

Several imageries classification with EEG

최 경호, 정 성재, 김 일환
(Choi Kyoung ho, Jung Sung jae, Kim Il hwan)

Abstract - Every movement, perception and thought we perform is associated with distinct neural activation patterns. Neurons in the brain communicate with each other by sending electrical impulses that produce currents. These currents give rise to electrical fields that can be measured outside the head. It shows some variation on the electroencephalographic signals. In recent devices, the EEG signals measured from head surface are a sum of all the momentary brain activation. With these EEG signals, it is difficult to distinguish the patterns correlated with a certain event from the signals. However, the system must discriminate some patterns with some events especially for any kind of device as a brain control interface system. In this experiment, the sensory-motor cortex of humans has been extensively studied. Activation related to several movements on both sides of the sensory-motor cortices in imaginary. The activation patterns during imagination of several movements resemble the activation patterns during preparation of movements. The result represents the system based on the optimal filters discriminated at least 60% of mental imageries.

Key Words :Brain waves, EEG, Neural networks, Independent Component Analysis, Classification

1. INTRODUCTION

It has been shown that it is possible to direct internal motor commands to specific pools of motoneurons[1]. This means that motor imagery subthresholded for muscle activity can modify brain electrical activity. Activation of hand area neurons either by preparation for a real movement or by imagination of the movement is accompanied by an circumscribed event-related desynchronisation(ERD, [3]) focused at the hand area. Recently, an analysis of multi-channel EEG has shown that classification accuracy can be increased by training an artificial neural network for each EEG channel and combining all networks to a committee. A different approach used specifically designed spatial filters obtained by the method of common spatial patterns(CSP) to extract very few new time-series whose variances contained the most discriminative information. These were classified by a linear discriminator[5].

The goal of the paper is to apply the method for CSP to 4 channel EEG recordings obtained during right left motor gestures and to investigate whether small number of channels can obtain the classification accuracy as compare to two channels. In a number of experiments, we found that EEG signals recorded on two bipolar electrodes over the left and right hand areas during imagined one-sided

hand movements could be differentiated with an accuracy of about 85%[2]. This accuracy compares quite well to other studies[4], but it is still too low for an EEG-based brain computer interface(BCI)

2. EXPERIMENT AND DATA ACQUISITION

A. Subject and Procedure

Three male right-handed subjects(age 20-31years) took part in the study. The subjects were sitting in an armchair and closed eyes in front of a computer monitor. They were asked to keep their arms and hands relaxed and to avoid eye movements during the recordings. Each trial started with the presentation of a short period of introduction. By following the introduction, the subject was instructed to imagine a movement of the right, the left fingers or right toes. The sequence of right and left trials, as well as the duration of the breaks between consecutive trials was randomized. Thus, the interval between consecutive cue stimuli was at least 9 sec. The experiment comprised three experimental runs of 10 trials each.

B. Recordings

EEG was recorded mono polarly from electrodes placed over frontal scales equally spaced with approximately 1cm distance. We positioned some electrodes around Fp1 and Fp2, even though the system offers 36 other channels in NF system. The reference electrode was mounted on the right ear and the grounding electrode on the left ear.

2.1 Applying ICA to EEG continuous signals

Use of Independent component analysis(ICA) for blind source separation of EEG data is based on two plausible premises: (1) EEG data recorded at multiple scalp sensors

저자 소개

* 準 會 員 : 岐 阜 大 學 機 械 工 學 科

** 準 會 員 : 江 原 大 學 制 御 計 測 學 科 博 士 課 程

*** 正 會 員 : 江 原 大 學 Multimedia 學 科 助 教 授 · 工 博

are linear sums of temporally independent components arising from spatially fixed, distinct or overlapping brain or extra-brain networks; (2) the spatial spread of electric current from sources by volume conduction does not involve significant time delays[6,7]. In EEG analysis, the rows of the input matrix are EEG signals recorded from NF 5201 processor's electrodes and the columns are measurements recorded at different time points. ICA finds an 'unmixing' matrix. Artifact-free EEG brain signals were obtained by projecting selected non-artifactual ICA components from EEG, EOG and EMG signals from the subject. In Fig. 1, the left row shows mixed brain waves from channel 1 to 4, the right shows artifacts removed unmixed EEG signal from the original mixed brain wave. It uncover that ICA can reveal the EEG present in the EOG or EMG artifacts

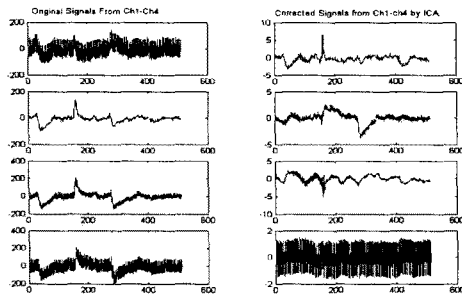


Fig. 1. Original and it's independent signals

3. FEATURE EXTRACTIONS

The features used for classification are obtained by decomposing (filtering) the EEG according to Wavelet and FFT representation.

3.1 Wavelet expansions to EEG signal

We use a Wavelet-transform as an alternative processing method. In recent times, the Wavelet-transform has more and more been used for signal processing tasks[8]. It describes a signal in its broad shape plus its details that may vary from coarse to very fine by looking at a signal from different "levels of resolution" or different scales.

We used Daubechies 6 tap (Daub6), since the shape of its mother Wavelet show the ability to extract features from EEG signal to be classified.

At every around 5 second, the system gathers 512 samples from original units, since each Wavelet level offers 512samples from the original with level 1 to 6. Fig.2. shows an example of one channel's Wavelet transformed approximations and details. The Wavelet transform maximizes the characteristic corresponding to the mental gestures in the several band of approximation. Furthermore, this choice minimizes the spread of disturbances to higher frequency bands. It has turned out

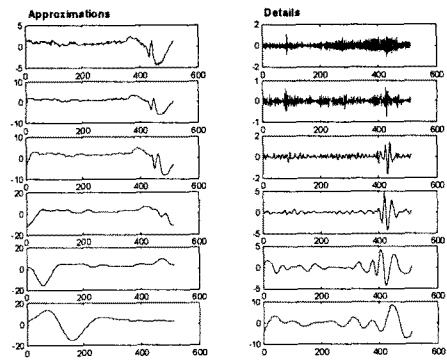


Fig. 2. Approximations and Details on Wavelet

that it works properly for the mental gesture tasks classification as well.

3.2 The Fourier Transform

The Fourier transform, in essence, decomposes or separates a waveform or function into sinusoids of different frequency which sum to the original waveform. It identifies or distinguishes the different frequency sinusoids and their respective amplitudes.

For our application, we chose the rhythmic structure of EEG as another features. The Fourier transform is the one to uncover the rhythmic one. It estimates the frequency spectrum in EEG signals. As we presented in some equations, it serves a sum of mutually orthogonal sinusoidal waves of different frequencies, amplitudes and phases. We hoped to present the rhythms in an analyzed segment of EEG by using FFT.

Finally it offered some other features, instant average values,for the neural networks to discriminate different gestures in mind. It served as a reliable estimation of EEG's spectrum.

Fig. 3. represents an example of FFT transformed alpha

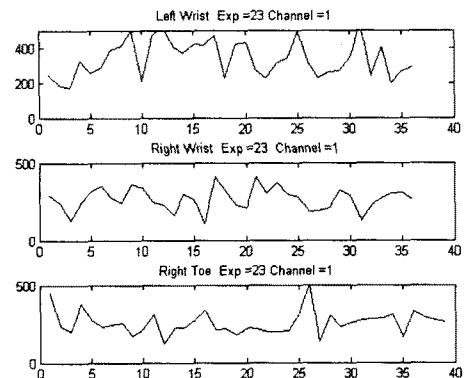


Fig. 3. FFT transformed images

region signal, channel 1 from subject 1. It showed some differences between several imageries.

4. Neural networks as classifiers

It is best way to use neural networks finding proper patterns in peoples brain waves. The diagram of neural networks with one hidden layer and one output layer for our experiments is shown in Fig. 4. We tried to find optimal time for our application. As a result, in this study we used 7 layers, feed-forward networks with classical sigmoidal transfer function nodes. The classifier implemented for this work is a standard, feed-forward, neural network with one hidden layer, contains 40 units, and one output layer, trained with the error back-propagation algorithm. In 37 different cases made MSE gives to the best results, under $1.5e-3$. And other 13 cases made MSE goes to over $1.5e-3$. 70% of all trials were used for the training set; the remaining trials were selected for validation and were used for testing. The output of any of the classifiers should be the proper value by following each mental imagery if the input pattern belongs to the mental state it has to be recognized by the network.

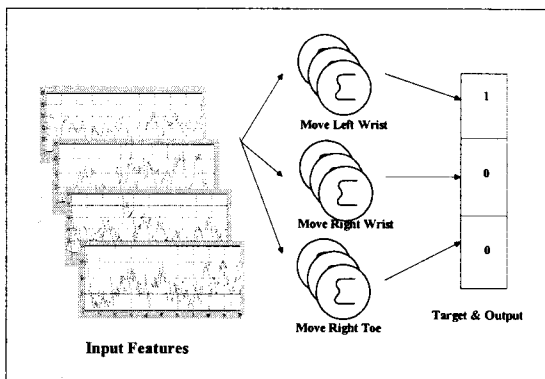


Fig. 4. Simple network architecture

5. RESULTS

For calculation of the spatial filters each trial is split into non-overlapping time-segments of 512 length by the Wavelet and different signal representations by the FFT. For each of these segments spatial filters and classifiers are trained and validated using the NNs pattern recognition. Table 1 shows the classification accuracy for each subject by the NNs pattern recognition.

Table.1 Experiment Results, Hit numbers(Success Rate)

	Right Wrist	Left Wrist	Right Toe
Subject 1	7(70%)	7(70%)	7(70%)
Subject 2	6(60%)	6(60%)	7(70%)
Subject 3	6(60%)	7(70%)	8(80%)

6. CONCLUSIONS

Various features based on several mental gestures by Wavelet and FFT transform were classified with the neural networks using the back-propagation training algorithm. All three subjects have participated in a series of motor imagery sessions. The best classification results in these sessions were 70% for subject 1. In this work, we have investigated an automated mental imageries classification system based on the Wavelet transformed feature extraction. For the first type of recognition system without Wavelet feature extractions was at level around 70%. Following the result, the trained neural networks based on the Wavelet based feature extraction would therefore be able to discriminate a subject's mental gestures. Now we believe it is possible to build an EEG-based communication device with several mental states, and we hope to build a prototype systems that can be used for people with severe physical disabilities.

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