COMPARISON BETWEEN DIFFERENT NEURAL NETWORKS AS EEG PATTERN CLASSIFIERS

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Abstract

In this paper the improvements in a system for a concrete human-machine interface especially adapted for physically disable are studied. This system is based on EEG signal analysis and it will try to discriminate mental states in order to translate these mental states into actions of a computer. Distinguishing EEG patterns related to different mental states could allow a paralyzed person to control devices such as wheelchairs or computers.

Key Words
Mental tasks, EEG pattern recognition, neural networks.

1. Introduction

In the last years human-machine interfaces have been improved aiming at modern, complete and comfortable systems which make a wide range of human activities easier.

One of the most important applications of these new interfaces is the development of new aids for disable people. Many of these aids are based on PC platforms with special interfaces, designed for each type of disability. Hearing, visually, speech impaired or physically disabled people have benefited from new adapted telephone systems, screen readers, communication system, etc. in last few years.

ICA, Independent Component Analysis, and Discrete Wavelet transform have been used in this study for pre-processing EEG signals. Then, signals have been classified by means of different neural networks in order to generate the algorithms needed for a human machine interface based on EEG signals.

Two mental states have been considered in this study: rest and motor imagery. In the first state, the instruction given to the subject of the experiment is not to think of anything. In the second state, the subject is asked to think in a motor action (close a fist), without moving.

2. Methods

2.1. Data Collection

EEG signals were collected for the purpose of developing and testing the system mentioned above. The subject of the experiments was a healthy, thirty-five-year-old, right-handed woman. The data were collected using the following procedure: The subject was asked to relax and try to think of nothing in particular during the first part of the experiment. The beginning of the experiments was indicated with the command "we are starting". Six seconds later, the subject was told to start thinking about a motor action with the indication "now". Six more seconds of recording were taken, after which the subject was told to relax once more, this then serving as the start phase for the next attempt. This process is illustrated in Figure 1

A 19-channel Biologic brain map was used for the EEG recordings. Signals were captured with Ag/AgCl contact electrodes, monopolar in form, i.e., related to one reference electrode: in our case we used the two ears united. The international 10-20 system for electrode placement was used, with information being read from the 19 channels (Fp1, Fp2, F7, F3, Fz, F4, F8, T3, C3, Cz, C4, T4, T5, P3, Pz, P4, T6, O1, O2), with the montage Φ, group A, programme 12 of Biologic.

Figure 1 Data collection procedure
2.2. Data Choosing

Three recording sessions were done involving an average of 40 attempts per session. 170 records were taken, 80 of which were considered for processing purposes, those with fewest artefacts and wherein the synchronic alpha reading was visible in the first half of the records. In these experiments, the reference elimination method used was the common mean reference, whereby the mean of all the scalp electrodes is subtracted from the potential measured in the electrode in question. The valid records of each session were divided into two groups: one group used to train the neural network and the other used for simulations.

The data processing segment of the rest and motor-image signal is 2 seconds long. Two seconds are taken from the six-second segment corresponding to the rest interval and two seconds from the motor action interval immediately after the sixth second, corresponding to the moment when the subject is told to start thinking about the motor action.

2.3. Data Processing

• Software

Specific software (see Figure 2) has been developed to do the experiments. The application allows doing Fourier Transform, Short Time Fourier Transform and Wavelet Transforms (continuous and discrete). It is also possible to concatenate different transforms on different combinations of data.

Finally, three different artificial neural (MLP, RBF, LVQ) networks can be used for classification purpose.

• Fourier Transform

Fourier transform is one of the first tools used for signal features extracting. It is widely known and gives a first approximation to EEG signal characteristics, as it will be shown in the results section.

Its most important weakness appears when analyzing non stationary signals which spectral component change with time. Fourier Transform does not give information about the moment in which those components exist.

• Wavelet Transforms

Wavelet transform (see Equation 1) is especially interesting for EEG analysis since it can detect transient waveforms that are almost impossible to detect with other analysis.

In this case, Discrete Wavelet Transform (DWT) has been employed for pre-processing EEG records (see [1][2]).

\[
WT(\tau, a) = \int_{-\infty}^{\infty} x(t)h^*(\frac{t-\tau}{a})dt
\]

Equation 1 Wavelet Transform

With this transform, filters of different cut-off frequencies are used to analyze the signals at different scales. The signal is passed through a series of low pass and high pass filters in order to separate its low frequency and high frequency components. High frequency components (called details or detail coefficient) are obtained with good time resolution and low frequencies (called approximations or approximation coefficients) with good frequency resolution.
family choosing is a critical task. Results are better when the signal and the wavelet show remarkable similarity.

In this study, the collected data have been processed with a wide range of wavelet families as it is shown in the results section.

• Independent Component Analysis

ICA, Independent Component Analysis, is a signal processing method that performs blind source separation [3][4]. It is ideally suited for performing this separation in domains where:

a) the sources are independent
b) the propagation delays of the mixing medium (the medium in which independent signals have been mixed) are insignificant
c) the sources have non-gaussian distributions
d) the number of independent sources is the same as the number of sensors.

As it is explained in detail in [3] and [4], the EEG signal processing problem satisfies assumption a, b and c. The most important problem is that assumption d is doubtful. Therefore, election of input channels will be a critical point.

The first immediate ICA application is removing artifacts from EEG. These artifacts are produced by muscles, line noise, cardiac signals, etc. It also appears as a good way of identifying and separating those signals generated by independent parts of the brain, responsible of different tasks. This has been the main utility of ICA in this work: trying to identify and separate those signals that could differentiate rest mental state from motor imagery. Once independent components have been obtained, another characteristic of EEG signals is used to remove no significant information. Cerebral activity signals are typically super-gaussians while other sources (artifacts) are sub-gaussians. In these experiments the five signals with highest kurtosis are selected as input data of the next step, despising the rest.

2.4. Classification

In the data classification block, three different ANN have been compared: MLP, RBF, LVQ

MLP represent a generalization of the single layer perceptron network. It typically consists of a set of source nodes that constitute the input layer, one or more hidden layers of computational nodes, and an output layer of computation nodes. The input signal propagates through the network in a forward direction, on a layer-by-layer basis [5].

LVQ is a method for training competitive layers in a supervised manner [6][7]. An LVQ network has a first competitive layer and a second linear layer.

The competitive layer learns to classify input vectors. The linear layer transforms the competitive layer's classes into target classifications defined by the user. In our case, these will be the two mental states previously defined [8].

Finally, the RBF networks, involves three layers with entirely different roles. The input one is made up of source nodes, the second layer applies a nonlinear transformation from the input space to the hidden one, and the third layer, which is linear, supplies the response of the network to the input applied [5].

Files obtained from ICA algorithm and the other signal processing methods are separated in two groups: one for supervised training and the other for testing. The number of files used for training has been also one parameter in the experiments.

3. Results

Best results using MLP are shown in Table 1.

<table>
<thead>
<tr>
<th>Signal</th>
<th>Correct classif.</th>
<th>Motor imagery</th>
<th>Rest</th>
</tr>
</thead>
<tbody>
<tr>
<td>FFT</td>
<td>93.24</td>
<td>94.59</td>
<td>91.89</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Wavelets</th>
<th>Correct classif.</th>
<th>Motor imagery</th>
<th>Rest</th>
</tr>
</thead>
<tbody>
<tr>
<td>Det2</td>
<td>db5</td>
<td>70.27</td>
<td>72.97</td>
</tr>
<tr>
<td>Det2</td>
<td>db6</td>
<td>68.81</td>
<td>64.86</td>
</tr>
<tr>
<td>Det2</td>
<td>db10</td>
<td>70.27</td>
<td>67.56</td>
</tr>
<tr>
<td>Det2</td>
<td>bior2.2</td>
<td>68.91</td>
<td>64.86</td>
</tr>
<tr>
<td>Det2</td>
<td>rbio2.6</td>
<td>74.32</td>
<td>75.67</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>FFT+DWT</th>
<th>Correct classif.</th>
<th>Motor imagery</th>
<th>Rest</th>
</tr>
</thead>
<tbody>
<tr>
<td>FFT(A1)</td>
<td>haar</td>
<td>85.13</td>
<td>86.48</td>
</tr>
<tr>
<td>FFT(D1)</td>
<td>haar</td>
<td>85.13</td>
<td>89.18</td>
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<tr>
<td>FFT(A2)</td>
<td>haar</td>
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<td>83.78</td>
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<tr>
<td>FFT(D2)</td>
<td>db10</td>
<td>85.13</td>
<td>83.78</td>
</tr>
</tbody>
</table>

Table 1 MLP Experiments

Best results using the LVQ neural network are shown in Table 2.
Correct classification  | Motor imagery  | Rest
--- | --- | ---
Signal | 71.6 % | 70.2 % | 72.9 %
FFT | 94.5 % | 94.5 % | 94.5 %

Wavelets | Wavelet | Correct classif. | M.I. | Rest
--- | --- | --- | --- | ---
Det2 | bior2.6 | 79.7 | 81 | 78.3
Det2 | bior3.7 | 79.7 | 78.3 | 81
Det1 | haar | 78.3 | 81.0 | 75.6
Det2 | bior3.5 | 78.3 | 75.6 | 81
Det1 | coif4 | 77.0 | 72.9 | 81
Det2 | bior3.3 | 77.0 | 70.2 | 83.7
Det2 | db2 | 75.6 | 75.6 | 75.6
Det2 | coif5 | 75.6 | 78.3 | 72.9
Det2 | bior3.9 | 75.6 | 64.8 | 86.4
Det1 | rbio3.7 | 75.6 | 72.9 | 78.3

FFT+DWT | Wavelet | Correct classif. | M.I. | Rest
--- | --- | --- | --- | ---
FFT(D2) | bior3.5 | 81.08 | 81.08 | 81.08
FFT(D2) | db10 | 91.8 | 94.5 | 89.1
FFT(D2) | haar | 91.8 | 86.4 | 97.2
FFT(D2) | bior2.8 | 91.8 | 94.5 | 89.1
FFT(D2) | bior3.3 | 91.8 | 97.2 | 86.4
FFT(D2) | bior5.5 | 91.8 | 86.4 | 97.2
FFT(D2) | db5 | 90.5 | 94.5 | 86.4
FFT(D2) | coif2 | 90.5 | 94.5 | 86.4
FFT(D2) | sym6 | 90.5 | 94.5 | 86.4

| Wavelet | Correct classif. | M.I. | Rest
--- | --- | --- | ---
Signal | 92 | 86 | 96
FFT | 78.37 | 70.67 | 94.5

Wavelets | Wavelet | Correct classif. | M.I. | Rest
--- | --- | --- | --- | ---
Ap1 | haar | 74.32 | 67.56 | 81.08
Det2 | haar | 74.32 | 75.67 | 72.97
Det2 | coif3 | 65.76 | 83.78 | 47.74

FFT+DWT | Wavelet | Correct classif. | M.I. | Rest
--- | --- | --- | --- | ---
FFT(D2) | db10 | 81.08 | 81.08 | 81.08
FFT(D2) | bior2.6 | 83.78 | 78.37 | 78.18
FFT(D2) | bior5.5 | 87.83 | 81.08 | 94.59
FFT(D2) | rbio6.8 | 81.08 | 78.37 | 83.78
FFT(D2) | sym7 | 81.08 | 86.48 | 75.67
FFT(D1) | db3 | 83.78 | 97.29 | 70.27
FFT(D2) | db7 | 83.78 | 94.59 | 72.97
FFT(D2) | rbio3.5 | 83.78 | 98 | 67.56

Concatenation | Correct classif. | M.I. | Rest
--- | --- | --- | ---

Table 2 LVQ experiments

Best results using PNN RBF networks are shown in Table 3.

4. Conclusion

In this paper a complete comparison between different techniques for EEG analysis is presented. Best results have been reached using a combination of FFT and Wavelet Transform and LVQ and RBF neural networks.

In future work different records from different subjects will be used. Main objectives will be:

- a) Keep on reducing the number of electrodes used, in order to implements a more comfortable system.
- b) Obtain a real time human-machine interface based on these experiments.

5. Acknowledgement

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References