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Piotr Augustyniak
Roman Maniewski
Ryszard Tadeusiewicz *Editors*

Recent Developments and Achievements in Biocybernetics and Biomedical Engineering

Proceedings of the 20th Polish Conference on Biocybernetics and Biomedical Engineering, Kraków, Poland, September 20–22, 2017

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Preface

We proudly present the Proceedings of the 20th Polish Conference on Biocybernetics and Biomedical Engineering, which will be held in Krakow from September 20 to 22, 2017. The conference was organized by the Committee of Biocybernetics and Biomedical Engineering of the Polish Academy of Sciences and the Polish Society of Biomedical Engineering and hosted by the AGH University of Science and Technology. The biannual meetings of the Polish Conference on Biocybernetics and Biomedical Engineering have been held for nearly four decades and attract scientists and professionals from the fields of engineering, medicine, physics, and computer science. After 30 years, this prestigious event returned to AGH University of Science and Technology and, thanks to English as the working language and an International Program Committee, opened to the scientists from the entire world. The 20th PCBBE was a great opportunity for an exchange of ideas and presentation of the latest developments in all areas within the field of biomedical engineering including biomedical signal processing, imaging and image processing, biosensors and bioinstrumentation, biomicro-/nanotechnologies, biomaterials, biomechanics, robotics and minimally invasive surgery, cybernetics, biomimetic and modeling of biological systems, neural and rehabilitation engineering, artificial organs, molecular, cellular and tissue engineering, bioinformatics and computational biology, clinical engineering and health technology assessment, health informatics, e-health and telemedicine and biomedical engineering education.

The conference attracted a total of 104 submissions, and after the refereeing process, only 27 were accepted for publication in this volume. Here, we would like to thank our participants, invited speakers, and reviewers for their scientific and personal contributions to the conference. In this Proceedings volume, the accepted papers are organized in five chapters concerning:

– signal processing,
– medical image analysis methods and applications,
– cell and tissue engineering,
– modeling in medicine and many others.

Aiming at high scientific merit of the meeting and international recognition of the Proceedings, all submissions are subjected to a thorough peer review process (three to four independent reviews per paper) and only those with a consistent and strong recommendation from reviewers have been accepted. We believe that this book will become a great reference tool for scientists working in the area of biocybernetics and biomedical engineering. The readers are kindly encouraged to contact the corresponding authors for further details of their research.

Many thanks and much appreciation are due to the peer reviewers from Belgium, Czech Republic, France, Germany, Hungary, Italy, Latvia, Poland, Portugal, and Slovakia, who have greatly contributed to a critical selection of the best papers and whose remarks and suggestions have helped the authors considerably improve the quality of the papers.

The 20th Polish Conference on Biocybernetics and Biomedical Engineering was an outstanding event thanks to the remarkable keynote speeches given by distinguished guest lecturers:

Prof. Metin Akay (USA),
Prof. n. med. Leszek Królicki (Poland),
Prof. Adam Liebert (Poland).

The scientific program of the conference was organized in plenary lectures, regular domain-oriented oral sessions, and poster sessions. Besides the topics traditionally covered by the conference (e.g., biomaterials, biosignal processing, modeling, cybernetics, artificial organs, imaging, sensors, e-health, telemedicine, rehabilitation engineering), we enjoyed five special sessions:

- Award nomination and presentation session for laureates of the Polish Society of Biomedical Engineering competition for the best BME Master's Thesis,
- Education and certification system for clinical engineers,
- Celebration of 70th birthday of Professor Ryszard Tadeusiewicz—one of the founding fathers of biocybernetics and biomedical engineering in Poland—with personal recollections from his colleagues,
- Work in progress—review of the best ongoing research projects, and
- Turning the idea into a commercial product—session on innovation, start-up initiatives, and support.

The conference was technically sponsored by Polish Chapter IEEE Signal Processing Society and was granted by the honorary patronage of His Magnificence Rector of AGH University of Science and Technology.

Finally, we would like to thank members of Local Organizing Committee in Krakow: Piotr Augustyniak (Chairman), Andrzej Izworski, Anna Broniec, Mirosława Długosz, Joanna Grabska-Chrząstowska, Daria Hemmerling, Katarzyna Heryan, Joanna Jaworek-Korjakowska, Aleksandra Jung, Eliasz Kańtoch, Paweł Kłeczek, Tomasz Orzechowski, Tomasz Pięciak, Elżbieta Pociask, Andrzej Skalski, and Magdalena Smoleń for their commitment and efforts to make the conference a very successful event.

Piotr Augustyniak
Roman Maniewski
Ryszard Tadeusiewicz

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Processing and Analysis of EEG Signal for SSVEP Detection

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Abstract. The aim of the article is to provide a systematic presentation of basic tools that are most commonly used to analyze electroencephalography signals (EEG) in brain–computer interfaces for detection of steady-state visually evoked potentials (SSVEP). We use a database of EEG signals containing SSVEP and demonstrate the desirability of the use of selected methods, showing their benefits. Methods such as independent components analysis (ICA), frequency analysis (DFT), and time-frequency analysis (STFT) are presented. For SSVEP, the features of EEG signal should be stable with time. Short-Time Fourier Transform (STFT) allows to confirm this stability. Independent Component Analysis is used to extract pure SSVEP components. The advantages of each method are described and the obtained results are discussed. Further, source location by the use of low-resolution electromagnetic tomography algorithm is demonstrated.

Keywords: Electroencephalography · Brain–Computer Interface (BCI) · Independent Components Analysis (ICA) · Frequency analysis · Time-frequency analysis · EEG inverse problem · LORETA

1 Introduction

A very popular and also quite effective brain–computer interfaces (BCI) [1–6] standard is based on the so-called Steady-State Visually Evoked Potentials (SSVEP) [7–12]. It uses the response of the brain to flickering light stimuli with a constant frequency. In EEG signal, during the stimulation, an increase of energy is observed in the frequencies equal to the flickering light frequency and its harmonics. SSVEP are best noticeable in the visual cortex.

In BCI based on SSVEP implementation, there is a problem of extracting, from noisy EEG signal, the useful information in the form of periodic waveforms of specific frequencies. As a solution for the problem, a whole range of methods for EEG signal processing, analysis, and classification were developed [13–15]. The basic methods include frequency and time-frequency analysis combined with filtration. Complementary methods include spatial filters (common

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average reference – CAR, local average technique - LAT or Laplace filter). Advanced methods include independent components analysis (ICA) [16–21]. Furthermore, it is reasonable to determine the spatial location of sources of electrical activity within the brain, throughout solving the EEG inverse problem [22–26]. Described below, EEG signal analysis algorithms for SSVEP recognition, were carried out in MATLAB using EEGLAB [27] and ICALAB toolboxes [28]. To determine the spatial localization of sources, low-resolution electromagnetic tomography algorithm (LORETA) was used [29].

2 Materials

EEG signals were recorded using 16-electrode g.tec EEG amplifier. Electrodes were attached to a cap and arranged according to the international 10–20 system (O2, AF3, AF4, P4, P3, Fz, F3, FCz, Pz, C4, C3, CPz, Cz, Oz, O1). Data were collected from five users aged from 23 to 46 years. In the carried out experiments, users were stimulated with LED light flickering with four different frequencies, that is, 5, 6, 7, and 8 Hz. The LED, about 1 cm in diameter, was placed at a distance of approximately 1 m from the user's eyes.

Each session lasted 30 s. EEG signals were recorded at a rate of 256 kHz. In order to avoid aliasing and eliminate interference from the power network, the signals were filtered by a bandpass filter (0.1–100 Hz) and Butterworth band-stop filter (48–52 Hz), respectively. Additionally, a spatial filter Common Average Reference type (CAR) was used for the reduction of biological artifacts. Basic parameters related to data acquisition, processing, and analysis are summarized in Table 1.

Table 1. Basic parameters of data acquisition and analysis

Parameters	Value
The number of classes (SSVEP channels)	4 (5, 6, 7, 8) Hz
Number of electrodes	16
Number of users	5
Sampling rate	256 Hz
Duration of experiment task	30 s
Number of samples per task	7680
Number of time windows per task	14
Number of samples per window	1024
Frequency range of analysis	0.1–100 Hz
Resolution of spectral analysis	0.25 Hz
Image resolution (LORETA)	5 mm

3 Methods

There are many methods of EEG signal processing. Below we presented a compact, supported by examples, overview of the most popular methods of EEG signal analysis, especially useful in the SSVEP detection. Use of these methods allows to determine:

– frequency range of electrical brain activity (frequency analysis)
– variability in the frequency of EEG signals (time-frequency analysis)
– independent components of EEG signal (Independent Component Analysis)
– the location of sources of brain activity (LORETA)
– EEG components associated with particular brain activity (classification).

3.1 Frequency Analysis

The basic features of EEG signal, used in the SSVEP classification process, are oscillations associated with light stimulus and their harmonics. Thus, frequency analysis is the most commonly used in EEG signal processing for SSVEP recognition. In a case of Discrete Fourier Transform (DFT), for N size time series x_n, the spectral coefficients X_k, are determined from the relationship (1).

$$X_k = \frac{1}{N} \sum_{n=0}^{N-1} x_n e^{-j(\frac{2\pi}{N}k)n} \tag{1}$$

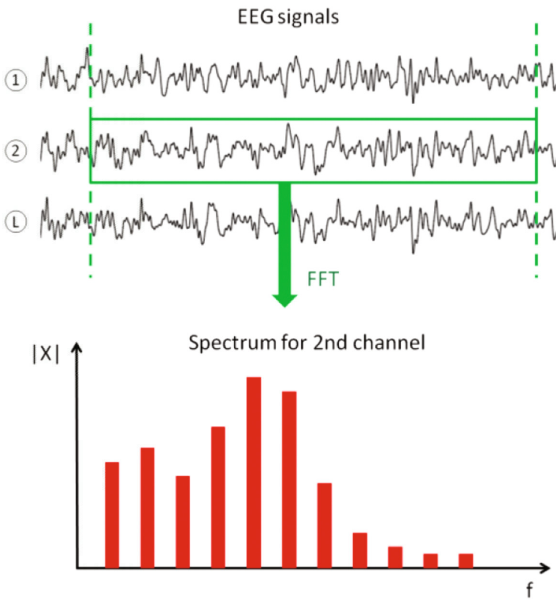


Fig. 1. Analysis in frequency domain for 2nd channel

The idea of such an analysis for the second channel of EEG recording is shown in Fig. 1. By combining the FFT results for data coming from different channels, it is possible to obtain distribution of potentials on the scalp for the selected frequency (i.e. EEG mapping).

3.2 Time-Frequency Analysis

The extension of analyses on time-frequency space is particularly useful in the study of brain functioning. For SSVEP, the features of EEG signal should be stable with time. Short-Time Fourier Transform (STFT) allows to confirm this stability.

The EEG signal is divided into narrow time windows, on which frequency analysis is performed. A spectrogram is the result of this analysis, for which the values of each t/f coefficient $X_{n,k}$ (for sliding time window φ_{n-m} of M width, located at n time point and k frequency point) are determined from the relationship (2).

$$X_{n,k} = \frac{1}{M} \sum_{m=0}^{M-1} x_m \varphi_{n-m} e^{-j(\frac{2\pi}{M}k)m} \tag{2}$$

By STFT analysis (spectrogram), we were able to determine which of the EEG signal fragments showed the frequencies interested to us. The idea of such an analysis for the second channel of EEG recordings is illustrated in Fig. 2.

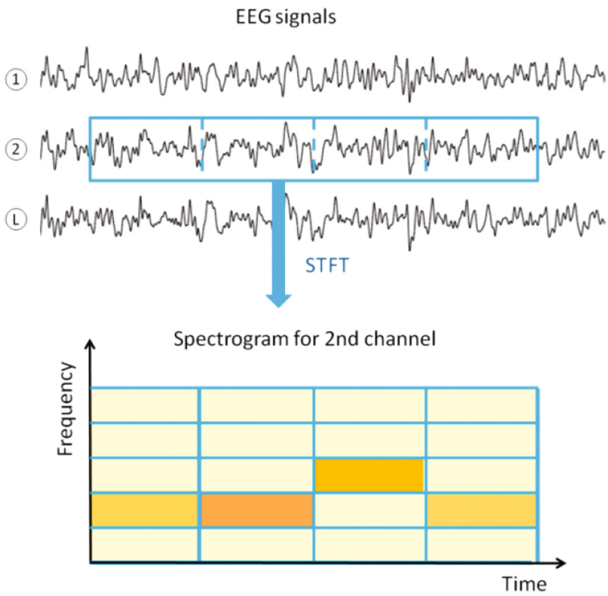


Fig. 2. Analysis in time-frequency domain for 2nd channel

3.3 Independent Component Analysis (ICA)

EEG signals recorded from the surface of the skull include not only components of the cerebral origin, but also noise and a lot of different independent artifacts. One of the most effective methods is Independent Components Analysis (ICA), which separates unknown desired signals from different sources. It not only enables the extraction of SSVEP components, but at the same time, helps in the reduction of noise and artifacts.

In ICA methods, it is assumed that the EEG signal is a linear combination of signals coming from different sources (3):

$$\mathbf{x} = \mathbf{A}\mathbf{s} + \mathbf{v} \tag{3}$$

where $\mathbf{x}$ is the vector of observed EEG signals, $\mathbf{s}$ is the vector of independent, source signals, $\mathbf{A}$ is the mixing matrix, and $\mathbf{v}$ is the additive noise vector (for simplicity, this parameter is usually omitted). Source separation task is to reverse the relation (3), which in turn leads to Eq. (4).

$$\mathbf{y} = \mathbf{W}\mathbf{x} \cong \mathbf{s} \tag{4}$$

where $\mathbf{y}$ is the vector of output signals (estimated source signals) and $\mathbf{W}$ is the separating matrix.

If matrix $\mathbf{A}$ is known, the task of sources separation is reduced to matrix inversion. Otherwise, the matrix is estimated from the recorded EEG signals ($\mathbf{x}$ vector). The solution in which the output signal vector $\mathbf{y}$ contains source components as independent as possible is sought. This is the aim of ICA, the concept of which is illustrated in Fig. 3. In the upper part of the figure, exemplary waveforms of EEG signals for the four electrodes are shown, and the lower part

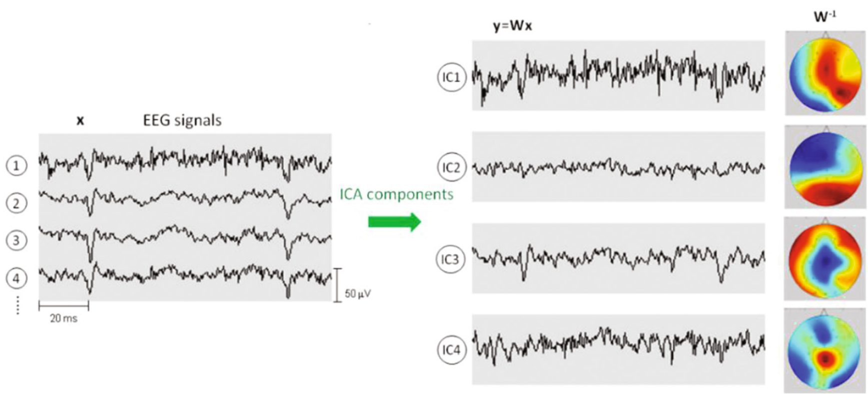


Fig. 3. A method of independent component analysis (ICA)

presents four independent components calculated for each of them. On the right side, the distribution of weights associated with a given component is shown.

Among the various known algorithms of ICA, we used fourth-order blind signal separation (BSS) algorithm in our experiments [19–21].

3.4 Spatial Distribution of Electrical Brain Activity

In order to determine electrical activity of brain (described by current densities $\mathbf{J}$), it is necessary to solve the so-called inverse problem. The current densities $\mathbf{J}$ calculated from the potentials $\mathbf{x}$ recorded at the head surface are described by Eq. (5).

$$\hat{\mathbf{J}} = \mathbf{K}^{-1}\mathbf{x} \tag{5}$$

where $\mathbf{K}$ is the transformation matrix binding EEG potentials with currents describing the activity of individual brain areas.

The calculation of brain activity is normally done by assuming a priori distribution of $\mathbf{J}$ and repeatedly solving the so-called forward problem ($\mathbf{x} = \mathbf{KJ} + \mathbf{v}$), while minimizing the noise $\mathbf{v}$. The transformation matrix $\mathbf{K}$ is determined by solving Maxwell's equations assuming a spherical head model, or a more realistic model obtained from individual testing of a person (e.g. functional magnetic resonance imaging) or taken directly from the atlas of the human brain [30]. Due to the ambiguity of the solution (5), EEG inverse problem is one of the most

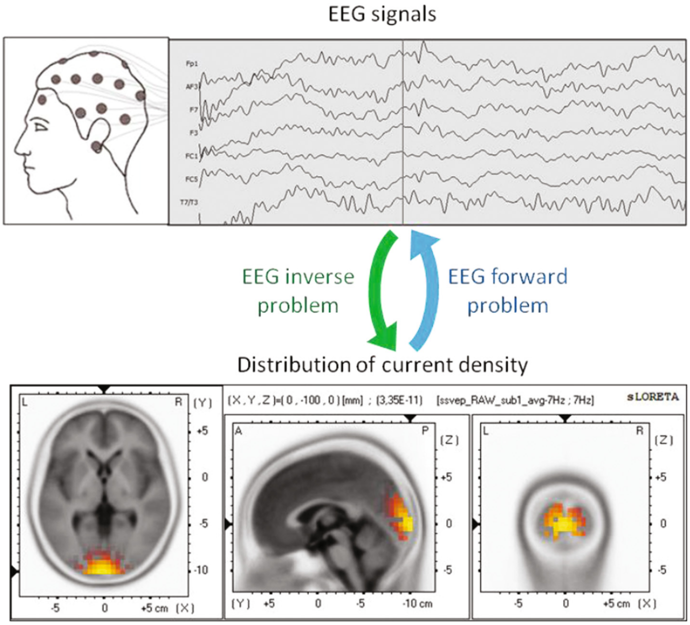


Fig. 4. Ideas of forward and inverse problems in EEG

difficult tasks in electroencephalography research. The ideas of a forward and inverse problems in EEG are illustrated in Fig. 4.

The methods of locating sources using EEG signals differ primarily by brain activity modeling, formulation of boundary conditions, and applied optimization methods [22,23]. They include parametric methods, in which the brain activity is modeled by a sufficiently small number of single current dipoles, and non-parametric methods, in which distributed sources are considered. sLORETA (standardized low-resolution electromagnetic tomography algorithm) is a software tool used to solve the inverse problem [24–26], and presents a very small location error even for deeply located sources.

3.5 Task Classification

The effectiveness of BCIs based on SSVEP detection, depends on the ability of proper classification of extracted EEG components - correct assignment of each SSVEP class to a particular task. The following are the commonly used tools in classification of EEG components: minimum distance estimation (k-nearest neighbors [k-NN]), feature space division (neural networks [MPL] or support vector machine [SVM]), probabilistic methods (naive Bayesian classifier), and discriminant analysis (linear/quadratic discriminant analysis [LDA/QDA]) [31–34]. For research related to SSVEP, relatively high efficiency has a fairly conceptually simple k-NN algorithm [34]. In the presented calculations, 3-NN version of the algorithm was used, while for learning and testing the classifier, 10-fold cross-validation test (10-CV) was implemented.

4 Results and Discussion

The results of EEG signal analysis, in the context of SSVEP detection, shows high efficiency of the considered methods. The results were presented in the form of charts, obtained using standard software packages such as: MATLAB, EEGLAB [27], ICALAB [28] and sLORETA [29].

4.1 Analysis in Frequency Domain

In a properly conducted experiment, the SSVEPs are most noticeable at occipital electrodes O1/O2/Oz, which are located above the visual cortex. A sample spectrum of an exemplary signal collected from Oz electrode for user #1, elicited with 7 Hz stimulus is illustrated in Fig. 5. The component corresponding to the frequency of the stimulus and its second and fourth harmonics (14 Hz, and 28 Hz) can be clearly seen.

EEG signal analysis in the frequency domain is particularly useful to verify on which electrodes the components, which are the response to a stimulus, are most visible. Mapping of EEG potentials for the considered case (7 Hz) showed greatest energy at the back of the head (Fig. 6).

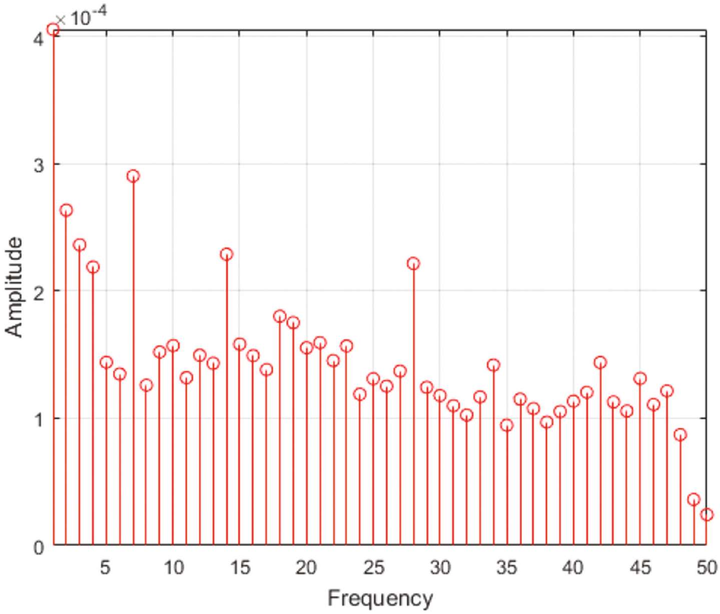


Fig. 5. Spectrum of signal from Oz electrode (user #1, 7 Hz session)

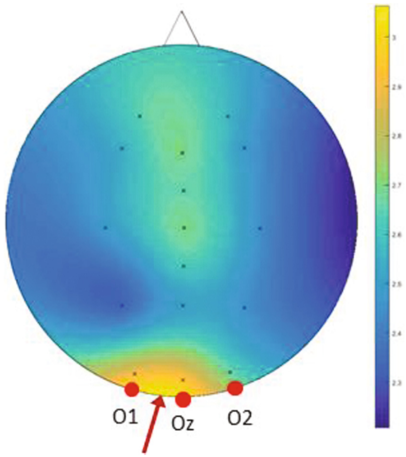


Fig. 6. Potential distribution on the surface of the head (user #1, 7 Hz session)

4.2 Analysis in Time-Frequency Domain

Short-Time Fourier Transform (STFT) was used to examine the temporal stability of the components of EEG signal related to SSVEP. For this purpose, spectrograms were calculated, particularly for signals from O1/O2/Oz electrodes. Spectrogram paced in Fig. 7, shows that during two consecutive sessions

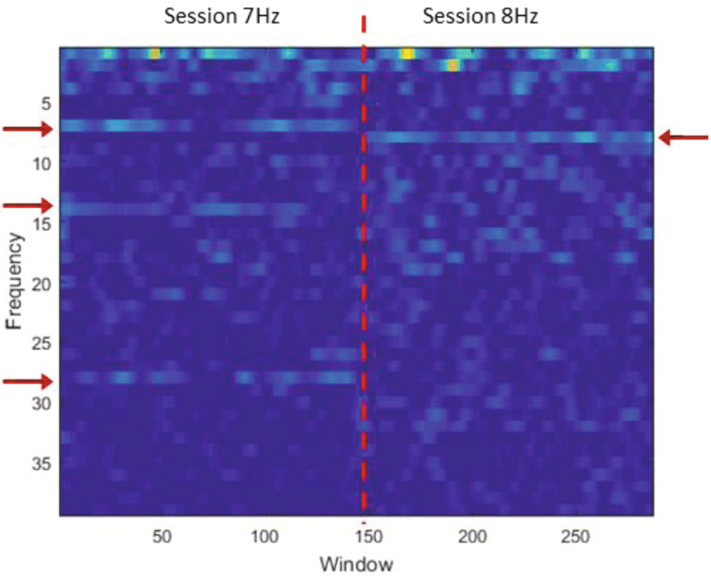


Fig. 7. Spectrogram of the signal from Oz electrode (user #1, 7 Hz and 8 Hz sessions)

(7 Hz and 8 Hz), the power of components associated with the stimulus frequency and their harmonics noticeably increases, which is visible from the very beginning to the end of the sessions.

4.3 Spatial Location of Brain Sources Based on Raw EEG

In the first step of experiments, spatial location of SSVEP sources was determined for raw EEG data (without ICA implementation) using sLORETA algorithm. The calculations were made separately for each channel of EEG signal (electrode) and the obtained results, for a specific user and SSVEP session, were averaged. An exemplary distribution of brain electrical activity for user #1, elicited with 7 Hz stimulus is shown in Fig. 8. Picture header contains information about the position of the voxel and maximum current density related to it and the frequency for which maximum current density was obtained.

Figure 9 shows the dependence of electrical brain activity (maximum current density) on the frequency, for 7 Hz stimulus. On stimulation with a 7 Hz stimulus, an increase of activity (in the visual cortex: O1, O2, Oz electrodes) in the frequency band of 7 Hz and its second harmonics is clearly observed.

Assessment of the differences between the two compared classes (7 Hz and 8 Hz) was also performed. Their measure F_{7-8} was calculated separately for each pixel, defined as the logarithm of the ratio of current densities J_7 and J_8 (6).

$$F_{7-8} = \log \left(\frac{1}{N_7} \sum_{i}^{N_7} J_{7,i} \ / \ \frac{1}{N_8} \sum_{i}^{N_8} J_{8,i} \right) \tag{6}$$

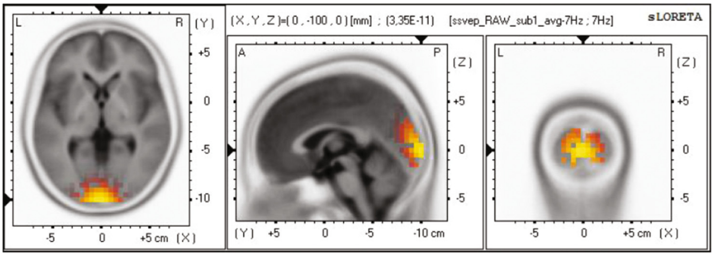


Fig. 8. Electrical activity of the brain (current density distribution) (user #1, 7 Hz session)

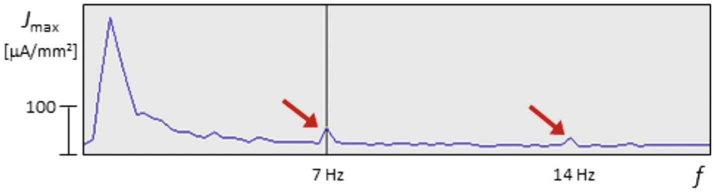
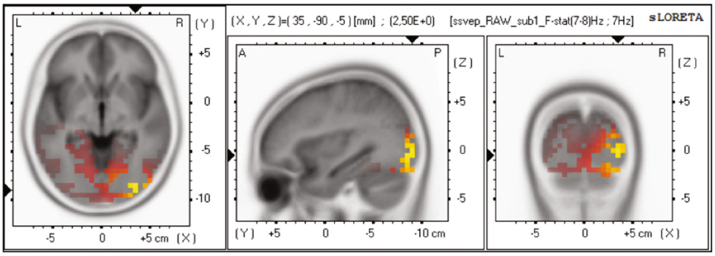
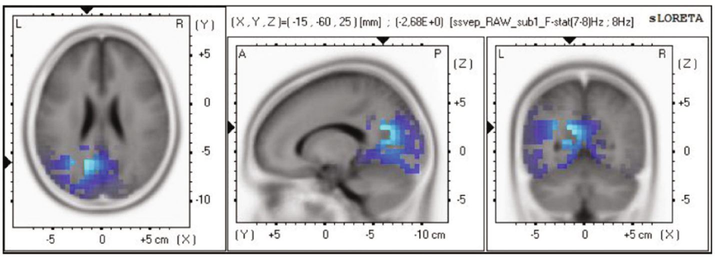


Fig. 9. Maximum current density as a function of frequency (user #1, 7 Hz session)



(a)



(b)

Fig. 10. Distributions of F_{7-8} coefficient for (a) 7 Hz and (b) 8 Hz for user #1

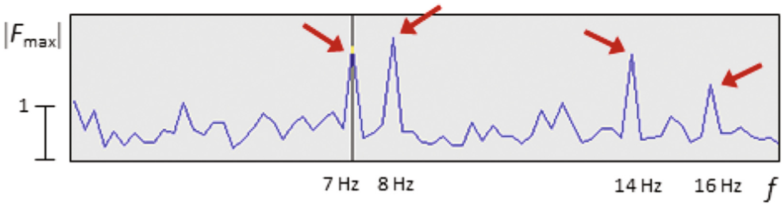


Fig. 11. Dependence of the maximum value of the F_{7-8} coefficient on the frequency

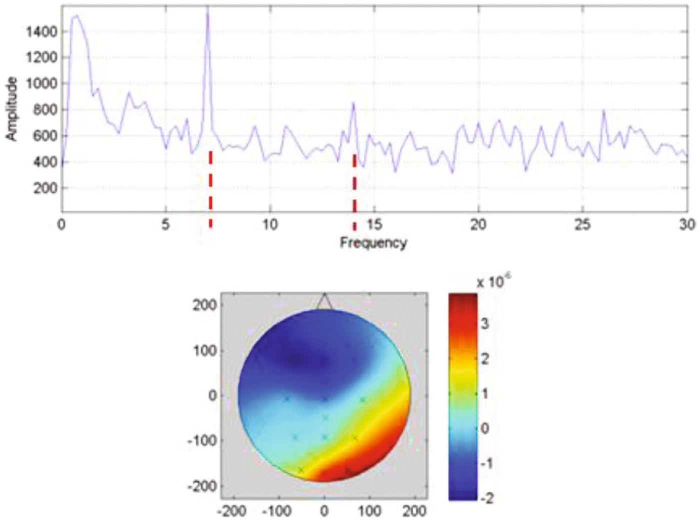


Fig. 12. Spectrum density (top) and the distribution of weights on the scalp (bottom) (user #1, 7 Hz session, IC10 component)

Distributions of F_{7-8} coefficient are shown in Fig. 10a for 7 Hz and in Fig. 10b for 8 Hz. In Fig. 11, the dependence of the maximum value of the F_{7-8} coefficient on the frequency is illustrated. Although low-frequency components of EEG signals that occur without stimulation had the largest energy, the obtained results confirm that the greatest differences between the classes were observed for frequencies associated with stimuli (7 Hz and 8 Hz) and their harmonics (in particular 2 and 4).

4.4 Analysis of Independent Components

As part of our research, we also calculated independent source components related to SSVEP. In the applied algorithm (Force Average Reference - FAR), the number of calculated independent components was equal to the number of channels (electrodes) decreased by 1 (that is 15) [35–37]. As a result of the analysis we obtained:

– 15 components (IC1–IC15) with the same number of samples as in EEG signals, and
– weight matrix binding a component with 16 recorded EEG signals (for each component).

For each component we performed spectral analysis, indicated the source of the component (sLORETA) and determined the accuracy of SSVEP classification.

4.5 Spectral Analysis of ICA Components

In another approach, the independent components were subjected to Fourier transform. The results achieved for IC10 component are presented in Fig. 12. Top figure shows the spectrum density and bottom the distribution of weight coefficients on the scalp (user #1, 7 Hz session). Presented spectrum, as well as weight distribution, indicates a potentially high correlation of IC10 component with SSVEP. However, for some people and SSVEP sessions, the results were less conclusive. For example, for user #5 and 7 Hz session, SSVEP was better represented in the spectrum for IC6 component (Fig. 13), although higher transition weights for O1/O2/Oz electrodes were observed for IC7 component (Fig. 14).

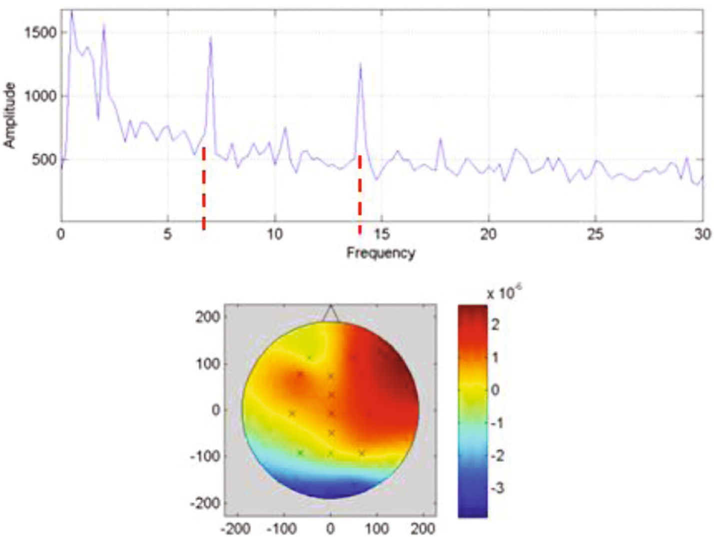


Fig. 13. Spectrum density and the distribution of weights on the scalp (user #5, 7 Hz session, IC6 component)

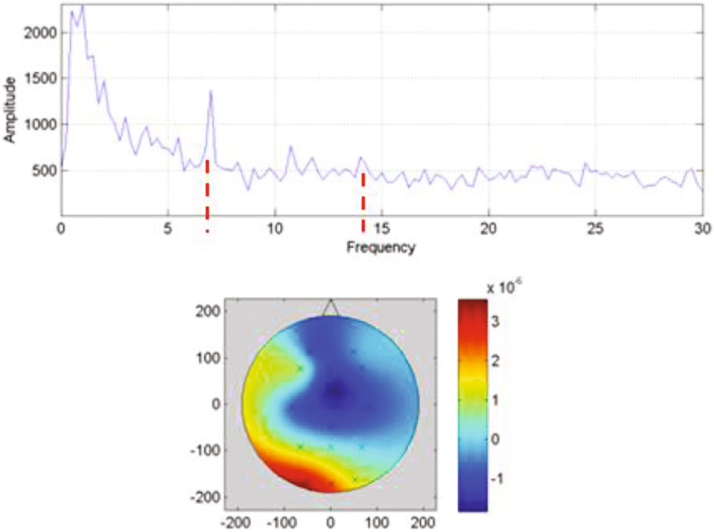


Fig. 14. Spectrum density and the distribution of weights on the scalp (user #5, 7 Hz session, IC7 component)

4.6 Spatial Location of Brain Sources Based on Independent Components

Location of sources performed using LORETA algorithm gives a very clear view of the structure of SSVEP. For example, for user #1 the greatest activity was observed in the rear part of the head for IC10 component (Fig. 15), which coincides with conclusions obtained from previous experiments. For comparison, IC9 and IC7 components, showed maximum activity in central parts of the head (Figs. 16 and 17), which clearly excludes their derivation from SSVEP.

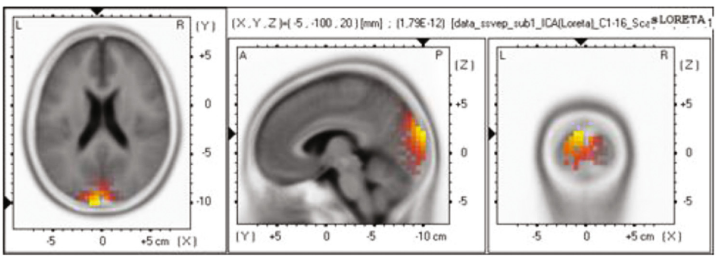


Fig. 15. Distribution of current density in the brain for IC10 (user #1)

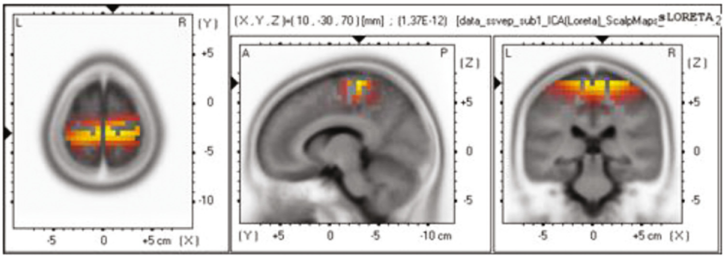


Fig. 16. Distribution of current density in the brain for IC9 (user #1)

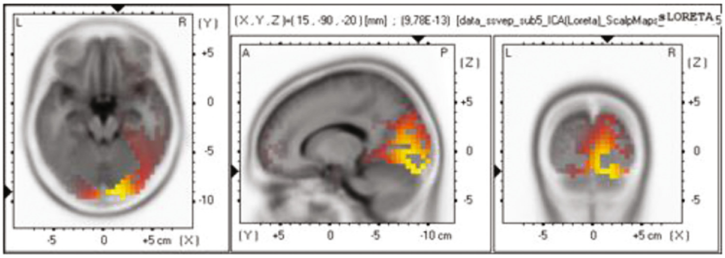


Fig. 17. Distribution of current density in the brain for IC6 (user #5)

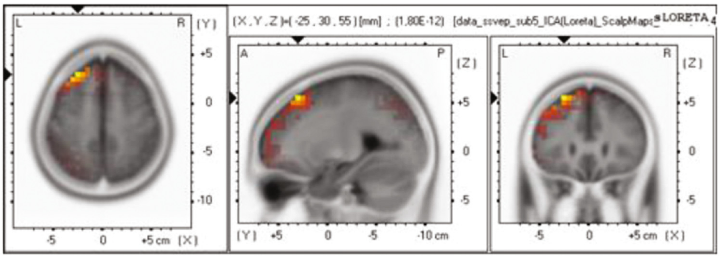


Fig. 18. Distribution of current density in the brain for IC7 (user #5)

Location of SSVEP sources proved to be useful also in less obvious cases, for example, in the aforementioned comparative analysis of components IC6 and IC7 for user #5. The results of inverse problem solution support the hypothesis of a greater connection of IC6 component with the SSVEP (maximum activity in the visual cortex Fig. 17) than IC7 component (the largest activity in the anterior cortex Fig. 18).

4.7 Results of Independent Components Classification

Finally, based on independent components, the classification of individual SSVEP was made. The results for users #1, #3, and #5 are illustrated in Figs. 19, 20 and 21, respectively.

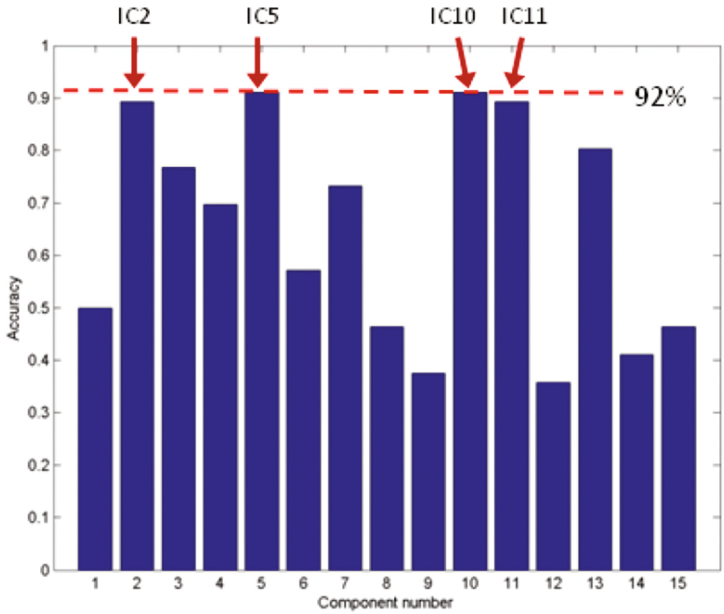


Fig. 19. Classification effectiveness for user #1

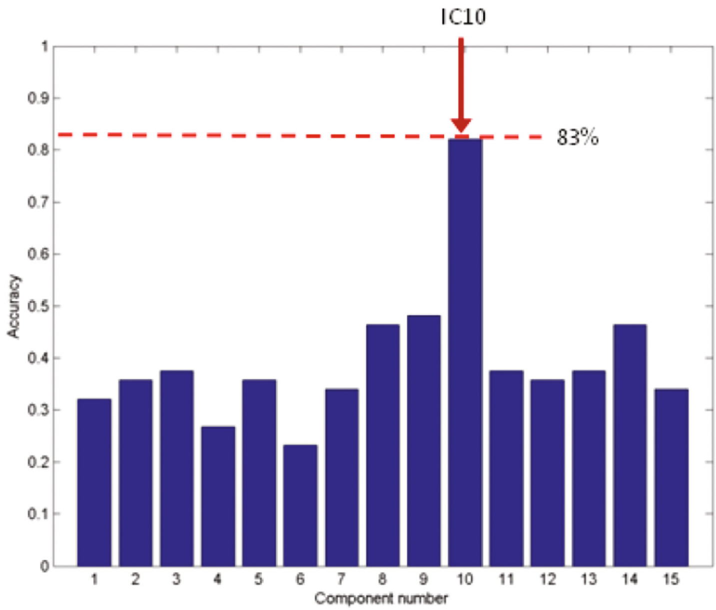


Fig. 20. Classification effectiveness for user #3

Classification results confirm the hypothesis presented earlier and observations from the harmonic analysis of independent components and location of sources in brain. For user #1, fairly good classification results were obtained for several components (IC10, IC5, IC2, and IC11). The best classification results were obtained for only one component in users #5 (IC6) and #3 (IC10). For users #2 and #4, ICA did not significantly improve classification accuracy. This may be due to artifacts and possibly weak concentration of the user on flashing LED.

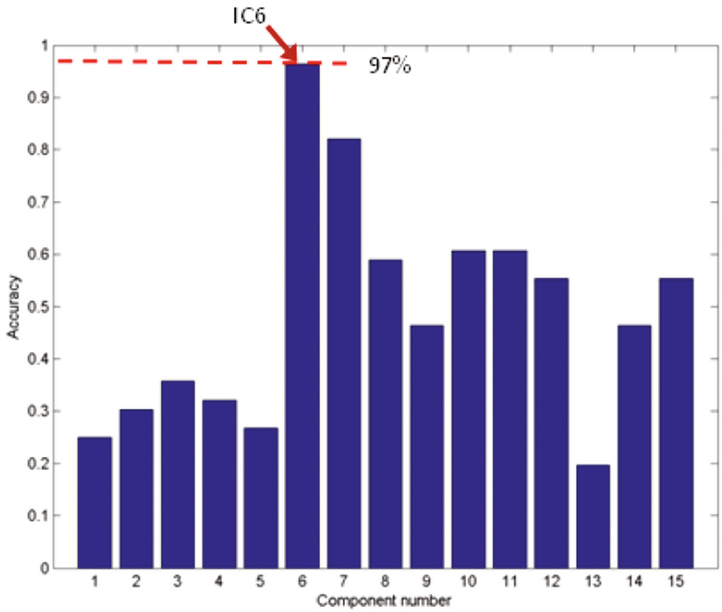


Fig. 21. Classification effectiveness for user #5

5 Conclusions

For a well-recorded EEG signal (including the lack of artifacts or their elimination), sufficiently good and unambiguous SSVEP detection can be obtained without the extraction of independent components (ICA). This was confirmed by the results of frequency and time-frequency analysis and the results of the location of sources of SSVEP. In more ambiguous cases, ICA proved to be an effective method of searching the most appropriate components related to SSVEP. However, the high correlation of independent component with SSVEP does not always mean higher energy of signals related to stimulus frequency, recorded on the electrodes located on the visual cortex (O1/O2/Oz).

Very reliable information was provided by SSVEP about source location and spectral analysis of independent components, which are consistent with the results of classification. Hence, the highest classification efficiency is observed for those components for which the largest current density appear in the visual cortex of the brain (the back of the head). In general, described EEG analysis tools (algorithms) developed for the detection of SSVEP are characterized by relatively high efficiency.

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