EEG Source Localization for Brain-Computer-Interfaces

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***Abstract*— While most EEG based Brain-Computer-Interfaces (BCIs) employ machine learning algorithms for classification, we propose to utilize source localization procedures for this purpose. Although the computational demand is considerably higher, this approach could allow the simultaneous classification of a multitude of conditions. We present an extension of Independent Component Analysis (ICA) - based source localization that is fully automatic, and apply this method to the classification of EEG data generated by imaginary movements of the right and left index finger. The results demonstrate that source localization provides a viable alternative to machine learning algorithms for BCIs.**

I. Introduction

EEG based Brain-Computer-Interfaces (BCIs) currently employed for translating thoughts into commands focus on machine learning techniques to correctly classify EEG signals [1]. For several reason signals generated through motor imagery are frequently used [2]. This approach requires the recording of a Training set consisting of EEG data caused by distinct conditions (e.g. imaginary movements of the left vs. the right index finger) for the adaptation of the learning algorithm to the specific user. The learned algorithm in turn is applied for the real-time classification of EEG data and often further adapted on-line.

Machine learning techniques offer several advantages, e.g. the low computational demand after the training has been completed, and the small number of electrodes necessary for correct classification. While encouraging results have been obtained for the classification of a maximum of two conditions [3], no such results have been reported, to the authors' knowledge, for more than two conditions. Since the number of conditions is directly related to the information transfer rate of BCIs [4], the capability to classify a multitude of conditions would significantly increase the usability of BCIs, e.g. by increasing the spelling rate of spelling devices.

Towards this goal we propose the use of EEG source localization. By reconstructing the sources of the measured surface potentials we can make use of two neuro-physiological principles, the lateralization of electrocortical activity (e.g., a stronger activation of the left sensomotoric cortex when the right hand is moved), and the spatially distributed representation of different extremities in motoric- and sensomotoric cortex. This should lead to spatially distinct activations during real as well as imaginary movements of different extremities [5]. These activations can be differentiated by sufficiently accurate source localization procedures, leading to BCIs capable of classifying a multitude of conditions.

A further advantage of BCIs based on source localization would be the robustness against small variations in the EEG signal. Changes in EEG patterns over time and subjects require repeated training sessions if machine learning algorithms are employed. By contrast, as long as the spatial location of sources remains constant BCIs based on source localization procedures would be unaffected by such variations.

One problem associated with source localization though is that the most commonly applied methods such as the BESA algorithm (BESA, MEGIS Software Inc.) are based on user defined constraints (e.g., the number of dipoles) that require an interactive fitting procedure. Since BCIs require autonomous use, these source localization procedures can not be employed for BCIs.

In this paper, we present an extension of EEG source localization based on Independent Component Analysis (ICA)

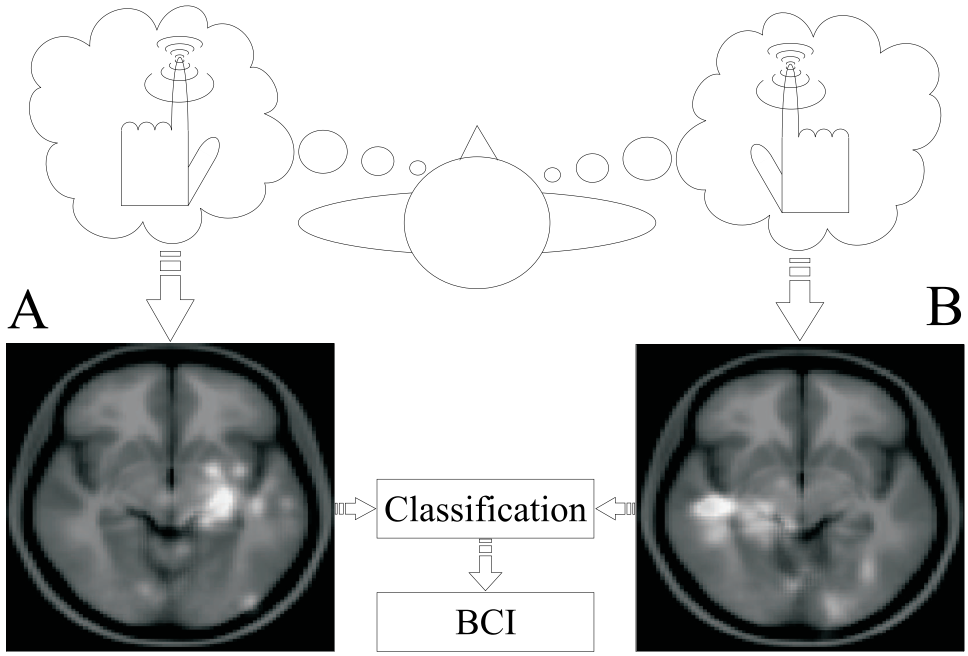

Fig. 1. EEG Source Localization for BCIs: Real as well as imaginary movements of the left or right index finger lead to brain activity contra-lateral to the movement. This activity can be visualized using our approach and employed for classification. The two images show the activity density function (ADF) for real movements of the left (A) and right (B) index finger averaged over all available trials, and superimposed on an fMRI - image from the publicly available MNI database.

to allow for the automatic localization and identification of task-relevant current sources generating the measured surface potentials. This method is applied to electrocortical activity generated by imaginary movements of the left and right index finger. We demonstrate that the obtained activity maps can be used to classify the two conditions, thereby proving the general feasibility of source localization for BCIs.

II. Methods

For the reconstruction of current source activity we apply equivalent current dipole localization in combination with Independent Component Analysis (ICA) [6]. By applying ICA to the EEG data we decompose the measurements into N maximally independent components (ICs), where N is the number of independent EEG electrodes. Each of the resulting ICs is then represented through an equivalent current dipole within a four-shell spherical head model [7]. Since the number of sources found to be responsible for a given set of EEG measurements is usually well below the number of electrodes, and thus the number of obtained ICs, the problem remains to identify ICs that constitute task relevant activity, and discard ICs that represent irrelevant activity, noise or indeterminacies in the ICA algorithm. This is done either by clustering, i.e. by determining which ICs are common across subjects and trials, by visual inspection, or by discarding all ICs whose residual variance (RV) exceed a certain threshold. However, all of these approaches are not feasible for application in BCIs. While clustering appears to be a reliable method for identifying task-relevant components [8], the BCI requirement of real-time classification renders the comparison of components across subjects and trials unfeasible. With respect to visual inspection as a means of identifying task relevant activity, a supervisor is required for the classification of the obtained ICs, and thus violates the requirement of automatic classification of a BCI. Finally, discarding ICs with a high residual variance is not applicable because the current sources caused by imaginary movements are usually weaker as compared to overt movements, and are thus contaminated by noise to a much greater extend. This in turn leads to high RV even in relevant ICs.

Here, we present a method to automatically identify task-relevant components, based on the observation that the obtained sets of ICs vary if ICA is applied several times to the same data set with only the initial conditions of the ICA algorithm being varied. Specifically, if each IC is represented by one equivalent current dipole within a spherical head model, the positions of some ICs vary with the initial conditions of the ICA algorithm, while the positions of other ICs remain constant. The obtained ICs thus divide into two classes, those dependent and those independent of the initial conditions of the ICA algorithm. We conjecture that only those ICs are task-relevant that are independent of the initial conditions of the ICA algorithm. The locations of these ICs are identified in the following way. Applying ICA M times with different random initial conditions to the same data set we obtain $M \times N$ components, each of which is represented by a single equivalent current dipole. Due to the randomness of the ICA algorithm's initial conditions the positions of ICs dependent on the initial conditions are also random. In contrast, we obtain an accumulation of dipoles at positions represented by ICs independent of the ICA algorithm's initial conditions. We thus regard the observed dipole distribution as realizations of an unknown activity density function (ADF), describing the relative probability of areas being involved in task-relevant information processing. This ADF can be estimated by using Gaussian Kernel - functions, where each IC is furthermore weighted by a function of its RV. This is done to exclude ICs corresponding to spatially distributed activity that can not be represented by a single dipole. The result is a continuous function for the head model, peaking at locations where accumulations of dipoles occur. These peaks represent the positions of ICs independent of initial conditions of the ICA algorithm, and are hence considered to identify areas of task-relevant activity.

If $\tilde{x}_i \in \mathbb{R}^3, i = 1 \ldots M \times N$ describes the location and the orientation of each IC as determined by ICA and subsequent localization within a four shell spherical head model, the ADF is formally expressed as

$$\mathrm{ADF}(x) = \frac{1}{V_f} \sum_{i=1}^{M \times N} f(RV_i) \cdot g(x, \tilde{x}_i) \tag{1}$$

where

$$g(x, \tilde{x}_i) = \sqrt{\frac{1}{\pi R_g}} \exp \frac{-\|x - \tilde{x}_i\|}{R_g} \tag{2}$$

is the Gaussian Kernel, and

$$f(RV_i) = c \cdot [1 - \tanh(a \cdot RV_i - b)] \tag{3}$$

the function weighting each IC according to its RV. This ensures that ICs with an unacceptable high RV are excluded from the analysis. The parameters used in the evaluation are shown in Table I, with M describing the number of electrodes, N the number of repeated application of the ICA - algorithm, V_f and R_g determining the amplitude and extent of the Gaussian Kernel, and a, b, and c determining the shape of the function weighting each IC as a function of its RV.

In this way we have a method available for the fully automatic localization of task-relevant current sources generating the EEG. This in turn can be utilized for BCIs in the following way. To classify K conditions, in a preliminary study EEG activity caused by real movements of K different extremities is recorded. The location of maximal activation within motor areas for each extremity $k = 1 \ldots K$, termed $x_{\max,k}$, is then determined as given by the corresponding ADF. For the classification of unknown EEG signals caused by imaginary movements of the same extremities the ADF representing the unknown EEG data is computed, and the resulting activities $\mathrm{ADF}(x_{\max,k}), k = 1 \ldots K$ are compared. The index of maximal activation $\max_{k=1\ldots K} \{\mathrm{ADF}(x_{\max,k})\}$ determines the classification of the unknown EEG set.

III. Results

To test our method, we recorded EEG signals caused by real and imaginary movements of the left and right index finger from one subject (age 26, normal vision, no known neurological disorders and no prior experience with BCIs or imaginary movements). The subject sat in a shielded and dimly lit room

TABLE I
PARAMETERS FOR (1) - (3)

M	N	V_f	R_g	a	b	c
60	50	1	20	30	10	0.5

in front of a computer screen, and was instructed to perform real and imaginary tapping movements with the left or right index finger. These tapping movements were to be performed in synchrony with a centrally displayed grey box, flashing with a frequency of 1.33 Hz on a black background. A control condition was added in which the subject passively had to watch the flashing box. Each of the five blocks (real movement right (MR), real movement left (ML), imaginary movement right (IR), imaginary movement left (IL), no movement (NG)) consisted of 100 movements/flashes, and was repeated ten times in pseudo-randomized order. Each block was followed by a break of five seconds in which the instructions for the next block were displayed. EEG was recorded continuously with BrainAmp-Amplifiers (BrainProducts Inc.) with 60 channels according to the extended 10-20 system at 5kHz sampling rate. Additionally vertical and horizontal eye movements were monitored. The data was recorded with FPz as reference, and re-referenced offline to common average reference.

To ensure that no covert muscle activation took place during the imaginary conditions, EMG activity was recorded bipolarely using standard forearm flexor placement [9]. EMG recordings were then band-pass filtered with 4 Hz and 100 Hz cut-off frequencies and half-rectified. Trials of imaginary movements were chosen to be rejected, if the mean EMG activity during the trial exceeded 10% of the maximal EMG activity of the corresponding real movememt [10]. No trials had to be rejected.

Ocular correction was performed [11], and trials with onset of flashing boxes were averaged separately for each condition. For conditions MR and ML the grand average of all 1000 trials for each condition was taken. For conditions IR and IL the average was computed for each block of 100 trials separately. This resulted in one data set per condition MR and ML, and ten data sets per condition IR and IL.

To prove the general applicability of our method for BCIs, the following steps were then applied to each of the data sets with the parameters shown in Table I. First, the grand average of condition NG was subtracted from each data set to eliminate task irrelevant activity (e.g. visual evoked responses). Subsequently, ICA was applied M times to the data set by using the Infomax - algorithm [12] as implemented in EEGLab [13]. This resulted in $M \times N$ ICs, each of which was then localized in four-shell spherical head model with standardized electrode positions [7]. In a fourth step, the locations of all ICs were used to compute the ADF as given in (1).

This resulted in one ADF for each of conditions MR and ML, and ten ADFs for each of conditions IR and IL. The classification procedure was then done in the following way. In a first step, the location of maximal activity for conditions MR and ML was determined as given by the corresponding

ADFs, i.e.,

$$x_{\text{max,MR}} = \max_x \{\text{ADF}_{\text{MR}}(x)\} \tag{4}$$

and

$$x_{\text{max,ML}} = \max_x \{\text{ADF}_{\text{ML}}(x)\} . \tag{5}$$

To determine the correct classification of a data set Ix caused by an imaginary movement, its respective ADF was evaluated at the positions of maximal activation for real movements $x_{\text{max,MR}}$ and $x_{\text{max,ML}}$. If the activity $\text{ADF}_{\text{Ix}}(x_{\text{max,MR}})$ exceeded the activity $\text{ADF}_{\text{Ix}}(x_{\text{max,ML}})$, the data set was classified as being caused by an imaginary movement of the right index finger and vice versa.

This procedure was used to classify all 20 data sets, and resulted in nine out of ten correct classifications for condition IR, and eight out of ten correct classifications for condition IL. Thus a total of 17 out of 20 data sets (85%) were correctly classified.

IV. Discussion

In this article, we proposed to utilize EEG source localization for BCIs. Even though the computational demand required by source localization is considerably higher than for machine learning algorithms, source localization approaches could offer the advantage of classifying a multitude of conditions. We pointed out some of the problems associated with the application of source localization to BCIs, specifically the requirement of fully automatic source localization. This problem was solved by extending ICA based source localization, utilizing inherent properties of ICA - algorithms and Kernel functions to estimate an activity density function. This was based on the conjecture that only task - relevant ICs are independent of the initial conditions of the ICA algorithm. We tested our approach on 20 EEG sets of imaginary movements of the left or right index finger, and showed how a correct classification of 85% could be obtained.

While we used a relatively large number of trials as input for the source reconstruction process, and obtained a classification error of 15%, these results were obtained without any previous training of the subject. We therefore conclude that source localization provides a viable alternative to machine learning algorithms for BCIs. While we expect a significant decrease of the classification error through training, our approach might be especially promising for subjects who are not able to perform extensive training procedures.

Further studies have to show if source localization approaches can hold the promise of classifying a multitude of conditions simultaneously. Furthermore, the signal-to-noise requirements for correct classification have to be further investigated, and the algorithms improved to handle noisy data. This is necessary to minimize the number of averages required for correct classification, and thus to improve the achievable information transfer rate.

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