Blind Source Separation in single-channel EEG analysis: An application to BCI

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Abstract—**In this work we present a technique for applying Blind Source Separation (BSS) to single channel recordings of Electromagnetic (EM) brain signals. Single channel recordings of brain signals are preprocessed through the method of delays, and the delay matrix processed with the BSS technique described here called $LSDIAG_{TD}$ which uses temporal decorrelation to implement the now popular Independent Component Analysis (ICA) algorithm. This allows the identification and extraction of statistically independent sources underlying these single channel recordings. In particular we depict the analysis of single channel recordings from a Brain-Computer Interfacing paradigm. We show that BSS technique applied in this way extracts a series of codebook vectors representing the spectral content underlying the recorded signal. It then becomes possible to identify and extract particular rhythmic activity underlying the recordings. We show that rhythmic activity in the 8 to 12Hz band can be extracted in the case of imagined hand movements for a particular BCI paradigm.**

Keywords—**brain activity, EEG, BSS, ICA, method of delays, BCI**

I. INTRODUCTION

In the analysis of electromagnetic (EM) brain signals it is required to extract neurophysiologically meaningful information either for clinical reasons, such as is the case with the analysis of the epileptic electroencephalogram (EEG) to extract information on underlying epileptogenic sources. Similarly EEG can be used as in the field of Brain-Computer Interfacing (BCI) where brain signals are interpreted to provide a means of communication. A powerful technique in the decomposition of multi-channel EM brain signals is the technique of Blind Source Separation (BSS), in particular recent efforts in Independent Component Analysis (ICA) to this end. BSS provides a means of decomposing multi-channel EEG recordings into a series of underlying neural sources as well as separating out artifactual components such as ocular artifact, line-noise contamination, etc. However, BSS techniques such as ICA are generally applied to multi-channel recordings and the analysis of single channel recordings with BSS techniques is not usually performed.

However, there are instances where just *one* recording channel is either available or desired, the difficulty of isolating signals of interest is greatly increased. In general, *rhythmic* activity in the EEG is of interest, (c.f. alpha-, beta-, delta- and gamma-band activities, or rhythmic seizure activity for example). It would be particularly useful to be able to automatically isolate, visualise and track multiple neurophysiologically meaningful sources underlying the ongoing single channel EEG recording.

In [1] we introduced a method whereby it is possible to break down single channel recordings of EM brain signals into their underlying components, irrespective of the components' origin. The method relies on a combination of a nonlinear dynamical systems framework and a standard implementation of ICA. In [2] we provide an innovation whereby we show how this technique could be used to automatically process single channels of EEG data through the introduction of constrained ICA which allows for the use of prior information in the ICA process and means that only a single statistically independent component (IC) will be extracted for each given reference.

In this work we present a further application and interpretation of the BSS technique based on temporal decorrelation known as $LSDIAG_{TD}$ [3], applied to single channel recordings of BCI data. A BCI system is a communication system in which messages or commands that an individual sends to the external world do not pass through the brain's normal output pathways of peripheral nerves and muscles but is detected through EEG activity. The original idea of brain-computer communication was first mentioned in [4], it was first presented to use the observable electrical brain signals as carriers of information in man-computer communication. Nowadays BCI has become a popular research topic in the biomedical signal processing area.

In the next section we overview the single-channel analysis technique based on the method of delays and BSS, followed by a brief explanation of the BCI dataset used to highlight the technique.

II. METHODOLOGY

A. Single Channel Analysis

ICA performs BSS of statistically independent sources, assuming linear mixing of the sources at the sensors, generally using techniques involving higher-order statistics or temporal decorrelation. Several different implementations of ICA to EM brain signals can be found in the literature; [5,6]. In the standard, noise free, formulation of the ICA problem, the observed signals $\mathbf{x}(t)$ are assumed to be a linear mixture of an equal number of unknown but statistically independent source signals $\mathbf{s}(t)$, i.e.,

$$\mathbf{x}(t)=\mathbf{A}\mathbf{s}(t), \quad (1)$$

where the square mixing matrix **A** is also unknown but invertible. The problem is solvable up to a permutation, and sign and power indeterminacy of the sources, by finding an appropriate de-mixing matrix $\mathbf{W}=\mathbf{A}^{-1}$ which allows estimation of the source waveforms by $\mathbf{s}(t) = \mathbf{W}\mathbf{x}(t)$.

In conventional (ensemble) ICA the columns of the mixing matrix **A** represent the spatial distribution of each of the n independent sources, $s_i(t)$ (i=1,…, n). This is in keeping with the popular view that EM brain signals as measured at the scalp are due to a linear instantaneous mix of a number of underlying sources.

ICA has previously been applied to single channel data to learn a codebook of features for the signal [7], and in [8] we introduced the technique applied to ictal EEG. This can also be interpreted as learning filters to discriminate between independent source processes with disjoint spectral support. To apply ICA to a single channel it is first necessary to form a 'multi-channel' data representation. This can be done by generating a series of delay vectors taken from the observed data **x**(t), given by:

$$\hat{\mathbf{X}}(t) = \{\mathbf{x}(t), \mathbf{x}(t-1), \ldots, \mathbf{x}(t-M+1)\} \in \Re^{M} \quad , \quad (2)$$

for a delay vector of length M. When ICA is applied to delay vectors formed from a mixture of bandlimited sources it will identify a multiple number of components with each source proportional to the source bandwidth. The columns of **A** associated with a given source can be interpreted as shifted versions of the mixing filter. Finally, to ensure that the sources can be separated (an implicit assumption in the ICA model) using the filters we clearly need to additionally assume that they all have disjoint spectral support. The ICA process when applied to a matrix of delay vectors is depicted graphically in Fig. 1, in essence it is possible to interpret the linear mixing model for the single channel case as

$$\mathbf{x}(t) = \sum_{i=1}^{M} \mathbf{s}_i(t) * \mathbf{a}_i(t), \quad (3)$$

where $*$ denotes convolution. In effect, this translates to the addition of a series of convolutions of M 'code-book' vectors, $\mathbf{a}_i(t)$, convolved with the impulse response of a corresponding set of M filters, $\mathbf{s}_i(t)$, where the impulse responses are assumed to be statistically independent of each other.

B. The Brain Computer Interfacing Paradigm

The single channel analysis technique is trialled here on the 2003 international BCI competition dataset III (motor imagery) [9], which was provided by the Department of Medical Informatics, Institute for Biomedical Engineering, University of Technology, Graz, Austria. This dataset was recorded from a normal 25-year old female subject who sat relaxed in a chair with armrests during the sessions. The task was to control a feedback bar by means of imagined left or right hand movements. The EEG from three channels (C3, Cz, and C4) was sampled at 128 Hz and bandpass-filtered between 0.5 to 30Hz initially. The experiment included 7 runs with 40 trials each. All runs were recorded on the same day with several short breaks in between. The data consists of 280 trials of imaginary hand movements, with an equal number of left and right hand trials. Each trial is of 9s duration: the first 2s were quiet; then at t=3s, a visual cue

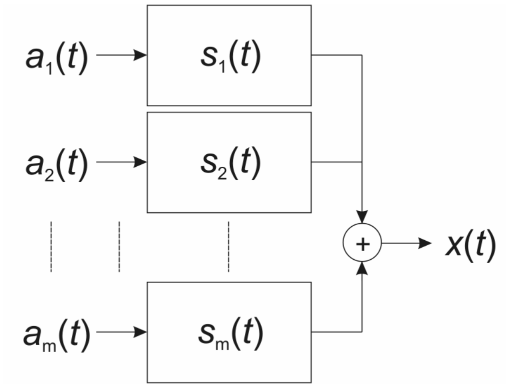

Fig. 1. The ICA problem when applied to a single channel measurement within a matrix-of-delays framework, translates into the addition of a series of convolutions of M code-book vectors $\{\mathbf{a}_i(t)\}$ convolved with the impulse response of a corresponding set of M filters $\{\mathbf{s}_i(t)\}$ – where the impulse responses are assumed to be as statistically independent of each other as possible.

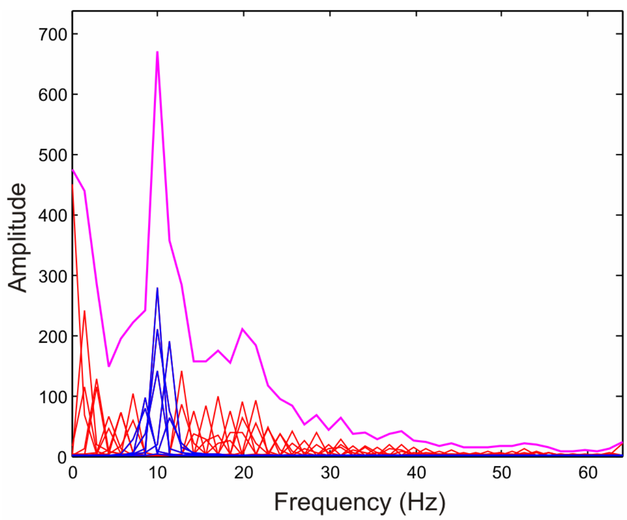

Fig. 2. A series of curves showing the FFTs of each of the codebook vectors (the columns of the mixing matrix $a_i(t)$) for one epoch data recorded from C3 (M=90, 5 lags for $LSDIAG_{TD}$). Each FFT consists of just a single maximum at a particular resonant frequency. The magenta line depicts the total sum of all spectra and spectra depicted in blue have peak frequencies in the interval $8\text{Hz} < f_p < 12\text{Hz}$.

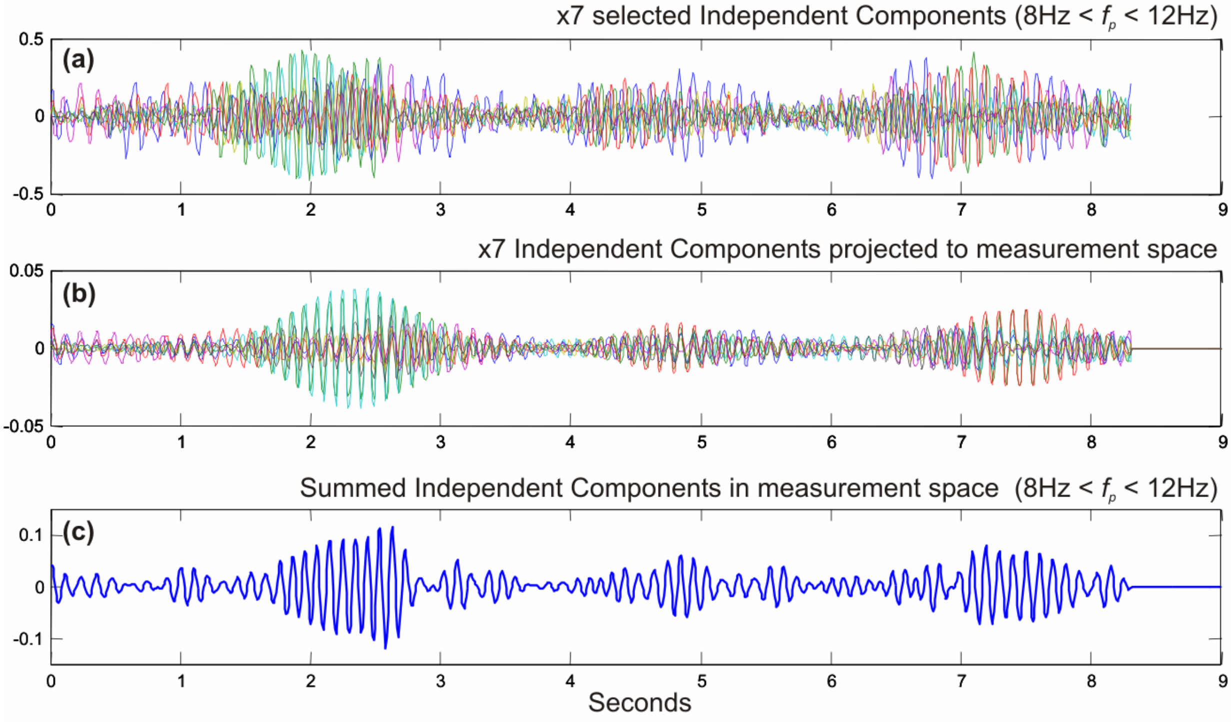

Fig. 3. (a) Seven independent components (ICs) chosen on the basis of the 7 codebook vectors in Fig. 2 which have a resonant frequency within the range 8Hz < f_p < 12Hz. (b) The ICs of (a) multiplied by their corresponding codebook vectors and the result of each projected back to the measurement space. (c) The summed, projected ICs depicted in (b) corresponding to cerebral activity within the defined frequency range.

(arrow) is presented pointing either to the left or the right (randomly). This is followed by another 6s where the subject uses imagined hand movements to move the feedback bar in the proposed direction. The specific task is to provide a classifier to identify each of the left and right movements for each of the 140 unlabeled single trials (we only analyse the labelled dataset for this analysis).

III. Results

Each epoch is analysed with this technique on an epoch by epoch basis. Fig. 2 depicts a series of curves showing the FFTs of each of the codebook vectors (the columns of the mixing matrix $\mathbf{a}_i(t)$) for one epoch data recorded from C3 (M was set to 90 based on previous analysis and the number of lags used for $\mathrm{LSDIAG}_{\mathrm{TD}}$ was 5). In each case the FFT contains just a single maximum at a particular resonant frequency, notice also that more than one 'component' is representative of a particulat codebook vector. The magenta line depicts the total sum of all the spectra and in particular the spectra depicted in blue have peak frequencies in the interval 8Hz < f_p < 12Hz, as the imagined hand movements in the BCI dataset are expected in this 8 to 12Hz band [10]. Fig. 3(a) depicts the 7 ICs corresponding to the 8 to 12Hz codebook vectors; Fig. 3(b) shows the ICs multiplied by their corresponding codebook vectors and the result of each projected back to the measurement space, and Fig. 3(c) depicts the summed and projected ICs corresponding to cerebral activity within the defined frequency range. An Event Related De-synchronisation (ERD) [10] of activity in this band is expected after the stimulus is presented at the 3s mark.

In Fig. 4 the results obtained from applying this technique a number of epochs of EEG recorded from channels C3, Cz and C4. Four sets of results are presented for each recording channel where the ERD is averaged over 5, 10, 30 and 70 averaged epochs. It can be seen that for as few as 10 averaged epochs it is clear that there is an ERD of activity in this band in the channel contraleral to the presented stimulus.

IV. Discussion and Conclusions

We show here how this single-channel BSS technique can be used to decompose a single-channel recording of brain activity into its consitutent components. Through an exemplar application of ERD extraction in motor imagery withiin a BCI paradigm, we show that this technique can be used to identify and isolate rhythmic components underlying the recordings. In practice it may still be more feasible to use band-pass filtering if a known, fixed frequency band is to be monitored, however, the technique described here is well suited to discovering rhythmic components/ sources underlying single channel brain recordings.

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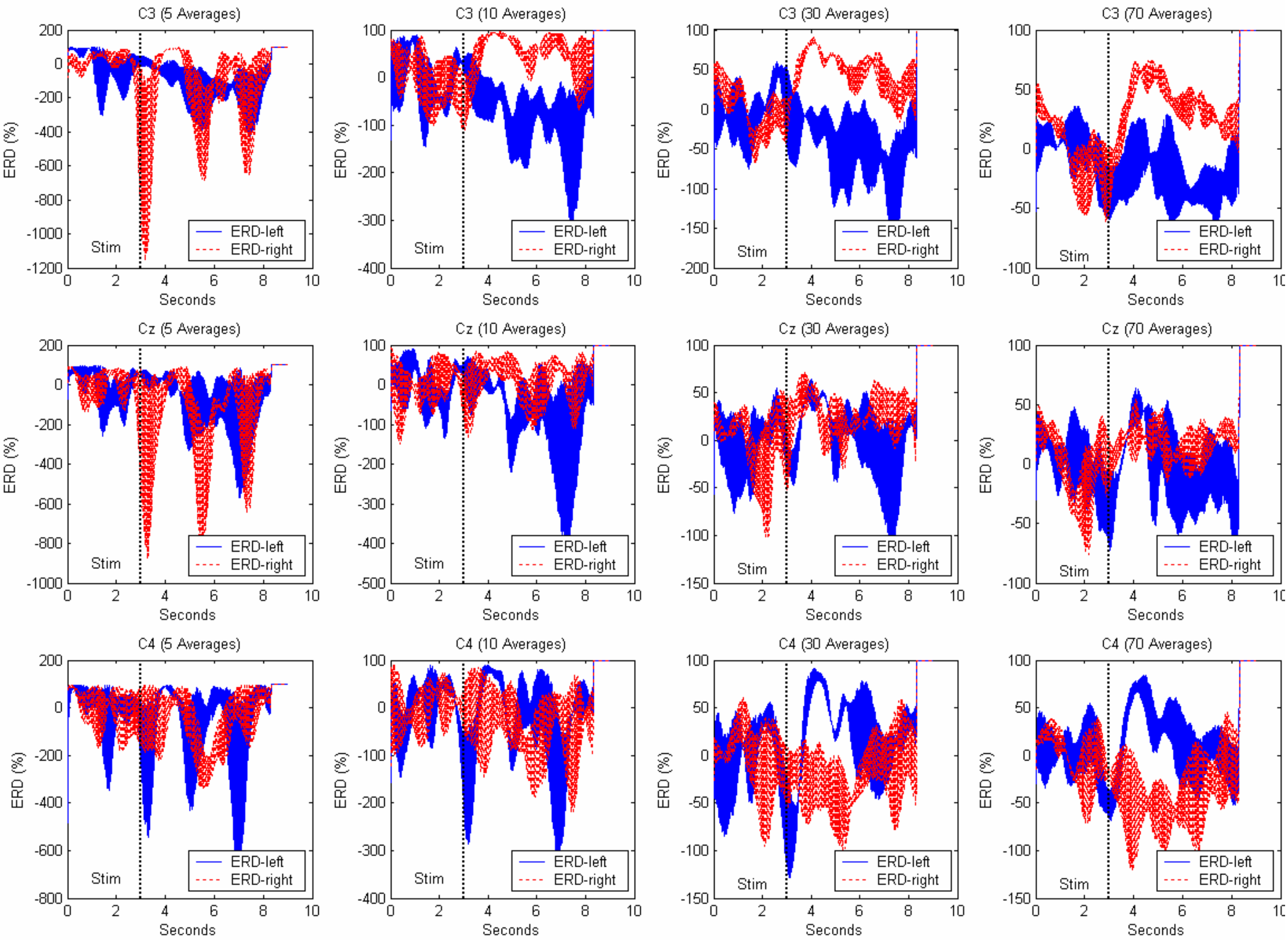

Fig. 4. Results obtained from applying the single channel analysis technique to a number of 9-second epochs of EEG recorded from channels C3, Cz and C4. The datasetset forms part of a BCI paradigm where an event related desynchronisation (ERD) of the 8~12Hz band power is expected after the stimulus onset (indicated by the vertical dotted line) on the channel contralateral to the visual stimulus. In each case the data was extracted by isolating those ICs within the frequency band of interest. Four sets of results are presented for each recording channel where the ERD is averaged over 5, 10, 30 and 70 averaged epochs.