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A New Method of Spatial Filters Design for Brain-Computer Interface Based on Steady State Visually Evoked Potentials

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Abstract—**In the article the authors present their own method of designing spatial filters to use in brain-computer interface, based on steady state visually evoked potentials. The spatial filter is calculated by minimizing a specially created objective function. The developed method allows us to create a dedicated filter for each user, however it demands a calibration session. By using designed spatial filters it is possible to identify visual potentials for very close frequencies of flickering light with good efficiency (information transfer rate at 27-57bit/min).**

Keywords—spatial filter, steady state visually evoked potentials, SSVEP, electroencephalography, EEG, brain-computer interface, BCI

I. INTRODUCTION

In brain-computer interfaces advanced methods of measuring brain activity and sophisticated methods of data processing and analysis are commonly used. A number of papers are devoted to brain-computer interfaces based on steady state visually evoked potentials (SSVEP) [1-8]. Generally speaking, in such interfaces the analysis of visual cortex response to light sources flickering with different frequencies is performed [8]. LEDs or display screen are the most commonly used as the sources of flickering light [3-5]. Brain-computer interfaces based on SSVEP are characterized by high information transfer rate (ITR) and do not require a long process of user training [7].

In accordance with neuropsychological knowledge it is possible to indicate the places on the user's head where the visually evoked potentials are expected to have significant values [1]. In literature many such interfaces are described as operating with several electrodes, most often located in O1, O2 and Oz positions of international 10-20 system [1]. However, to get better results a higher number of electrodes can be used. In this case spatial filters that maximize the amplitudes of the interesting to us visual potentials and increase the signal to noise ratio are very helpful [6].

There are several methods of designing spatial filters. In the article the authors present their own method and describe the implementation results of the designed filters, which show significant improvement of the ability to identify SSVEP in EEG signal.

II. SIGNAL PROCESSING

In the EEG signal analysis, filtering in frequency domain is of great importance for the identification of useful potentials. Spatial filters have proven to be equally useful in this task [2]. There is a whole range of methods of designing spatial filters including: simple average combination, principal component analysis, independent component analysis, common spatial patterns and maximum contrast combination [2]. In all the approaches, such a linear combination of input signals is sought that will maximize signal-to-noise ratio for the desired frequencies. Thus a new signal S is a linear combination of potentials of N electrodes x_n with weights w_n.

$$S = \sum_{n=1}^{N} w_n x_n \quad (1)$$

There are several possibilities for choosing the weights w_n to create the new signal S. The authors propose to calculate the w_n weights to minimize a specially created objective function f. By the use of a spatial filter it is possible to maximize the amplitudes of the signal in the first harmonic (k [Hz]) and subsequent harmonics in 2k, 3k [Hz] (of the flickering light used as stimuli).

We propose objective function f as follows:

$$f(k) = \left\{\boldsymbol{DFT}(k) - \frac{\boldsymbol{DFT}(k-1)+\boldsymbol{DFT}(k+1)}{2}\right\} \quad (2)$$

where **DFT** depicts a module vector of the discrete Fourier transform of signal S [1]. In other words, the objective function enables us to maximize "peaks" of signal at stimulation frequency f in the neighborhood of (k-1) and (k+1) [Hz] (Fig. 1).

To calculate the filter weights w_n a calibration session is required. During the session a user is stimulated with light flickering with k Hz and for the registered EEG data a spatial filter that minimizes the function f is sought. The authors decided to use light flickering with 7Hz as a stimulation to calculate the coefficients of spatial filter (calibration session).

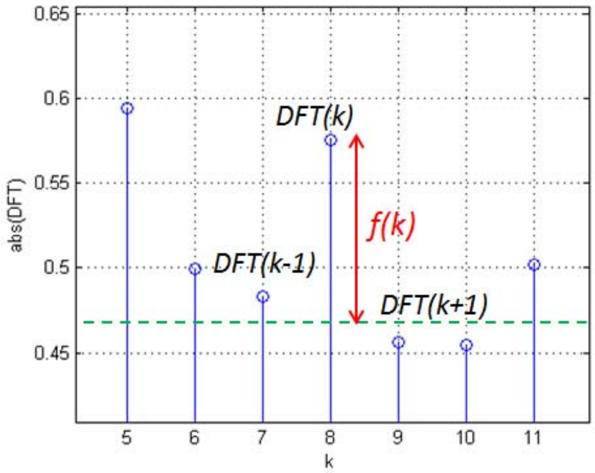

Figure 1. The objective function *f(k)* that maximizes the value of spectral line in *k* Hz in neighborhood of (*k-1*) and (*k+1*) Hz.

The authors tested several methods for finding the minimum of the objective function *f*. These were: quasi-Newton method, simplex search method of Lagarias and genetic algorithms. None of these methods give any guarantee of obtaining the global minimum. For that reason the minimum was calculated several times and the results were averaged. This way we calculated a spatial filter for the detection of SSVEP.

III. EXPERIMENT

Five users, at the age of 23, 25 31, 42, and 46 participated in the experiment. Users sat comfortably in a chair. A green LED of a 1cm diameter was placed at a distance of about 1 meter from the eyes of a person. EEG signals were recorded using g.USBAmp with 16 active electrodes. The electrodes were placed according to the international 10-20 system at positions: O2, AF3, AF4, P4, P3, F4, Fz, F3, FCz, Pz, C4, C3, CPz, Cz, Oz, O1. EEG sampling frequency was 256Hz. The signals were recorded using a Butterworth bandpass filter (0.1-100Hz) and notch filter (48-52Hz) to correct a technical artifact from the power network.

Users were stimulated with flickering LED light of frequencies: 5Hz, 6Hz, 7Hz and 8Hz. The stimulation lasted 30 seconds. Additionally, for each user five calibration sessions (for 7Hz) were performed. All sessions took place at the same time of the day to avoid circadian influences on the measurements.

IV. RESULTS AND DISCUSION

The results clearly showed that the presented method allows us to enhance SSVEP in EEG signals. Some objections to the proposed method may arise from the fact that the created spatial filter might maximize the value of spectral line only for calibration frequency k. But, as it turned out, the filter also enables us to strengthen the SSVEP for its subsequent harmonics (Fig. 2). This statement is true for different frequencies of flickering light.

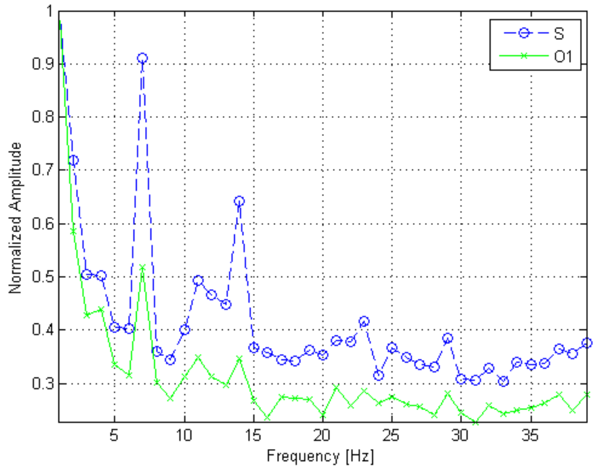

Figure 2. The spectrum of 30 seconds of signal for the O1 channel and the *S* signal created with the use of spatial filter. For 7 Hz stimulation a 14 Hz spectral line is also clearly visible.

In addition, we analyzed obtained weight values of the designed spatial filters. The highest weight values were associated with electrodes located at the back of the head (visual cortex), that is electrodes O1, O2 and Oz (Fig. 3). This is consistent with the neuropsychological knowledge and confirms the correctness of the proposed method of spatial filter design. The designed spatial filters eliminate differences in placement and gains of individual electrodes. For each user a cap may be slightly differently worn on the head, for example due to different anatomy of the skull. Also skin/electrode conductivity may be different for different users.

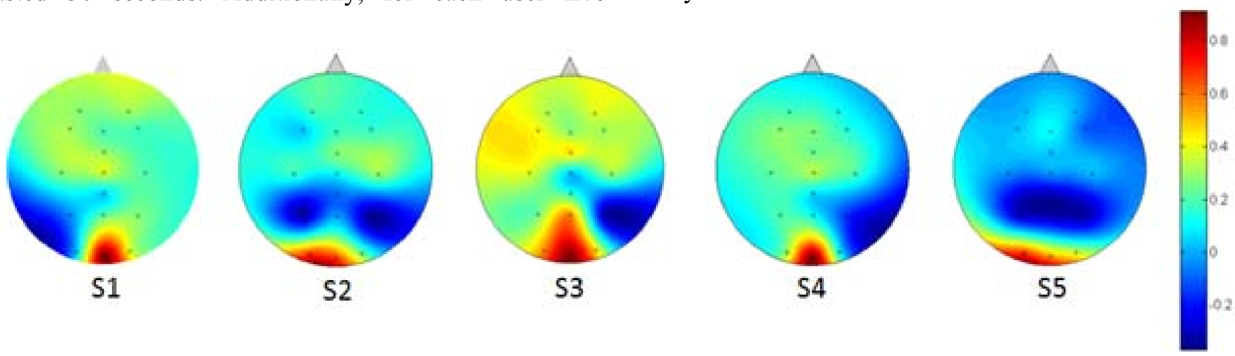

Figure 3. Distribution of weight values for users S1-S5.

The authors performed classification tests in order to prove the usefulness of the designed spatial filters in the SSVEP recognition task. Four classes, corresponding to frequencies 5Hz, 6Hz, 7Hz, 8Hz were taken into account. For each user, the spatial filter was designed during calibration session performed for light flickering with 7Hz frequency. The designed filter was used to determine the new S signals for frequencies: 5Hz, 6Hz, 7Hz, 8Hz. Features of the S signal (for a particular frequency) were calculated for 2s and 4s width windows. The signal feature vectors constitute of values of the first, second and third harmonics of flickering light at frequencies: 5Hz, 6Hz, 7Hz, 8Hz, 10Hz, 12Hz, 14Hz, 15Hz, 16Hz, 18Hz, 21Hz, 24Hz. Examples of obtained averaged spectra for four classes of frequencies 5Hz, 6Hz, 7Hz, 8Hz (flickering light) for the user S1 are shown in Fig. 4.

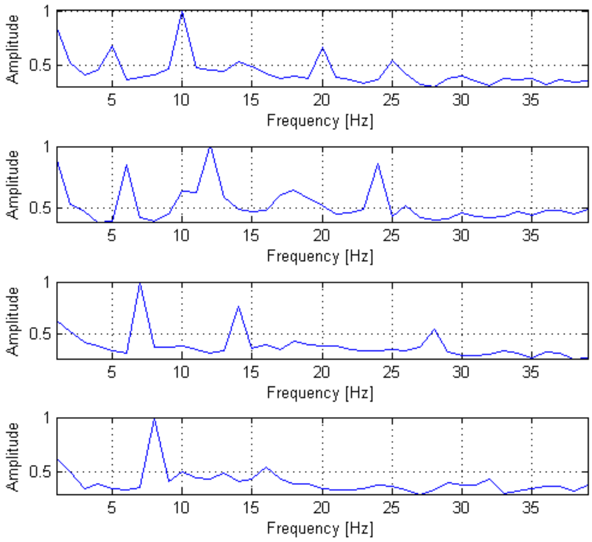

Figure 4. Figure 4.Averaged spectra for four classes of frequencies 5Hz, 6Hz, 7Hz, 8Hz for the user S1

For classification the nearest neighbor classifier K-NN and 10-fold cross validation test were used. Classification accuracy was defined as the correctness of the assignment of the EEG potentials into one of four classes corresponding to frequencies 5, 6, 7 and 8Hz. Classification accuracy for random signal was 0.25 in each case. The results of classification accuracy (ACC) for individual users are presented in Table 1.

TABLE I. CLASSIFICATION ACCURACY

	S1	S2	S3	S4	S5
ACC for 2s window	0.99	0.86	0.99	0.77	0.68
ACC for 4s window	0.99	1	0.99	0.99	0.99

Classification results indicate that the features determined for the four classes (frequencies) after applying a spatial filter enable efficient recognition of SSVEP. This results in ITR coefficient at 27-57 bit/min. It should be noted that flickering light frequencies used for user stimulation differ only in 1 Hz.

It is worth mentioning that for only one electrode O1, without the use of EEG signal preprocessing, described above, we achieved an average (for all users) classification accuracy of 0.61.

It is difficult to directly compare the achieved results with the results published in the literature by different teams. The main reason for that is the difference between used frequencies of flickering light. Here, we compare the obtained accuracy with the most similar existing studies. In [10] there were presented the results of SSVEP potential classification for four frequencies 30, 35, 40 and 45Hz. For 6 users the classification accuracy ranged from 0.83 to 1. It should be noted, however, that the distance between stimuli was 5Hz. In [1] there were shown the classification results for five subjects and frequencies 6, 7, 8 and 13Hz. The achieved classification accuracy for an individual user was between 42.5% and 94.4%.

During the experiments we also examined the impact of the method used to find the minimum of the objective function: quasi-Newton method, simplex search method of Lagarias and genetic algorithm. All of these methods gave very similar results.

The authors also tried to use objective functions that take into account not only two adjacent to stimulus spectra lines, but also the average value of several spectra lines in the neighborhood of the stimulus. Each of the tested objective functions gave similar results.

V. CONCLUSIONS

In this paper a new method for creating spatial filters for use in BCI based on SSVEP is presented. The developed method allows us to create a dedicated filter for each user. With the filter it is possible to find such a combination of electrodes that enhance the SSVEP. Experiments showed that the method helps to identify SSVEP for very close frequencies of flickering light with good efficiency. The disadvantage of the proposed method is the relatively long time needed to create a spatial filter (calibration session).

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