Chapter 27
Anfis-Based P300 Rhythm Detection Using Wavelet Feature Extraction on Blind Source Separated Eeg Signals

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27.1 Introduction

This article presents a revised and extended version of a paper presented at the World Congress on Engineering and Computer Science 2011, International Conference on Signal Processing and Imaging Engineering (Ramírez-Cortes et al. 2010). In recent years, there has been a growing interest in the research community on signal processing techniques oriented to solve the multiple challenges involved in Brain Computer Interfaces (BCI) applications (Paul et al. 2008; Theodore et al. 2007; Bashashati et al. 2007). Brain Computer Interfaces (BCIs) are systems which allow people to control some devices using their brain signals. An important motivation to develop BCI systems, among some others, would be to allow an individual with motor disabilities to have control over specialized devices such as computers, speech synthesizers, assistive appliances or neural prostheses. A dramatic relevance arises when thinking about patients with severe motor disabilities such as locked-in syndrome, which can be caused by amyotrophic lateral sclerosis, high-level spinal cord injury or brain stem stroke. In its most severe form people are not able to move any limb. BCIs would increase an individual's independence, leading to an improved quality of life and reduced social costs. Among the possible brain monitoring methods for BCI purposes, the EEG constitutes a suitable alternative because of its good time resolution, relative simplicity and noninvasiveness when compared to other methods such as functional magnetic resonance imaging, positron emission tomography (PET), magnetoencephalography or electrocorticogram systems.

There are several signals which can be extracted from the EEG in order to develop BCI systems, including the slow cortical potential (Bashashati et al. 2007), μ and β

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rhythms (Royer et al. 2009; Delaram et al. 2009), motor imagery (Thomas et al. 2009), static-state visually evoked potentials (Zhu et al. 2010; Christian et al. 2009), or P300 evoked potentials (David 2005; Seno et al. 2010; Brice et al. 2006). P300 evoked potentials occur with latency around 300 ms in response to target stimuli that occur unexpectedly. In a P300 controlled experiment, subjects are usually instructed to respond in a specific way to some stimuli, which can be auditory, visual, or somatosensory. P300 signals come from the central-parietal region of the brain and can be found more or less throughout the EEG on a number of channels. The P300 is an important signature of cognitive processes such as attention and working memory and an important clue in the field of neurology to study mental disorders and other psychological disfunctionalities (Kun et al. 2009).

In this work, an experiment on P-300 rhythm detection using wavelet-based feature extraction, and an ANFIS algorithm is presented. The experiment has been designed in such a way that the P300 signals are generated when the subject is exposed to some visual stimuli, consisting of a sequential group of slides with a landscape background. Images of a ship are inserted using a controlled non-uniform sequence, and the subject is asked to press a button when the ship unexpectedly appears. The EEG signals are preprocessed using an Independent Component Analysis (ICA) algorithm, and the P300 is located in a time-frequency plane using the Discrete Wavelet Transform (DWT) with a sub-band coding scheme. The rest of the paper is organized as follows: Sect. 27.2 presents the theory associated to the wavelet sub-band coding algorithm. Section 27.3 describes Independent Component Analysis (ICA) as part of the pre-processing stage. Section 27.4 reports the evoked potential experiment and the proposed method on P300 signal detection. Section 27.5 describes the ANFIS model and its application to the EEG signals. Section 27.6 presents obtained results, and Sect. 27.7 presents some concluding remarks, perspectives, and future direction of this research oriented to the implementation of a BCI system.

27.2 Discrete Wavelet Transform

The Discrete Wavelet Transform (DWT) is a transformation that can be used to analyze the temporal and spectral properties of non-stationary signals. The DWT is defined by the following equation (Priestley 2008):

$$W(j,k) = \sum_j \sum_k f(x) 2^{-j/2} \psi(2^{-j}x - k) \tag{27.1}$$

The set of functions $\psi_{j,k}(n)$is referred to as the family of wavelets derived from $\psi(n)$, which is a time function with finite energy and fast decay called the mother wavelet. The basis of the wavelet space corresponds then, to the orthonormal functions obtained from the mother wavelet after scale and translation operations.

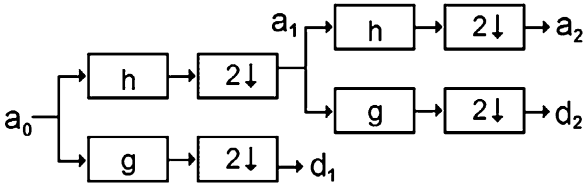

Fig. 27.1 Two-level wavelet filter bank in the sub-band coding algorithm

The definition indicates the projection of the input signal into the wavelet space through the inner product, then, the function $f(x)$ can be represented in the form:

$$f(x) = \sum_{j,k} d_j(k)\psi_{j,k} \tag{27.2}$$

where $d_j(k)$ are the wavelet coefficients at level j. The coefficients at different levels can be obtained through the projection of the signal into the wavelets family as expressed in Eqs. 27.3 and 27.4.

$$\left\langle f, \psi_{j,k} \right\rangle = \sum_l d_l \left\langle f, \phi_{j,k+l} \right\rangle \tag{27.3}$$

$$\left\langle f, \phi_{j,k} \right\rangle = \frac{1}{\sqrt{2}} \sum_l c_l \left\langle f, \phi_{j-1,2k+l} \right\rangle \tag{27.4}$$

The DWT analysis can be performed using a fast, pyramidal algorithm described in terms of multi-rate filter banks. The DWT can be viewed as a filter bank with octave spacing between filters. Each sub-band contains half the samples of the neighboring higher frequency sub-band. In the pyramidal algorithm the signal is analyzed at different frequency bands with different resolution by decomposing the signal into a coarse approximation and detail information. The coarse approximation is then further decomposed using the same wavelet decomposition step. This is achieved by successive high-pass and low-pass filtering of the time signal and a down-sampling by two (Pinsky et al. 2009), as defined by the following Eqs. 27.5 and 27.6:

$$a_j(k) = \sum_m h(m-2k)\, a_{j+1}(m) \tag{27.5}$$

$$d_j(k) = \sum_m g(m-2k)\, a_{j+1}(m) \tag{27.6}$$

Figure 27.1 shows a two-level filter bank. Signals $a_j(k)$, and $d_j(k)$ are known as approximation and detail coefficients, respectively.

This process may be executed iteratively forming a wavelet decomposition tree up to any desired resolution level. In this work the analysis was carried out up to the 11 decomposition level (16 s windows with sampling frequency of 128 sps) applied on the signals separated from the ICA process described in the next section.

27.3 Preprocessing of Eeg Signals Using Independent Component Analysis

Independent Component Analysis (ICA), an approach to the problem known as Blind Source Separation (BSS), is a widely used method for separation of mixed signals (Amar et al. 2008; Keralapura et al. 2011). The signals $x_i(t)$are assumed to be the result of linear combinations of the independent sources, as expressed in Eq. 27.7.

$$x_i(t) = a_{i1}s_i(t) + a_{i2}s_2(t) + \cdots + a_{in}s_n(t) \tag{27.7}$$

or in matrix form:

$$\mathbf{x} = \mathbf{As} \tag{27.8}$$

where A is a matrix containing mixing parameters and S the source signals. The goal of ICA is to calculate the original source signals from the mixture by estimating a de-mixing matrix U that gives:

$$\widehat{\mathbf{s}} = \mathbf{Ux} \tag{27.9}$$

This method is called blind because both the mixing matrix **A** and the matrix containing the sources **S** are unknown, i.e., little information is available. The de-mixing matrix **U** is found by optimizing a cost function. Several different cost functions can be used for performing ICA, e.g. kurtosis, negentropy, etc., therefore, different methods exist to estimate **U**. For that purpose the source signals are assumed to be non-gaussian and statistically independent. The requirement of non-gaussianity stems from the fact that ICA relies on higher order statistics to separate the variables, and higher order statistics of Gaussian signals are zero (John 2008).

EEG consists of measurements of a set of N electric potential differences between pairs of scalp electrodes. Then the N-dimensional set of recorded signals can be viewed as one realization of a random vector process. ICA consists in looking for an overdetermined $(N \times P)$ mixing matrix **A** (where P is smaller than or equal to N) and a P-dimensional source vector process whose components are the most statistically independent as possible. In the case of the P300 experiment described in this paper, ICA is applied with two objectives; denoising the EEG signal in order to enhance the signal to noise ratio of the P-300, and separating the evoked potential from some artifacts, like myoelectric signals derived from eye-blinking, breathing, or head motion.

27.4 Experimental Setup and Proposed Methodology for P-300 Signal Detection

In this work the EPOC headset, recently released by the Emotiv Company, has been used (Emotiv Systems Inc.). This headset consists of 14 data-collecting electrodes and 2 reference electrodes, located and labeled according to the international 10–20 system (John 2008). Following the international standard, the available locations are: AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8 and AF4. The EEG signals are transmitted wirelessly in the frequency of 2.4 GHz to a laptop computer. This experiment consists of presenting a non-persistent image to cause a P300 response from the user. The block diagram of the system to evoke and capture P300 signals, and a picture of the described setup are shown in Figs. 27.2 and 27.3, respectively. The subject is resting in a comfortably position during the testing. A simple graphical application shows in the screen a starship attacking a neighborhood in a fixed time sequence not known by the subject, as represented in Table 27.1. Recognition of the ship by the subject, when it suddenly appears in the screen, is expected to generate a P300 evoked potential in the brain central zone. The serial port is used for sending time markers to the Emotive testbench, in synchrony with the moments when the ship appears in the screen. The Testbench application provided by Emotiv System Co., is used to capture raw data from the 14 electrodes, as shown in Fig. 27.4.

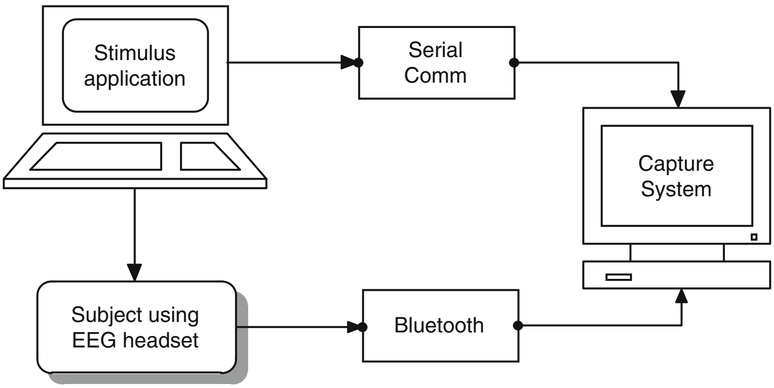

Fig. 27.2 Block diagram of the experimental setup used during the P300 signals detection

Fig. 27.3 Headset and stimulus used for the experiment on P300 signal detection

Table 27.1 Event time sequence examples

Event	Time difference	Time (mS)
1	4000	4000
2	3000	7000
3	4000	11000
4	3000	14000
5	5500	19500
6	3000	22500
7	4000	26500
8	4500	31000

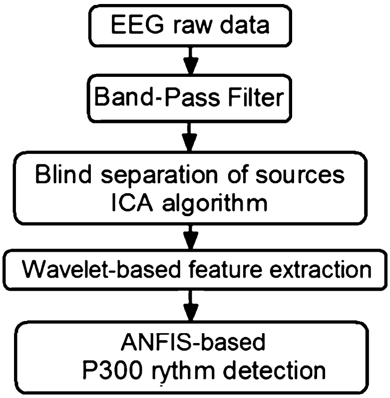

Fig. 27.4 Block diagram of the proposed system for ANFIS-based P-300 signal detection

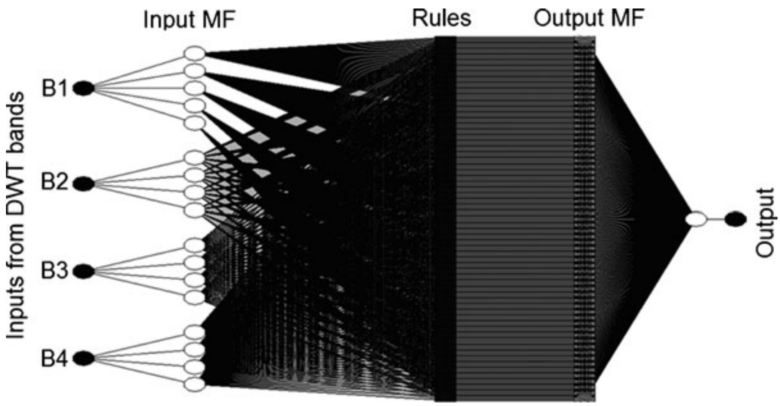

Fig. 27.5 ANFIS structure

The operations proposed to detect the P300 rhythm are summarized in the block diagram of Fig. 27.5. First, a band-pass filter selects the required frequency components and cancels the DC value. Then, ICA blind source separation is applied with the purpose of denoising the EEG signal and separating the evoked potential from artifacts, like myoelectric signals derived from eye-blinking, breathing, or head motion, as well as cardiac signals.

The P300 is further located in time and scale through a wavelet sub-band coding scheme. This information is further fed into an Adaptive Neurofuzzy Inference System (ANFIS), as described in the next section.

27.5 Adaptive Neurofuzzy Inference System

Adaptive Neuro Fuzzy Inference Systems (ANFIS) combine the learning capabilities of neural networks with the approximate reasoning of fuzzy inference algorithms. Embedding a fuzzy inference system in the structure of a neural network has the benefit of using known training methods to find the parameters of a fuzzy system. Specifically, ANFIS uses a hybrid learning algorithm to identify the membership function parameters of Takagi-Sugeno type fuzzy inference systems. In this work, the ANFIS model included in the MATLAB toolbox has been used for experimentation purposes. A combination of least-squares and backpropagation gradient descent methods is used for training the FIS membership function parameters to model a given set of input/output data through a multilayer neural network. ANFIS systems have been recently used for optimization, modeling, prediction, and signal detection, among others (Douglas et al. 2004; Chang and Chang 2006; Subasi 2007). In this paper, the ANFIS system is proposed to be used for the detection of the P-300 rhythm in an EEG signal, for BCI applications. Frequency bands with the most significant energy content, in the

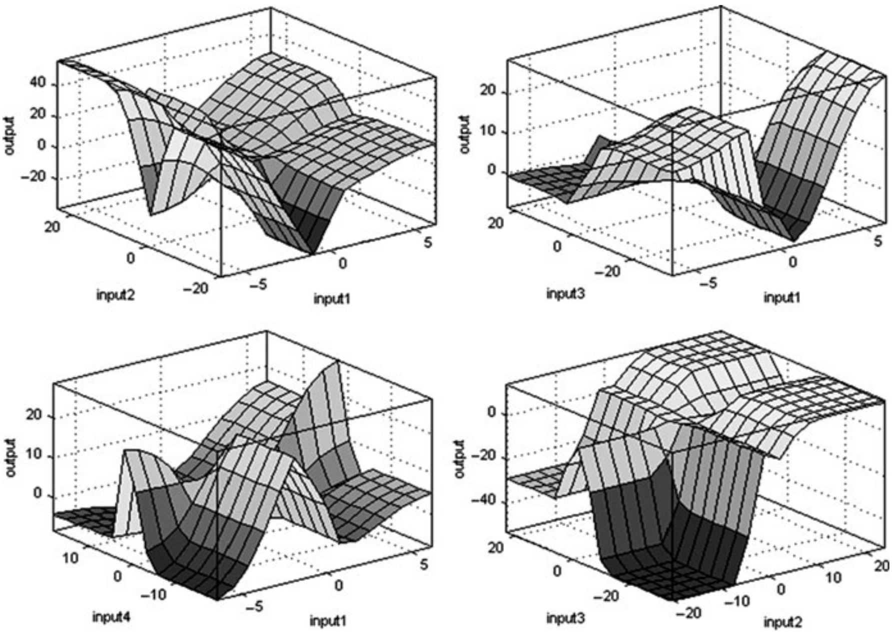

Fig. 27.6 Control surfaces of input B1 and B2 related to the output

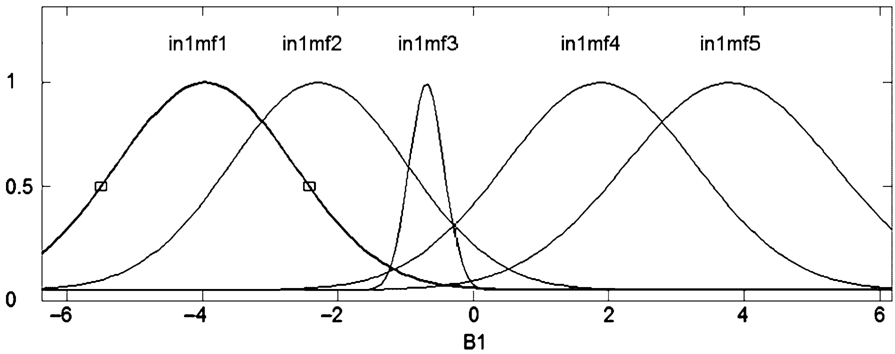

Fig. 27.7 Gaussian membership functions corresponding to the input B1

range of the P-300 signal, are selected from the wavelet decomposition, as the input for the ANFIS system. These bands are 8–4, 4–2, 2–1, and 1–0.5 Hz, which are considered as the linguistic variables B1, B2, B3 and B4, respectively. The ANFIS structure is depicted in Fig. 27.6. Figure 27.7 shows the control surfaces corresponding to inputs B1 and B2 related to the output. Figure 27.7 shows the input Gaussian membership functions for input B1.

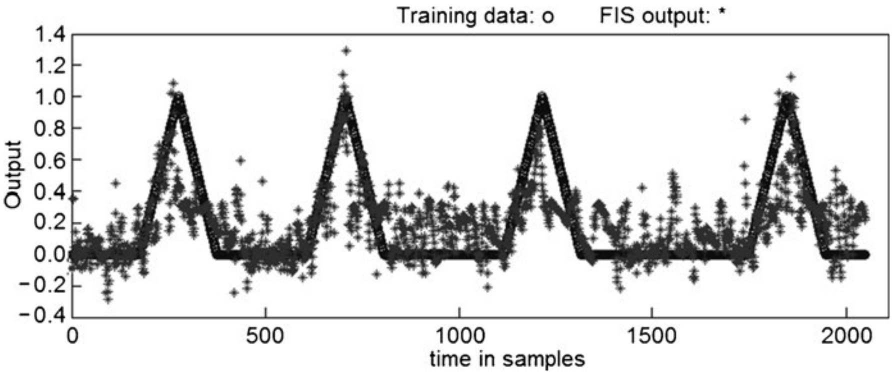

Fig. 27.8 ANFIS output and triangle pulses

The ANFIS is used to map the P300 signal composition to a triangle pulse occurring simultaneously during the training stage. Figure 27.8 shows the ANFIS output following triangle pulses after a 400 epochs training. A trained ANFIS is further used during a verification stage, using the EEG signals obtained from eight test subjects performing the same experiment with 10 trials of 16 s each.

27.6 Results

The captured signals were analyzed using a time window of 16 s, with a sampling frequency of 128 samples per second. Figure 27.9 shows the 14 electrodes raw signals obtained from the emotive headset. As described before, a band-pass filtering stage is applied to the raw data. Figure 27.10 shows information from the electrodes T8, FC6, F4, F8 and AF4 signals, after the filter is applied.

The P300 signals are predominant in the brain central area, thus the P300 is typically measured from the Pz, Cz, Fz electrodes. The Emotive headset does not include specific electrodes over the brain central area, however, the headset can be positioned in such a way that the electrodes AF3, AF4, F3, and F4, are able to collect the EEG signals relevant to the P300 experiment described in this work. The EEG signals obtained from the 14 electrodes are then processed through the ICA algorithm. The 14 channels are shown in Fig. 27.11. Typically, the P300 signals are embedded in artifacts, and they appear in two different channels; in this case channel 2 and 3. After the blind source separation applied to electrodes AF3, AF4, F3, and F4 signals, it can be noticed that P300 signals are visible on channel 2, while the others separated channels show some artifacts such as the myoelectric signal from blinking, which is predominant in AF3 and AF4 electrodes, cardiac rhythm, and system noise. The signals obtained after the ICA separation, are shown in Fig. 27.12.

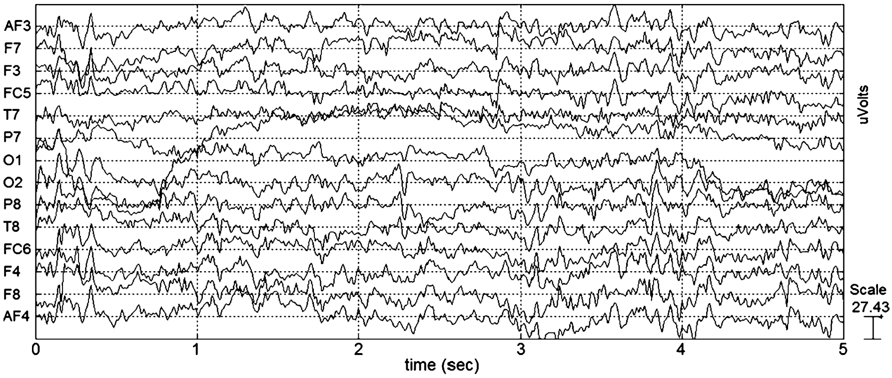

Fig. 27.9 Raw data obtained from the EEG headset

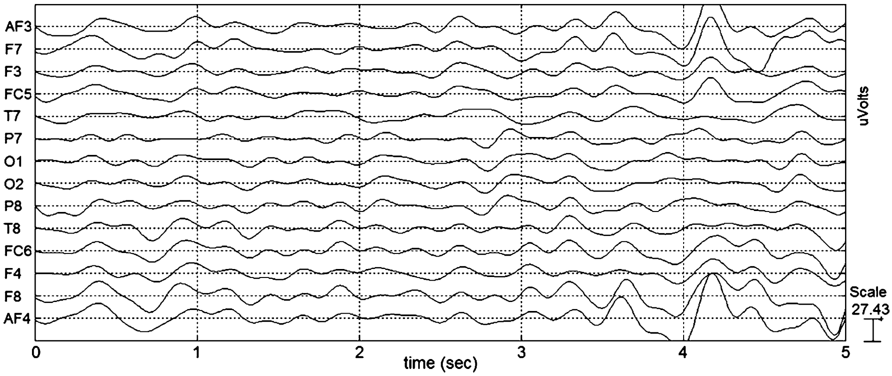

Fig. 27.10 Prefiltered EEG signals

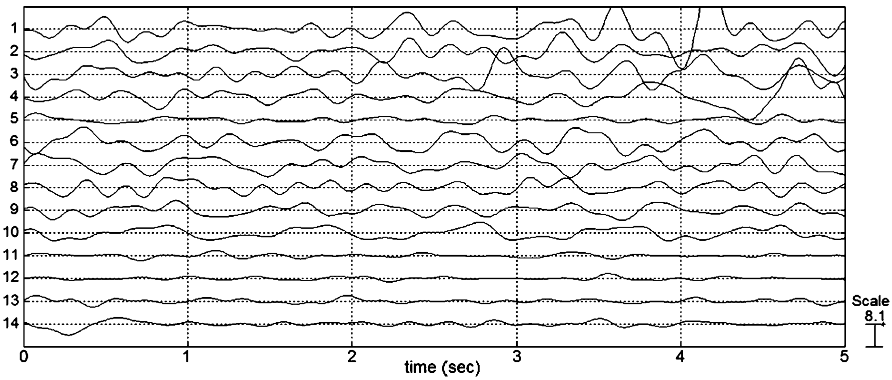

Fig. 27.11 Fourteen channels entered to the ICA algorithm

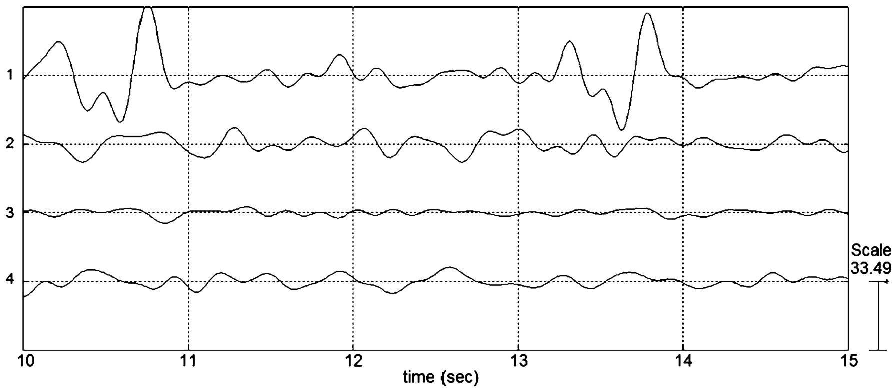

Fig. 27.12 Separated signals obtained from the ICA algorithm

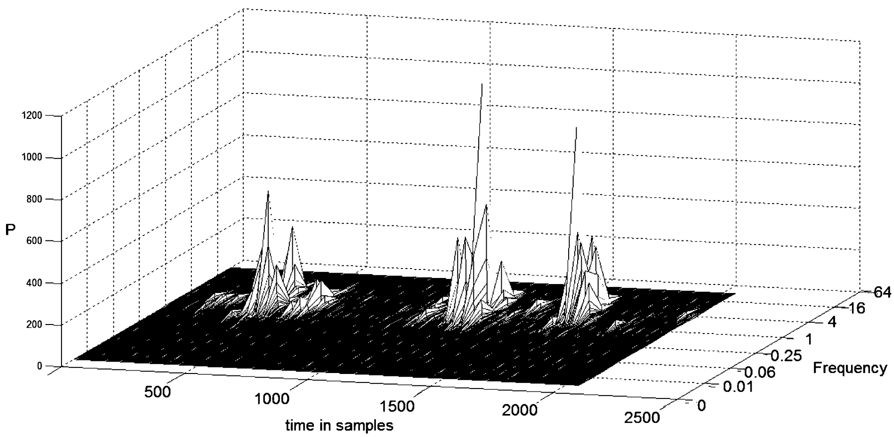

Fig. 27.13 Scalogram of signal obtained from channel 2

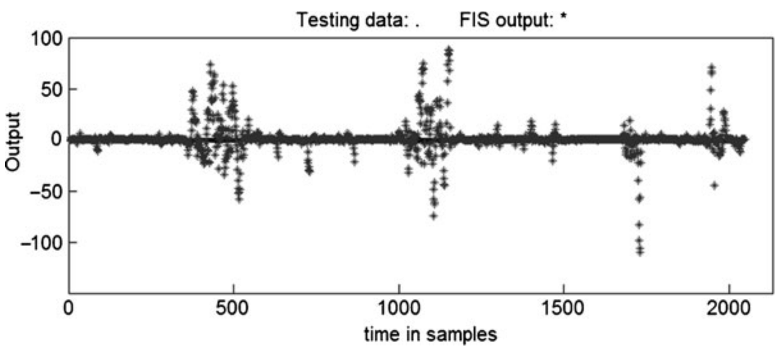

Fig. 27.14 ANFIS output showing detection of P-300 events

Table 27.2 Results obtained on the P300 rhythm detection

Result	Rate
Detected	85%
Undetected	15%
Detected taking account false positive events	60%

A time-scale analysis in the wavelet domain was then performed in order to locate the energy peaks corresponding to the P300 rhythm. DWT sub-band coding with 11 decomposition levels, using a Daubechies-4 wavelet was applied to channel 2, as shown in Fig. 27.13. It can be seen that the P300 peaks are easily distinguished in the wavelet domain. The energy peaks in the scalogram of Fig. 27.13, are located in the bands 0.5–1 Hz and 1–2 Hz, as expected. It was noted that P300 rhythms were distinguished better in the EEG signals corresponding to the eight first events in the experiment. After that time lapse, the experiment became tedious for most of the users, with the consequence of generating low-level P300 signals, undetectable in the experiments. Figure 27.14 shows a typical obtained signal, corresponding to the detection of P300 rhythms, as the output of the ANFIS system. Table 27.2 summarizes the total detection accuracy obtained with the proposed system.

27.7 Concluding Remarks

This paper presented an experiment on P300-rhythm detection based on ICA-based blind source separation, wavelet analysis, and an ANFIS model. The results presented in this paper are part of a project with the ultimate goal of designing and developing brain computer interface systems. These experiments support the feasibility to detect P300 events using the Emotiv headset through an ANFIS approach. The proposed method is suitable for integration into a brain-computer interface, under a proper control paradigm. DWT coefficients could be used further as input to a variety of classifiers using different techniques, such as distance-based, k-nearest neighbor or Support Vector Machines (SVM).

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