Multiple Channel Detection of Steady-State Visual Evoked Potentials for Brain-Computer Interfaces

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***Abstract*—In this paper, novel methods for detecting steady-state visual evoked potentials using multiple electroencephalogram (EEG) signals are presented. The methods are tailored for brain-computer interfacing, where fast and accurate detection is of vital importance for achieving high information transfer rates. High detection accuracy using short time segments is obtained by finding combinations of electrode signals that cancel strong interference signals in the EEG data. Data from a test group consisting of 10 subjects are used to evaluate the new methods and to compare them to standard techniques. Using 1-s signal segments, six different visual stimulation frequencies could be discriminated with an average classification accuracy of 84%. An additional advantage of the presented methodology is that it is fully online, i.e., no calibration data for noise estimation, feature extraction, or electrode selection is needed.**

***Index Terms*—BCI, EEG, signal detection, SSVEP, subspace, VEP.**

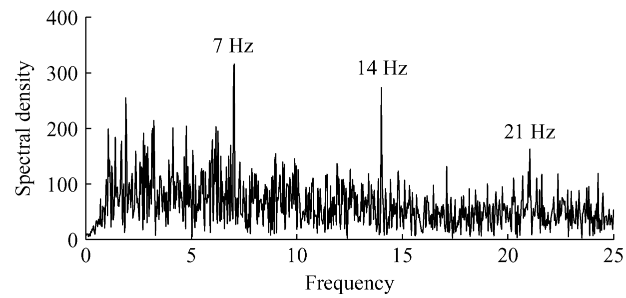

Fig. 1. Typical frequency spectrum of an EEG signal acquired during visual stimulation with a flickering frequency of 7 Hz. The SSVEP response can be seen as the peaks at 7 Hz and the harmonic frequencies at 14 and 21 Hz.

I. Introduction

STEADY-STATE visual evoked potentials (SSVEP) is a resonance phenomenon arising mainly in the visual cortex when a person is focusing the visual attention on a light source flickering with a frequency above 4 Hz [1]. The SSVEP response is most commonly investigated using electroencephalography (EEG), i.e., with electrodes placed on the surface of the scalp. It consists of a periodic component of the same frequency as the flickering light source, as well as of a number of harmonic frequencies, see Fig. 1. The strongest response is obtained for stimulation frequencies in the range 5–20 Hz [2], [3]. Since the SSVEP is an intrinsic neuronal response which is relatively independent of higher level cognitive processes, it has been extensively used for studying low-level processing in the brain and for making clinical assessments of visual pathways [4]. Recently, the SSVEP phenomenon has found a new application in so-called brain-computer interfaces (BCIs) [5]–[11]. A BCI translates brain activity patterns into control commands [12]–[14], e.g., for moving a cursor on a computer screen or for controlling a robot arm. The interest in basing a BCI on SSVEP patterns is mainly due to the robustness of the SSVEP phenomenon. Since it is an inherent response of the brain, very little training is required of a person before he or she is able to operate the BCI. The SSVEP response is also straightforward to model and characterize, a fact that is extensively utilized in this work.

The neuroscientific and clinical interest in SSVEP has spawned a number of signal processing methods for detecting and extracting the SSVEP signal. For example, in [15] a method for detecting a single frequency component in a single electrode signal is proposed. Following the development of matched subspace detectors [16], it was noted that this detector is well suited for finding the well-known and distinct frequency components constituting the SSVEP signal [17], [18]. While the focus in a clinical application of SSVEP usually is on some parameter of the SSVEP response [19], the BCI application puts different and more challenging demands on the signal processing and detection. Typically, an array of light sources flickering with different frequencies is used as stimuli, where each frequency encodes a certain control command. The task for the signal processing is to decide which light source the person is looking at based on the evoked SSVEP response. To obtain an acceptable speed of the BCI, correct decisions must be made based on short signal segments, usually between 0.5 and 4 s. To meet this demand, good detection methods are required. For related EEG signal processing problems, it has been shown that it is beneficial to exploit the information in multiple electrode signals [20], [21]. However, while it is known that the SSVEP response is widely distributed over the occipital and parietal lobes [22], to date, no investigation of how to detect SSVEP signals using multiple electrodes placed at different scalp locations has been presented.

In this paper, a novel approach for multichannel detection of SSVEP responses is proposed. The application in mind is brain-computer interfacing, but the methodology is general and applicable in all situations where SSVEP signals are utilized. An important feature of the presented method is that it is fully

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online, i.e., there is no need to acquire calibration data for feature selection or noise estimation. In the following sections, the SSVEP model used in this work and the proposed methodology are presented in detail.

II. Modeling

Assuming that visual stimulation with a flicker-frequency of f Hz is applied, we use the following model for the signal $y_i(t)$ measured as the voltage between a reference electrode and electrode number i

$$y_i(t)=\sum_{k=1}^{N_h} a_{i,k}\sin(2\pi kft+\phi_{i,k})+\sum_j b_{i,j}z_j(t)+e_i(t). \quad (1)$$

The model is linear and decomposes the electrode signal $y_i(t)$ into three parts: The first part is the evoked SSVEP response signal, which consists of a number of sinusoids with frequencies given by the stimulus frequency and a number of harmonic frequencies, see Fig. 1. Each sinusoid has an electrode specific amplitude and phase, $a_{i,k}$ and $\phi_{i,k}$ respectively.

The second part of the model is a set of nuisance signals $z_j(t)$ stemming, for example, from concurrent brain processes or external disturbances such as breathing artifacts and power line interference. These nuisance signals are added to each electrode signal scaled with the weight factors $b_{i,j}$. Finally, there is a measurement noise component $e_i(t)$ which is specific for electrode number i.

For a time segment of N_t samples of the signal, sampled at a sampling frequency F_s, the model can be expressed in vector form

$$\mathbf{y}_i = \mathbf{X}\mathbf{a}_i + \mathbf{Z}\mathbf{b}_i + \mathbf{e}_i \quad (2)$$

where $\mathbf{y}_i = [y_i(1),\ldots,y_i(N_t)]^T$ is a $N_t \times 1$ vector, and $\mathbf{e}_i$ is a similar vector with noise. The SSVEP model matrix $\mathbf{X}$ is of size $N_t \times 2N_h$

$$\mathbf{X} = [\mathbf{X}_1 \ \mathbf{X}_2 \ \cdots \ \mathbf{X}_{N_h}] \quad (3)$$

where each submatrix $\mathbf{X}_k$ contains a $\sin(2\pi kft)$ and $\cos(2\pi kft)$ pair in its columns. The $2N_h \times 1$ vector $\mathbf{a}_i$ contains the corresponding amplitudes. Similarly, $\mathbf{Z}$ is a matrix with the nuisance signals in its columns, and $\mathbf{b}_i$ the corresponding vector with weights. We assume that the time segment is short enough for the noise to be stationary within this segment.

Finally, assuming that we have signals $y_i(t)$ from a number of electrodes $i=1,\ldots,N_y$, the model can be further generalized to

$$\mathbf{Y} = \mathbf{X}\mathbf{A} + \mathbf{Z}\mathbf{B} + \mathbf{E} \quad (4)$$

where $\mathbf{Y} = [\mathbf{y}_1,\ldots,\mathbf{y}_{N_y}]$ is a $N_t \times N_y$ matrix with the sampled signals from the all the electrodes as columns, and $\mathbf{E}$ is a noise matrix constructed in the same way. Similarly, $\mathbf{A}$ and $\mathbf{B}$ contain the amplitudes and scaling factors for all sinusoids and nuisance signals, and for all electrode signals.

One of the nuisance signals is well known and easily characterized, and that is the interference from the power-line. We use the notation $\mathbf{Z}_p$ for a $N_t \times 2$ matrix containing a sine/cosine pair with the power line frequency of 50 or 60 Hz. In the following sections, we assume that the power line interference has been removed, either via a notch filter during signal acquisition, or as a preprocessing step via a projection operation which replaces $\mathbf{Y}$ with a signal cleaned from the power line signal

$$\mathbf{Y} \leftarrow \mathbf{Y} - \mathbf{Z}_p\left(\mathbf{Z}_p^T\mathbf{Z}_p\right)^{-1}\mathbf{Z}_p^T\mathbf{Y}. \quad (5)$$

It is also assumed that all electrode signals have, or are normalized to have, equal energy or variance.

III. Methods

In this section, the detection of an SSVEP response using multiple electrode signals is presented. The term *channel* is used for a combination of the signals measured by different electrodes, and a vector of channel data is denoted by $\mathbf{s}$. Thus, a channel signal $\mathbf{s}$ can be equal to an electrode signal $\mathbf{y}_i$, but in general it will consist of an aggregate of several $\mathbf{y}_i$'s. As will be shown in the Results section, the detection is improved by considering several channels $\mathbf{S} = [\mathbf{s}_1,\ldots,\mathbf{s}_{N_s}]$, where N_s is the number of channels. The goal is to combine electrode signals into channel signals where the SSVEP response is magnified and/or the nuisance signals and noise are canceled. In the next section, different strategies for creating such channel signals are discussed. Subsequently, the test statistic used for detecting an SSVEP response is presented, as well as the required estimators of SSVEP signal power and noise power.

A. Combining Electrode Signals to Channel Signals

Given a number of electrode signals stored in the matrix $\mathbf{Y}$ introduced in (4), a core question in this work is how to combine the information present in these signals so as to obtain an optimal detection of a potential SSVEP response. Since the model in Section II is linear, it is natural to create a channel signal by combining the original electrode signals linearly using a $N_y \times 1$ vector of weights $\mathbf{w}$. A channel $\mathbf{s}$ is, thus, obtained as

$$\mathbf{s} = \sum_{i=1}^{N_y} w_i\mathbf{y}_i = \mathbf{Y}\mathbf{w}. \quad (6)$$

More generally, we can create several channels by making different combinations of the original electrode signals

$$\mathbf{S} = \mathbf{Y}\mathbf{W} \quad (7)$$

where $\mathbf{W}$ is a $N_y \times N_s$ matrix containing the weights for each combination in its columns. The optimal choice of weight matrix $\mathbf{W}$ depends on the nature of the SSVEP signal, the nuisance signals, and the noise in (1). Below, six different choices of $\mathbf{W}$ are devised, and the conditions under which each choice would work well are discussed.

Method I—Average Combination: If the SSVEP sinusoids in (1) have equal phases [$\phi_{i,k}$ in (1)], and if the nuisance signals are sparsely distributed across the electrodes so that the spatial correlation between the electrodes is low, a good approach would be to just average the electrode signals into one channel signal. This would amplify the SSVEP component and cancel the electrode-specific noise, and thereby increase the signal-to-noise ratio (SNR). Such an average is obtained by choosing a weight matrix with a single column $\mathbf{W} = [1, 1, \ldots, 1]^T$.

Method II—Native Combination: It is known that the phases of the SSVEP sinusoids vary with the scalp location of the electrodes [22]. This makes the Average combination above less efficient because the nonaligned sinusoids do not add well, and in a worst case scenario they may even cancel each other completely. Under these circumstances, a better approach may be to use the original electrode signals directly as channels, i.e., setting $\mathbf{W}$ to the identity matrix, $\mathbf{W} = \mathbf{I}_{N_y}$. This choice has been used previously for a SSVEP-based BCI [8], and we call it the Native combination.

Method III—Bipolar Combination: In practice, the nuisance signals are strong and present in all electrode signals. Hence, an averaging operation will not cancel the nuisance signals; they will instead be amplified just as the SSVEP response. A well known remedy for this is to acquire the EEG data using a so-called bipolar electrode placement, where the voltage difference between two closely placed electrodes is measured [4]. Hence, in the bipolar approach the strategy is to obtain a cleaner channel signal by canceling common nuisance signals. The SSVEP signal will also be reduced in a differential operation, but, due to differences in phase and amplitude of the sinusoids across electrodes, hopefully to a lesser extent than the nuisance signals. It is not necessary to actually acquire the signals using a bipolar signal amplification [23]; the signals can be measured using monopolar amplification, and then differentiated digitally. To this end one would for example choose the weight matrix as

$$\mathbf{W} = [1, -1]^T \quad \text{or} \quad \mathbf{W} = \begin{bmatrix} 1 & -1 & 0 & 0 \\ 0 & 0 & 1 & -1 \end{bmatrix}^T \tag{8}$$

in order to create one channel signal from two electrode signals, or two channel signals from four electrode signals, respectively. The bipolar technique has been employed previously in [5], [10] for brain-computer interfacing based on SSVEP.

Method IV—Laplacian Combination: An alternative to the bipolar montage is the surface Laplacian [24], where one center electrode and four surrounding electrodes are used to make a symmetric differentiation, i.e., with weights $\mathbf{W} = [4, -1, -1, -1, -1]^T$. The advantage over the Bipolar combination is that the Laplacian combination does not have a preferred spatial direction.

Method V—Minimum Energy Combination: A limitation of the Bipolar and Laplacian methods above is that they only operate on pairs or groups of electrodes that must be chosen beforehand. Here we propose the minimum energy combination method, which can be seen as a generalization of the Bipolar combination to an arbitrary number of electrodes. The idea is to form combinations of the electrode signals which cancel as much of the nuisance signals as possible. To achieve this, the first step is to remove any potential SSVEP components from all the electrode signals, which is done by projecting them onto the orthogonal complement of the SSVEP model matrix $\mathbf{X}$ defined in Section II

$$\tilde{\mathbf{Y}} = \mathbf{Y} - \mathbf{X}(\mathbf{X}^T\mathbf{X})^{-1}\mathbf{X}^T\mathbf{Y}. \tag{9}$$

After this operation, $\tilde{\mathbf{Y}}$ will contain only nuisance signals and noise, i.e., $\tilde{\mathbf{Y}} \approx \mathbf{ZB} + \mathbf{E}$, where the approximation is due to the small unavoidable effect the projection in (9) has on the nuisance signals and noise.

The next step is to find a weight vector $\hat{\mathbf{w}}$, which is constrained to have unit norm and constructed so as to minimize the resulting energy of the combination of electrode signals $\tilde{\mathbf{Y}}\hat{\mathbf{w}}$. That is, we have the following optimization problem:

$$\min_{\hat{\mathbf{w}}} \|\tilde{\mathbf{Y}}\hat{\mathbf{w}}\|^2 = \min_{\hat{\mathbf{w}}} \hat{\mathbf{w}}^T\tilde{\mathbf{Y}}^T\tilde{\mathbf{Y}}\hat{\mathbf{w}}. \tag{10}$$

The quadratic form on the right hand side in (10) is bounded by the minimal and maximal eigenvalues, λ_1 and λ_{N_y} (note notation and order: $\lambda_1 \leq \lambda_{N_y}$), of the symmetric matrix $\tilde{\mathbf{Y}}^T\tilde{\mathbf{Y}}$. The solution to the minimization problem is, therefore, given by the smallest eigenvector $\mathbf{v}_1$, and the energy of the resulting combination equals the smallest eigenvalue λ_1. Moreover, since the matrix $\tilde{\mathbf{Y}}^T\tilde{\mathbf{Y}}$ is symmetric, the eigenvectors will be orthogonal, and a combination of the electrode signals using the second largest eigenvector $\mathbf{v}_2$ produces a second channel signal which is uncorrelated with the first channel, and with somewhat higher energy λ_2. Hence, by choosing the eigenvectors as columns in the weight matrix $\mathbf{W}$, the channel signals resulting from (7) are uncorrelated and have an increasing energy stemming from nuisance signals. Although the SSVEP response also will be affected by the weight matrix, *a priori*, one can predict that it is more easily detected in the first channels with the lowest content of nuisance signals. This conjecture will be investigated in the Results section.

To be more specific, we choose the weight matrix as follows:

$$\mathbf{W} = \begin{pmatrix} \dfrac{\mathbf{v}_1}{\sqrt{\lambda_1}} & \cdots & \dfrac{\mathbf{v}_{N_s}}{\sqrt{\lambda_{N_s}}} \end{pmatrix} \tag{11}$$

where, again, N_s denotes the number of channels. The normalization of each eigenvector with the square-root of the corresponding eigenvalue is not strictly necessary; we do it for convenience because the resulting channel signals $\mathbf{s}_1, \ldots, \mathbf{s}_{N_s}$ will then have the same energy, which facilitates presentation in the Results section. More important is the number of channels to produce, i.e., the number of eigenvectors to include in the weight matrix. This is a classical model selection problem, for which no single optimal solution exists. Here we adopt the following approach: Choose N_s to the smallest number for which

$$\frac{\sum_{i=1}^{N_s} \lambda_i}{\sum_{j=1}^{N_y} \lambda_j} > 0.1. \tag{12}$$

The denominator in (12) is the total energy in the nuisance signals and noise, and the numerator is the total energy retained when N_s combinations are used. Expressed in words, N_s is chosen so as to discard as close to 90% of the nuisance signal energy as possible.

Method VI—Maximum Contrast Combination: As a final alternative we investigate a variation of the minimum energy combination, in which the energy in the SSVEP frequencies is maximized and the energy in the nuisance signals is minimized simultaneously. To achieve this we use the following contrast function:

$$\max_{\hat{\mathbf{w}}} \frac{||\mathbf{Y}\hat{\mathbf{w}}||^2}{||\tilde{\mathbf{Y}}\hat{\mathbf{w}}||^2} = \max_{\hat{\mathbf{w}}} \frac{\hat{\mathbf{w}}^T\mathbf{Y}^T\mathbf{Y}\hat{\mathbf{w}}}{\hat{\mathbf{w}}^T\tilde{\mathbf{Y}}^T\tilde{\mathbf{Y}}\hat{\mathbf{w}}}. \quad (13)$$

Equation (13) is a so-called Rayleigh quotient whose maxima are found by a generalized eigen-decomposition of the matrices $\mathbf{Y}^T\mathbf{Y}$ and $\tilde{\mathbf{Y}}^T\tilde{\mathbf{Y}}$. The eigenvectors give the locations of the local maxima and the eigenvalues give the values of the quotient at these maxima. By construction, all eigenvalues are larger or equal to one. For example, an eigenvalue of 1.2 means that the energy in the SSVEP frequencies is 20% larger than the energy in the nonSSVEP frequencies. The eigenvectors belonging to the largest eigenvalues give channels with the largest SNRs, and these are, therefore, used in the weight matrix $\mathbf{W}$. We choose to include all eigenvectors that produce channels where the energy per dimension in the SSVEP subspace is larger than the energy per dimension in the rest of the signal. This means that only eigenvectors with eigenvalues larger than $N_t/(N_t - 2N_h)$ will be included in $\mathbf{W}$.

B. SSVEP Detection

Since the SSVEP response is as a periodic signal with energy only in a few distinct frequencies, a test statistic for testing the presence of an SSVEP response can be calculated as

$$T = \frac{1}{N_s N_h} \sum_{l=1}^{N_s} \sum_{k=1}^{N_h} \frac{\hat{P}_{k,l}}{\hat{\sigma}_{k,l}^2}. \quad (14)$$

Here, $\hat{P}_{l,k}$ is the estimated power in SSVEP harmonic frequency number k in channel signal $\mathbf{s}_l$, and $\hat{\sigma}_{k,l}^2$ is an estimate of the noise power in the same frequency. The estimation of these quantities is detailed in the following sections. Expressed in words, the test statistic averages the SNRs across N_h harmonic frequencies and N_s channel signals. The interpretation is that the test statistic T tells us how many times larger the estimated SSVEP signal is compared to the case where no visual stimulus is present. The test statistic in (14) is essentially the same test statistic used in [17], [18] and due to the (approximate) orthogonality of the sinusoids it is also equal to the matched subspace test statistic [16]. Dividing with the estimated noise power $\hat{\sigma}_{k,l}^2$ is commonly referred to as a whitening operation, which in the current case can be expressed in the form of (14) due to the sinusoidal form of the SSVEP signal.

C. SSVEP Signal Power Estimation

We use the following formula for estimating the power in the kth SSVEP harmonic frequency in channel signal $\mathbf{s}_l$

$$\hat{P}_{k,l} = \left\|\mathbf{X}_k^T\mathbf{s}_l\right\|^2. \quad (15)$$

The motivation for using this definition of signal power is that it equals the squared Discrete Fourier Transform (DFT) magnitude when the frequency coincides with one of the frequencies in the DFT. However, since the SSVEP stimulation frequency and its harmonics not necessarily coincide with the DFT frequencies, (15) offers a more general formula because it can estimate the power in any frequency.

D. Noise Power Estimation

The final part required to calculate the test statistic in (14) is estimates of the noise levels $\hat{\sigma}_{k,l}^2$, i.e., the power in the SSVEP frequencies if no SSVEP response would be present. One approach is to use a calibration data set acquired with no stimuli present [18]. This is a simple approach, but with the disadvantage of requiring a separate calibration data set. It also disregards the fact that the noise and nuisance signals in EEG data are nonstationary. To take the nonstationarity into account, the estimation of the noise level must be based on the same data segment used for estimating the SSVEP signal power. A method advocated in [25] is to use the power in two neighboring frequencies, where no SSVEP response is present, and estimate the power of the noise in the SSVEP frequency via a linear interpolation. In [17], yet another method is employed, where an auto-regressive $AR(p)$ model of order $p = 15$ is fitted, and then used in a whitening operation which transforms the colored noise into white noise with unit power [26]. Here we adopt a similar approach, but slightly modified and tailored to our application. The idea is to fit $AR(p)$ models to the channel signals, and use the fitted models to interpolate the noise power in the SSVEP frequencies. However, the potential presence of the SSVEP response may produce slightly overestimated noise powers. Therefore, as a precaution we again remove all energy in the SSVEP frequencies before fitting the $AR(p)$ model. By combining (7) and (9), some operations can be saved

$$\tilde{\mathbf{S}} = \mathbf{S} - \mathbf{X}(\mathbf{X}^T\mathbf{X})^{-1}\mathbf{X}^T\mathbf{S} = \tilde{\mathbf{Y}}\mathbf{W}. \quad (16)$$

The noise power estimated using the modified channel signals $\tilde{\mathbf{S}} = [\tilde{\mathbf{s}}_1, \ldots, \tilde{\mathbf{s}}_{N_s}]$ will instead be slightly underestimated, but the bias will be independent of the strength of the SSVEP response and hence stable over time. The bias can also be expected to be small, as shown in [17], and it can be corrected for using a method presented in [27].

The $AR(p)$ models are efficiently fitted by invoking the Wiener-Khinchin theorem for computing the autocovariance of each channel signal and then solving the Yule-Walker equations using a Levinson-Durbin recursion [28]. This yields the $AR(p)$ model parameters $\alpha_1, \ldots, \alpha_p$, as well as an estimate of the variance $\hat{\sigma}^2$ of the white noise driving the $AR(p)$ process. Assuming that we have fitted the $AR(p)$ model to channel signal $\mathbf{s}_l$, the noise level predicted by the model at SSVEP harmonic frequency number k is given by the following formula for the power spectrum of the $AR(p)$ process:

$$\hat{\sigma}_{k,l}^2 = \frac{\pi N_t}{4} \frac{\hat{\sigma}^2}{\left|1 + \sum_{j=1}^{p} \alpha_j \exp\left(-2\pi ijkf/F_s\right)\right|^2}. \quad (17)$$

To repeat the parameters used, N_t is the number of samples, $k = 1, \ldots, N_h$ is the SSVEP harmonic frequency number, f is the SSVEP stimulation frequency, F_s is the sampling frequency, and i in the above formula is the complex $\sqrt{-1}$. Note that a separate $AR(p)$ model must be fitted to each channel signal $\mathbf{s}_l$, $l = 1, \ldots, N_s$.

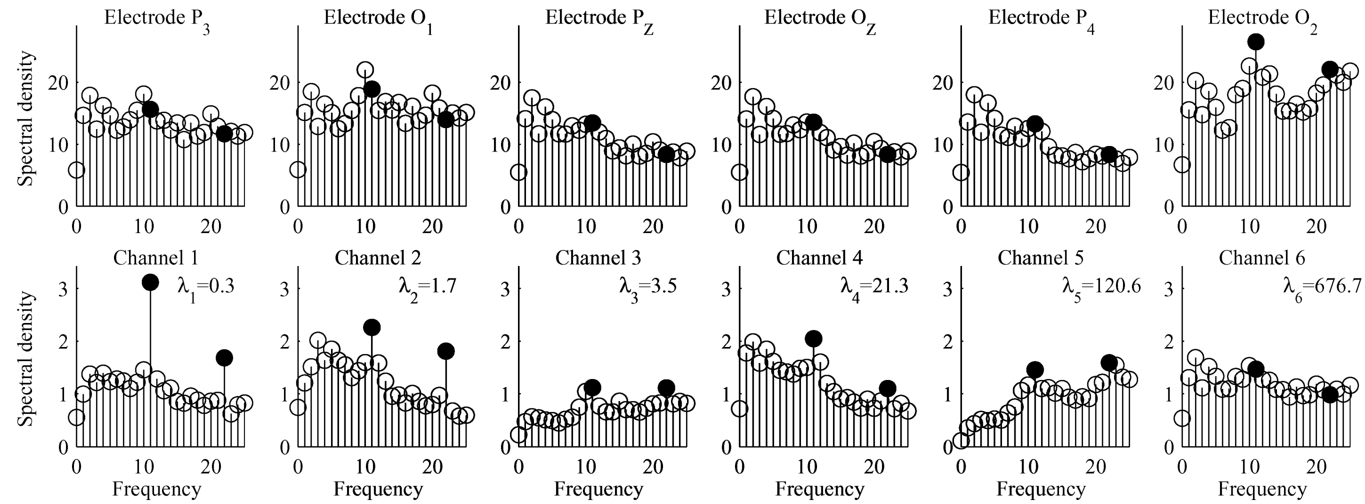

Fig. 2. Spectra for Subject 9 and 11 Hz stimulation. An SSVEP response is expected in the 11- and 22-Hz frequencies, marked with filled circles. The upper row shows the spectra for each of the original electrode signals. The bottom row shows the spectra for each of the six possible minimum energy channel signals. The eigenvalues, i.e., the variances of the channel signals, are also reported. Note that the SSVEP response cannot be detected in the original electrode signals, whereas it is clearly visible in the minimum energy channel signals.

IV. Material

Data from 10 subjects in the ages between 20 to 30 years were acquired. Six gold electrodes were attached at the locations P_3, O_1, P_Z, O_Z, P_4, and O_2 in the international 10–20 system, and referenced to a ground electrode placed at F_Z. EEG paste was applied to bring impedances below 5 $k\Omega$. An EEG amplifier from g.tec and a National Instruments acquisition card was used to acquire the electrode signals. An analog highpass filter with cutoff frequency 0.5 Hz was used in the amplifier, and the signals were digitized with a sampling rate of $F_s = 128$ Hz. For generating SSVEP stimuli, a plate with light diodes arranged in a grid covering an area of about 30 cm^2 was prepared and connected to a signal generator with which the flickering frequency of the diodes could be controlled. All diodes where flickering in unison with the same frequency. For each subject, $30+30$ s of data was recorded for each of the stimulation frequencies 5, 7, 9, 11, 13, and 15 Hz. The subjects were seated in a comfortable chair with a viewing distance of about 0.5 m to the diodes, and during the acquisition the room was dimmed. To facilitate presentation, the subjects have been ordered according to the strength of the SSVEP response, i.e., Subject 1 exhibits the strongest signal and Subject 10 the weakest signal.

V. Results

In this section, the six methods for combining electrode signals presented in Section III-A are compared, and the efficacy with which the minimum energy combination method detects an SSVEP response is demonstrated. Since six electrodes were used, we have $N_y = 6$ electrode signals. All results below are based on analyzing 1-s segments of these signals, where each segment contains $N_t = 128$ samples ($F_s = 128$ Hz). Moreover, we base the detection of the SSVEP response on the frequency content in the fundamental stimulation frequency and the first harmonic frequency, i.e., $N_h = 2$. Matlab code is available on request.

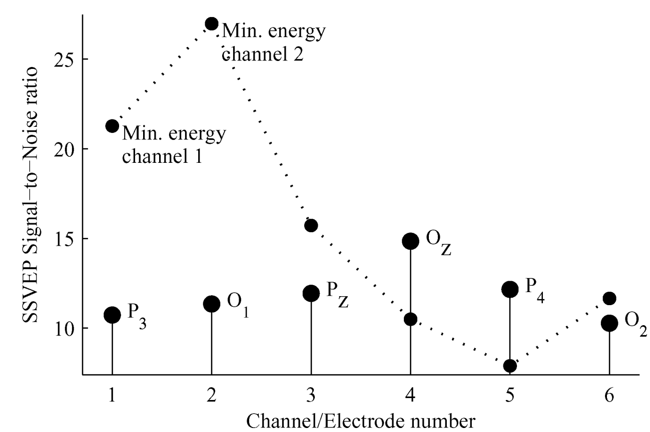

Fig. 3. The bars show the SSVEP SNR, defined in (14), for each of the original electrode signals. The dots connected with the dotted line show the same SNRs for the minimum energy channel signals.

A. Minimum Energy Combination

We begin with presenting results that demonstrate the minimum energy combination. In Fig. 2, spectra for Subject 9 and the 11-Hz stimulation are shown. The fundamental 11-Hz frequency and the first harmonic frequency at 22 Hz are marked with filled circles. The upper panels in Fig. 2 show the spectra for the six original electrode signals, and the lower panels the spectra of the channel signals obtained with the minimum energy combination (all possible $N_s = 6$ channels are shown). In the original electrode signals, the SSVEP response cannot be distinguished from the noise and nuisance signals. In contrast, in the minimum energy channel signals the SSVEP response is clearly visible, especially in the first channels. To investigate the conjecture that the SSVEP response is more easily detected in the first minimum energy channels, the test statistic in (14) was averaged across all subjects, all stimulation frequencies and all 1-s signal segments.

The resulting average test statistics, or SNRs, for each electrode signal and minimum energy channel are plotted in Fig. 3.

TABLE I
CLASSIFICATION ACCURACIES FOR EACH TEST SUBJECT AND EACH DETECTION METHOD

	Method I Average	Method II Native	Method III Bipolar	Method IV Laplacian	Method V Min energy	Method VI Max contrast
Subject 1	85 %	90 %	94 %	100 %	100 %	100 %
Subject 2	85 %	86 %	73 %	81 %	95 %	91 %
Subject 3	79 %	83 %	88 %	89 %	97 %	96 %
Subject 4	75 %	76 %	79 %	99 %	97 %	95 %
Subject 5	61 %	65 %	68 %	93 %	93 %	90 %
Subject 6	56 %	60 %	88 %	85 %	91 %	89 %
Subject 7	47 %	54 %	57 %	66 %	83 %	74 %
Subject 8	34 %	39 %	61 %	39 %	59 %	56 %
Subject 9	35 %	37 %	56 %	59 %	77 %	76 %
Subject 10	29 %	32 %	48 %	40 %	52 %	48 %
Average	59 %	62 %	71 %	75 %	84 %	81 %

A first observation one can make in Fig. 3 is that the bars show that a slightly stronger SSVEP response can be found at the O_Z location compared to the other electrode locations. Second, the SNRs in the first minimum energy channels are much larger than both in the higher channel numbers and in all the electrode channels. Hence, using the first minimum energy channels for detecting the SSVEP response will improve the detection accuracy.

The rule for selecting the number of channel signals to use in the detection was described in (12). This rule is based on the amount of nuisance signal energy or variance captured in each channel, which equals the eigenvalue associated with the channel combination. The relative sizes of the eigenvalues, again averaged across all subjects, stimulation frequencies and 1-s time segments, are $\lambda_1 = 0.2\%$, $\lambda_2 = 0.4\%$, $\lambda_3 = 0.8\%$, $\lambda_4 = 2.8\%$, $\lambda_5 = 8.2\%$ and $\lambda_6 = 87.5\%$. Thus, the last minimum energy channel captures 87.5% of the variance of the nuisance signals. This reflects the high spatial correlation between the electrode signals. Furthermore, this result also indicates that the rule in (12) will select, on average, the first 4 or 5 channels for detection.

B. Method Comparison

In Section III-A, six different ways to combine the information in the electrode signals were described: the average, the native, the bipolar, the Laplacian, the minimum energy, and the maximum contrast combinations. Here the SSVEP response detection accuracies obtained with these methods are compared. The bipolar combination was chosen to produce channel signals as the differences between electrodes $P_3 - O_1$, $P_Z - O_Z$, and $P_4 - O_2$. The Laplacian combination was formed with O_Z as center electrode, and P_3, O_1, P_4, and O_2 as surrounding electrodes.

The detection was carried out as follows: For each 1-s time segment of 128 samples, the test statistic in (14) was calculated for each of the six possible stimulation frequencies 5, 7, 9, 11, 13, and 15 Hz. The six ensuing test statistics indicate the likelihood of stimulation with the above six frequencies respectively. The time segment is then classified as acquired during stimulation with the frequency associated with the largest test statistic. Since we know which stimulation frequency was actually used for the given time segment, we can calculate the number of correct and erroneous classifications and assess the classification accuracy. For each test subject there are $60 \times 6 = 360$ time segments to classify, summing to 3600 segments in total. Table I presents the percentage of correct classifications for each method and each subject, and the average classification accuracy in the bottom row.

Like in previous studies [8], [10], there is a significant intersubject variation in SSVEP response strength and classification accuracy. As predicted and motivated in Section III-A, the Average combination yields the lowest performance and the minimum energy and maximum contrast combinations yield the best detection accuracy. The Bipolar and Laplacian methods are for most subjects better than the Average and Native methods. However, for Subject 2, who has a very strong SSVEP response, the Bipolar method performs poorly with only 73% classification accuracy, and the Laplacian method is also inferior to the Average and Native methods for this subject. The Laplacian method is in most cases better than the Bipolar method. For Subject 4 the Laplacian combination performs very well, but for Subject 8 it performs unsatisfactory. This shows that the Bipolar and Laplacian methods can vary significantly in performance and, therefore, lack robustness. The minimum energy and maximum contrast methods, which both take the SSVEP model into account, perform well for all subjects. Overall, the minimum energy method works best. A paired t-test indicates that the minimum energy method performs better than both the Bipolar and Laplacian methods with a significance of $p < 0.005$. Finally, using Matlab, it takes about 4 ms for a conventional 3-GHz PC to calculate the test statistics for all six classes and make a classification. Thus, the minimum energy and maximum contrast detectors can clearly be used in a real-time application like brain-computer interfacing.

C. Number of Electrodes

Another interesting result emerges when the impact of the number of electrodes used for detection is investigated. For this experiment the classification accuracy was assessed as in the previous section, but with one or several of the original electrode signals systematically excluded from the analysis. For example, to examine the detection accuracy using only 4 of the 6 electrode signals, the analysis was repeated for all $\binom{6}{4} = 15$ possible ways to choose 4 out of 6 signals. The combination of 4 electrodes that gave the best average detection accuracy was then stored for each method. This procedure was applied for 6,5,4,3,2 and 1 electrode signals. As the Bipolar and Laplacian methods do

TABLE II
CLASSIFICATION ACCURACIES FOR DIFFERENT NUMBER OF ELECTRODE SIGNALS AND FOR DIFFERENT METHODS

Nbr. of electrodes	Method I Average	Method II Native	Method III Bipolar	Method IV Laplacian	Method V Min energy	Method VI Max contrast
6	59 %	62 %	71 %	-	84 %	81 %
5	59 %	63 %	-	75 %	84 %	81 %
4	60 %	64 %	-	-	82 %	80 %
3	61 %	64 %	-	-	80 %	79 %
2	62 %	63 %	69 %	-	69 %	76 %
1	-	64 %	-	-	-	-

not easily lend themselves to this kind of analysis, the procedure was only carried for some special cases for these methods. In Table II, the best detection accuracies for each number of retained electrode signals are presented.

Note that the detection accuracy improves with fewer electrodes for the Average and Native combinations, indicating that it is better use a very low number of well-placed electrodes, for example chosen via a channel selection approach [29]–[31], with these methods. In contrast, the minimum energy and maximum contrast detection methods benefit from more electrodes because of the extra information gained about the nuisance signals.

VI. DISCUSSION

The problem addressed in this work is how to detect the presence of an SSVEP response in multiple electrode signals. The incentive for developing the presented methodology is the requirement of fast and accurate detection in BCI applications. The single most important parameter in brain-computer interfacing is the information transfer rate, which usually is measured as transferred bits per minute [32]. A good transfer rate is obtained if an accurate classification between many SSVEP frequencies using short signal segment lengths can be achieved. Thus, a good detection algorithm is a core component in a well working BCI. Another important consideration in brain-computer interfacing is whether the BCI is of a *dependent* or *independent* type [13]. Most SSVEP BCI's are dependent, because they depend on the subject being able to move the eyes. A patient group that potentially could benefit from such a SSVEP BCI is for example elderly people with declining motor control. Subjects with no muscle control, including the muscles used for moving the eyes, need an independent BCI. Kelly *et al.* [8], [9] have shown that the SSVEP phenomenon can be used also for independent brain-computer interfacing by letting the subjects covertly, i.e., without eye movement, attend one of two flickering stimuli. In the experiments carried out in this paper, the subjects were allowed to move their eyes to focus on the light diodes, but the proposed algorithms are applicable also for covert attention.

To extract information from several electrode signals, our first step is to combine the signals linearly. In the EEG literature, this is sometimes referred to as a spatial filter, and producing such combinations is a well established procedure in EEG signal processing [33]–[35]. In this paper, we compare six different methods for combining electrode signals. The first four of these methods are reference methods which have been used before for detecting SSVEP responses. The last two methods, the minimum energy and the maximum contrast methods, are new. The crucial difference between these new methods and the reference methods is the use of a model of the SSVEP phenomenon for finding combinations which enhance the SSVEP signal and cancel nuisance signals. As is shown in the Result section, this is critical to obtain good detection performance. There are other related methods which were not included in the comparison. One such method is principal component analysis (PCA). PCA identifies high variance signal components, and would, thus, be useful if the SSVEP signal would be the strongest signal in the data. However, as was shown in Fig. 2, this is generally not the case. Independent component analysis (ICA) is another related technique that has received much attention in the literature. Apart from not utilizing explicit model information, ICA differs from the techniques presented here in a number of other aspects: First, in ICA, the goal is to identify the signals mixed according to a linear model similar to the one presented in (1). That is, one is explicitly interested in the signals entering the mixing process. In the current case, we are not interested in the nuisance signals per se; we just want to find a subspace basis for them in order to exclude them from the SSVEP response detection. Second, ICA employs measures such as neg-entropy and kurtosis as indicators of statistical independence to identify signals. For signal detection purposes, the relevant quantity is the energy or variance of the nuisance signals; the larger the energy the more likely it is that the nuisance signals mask the interesting SSVEP response. Third, ICA does not provide a ranking of the unmixed signals it produces. In contrast, the eigenvalue-decomposition used for finding a basis for the nuisance signals provides the variance or energy captured by the removed subspace, and this is used to choose the dimensionality of the subspace.

The minimum energy and maximum contrast methods achieve the best detection accuracies among the investigated methods. The minimum energy method can be seen as a generalization of the bipolar signal acquisition scheme, where the aim is to cancel the strong nuisance signals, and thereby obtain a better SNR. In the maximum contrast method, the aim is to explicitly optimize the SNR, and it is, therefore, known that the channel signals are ordered according to their importance for the detection. This is an advantage over the minimum energy method; though it was shown that the SSVEP response tended to be strongest in the first channels in the minimum energy method, there is no guarantee for this, and one might need to include a few more channels to compensate for this lack of information. The drawback of the maximum contrast method lies in the explicit search for electrode combinations with high energy in certain frequencies. This may result in channel signals with spurious energy in the hypothesized SSVEP frequencies, which in turn may produce erroneous classifications.

In contrast, in the minimum energy method the probability of producing spurious energy in the SSVEP frequencies is low. Our results show that the minimum energy method is slightly but consistently better than the maximum contrast method, except for the case where only two electrodes are used in Table II. This indicates that it is the spurious energy problem that hampers the maximum contrast method, because the more electrode signals the maximum contrast method has available, the more possibilities it has in producing combinations with an artificially inflated power in a selected frequency.

From the brain-computer interfacing point of view, a major advantage of the proposed detection methodology is that there is no need to acquire any calibration data for feature selection, electrode selection or noise estimation. Again, this feature can be attributed to having an accurate model of the SSVEP response. While it can be argued that acquiring session specific calibration data prior to the usage of the BCI does not require much extra work, it may also be the nuisance that makes the end-user abandon the BCI in favor for a competing technology. To obtain the full online operation, both the SSVEP response power and the noise power must be estimated using the same signal segments. To this end, autoregressive models were utilized to perform a model-based interpolation of the noise power in the SSVEP frequencies. An additional advantage of this approach is that it takes the nonstationarity of nuisance signals and noise into account.

VII. Conclusion

A detection methodology tailored for detecting SSVEP responses in EEG data has been presented. Several strategies for extracting information from multiple electrode signals have been investigated. Best detection accuracy was achieved with the minimum energy method, which utilizes an SSVEP model to produce uncorrelated channels containing a minimum of energy from nuisance signals. The significantly improved detection accuracy implies that an increased information transfer rate can be achieved in BCIs based on the SSVEP phenomenon. Moreover, the noise level is estimated using autoregressive models, which are fitted to a modified signal in order to avoid an unpredictable bias stemming from the potential presence of an SSVEP signal. This makes the method fully online and there is no need to acquire calibration data prior to operation.

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