A Novel Approach for Focal Seizure Detection Using Constrained Blind Source Separation

Kaashif Khawaja and Saeid Sanei

Centre for DSP Research, King's College London, UK, {kaashif.khawaja, saeid.sanei}@kcl.ac.uk

Abstract. Development of a robust technique for automatic detection of the epileptic seizures is an important goal in clinical neurosciences. In this paper a novel technique for detection of epileptic seizure based on constrained blind source separation (CBSS) has been developed. The BSS algorithm separates the electroencephalograms (EEGs) into their constituent independent components whereas imposing a constraint into the learning process highlights the epileptic source in the output of the separator. A reference signal (as a constraint) is modelled as a segment of a sine wave with a peak representing the seizure spike. The cycle frequency of the reference signal is estimated by looking at the spectrum of the separated EEG segment in the previous iteration. The results show an improvement in terms of computational speed in comparison with other systems.

1. INTRODUCTION

Analysis of the EEG is the primary method for diagnosis of epilepsy. Based on the EEG patterns during epileptic seizures, physicians can determine the type of epileptic syndrome. Long term monitoring is the common procedure to register the occurrence of epileptic events, which may last from seconds to hours.

Traditionally, seizure has been detected in hospitals by means of continuous observation and possibly the use of an alarm button activated by the patient. Otherwise, the patient reports it. Nevertheless, many epileptic seizures imply loss of consciousness, confusion or even loss of memory, making patient's registrations inaccurate. Moreover, some seizures do not present clinical symptoms and can be unnoticed even by the patient himself. Automatic detection of epilepsy has been investigated for the past few years. Murro [1] proposed a method based on spectral analysis in which he used the dominant frequency, the relative amplitude and the power of the spectrum around the dominant frequency divided by the total power as features. Harding exploited the increase of spikes in the EEG in his proposal [2]. The use of neural networks has been common in the field of automatic detection since Webber [3] used a 31-30-8 network combining statistical features such as mean, variance and skewnes with morphologic features like amplitude, slope or duration of waves. Neural networks were also use Pradhan [4]. He used raw EEG as the input. Weng et al. used those features proposed by Gotman as the inputs to their NN [5]. In 1996, Gabor et al. brought the dynamics of the brain insight with the help of wavelets [6]. In a recent paper, Qu and Gotman used a nearest neighbour classifier with features from both time and frequency domain extracted from overlapping EEG epochs of 2.56 sec length [7]. A popular method called Matching pursuit (MP) algorithm was introduced by Durka et al., based on time-frequency decomposition, using Gabor functions called atoms [8]. Finally, support vector machines (SVM) was introduced recently as another alternative for detection of tonic-clonic seizures [9].

Blind separation of the EEG signals on the other hand, has been followed by a number of researchers [10] [11]. Some source separation problems such as signal detection and noise cancellation often expect to estimate a desired single source or a subset of sources from the mixtures. In such cases a separate objective function, as a constraint, has to be minimized (or maximized) in parallel with minimization of the original cost function. Exploitation of Lagrange multipliers and nonlinear penalty functions [12] incorporate the constraint terms into the original cost functions thereby convert the constrained problems to unconstrained algorithms. The BSS criterion (or equivalently ICA) for instantaneous mixtures such as EEGs, is formulated as follows. Denote the time varying observed signals by $\mathbf{x} = [x_1(t), x_2(t), \ldots, x_n(t)]^T$ where $\mathbf{x} \in R^n$ and the unknown independent sources $\mathbf{s} = [s_1(t), s_2(t), \ldots, s_m(t)]^T$ where $\mathbf{s} \in R^m$.

$$\mathbf{x} = A\mathbf{s} + \mathbf{v} \tag{1}$$

and

$$\mathbf{y} = W\mathbf{x} \tag{2}$$

Here $\mathbf{v} \in R^n$ is assumed to be a white Gaussian noise vector, $A \in R^{m\times n}$ and $W \in R^{n\times m}$ are unknown constant mixing and unmixing matrices respectively, and $(.)^T$ is vector transpose. The mixture is assumed to be over-determined (valid for usual cases), i.e. $m<n$. $\mathbf{y} = [y_1(t), y_2(t), \ldots, y_m(t)]^T$, where $\mathbf{y} \in R^m$ is the

output vector. The unconstrained separation matrix can be found by finding the global minima of a cost function $J_M(W)$, which provides a measure of independency of the estimated sources. Incorporation of the constraint requires another cost function such as $J_C(W)$ to be minimized together with $J_M(W)$. The constraint term is then joined to the main objective function by using either a Lagrange multiplier or a set of penalty functions. Application of the Lagrange multiplier however, ignores nonlinearity of the system whereby the nonstationarity of the mixtures is not exploited. A general overall cost function is best defined as follows:

$$J(\mathbf{W}) = J_M(\mathbf{W}) + kG\left(J_C(\mathbf{W})\right) \quad (3)$$

where $G(.)$ is the penalty function and k is the matrix of penalty coefficients.

2. CONSTRAINED BSS FOR SEIZURE DETECTION

In an undetermined BSS system the estimated ICs do not necessarily represent the actual sources. This happens when EEGs are to be separated. In the development of this project we aim at separation of the scalp EEG mixtures so that the desired signal with seizure spikes is one of the estimated ICs. The NGA BSS algorithm aims to maximise the decorrelation of the ICs. The NGA cost function $J_M(\mathrm{w})$, can be found in the literature [13]. The unmixing matrix is recursively updated by finding a solution to the minimization of such unconstrained overall cost function i.e.

$$arg\,\min_{\mathbf{w}} J(\mathbf{w}) = arg\,\min_{\mathbf{w}}\left[J_M(\mathbf{w}) + G\left(J_C(\mathbf{w})\right)\right] \quad (4)$$

where $J_M(\mathbf{w})$ is the main objective function of the BSS algorithm as [14]

$$J_M(\mathbf{w}) = \left\lfloor \mathbf{I} - \mathit{off}\left(R_{yy}\mathbf{w}R_{xx}\right)\right\rfloor \quad (5)$$

and , G, in general, can be a nonlinear function. Here we consider a simple case of $G\left(J_c(\mathbf{w})\right) = \lambda\left\|\mathbf{gy}^T\right\|^2$ where ||.|| is the Frobenius norm, **I** is the unitary matrix, *off* refers to off-diagonal elements, and λ is the Lagrange multiplier to cater for the differing rate of convergence between the ICA and cICA cost functions. The reference signal is obtained cleverly by measurements of peak-frequency to the average of the frequency spectrum of the estimated sources after each iteration i.e.

$$peak\ \ freq. = \sup_{f_n} \max\left(\frac{p}{\frac{2}{K}\sum_{i=0}^{K/2-1} q_n(i)}\right) \quad (6)$$

Where K represents the DFT point, p is the peak value, and n points to the nth IC. The peak frequency is then compared with a predefined threshold level to identify whether there is any possible cyclo-stationarity in the ICs. A suitable model for the signal during the occurrence of seizure can be a sine wave whose cycle frequency is measured in (6) and the amplitude of half a cycle in that is reasonably high. A simulation of such signal may look like that in Figure 1.

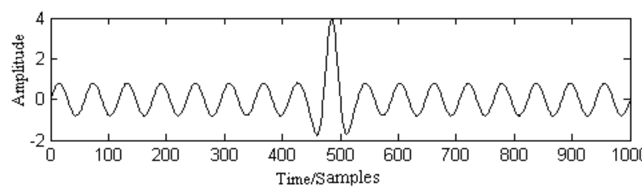

Figure 1. A typical Seizure segment

We adapt W by a stochastic-gradient learning algorithm, the update equation is generally denoted as

$$\mathbf{w}(t+1) = \mathbf{w}(t) + \Delta\mathbf{w}(t) \quad (7)$$

where by considering the extension to the NGA proposed by Amari [14] we have

$$\Delta\mathbf{w}(t) = \mu\frac{\partial J(\mathbf{w})}{\partial\mathbf{w}} = \mathit{off}\left(R_{yy}\mathbf{w}R_{xx}\right) + \lambda\left\|\mathbf{gy}^T\right\| \quad (8)$$

Where $R_{yy} = WR_{xx}W^T$ defines the autocorrelation of the ICs, μ is the learning rate, γ is a constant, and **I** is a unitary matrix. **w** is initialised to $\mathbf{w}_{init}$ = **I** and μ is calculated empirically via the following adaptive criterion:

$$\mu(t) = \mu_0\left(\frac{\alpha}{\left\|\mathrm{Rx}\right\|_F^2} + \frac{\beta}{\zeta + \left\|\Delta J_C\right\|}\right) \quad (9)$$

where μ_0, α, β, and ζ are constants adjusted for adaptation. In the above analysis we ignored the effect of noise, which is inherently contained in **x**. However, incorporation of the constraint into the original NGA update equation does not change the performance of the system in terms of noise effect.

3. EXPERIMENTAL RESULTS

The EEG data is obtained from epileptic patients in St. Thomas hospital London. The EEGs are digitally recorded at a rate of 200 samples per second. Conventional 10-20-electrode placement system was used. The recordings consisted of over 20 minutes of brain activity with the seizure duration of approximately 10 seconds. We therefore processed the blocks of 2000 samples to account for approximately, the full duration of the focal seizure. The algorithm performs well highlighting the seizure segments. After performing the CBSS the spike like characteristics are clearly visible exhibiting a rhythmic structure to the temporal components. This provides to be a valuable tool for the adaptation of the seizure characteristics as obtaining a reference signal for the detection of focal epilepsy is very problematic. One similarity that can be stated for the seizure segments in the IC is the sharp peaks of the seizure surrounded by a long tail of oscillation.

As a trial based on synthetic data, we applied two deterministic signals and a uniformly distributed random signal. The signals are pre-whitened prior to the CBSS application. We set K=512, λ=0.006, α=0.001, β=0.2 and ζ=0.04. [13]. The sources were linearly mixed from randomly generated mixing matrices and the algorithm was performed. The reference signal was set to be one of the three source signals. Figures 2 and 3 are the original sources and the mixtures respectively. Figures 3 and 4 are the estimated sources using traditional and the proposed CBSS respectively. Below we illustrate the results when the second signal is set to be the reference signal.

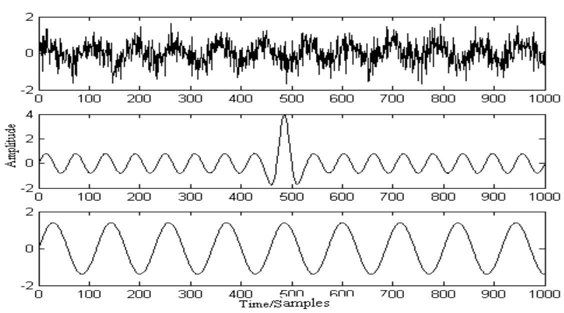

Figure 2. Three simulated source signals

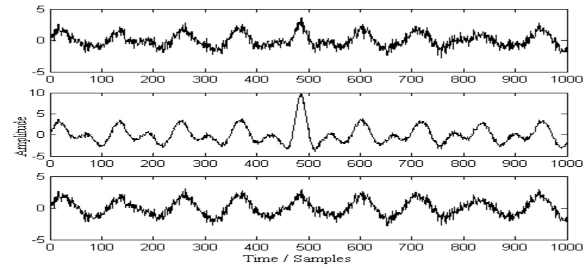

Figure 2. Mixed signals

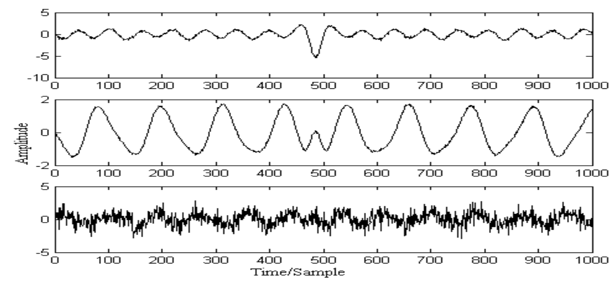

Figure 3. The estimated sources using NGA.

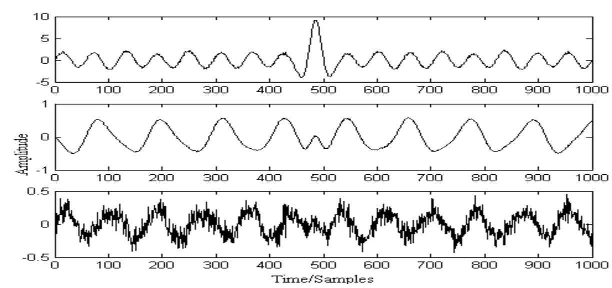

Figure 4. The separated signals using CBSS. The reference signal is greatly enhanced.

Figure 5 compares the convergence rate and Figures 6 and 7 are the mixtures and the estimated sources using the proposed algorithm respectively.

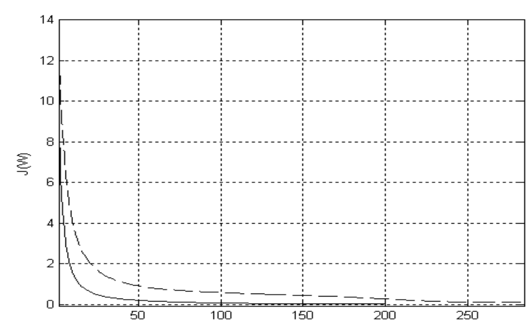

Figure 5. Comparison of the cost function, solid line for NGA and dashed line for CNGA.

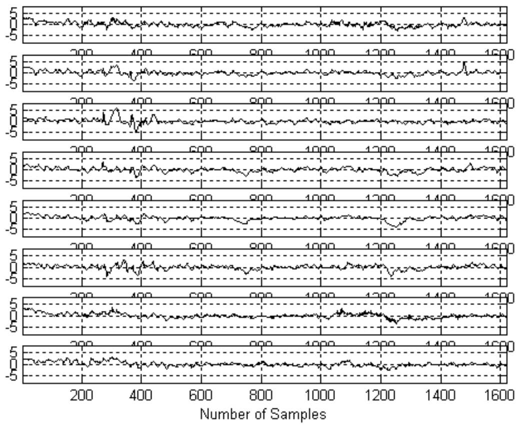

Figure 6. The original EEG signals of an epileptic patient.

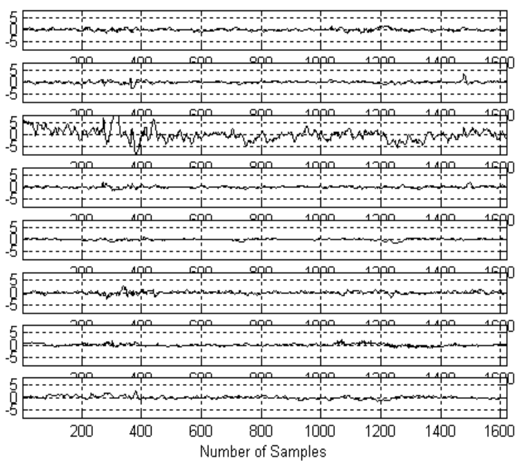

Figure 8. The estimated sources with emphasis on the seizure signal.

4. CONCLUSIONS

An effective CBSS method has been developed and used for detection of seizures from EEGs. The algorithm is an extension of NGA algorithm for which an estimated reference signal is used as a constraint. The constrained problem is then converted to an unconstrained problem by means of nonlinear penalty functions weighted by the penalty terms. The algorithm has been examined on both simulated and natural EEG signals of both healthy and epilepsy patients. The segments with seizure are clearly highlighted and detected. The reference signal forces the unmixing matrix to separate the sources of epilepsy resulted from the corresponding stimulations. The results are compared with those of the traditional NGA algorithm in terms of the convergence speed. The method is an effective tool in investigation of the epilepsy disease (as well as some other neurological disorders such as drowsiness, tumour, and brain damage) in the clinics

REFERENCES

[1] Murro AM, King DW, Smith JR, Gallagher BB, Flanigin HF, Meador KJ. Computerized seizure detection of complex partial seizures. *Electroencephalography and Clinical Neurophysiology* 1991;79:330-333.

[2] Harding GW. An automated seizure monitoring system for patients with indwelling recording electrodes. Electroencephalohraphy. and Clinical Neurophysiology 1993; 86(6): 428-437.

[3] Webber WRS et al, An approach to seizure detection using an artificial neural network. *Electroenceph. and Clinical Neurophysiology* 1996; 98:250-272.

[4] Pradhan N, et al. Detection of seizure activity in EEG by an artificial neural network: a preliminary study. Comp. and Biome. Research 1996;29(4):303-313.

[5] Weng W, Khorasani K. An adaptive structure neural network with application to EEG automatic seizure detection. *Neural Networks* 1996;9(7):1223-1240.

[6] Gabor AJ et al. Automated seizure detection using a self-organizing neural network. Electroencephalography and Clinical Neurophysiology 1996;99:257-266.

[7] Qu H, Gotman J. A patient-specific algorithm for the detection of seizure onset in long-term EEG monitoring: possible use as a warning device. *IEEE Transactions on Biomedical Engineering* 1997;44(2):115-122.

[8] Durka P. J, D. Ircha, and K. J. Blinowska, “Stochastic Time-Frequency Dictionaries for Matching Pursuit”, *IEEE Trans. on* Sig. Proc., 2001, 49(3), pp. 507-510,

[9] B. Gonzalez and S. Sanei, “Support vector machines for seizure detection”, Proc. of IEEE, ISSPIT2003, pp. 238-241, December 2003, Germany.

[10] L. Shoker, S. Sanei, W. Wang, and J. Chambers, “Removal of eye blinking artifact from EEG incorporating a new constrained BSS algorithm,” To be published in IEE J. of Med. & Biolog. Eng. & Comp.

[11] C. James and D. Lowe, ‘Using Dynamical Embedding To Isolate Seizure Components In The Ictal EEG’, Advances in Medical Signal and information Processing. No. 476, copyright IEE, 2000

[12] W. Wang, M. Jafari, S. Sanei, J. Chambers, “Penalty function-based joint diagonalization approach for convolutive blind source separation of non-stationary sources,” To be published. IEEE Trans. on Signal Proc.

[13] A. Hyvarinen, J. Karhunen, and E. Oja Independent Component Analysis John Wiley & Sons, A Wiley-Interscience Publication, U.S.A, 2001

[14] M. Joho, R. H. Lambert and H. Mathis Elementary cost functions for blind source separation of non-stationary source signals, ICASSP 2001, Vol 5. pp 2793-2796.