
Features Extraction Techniques of EEG Signals for BCI Applications

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Abstract:

The use of Electroencephalogram (EEG) signals in the field of Brain Computer Interface (BCI) has obtained a lot of interest with diverse applications ranging from medicine to entertainment. In this paper, BCI is designed using electroencephalogram (EEG) signals where the subjects have to think of only a single mental task. EEG signals are recorded from 16 channels and studied during several mental and motor tasks. Features are extracted from those signals using several methods: Time Analysis, Frequency Analysis, Time-Frequency Analysis and Time-Frequency-Space Analysis. Extracted EEG features are classified using an artificial neural network trained with the back propagation algorithm. Classification rates that reach 99% between two tasks and 96% between three tasks using Space-Time-Frequency-Analysis and Time-Frequency-Analysis were obtained.

Keywords: Brain Computer Interface BCI; Electroencephalograph EEG; Fast Fourier Transform FFT; Short Time Fourier Transform STFT; Neural Networks NN.

1. INTRODUCTION

Electroencephalograph (EEG) was first recorded by Berger in 1929 by externally attaching several electrodes on the human skull [1]. Such signals generally deliver in indirect way information about physiological functions, which are related to the brain. Possible applications using such signals are very numerous. They are for example integrated in the design of new technological devices with embedded intelligence and allow for Brain-Computer-Interfaces. There is also an important demand, in the medical domain, for automatic signal interpretation systems [2]. BCI is composed of signal collection and processing, pattern identification and control systems [3].

There are five major brain waves distinguished by their different frequency ranges [4]: Delta waves lie within the range of 0.5 to 4 Hz, Theta waves lie within the range of 4 to 7 Hz, with an amplitude usually greater than 20 μ V, Alpha with a rate of change lies between 8 and 13 Hz, with 30-50 μ V amplitude, Beta, the rate of change lies between 13 and 30 Hz, and usually has a low voltage between 5-30 μ V. Beta is the brain wave usually associated with active thinking, active attention, focus on the outside world or solving concrete problems and finally the Gamma waves which lie within the range of 35 Hz and up. It is thought that this band reflects the mechanism of consciousness. Theta, alpha and beta frequencies are used in our work to classify the mental tasks.

The first step in BCI systems is the data collection and filtering, the filters are designed in such a way not to introduce any change or distortion to the signals. High pass filters with a cut-off frequency of usually less than 0.5 Hz are used to remove the disturbing very low frequency components such as those of breathing. On the other hand, high-frequency noise is mitigated by using low pass filters with a cut-off frequency of approximately 40–70 Hz [4].

In dealing with EEG classification, an important problem is the huge number of features. It comes from the fact that (i) EEG signals are nonstationary, thus features must be computed in a time-varying manner and (ii) the number of EEG channels is large. Solutions to alleviate this problem, “the curse of dimensionality,” consist of feature selection and channel selection methods [5]. We used spectral analysis in our project including the Fast Fourier Transform FFT, the Short Time Fourier Transform STFT and the space time-frequency analysis. For the classification process, a multilayer perceptron MLP neural network was trained with the back propagation algorithm.

Figure 1 illustrates the parts of the work. The EEG signals are collected and preprocessed using special

filters, the EEG features are extracted using several methods and finally those features are classified depending on the mental task they represent.

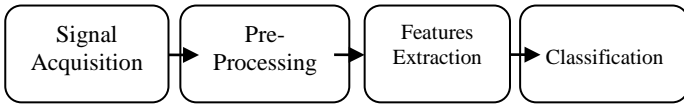


Figure 1. The Block Diagram of the Work

2. METHODOLOGY

2.1 DATA COLLECTION AND PREPROCESSING

The EEG data were recorded for a 24 years old healthy male subject working as an engineer. The subject executes different tasks while remaining in a totally passive state, no overt movement were made during the performance of the task and the subject is asked to close his eyes. The subject was trained to do the tasks many times. The performed tasks are:

Task1: baseline measurement: the subject is told to relax and try to think of nothing in particular.

Task2: mental arithmetic, the subject performs mental multiplication of two digit number by a two digit number, such as 49×15 . The complexity of the problem was chosen so that it is not so difficult as to be discouraging. The subject was told to double check his answer if he finished before the time expired, this ensured that he was performing the intended task as well as he could throughout the task period.

Literatures specifically chose these tasks since they involve hemispheric brainwave asymmetry. For example, it was shown that arithmetic tasks exhibit a higher power spectrum in the right hemisphere whereas visual tasks do so in the left hemisphere. As such, these tasks are proposed for brain computer interfacing [6].

Task3: a right click on the mouse, this task is a motor task.

The EEG potentials were recorded at 10–20 EEG electrode positions over the scalp Fig. 2 [7], with a cap and integrated electrodes. These electrodes measure the weak (5–100 μ V) electrical potentials generated by brain activity. Each electrode typically consists of a wire leading to a disk that is attached to the scalp using conductive paste or gel. Each pair of electrodes was denoted by a channel name, Tab. 1.

The data acquisition was performed using Micromed Digital Acquisition System at a 256 sample per second sampling frequency. This system contains an amplifier and an ADC.

Figure 2. International 10-20 Electrode Placement System

Table 1. Channels and Electrodes Names

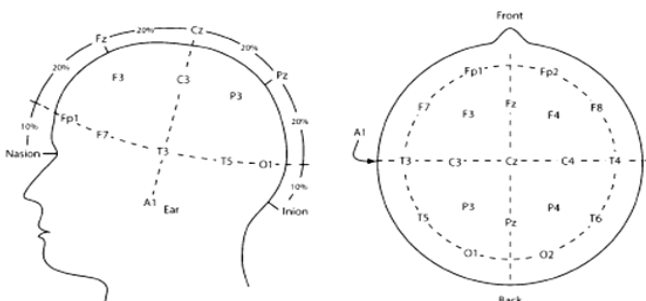
<i>Channel Name</i>	<i>Differential Electrodes</i>
<i>Ch1</i>	<i>Fp2- F4</i>
<i>Ch2</i>	<i>F4 - C4</i>
<i>Ch3</i>	<i>C4- P4</i>
<i>Ch4</i>	<i>P4 -O2</i>
<i>Ch5</i>	<i>Fp2- F8</i>
<i>Ch6</i>	<i>F8 - T4</i>
<i>Ch7</i>	<i>T4- T6</i>
<i>Ch8</i>	<i>T6- O2</i>
<i>Ch9</i>	<i>Fz- Cz</i>
<i>Ch10</i>	<i>Cz- Pz</i>
<i>Ch11</i>	<i>Fp1- F3</i>
<i>Ch12</i>	<i>F3 - C3</i>
<i>Ch13</i>	<i>C3- P3</i>
<i>Ch14</i>	<i>P3- O1</i>
<i>Ch15</i>	<i>Fp1- F7</i>
<i>Ch16</i>	<i>F7- T3</i>

Signal preprocessing is necessary to maximize the signal-to-noise ratio (SNR) since there are many noise sources encountered with the EEG signal. Noise sources can be nonneural (eye movements, muscular activity, 50Hz power-line noise) or neural (EEG features other than those used for control [8]. Notch filters with a null frequency of 50 Hz are used to ensure perfect rejection of the strong power supply. High pass filter with a cut-off frequency of than 0.3 Hz is used to remove the disturbing very low frequency components such as those of breathing. On the other hand, high-frequency noise is mitigated by using low pass filters with a cut-off frequency of 40 Hz. For eye-movement artifacts and muscular artifacts, it was tried to reject a trial containing any of these artifacts.

Further preprocessing was not performed because the purpose is to be as close as possible from a BCI for real-time applications and preprocessing would slowdown the process of data analysis. Moreover, data recorded outside the laboratory are likely to be noisier than those recorded inside. So it is assumed that processing noisier data would have better generalization properties.

2.2 FEATURES EXTRACTION

The original EEG signal is time domain signal and the signal energy distribution is scattered. The signal features are buried away in the noise. In order to extract the features, the EEG signal is analyzed to give a description of the signal energy as a function of time or/and frequency. Based on previous studies, features extracted in frequency domain are one of the best to recognize the mental tasks based on EEG signals [9].



The first analysis method was the Fast Fourier Transform (FFT) by applying the discrete FFT to the signal and find its spectrum.

EEG signal is non-stationary that means its spectrum changes with time; such a signal can be approximated as piecewise stationary, a sequence of independent stationary signal segments [9]. Although the field of spectral analysis has been dominated by use of the Fourier transform. The Fourier functions do not adequately represent nonstationary signals. Therefore, appropriate windows have been applied to the Fourier functions which provide short time Fourier transform (STFT) which is a type of Time-Frequency Representation (TFR). The discrete STFT equation is in 1

$$X_{STFT}[m,n] = \sum_{k=0}^{L-1} x[k]w[k-m] e^{j2\pi nk/L} \quad (1)$$

Where $x[k]$ denotes a signal and $w[k]$ denotes an L -point window function. The STFT can be defined as the Fourier transform of the product $x[k]w[k-m]$ [10].

In STFT, the signal is divided into small sequential or overlapping data frames and fast Fourier transform (FFT) applied to each one. The output of successive STFTs can provide a time-frequency representation of the signal. To accomplish this, the signal truncated into short data frames by multiplying it by a window so that the edified signal is zero outside the data frame. In order to analyze the whole signal, the window is translated in time and then FT is reapplied to each one [11].

The STFT is applied to one second EEG signal segmented into a 128 point segments with 50% overlapping between each successive segments. Each segment is multiplied by a 128 point Hamming window, then the FFT algorithm is applied to each segment. The result is summated and 30 bands of 1 Hz of the frequency spectrum are used and normalized from 1 to 30 Hz. In this way each 1 sec physiological signal is transformed into 30 values through a spectral transformation which will be used later as an input to the neural network. Fig. 3 shows the basic idea of this process.

In the case of multichannel EEGs, where the geometrical positions of the electrodes reflect the spatial dimension, a space-time-frequency (STF) analysis through multi-way processing methods has also become popular [4]. We apply this method by taking the STFT over multiple electrodes, in this way the data from a wider region of the scalp are used to discernment between tasks, choosing the best region depending on the subject and the type of the tasks that the system is used to classify. As an example to this approach, channel fourteen is used with all other channels as an input to the classification system.

2.3 CLASSIFICATION

Formally, classification consists of finding the label of a feature vector x , using a mapping f , where f is

learnt from a training set T . The purpose of the learning stage is to provide the algorithm with pre-classified labeled data (here, vectors of 320 features), from which the algorithm builds the mapping in order to predict the labels of new data. Neural networks have the characteristic of self-study, self-organization, associational memory, parallel processing and distributed storage compared with traditional methods. With the strong fault tolerance, based on neural networks, identification models are not only steady but also can be run repeatedly [3].

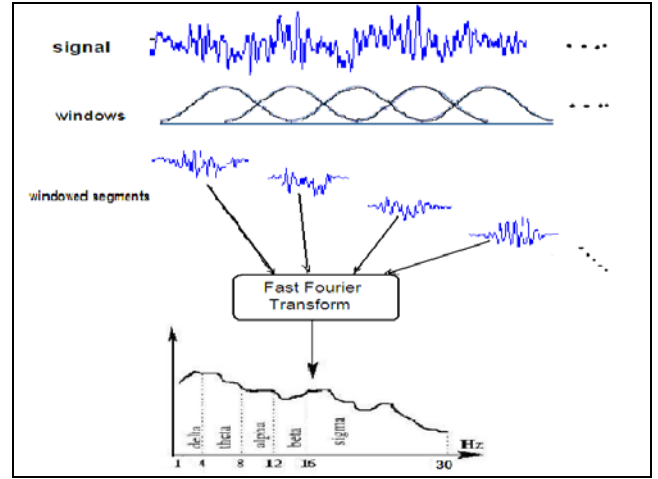


Figure 3. Spectral Transformation

An artificial neuron represents the basic unit of artificial neural networks and it is an arithmetic module and similar to the biological model. The basic elements of an artificial neurons are (1) a set of input nodes, indexed by I say, $1, 2, \dots, I$, that receives the corresponding input signal or pattern vector, say $\mathbf{x} = (x_1, x_2, \dots, x_I)$; (2) a set of synaptic connections whose strengths are represented by a set of weights, here denoted by $\mathbf{w} = (w_1, w_2, \dots, w_I)$; and (3) an activation function Y that relates the total synaptic input to the output (activation) of the neuron.

For implementing Artificial Neural Networks (ANN) there are three phases: design, training and execution. In the design phase the architecture of the network is defined: number of inputs, outputs and layers, and the activation function of neurons. The training phase consists of determining the weights of the connections of the network through a learning algorithm such as Back propagation. Finally the execution phase is performed using the fixed parameters of the network obtained during the learning phase [11].

Back Propagation BP network is the most famous and activity model in all the feed forward neural networks. Its kernel is the back propagated algorithm. BP neural network consists of input layers, hidden layers and output layers. The number of hidden layer is determined by practical situation. The pattern of BP neural network is shown as in Fig. 4. The relation between input pattern

and corresponding output pattern can be obtained by learning arithmetic and can be any nonlinear function [3].

In this work, to perform the learning, the data has been divided into two parts: the learning part and the testing part, with the rest of the data. Each trail is composed of feature vectors. The selection of the patterns for training and testing were chosen randomly. Training was conducted until the mean square error MSE fell below 0.0001 or reached a maximum iteration limit of 20000. The mean square error denotes the error limit to stop NN training. The MSE is the average of NN target output subtracted by the desired target output from all the training patterns. The desired target output was set to 1.0 for the particular category representing the task of the EEG pattern being trained.

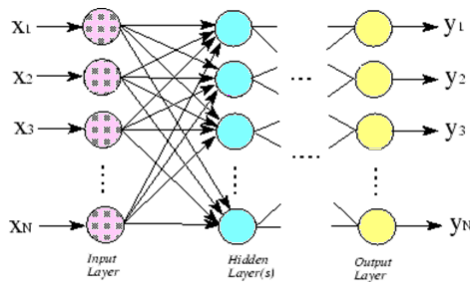


Figure 4. Pattern of BP Neural Network

Multilayer back-propagation neural networks are trained to classify the two motor tasks (baseline and mouse click) and the two mental tasks (baseline and mental multiplication), the two classes were coded by 2 output unit, then a network is trained to classify the three classes EEG signals with three neurons in the output layer. Each input layer consist of 30 neurons for the 30 feature bands.

The network training function updates weight and bias values according to Levenberg-Marquardt optimization. Several ANN architectures have been tested. But in general satisfactory results have been obtained with a MLP that contains two hidden layers. Every neuron applies the same transfer function, which is a sigmoidal function for the hidden layers and the linear activation function for the output layer. Fig. 5 shows the classification scheme, where the accuracy obtained is the number of correctly classified sets divided by the total number of tested sets.

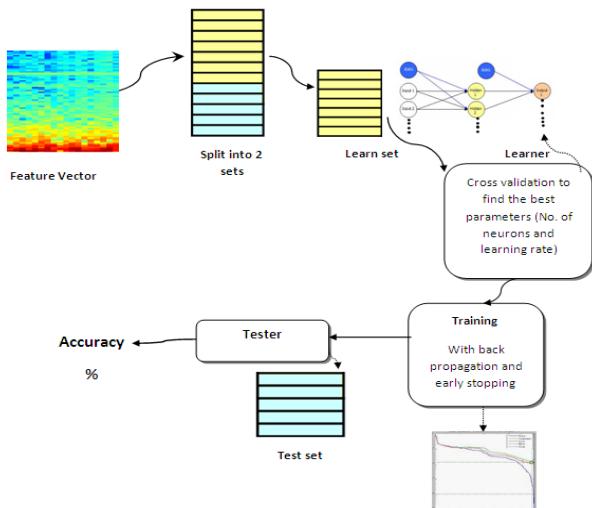


Figure 5. The Classification Scheme

3. RESULTS

At the beginning the time series EEG is fed to the ANN classifier, we use one second data as an input layer (each sample entered to an artificial neuron).

Then frequency analysis is used by taking the Fourier transform of the signal and dividing the spectrum into 30 frequency bands each band was fed to a neuron.

Time-frequency analysis is used by taking the STFT of the EEG signal which improves the classification rate. Finally space-time-frequency analysis were used by considering the data from two channels at the same time (again each channel represents the data of two electrodes). In our work, channel fourteen is chosen with the other fifteen channels, Tab. 1 listed the obtained classification accuracy between the baseline state and the mental arithmetic multiplication of the sixteen channels for different type of EEG data processing.

Fig. 6 shows the accuracies for different types of signal for the discrimination between the baseline relax state and the mental multiplication state.

Table 2. The Obtained Classification Accuracies from All Channels for Different Features Extraction Techniques

Channel	Time Series	Frequency Analysis	Time-Frequency Analysis	Space-Time-Frequency Analysis
Ch1	63.88%	80.00%	98%	75.83%
Ch2	68.33%	90.50%	96.9%	80.00%
Ch3	85.00%	98%	98%	99%
Ch4	61.66%	73.33%	97.7%	76.66%
Ch5	42.22%	84.44%	99%	99%
Ch6	43.88%	6.66%	99%	99%
Ch7	3.88%	16.66%	97.7%	99%
Ch8	19.44%	20.55%	99.2%	99%
Ch9	33.88%	84.44%	100%	99%
Ch10	57.22%	69.44%	86.3%	80.83%
Ch11	59.44%	83.33%	93.1%	100%
Ch12	48.33%	70.00%	99.2%	76.60%
Ch13	43.88%	67.22%	98.4%	90.00%
Ch14	66.66%	72.77%	92.4%	92.4%
Ch15	5.00%	5%	00. %	99%
Ch16	10.00%	00.00%	18.3%	99%

Another comparison is made between the accuracies obtained for the discrimination between the three tasks using the time series signal as an input to the classification system and the STFT of the signal. Tab. 3 shows the accuracies for the sixteen channels. The designed neural network contains 30 input neurons, two hidden layers and three output neurons for the three tasks.

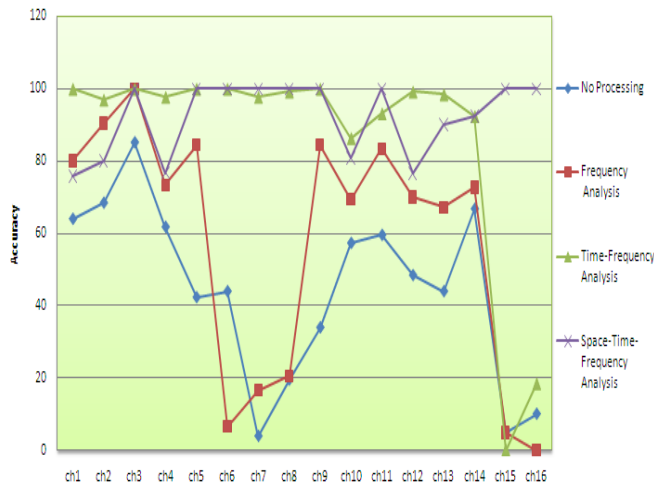


Figure 6. The Accuracies for Different Feature Extraction Methods

Table 3. The Classification Accuracies for Three Tasks

Channel	Time Series	STFT
Ch1	23.74%	86.27%
Ch2	24.10%	95.09%
Ch3	21.58%	94.11%
Ch4	19.42%	100%
Ch5	16.18%	91.17%
Ch6	25.53%	91.17%
Ch7	8.99%	82.35%
Ch8	7.19%	78.92%
Ch9	28.77%	97.05%
Ch10	21.94%	88.23%
Ch11	24.82%	92.15%
Ch12	30.21%	65.68%
Ch13	26.25%	60.29%
Ch14	20.50%	81.37%
Ch15	00.3%	00.00%
Ch16	00.00%	00.00%

4. CONCLUSION AND DISCUSSION

While the electroencephalograph was invented nearly a century ago, it is only recently that researchers have begun to apply it to problems outside the medical and neuroscience domains such as the brain computer interface systems. The role of signal processing is crucial in the development of a Brain Computer Interface system. We evaluated the ability of the frequency analysis (FFT), time-frequency analysis (STFT) and space-time- frequency analysis (STFT) over multiple electrodes) to discriminate between EEG signals for different tasks. The best classification results were obtained from the space-time-frequency analysis. MLP neural networks that are trained with the back propagation algorithm are used to classify the extracted EEG features, which is adaptive for complicated

nonlinear systems because of simple configuration, little input variables, strong learning ability and high precision.

5. FUTURE WORK

Further work suggestions include finding the best combination of channels in the case of space-time-frequency analysis for a specific task.

Also one of our suggestions for the future is building the hardware model for the EEG feature extraction and classification system using the Field Programmable Gate Array (FPGA).

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