AUTOMATIC CORRECTION OF EYE BLINK ARTIFACT IN SINGLE CHANNEL EEG RECORDING USING EMD AND OMP

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ABSTRACT

In this paper we propose a new technique for automatic correction of eye blink artifact in single channel EEG recording. The proposed technique consists of three steps. In the first two steps a dictionary matrix and a reference signal to the eye blink artifact are constructed from the recorded data, respectively. In the proposed technique we suggest building the dictionary matrix using empirical mode decomposition (EMD). In the last step, orthogonal matching pursuit (OMP) is utilized to find the minimum number of columns of the constructed dictionary matrix that fit the reference signal. Simulation results on real EEG data show that the proposed technique outperforms some of the existing single channel blind source separation techniques.

Indexing Terms: *Single–Channel BSS, Empirical Mode Decomposition, EEG, Orthogonal Matching Pursuit.*

I. INTRODUCTION

The electroencephalogram (EEG) is a noninvasive measure of brain electrical activity. EEG can be used as a clinical tool for studying the nervous system, monitoring of sleep stages, and diagnosing diseases such as epilepsy. Unfortunately, The measured EEG signal is usually contaminated with different kinds of artifacts such as eye blink, eye movement, and muscle artifacts. These kinds of artifacts are very common in EEG recordings and they complicate the analysis of the EEG data. Therefore, artifacts must be removed from the EEG signals before analysis.

In this paper we are concerned with correcting eye blink artifact. A traditional approach for dealing with such artifacts is to simply exclude the contaminated epochs from the analysis. However, following this approach, useful EEG data may be rejected, too. Since the recorded EEG data can be modeled as a linear combination of underlying brain activity, as well as artifact signals, the recorded EEG data can be decomposed into a set of source signals using blind source separation (BSS) techniques [1], [2], [3], [4].

The most powerful BSS technique known in the literature is independent component analysis (ICA) [2], [3]. ICA is a BSS technique that decomposes the measured signals into a set of *independent* components (sources). However, for the hidden source signals to be recovered successfully using ICA, *all* source signals have to be *independent*, and the number of channels have to be greater than or equal the number of the hidden source signals [1]. Even though eye blink artifact can be considered independent from brain signals, the assumption that brain signals themselves are independent is questionable. In addition, the number of brain sources that generate the measured EEG data is generally unknown, and hence can not be assumed to be equal to the number of the measuring electrodes, which vary according to the available measuring system. Therefore, in general, EEG data does not fulfill the assumptions associated with ICA. As a result, eye blink artifact separated using ICA is usually contaminated with other brain source signals. In addition, and as shown by the example presented in Section IV, the performance of different ICA algorithms depend on the objective function utilized for measuring the independency of the separated signals.

Since ICA requires the number of the recording electrodes to be at least equal the number of the hidden source signals, another BSS technique was developed in the literature for solving the *under–determined* BSS problem. In the under–determined BSS problem it is assumed that the number of source signals is known *a priori* and is greater than the number of sensors [4]. Some techniques were developed in the literature for the case of unknown number of source signals [5]. This BSS technique is known in the literature as sparse component analysis (SCA). The success of the SCA technique depends *crucially* on the *sparsity* of the hidden source signals in the original domain, or in a transform domain. Unfortunately, finding a transform domain in which both the eye blink artifact and the hidden brain source signals are sparse is not a trivial task, and, hence, there is a difficulty in utilizing the SCA technique for correcting eye blink artifacts.

The extreme case of the under–determined BSS is the case of having a *single* measuring electrode (channel). In this case the BSS problem is called single–channel BSS (SC-BSS). The SC-BSS problem is also applicable to multichannel

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recordings for the case when each measuring channel has to be analyzed separately due to the nature of the contaminating artifacts. Several techniques have been developed in the literature for solving the SC-BSS problem. One of these techniques, which is relevant to the proposed approach, solves the SC-BSS problem by converting the single channel data into a *virtual* multichannel recording, and then applying a BSS technique on the constructed multichannel signals [8], [9], [10], [12]. A summary of some of these techniques is presented in Section II.

Correcting eye blink artifact from a single channel recording using one of the techniques summarized in Section II suffer from the following limitations: 1) some of the techniques described in Section II are not appropriate for handling EEG data, 2) the number of rows in the virtually constructed multichannel data may be less than the number of hidden source signals, and hence ICA may fail in this case, 3) the separated sources has to be investigated to recognize the separated source signal corresponding to the eye blink artifact. This is typically done by visual inspection, and as such is a very time consuming and tedious process. Thus, there is a need for this process to be automated.

In this paper we propose a new technique for automatic correction of eye blink artifact in a single channel EEG recording. The proposed technique consists of three steps. In the first step we suggest building a dictionary matrix from the measured EEG data using empirical mode decomposition (EMD) [6]. See Section II for a brief description of EMD. Then, in the second step, a reference signal for the eye blink artifact is constructed from the measured data. Finally, the waveform of the contaminating eye blink artifact is estimated as the weighted sum of few columns of the constructed dictionary matrix. The indices of the selected columns, as well as the associated weights, are estimated using orthogonal matching pursuit (OMP) [7]. The eye blink artifact is then corrected by subtracting the estimated eye blink signal from the original EEG data.

II. SINGLE CHANNEL BLIND SOURCE SEPARATION (SC-BSS) TECHNIQUES

In this section we provide a brief summary of some SC-BSS techniques. These techniques consist of two steps. In the first step the single channel recording is converted into a virtual multichannel data, and then a matrix factorization technique is utilized in the second step to separate the constructed multichannel data into different source signals.

1) Nonnegative Matrix Factorization of a Time Frequency Representation. In this approach the measured signal is converted into a virtual multichannel data by transforming the data into the time-frequency (TF) plane using short time fourier transform (STFT). Then the magnitude spectrum of the TF data is decomposed using nonnegative matrix factorization (NMF) [8]. This approach works properly when the spectrum of the hidden source signals are not overlapped in the TF domain. A condition which is not satisfied for EEG data.

2) Singular Spectrum Analysis (SSA) In this approach the measured signal $x(t), t = 1, \dots, T$, where T is the number of samples, is converted into a virtual multichannel data by constructing a dynamical embedding (DE) matrix $X \in R^{M \times L}$, where M is called the *embedding parameter*, and $L = T - M + 1$. The kth column of the DE matrix X consists of M successive samples of $x(t)$ starting from $x(k)$. After constructing the DE matrix, either principal component analysis (PCA) [9], or ICA [10] is utilized to decompose X into different components. Each one of the separated components is considered as an estimate of one of the hidden source signals. Unfortunately, this approach critically depends on the value of the embedding parameter M, and it assumes that the hidden source signals are stationary and independent. These condition are generally not applicable on EEG data.

3) Wavelet-ICA (WICA) In this approach the measured signal $x(t)$ is decomposed into spectrally nonoverlapping components using wavelet decomposition to construct a virtual multichannel data matrix $X(t)$. Then an ICA algorithm is applied on the data matrix $X(t)$ to produce a set of independent components [11]. The main difficulty associated with this approach is selecting an appropriate mother wavelet, especially when no a priori knowledge of the source of interest is available [12].

4) Ensemble EMD-ICA (EEMD-ICA) Before explaining the EEMD-ICA technique, we start first by describing the main idea of the empirical mode decomposition (EMD) technique [6]. EMD assumes that every signal $x(t)$ consists of a superposition of zero-mean, narrow–band, and quasi-symmetrical components $c_i(t)$ called intrinsic mode functions (IMFs). Following this model, a signal $x(t)$ can be expressed as $x(t) = \sum_i c_i(t) + r(t)$, where $r(t)$ is a residual that represents the trend of the signal $x(t)$, and each IMF $c_i(t)$ is meant to be *mono–component* and satisfies the following two conditions: 1) its number of extrema and zero-crossings must be equal or differ at most by one, 2) at any point, the mean value of its upper and lower envelopes, which are defined respectively by the local maxima and the local minima, should be zero. The IMFs $c_i(t)$ are identified by following the following *sifting* process [6].

1) Set $r(t) = x(t)$, $h(t) = r(t)$, and $i = 1$
2) For $k = 1, \dots$ repeat the following steps until $h(t)$ is an IMF
   a) Find all local minima and maxima of $h(t)$.
   b) Interpolate between the minima (resp., maxima) to calculate the lower envelope $E_l(t)$ (resp., the upper envelope $E_u(t)$).
   c) Compute the mean envelope $m(t) = \frac{E_l(t)+E_u(t)}{2}$.
   d) Update $h(t) \leftarrow h(t) - m(t)$.
3) Set $c_i(t) = h(t)$.
4) Update $r(t) \leftarrow r(t) - c_i(t)$.
5) If the number of extrema of $r(t)$ is less than three, stop; otherwise increment $i \leftarrow i + 1$, set $h(t) = r(t)$, and go to Step 2.

As can be recognized from the above steps, and in contrast to the Fourier or the Wavelet decompositions, the EMD decomposition does not depend on predefined bases functions. Rather, it is adaptive, and it follows the intrinsic oscillations within the analyzed signal. However, one of the problems associated with EMD is what is known as *mode–mixing* phenomenon. This phenomenon is defined as the mixing of different time scales in an IMF. This phenomenon can be caused by intermittent signals and/or noisy data. The main consequence of the mode–mixing phenomenon is getting IMFs that are not monocomponents. Many approaches have been developed in the literature for solving the mode–mixing problem. One of these techniques is ensemble EMD (EEMD) [13].

The EEMD-ICA technique suggested in [12] for solving the SC-BSS problem is based on constructing virtual multichannel recordings by decomposing the recorded single channel EEG data into a set of IMFs $\{c_i(t)\}$ using EEMD. The derived IMFs are then arranged in a data matrix $C \in R^{N\times T}$, where N is the number of the constructed IMFs, and T is the number of samples of the original signal $x(t)$. The constructed multidimensional data matrix C is then decomposed into a set of independent components using ICA. The authors of [12] suggested utilizing the well known ICA algorithm called FastICA [2]. The sources of interest are then identified by visual inspection.

III. PROPOSED TECHNIQUE

As shown in the previous section, all the described techniques have some common drawbacks. For EEMD-ICA, we summarize these drawbacks in the following points: 1) the number of rows N of the constructed data matrix C may not be greater than or equal the number of the hidden source signals, and hence the source(s) of interest may not be fully extracted by the utilized ICA algorithm, 2) the decomposition may depend on the objective function utilized by the ICA algorithm for measuring the independency of the separated source signals, and finally 3) the separated source signals have to be manually investigated to select the source(s) of interest.

In this section we propose a new technique for automatic correction of eye blink artifact in single channel EEG recording. The proposed technique does not perform BSS on the measured EEG data $x(t)$. Rather, it utilizes a reference signal $y \in R^{T\times 1}$ to estimates the eye blink artifact as a weighted sum of few columns of a dictionary matrix $A \in R^{T\times L}$. The reference signal is selected to have some information about the eye blink artifact. In the proposed technique we propose methods for constructing both A and y from the signal $x(t)$. The proposed technique consists of the following three steps.

III-A. Step 1: Building a dictionary matrix A

In this paper we suggest building a dictionary matrix A from the recorded EEG data $x(t)$ using EMD decomposition. Recall that the EMD decomposition suffers from the *mode–mixing phenomenon* associated with decomposing noisy data. This phenomenon can be caused also by the presence of intermittent signals (like the eye blink artifact) in the decomposed signal $x(t)$. Therefore, by adding a random noise $n(t)$ to the recorded EEG data $x(t)$, and then performing the EMD decomposition on the mixture $x(t) + n(t)$, the eye blink artifact is expected to either split between different IMFs, or combine with other brain oscillatory in a single IMF. In addition, every time a new noise component $n(t)$ is added to the recorded EEG data $x(t)$, a *new set* of IMFs results from applying the EMD decomposition on the mixture $x(t) + n(t)$. Therefore, in the proposed approach we suggest utilizing the mode–mixing phenomenon to build a dictionary matrix A from IMFs resulting from applying the EMD decomposition on a constructed noisy data $x(t) + n(t)$. The proposed approach is summarized in the following steps.

1) Initiate an empty dictionary matrix $A = [\ ]$, select a number of iterations I_{max}, and select a noise standard deviation (SD) level ρ.
2) For $i = 1,\ldots,I_{max}$ repeat the following steps
    a) Generate an *i.i.d.* Gaussian random noise $n(t)$ and adjust its amplitude such that its SD equals ρ.
    b) Construct the noisy signal $x_n(t) = \text{filter}(x(t) + n(t))$.
    c) Calculate the EMD decomposition of $x_n(t)$, $C = \text{EMD}(x_n(t))$.
    d) Update the dictionary matrix $A = [A\ \ C^T]$.

The following notes are in order. 1) In Step 2b the noisy signal $(x(t) + n(t))$ is filtered to the bandwidth of the original signal $x(t)$ to avoid getting IMFs that do not belong to the bandwidth of $x(t)$, 2) in Step 2c the matrix C is calculated using the procedure described in Section II.4, and 3) in Step 2d the matrix C is transposed because the IMFs obtained by the procedure described in Section II.4 are assumed to be row vectors, rather than column vectors.

III-B. Step 2: Constructing a reference signal y

In this subsection a procedure for constructing a reference signal $y \in R^{T\times 1}$ (for the eye blink artifact) from the recorded EEG data $x(t)$ is suggested. The reference signal has to be selected to have enough information about the eye blink artifact to guide the algorithm towards the desired signal. However, the reference signal is not required to be an exact replica of the eye blink artifact. To construct the reference signal from the recorded EEG data we make use of the following two facts: 1) under normal brain operation, the EEG data has Gaussian distribution [14], and 2) the amplitude of the eye blink artifact is much greater than the amplitude of the normal EEG data. Accordingly, due to the presence of eye blink artifact, a histogram of an EEG data contaminated with eye blink artifact will show some outlier samples that do not follow the Gaussian distribution. Therefore, if the mean μ and the standard deviation σ of the Gaussian distribution of the clean EEG data are known *a priori*, the samples of the measured EEG data that most probably correspond to the eye blink artifact can be identified as those samples that deviate $\alpha\sigma$ from the mean μ, where $\alpha > 1$ is some constant. Accordingly, we suggest constructing a reference signal to the eye blink artifact using the following thresholding equation

$$y_k = \begin{cases} 0 & \theta_l \le x(k) \le \theta_u \\ x(k) & \text{otherwise,} \end{cases} \tag{1}$$

where y_k is the kth entry of y, and θ_l and θ_u are respectively the lower and upper thresholds calculated using the following equation.

$$\theta_u,\ \theta_l = \mu \pm \alpha\sigma, \tag{2}$$

Note that selecting a small value for α causes EEG signal to be represented in the reference signal y, and hence more atoms will be selected in the third step to approximate the EEG signal in y. On the other hand, selecting large value for α will result in losing fine details of the artifact in

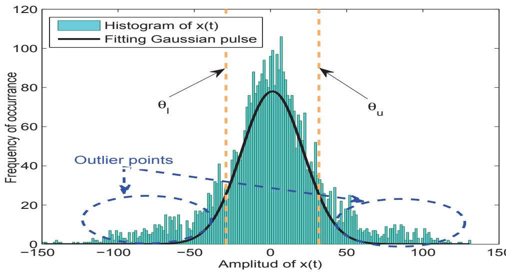


Fig. 1. Selecting the upper and lower thresholds associated with the EEG data in Fig. 2 by fitting its histogram by a Gaussian pulse.

the reference signal, and hence eye blink artifact may not accurately fitted in the third step. Empirically, we found that the proposed technique works fine for the range $1 \leq \alpha \leq 2$.

Unfortunately, however, the parameters μ and σ of the Gaussian distribution are not known, and, therefore, they have to be estimated. To accomplish this goal, we suggest building a histogram from the samples of $x(t)$, and then fitting the constructed histogram using a Gaussian pulse of the form $p_x(x) = a_f \exp\left(-\frac{(x-\mu_f)^2}{2\sigma_f^2}\right)$, where a_f, μ_f, and σ_f are respectively the amplitude, mean, and standard deviation of the fitting Gaussian pulse. The fitting parameters μ_f, and σ_f can then be utilized in (2) to estimate the upper and lower thresholds. Since the outlier points in the histogram of $x(t)$ (see Fig. 1) can affect the estimated values of the parameters of the fitting Gaussian pulse, we can perform the fitting process in two steps. In the first step, initial guess a_1, μ_1, and σ_1 of the fitting parameters are calculated using all samples of $x(t)$. Then, more accurate estimate of the fitting parameters μ_f, and σ_f are calculated using only the samples of $x(t)$ that have amplitude values within one standard deviation σ_1 from the estimated mean μ_1. The histogram of the EEG data represented by the last waveform in Fig. 2(a), as well as the associated fitting Gaussian pulse and the estimated thresholds, are shown in Fig. 1.

III-C. Step 3: Estimating the eye blink artifact

Recall from Section III-A that, due to the mode–mixing phenomenon associated with the EMD decomposition, the eye blink artifact is represented in some columns of the constructed dictionary matrix A. Therefore, an estimate of the waveform of the eye blink artifact can be obtained as the *weighted sum* of these columns. Since the indices of these columns are unknown, we can utilize the reference signal y as a guide to select the desired columns of A, as well as the associated weighting coefficients. Therefore, the last step in the proposed approach is to select the minimum number of columns of A that best fit the reference signal y. This can be described mathematically by the following optimization problem

$$\min \|b\|_{\ell_0} \quad \text{s.t.} \quad \|Ab - y\|_{\ell_2} \leq \sigma_0 \qquad (3)$$

where $\|b\|_{\ell_0}$ is the cardinality (i.e. the number of nonzero entries) of the coefficient vector b, and σ_0 is a constant proportional to the standard deviation of the difference between the estimated artifact Ab and the reference signal y. Recall from (1) that y equals zero over the range at which the recorded EEG data $x(t)$ does not exceed the thresholds. However, the estimated artifact Ab is expected to have residual EEG signal over the same range. (See the second and the third waveforms in Fig. 2(b).) Therefore, the quantity $\|Ab - y\|_{\ell_2}$ is expected to be proportional to the standard deviation of the clean EEG data. Since the distribution of the clean EEG data is approximated by the fitting Gaussian pulse obtained in the previous subsection, we empirically set $\sigma_0 = 0.7\sigma_f$, where σ_f is the standard deviation of the fitting Gaussian pulse obtained in the previous step.

The optimization problem (3) can be solved using the orthogonal matching pursuit (OMP) technique [7]. OMP is an iterative technique, where in each iteration a single column of A is selected, and the corresponding entry of b is calculated using least squares. The selected columns of A are selected based on their vicinity to the reference signal y. See [7] for more details about the OMP technique and its properties.

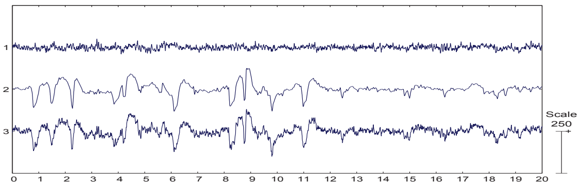
After convergence, the eye blink artifact is estimated as $x_{ar}(t) = (Ab)^T$, and the cleaned EEG signal is calculated as $x_c(t) = x(t) - x_{ar}(t)$.

IV. SIMULATION RESULTS

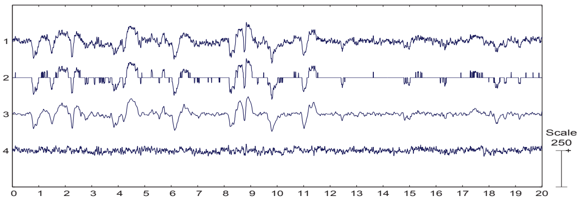
In this section we present an example to demonstrate the efficiency of the proposed technique in removing eye blink artifact from real EEG data. The EEG data were collected using 20 electrodes placed according to the International 10-20 System, and one EOG electrode to recorde the EOG artifact. The sampling frequency was 205 Hz, and an average reference was used. The signal $x(t)$ is constructed as $x(t) = s(t) + v(t)$, where $s(t)$ is a 20 seconds of clean EEG data recorded at one of the recording electrodes, and $v(t)$ is 20 seconds of the eye blink artifact recorded at the EOG electrode. Constructing $x(t)$ using this technique, rather than utilizing the data at one of the contaminated channels directly, allows us to compare the estimated artifact with the *known* implanted artifact $v(t)$. The waveforms presented in Fig 2(a) from top to bottom represent respectively the signals $s(t)$, $v(t)$, and $x(t)$.

For estimating the eye blink artifact using the proposed approach, a dictionary matrix A is constructed using the procedure described in Section III-A with $I_{max} = 100$, and the noise standard deviation ρ is selected as 0.25 times the standard deviation of $x(t)$. On the other hand, the reference signal to the eye blink artifact is constructed from $x(t)$ using (1) and (2). The reference signal is presented by the second waveform in Fig. 2(b). The extracted eye blink artifact $x_{ar}(t)$ is presented by the third waveform in Fig. 2(b), and the lower waveform in Fig. 2(b) represents the cleaned EEG data $x_c(t) = x(t) - x_{ar}(t)$. As shown in the last two signals, the eye blink artifact was extracted correctly by the proposed technique. The correlation coefficient between the extracted eye blink artifact and the implanted artifact $v(t)$ is 0.93.

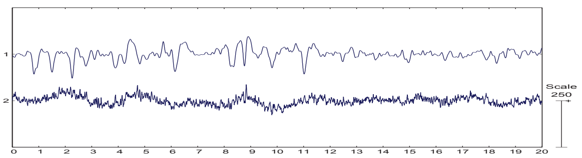
For comparison, we applied the EEMD-ICA algorithm on $x(t)$. In addition, two well known ICA algorithms (FastICA [2] and Jade [3]) were utilized in the EEMD-ICA algorithm to examine the impact of the utilized ICA algorithm on the performance of the EEMD-ICA algorithm. The result of utilizing FastICA and Jade are shown in Fig. 2(c), and Fig. 2(d), respectively. The upper waveform in each figure represents the extracted artifact, and the lower waveform represents the corrected EEG data. As shown in these figures, there is a difference between the performance of the two



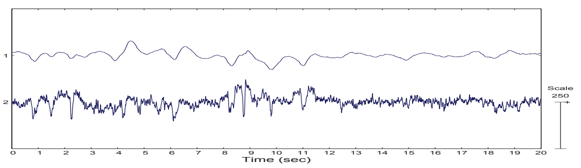
(a)



(b)



(c)



(d)

Fig. 2. Correcting eye blink artifact in single channel EEG recording using different techniques. (a) Original EEG data. The curves from top to bottom are the clean EEG data, the eye blink artifact, and the contaminated data $x(t)$. (b) Results of the proposed technique. (c) Result of EEMD-ICA when the sources are separated using FastICA. (d) Result of EEMD-ICA when the sources are separated using Jade.

algorithms, and FastICA performed better than Jade. The correlation coefficients between the estimated artifact and the implanted artifact in this case are 0.79 and 0.59, when FastICA and Jade are utilized in EEMD-ICA, respectively. In addition, a residual artifact is noticeable in the corrected EEG data in both cases. The main reason behind the poor performance of the EEMD-ICA algorithm in this example is that the eye blink artifact in both cases is not confined in a single component of the separated components. The ones shown in the upper traces in Fig. 2(c), and Fig. 2(d) are the closest components (among all the separated components) to the implanted eye blink artifact $v(t)$. Combining more components to better approximate the eye blink artifact will result in a loss of useful EEG data.

V. CONCLUSION

In this paper we proposed a new technique for automatic correction of eye blink artifact in single channel EEG recording. The proposed technique is based on estimating the eye blink artifact by selecting the minimum number of columns (from a constructed dictionary matrix) that match a reference signal to the eye blink artifact. Both the dictionary matrix and the reference signal are estimated from the analyzed data itself. The dictionary matrix was built using EMD, and the atoms are selected using OMP. Simulation results show that the proposed technique outperform some of the existing SC-BSS techniques.

VI. REFERENCES

[1] A. Cichocki and S. Amari, ”Adaptive Blind Signal and Image Processing: Learning Algorithms and Applications,” John Wiley & Sons, Ltd.

[2] A. Hyvrinen. ”Fast and Robust Fixed-Point Algorithms for Independent Component Analysis.” *IEEE* Transactions on Neural Networks, vol. 10, no. 3, pp.626-634,1999.

[3] J. F. Cardoso, “High-order contrasts for independent component analysis”, Neural Compuutation, vol. 11. no. 1, pp. 157-192, 1999.

[4] M. Zibulevsky, and B.A. Pealmutter, ”Blind Source Separation by Sparse Decomposition in a Signal Dictionary,” in Neural Comp., vol. 13, pp. 863-882, 2001.

[5] N. Mourad, and J.P. Reilly, “Modified hierarchical clustering for sparse component analysis,” *ICASSP2010*, Apr. 2010, Dallas, Texas, USA.

[6] Norden E. Huang, Zheng Shen, Steven R. Long, Manli C. Wu, Hsing H. Shih, Quanan Zheng, Nai-Chyuan Yen, Chi Chao Tung, and Henry H. Liu. “The empirical mode decomposition and the Hilbert spectrum for nonlinear and non-stationary time series analysis.” *Proc. R. Soc. Lond.*, vol. 454, pp. 903–995, 1998.

[7] Y. C. Pati, R. Rezaiifar, and P. S. Krishnaprasad, “Orthogonal matching pursuit: Recursive function approximation with applications to wavelet decomposition,” in Proc. 27th Annu. Asilomar Conf. Signals Syst. Comput., Nov. 13, 1993, vol. 1, pp. 4044.

[8] M. Heln and T. Virtanen, Separation of drums from polyphonic music using nonnegative matrix factorization and support vector machine, in Proc of 13th European Signal Processing, 2005.

[9] A.R. Teixeira, A.M. Tome, E.W. Lang, P. Gruber, and A. Martins da Silva “Automatic removal of high-amplitude artefacts from single-channel electroencephalograms,” Computer Methods and Programs in Biomedicine, vol. 8, no. 3, pp. 125138, 2006.

[10] C.J. James, and D. Lowe, “Extracting multisource brain activity from a single electromagnetic channel,” Artificial Intelligence in Medicine, vol. 28, pp. 89104, 2003.

[11] J. Lin and A. Zhang, “ault feature separation using wavelet-ICA filter,” *NDT & E Int.*, vol. 38, no. 6, pp. 421427, 2005.

[12] B. Mijović, M. De Vos, I Gligorijević, J. Taelman, and S.V. Huffel, “Source Separation From Single-Channel Recordings by Combining Empirical-Mode Decomposition and Independent Component Analysis,” *IEEE Trans. Biomed. Eng.*, vol. 57, no. 9, pp. 2188-2196, 2010

[13] Z. Wu and N.E. Huang, “Ensemble empirical mode decomposition: A noise-assisted data analysis method,” *Adv. Adaptive Data Anal.*, vol. 1, no. 1, pp. 141, 2009.

[14] Saeid Sanei, and J. A. Chambers, “EEG Signal Processing,” John Wiley & Sons, 2007.