Brain - Computer Interface for Communication and Estimation of Human Emotion from EEG and Video

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ABSTRACT

The brain-computer interface (BCI) aim to use Electroencephalography (EEG) or other measures of brain functions can be implemented for communication with smart devices for disabled persons. For connection with different smart devices was used recorded with experimental setup electrophysiological signals for execution of five different mental tasks. The recorded brain signals were processed for their transformation into commands to different devices. This signal processing aims to extract some specific features of brain signals and transform them into algorithms for connection with smart devices. Processed signals after noise filtering, clustering and classification with Bayesian Network classifier and pair-wise classifier was estimated and put into brain-computer interface for connection with smart devices. Recent advances in emotion recognition use a combination of two intrapersonal modalities - face and EEG to estimate emotion. In this research is made an attempt to combine received results on the base of record electrophysiological signals at execution of five different mental tasks with estimation of human emotion. This will help to provide a framework for reliable EEG emotional state estimation combined with facial emotion analysis in developed task-oriented BCI.

KEYWORDS

Brain-Computer Interface, Signal Processing, Neural Networks, Communication and Control.

1 INTRODUCTION

The brain-computer interface (BCI) aim to use different measures of brain functions for communication and control [1, 2]. Developing of such communication and control technology will improve the life of disabled persons. The brain-computer interfaces gives to these users possibility to switch on and off different devices [3, 4, 5], to run computer programs, to operate word-processing programs or neuro-prostheses [6, 7, 8].

The BCI gives possibility to control computer using brain directly, which is a very promising features for persons who cannot access traditional computer system due to their physical disabilities [9, 10, 11, 12].

The principle of BCI is based on measured brain activity while the user generates brain signals and to transform these signals into computer commands [13] for connection with smart device [14, 15, 16, 17].

Emotion analysis from human EEG signals is as well very attractive area for researchers. There already exist few types of approaches using EEG which are said to deliver promising emotion recognition results [18, 19].

The analysis of the existing research in the area shows that there is a large potential for improvement of the existing methods by means of using a novel approach to EEG emotion estimation combined with facial emotion analysis [20, 21].

Recent advances in emotion recognition use a combination of two intrapersonal modalities -
face and EEG to estimate emotion. This research consider implementation of BCI for communication and control, where estimation of emotional state supported by facial analysis is combined with estimation of different mental tasks execution.

2 SIGNAL PROCESSING AND CLUSTERING OF NEURONS

BCI system is realized on the following steps: when something has to be done a thought is developed into the brain which leads to development of a neuron potential pattern. Reading brain by register electrophysiological signals the developed potential pattern is transformed into an analyzable signal patterns. These signal patterns developed by BCI equipment and their spectrum is analyzed using various pattern analysis techniques. After recognition of human’s intention about the task that brain wants to get from smart device or computer we can determine proper command (or sequence of commands) to execute the required task. Feedback to the user can be realized in various feedback-forms e.g. device switching on/off, emergency call, video, audio etc.

As is seen, for BCI communication with smart devices it is necessary to provide filtering of register brain signals and pattern analysis techniques for clustering of neurons and pattern recognition.

At any moment the human brain generates wave for a particular thought, but at the same time generates also some waves corresponding to other unnecessary thoughts. These additional waves appear because sometimes it is not possible to concentrate fully on a particular thought and they act as noise for the original waves. For handling with these noise-waves the user have to increase his concentration during the BCI process.

For solving this problem it is necessary to develop noise filtering mechanism that can detect the unrelated spectrum and filter them out from the useful spectrum [22]. The process of noise filters design requires some situation and application of specific knowledge from neurology. After some experiments for finding out the pattern of the signals was prepared and calibrated noise filter.

Another problem that has to be solved is connected with clustering of neurons, where it is necessary to divide 80-120 billion brain-neurons into few clusters. There is no exact answer on the question on what basis we should divide the neurons and the problem can be solved only experimentally. For solving these clustering problems is involved Artificial Intelligence and Artificial neural network [23]. There exists several alternatives for pattern analysis and recognition [24], but Artificial Intelligence and Artificial Neural Network provides provide very effective and useful algorithms for pattern recognition [25].

3 EXPERIMENTAL METHODS AND MEASUREMENTS

The experimental bran-computer interface setup for communication with smart devices was worked out at the University of Telecommunications and Post at Sofia. The experimental BCI system includes 3D camera Panasonic HDC-Z0000, sender Spectrum DX9 DSMX, Sony GoPRO – GoPro HERO3, Nikon D902D smart TV Samsung UE-65HU8500 + LG60LA620S, ACER K11 Led projector, Linksys EA6900 AC1900 smart router, Pololu Zumo Shield, 8 core/32GB RAM/4TB HDD/3GB VGA computer for video processing that translate EEG signals into computer commands.

Two Electro-Caps (elastic electrode caps) was used to record each from positions C3, C4, P3, P4, O1, and O2, defined by the most popular “10-20 System of electrode placement” at experimental setup.

The implemented standard system of electrode placement defines a grid of most appropriate places for brain signals measurements on the human head.
The electrode locations are defined by either 10% or 20% increments between these specific positions. The possible placements of electrodes on the human scalp is presented on Figure 1.

![Figure 1. Electrodes placements model in experimental setup](image)

Measurements were provided for the regions P3, P4 and Cz. The used device also includes a ground electrode connection that we attached to an ear lobe to provide electrical protection. The electrodes were connected through a bank of Grass amplifiers. Data was recorded at a sampling rate of 250 Hz with a Lab Master 12 bit A/D converter mounted in computer.

Eye blinks were detected by means of a separate channel of data recorded from two electrodes placed above and below left eye. Data was recorded for 14 seconds during each task and each task was repeated 10 times per session.

After ensuring that participants are ready, the EEG electrodes are put on their scalp. The five cognitive tasks were explained and the participants have to perform them several times to ensure that they understood the tasks. Participants at experiments performed the following tasks within experiments with their eyes closed:

- calm and relax task;
- letter - emergency call - subjects dial up
- math task - imagined addition;
- counting task - count edges or planes of 3D graphics;
- imagine rotation of shown figure.

The recorded signals were passed through worked out filters realized by implementation of weights [26] and regression approach for modification of amplitude, which helps to remove noise from the original EEG signals. During the measurements every task was repeated 20 times and register signal was divided into 200 sampling points. The duration of each record was 14 sec. and from each channel was received 4 000 samples.

### 4 DATA ANALYSIS AND CLASSIFICATION

Some basic signal processing of received time series was performed for classification of measured signals. The EEG signals were divided into small overlapping by 1 second intervals of 2 seconds.

For each of selected interval was computed the most significant features. These features was used for training a Bayesian Neural Network used for classification. After 10 000 training epochs the neural network is capable to provide classification of brain-neurons into clusters in real-time implementation.

The spectral power of the signal was investigated into a set of six standard frequency bands, according to different types of neural activity.

The frequency content of the processed signals was received after Fourier transform.

For comparison was provided classification of brain-neurons into clusters with pair-wise classifier.

Table 1 presents received results of the classification accuracies for each of 6 subjects, where \( N \) is subject number and \( M \) is mean value.
The classification accuracies depending on the user fall into the interval between 62.6% and 81.1%.

Table 1. Classification accuracies with Bayesian Network classifiers for five mental tasks

<table>
<thead>
<tr>
<th>N</th>
<th>Mental Tasks</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Base</td>
</tr>
<tr>
<td>1</td>
<td>91.3%</td>
</tr>
<tr>
<td>2</td>
<td>92.4%</td>
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<tr>
<td>3</td>
<td>87.8%</td>
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<tr>
<td>4</td>
<td>90.2%</td>
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<tr>
<td>5</td>
<td>93.7%</td>
</tr>
<tr>
<td>6</td>
<td>89.3%</td>
</tr>
<tr>
<td>M</td>
<td>90.8%</td>
</tr>
</tbody>
</table>

In this investigation was used 18-fold cross validation. The classification accuracies with pair-wise classifier for the same five mental tasks is shown in Table 2.

Table 2. Classification accuracies with pair-wise classifier for five mental tasks

<table>
<thead>
<tr>
<th>N</th>
<th>Mental Tasks</th>
</tr>
</thead>
<tbody>
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<td></td>
<td>Base</td>
</tr>
<tr>
<td>1</td>
<td>93.5%</td>
</tr>
<tr>
<td>2</td>
<td>92.4%</td>
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<td>3</td>
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<tr>
<td>4</td>
<td>90.2%</td>
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<tr>
<td>5</td>
<td>93.7%</td>
</tr>
<tr>
<td>6</td>
<td>89.3%</td>
</tr>
<tr>
<td>M</td>
<td>90.8%</td>
</tr>
</tbody>
</table>

The classification accuracies depending on the user fall into the interval between 62.6% and 81.1%.

5 EEG EMOTION RECOGNITION

Developed task-oriented BCI includes EEG emotion estimation combined with facial emotion analysis.

The technique for EEG analysis and feature extraction includes the following steps: first step is a preprocessing of EEG signals, the second step is built an augmented feature vector from statistical and time-frequency features, and the third step is classification, which consists of SVM core with probabilistic outputs.

For accuracy improvement in terms of facial muscle movement influence on system performance at EEG emotion recognition was made the following assumptions: the muscle movement is an additive noise and its influence can be reduced by filtering. The accuracy of the modality with better performing classifier can be used as a reliable output for the combined system output.

Prior to features extraction, the baseline drift in EEG and signals has to be removed. For this purpose was used mathematical morphology to get a filtered EEG signal \( x \) according to:

\[
x = x' - \frac{(x' \circ SE) \bullet SE + (x' \bullet SE) \circ SE}{2}
\]

(1)

where \( x' \) is the raw input signal, SE is a structuring element of type horizontal line with length \( l = 500 \), \( \circ \) denotes morphological opening and \( \bullet \) denotes morphological closing. The length \( l \) meets the condition:

\[
l = \frac{f_s}{2f_b},
\]

(2)

where \( f_b = 0,1 \text{ Hz} \) is the lowest frequency in the spectrum of EEG signals and \( f_s = 100 \text{ Hz} \) is the sampling frequency.

After decomposition of the signal into separate components \( h_k[n] \) with defined instantaneous frequency:

\[
x[n] = \sum_{k=1}^{K} h_k[n] + r[n],
\]

(3)

where \( K \) is the number of intrinsic mode functions (IMF) and \( r[n] \) is the residual. The decomposition is iterative procedure and it repeats until the residual becomes a monotonic function. Since the IMFs of an EEG signal represent the activity of the well-known waves (delta, theta, alpha and beta), we have
restricted the available IMFs up to 4 plus the residual. For each \( k \)th IMF was calculated its Hilbert transform \( H_k[n] \) and the instantaneous frequency:

\[
f_k[n] = \frac{f_s}{2\pi} \left( \theta_k[n] - \theta_k[n] - 1 \right)
\]

The instantaneous frequency determined according to (4) appeared to be unstable, so for the final experiments was used Savitzky–Golay filter with polynomial order of 4 for \( f_k[n] \) calculation. The window length for computation is chosen to be 41. The IMFs are not perfect analytic signals and we encountered the problem with negative values in \( f_k[n] \). An IMF can be regarded as combination of amplitude and narrow-band frequency modulation. Suppressing the amplitude modulation part significantly reduces the appearance of negative frequencies. In a fixed number of iterations we normalize the IMF by its Hilbert envelope and finally the amount of negative frequencies is negligible. For a particular frequency band, we extract a signal \( m[n] \) as follows:

\[
m[n] = \begin{cases} 
\max \| H_k[n] \| & f_l \leq f_k[n] \leq f_h \\
0 & \text{otherwise}
\end{cases}
\]

where \( f_l \) and \( f_h \) are the lowest and the highest frequency in the band. The relative duration of a given EEG wave activity is found according to:

\[
d = \frac{1}{N} \sum_{n=1}^{N} m'[n],
\]

where \( m'[n] \) is:

\[
m'[n] = \begin{cases} 
1 & V_l \leq m[n] \leq V_h \\
0 & \text{otherwise}
\end{cases}
\]

In (7) \( V_l \) and \( V_h \) are the lower and the higher voltages of a given wave activity. The upper threshold is used to avoid the possible artifacts in the signal.

The proposed model relies on a new approach for multi-view facial expression recognition, where was encoded appearance-based facial features using sparse codes and learn projections from non-frontal to frontal views using linear regression projection. We then reconstruct facial features from the projected sparse codes using a common global dictionary. Finally, the reconstructed features are used for facial expression recognition.

For detection of the frontal face and improved accuracy at face detection was used sub-window with the detected face through a Convolutional Neural Network.

At the process of face extraction it is necessary to detect and recognize a few face samples within the proposed detection interval. Afterwards was calculated an average feature vector which is estimated in the classifier for each window.

With the help of common spatial patterns (CSP) and linear SVM (support vector machines or support vector networks) was classified two emotional state – sad and happy. The received results show that Gamma band (30–100 Hz) is the most appropriate for EEG-based emotion classification.

After learning with supervised learning model and training with 6 000 epochs the classification process can be used in real-time for classification, where all samples are divided into two categories. The achieved classification accuracy is 70.78%.

**6 CONCLUSIONS**

An approach for human-computer interaction with classification of electrophysiological signals, recorded with brain-computer interface at different mental tasks is presented. With considered experimental setup of BCI were provided experiments with six subjects for execution of five mental tasks. The measured outputs after noise filtering were
classified with Bayesian Neural Network classifier and with pair-wise classifier. Developed task-oriented BCI includes EEG emotion estimation combined with facial emotion analysis based on the following steps: preprocessing of EEG signals, built augmented feature vector from statistical and time-frequency features, and classification which consists of SVM core with probabilistic outputs. The received results are compared and shown.

7 ACKNOWLEDGMENTS

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REFERENCES


