35th Annual International Conference of the IEEE EMBS
Osaka, Japan, 3 - 7 July, 2013

EEG Epileptic Seizures Separation with Multivariate Empirical Mode Decomposition for Diagnostic Purposes

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***Abstract*— We present a successful application of a soft computing approach based on the multivariate empirical mode decomposition (MEMD) method to EEG epileptic seizures separation. The results of the automatic multivatiate intrinsic mode functions (IMF) clustering allowed us to separate the seizure related spikes and sharp waves. The results of the proposed method have been compared with classical blind separation approach based on ICA, which failed to identify the non–linear and non–stationary signals related to the brain seizures. The proposed method supports epileptic seizure diagnostic methods.**

I. INTRODUCTION

The epileptic seizure automatic identification and further brain localization are hot topics in neurotechnology research [1]. In this paper we report an application of MEMD data–driven technique to the seizures separation. We test our approach on a public domain epileptic seizures dataset [2] available from the Warsaw University, Poland [1].

There exist several signal processing methods focusing on the removal of non–brain related electrophysiological signals (e.g. eye– or muscle–movement interferences). In recent years successful developments has been reported, which are based on empirical mode decomposition (EMD) [3] and on its multivariate extension [4]. Those methods outperform the ICA and blind source separation based approaches [5].

The classical EMD [6] concept constitutes an univariate fully data adaptive technique to decompose any non–linear or non–stationery signal into a finite set of band-limited basis functions called intrinsic mode functions (IMFs). The recently proposed MEMD [7] method, which is a multivariate extension of the above concept, allows for simultaneous data–driven decomposition of multichannel complex signals such as EEG.

In this paper we introduce a MEMD based epileptic seizures separation method which allows for automatic identification of those oscillation. The soft computing diagnostic approach is based on Hilbert–domain amplitude ridges hierarchical clustering.

The paper is organized as follows. In the next section we introduce the MEMD approach with example of EOG and *alpha*–wave separation. Next we present an application of the proposed technique to EEG with seizures. Discussion of the results with comparison of classical methods concludes the paper.

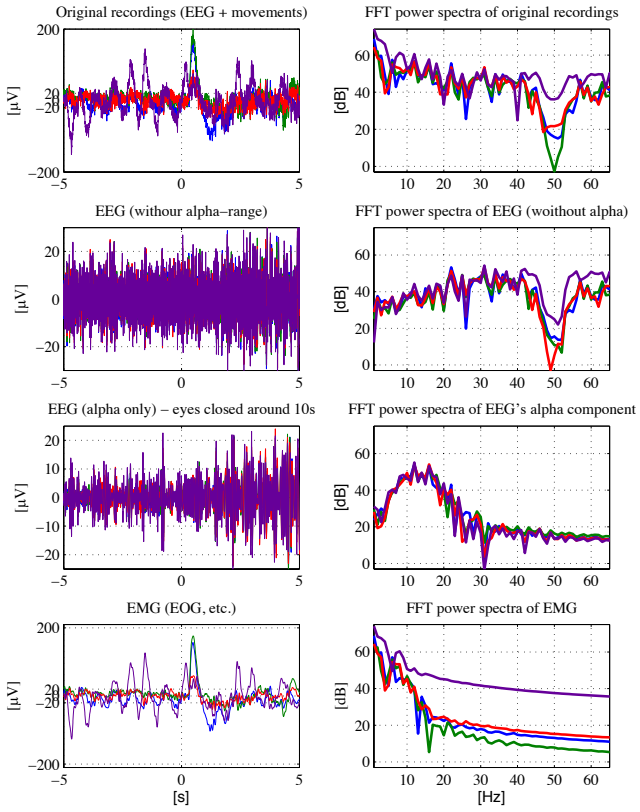

Fig. 1. An example of successful automatic EEG decomposition using MEMD approach with amplitude and frequency ridges clustering as in [8]. The top panel presents time series and Fourier power spectrum of the eye–movements (eye–rolling) contaminated fourth channels EEG. The subject closed his eyes at the 0 seconds time stamp. The second from the top panel presents the separated from *aplha*–wave and from the eye-movements EEG. The second from the bottom panel presents the *alpha*–frequency EEG with visible amplitude increase after the eye closing at 0 s. The bottom panel presents the isolated eye–movement artifacts.

II. METHODS

The very recent development in the field is the MEMD [7], which is a more generalized extension of the classical univeriate EMD, created a possibility to instantaneously process the multivariate signals such as EEG. The major novelty proposed in [7] is based on a possibility to process n-dimensional signals in the same number of spaces. This allows at each decomposition step the to generate the multiple n-dimensional envelopes by taking signal projections along

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different directions in n-dimensional spaces. The concept was very elegantly resolved by authors in [7] by utilizing a sampling concept based on low discrepancy Hammersley sequence to generate projections of the n-dimensional input signal due to a lack of formal definition of maxima and minima in multidimensional domains. As the result, the MEMD decomposition procedure of an input multivariate signal $s(t)$ into a multidimensional set of IMFs could be outlined as follows,

1) First, generate the point-set based on a Hammersley sequence in order to obtain an uniform sampling of the input multivariate signal on the $(n-1)$ dimensional sphere;
2) Next, compute the projection $\{p^{\theta_k}(t)\}_{t=1}^{T}$ of the signal $\{s(t)\}_{t=1}^{T}$ along the direction vector X^{θ_k}, for all k (the complete set of direction vectors) which will result in $\{p^{\theta_k}(t)\}_{k=1}^{K}$ projection set;
3) After that, find the samples $\{t_i^{\theta_k}\}_{k=1}^{K}$ with the maxima in the projected signals set $\{p^{\theta_k}(t)\}_{k=1}^{K}$;
4) In the following step, perform an interpolation $[t_i^{\theta_k}, s(t_i^{\theta_k})]$, for all values of k, for the resulting multivariate envelope curves $\{v^{\theta_k}(t)\}_{k=1}^{K}$;
5) Next, for the set of k direction vectors, compute a mean $m(t)$ of the previously obtained envelope curves as,

$$m(t) = \frac{1}{k}\sum_{k=1}^{K} v^{\theta_k}(t) \tag{1}$$

6) Finally, extract ("sift" - as it is commonly referred in *EMD–comminity*) the "detail" $d(t)$ using $d(t) = X(t) - m(t)$. Comparably as in the univariate EMD, the detail $d(t)$ shall fulfill the stoppage criterion for a multivariate IMF, thus apply the above procedure to $X(t) - d(t)$, otherwise apply it only to $d(t)$.

Once the first multivariate IMF is identified, it is subtracted from the input signal and the process is applied again yielding the next one. In the multivariate case, similarly as in univariate, the residue corresponds to the signal of which projections do not have enough extrema to form the multivariate envelope. Also the stopping criterion in MEMD is similar to univariate EMD [6]. The only difference is that the condition for equality of the number of extrema and zero crossings is omitted since the extrema for the multivariate signals are not properly defined.

Resulting from the MEMD decomposition application filter banks act as an array of band–pass filters (possibly with overlapping bands). The interesting part of MEMD technique is, that the frequency bands are the same for all the IMFs. In case of the sequential implementation of classical univariate EMD units, each signal would be decomposed into different number of IMFs with various (data–driven) frequency bands.

A. Hilbert-Spectral Clustering of EMD Components

In order to identify the IMFs carrying similar EEG patterns in multivariate data we cast them separately to Hilbert spectra domain in order to capture the detailed content (intrinsic frequency and amplitude tracks/ridges). The amplitude ridge traces of all IMFs (note that adaptive nature of MEMD results in the same number of IMFs in each channel) are combined together and correlated.

For each IMF separately the corresponding time–frequency representation can be produced by applying the Hilbert–transform [6]. The Hilbert transform allows us to observe the variable amplitude and the instantaneous frequency in a form of very sharp and localized functions of frequency and time (in contrast to Fourier expansion, for example, where frequencies and amplitudes are fixed for their bases). This approach is fits the analysis of non–stationary and non–linear EEG. It allows for modeling of the synchronized activities within the identified channels.

Using the above procedure the EEG components from various electrodes could be grouped separately, thus forming subsets of IMFs, from which common time–frequency patterns can be identified. To this end, use the zero–lag correlations coefficients of Hilbert amplitude only traces (a simplified approach comparing to the one in [8]) as "a distance measure" in order to capture spectral similarity across the IMFs. Once the correlation procedure is performed for all IMFs in Hilbert domain a hierarchical cluster analysis using a set of dissimilarities for the n objects is performed [9] for amplitude ridges only. Initially, each vector representing time series of amplitude ridges values is assigned to its own cluster and then the algorithm proceeds iteratively, at each stage joining the two most similar clusters. This procedure continues until a single cluster remains. At each stage distances between clusters are recalculated by the *Lance–Williams* update formula of dissimilarity with a single linkage clustering method. This method adopts a "friends of friends" strategy for clustering [9].

A result of such procedure is presented in Figure 1 where three separate EEG activities have been identified and separated. The example EEG signal was recorded from a subject rolling (moving) his eyes while keeping them open for 5 seconds and next closed for the same amount of time. The MEMD application supported with hierarchical clustering allowed us to identify the eye–movements depicted in the bottom panel of Figure 1, *alpha*–wave and the remaining EEG as visualized in the middle panels of that figure.

B. MEMD Application to EEG Epilepsy Dataset

The MEMD method supported with Hilbert domain amplitude ridges clustering method has been applied to separation and identification of epileptic seizures data provided by the University of Warsaw, Poland [1], [2]. The *CHIMIC* dataset has been chosen for evaluations, which was a recording from a nine years old male with temporal lobe epileptic seizures with a simple partial onset (epigastric sensations). The subject's seizures were evolving to partially complex (motor automatisms) with or without a secondary generalization. None of the anti–epileptic–drugs were effective, thus a surgical intervention was determined. EEG examination revealed generalizing sharp waves, spikes, and some focal slow waves.

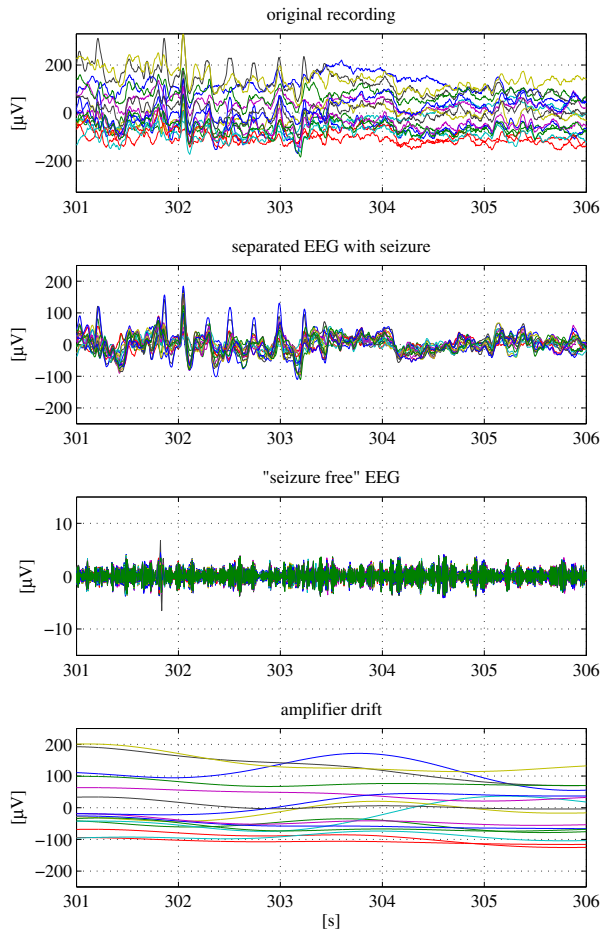

Fig. 2. The result of the proposed application of MEMD decomposition with spectral Hilbert–domain amplitude ridges clustering. The top panel (*original recording*) presents the original EEG data recording. The epileptic seizure with sharp waves and spikes is visible there in the range of $301 - 303.5$ s (the original time course of the *CHIMIC* dataset) [1], [2]. The second from the top panel (*separated EEG with seizure*) presents the separated epileptic oscillations with the proposed method. The second from the bottom panel (*"seizure free" EEG*) depicts the remaining separate EEG activity, while the bottom graph (*amplifier drift*) represents the low frequency drift registered by the bio–amplifier.

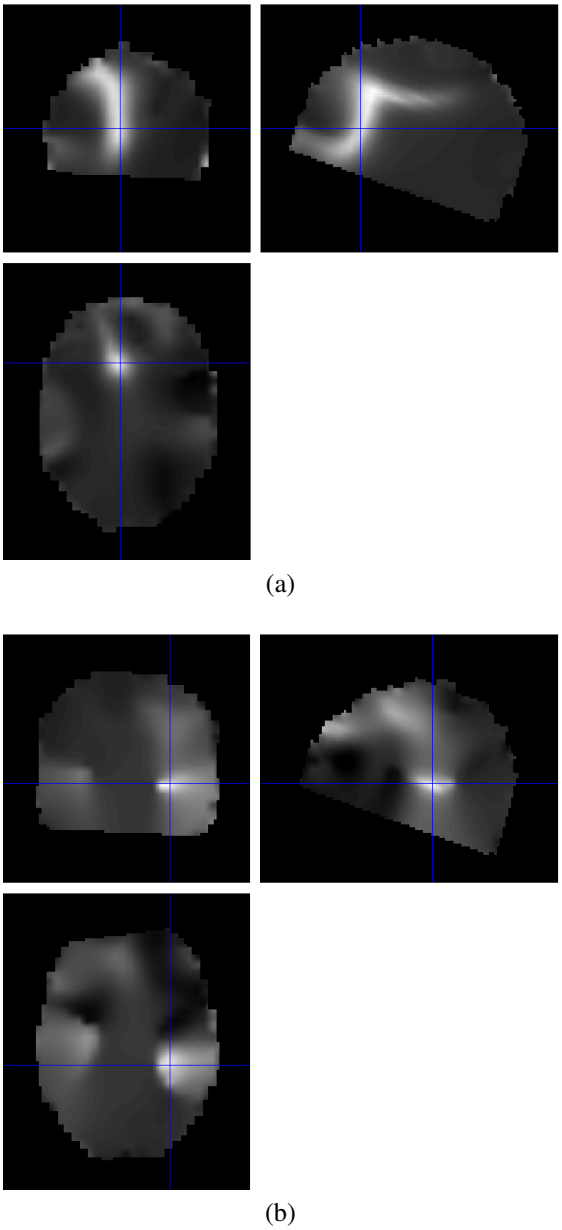

Fig. 3. EEG LCMV beamforming [10] projected on a model head result of the original EEG in (a) and the processed with the proposed method in (b) panels respectively. The original EEG source localization is in the right frontal, while the proposed method localized the epileptic center in the right temporal hemisphere, which agrees with the localization originally reported in [1].

The EEG signals were recoded with *DigiTrack EEG System* using 10 mm Ag/AgCl electrodes with a reference placed at *Fpz*. Sampling frequency was set at 250 Hz; hardware filters for a pass-band of $0.5 - 70$ Hz; notch filter set at 50 Hz.

For the evaluation purpose of the proposed method we chose a subset of 16 EEG channels as follows *F7, F3, Fz, F4, F8, T3, C3, Cz, C4, T4, T5, P3, Pz, P4,* and *T6* in order to uniformly sample the human scalp and to reduce the MEMD method computational load, which could be significant for high dimensional signals [7]. The EEG signals were further stop–band filtered with a third order Butterworth filter to remove the remaining, after the original notch filter, electrical power inferences in a range of $48 - 52$ Hz. A result of the epileptic seizures separation is presented in Figure 2 and discussed in the next section.

III. RESULTS

As a result of the proposed MEMD based EEG decomposition it was possible to cluster the multivariate IMF components into those related to epileptic seizures, the remming EEG and the low frequency drifts as depicted in the lower panels of Figure 2 respectively. The resulting, separated with amplitude ridges hierarchical clustering, epileptic spikes has been clearly identified and enhanced in the all analyzed channels. The remaining "seizure free" cleaned EEG and the low frequency drifts did not contain any remains of the epileptic oscillations.

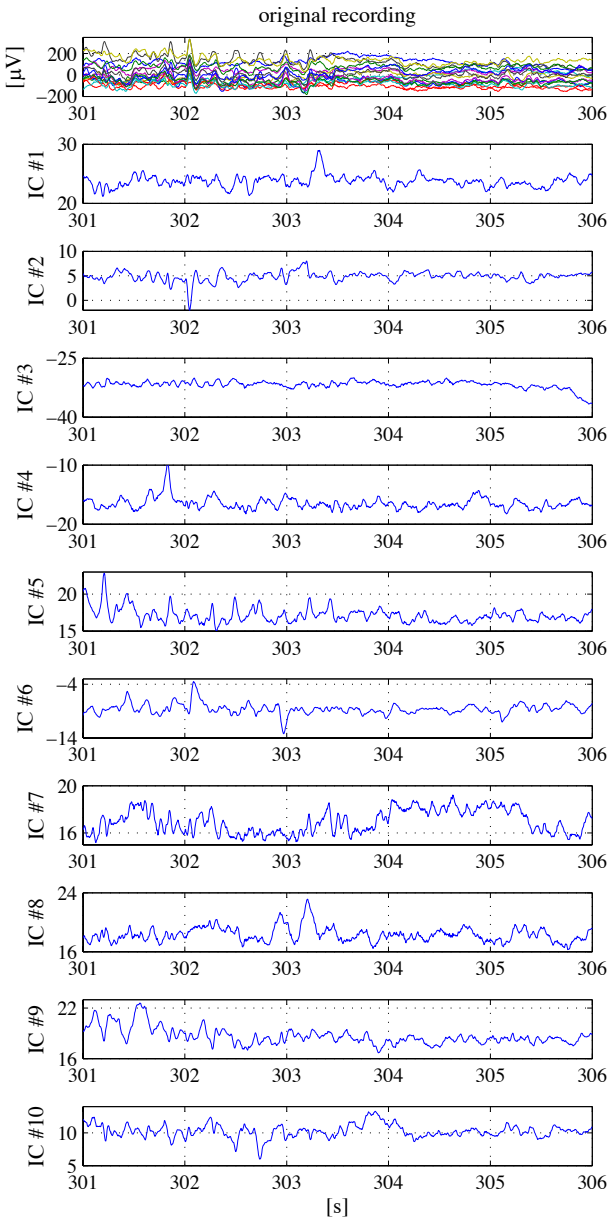

Fig. 4. The result of ICA blind separation method applied to the EEG data resulting with unsuccessful outcome. The top panel presents to original EEG 16 channels with epileptic seizure in the range of $301-303.5$ s (the original time course of the *CHIMIC* dataset) [1], [2]. None of the independent components (IC) resulted with a separated seizure activity (compare with the proposed MEMD based approach presented in Figure 2.

EEG LCMV beamforming [10] based source localization is presented in Figure 3 where the original and MEMD processed epileptic centers are depicted. The proposed method allows for correct localization as compare with originally reported in [1].

For a comparison with the classical methods usually applied in EEG community we tested ICA based technique which failed to identify the epileptic oscillations as shown in Figure 4. Non of the ICA resulting components had a separated oscillation as clearly obtained with the proposed method in Figure 2.

IV. CONCLUSIONS

A framework to separate and enhance the components carrying the epileptic seizure activities within multichannel EEG recordings has been presented. This has been achieved by applying an EEG decomposition technique, which allows a flexible sub-band multivaiare signal decomposition while preserving the non–linear and non–stationary features of the signals which is fundamental for epileptic brain activity analysis. The so obtained components from each EEG channel processed simultaneously by MEMD have been further transformed to the Hilbert domain and compared within amplitude domain using the clustering technique in order to identify those similar (correlated) across channels.

The resulting reconstruction has allowed us to separate common epilepsy related interferences from underlying brain activity in the data–driven signal processing approach without information leakage between channels.

This is a step forward in EEG signal processing applications which could be useful for creating new soft computing and date driven diagnostic methods.

ACKNOWLEDGMENT

This research was supported in part by the Japan Society for the Promotion of Science grant no. 12010738.

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