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Finding Optimal Frequency and Spatial Filters Accompanying Blind Signal Separation of EEG Data for SSVEP-based BCI

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Abstract—**Brain-computer interface (BCI) is a device which allows paralyzed people to navigate a robot, prosthesis or wheelchair using only their own brains reactions. By creating a direct communication pathway between the human brain and a machine, without muscles contractions or activity from within the peripheral nervous system, BCI makes mapping persons intentions onto directive signals possible. One of the most commonly utilized phenomena in BCI is steady-state visually evoked potentials (SSVEP). If subject focuses attention on the flashing stimulus (with specified frequency) presented on the computer screen, a signal of the same frequency will appear in his or hers visual cortex and from there it can be measured. When there is more than one stimulus on the screen (each flashing with a different frequency) then based on the outcomes of the signal analysis we can predict at which of these objects (e.g., rectangles) subject was/is looking at that particular moment. Proper preprocessing steps have taken place in order to obtain maximally accurate stimuli recognition (as the specific frequency). In the current article, we compared various preprocessing and processing methods for BCI purposes. Combinations of spatial and temporal filtration methods and the proceeding blind source separation (BSS) were evaluated in terms of the resulting decoding accuracy. Canonical-correlation analysis (CCA) to signals classification was used.**

Keywords—**BCI, SSVEP, BSS, FastICA, AMUSE, Infomax, Extended Infomax, CAR, Large Laplacian, Small Laplacian, CCA**

I. INTRODUCTION

WITH an increasing interest in brain-computer interfaces (BCI) there emerges a need for more accurate methods for decoding information from signals generated within cerebral cortex. One of the recent developments in the field of BCIs is utilizing blind signal separation (BSS) algorithms (e.g., independent components analysis, ICA [1]) in signal preprocessing pipeline. For signals acquired with an electroencephalograph (EEG) ICA is usually used as a denoising technique that allows removal of artifacts like eye and facial muscles activity (primarily blinks), heart beat/blood flow, chest and respiratory system's muscles contraction, signals from outside region of interest, etc. [2].

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Various BSS methods were successfully exploited to separate meaningful EEG signal from the noise (e.g., for P300 potentials [3] and for steady-state visual evoked potentials, SSVEP [4], [5]). In our previous work [6] we asked whether BSS algorithms may improve the accuracy of SSVEP decoding, and if it would be the case, which of the commonly used ICA algorithms (FastICA [7], Infomax [8], Extended Infomax [9] and AMUSE [10]) would be the most suitable for that purpose. The results we obtained implied that regardless of ICA method applied BSS preceding decoding of visually evoked potentials significantly increased the signal-to-noise ratio (SNR) and signal energy. There were also other attempts to establish which ICA algorithm should be used in order to increase SSVEP decoding [11][12]. However, up to date, we found no reports on the possible interaction between the kind of ICA method adapted and the other signal preprocessing procedures (e.g., filtering).

Therefore, in the current study, we asked what preprocessing techniques (frequency and spatial filtering [13]) should be conducted alongside ICA methods. Four hypotheses were tested: (1) whether BSS should be applied at the beginning or at the end of processing workflow; (2) would digital band-pass (frequency) filtration differentiate decoding accuracy; (3) similarly for spatial filters; (4) does general filter class used (frequency vs. spatial) influence the outcomes of the classification. Decoding measure metric chosen was information transfer rate (ITR), as it is a widely used method for estimating BCI performance [14].

II. MATERIALS AND METHODS

The high dimensional EEG dataset was collected from SSVEP database [5][10]. Signal acquisition was performed with 128 active electrodes, but in further analyses only seven were used: PO7, O1, POz, Oz, O2, PO8, FPz (according to the international standard of 10-20 [15]; correspondingly, in Biosemi-128 standard: A10, A15, A21, A23, A28, B7 and C17). The exception was CAR-all method (see below for its detailed description), where a signal from the whole scalp was utilized.

Four healthy subjects were told to observe two small reversing black and white checkerboards displayed at 21" CRT computer screen. The checkerboards were flickering at the frequency of 8 and 14 Hz. Each dataset contained 5 trials (25-second sample for each trial). Within each trial, there were 5 seconds of baseline at the beginning, 15 seconds of the stimulus exposition and the concluding 5 seconds without checkerboards. Signal analysis was carried out in Python (in particular with Python-MNE v. 0.15 [16][17]).

The research was conducted in three stages.

At the first stage we created various combinations of BBS algorithms and digital filters, which was roughly as follows (list of all used sequences are summarized in Table I):

1) BBS algorithm; digital and/or spatial filtering;
2) BSS algorithm; spatial and/or digital filtering;
3) digital and/or spatial filtering; BSS algorithm;
4) spatial and/or digital filtering; BSS algorithm.

TABLE I
CONDITIONS, KINDS OF FILTERS AND ICA ALGORITHMS UTILIZED

Group	Method or algorithm
BSS	BSS initiates signal processing
	BSS at the end of signal processing
band od Butterworth digital filter	1-40 Hz
	1-50 Hz
	8-42 Hz
	none
spatial filter	CAR - all electrodes
	CAR - selected electrodes
	Large Laplacian
	Small Laplacian
	none
BSS algorithm	AMUSE
	Infomax
	Extended Infomax
	FastICA
	none

As an expansion of these major groups, 221 combinations were created in total. If BSS algorithm was used at the beginning of the processing pipeline a high-pass filter at 1 Hz had to be applied before the BSS itself, as ICA is sensitive to low-frequency signal drifts. Withing these groups (possible processing setups) we used 2 filtering methods: digital (frequency bandpass of 1-40 Hz, 1-50 Hz or 8-42 Hz) and spatial (CAR-all, CAR-selected, Small Laplacian and Large Laplacian). For the detailed description of these filters see sections below.

During the second stage, each of the 221 sets of combinations was evaluated in terms of its informational value. Utilizing canonical-correlation analysis (CCA) [18] (please refer to CCA section below for characteristics of this algorithm) we classified signals from within different time periods, from 1 to 15 s, with a step of 0.5 s (four CCA reference signals were created consisting of the main frequency and its second harmonic). This way, we received a 29×221 matrices of the classification values (29 time periods per 221 sets of algorithms). Subsequently, we calculated the ITR coefficient for each element of the matrix, and finally, the highest ITR value for each combination was passed for further analysis.

Since data from our groups (processing setups) did not follow a normal distribution (as assessed with Shapiro-Wilk test) we used one-way analysis of variance Kruskal-Wallis procedure to test for statistical differences between these groups. The proceeding pairwise comparisons were performed with Mann-Whitney test.

All statistical analyses presented in this article were carried out with IBM SPSS Statistics for Windows, v. 24 (24.0.0.0), Armonk, NY: IBMcorp.

A. *Digital and spatial filters*

Digital frequency filtering was performed as-implemented in Python-MNE (v. 0.15), with finite impulse response (FIR) 'firwin' filter design.

'CAR-all' was used as described by McFarland et al. [13]. 'CAR-selected' was similar, yet the only signal from the electrodes of interest was subtracted from the particular channel. 'Laplacians' were in our case not exactly the same method as used by McFarland and collaborators, with the difference being that instead of referencing the signal from the single electrode with respect to 4 surrounding (neighboring) ones we arbitrarily chose electrodes of reference. It was necessary in this case to prevent removing the meaningful signal by using one of the other electrodes of interest as a reference (see Fig. 1 for visualization).

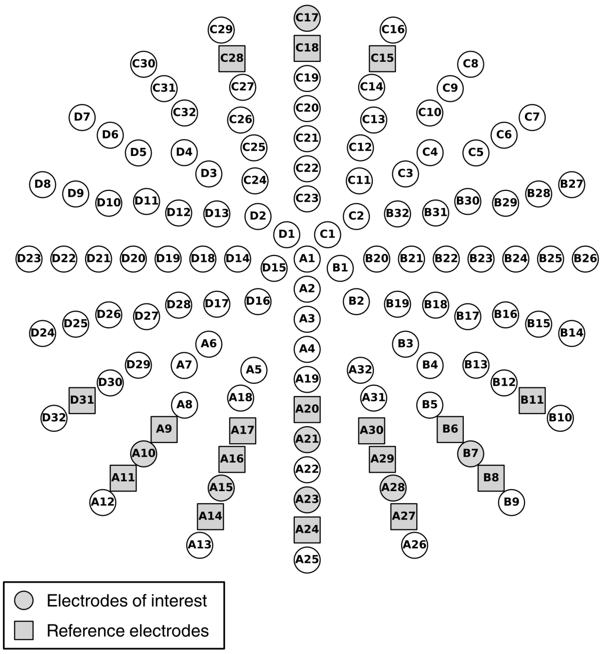

Fig. 1. Electrodes of interest and reference channels for 'small-laplacian' (Biosemi-128 standard). Light red circles are electrodes that were essential for performing ICA preprocessing for SSVEP decoding (occipital channels and one frontal electrode for blinks removal). Light gray rectangles are reference required for 'small-laplacian' spatial filter. E.g., reference electrodes for A10 were: A11, D31 and A9 for 'small-laplacian' (as visualized in the figure above); and: A12, D24 and A8 for 'large-laplacian' (not visualized here).

B. *Information Transfer Rate*

We used information transfer rate to describe the overall performance of the BCI system. ITR is based on the formula [14]:

$$B_m = log_2 N + P log_2 P + (1-P) log_2 (\frac{1-P}{N-1}) [\frac{bits}{trial}]$$

and:

$$B_t = \frac{60}{T} B_m [\frac{bits}{min}]$$

where P is the classification accuracy, N is the number of targets and T is the time it takes to reach the target. B_m is expressed in bits per trial, and B_t is bits per minute.

C. Canonical Correlation Analysis

Canonical-correlation analysis has been one of the most popular methods for frequency recognition in SSVEP-based brain-computer interfaces. Consider two multidimensional random variables X, Y and their linear combinations $x = X^T W_x$ and $y = Y^T W_y$, respectively. CCA finds the weight vectors, W_x and W_y, which maximize the correlation between x and y, by solving the following problem [19][20][21]:

$$\rho(x, y) = max_{W_x, W_y} \frac{E[xy^T]}{\sqrt{E[xx^T]E[yy^T]}} =$$

$$max_{W_x, W_y} \frac{E[w_x^T X Y^T w_y]}{\sqrt{E[w_x^T X X^T w_x] E[w_y^T Y Y^T w_y]}}$$

The maximum of correlation coefficient ρ with respect to w_x and w_y is the maximum canonical correlation.

CCA in frequency recognition of the SSVEP-based BCI, where there are K targets, with the stimulus frequencies $f = f_1, f_2, ..., f_K$, being finds the maximum correlation between M samples of EEG signal recorded from N channels, $X(N \times M)$ and the reference signal $Y_f(R \times M)$. R is the number of variables in the reference signal. The reference signals Y_f is set as:

$$Y_f = \begin{bmatrix} sin(2\pi f t) \\ cos(2\pi f t) \\ . \\ . \\ . \\ sin(2\pi N_h f t) \\ cos(2\pi N_h f t) \end{bmatrix}$$

and:

$$t = \frac{1}{f_s}, \frac{2}{f_s}, ..., \frac{M}{f_s}$$

where N_h is the number of harmonics and f_s denotes the sampling rate.

The command C is recognized as:

$$C = max \rho_i \qquad i = 1, 2, ..., K$$

where ρ_i are the CCA coefficients obtained with the frequency of reference signals being $f = f_1, f_2, ..., f_K$.

D. Blind Source Separation

The general goal of blind source separation (BSS) is to estimate unknown sources from a set of observed mixtures. The estimation is performed with no prior information about neither the sources nor the mixing process.

The linear and instantaneous models of BSS can be formulated as:

$$x(t) = As(t)$$

where $A \in R^{nxn}$ in an unknown non-singular mixing matrix, $s(t) = [s^1(t), ..., s^n(t)]^T$ and $x(t) = [x^1(t), ..., x^n(t)]^T$ Without knowing the source signals and the mixing matrix, we want to recover the original signals from the observations $x(t)$ by the following linear transform:

$$y(t) = Wx(t)$$

where $y(t) = [y^1(t), ..., y^n(t)]^T$ and $W \in R^{nxn}$ is a demixing matrix [22][23][24].

III. Results

Our goal was to determine which set of algorithms provides the highest ITR value (and thus the highest accuracy of recognition in the shortest possible time).

First, we checked whether the BBS algorithm should be the first or the last element of signal processing. We ran a one-way analysis of variance Kruskal-Wallis test to account for the statistically significant differences. We obtained the significance level of p=0.019 with statistic=7.960 (Fig. 2). The only significant pairwise comparison (p<0.019, Bonferroni-corrected) was BBS initiating processing vs. finalizing it. There are significant differences between the proposed solutions, so we decided that BSS algorithm should be used as the first element of signal processing.

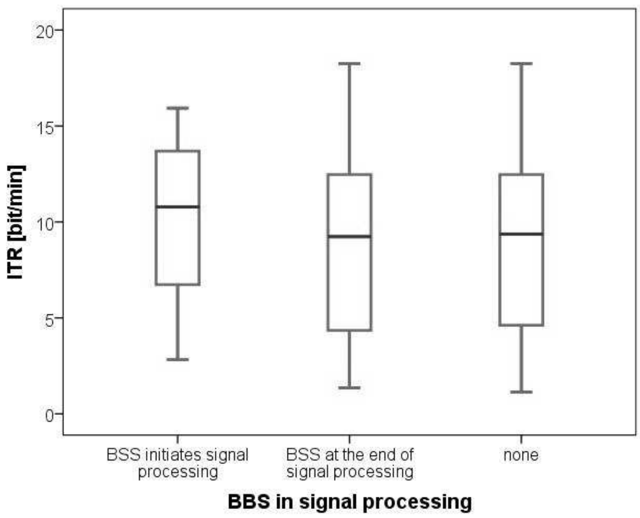

Fig. 2. Boxplot showing results within BSS performed before other preprocessing steps, after them and with no BSS at all. The horizontal lines within boxes represent medians of these groups. The whiskers reach the first datum beyond 1.5 interquartile range (IQR) of the first and third quartiles (box range).

Then we checked whether the use of digital filters affects the value of ITR and what bandwidth should be used. We ran a one-way analysis of variance Kruskal-Wallis test to check the significant differences. The probability reported with the test was p<0.659; statistic=1.608 (see Fig. 3). Hence, there are no significant differences between the 5types of digital filter applied.

Subsequently, we checked whether performing spatial filtering affects the ITR value. We ran a one-way analysis of

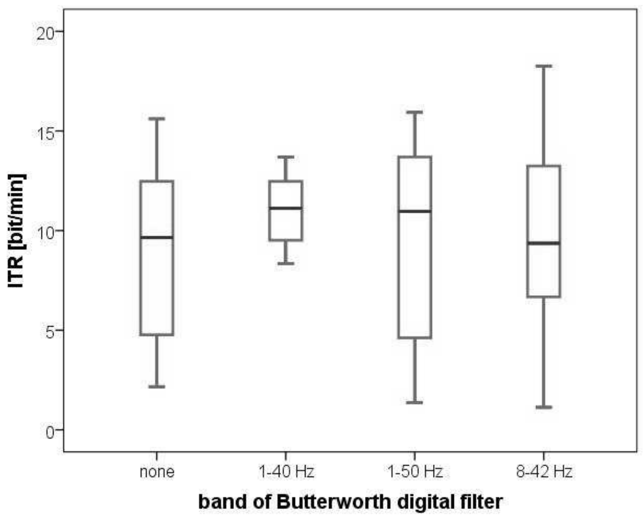

Fig. 3. Results for a band of digital filter used. The horizontal lines within boxes represent medians of these groups. The whiskers reach the first datum beyond 1.5 interquartile range (IQR) of the first and third quartiles (box range). Values beyond whiskers are considered outliers.

variance Kruskal-Wallis procedure to test for the statistical differences. The resulting significance level of $p<0.001$ (statistic=168.859) implies strong differences depending on what kind of spatial filter was utilized (see Fig. 4). Statistically significant ($p<0.001$, Bonferroni-corrected) pairwise comparisons were observed between members of (1) none, CAR-all and CAR-selected group and (2) Large and Small Laplacian group; within these two groups there were no differences as measured with Mann-Whitney test.

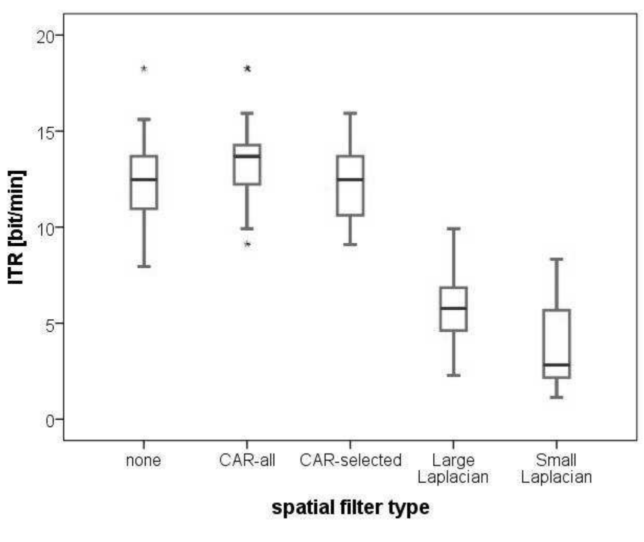

Fig. 4. Results for different kinds of spatial filters used. The horizontal lines within boxes represent medians of these groups. The whiskers reach the first datum beyond 1.5 interquartile range (IQR) of the first and third quartiles (box range). Values beyond whiskers are considered outliers.

At last, we asked which BSS algorithms provide the highest ITR value. One-way Kruskal-Wallis test was run to analyze the variance of results for each ICA procedure. Fig. 5 shows the results, however, we report no statistical significance of these differences ($p<0.797$; statistic=1.670).

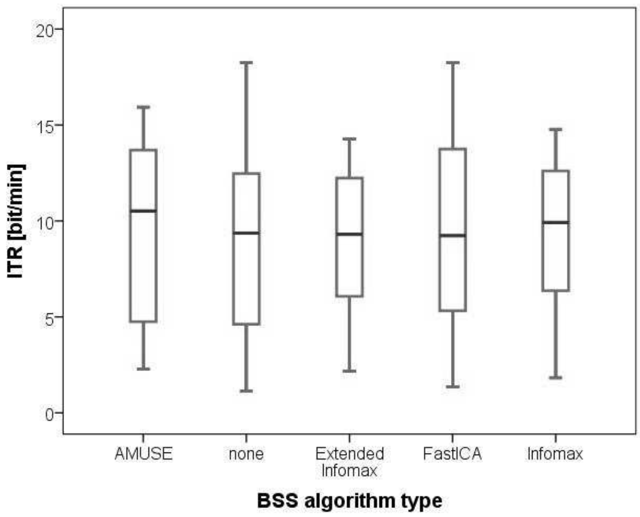

Fig. 5. Type of BSS algorithm applied. The horizontal lines within boxes represent medians of these groups. The whiskers reach the first datum beyond 1.5 interquartile range (IQR) of the first and third quartiles (box range). Values beyond whiskers are considered outliers.

We also computed 'baseline ITR'. ITR was determined for a combination in which no signal processing algorithms were used. That 'baseline ITR' equals 12.47 bits/min.

To find the best set we have to reduce a list of 221 algorithms. All combinations that contained: Small Laplacian, Large Laplacian and/or BBS algorithm at the end of processing (based on results described above), as well as combinations with ITR lower than 'baseline ITR' were rejected.

If we assume that we want to minimize the number of electrodes, we should also reject all combinations containing "CAR-all", because this solution uses a full set of electrodes.

The resulting list of 18 sets of algorithms is presented in Fig. 6 and Table II.

TABLE II
EIGHTEEN HIGHEST ITR SCORES THAT REACHED 12.47 BITS/MIN BASELINE THRESHOLD.

BSS algorithm type	spatial filter type	band of Butterworth filter	ITR [bits/min]
none	none	none	12,47
none	none	1-40 Hz	12,47
none	none	1-50 Hz	12,47
none	none	8-42 Hz	**18,26**
none	CAR-selected	none	12,47
AMUSE	none	none	13,69
AMUSE	CAR-selected	none	13,69
AMUSE	CAR-selected	1-50 Hz	**15,93**
AMUSE	CAR-selected	8-42 Hz	13,69
Extended Infomax	CAR-selected	none	12,74
Extended Infomax	CAR-selected	1-50 Hz	12,74
FastICA	none	none	**15,61**
FastICA	CAR-selected	none	**15,61**
FastICA	CAR-selected	1-50 Hz	14,78
FastICA	CAR-selected	8-42 Hz	13,24
Infomax	CAR-selected	none	12,74
Infomax	CAR-selected	1-50 Hz	13,69
Infomax	CAR-selected	8-42 Hz	13,24

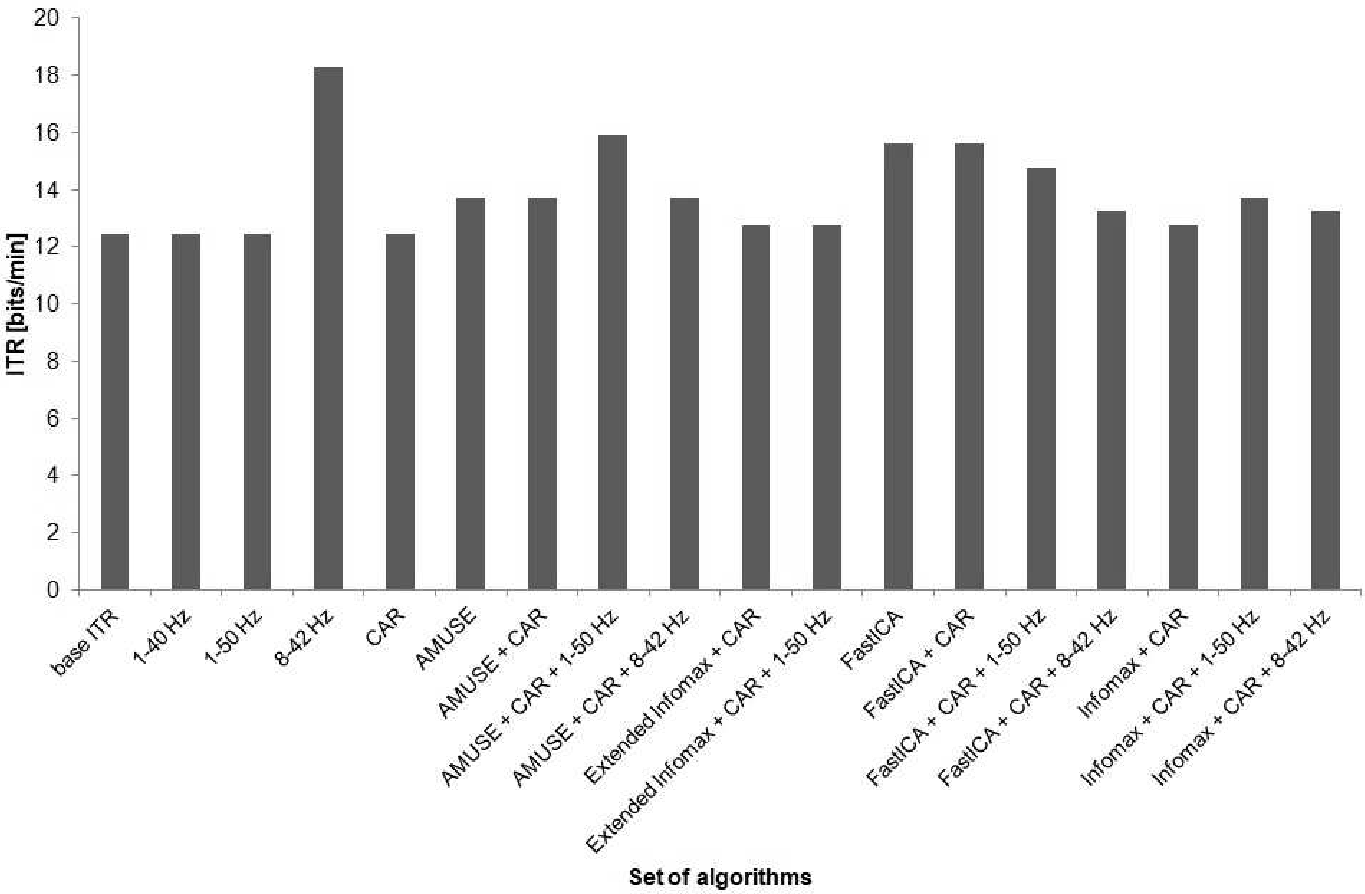

Fig. 6. The highest results for particular preprocessing setups (ITR). These are 18 of the initial 221 results, the cut-off threshold was 12.47 bits/min (baseline ITR). For detailed ITR scores please refer to Table II.

IV. Conclusion

Based on the obtained results, it is possible to create guidelines for designing signal preprocessing stage. It is advisable to use BSS, although it does not matter exactly which algorithm. Confirmation of this hypothesis may be found in previous studies and current research. We checked the possibility of using the spatial filtering algorithms, which are usually used in motor imaginary based brain-computer interfaces. Most of these algorithms (except CAR with selected electrodes) were rejected due to unsatisfactory results of signal classification or channels minimization criterion. Therefore, we conclude that spatial filtering algorithms do not apply to SSVEP-based brain-computer interfaces. Lastly, we tested for the differences in ITR values depending on Butterworth filter type used. For this comparison no statistically significant differences were obtained. Nevertheless, it seems that this part of our research should be extended by several additional bandpass filter bands (e.g., in narrow bands corresponding to frequencies of interest). In addition to that, also a number of harmonics of the CCA reference signal ought to be studied.

In this article we compared various preprocessing and processing methods for BCI purposes. As far as there were studies concerning which of BBS algorithms would be the most suitable for signal processing preceding SSVEP decoding, no outcomes on the possible interactions between BSS and other processing methods (filtration) were reported until now. Our study shows that this issue can't be marginalized because we revealed statistically significant differences in ITR value depending on various spatial and temporal filtering methods applied, as well as whether BBS was performed on the beginning of the processing or not. All in all, our current results delineate new fields in signal processing for SSVEP-based BCIs worth studying.

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