

Muscle Pain and Blink Classification using a Brain Computer Interface

Oscar Montiel, Roberto Sepúlveda, Gerardo Díaz, Daniel Gutierrez, and Oscar Castillo

Instituto Politécnico Nacional, CITEDI. Tijuana, B.C., México

{oross,rsepulvedac}@ipn.mx

{gdiaz,dgutierrez}@citedi.mx

Instituto Tecnológico de Tijuana-ITT. Tijuana, B.C., México

{ocastillo}@tectijuana.mx

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Abstract. In this paper, two different architectures of artificial neural network (ANN) for the classification of blinking and arm pain caused by an external agent are used. The electroencephalographic (EEG) dataset is obtained from 20 people in the range of 23 to 30 years of age using a Brain Computer Interface (BCI), it is divided into a batch of necessary patterns to train and test the ANN. Experimental results using different training algorithms are shown.

Key words: EEG, BCI, ANN, FFT, Arm Pain, Blink, Adaptation Algorithm, MLP

1 Introduction

The human brain is a complex network of synaptic connections between neurons, which generate the electric impulses necessary to develop human functions like movements, communication, language, feelings, memory, reasoning, etc.; these functions are represented by EEG signals [1]. Since Human Computer Interface (HCI) technology has allowed to read EEG signals in humans, it was thought for interpreting and using them as communication channels with auxiliary devices that can help people with mental and physical problems [7].

EEG signals are read and interpreted by a BCI system; these electrical signals are produced by the different stimulus as physical action (motion) or mental status as feeling, imagination, memory, etc. Using BCI devices have many applications in robotic prostheses, pattern recognition, studies of pathologies such as epilepsy, Alzheimer, Parkinson, etc.

This paper presents a methodology to classify EEG signals using a multilayer perceptron (MLP) trained with the backpropagation algorithm, to find patterns produced by different external stimulus, specifically muscle pain and eye blinking. It is organized as follows: In Section II, the Backpropagation algorithm is explained as a method of ANN training as well as an EEG overview for understanding how signals are interpreted and manipulated. Section III deals with the

problem formulation, here the process used for implementing EEG Signal Processing and Classification is shown. In Section IV the methodology to present training patterns to the ANN is explained. In Section V and Section VI, the analysis of results and conclusions are shown, respectively.

2 Artificial Neural Network Overview

An Artificial Neural Network (ANN) is an assembly of interconnected and hierarchical organized simple processing elements; its functionality is inspired by the biological nervous system. The processing ability of the network is contained in the strength of the interconnection (weights) of its units, which is obtained through a process of adaptation of its parameters; the idea is to learn a set of patterns, which are the training examples [18] [20]. An ANN is a machine learning method inspired in how the brain works to solve any kind of problems by the association of neural information.

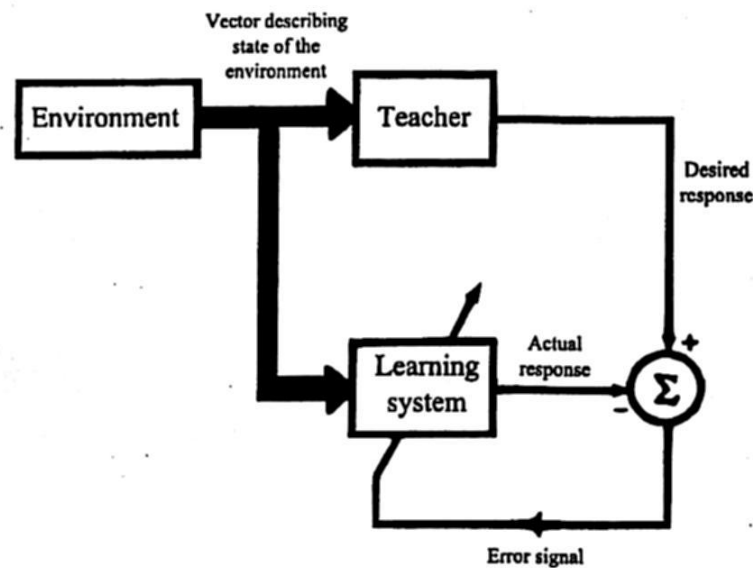


Fig. 1. Model representation of supervised mode training. This figure shows the different elements that conform this learning process.

2.1 Backpropagation Algorithm

This algorithm is a method of ANN training; it basically consists in using an error signal calculated by the difference between the actual $y_j(n)$ and desired output $d_j(n)$ of the network to correct the weights, in this algorithm the error is retropropagated from the output to the input then an optimization algorithm modifies the weights with the aim to reduce the error $e_j(n)$ at the individual neurons, hence the global output error called Mean Squared Error (MSE), the training finished when the MSE is less than the convergence error ε_0 , see

Algorithm 1. Once trained the network, it has the ability to focus on the characteristics of an arbitrary input that resembles other previously seen, regardless any noise signals affecting the patterns [17].

The Backpropagation Algorithm could be used in two modes of training; supervised and non-supervised mode, respectively. The first one is defined as a type of network learning with a teacher, which is the expert problem solver, the knowledge is provided by tagged pairs of inputs and outputs to achieve the training, see Fig. 1. In the non-supervised mode, the ANN learns with no teacher, in this mode, there are no tagged examples of a function to be learn [18] [17].

The experiments shown in this paper were achieved using the supervised training mode; so, the teacher presents to the network the training dataset. In Algorithm 1, the pseudocode for implementing the Backpropagation Algorithm is shown [17].

Algorithm 1 Backpropagation Algorithm

```

1: procedure BACKPROPAGATION(pattern,maxepoch, $\epsilon_0$ ,Target) ▷
    $\epsilon_0 :=$ convergency error
2:   while  $|MSE| < \epsilon_0$  do
3:     repeat
4:       Calculate for each node
5:        $w_{ji} := d_j(n) + y_j(n)$ 
6:        $MSE(n) := \frac{1}{2} \sum_j |e_j(n)|^2$ 
7:        $w_{ji}(n+1) := d_j(n+1) + y_j(n+1)$ 
8:        $MSE(n+1) := \frac{1}{2} \sum_j |e_j(n+1)|^2$ 
9:        $epoch := epoch + 1$ 
10:    until maxepoch ||  $\epsilon_0$  achieved
11:  end while
12:  return y
13: end procedure

```

2.2 EEG Overview

The technique of electroencephalography (*EEG*) is used to analyze the brain activity, which is manifested in electric waves. To accomplish EEG technique, an array of electrodes are placed on the scalp over multiple areas of the brain to detect and record the patterns of electrical activity. The electrodes are placed on the scalp according to the international 10-20 system of electrode position [10].

It is important to know that the brain is divided by sections, two hemispheres (left and right) and four lobules (frontal, parietal, temporal and occipital), where each section is related to specific sections of the human body. For example, to analyze a stimulus on the left side of the body the right hemisphere has to be analyzed, and viceversa. The scheme of a BCI presented in the Fig. 2 is divided into three main sections: In the first section, the electric activity generated by the brain as well as the interface to acquire the activity is shown. In the second

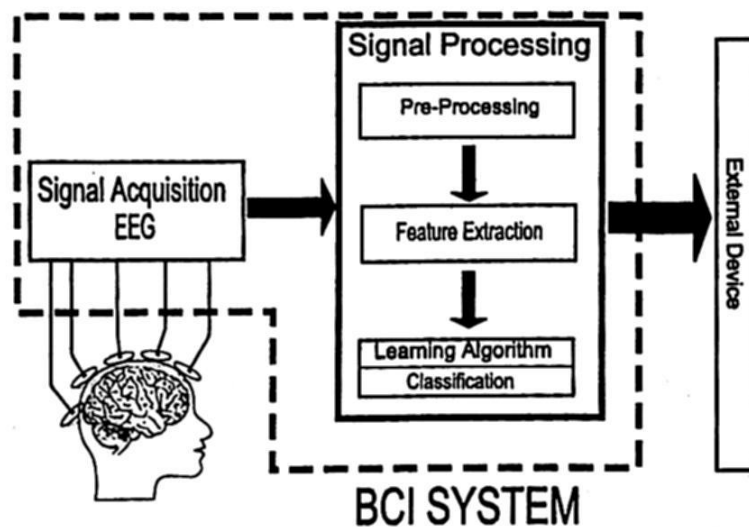


Fig. 2. Scheme of a Brain Computer Interface (BCI) system

section, the signal-processing block is in charge of conditioning and manipulating data using methods as correlation, Artificial Neural Networks, ANFIS, etc., to accomplish a task. The third section consists in the application, here a variety of algorithms can be implemented, for example, wheel chair control by mind, health assistant, rehabilitation, epilepsy detection, mind control of a prosthesis [7] [12] [8] [15].

The brain activity has specific characteristics like time, frequency, amplitude, magnitude and kurtosis; some of them can be analyzed in time or frequency domain.

3 Problem Formulation

The experimental platform of Fig. 3 shows the modules used to process EEG signals; it is a flexible system based on the described block diagram shown in Fig. 2 that supports the process of research and development.

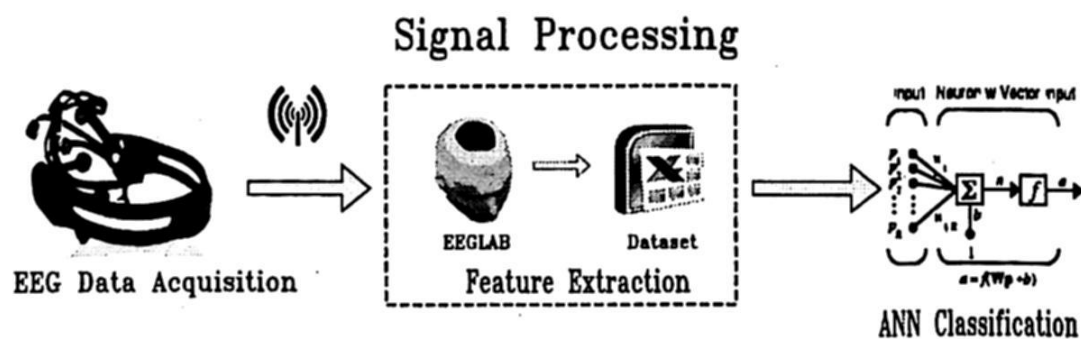


Fig. 3. EEG Signal Processing and Classification using a BCI system.

In the first section of Fig. 3, the EEG Data is acquired by the EPOC Neuroheadset and is transmitted using wireless communication. Once the data has

been received by the computer system, it is recorded for postprocessing, then using a Feature Extraction method some aspects of the signal like, amplitude, time duration, form, magnitude, frequency bands, etc., are determined, to accomplish this EEGLab and Excel are used. The EEGLab is an open-source toolbox for Matlab, which is used to study the offline EEG data already recorded; this software package has different properties for analyzing dipole sources, Independent Component Analysis (ICA), Fast Fourier Transform (FFT), Wavelet Transform, etc. The EEGLab software can read samples from EPOC Neuroheadser and save them in Excel format. Then, the dataset is divided in patterns that are used for training and testing the Neural Network [21].

4 Proposed Methodology

Once the data has been processed, the next step is to select patterns based on a teacher heuristic. All EEG signals are divided in patterns to build the batch of patterns used as input of the ANN. Fig. 4 illustrates how the batch of patterns feed the ANN.

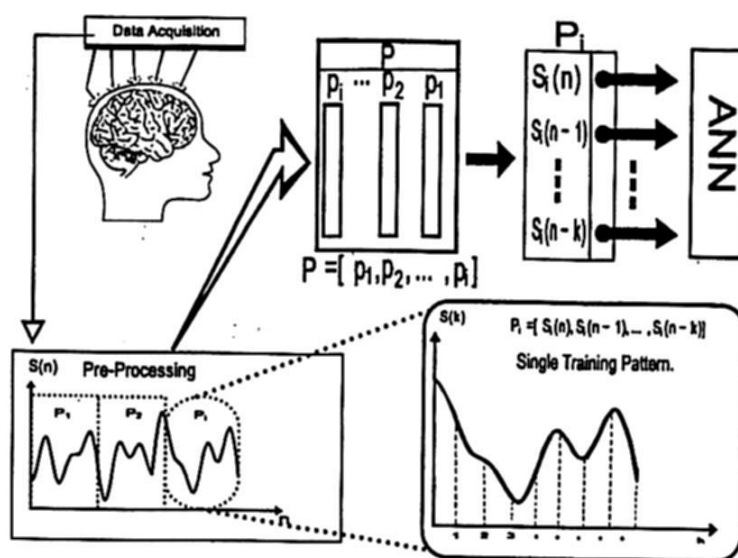


Fig. 4. The EEG signals are sampled using the EPOC neuroheadset; a time series is divided into lots of training patterns P , each pattern consists of multiple data streams that will serve either to train the network, or to verify the training.

Each pattern contains a number of samples to train and test the ANN; the number of samples for each pattern depends on the stimulus that required to be classified. In Algorithm 2, the pseudocode for EEG signal processing is shown.

4.1 Muscle Pain Classification

The first stimulus to classify is the pain induced by an external agent [4] [14], this stimulus is induced by a prick in the right arm; the subject must be in a relaxed status for two minutes approximately, and then, the pain is induced [6].

Algorithm 2 EEG Signal Processing general method proposal

```
1: Initialize variables
2: Select electrodes to be analyzed
3: Create Inputelectrode matrix from EEG readings ▷ If it is necessary, apply FFT
   to Inputelectrode matrix
4: Normalize Inputelectrode matrix already changed
5: Select TRAINDATA, TARGET and TESTDATA to train ANN
6: while Any data be minor than size of train dataset do           ▷ Training Data
7:   TRAINDATA accumulate pattern for each iteration
8: end while
9: while Any data be minor than size of test dataset do           ▷ Testing Data
10:  TRAINDATA accumulate pattern for each iteration
11: end while
12: Define ANN TARGET           ▷ Depending activation function
13: Define ERROR, MAXEPOCH      ▷ ANN training parameters
14: Train ANN
15: Test ANN
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The EEG signal obtained after the prick is the most important information used for training and testing the ANN [5]. Fig. 5 explains the experimental process of pain activity classification.

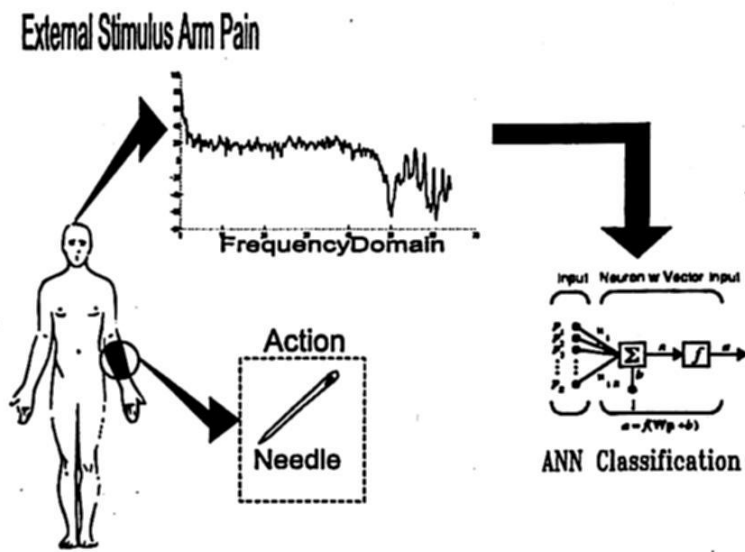


Fig. 5. Scheme for implementing EEG signal processing and classification of muscle pain.

It is worthwhile to mention that the pain cannot be appreciated in the time domain; therefore, the signal has to be converted to frequency domain using the Fast Fourier Transform, then a filter is applied to eliminate noise in the signal. All the experiments were saved in an Excel Table (dataset); it was divided into two sets; one set is used to train the ANN, and the second set for testing it, which is important for proving the network knowledge generalization capability.

4.2 Eye Blinking Classification

Fig. 6 shows the experimental process to achieve the eye blinking classification; although, it is considered an artifact, it is important to take care of it because this artifact is present in the whole EEG encephalographic readings. Blinking is a natural body movement that helps to maintain the eyes wet and protected from external elements [16] [11].

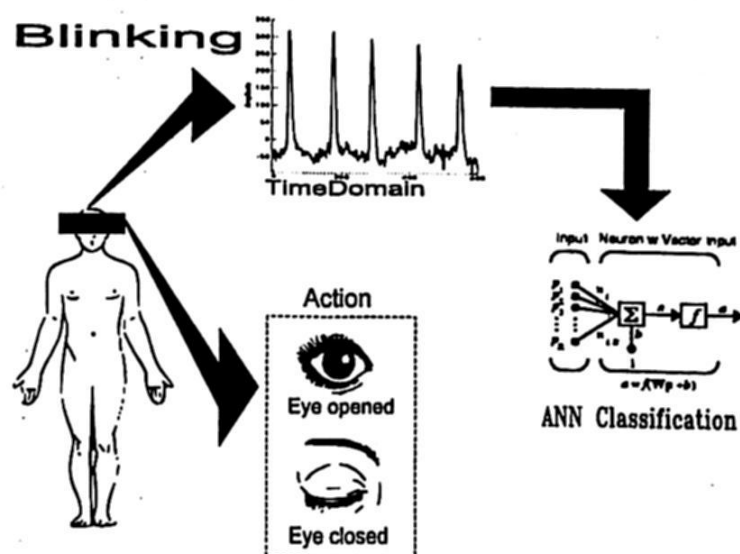


Fig. 6. Implementing eye blinking signal processing and classification.

As it is seen in Fig. 6 each time the eyelid changes from open to close, an increment of amplitude in microvolts appears in the readings, this data can be used to generate the dataset for the ANN [9].

It is important to achieve a proficient identification and classification of eye blinking for a good management of EEG signals, because it may affect the analysis of other EEG stimulus classifications [16].

5 Experimental Results

Two cases of study for the classification of EEG signals are presented using ANN multilayer perceptron type with hyperbolic tangent activation functions, it was trained in supervised mode with the backpropagation algorithm. For training, a +1 value is assigned to a valid stimulus, and -1 for a non-valid stimulus. In the operation mode, the ANN returns values between 1 and -1, to make the classification possible a threshold of +0.9 is applied, hence any value equals or over the threshold is considered a valid stimulus, otherwise it is a non-valid stimulus.

The first case shown in Fig. 5 consists in identifying muscle pain induced by an external agent. The second case is to identify the blink of both eyes as it is shown in Fig. 6; although the blink signals are not true encephalographic signals, they are artifacts and their study is considered important, because they interfere

with the EEG results and their interpretation. In all the conducted experiments in this work, the scheme shown in Fig. 3 was used.

The adaptive algorithms have the purpose to accelerate the convergence of the error for neural network by optimizing the weights in the learning process. In this research, the adaptive algorithms shown in Table 1 were used to investigate which one have the best characteristics in this kind of classification.

Table 1. Adaptive algorithms used for experiments.

Acronym	Adaptive algorithm
LM	Levenberg Marquardt
OSS	One Step Secant
BFGS	BFGS Quasi-Newton
RP	Resilient Backpropagation
GD	Gradient Descent

The ANN architectures used for both experiments are summarized in Table 2. To establish a benchmark to compare different adaptive algorithms, a convergence error of $1e^{-3}$ was established. Fig. 4 illustrates in general terms, how the different training patterns were generated and used in batch mode. To perform the experiments, a computer with a processor I7 2.67Ghz 920A, with 6GB of RAM and OS Windows 7 of 64 bits was used.

Table 2. ANN architectures for external stimulus classification.

Stimulus	ANN Architectures
Blinking (both eyes)	120:20:10:5:1
Pain (right arm)	1280:20:10:5:1

Table 3 shows some parameters about training ANN for the pain arm stimulus. The LM algorithm has the best qualities for training and testing (i.e. knowledge generalization), 99.7% and 98.8%, respectively; moreover, it is the fastest algorithm in the training mode, it last a meantime of 1167 seconds.

Table 4 shows statistical values of time about training ANN for blinking. The RP last a meantime of 0.50 seconds, which means that RP was the fastest algorithm to train the blinking patterns. Also, the best rate of classification was obtained with this algorithm, for the training patterns a 99.5% of successful was achieved, and 96.4% for the test pattern.

Table 3. Statistical results of ANN training to classify pain in the right arm. Different adaptive learning algorithms were used.

Adaptive learning algorithm	Mean time(sec)	Min time(sec)	Max time(sec)	Desv. Std(sec)	Mean epochs
LM	1167.00	420.00	2700.00	468.53	33344
OSS	1864.43	840.00	5687.00	1012.52	36462
BFGS	1403.60	600.00	4140.00	706.33	33677
RP	1568.00	840.00	4800.00	771.39	48982
GD	1290.00	720.00	4140.00	728.87	39677

Table 4. Statistical results of ANN training to classify eye blinking. Different adaptive learning algorithms were used.

Adaptive learning algorithm	Mean time(sec)	Min time(sec)	Max time(sec)	Desv. Std(sec)	Mean epochs
LM	9.43	2.00	28.00	5.89	11
OSS	0.83	0.49	1.70	0.26	27
BFGS	145.97	59.00	269.00	60.32	18
RP	0.50	0.36	2.79	0.43	27
GD	22.43	10.00	55.00	10.20	3825

Table 5. Classification results for the blinking activity using the training and testing data. The values express the percentage of true classification.

Learning algorithm	Train data	Test data
LM	98.7	93.5
OSS	99.3	94.1
BFGS	99.3	93.0
RP	99.5	96.4
GD	99.7	88.8

Table 6. Classification results for the right arm pain using the training and testing data. The values express the percentage of true classification.

Learning algorithm	Train data	Test data
LM	99.7	96.9
OSS	96.6	95.4
BFGS	97.4	93.1
RP	95.3	93.0
GD	98.7	96.8

6 Conclusions and Future Work

It is known that the use of ANNs is a powerful and efficient tool to classify EEG signals; however, there is not enough research works focused to pain detection caused by external agents; this work provides valuable information in this field. In addition, eye blinking signals classification has been included because at the present, it is well known its precise classification importance to improve EEG interpretation.

Several experiments with different learning algorithms for a multilayer perceptron type ANN were achieved. In all the experiments, we used a dataset consisting of 60 patterns of each person; 30 of them were used for training, and the rest for testing the network; a total of 20 people in the range of 23 to 30 years of age were used to complete the whole dataset.

The muscle pain classification experiments were performed by inducing pain with a needle in the right arm of a person. Statistical results demonstrate that the LM algorithm performs better than the others shown in Table 3, with this algorithm once trained the network, we obtain a 99.7% of reliability classifying the training dataset, and 96.9% using the test dataset which is fine because the patterns in the test set are unknown for the ANN. It is worth mentionion that the LM proved to be the fasted algorithm for training.

For eye blinking classification, the GD was the better recognizing the training patterns but the less reliable with the test pattern. The RP is almost as good as the GD recognizing training patterns, and it is the most reliable classifying the test patterns; with the RP, a reliability percentage of 99.5% with the training patterns and 96.4% of reliability with the test patterns was obtained.

With respect to the statistical results, hence the reliability percentages, it is important to mention that a 0.9 recognition umbral was used; therefore, these results might be improved by reducing the umbral value.

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