CLASSIFICATION OF WAVELET TRANSFORMED EEG SIGNALS WITH NEURAL NETWORK FOR IMAGINED MENTAL AND MOTOR TASKS

Martina Tolić and Franjo Jović

Faculty of Electrical Engineering, University J.J. Strossmayer in Osijek, Croatia

Preliminary communication
UDC: 611.8:004.7:159.91

Abstract:

Brain-computer interfaces (BCI) are devices that enable communication between a computer and humans by using brain activity as input signals. Brain imaging technology used in a BCI system is usually electroencephalography (EEG). In order to properly interpret brain activity, acquired signals from the brain have to be classified correctly. In this paper EEG signals are transformed by means of discrete wavelet transform. Thus the obtained signal features are used as inputs for a neural network classifier that should separate five different sets of EEG signals representing various mental tasks. Mean classification accuracy for the recognition of all five tasks was 90.75% and mean classification accuracy for the recognition of two tasks (baseline and any other mental task) was 99.87%. The same procedure was also used on the motor imagery dataset. A mean classification accuracy of 68.21% suggests alternative methods of feature extraction for motor imagery tasks.

Key words: *brain-computer interface, mental tasks, motor imagery, independent component analysis, discrete wavelet transform*

Introduction

Brain-computer interfaces (BCI) provide a new way of communication between humans and computers. They measure and process brain activity and after successfully recognizing the input, perform given actions. BCI systems can be divided into the following categories: invasive BCI have surgically implanted sensors into the brain, whereas non-invasive BCI use sensors placed on the scalp. Dependent BCI require the use of additional motor movements, while independent BCI are independent of any muscle activity. A synchronous BCI–user interacts with the system only in specific time frames, but asynchronous or "self- paced" can be used any time. BCI systems are of great importance to people with disabilities as they can help them perform certain activities without muscle movements. The initial use of BCI was for medical reasons, but today BCI systems are also being developed for general population – mostly for the purposes of entertainment.

The main technology used in these systems for recording brain activity is electroencephalography (EEG). Although it is an imperfect indicator of brain activity, compared to other technologies (MEG, fMRI, SPECT, fNIR), EEG possesses the most advantages for BCI systems. The main advantages are high temporal resolution, portability and it can be acquired at low cost (Berger, et al., 2008).

The process of obtaining control signals for BCI systems consists of signal acquisition, preprocessing, feature extraction and classification. This paper deals with offline classification of EEG signals from the databases of mental tasks (Keirn & Aunon, 1988) and imagined motor tasks (Schalk, 2009).

The purpose of classification is to sort the data into suitable inputs to the BCI system. It is important to achieve high classification accuracy so that a BCI system can effectively execute its commands. Prior to the classification, recorded EEG data needs to be processed in order to make classes of data as distinct as possible. That is performed by feature extraction.

Keirn and Aunon's (1988) data consists of EEG records of five different mental tasks. The goal is to find suitable features that provide acceptable classification accuracy. The authors used feature vectors of 144 elements that represent the spectral powers of four frequency bands and power differences between each channel for every frequency band. Bayes quadratic classifier was used to discriminate between task pairs. The percentage of correct outputs was 90–100% for distinct cases. For the same dataset Palaniappan (2005) used energy from the Elliptic FIR filter output as features and Multilayer Perceptron as the classifier. He achieved a classification accuracy of 95% for the first two subjects for the best of two tasks. Liu, Wang, Zheng and He (2005) used the sum of weighted power spectrum values in ten subbands (0–100 Hz) at each channel as features and Fischer's linear discriminant to classify task pairs. Classification accuracy was 98.3% for task pairs.

This paper presents the classification for all five mental tasks together, as well as the task pair classification. There are multiple options when it comes to choosing suitable feature extraction methods and classifiers. Lotte, Congredo, Lecuyer, Lamarche, and Arnaldi (2007) surveyed the most common classification algorithms used in BCI research. They also displayed classification results for papers dealing with EEG classification grouped by specific datasets (and BCI types). In this paper, wavelet transform was used for feature extraction and a neural network was applied for signal classification.

The proposed methodology was used on a different dataset from another study (Schalk, 2009) that consists of imagined motor movement EEG signals. Motor imagery can be described as a state during which a subject mentally imagines a given action (such as the movement of the left or right foot). Roth et al. (1996) showed a similarity in mental states during motor imagery and related executed movements. Data (Schalk, 2009) consists of brief segments of motor movement EEG signals (executed or imagined). Sleight, Pillai and Mohan (2009) performed a classification of the executed motor signals from imagined motor movement signals on the same dataset (Schalk, 2009), while in this work the classification is done for the imagined movements only (opening and closing of either the right or left fist).

Data

A. Mental tasks dataset

It consists of a total of 325 EEG records each lasting ten seconds. Each of the seven subjects was asked to perform five different mental tasks. These mental tasks were chosen to evoke hemispheric brainwave asymmetry. The performed tasks were the following:

1. *Baseline mental task*. All subjects were asked to relax and think of nothing in particular.
2. *Math task*. Subjects were asked to multiply two numbers (e.g. 54*28). They were not supposed to make movements or vocalize while solving math problems.
3. *Mental letter composing task*. Subjects were instructed to mentally compose a letter to a close person without vocalizing.
4. *Geometric figure rotation task*. A rotating 3D object was shown to the subjects for 30 seconds and then removed. Subjects had to visualize that object being rotated about an axis.
5. *Visual counting task*. Subjects were asked to imagine a blackboard and to visualize numbers being written sequentially.

All subjects (volunteers) were seated in a soundproof booth, with dim lighting and no noise sources. An electro-cap was used for recording seven channels by 10-20 system: C3, C4, P3, P4, O1, O2 and EOG. Sampling rate was 250 Hz recorded with Lab master 12 bit A/D converter mounted on a computer. All signals were band-pass filtered from 0.1-100 Hz. Reference electrodes were A1 and A2.

Although the entire examined dataset consisted of records of seven healthy subjects, in this paper classification was performed only for the first two subjects. They were university employees (48-year-old left-handed male and 39-year-old right-handed male). The first subject performed ten trials (in two days) and the second subject did five in one day. With a sampling rate at 250 Hz, each trial of ten seconds contains 2,500 samples per channel.

B. EEG motor movement/imagery dataset

This dataset consists of over 1,500 EEG recordings that are one or two minutes long, obtained from 109 volunteers. They performed different motor/imagery tasks while 64-channel EEG was recorded using the BCI2000 system (Schalk, McFarland, Hinterberger, Birbaumer, & Wolpaw, 2004) and contributed to PhysioNet (Moody, Mark, Goldberger, et al., 2000). Each subject performed 14 experimental runs: two one-minute baseline runs and three two-minute runs of each of the four tasks. In this paper the second task was used for classification: "A target appears on either the left or the right side of the screen. The subject imagines opening and closing the corresponding fist until the target disappears. Then the subject relaxes." (Schalk, 2009).

Signal preprocessing

In the signal preprocessing phase, artifacts were removed. This was done only for the mental tasks dataset. EOG channel was not used in classification, its purpose is eye blink recognition. Six other channels were located at the central and occipital region where the effect of eye blink is lower, but still adds some signal bias, as visible in Figure 1.

For these reasons, it is useful to remove artifacts for each channel. This is performed using an ICA transform. Independent component analysis (ICA) is a method of blind source separation (BSS). The goal of ICA is to find the independent sources of signals when the observations of their joint action only are known. ICA is a way of finding a linear orthogonal coordinate system in any multivariate data. The directions of axes in that coordinate system are determined by a second and higher statistics order of original data. The goal is to implement a linear transform which makes the obtained variables as statistically independent as possible.

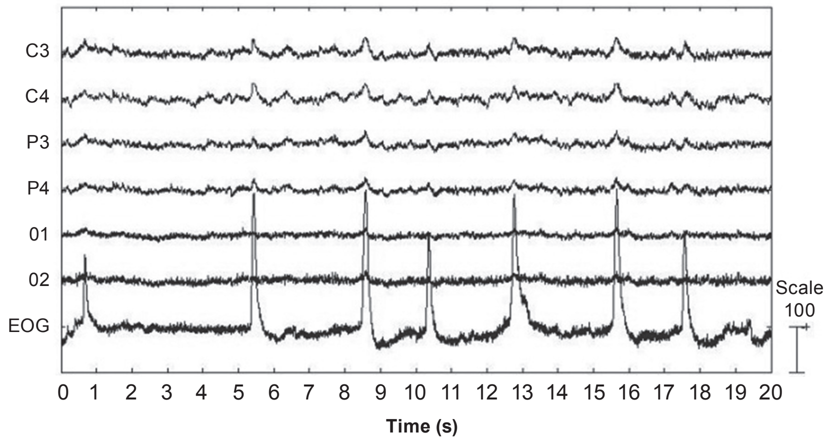

Figure 1. Effect of eye blinks in EEG signals. Mental task dataset – first 20 seconds of recording for subject 1, task 2.

Observations of random variable $(x_1(t), x_2(t), \ldots x_n(t))$ are given, where t is time or sample index. They are generated as a linear mixture of independent components:

$$\begin{pmatrix} x_1(t) \\ x_2(t) \\ \vdots \\ x_n(t) \end{pmatrix} = A \begin{pmatrix} s_1(t) \\ s_2(t) \\ \vdots \\ s_n(t) \end{pmatrix} \qquad (1)$$

where A is some unknown matrix. ICA then consists of an estimation of matrix A and $s_i(t)$ with $x_i(t)$ only observed. The number of independent components s_i is equal to the number of the observed variables (Hyvarinen, Karhunen, & Oja, 2001).

ICA method is ideal for source separation when:

a) sources are independent
b) propagation delay is negligible for a medium that creates a mixture of signals
c) signal sources are analog
d) number of independent signal sources is equal to the number of sensors.

According to Makeig, Bell, Jung and Sejnowski (1996), EEG signals satisfy all four conditions. Besides a separation of sources of brain signals, ICA demonstrates noticeably good results in finding the sources of artifacts.

EEGLAB (*Open Source Matlab Toolbox for Electrophysiological Research*) was used for this purpose (Delorm & Makeig, 2004). After importing EEG data for each task, the sampling time of 250 Hz was entered with a corresponding map of electrode locations (Figure 2). After running the ICA algorithm, independent components were displayed in spatial graphs (Figure 3).

Properties that describe eye artifacts are a strong far-frontal projection in the scalp map and individual eye movements in a detailed component view. After component examination, the artificial one is removed.

Feature extraction

Feature extraction for EEG signals includes finding signal properties that describe EEG activity in such a way that they show the greatest difference between the groups of EEG signals that are later classified. Feature extraction also reduces the amount of data used in classification. Finding

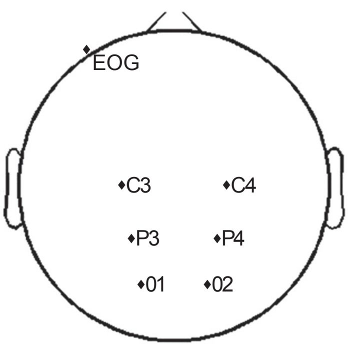

Figure 2. Map of electrode locations for mental tasks dataset.

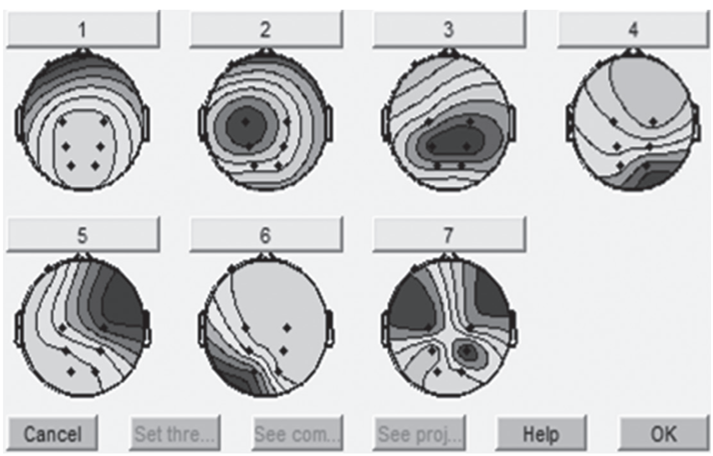

Figure 3. Independent components (mental task dataset).

suitable features is often crucial for efficient classification (Guyon, Gunn, Nikravesh, & Zadeh, 2006).

Among the most common EEG signal analysis and feature extraction methods are autoregressive models (Anderson & Stolz, 1995), power spectral density (PDS), independent component analysis (ICA) and wavelet transform (Jahankhani, Kodogiannis, & Revett, 2006; Omerhodzic, Avdakovic, Nuhanovic, & Dizdarevic, 2010).

Wavelet transform is a method of changing a function or a signal into another form generating features more favorable for investigation and also it enables a concise recording of the original signal.

Continuous wavelet transform (CWT) of the signal *f(t)* is defined as:

$$CWT(b,a) = \int_{-\infty}^{\infty} f(t)\overline{\frac{1}{\sqrt{a}}\psi\frac{t-b}{a}}dt \tag{2}$$

where ψ is wavelet function (*mother wavelet*), a dilatation parameter (enables dilatation and compression of wavelet) and *b* is translation parameter.

Discrete wavelet transform (DWT) reduces the amount of data that is generated with CWT. DWT keeps enough information thus enabling a very good signal reconstruction from the wavelet coefficients. The number of coefficients needed for perfect reconstruction corresponds to the number of data samples (Goswami & Chan, 1999).

With dilatation parameter $a=1/2^s$, and translation $b=k/2^s$, where s, $k \in Z$, for the signal *f(n)* discrete *wavelet* transform is defined as:

$$DWT\left(\frac{k}{2^s},\frac{1}{2^s}\right) = 2^{s/2}\sum_n f(n)\psi(2^s n - k) \tag{3}$$

DWT has good signal compression properties; it is applicable for many real signals and it is also computationally efficient. For these reasons it is used for many purposes including image compression, noise reduction, numerical integration and pattern recognition (Addison, 2002).

Discrete wavelet energy is computed at various decomposition levels generated by DW transform.

$$E_n = \sum_{m=1}^{M} |T_{nm}|^2 \tag{4}$$

Equation (4) represents the energy at decomposition level *n*, where $n=1,...,N$ are decomposition levels, which is a sum of squares of discrete wavelet coefficients T (M is the number of coefficients at each level) (Addison, 2002).

Neural networks

According to DARPA neural network study (MIT Lincoln Laboratory, 1988), neural network is defined as a system composed of several simple processing units working in parallel. Their function is determined by network structure, structure connection intensity and processing performed by the processing units or nodes. The main unit of neural networks, artificial neuron, emulates the main functions of biological neurons. Neuron *k* can be described as (Haykin, 1999):

$$u_k = \sum_{j=1}^{m} w_{kj}x_j \tag{5}$$

$$y_k = \varphi(u_k + b_k) \tag{6}$$

where $x_1,x_2,...,x_j$ are input signals, $w_{k1},w_{k2},...,w_{kj}$ are sinaptic weights of neuron *k*, u_k is linear combiner output because of the input signals, b_k is the bias, $\varphi(\cdot)$ is the transfer function, and y_k is the output signal of the neuron (Figure 4). The structure of neural networks determines the way of connecting between neurons. The main types of neural networks, according to structure, are: single-layer feedforward networks, multi-layer feedforward networks, recurrent networks and lattice structures. Neural network possesses the ability to learn and, with adaptive function, it changes the weights on the inputs of each neuron according to some algorithm (Haykin, 1999).

After the learning phase, which requires training data, the network can recognize new inputs (test data). Neural networks are applicable in different fields and regarding their structure and parameter settings are used for data classification, data prognostics although to a limited amount, function approximations, data filtering and many others.

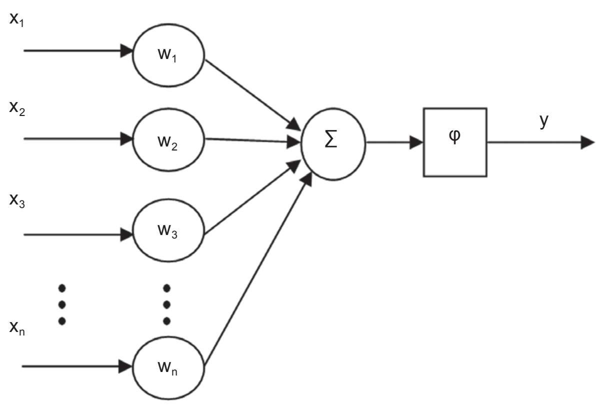

Figure 4. Model of neuron

Classification

After the preprocessing (artifact removal), it is necessary to find features that form an input to the classifier. There are several methods for feature extraction, but for the needs of this classification, discrete wavelet transform was used with MATLAB function *mdwtdec* (*Multisignal 1-D wavelet decomposition*).

F_s represents sampling frequency which is 250 Hz for the mental task dataset and 160 Hz for the motor imagery dataset. Transform level n is 5 and used wavelet was Daubechies 4 ('db4'). According to the expression for approximation:

$$[0, \frac{F_s}{2^{(n+1)}}] \qquad (7)$$

and details:

$$\left[\frac{F_s}{2^{(n+1)}}, \frac{F_s}{2^{n}}\right] \qquad (8)$$

Table 1 shows frequency bands obtained by a discrete wavelet transform for both datasets (the mental and motor imagery tasks). Decompositons D0-D5 were calculated by (8) and A5 by (7).

Table 1. Frequency bands

Signal decomposition	Frequency bands [Hz]	
	Mental tasks dataset	Motor imagery dataset
D1	62.5–125	40–80
D2	31.5–62.5	20–40
D3	15.3–31.5	10–20
D4	7.8–15.3	5–10
D5	3.9–7.8	2.5–5
A5	0–3.9	0–2.5

Discrete wavelet energy is computed for half second segments of EEG data. For each of these segments, signals are decomposed into approximation and details. Features are then formed as wavelet energies related to corresponding decompositions. This shows the differences between channels by frequency bands.

All input samples are randomly divided into three sets: 70% of data is the training set, 10% of data is used for validation and 20% for testing (performed with MATLAB commands: net.divideParam.trainRatio = 70/100, net.divideParam.valRatio = 10/100, net.divideParam.testRatio = 20/100). Training and testing is repeated 20 times and as a final result of classification accuracy, the average values of correctly classified samples are taken.

A. Mental tasks dataset

Each channel is determined by six features, so the input vector is then formed of 36 elements. Classification is performed for the EEG data of the two subjects. One recording for each subject contains all tasks repeated five times for a period of 10 seconds. The first subject performed two of these recordings in two days, and the second subject did only one. One recording of each task is 50 seconds long, which makes 500 input vectors of 36 elements (100 inputs of each task – the signals are divided into half second segments).

B. EEG motor movement/imagery dataset

Classification was performed on two types of data: imagining opening/closing the right fist and the same for the left fist, extracted from two-minute EEG recordings. Only three channels of 64 were used for the classification (C3, Cz and C4), since they captured sufficient neural activity responsible for the left and right movement (Sleight, et al., 2009). Input vectors contain 18 elements (three channels with six features). Classification is performed separately for only four subjects from the datasets (Schalk, 2009) – and that is for subjects numbered: 1, 3, 5 and 7.

The neural network used was feedforward network with one hidden layer and the sigmoid activation function. The process of finding the most suitable neural network properties was done by using different:

a) learning functions
b) number of neurons in the hidden layer
c) number of tasks (all five, four tasks without baseline, and task pairs – only for the mental tasks dataset)
d) number of samples.

Tested learning functions were:

a) resilient backpropagation (Riedmiller & Braun, 1993) – a local adaptation of the weight updates according to the behavior of the error function is performed. Influence of the size of the derivative is eliminated – the adaptation process depends only on the temporal behavior of its sign;
b) scaled conjugate gradient backpropagation (Moller, 1993) – a supervised learning algorithm that uses second-order information from the neural network but requires only O(N) memory usage (N is the number of weights in the network);
c) Levenberg-Marquardt backpropagation (Hagan, Demuth, & Beale, 1996) – based on the Levenberg-Marquardt algorithm which is a variation of Newton's method that was designed for minimizing functions that are the sums of the squares of other nonlinear functions (well suited for neural network training where the performance index is the mean squared error).

The number of hidden neurons was changed for the learning function that showed the best classification accuracy.

Results

The following tables show the settings that were changed for neural networks and the classification results of certain sets of EEG data.

A. Mental task dataset

Table 2 shows the effect of different learning functions for three sets of data (two different subjects in three sets), with the sigmoid activation function with 10 neurons in one hidden layer. Size of input set was 500 samples: 100 samples for each mental task (except for Table 6). The chosen learning functions are usually used in pattern recognition (Demuth & Beale, 2002). The best classification is with a resilient backpropagation function. Besides the good performances, that is one of the fastest functions in pattern recognition. Acceptable performances were for conjugate gradient backpropagation function, but with a higher number of iterations. The function with the worst performances was Levenberg-Marquardt backpropagation, which covers a large specter of applications and is the fastest of all. However, it is better for function approximation than for pattern recognition.

The increase in neuron number gives an improvement of ≈10% (Table 3). Therefore, 20 neurons were finally chosen in the hidden layer and resilient backpropagation as a learning function. With these settings, classification was repeated for the recognition of four tasks (Table 4) and task pairs. Table 5 shows the classification of the first task (baseline) with one of the mental tasks. In most cases accuracy of 100% was obtained and the tables show average results for 20 repetitions.

Table 6 shows how the size of input set affects classification accuracy. Twenty-five samples represent EEG recording of 12.5 seconds. According to the results, sufficient input size was 50 samples, which represents 25 seconds of EEG recording.

B. EEG motor movement/imagery dataset

Classification was performed with the same neural network parameters as in the mental tasks dataset (one hidden layer with sigmoid activation function). Tables 7–9 show the classification results of the right and left motor imagery. The size of input set was 56 samples: 28 samples for each mental task (except for Table 9).

The best average classification accuracy for all subjects was 68.21% and it was obtained for the neural network of 20 hidden neurons, with 28 samples of data and resilient backpropagation as the learning function. Table 8 shows that the sufficient number of neurons is 20. Increased input size did not significantly affect the classification accuracy (Table 9).

Table 2. Learning functions – 10 neurons, 100 samples of each task (mental task dataset)

Successfully classified test data [%]	*Resilient backpropagation*	*Scaled conjugate gradient backpropagation*	*Levenberg-Marquardt backpropagation*
Subject 1, Day 1	84.96	83.49	80.06
Subject 1, Day 2	88.37	87.05	77.93
Subject 2, Day 1	73.30	71.71	66.68

Table 3. Number of neurons (resilient propagation learning function, subject 1, day 2) (mental task dataset)

	Successfully classified test data [%]
5 neurons	81.24
10 neurons	88.37
15 neurons	90.33
20 neurons	90.75

Table 4. Resilient propagation learning function, 20 neurons, four tasks (mental task dataset)

	Successfully classified test data [%]
Subject 1, Day 1	87.12
Subject 1, Day 2	90.02
Subject 2, Day 1	84.88

Table 5. Resilient propagation learning function, 20 neurons, task pairs (mental task dataset)

Baseline task (1) in combination with:	Subject 1, Day 1	Subject 1, Day 2	Subject 2
	Successfully classified test data [%]		
Math (2)	96.20	99.72	92.50
Letter (3)	99.45	98.42	89.90
Rotation (4)	99.60	98.40	96.17
Visual counting (5)	99.87	99.77	94.27

Table 6. Number of samples of each task – subject 1, day 2, 20 neurons, resilient propagation learning function (mental task dataset)

	Successfully classified test data [%]
25 samples	84.64
50 samples	89.80
75 samples	90.48
100 samples	90.75

Table 7. Learning functions – 28 samples of each task, 20 neurons (EEG motor movement/imagery dataset)

Successfully classified test data [%]	*Resilient backpropagation*	*Scaled conjugate gradient backpropagation*	*Levenberg-Marquardt backpropagation*
Subject 1	65.37	61.69	68.57
Subject 3	72.82	71.42	71.51
Subject 5	68.48	65.08	63.21
Subject 7	66.16	56.25	67.43
Average	68.21	63.61	67.68

Table 8. Number of neurons (resilient propagation learning function, subject 3, 28 samples of each task) (EEG motor movement/imagery dataset)

	Successfully classified test data [%]
5 neurons	66.42
10 neurons	70.00
15 neurons	69.19
20 neurons	72.82
40 neurons	72.32
60 neurons	72.23

Table 9. Number of samples – subject 1, 20 neurons (EEG motor movement/imagery dataset)

Number of samples	*Resilient backpropagation*	*Scaled conjugate gradient backpropagation*	*Levenberg-Marquardt backpropagation*
	Successfully classified test data [%]		
28	65.37	61.69	68.57
56	61.16	61.60	69.19
84	62.26	60.74	66.10
112	60.35	62.43	65.31

Discussion and conclusions

The data used consists of two datasets – EEG recordings of different brain states while performing mental tasks and motor imagery. The most important difference between mental tasks is that they activate different brain parts, which is recorded by multichannel EEG. According to this property, it can be assumed that there will be some difference between classes of input data for neural network.

The method used for feature extraction was a discrete wavelet transform; one paper (Jahankhani, Kodogiannis, & Revett, 2006) suggests using statistics of wavelet coefficients. Omerhodzic et al. (2010) and Guo et al. (2009) used wavelet energy in their work, but for a different set of data – a single channel of normal and EEG recording containing epileptic seizures. Both of these papers use neural networks as classifiers. In this paper it is shown that the use of discrete wavelet energy provides good features for multichannel EEG in mental tasks dataset.

The best average classification accuracy for all five mental tasks was 90.75% and it was obtained for the neural network of 20 hidden neurons, with 100 samples of each task and resilient backpropagation as the learning function. With these settings, classification of task pairs, i.e. recognition if a mental task is being performed or if the subject is in a state of relaxation, gives the best average accuracy of 99.87%. This information tells us that it is possible to construct the simplest reliable BCI system with two control commands.

Repeated testing for motor imagery dataset showed notably worse classification accuracy than for mental tasks (motor imagery classification results are compared to mental task pairs). Possible causes could be the differences in the subject's environments at the time of recording the EEG signals, the nature of tasks – evocation of different brain areas, number of relevant electrodes – for motor tasks it is sufficient to use two electrodes and the different frequency of EEG recording. Therefore, it is advisable to experiment with different methods of feature extraction which may result with a better classification accuracy.

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KLASIFICIRANJE EEG SIGNALA ZAMIŠLJENIH MENTALNIH I MOTORIČKIH ZADATAKA POMOĆU TRANSFORMACIJE WAVELET I NEURONSKE MREŽE

Sučelja mozak-računalo (eng. *brain-computer interfaces – BCI*) su uređaji koji omogućavaju komunikaciju između računala i ljudi, a kao ulazne signale koriste podatke o moždanoj aktivnosti. U sustavima BCI najčešća tehnologija za snimanje moždane aktivnosti jest elektroencefalografija (EEG). Kako bi se ispravno interpretirala moždana aktivnost, prikupljeni moždani signali moraju biti točno klasificirani. U ovom članku EEG signali su predstavljeni pomoću diskretne transformacije *wavelet*. Značajke dobivene tim postupkom čine ulaz u neuronsku mrežu kojoj je zadatak klasificirati pet različitih skupova EEG signala za različite 'mentalne zadatke'. Dobivena je prosječna točnost klasifikatora od 90,75% za raspoznavanje svih pet zadataka te prosječna točnost od 99,87% za klasifikaciju dva zadatka (osnovni i bilo koji drugi zadatak). Ista metodologija se rabila i za klasificaranje skupa podataka motoričke predodžbe. Prosječna točnost klasifikacije iznosila je 68,21%, pa se preporuča izrada alternativne metode za izdvajanje značajki za podatke zamišljanja motoričkih zadataka.

Ključne riječi: *sučelje mozak-računalo, mentalni zadaci, motorička predodžba, analiza nezavisnih komponenata, diskretna wavelet analiza*

Submitted: November 7, 2011
Accepted: March 3, 2013

Correspondence to:
Martina Tolić, mag.ing.comp
Faculty of Electrical Engineering
University J.J. Strossmayer
Kneza Trpimira 2b, 31000 Osijek, Croatia
E-mail: mtolic8@gmail.com