nerves in the body (4). Simplified one might say that it is the duty of the PNS to gather information about the internal and external environment of the body and up to the CNS to process the information gathered.

The nervous system is composed of two types of cells: nerve cells and glial cells. A nerve is a cell type specialised in transmitting information rapidly between one cell to another. The glial cell help to maintain the environment surrounding the nerve cells and aid the information transmission.

A nerve cell (see figure 3.1) has a head called soma which includes the cell nucleus. From soma it runs a long tail called axon, which is covered in a sheet of fat isolator called myelin. Nerves communicate with each other by electrical signals called action potentials. An action potential appears when the nerve cell experiences certain changes in the levels of the ions Na+, Cl- and K+. The nerve then has the ability to transport the electrical charge through the long axon fibre. This is done by the weak current jumping along the axon on the sites called nodes of ranvier.

Figure 3.1: Nerve cell in the central nervous system wrapped in the glial cell oligodendrocyte (5)



The fat isolator is actually a glial cell and together with a refractory period it helps the electrical signal to go in only one direction. The signal is then transferred to another nerve cell via synapses until it reaches its destination.

3.2 Methods for mapping the brain

When studying the brain one might use imaging methods such as X-ray and magnetic resonance imaging or functional methods e.g. positron emission tomography, functional magnetic resonance imaging and electroencephalography. Positron emission tomography, PET, indicate which part of the brain being responsible for different processes. This is done with the help of the energy metabolism in the different parts of the brain by injection of a radioactive isotope, which emits gamma-radiation. Functional magnetic resonance imaging, fMRI, also indicates the active part of the brain but is using the different magnetic characteristics of oxygen saturated and oxygen unsaturated hemoglobine. fMRI is a relatively new method and believed to replace PET as the method develops (6).

Electroencephalography, EEG, is quite an old method used in hospitals mainly for screening for epilepsy but also for diagnosing mental disorders and brain death. By the use of small silver electrodes placed in certain orders, monitoring of the

Table 3.1: The EEG subgroups presented with their frequencies and physiological point of interest (3, 6, 8)

Sub group	Frequency (Hz)	Location
Alpha	8-13	Occipital parts of cortex Central sites at rest c3 and c4
Beta	13-30	Frontally with symmetric distribution on both sides
Gamma	30-100	Somatosensory cortex
Delta	<4	Frontally in adults. Varies with age
Theta	4-7	n/a
Mu	8-12	Sensorimotor cortex

electric signals in the brain cortex is made possible. Monitored is the differences in electric potential between two nearby electrodes, which will vary as the brain activity in the region of interest changes. The final registration summarized is the result of the synaptic potential from about one million nerve cells and is presented as typical rhythmic fluctuations. (6)

3.3 The signals of EEG

As mentioned in the paragraph above the EEG electrodes are placed in a specific order. One method of placement is the international 10-20 system. This is based on the electrode and the underlying area of the cerebral cortex. The measuring site is given one of letters F (frontal), T (temporal), C (central), P (parietal) or O (occipital) to indicate the relevant brain lobe and a number to identify hemisphere location. The right hemisphere is given even numbers and the left are given odd numbers. For example the site C3 indicates the left hemisphere of the central lobe. The numbers in the system name above, 10 and 20, merely indicate the interelectrode distance of 10% or 20 % (7).

The rhythms of EEG are classified into sub groups: alpha, beta, gamma, delta, theta and mu (3, 6, 8) and each of the subgroups are given an EEG band of its own. In humans the alpha rhythm is dominant and is strongest at the occipital parts of the frontal lobe. The alpha rhythm interacts with the theta rhythm in a way that one is suppressed while the other is strong. Both alpha- and mu-rhythms are oscillatory components, where the latter with its arched shaped wave, becomes suppressed during motor related tasks (8).

3.4 Usage of EEG signals in BCI

The research field of BCI often use the beta and mu rhythms of the EEG when attempting to artificially mimic the human brain. The mu rhythm is of interest since it is produced in the cortical areas most concerned with normal motor control. There are numerous recordings of the mu rhythm decreasing not only when performing concurrent muscle activity, but also when imagining doing so. Most beta rhythms are depended on mu rhythms as they together form non-sinusoidal waveforms, though recent studies indicate some beta rhythms being able to form their own topography in relation to motor cortex activity (3).

It has been shown that people can learn to control the beta and mu rhythm amplitudes recorded over the sensorimotor cortex (9). As such, they are good signals to record for a BCI system.

3.5 Definition of classification methods

When using measured EEG rhythms for BCI applications the data must be analyzed. This can be done by a linear statistical method e.g. linear discriminant analysis. Another approach is to utilize an multilayer feedforward artificial neural network. This is a method capable of approximating any continuous function (10).

In our classification task, we are to determine which of a binary set of classes our input data belong to. The process of classification will be referred to as 'labeling' or 'classifying'. The methods described below are trained by utilizing data sets of elements which are already correctly classified. These data sets will be referred to as 'labelled'.

3.5.1 Linear Discriminant Analysis

In a binary classification problem using Linear Discriminant Analysis (LDA) an n-dimensional data set is input and a linear discriminating function will classify each element. The function is on the form (11):

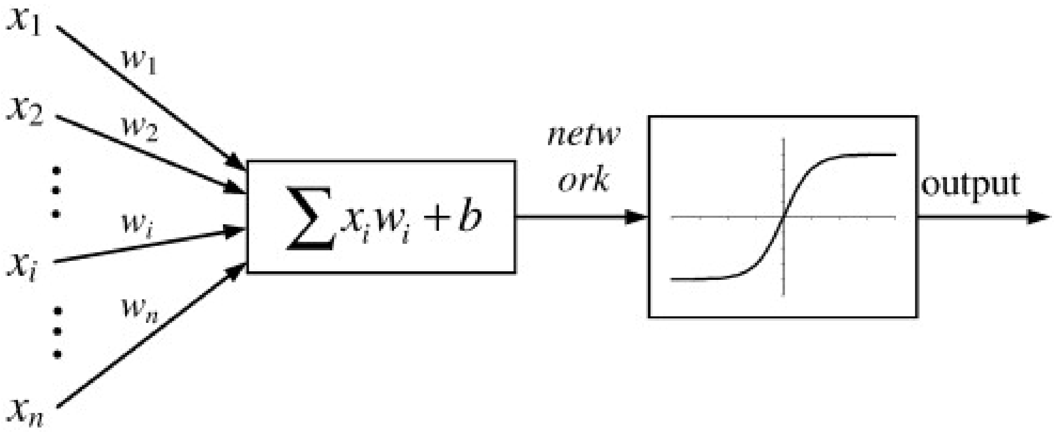
$$g(x) = w^t * x + w0 \tag{3.1}$$

and, in the binary case, the sign of $g(x)$ determines the class of x. The parameter w is known as the weight vector and is determined during training as the vector that maximizes correct classifications, and $w0$ determine the distance of the boundary to origo.

3.5.2 Artificial Neural Networks

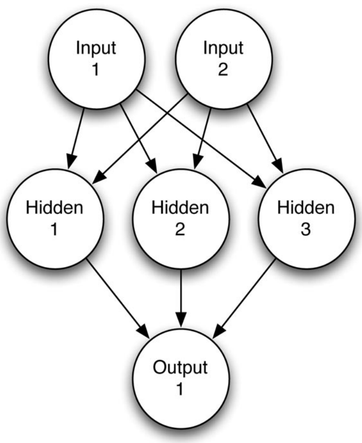
An Artificial Neural Network (ANN) emulates the human nervous system. The ANN can be thought of as a function that accepts a vector of size n as input, and produces a vector of size m. It accomplishes this by a concept called Artificial Neuron (or 'unit'), which is an abstraction of the workings of a biological neuron. The unit consists of weighted incoming values, an activation function, and an outgoing value. The weights represent the synapses of the nerve cell and the input and output represents the signal transported by the nerve. The workings of an ANN unit is very straightforward. Each incoming value is multiplied by it's weight, the products are summed and used as input to the nonlinear activation function. The resulting value is given as the outgoing value (11).

Figure 3.2: The workings of a single artificial neuron (12)



The network is formed by placing several units next to each other in a layer. In a feedforward network, the units in the same layer do not pass values between them, but they accept input values from the layer before them, and passes their output to the next layer ahead. Each units outgoing value features as one input value to all units in the next layer. This project will only deploy Multilayer Perceptrons (MLP), which are a kind of feedforward type ANNs. An MLP has one input layer, one output layer, and one or more hidden layers in between, so called because their workings are not directly visible to the external environment. (11)

Figure 3.3: A simple feedforward network, with three hidden units in one hidden layer (13)



In the beginning, the weights of the units input values are randomly assigned (11). Before useful information can be produced from the ANN, the network must be trained on labeled data. During training, a sample from the labelled data set is sent as input to the ANN. The output is compared to the correct classification ('target') of the given sample. The weights are then updated to give an answer slightly more in line with the target values on subsequent tests. The Backprop algorithm is a useful method for this task in a multi layer network. In this project, Levenberg-Marquardt backpropagation was used as a training function (14).

A well known problem in the field of ANN, or machine learning in general, is the one of overfitting. Overfitting is when the decision boundary adapts to the random fluctuations of the training data, instead of following the general trend. This will result in good classifications on data trained on, but poor predictive capabilities. A method to combat this problem is called Early Stopping. This works by first training the ANN on the training partition normally. After training, the ANN tries to classify the inputs from the validation partition, and the number of correct classifications is recorded. The ANN then goes back to the training phase, and keeps training on the training partition, until it's time to go into the validation phase again. It keeps on doing this, as long as the number of correct classifications on the validation set is increasing. Because the weights are not updated while in the validation phase, there is no risk of the ANN overfitting to a combination of training and validation data. Eventually, improvement in validation classification will plateau, and then performance will start declining. When this happens, the ANN internal weights that gave the best results on validation data will be used. Finally, the testing partition is used as input to the ANN, to see how it performs on novel data (15).

3.6 Aim

The aim of this study is to, based on EEG mu and beta rhythm recording, compare a Linear Discriminant Analysis-based classifier and a series of Artificial Neural Networks (ANN) with different configuration parameters in order to determine which of two possible cognitive tasks a user is performing. The comparison will be based on the number of correct classifications performed on novel data.

Chapter 4

Method

Two sets of data were provided by the supervisor of this essay, since gathering this information would be exceeding the limitations of this project. Both sets contained EEG data extracted from BCI equipment at two points on the skull, named C3 and C4 in the 10-20 System (7). The recordings were on two different frequency bands, mu and beta. Each data set provided data from 160 subsequent trials, with every trial lasting 4 seconds. From each trials frequency data, 71 time spans were extracted and each time span being approximately 60 ms spaced to the previous and slightly overlapping. The signal for each time span was mapped to a decimal value. This means our input feature vector was of size 4 and each trial had 71 input vectors (The 71 input vectors per trial will be referred to as 'time slices' through this report). As targets, two small binary vectors, [1,0] and [0,1] were used. This means the output vector was of size 2.

The computer utilized was an Intel® Core™2 Quad CPU Q9550 at 2.83GHz $\times$ 4 with 3.8 GiB memory, running 64-bit Ubuntu 12.04 LTS.

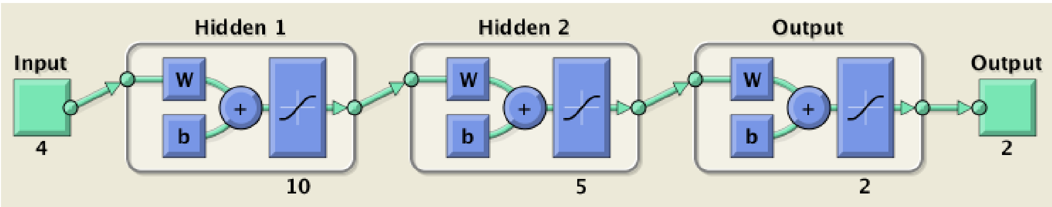
4.1 Linear Discriminant Analysis

To extract the time slices that offered the highest number of correct classifications the linear discriminant analysis was utilized on a labeled test data set. A method called K-fold Cross Validation was utilized to avoid overfitting. The K-fold Cross Validation split the data into five partitions and for each stage utilized four partitions for training and the fifth for validation. The validation was performed by classifying this partition using the trained discriminating function and comparing this with the already known labels for the partition, giving 1 point where matching and otherwise 0. The process was looped five times, iterating over all partitions. The results of the validation was then summed, and saved. Performing this test over all 71 time slices, we could determine the time slice with the largest number of correct classifications. This knowledge was utilized in the ANN phase to train the ANN on the input data where the classes features were most distinct.

4.2 Artificial Neural Networks

We tested a series of ANN configurations, with varying number of hidden layers and neurons. The values corresponded to the number of hidden neurons in the layer, and the number of values corresponded to the number of hidden layers. For example, [10, 5] refers to an ANN with 4 number of inputs (dimensionality of input vector is 4), 10 neurons in the first hidden layer, 5 neurons in the second hidden layer, and 2 neurons in the output layer.

Figure 4.1: The topology of a [10, 5] network



For input, we loaded the time slice selected during LDA. The data set loaded is divided into three approximately equal partitions. These were used for training, validating, and testing respectively, using the method Early Stopping. The performance during testing was saved, along with the trained ANN, for future restoration. When all configurations of hidden layers had been tested, the best performing ANN was selected to classify our unclassified data set.

In the second phase of the ANN part of the trials, we loaded the second, unlabelled data set, and the ANN configuration selected in the previous phase. The differences from the first phase are as follows; we do not know which time slice to run the classification on, and we do not know the correct classes. What we did first was to run the classification over all 71 time slices, and sum up the outputs. These were then divided by 71, to give 160 1x2 vectors, each containing two decimal values between 0 and 1. The larger of these was determined the victor, and mapped the trial to either [1,0] or [0,1]. Another method utilized was to map the initial output per time slice to one of the classes, instead of summing them. This constituted a vote for that class. The method resulted in 71 votes per trial in the end, and the trial was mapped to the class with the majority of votes.

Chapter 5

Results

During the LDA part of the trials, it was discovered that time slice 13 was the peak of a positive curve of increasing correct classifications. 128 of 160 trials were correctly classified in that time slice. The unlabelled data set was also classified, with the entirety of the labelled data set as training data, and the results were saved. Eventually, this turned out to give a maximum of 132 correct classifications, with a mean of 100.

Tests were run on specific ANN configurations instantiated 50 times. The ANN networks performance hovered around the 130-mark, or 80 % correct, on the labelled testing set. What we also can see are random dips into the 80 points bottom line (this is the same performance as one would expect from randomly labelling the instances). We will categorize these network instances as 'obstinate', for reasons that will become apparent, and discuss them in the next section.

By averaging the number of correct classifications, filtering out the sporadic obstinate networks as noise, the results shown in table 5.1 are aquired.

Table 5.1: Average number of correct classifications, obstinate networks filtered

[1]	128
[2]	128
[10, 5]	125
[40, 20]	125

For the second part, a classification of the unlabelled data set was produced and submitted to the supervisor. The results were good - 90 % correct. We later got the solution for the second data set, and produced figure 5.2 of the percentage of correct classifications for each time slice over the whole data set.

Figure 5.1: The number of correct classifications per instance from trials on a ANN with four different hidden layer configurations.

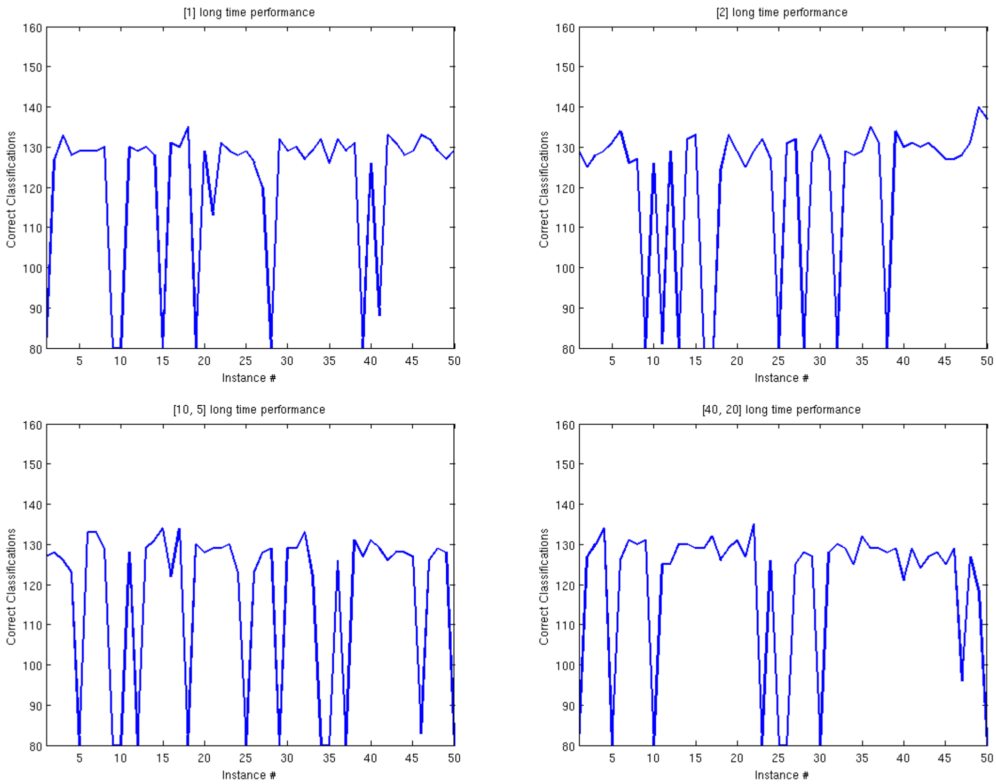
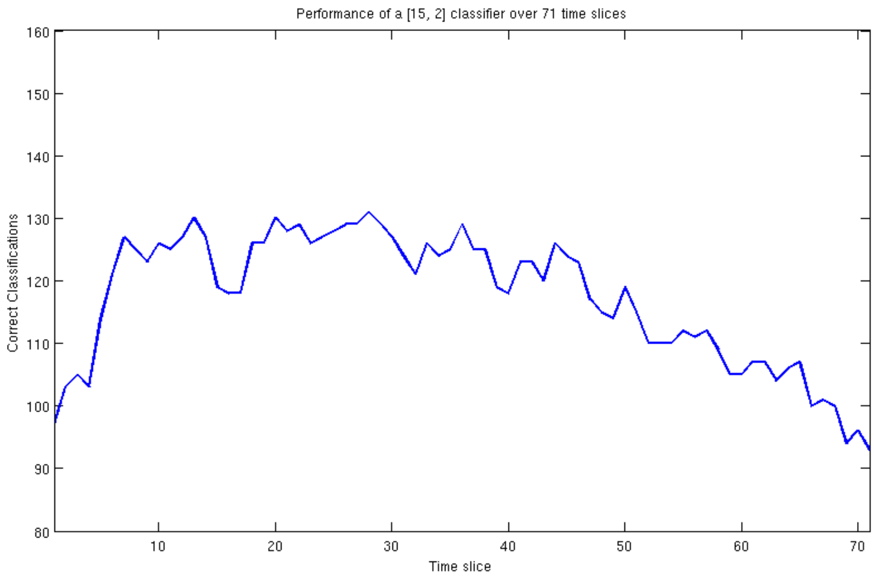


Figure 5.2: The topology of a [10, 5] network



Chapter 6

Discussion and conclusion

As shown in the graphs in figure 5.1, above, given a large number of instances of a fixed ANN configuration, a subset gave really poor results (80/160 correct classifications, or 50%). Those obstinate instances had been suboptimally trained, and gave the same output for all trials, hence the name. As the number of left- and right-trials were balanced, this naturally resulted in a 50% correct ratio. A possible idea for future studies would be to compare different ANN training methods, and see how one can minimize or even completely abolish these mistakes in training. For the aims of this study, the obstinate instances were simply discarded. The likelihood of them occurring did not change with the changing of the ANN configuration, so it is not of our opinion that they should have any importance in our conclusions.

As shown in figure 9 and the following paragraph, the performance of the ANN at any given time slice was worse (at least 8 percentage points) than the classification of the summed output over the whole trial. While our best result in our trials, in a BCI system in a live environment (online), the summation approach is less useful. The reason for this is that it would take 4 seconds, plus processing time, for one bit of information. This would give an information transfer rate (ITR) of 15 bits/minute, if a 100% correctness could be guaranteed. In an online system, this would be a poor result. For comparison, recent research by Guangyu Bin et.al. (16) achieved an average ITR of 108 ± 12 bits/min.

What is apparent when looking at the average performance of the different configurations is the similarity in outcomes, from the smallest possible configuration (one hidden unit in one layer), to a network of a considerable size (40 and 20 units respectively, in two layers). What is not apparent from the graph is the time each network spent in training. While a [1]-network trains on average 0.6 seconds, a [40, 20] network takes on average 3.2 seconds, or more than five times as long. It seems that for binary classifications of this input vector size, the smallest possible Multi Layer Perceptron ANN will suffice, and offers the best performance in terms of both speed and accuracy. However, when it comes to application to a real world BCI system Dennis McFarlands (9) research must be mentioned. While he points out the importance of selecting classes and trial lengths on an individual basis, for the average user, four classes gave the highest ITR. This suggests the binary classification performed in this experiment might be suboptimal to implement in most cases.

To conclude, when performing binary classification of a combination of mu and beta waves, a small multi layer perception is sufficient.

Chapter 7

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Appendix A

Raw Data, LDA

A.1 Correct classifications, LDA, labelled data set, all time slices:

98 100 105 108 112 119 120 119 120 119 122 126 128 127 122 119 120 118 115 117 112 114 111 109 104 102 99 102 96 98 96 95 90 95 94 88 86 85 83 83 87 89 87 89 93 86 92 89 89 93 94 92 88 86 87 88 90 88 89 89 92 84 89 88 88 93 94 93 92 94 94

A.2 Correct classifications, LDA, unlabelled data set, all time slices:

117 118 118 125 124 121 127 127 122 121 119 113 109 112 112 108 109 115 118 120 124 123 126 123 123 123 122 122 127 132 132 130 132 129 119 118 120 115 98 91 80 79 72 70 69 76 71 76 75 85 88 91 86 83 83 79 75 68 70 62 59 46 50 53 62 67 77 76 79 82 92

Appendix B

Raw Data, ANN

B.1 Correct classifications, ANN [1], unlabelled data set, all time slices:

94 94 97 105 106 111 116 118 115 119 124 119 118 119 117 115 118 122 124 122 121 119 121 116 121 123 120 124 121 120 120 119 125 124 124 128 127 124 123 120 120 121 118 118 116 114 114 108 110 111 107 103 103 104 109 113 115 115 111 111 111 111 114 109 111 108 102 99 97 98 96