COMBINING BLIND SOURCE SEPARATION AND EMPIRICAL MODE DECOMPOSITION APPLIED TO SOURCE SEPARATION FROM SINGLE CHANNEL BIOMEDICAL SIGNALS

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Abstract-Nowadays, Blind Source Separation (BSS) techniques are very common and useful in signal processing. In the field of multichannel recording, there are many techniques of BSS that work accurately, but in the single channel measurement, only a few methods are existed. One of the much popular algorithms of BSS is Independent Component Analysis (ICA). This technique is applied to separate the independent component from multi channel measurements. In this paper, we proposed two new algorithm that called Automated EE-ICA and EE-ICA with post processing, these methods are based on combination the Empirical Mode Decomposition (EMD) and ICA in a new manner and for separating the sources from single channel measurement then we will investigated accuracy of our methods in source separation in biomedical signals.

Keywords: Empirical Mode Decomposition, Blind Source Separation, Independent Component Analysis, Single channel signal analysis.

1 INTRODUCTION

In the field of single-channel signal processing, the number of methods are reported, for example Single-Channel ICA (SCICA) that proposed in [4] and Wavelet-ICA [5]. ICA is a multichannel technique [3]. In the biomedical signal processing if the number of channels (mixed signals) are more than or equal to the sources, ICA algorithm and several techniques of BSS can work well, but when the number of sources are higher than the number of channels, only a group of algorithms called "undetermined ICA" can recover these sources. SCICA is the adaption of ICA to single channel signal analysis. This algorithm is established on two assumptions: the sources are stationary and disjoint in the frequency domain. Actually, these assumptions are limitations of SCICA to apply it, because these assumptions are not true in all of the applications. Wavelet-ICA combines Wavelet transform and ICA for single-channel signal analysis. At first, wavelet transform is performed for segmenting the mixed signal at each step in the predetermined path by predefined linear time invariant filters, then the ICA method is used to extract the independent sources.

In [1] another approach for splitting up a signal into different signals is introduced. This approach is EMD. EMD is an adaptive algorithm. It hasn't the limitations of two already methods for splitting the signal. EMD is an adaptive instrument for decomposing a signal into its component that is called Intrinsic Mode Function (IMF). One of the approaches for extracting the sources from single channel recording is combining EMD and ICA algorithms. In this course first EMD splits up the mixed signal to its components and then ICA applied to these components to extract the independent sources. EMD is similar to Wavelet, but it is a data-driven and adaptive algorithm, which decomposes a signal without a priori knowledge about it and this property, gives the possibility of adapting the decomposition to local variations of the oscillation, in conclusion, EMD-ICA outperforms rather than W-ICA. The weakness of EMD is its high sensitivity to noise, therefore, in the case of implementation that the rate of noise is high, EMD can't work perfect specially when the signal of interest is oscillation type. A more powerful noise-assisted version of EMD is EEMD [3]. In this paper, we used EEMD and Fast ICA to extract the signals. The paper is set as follows. In the section 2 at first the based algorithms are described briefly and then the proposed algorithms are explained, in section 3 we will illustrate our methods performance in two simulations in MATLAB program.

2 ALGORITHMS AND METHODES

2.1 Empirical Mode Decomposition

EMD is a powerful method which can decompose adaptively the nonlinear and nonstationary signal into its component. As mentioned in introduction, these components are called IMFs. IMFs must be valid under these conditions: 1) the number of maximum and minimum of IMF and its zerocrossing must be the same or only differ one point at most in the whole data set 2) the mean of upper and under envelope which respectively defined by the maximum and minimum must be equal to zero.
EEMD is a noise-assisted data analysis method [2], when the rate of noise is very high, this algorithm is more forceful than EMD. In the first step of EEMD algorithm, an independent, identically distributed and zeromean white noise by SD (Standard Deviation) equal to Np (Noise parameter) times of the SD of the original signal is added to it, in the next step EMD is applied to drive a set of IMFs, then these steps are repeated for a number of trails to conclude the ensemble of IMF sets. At last it should be averaged over the ensemble to receive a set of average.

2.2 Independent Component Analysis

Mixing process of the sources in BSS algorithms are modeled into two major categories: convolutive mixing model and instantaneous mixing model. ICA is in the instantaneous mixing model domain. Combination of source signals in the instantaneous model had a linear equation X=AS, in this model X is the mixed signals matrix, A is mixing matrix and S is the sources that called independent components (IC's). In this paper, we apply FastICA algorithm [3], this algorithm is established on non-Gaussianity of the sources.

2.3 Automated EE-ICA

At first EEMD algorithm splits up the single channel mixed signal into its IMF set, then in a automatic procedure based on the amplitude-frequency spectrum, the noisy IMFs are deleted, after this step FastICA are performed on all the remained IMFs, for extracting the ICs. After that, similar to noisy IMF cancelation step, the noisy ICs are omitted, at last remained ICs multiply to their corresponding rows of mixing matrix A and after that the new IMFs sum together and the signal of interest is extracted.

2.4 EE-ICA with post processing

Another approach is suggested in this paper is EE-ICA with post processing. In this method at first we perform EEMD on mixed signal to obtain the IMF sets, then FastICA is performed on all the IMF set and extracts ICs, later, one of the ICs which its amplitude-frequency spectrum is much similar to the signal of interest is picked up and at last, it is filtered for post processing.

3 SIMULATION RESULTS

In the simulation the noise parameter is equal to 2 in EEMD algorithm. In the FastICA we select $p(x) = C \times e^{-\alpha|x|\gamma}$, $\gamma \neq 2$ for distribution of the sources. We select the record No.103 of the MITBIH database for ECG signal, EMG Healthy database for EMG signal and EEG Motor Movement-Imagery Dataset for EEG signal from Physionet web site. Figure1 shows our source signals those used in this paper.

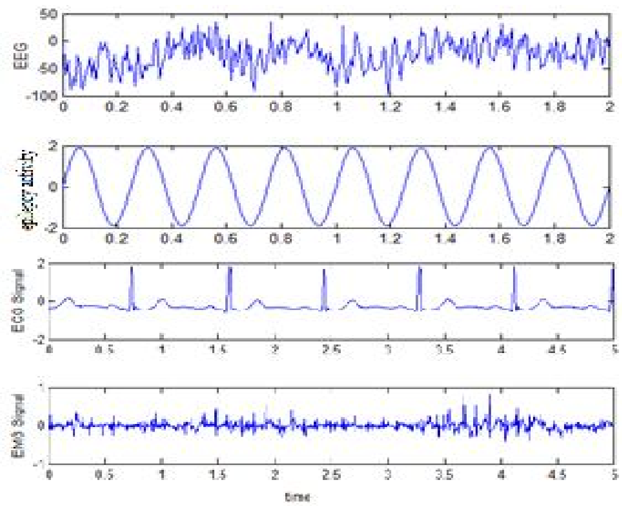

Figure 1. The source signals, used in this paper: EEG, simulated epilepsy activity, ECG and EMG signals.

In the first simulation we mixed an EEG signal with a sinusoidal wave by 160 Hz sampling frequency, sinusoidal wave is representative of epileptic activity, in this simulation our interested signal for extracting is the stationary oscillatory type sinusoidal signal. In the second simulation we composed two real life signals: ECG with EMG signal, by 360 Hz sampling frequency to extract a spike type (ECG) signal. The EMG signal is noise, and we want to extract the spike type signal, ECG.

Figure2 shows the EEMD decompositions of the mixed signal and their amplitude-frequency spectrums. In two simulations, NSR and Np are 1 and 2 respectively. Because of our oscillatory wave's frequency is equal to 4, the number of IMFs those their frequency range is higher than 20Hz are omitted, and then FastICA is performed on the remained IMFs. Figure3 illustrates the extracted ICs and their amplitude-frequency spectrum. In IC selection two factors are used, the maximum value of amplitude and its frequency's value. By an appropriate choice of the threshold value for these factors, ICs are selected. For example in this simulation we select the IC provided that, its maximum value of amplitude is more than 50% of maximum value of originally sinusoidal wave's amplitude and the frequency of it not less or more than 50% of maximum amplitude's frequency value of original signal. If the IC doesn't right in these conditions, will be deleted. In this simulation, only, IC1 and IC4 are valid. After selecting the ICs by inversing ICA and EEMD, the signal is recovered.

Figure4 illustrates EEMD decompositions of the mixed signal and their amplitude-frequency spectrums for second simulation. Figure5 shows the interested ECG signal and its spectrum, the frequency range of ECG is between 0-50 Hz, therefore in this step the number of IMFs, those their frequency range are more, are deleted. And remained IMFs (4-10) go to FastICA.

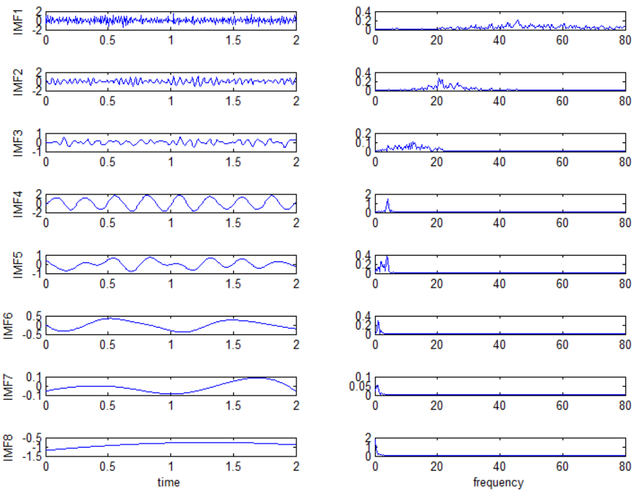

Figure 2. EEMD decomposition of the signal mixed of EEG and epilepsy activity (sinusoidal) and their spectrum in NSR=1.

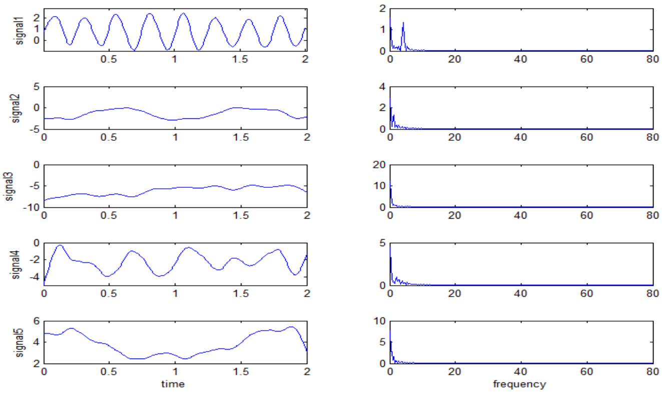

Figure 3. The extracted ICs and their spectrum by EE-ICA in first simulation for NSR=1.

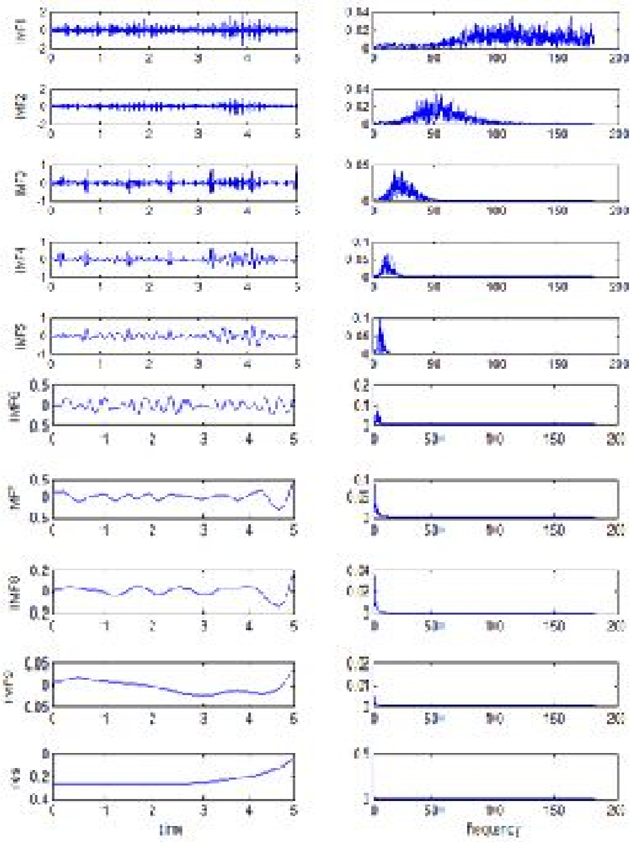

Figure 4. EEMD decomposition of the signal mixed of ECG and EMG signals and their spectrum in NSR=1.

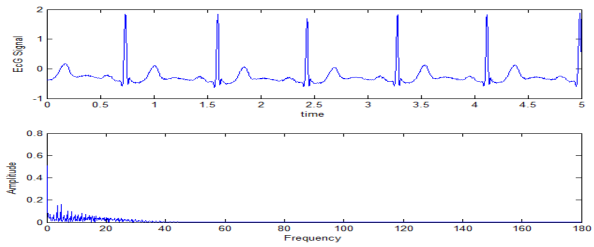

Figure 5. ECG signal and its spectrum

Figure6 illustrates the separated sources and their spectrums. All of the sources remain, because their frequency ranges are in 0-50 Hz. In selecting the IC or IMF, in this signal, which has a frequency rang instead of one frequency, our choices are based on frequency range.

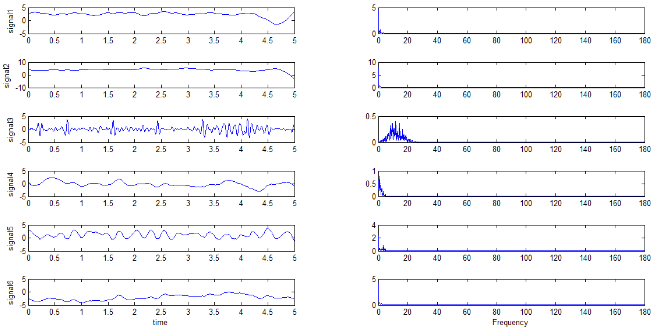

Figure 6. The extracted ICs and their spectrum by EE-ICA in second simulation for NSR=1.

The Np parameter is too essential in EEMD. We investigate our method's performance for two values of Np, 0.2 and 2 The results are expressed in Table1 and Table 2 for first and second simulation consecutively in RRMSE format. We use RRMSE to state our methods performance accuracy in this paper, Relative Root Mean Square Error (RRMSE) defines by equation (1). In this equation $S'(t)$ is estimated signal.

$$\mathrm{RRMSE} = \frac{\mathrm{RMS}(S(t)-S'(t))}{\mathrm{RMS}(S(t))} \times 100 \qquad (1)$$

RMS is Root Mean Square, the RMS value for a sequence x is defined as follows:

$$\mathrm{RMS}\{x\} = \sqrt{\frac{1}{N}\sum_{n=1}^{N} x[n]} \qquad (2)$$

N is the number of samples of x[n]. As well as, we use NSR to express the signal and noise ratio, NSR is defined by equation 1.

$$\mathrm{NSR}=\frac{\mathrm{RMS}(\lambda N(t))}{\mathrm{RMS}(S(t))} \qquad (3)$$

In this equation S(t) is the signal of interest and N(t) is the noise signal which mixed by S(t) and λ is the ratio of noise that alters the NSR value.

As mentioned in [2] and shown in the tables, when signal is low frequency, with low values of Np and when the signal is high frequency, with large values of Np, the error will be reduced, and in some cases those the noise ratio is high by large amount of Np, EEMD has good answer.

NSR	RRMSE , if Np=0.2	RMSE , if Np=2
0.05	4.8958	12.315
0.5	18.3256	18.848
1	32.59	31.579
1.5	33.1799	40.7664
2	53.7631	45.41126

Table 1. RRMSE values of the extracted signal (output) of the Automated EE-ICA algorithm in different levels of added noise for first simulation.

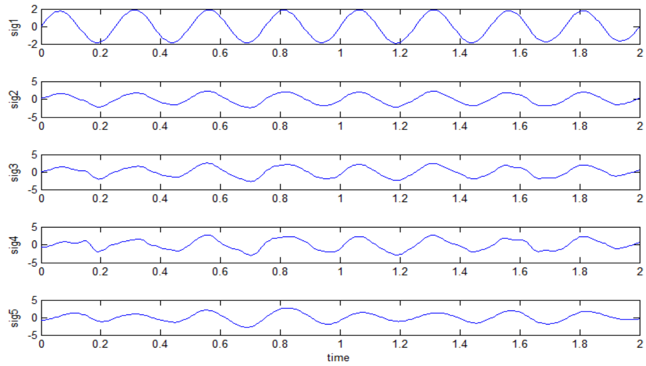

Figure 7. the extracted signal (output) of the Automated EE-ICA algorithm for first simulation in Np=0.2 and for NSR=0.05,0.5,1,1.5 and 2 from up to down, respectively.

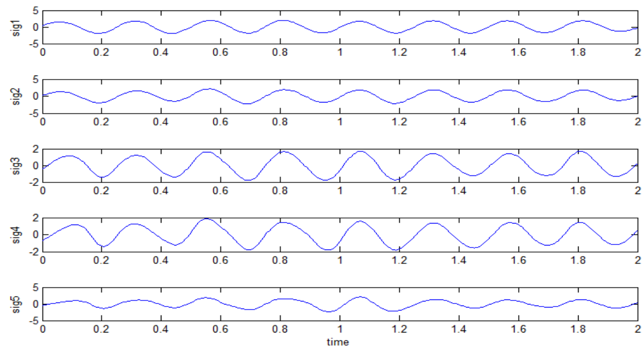

Figure 8. The extracted signal (output) of the Automated EE-ICA algorithm for first simulation in Np=2 and for NSR=0.05, 0.5, 1, 1.5 and 2 from up to down, respectively.

NSR	RRMSE , Nnp=0.2	RRMSE , Np=2
0.05	14.8951	13.3339
0.5	43.9791	35.1739
1	59.9529	58.24
1.5	84.6399	73.3290
2	91.3255	80.8701

Table 2. RRMSE values of the extracted signal (output) of the EE-ICA algorithm in different levels of added noise for second simulation.

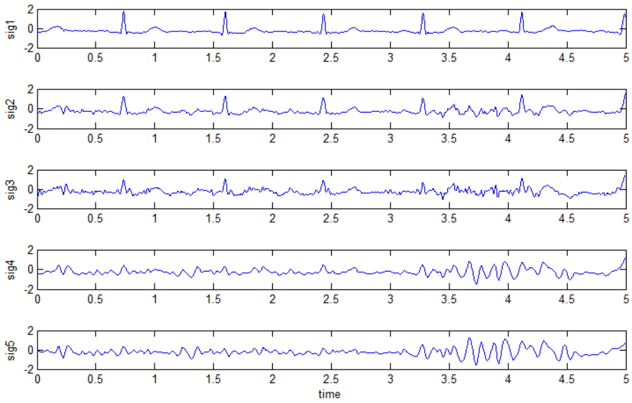

Figure 9. The extracted signal (output) of the Automated EE-ICA algorithm for second simulation in Np=0.2 and for NSR=0.05, 0.5, 1, 1.5 and 2 from up to down, respectively.

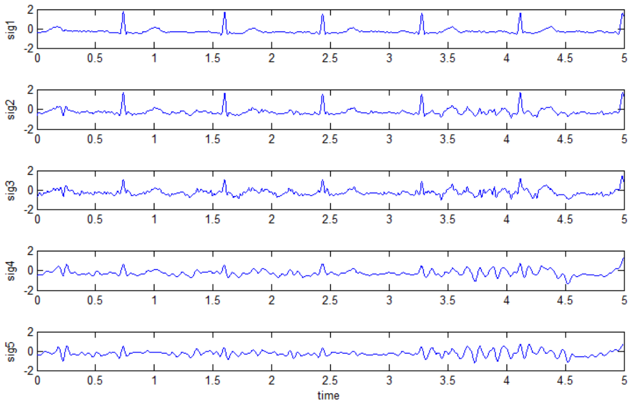

Figure 10. The extracted signal (output) of the Automated EE-ICA algorithm for second simulation in Np=2 and for NSR=0.05, 0.5, 1, 1.5 and 2 from up to down, respectively.

Figures 7, 8, 9 and 10 show the extracted signal of the Automated EE-ICA algorithm in Np=0.2, 2, and NSR=0.05, 0.5, 1, 1.5, 2 for first and second simulation, respectively.

EEMD-ICA with post processing is our another algorithm. The weakness of this algorithm is its performance in the case of high frequency signals specially when the noise ratio is high but when the signal of interest to extract is low frequency even if the noise ratio is high this algorithm works well. For example we simulate sinusoidal signal with EEG background in here. Figure 11 illustrates the extracted sources those obtained by applying EEMD and FastICA on the mixed signal by NSR=1, as shown in figure12 the IC4 is selected for filtering step. Figure13 shows the passband filter that used for post processing, filter's band wide is 2-20 Hz, after applying filter on IC4, the source of interest is extracted with RRMSE=31.6636. Figure14 shows the signal.

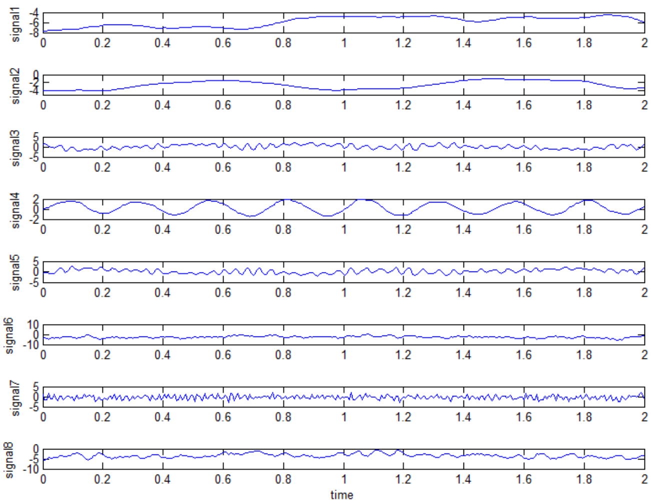

Figure 11. The extracted ICs by EE-ICA with post processing in first simulation for NSR=1.

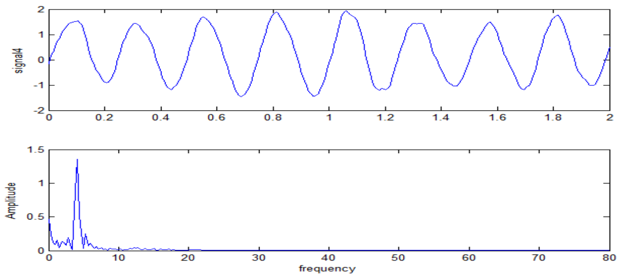

Figure 12. IC 4 and its spectrum.

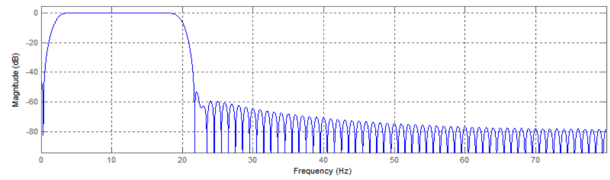

Figure 13. Bandpass filter for EE-ICA with post processing.

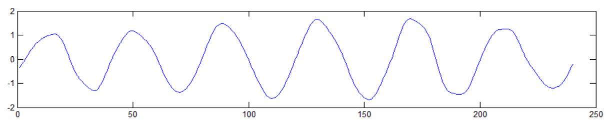

Figure 14. The extracted source of first simulation by for EE-ICA with post processing algorithm.

4 CONCLUSION

In this paper, we suggested two new algorithms to separate single channel signals based on EMD and ICA, and illustrated our algorithm's performance in two simulations. The combine of EMD and ICA is used in [6, 7] already. In [7] the authors combined EMD and Infomax ICA to separate the mixed signal, and in [7] EEMD and FastICA are combined to extract the single channel signal, but our Automated EE-ICA method combined the EEMD and FastICA and extract the single channel signal in automatic path based on the spectrum of the component, and have two step of noisy component cancelation, first after applying EEMD on Mixed signal and second after applying FastICA on IMFs, and in EE-ICA with post processing, we used filtering for post processing, our methods are fully automatic and performs in MATLAB.

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