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# ADAPTIVE SPATIAL FILTERING: INCREASING THE EFFECTIVENESS OF MOTOR IMAGERY BASED BCI

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ABSTRACT: In this article a novel approach to spatial filtering of electroencephalographic (EEG) signals – Adaptive Spatial Filtering (ASF) is proposed. The goal of ASF is to enhance the components of EEG signals that are specific to the spatial location of analyzed electrode, while at the same time to reduce the influence of components originating from distant sources of brain's bioelectrical activity. For that purpose an approach is utilized, where electrodes uncorrelated with analyzed electrode are used as noise input for the multichannel Adaptive Noise Cancelling algorithm. Proposed method is evaluated and compared with most popular approaches to spatial filtering: Common Spatial Patterns and its Filter Bank extension. Influence of compared algorithms on the classification accuracy of motor imagery tasks is tested on the data from 'Dataset IVa' provided for the 'BCI Competition III' and 'EEG Motor Movement/Imagery Dataset' provided by the BCI2000 group. During all performed tests ASF outperformed reference methods achieving $94\%$, $84\%$ and $82\%$ mean classification accuracies.

## INTRODUCTION

Interpretation of the electroencephalographic (EEG) data often involves speculation about the possible locations of the sources inside the brain that are responsible for the observed activity on the scalp [1]. Since it is difficult to interpret recorded EEG signals in terms of the site of the underlying neuronal process, determining the relationship between different signals recorded at various scalp locations is required. It is desirable to eliminate or account for the possible linear relation resulting from the volume conduction [2]. This relation can be represented in a form of weighted combination of some or all measurement channels inside a defined neighbourhood of the channel of interest. Such approach is often related to as *spatial filtering*. It has gained a great popularity for EEG processing problems in Brain-Computer Interface (BCI) applications [3, 4]. In theory, use of spatial filters should either lead to decomposition of the EEG data into components containing activity related to specific sources or elimination of the overlapping signals originating from sources other than those in the direct neighbourhood of the measurement electrode. The Common Spatial Pattern (CSP) method represents one of the most popular approaches to the spatial filtering. Is is a technique used for the analysis of multichannel EEG recordings with two classes of different EEG phenomena present [3]. For that purpose it provides the set of spatial filters in form of the transformation matrix. One of the drawbacks of the CSP is that it's performance is highly dependent on the selected frequency bandwidth in which signals are analyzed. Thus, the theoretical assumption that the analysed signals have been bandpass filtered to the most discriminative frequency range for both classes [3]. An effective solution to this problem was presented as the Filter Bank CSP (FBCSP) [5]. In this method the EEG signals are first bandpass filtered into few frequency subbands. Then, the CSP algorithm is applied independently to each subband. Since its introduction, FBCSP has become a state-of-art approach for the spatial filtering of EEG signals containing motor imagery related tasks [5, 6].

In this article use of the Adaptive Noise Cancelling (ANC) techniques for the elimination of source overlapping effects from EEG recordings presented as a novel algorithm - the Adaptive Spatial Filtering (ASF) is being examined. The general idea of the proposed approach is based on the assumption that signal measured by each electrode consists not only of component that contains information specific to the location of that electrode, but also of unwanted ones that originate from sources closer to other electrodes available in the experiment. Therefore, signals recorded by these distant electrodes can be used as a noise reference for any multichannel algorithm of adaptive filtering. In theory, signal achieved as a result of such filtering will be free from the influence of electrical sources that are distant from the analysed electrode. At the same time, this decoupled recording will be a reliable representation of the neuronal activity occurring in the close localization of the measurement point. Use of adaptive filters is a known practice in the processing of EEG signals. Such algorithms are widely used for the removal and correction of artifacts that, due to their amplitude and shape, are clearly distinguishable from the background EEG activity (e.q. eye blinks, muscular artifacts, electrode movement) [7]. In these classical applications some additional reference recording of noise signal (i.e. electrooculogram) must be provided for the adaptation algorithm. Since such signal is not always available, a focus of researchers have been already drawn to

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the problem of utilizing EEG recordings for that purpose [7]. However, to the best knowledge of the Author of this article no research has ever been conducted on the use of such approach for the problem of elimination of source overlapping in EEG.

## MATERIALS

*Dataset IVa:* One of two datasets used for the evaluation of proposed method was the 'Dataset IVa' provided for the 'BCI Competition III' organized by the Berlin Brain-Computer Interface group which took place in 2005 [4, 8]. All available signals were recorded using BrainAmp amplifiers with 118 EEG channels with 1000 Hz sampling frequency and 16 bit accuracy, band-pass filtered to the $0.05 \div 200$ Hz range and then downsampled to 100 Hz. The measurement electrodes were positioned with regard to the extended *10-20* montage system. Data was recorded from five healthy subjects denoted as *aa, al, av, aw, ay*. For each subject 280 trials of either right hand or foot movement imagination were available. Visual cues indicated for 3.5 s which of the motor action the subject should imagine [4]. Detailed information about used dataset can be found in [8].

*EEG Motor Movement/Imagery Dataset:* Second dataset used in this research was 'EEG Motor Movement/Imagery Dataset' (EEGMMI) provided by the BCI2000 group [9] and contributed to the PhysioNet platform [10]. Signals were recorded using 64 electrodes placed accordingly to the *10-10* montage system with $160Hz$ sampling frequency. The EEGMMI consists of data recorded from 109 subjects. Each of whom was asked to perform specific tasks organized in the following sessions (either 7 or 8 repetitions per task): right vs. left hand movement, imagination of right vs. left hand movement, both hands vs. feet movement and imagination of both hands vs. feet movement. Each session was repeated 3 times and lasted approximately 2 minutes. As a result between 21 and 24 trials per class were obtained. Duration of one trial was about 4-s long. In this research only sessions with tasks involving motor imagery were used. Additionally, since this work is focused on the two class problems, sessions involving Left vs. Right hand motor imagery were treated separately from the Hands vs. Feet sessions. As a result, two different validation experiments could be performed on the EEGMMI dataset.

*Validation and parameter tuning:* To test the proposed ASF algorithm the following validation procedure was performed. For 'Dataset IVa' all trials were divided into two sets depending on their class membership. Then trials in each set were sorted chronologically. 70% of consequent trials from each class were used to create a set used for the classifier training and parameter tuning purposes. The remaining samples formed a test set, which was used only once, to evaluate algorithm's accuracy. Both sets were designed in way so that both classes were represented equally. In order to assure that the results achieved during the experiment are statistically meaningful such validation was repeated 7 times. The new folds were created by selecting consecutive 70% of trials beginning from a different trial each time. These starting trials were evenly distributed across all examples, so that the best data coverage was provided. Consistency of the data was achieved by implementing the circular buffer idea in cases where the length of the training window exceeded the total data length. Organization of sessions in the EEGMMI dataset allowed to approach the problem of creating the data folds in a slightly different way. Since there were 3 repetitions of both Left vs. Right and Hands vs. Feet sessions (each containing $7 - 8$ trials per class) a more natural division was possible. In this research one complete session of specific motor imagery tasks was used as an independent test set, while remaining two sessions containing the same mental actions were used for training and parameter tuning purposes. That way it was ensured that both classes will be represented by a similar amount of examples. Additionally, such way of dividing data guarantees that trials used for testing were recorded during the same time window and that both test and train examples maintain some kind on continuity. Described validation procedures implemented for both datasets allow to take into consideration not only the order of samples from each trial but also the chronological order of the trials. Proposed approach resembles a real life case where training trials for the BCI calibration are recorded consequently during specified time frame. Such examples will share some common characteristics, that might differ for trials recorded in later stages (i.e. during the operation of the system). The resemblance of the proposed procedure of data partitioning to the real applications is a significant advantage over random choice of trials or individual samples. For most of the spatial filtering approaches presented in the METHODS section to perform on a satisfactory level, some parameters need to be properly selected. The method of parameter tuning used in this work requires that the data dedicated for training purposes is divided accordingly to the procedure described for the 'Dataset IV' earlier in this section. As a result two subsets of the training set are created, which will be referred to as subtraining and subtest. Then, the EEG signals are processed with the different values of the tuned parameter of specific spatial filtering method, the classifier is trained on a subtraining dataset and the accuracy on the subtest set is obtained. This is repeated 7 times and the parameter which achieved the highest median accuracy is selected for the specific validation session. It must be noted that the training data of the current validation session remains uninvolved in the parameter tuning process. Since Author of this article prioritize the research on the real-time BCI applications, instead of classifying each trial as a whole, the classifier output was provided for every sample tagged as containing imagination of motor movement and belonging to the assumed region of interest. Due to the nature of the experiment, the reaction time of the subject could potentially become a variable in the process of evaluation of system's accuracy. Since such influence

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is an uncontrollable factor, it is desirable to diminish or remove it's impact on the results. In this research, this problem was avoided by selecting and classifying only samples that appear after 0.5 s from the moment tagged as a start of the trial.

METHODS

*Adaptive Spatial Filtering:* The idea behind the Adaptive Spatial Filtering of EEG signals proposed in this work stems from the concept of Adaptive Noise Cancelling [11]. In this methodology an auxiliary (reference) input from at least one sensor is used in process of the elimination or attenuation of the noise present in the primary input $s$. Let us assume that the analyzed signal $s$ consists of two additive components $d_0$ and $n_0$. Therefore, it can be represented as $s = d_0 + n_0$, where $d_0$ denotes the desired part of the $s$ and $n_0$ is a noise that is not correlated with $d_0$. Additionally, present is an auxiliary signal $n$ which also is not correlated with $d_0$, but in some unknown way correlates with the noise $n_0$. Such signals are often called reference and should be recorded at noise field locations where the signal of interest $d_0$ is weak [11]. Providing more than just one reference input to the ANC algorithm can improve it's performance in scenarios where one source of noise is present [11]. Moreover, if there are many sources of noise coming from different locations, increased number of auxiliary signals recorded by specific sensors can be very effective [11]. In such cases $n$ will consist of $N$ signals recorded by different sensors at varying locations. This can be noted as $n = \{n_1, n_2, \ldots, n_N\}$. For applications where $N > 1$ the algorithm is often referred to as Mutichannel Adaptive Noise Canceller. If each of the input reference signal components $n_k$ ($k = 1, \ldots, N$) could be transformed (filtered) so that the their summed output $y = \sum_{k=1}^{N} y_k$ would resemble the unknown noise component $n_0$ it could then be subtracted from the analyzed signal $s$. Assuming that the signal $n_k$ after the transformation is denoted as a $y_k$, described operation can be presented as in Eq. 1. As a result the estimate of uncorrupted desired signal $e \simeq d_0$ will be achieved. Signal $e$ can also be treated as the error of adaptation.

$$e = d_0 + n_0 - y \tag{1}$$

In an ANC applications said transformation of recorded noise input $n$ is realized by an adaptive filtering. An adaptive filter automatically adjusts its own impulse response through an algorithm that responds to an error signal $e$ [11]. If $n_k(t) \in \mathbb{R}^M$ is a segment of signal $n_k$ a time index $t$ consisting of $M$ discrete samples with indexed $[t - M + 1, \ldots, t - 1, t]$, then the output of a adaptive filter at discrete moment $t$ can be calculated as in Eq. 2.

$$y_k(t) = n_k(t)^T w_k(t) \tag{2}$$

The coefficients $w_k(t) \in \mathbb{R}^M$ of the filter are being adjusted individually for every input with each new sample. The adaptive algorithm used for that in this work is the Normalized Least Mean Squares (NLMS). If algorithm's error at index $t$ is denoted as $e(t) \in \mathbb{R}$ and calculated accordingly to the Eq. 1, then the formula for updating the filter coefficients for $t + 1$ sample is presented in Eq. 3.

$$w_k(t + 1) = w_k(t) + \mu(t)e(t)n_k(t) \tag{3}$$

The NLMS guarantees a better stability than the classical Least Mean Square algorithm thanks to the normalisation of the fixed adaptation step $\mu_0$ with the power of input [12]. The purpose of $\gamma$ parameter is to prevent situations where the denominator of that expression approaches 0.

$$\mu(t) = \frac{\mu_0}{\gamma + n_k^T(t) n_k(i)} \tag{4}$$

It should be particularly emphasized that the described Multichannel ANC algorithm satisfies all the causality requirements and therefore is suitable for the real time applications. The block diagram of the described algorithm is presented in Fig. 1.

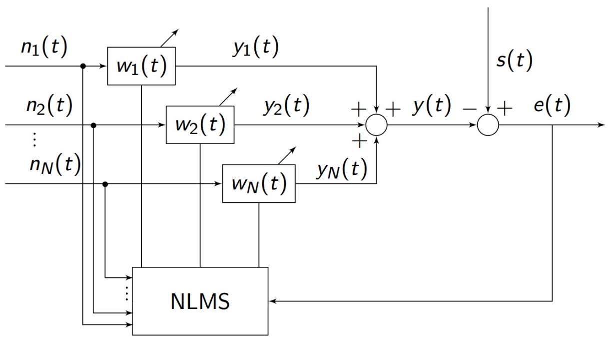


Figure 1: Block diagram of a Multichannel ANC filter.

The general idea of proposed ASF approach is based on the assumption that signal recorded by each electrode consists of desired component which contains information specific to the location of that electrode and unwanted, noise that originates from sources closer to other electrodes available in the experiment. Additionally, undefined measurement noise and artifacts (i.e. muscular) are in some way present in all recordings measured by all electrodes. With simplification it can be assumed that as the distance of the electrical signal from its bioelectrical source increases, its amplitude decreases [2]. However, it must be emphasized that said assumption does not state that activity originating from the source closest to the electrode will be the strongest one present in the raw EEG recording [13]. Nevertheless, the introduced assumption leads to an observation, that for the electrode labeled $ch$ signals recorded by electrodes from some subset electrode labels $L_{ch} = \{L \setminus ch\}$ can be used as a noise reference for the multichannel ANC algorithm described earlier in this section. In this scenario, $L$ denotes the set of all electrode labels that are available in the experiment. In

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theory, signal achieved as a result of such adaptive filtering would be free from the influence of electrical activity of sources that are distant from the analysed electrode $ch$. At the same, this decoupled recording will be a reliable representation of the neuronal activity occurring in the direct localization of the measurement point. To guarantee a satisfactory performance of the ASF, a proper selection of the subset of electrodes used as the multichannel noise reference must be ensured. According to the basic principles of the ANC algorithms, signals used for that purpose cannot be correlated with the filtered signal [11]. Therefore, for the analyzed electrode $ch \in L$ adaptation is performed only on the subset of electrodes $L_{ch}$ for which the Pearson's correlation coefficient $r(ch, l)$ $(\forall_{l \in L})$ with signal from $ch$ is lower than some user-defined parameter $T_r$. To maintain the compatibility with previously introduced symbols, in this scenario, the secondary input to the Multichannel ANC filter $n$ will be composed of signals recorded by the electrodes whose labels belong to the subset $L_{ch}$. Therefore, proposed ASF algorithm requires for a few parameters to be specified, such as the number of filter coefficients $M$, initial adaptation step $\mu_0$, parameter $\gamma$ and the Pearson's correlation threshold used for selecting the reference electrodes $T_r$. During the experiments performed for the purpose of this work, the following, exemplary parameters were chosen for both datasets: $M = 3$, $\gamma = 0.01$, $T_r = 0.6$. To ensure the improved stability and effectiveness of the ASF algorithm the $\mu_0$ was selected individually form the set of values $\mu_0 = \{0.0001, 0.0005, 0.001, 0.005, 0.01\}$ for each test with respect to the parameter selection approach described in the MATERIALS section of this article. During the experiment the ASF algorithm was applied to the raw EEG data. The subset of electrodes used as the reference $L_{ch}$ was selected individually for each analysed electrode. The Pearson's correlation values $r(ch, l)$ were calculated only on the basis of time segments containing the interesting brain activity (i.e. during motor imagery periods) from training sessions. Therefore, $L_{ch}$ was not updated after the training stage. The signal power features were extracted directly form the filtered data. All of them were passed to the classification algorithm (no feature selection stage was implemented). No artifact correction or bandpass filtering was applied for the additional processing of the EEG signals.

*Reference methods:* The influence of the proposed ASF algorithm on the accuracy of classifying various mental activity tasks was compared with three classical approaches. First method used as the reference during the comparison does not involve any spatial filtering and will be referred to as the *basic* approach. Here, the raw data is only bandpass filtered to the frequency range from 8 to $30Hz$. This specific band was selected as it is often associated with brain activity related to the planning of movement [3, 14]. The bandpower features are then extracted directly from the filtered data. No additional steps like feature/channel selection are used in this approach. The Common Spatial Pattern method is a technique used for the analysis of multichannel EEG recordings with two classes of different EEG phenomena present [3]. As a result of CSP the variance of the transformed signals is maximized for examples from one class, while at the same it is minimized for the other class. For that purpose it provides the set of optimal spatial filters in form of the transformation matrix. In general, only a few pairs of filters from both ends of eigenvalue spectrum carrying a discriminant information are used [3]. Therefore, a feature selection step is often required in order to maximize the effectiveness of CSP decomposition. In this work, the best number form between 1 and 8 of the consecutive CSP filter pairs were selected for each subject and each validation session during parameter tuning stage. Since performance of the CSP method is highly dependent on the selection of frequency bandwidth in which signals are analyzed, they were bandpass filtered to the frequency range from 8 to $30Hz$ befor the applying CSP. Third method used for the comparison in this research is the FBSCP [5]. In this method the recorded EEG signal is first bandpass filtered into $B$, small and consequent frequency subbands. In this research the same $B = 9$ subbands as in the original paper of FBCSP were selected: $[4-8]$ Hz, $[8-12]$ Hz, $[12-16]$ Hz, $[16-20]$ Hz, $[20-24]$ Hz, $[24-28]$ Hz, $[28-32]$ Hz, $[32-36]$ Hz, $[36-40]$ Hz [5]. After filtering, the CSP algorithm is applied independently to each frequency band. Then, for each CSP transformation a $C = 3$ pairs of filters were selected and bandpower features were calculated for each sample. As a result $F_0 = 2 \times C \times B = 54$ features were extracted for each time index in the region of interest. To avoid overfitting of the classifier to the training data, the FBCSP requires for the feature selection step to be performed. Authors of this method have validated it with multiple feature selection algorithms [5]. According to the results of the mentioned study, the Mutual Information-based Best Individual Feature (MIBIF) method works very effectively with the FBCSP. Based on the MIBIF only $F_1$ best features from the original subset of $F_0$ is chosen for the further analysis. In this work the number $F_1$ was selected individually for each subject and each validation session from the subset $F_1 \in \{1, 2, 3, 4, 5\}$ during the parameter tuning stage. It must be noted that due to the pairing of the CSP features, the corresponding feature from the pair had to be additionally included if it was not selected by the MIBIF algorithm.

All spectral filtering operations in this research were performed with the Finite Impulse Response (FIR) filter of order 364. Coefficients of the used filters were designed using the Kaiser window. Linear phase characteristics of the FIR filters make them ideally suited for the processing of biomedical signals. On the other hand, the delay introduced by such filtering may significantly influence the quality of the BCI systems in terms of real-time performance. Since the focus of this research was mostly placed on the evaluation of the proposed spatial filtering method it was decided that the filter's delay should be neglected. Therefore, the zero-phase filtering was applied

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during offline processing. This was achieved by a recursive filtering of the original signal both forward and backward in time [15]. As a result, a perfect frequency filtering could be assumed in the performed experiment. This operation was applied to all of the reference methods used in the experiment. It must be noted that such approach favours slightly these approaches as in the normal scenario their output would be delayed resulting in worse classification accuracy and generally decreased performance of the BCI system.

*Machine learning:* The characteristics of the signals achieved after their processing were described by the logarithm of their power in specific frequency ranges. To ensure the causality of the feature extraction step only the analysed time index and those that precede it were taken into consideration. In this research the 0.5 s-long time window was used. The features were extracted for every sample during each trial and provided as an input to the Linear Discriminant Analysis (LDA) classifier. This simple classifier has been successfully used in many BCI systems and has generally produced a satisfactory results [16]. One of the main motivations for the choice of LDA classifier in this experiment was it's simplicity and transparency in data processing. Thanks to these features, the participation of the classification algorithm in the feature engineering process has been restricted. Thanks to that, the results achieved in this research will not be biased by the quality of cooperation between spatial filtering algorithm and classifier in extracting features of the data.

## RESULTS

In Tab. 1 presented are the mean accuracies obtained after 7 cross-validations performed for each subject from the Dataset IVa. For each sessions used in this test the best set of parameters was selected for each method. This was achieved with accordance to the parameter tuning approach described in the METHODS section of this work.

Table 1: Dataset IVa - mean accuracies

| Method | Avg | aa | al | av | aw | ay |
|---|---|---|---|---|---|---|
| **ASF** | 0.94 | 0.93 | 0.95 | 0.89 | 0.96 | 0.96 |
| FBCSP | 0.81 | 0.78 | 0.92 | 0.66 | 0.86 | 0.84 |
| CSP | 0.79 | 0.71 | 0.90 | 0.67 | 0.85 | 0.84 |
| basic | 0.70 | 0.62 | 0.82 | 0.57 | 0.71 | 0.76 |

A more informative summary of the experiment performed on the Dataset IVa can be found in Tab. 2. The statistics used for the description of the achieved results were the first quartile $Q_1$, mean value, third quartile $Q_3$ and standard deviation $\sigma$ calculated from the accuracies of all tests performed on all subjects for each method. Therefore a more complex and profound overview of the experiment was achieved.

Table 2 - Dataset IVa - statistics

| Method | $Q_1$ | Mean | $Q_3$ | $\sigma$ |
|---|---|---|---|---|
| **ASF** | 0.88 | 0.94 | 1.00 | 0.08 |
| FBCSP | 0.74 | 0.81 | 0.87 | 0.10 |
| CSP | 0.71 | 0.79 | 0.86 | 0.09 |
| basic | 0.62 | 0.70 | 0.77 | 0.10 |

Since the EEGMMI dataset contains a large number of subjects it was decided to omit the presentation of the average accuracies achieved for each of them. Instead, in Tab. 3 the statistics calculated for Hand vs. Foot classification task are shown. Likewise, same summary for Left vs. Right hand discrimination task is presented in Tab. 4. Values contained in both of these tables were obtained analogously to those presented in Tab. 2.

Table 3: EEGMMI (Hand vs Foot) - statistics

| Method | $Q_1$ | Mean | $Q_3$ | $\sigma$ |
|---|---|---|---|---|
| **ASF** | 0.78 | 0.84 | 0.90 | 0.08 |
| FBCSP | 0.54 | 0.63 | 0.69 | 0.11 |
| CSP | 0.58 | 0.66 | 0.74 | 0.11 |
| basic | 0.54 | 0.60 | 0.63 | 0.09 |

Table 4: EEGMMI (Left vs Right) - statistics

| Method | $Q_1$ | Mean | $Q_3$ | $\sigma$ |
|---|---|---|---|---|
| **ASF** | 0.76 | 0.82 | 0.89 | 0.10 |
| FBCSP | 0.52 | 0.57 | 0.60 | 0.08 |
| CSP | 0.55 | 0.62 | 0.66 | 0.10 |
| basic | 0.51 | 0.56 | 0.60 | 0.08 |

## DISCUSSION

Proposed in this work ASF algorithm significantly outperforms classical spatial filtering methods like CSP and FBCSP during tests performed on two class motor imagery-based BCI datasets. Statistics calculated for the distributions of the achieved accuracies presented in Tab. 2- 4 allow further assessment of the ASF performance. It can be observed that for all three datasets the mean accuracies of ASF are higher than for the reference methods. Additionally, in all cases first quartile $Q_1$ of ASF is higher than third quartile $Q_3$ of other methods tested in this work. Although FBCSP and CSP achieved expected mean accuracies on the Dataset IVa their performance on the EEGMMI dataset is unsatisfactory. This might be explained by a relatively small number of training trials for each validation session which ranged from 14 to 16 per class. As a result the number of training examples provided for the CSP and its Filter Bank modification might be too small for them to achieve their full potential. Training BCI systems with a limited number of trials is a known problem which has been discussed in the literature [4].
The tests to which the ASF and reference methods were subjected to can be considered to be demanding not only due to the high number of repetitions performed for each dataset. The goal of providing the output for each sample is generally considered to be more a more difficult task

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than the classification of the whole trial [6]. However, since ASF was designed for the real-time BCI applications such approach to testing was necessary.
It must be noted that the due to their nature the adaptive filters and ANC algorithms (such as ASF) are susceptible to instabilities [12]. Therefore, selecting the proper adaptation step during the parameter tuning stage of the ASF method was very important. The issue of stability of the adaptive filtering algorithms used with the ASF method should be a subject of further research. Due to the preliminary character of this work the tuning of the channel correlation threshold $T_r$ was omitted in this work. This shows that tuning of this parameter is not necessary for the ASF to achieve a high level results. Nevertheless, some future work must be devoted to the analysis of the influence of this parameter on the effectiveness of ASF, as it has the potential to additionally improve its performance.

## CONCLUSION

In this article a novel approach to spatial filtering of EEG signals the Adaptive Spatial Filtering is proposed. The algorithm has proved to significantly outperform the classic reference methods for two class BCI problems. The fact that the ASF does not require providing the number of classes present in the experiment is a great advantage over CSP-based approaches. As a result it can be easily used with the multiclass problems without the need of implementing strategies like *One vs. One* or *One vs. All*. Additionally, adaptive properties of the algorithm make it insusceptible to the changes of the EEG characteristics which occurs with the passing of the experiment time. Author of this work believes that the introduction of the ASF algorithm can lead to an advancement in the usable BCI technology capable of operating in the real time. Future research regarding the ASF algorithm will focus on its application to multiclass BCI problems. Additionally, its performance with limited electrode configurations (i.e. International *10-20* Standard) and with feedback BCI systems will be evaluated.

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