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A Single Channel EMI Signal Separation Method Based on Directly-mean Empirical Mode Decomposition ⋆

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Abstract

ICA is a powerful decomposition method for time-domain series, except for the requirement that the number of observed signals and the source signals should be the same, which makes ICA fail to process single channel signals. In this paper, we propose a new method using directly-mean EMD, which is utilized to extract independent components from a single channel mixture. The proposed method could overcome the side effect of original EMD, and can be applied to the separation of EMI signals to locate interference sources. Simulation experimental results demonstrate the effectiveness of the proposed method, and show that the proposed method outperforms the comparison methods, such as the original EMD ICA and wavelet ICA.

Keywords: Electromagnetic Interference; Independent Component Analysis; Single Channel Signal; Empirical Mode Decomposition

1 Introduction

Electronic devices are becoming smaller and smarter, and the electromagnetic interference is more and more common and must be taken into consideration in the design of electronic devices. In order to locate the interference sources, it is necessary to extract the interference signals from the mixed signals.

Independent Component Analysis (ICA) was proposed as a solution to the cocktail party problem, which deals with the blind separation of multi-channel time series. ICA has been applied in many fields, including electromagnetic signal processing. In complex electromagnetic environment, however, the interference source is vast while the observed signal is few where ICA cannot

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be used. In fact, ICA requires the number of observation is at least the same as sources component, which is not available in practice. An extreme occasion is that there is only one single observation. In the field of Computational Audio Scene Analysis (CASA), the short-time stationarity property of the music signal can be used to extract each individual component from the mixed sound signals. However, in practice, the electromagnetic signals is usually not short-time stationary.

Single-channel signal separation belongs to a field called signal separation, which can be divided into supervised separation and unsupervised separation by the implementation, where the unsupervised one is also called Blind Source Separation (BSS). Single signal separation is used in many audio processing tasks [3], and can be divided into diction-based methods and non-diction-based methods [4]. Diction-based method performs well with priori-knowledge of the independent component [5], but its usage is limited to audio processing.

Besides, the rest of single-channel signal blind separation falls into two categories-pure time-domain methods and non-pure time-domain methods. The former first decomposes the signal completely in time-domain using techniques like Empirical Mode Decomposition (EMD) or Hilbert spectral analysis [8] and then feed as the output of PCA to obtain independent sources. Non-pure time domain methods leverages STFT, Z transformation, Independent Subspace Analysis (ISA) [7] to transform time series into spectrum, and apply ICA to this representation. Finally, conducting the reverse transformation could recover the time domain representation. The recent popularity in matrix decomposition [6] shows another potential way to do single channel signal blind separation. As the pure time domain method is more intuitive, we adopt the pure time domain approach to decompose the signal into pseudo-multi-channel representation, and then apply primitive ICA to it to get source estimation.

The rest of this paper is organized as follows. Section 2 firstly provides the formal description of the blind separation problem, together with brief introductions to EMD and wavelet transformation. Subsequently, in Section 3, the details of the proposed method is dictated. And in Section 4, experimental results are given to demonstrate the performance of the proposed method, compare with existing approaches. Finally, the last section draws the conclusion of this paper.

2 Preliminaries

2.1 Single Channel Signal Blind Separation

Suppose there are N independent signal sources, and signals are emitted from them simultaneously, which are mixture in the environment and recorded in a single receiver. We consider the mixing is an instant and additive procedure, so we have the following formula.

$$y[t] = \lambda_1 x_1[t] + \lambda_2 x_2[t] + \cdots + \lambda_N x_N[t]. \tag{1}$$

In Eq. (1), $x_i[t]$ stands for signal source, λ_i is the weight of each source, $y[t]$ is the single channel mixture, and also the only observation in the separation process. The aim of single channel blind separation is to estimate the entire source components with only $y[t]$.

2.2 Time Domain Single Channel Signal Separation Techniques

Traditional ICA needs the observation to be as many as source components, which cannot be applied to single channel separation directly. Thus, a popular approach is to decompose the mixture into a bunch of pseudo signal using time domain decomposition techniques. Pseudo signal means they are not independent, so an ICA cannot be omitted. The difference of different methods lies in the time domain decomposition method they employ, primarily Empirical Mode Decomposition (EMD), discrete wavelet transformation, Singular Spectrum Analysis (SSA), Non-negative Matrix decomposition (NMF), etc. This passage will take EMD and wavelet transformation as two example.

2.2.1 Empirical Mode Decomposition

E. Huang et al. proposed Hilbert-Huang Transformation (HTT) in the last century in order to describe nonlinear and non-stationary signals better. In HHT, Empirical Mode Decomposition (EMD) is used to decompose signal as the sum of a set of Intrinsic Mode Functions (IMF) and a trend function [2].

$$x[t] = Sum_{i=1}^{n} c_i[t] + r[t]. \tag{2}$$

As the name suggests, EMD is totally empirical and data driven. No priori information about the signal needed, and EMD was used in [1] to obtain IMFs, which is then processed by ICA to extract the independent component.

However, the primitive EMD has many shortcomings. The cubic spline interception used in the calculation of the local maximum and minimum is quite sensitive to the side value, while the side value is mostly not the maximum nor minimum. This can influence the shape of the curve severely, which is called the "side effect" of EMD. In the algorithm of E. Huang, a method called mirror prolongation is adopted to overcome this, but still can get rid of it. The experiment in the next also demonstrated this.

2.2.2 Discrete Wavelet Transformation

Discrete Wavelet Transcription (DWT) divides the signal into high-frequency component and low-frequency component. Applying DWT to the low-frequency part can obtain the second-high-frequency component, which in turn creates a series of components.

The idea of DWT is somewhat same to EMD, both divide signal into a set of additive components, the sum of those component recovers the original signal. So the set of signal can be used as input for ICA. However, the choosing of mother wavelet function is the key to the DWT, which often needs the priori information about the distribution of the source signal. Another drawback of DWT is that when the frequency of different component is close, DWT fails to separate them because DWT divide signal based on their frequency.

3 A Novel Single Channel Blind Separation Method Using Directly-mean EMD and ICA

We propose a new blind separation method for single signal observation using directly-mean EMD, which is an improvement over primitive EMD. Directly-mean EMD can reduce the computation burden and overcome side effect well.

3.1 Directly-mean EMD

Primitive EMD involves finding all the local minimum and maximum and interpolate using cubic spline to get two envelopes. Subtract the mean value curve of the maximum and the minimum from the original signal. Repeat the steps above until the remaining satisfy the requirement of IMF.

Unlike primitive EMD, directly mean EMD only need to calculate one curve. The algorithm is described as follows.

For the observation $y[t]$, find all the local extreme point $m_1, m_2, \cdots, m_M$ which are arranged in the ascending order of variable t. Since is ascendant, each element in the series has different type of extreme point with its immediate priori and immediate successor.

Then, for every extreme point $m_i (2 \leq i \leq M-1)$, draw a straight line l_i between m_{i-1} and m_{i+1}. Find a point on line l_i with the same t value with m_{i-1}. So that m_{i-1} and m_i are located in the same vertical direction. Calculate the middle point of m_{i-1} and m'_{i-1}, which we mark as c_i. After this, we came out with a series of middle points $c_2, c_3, \cdots, c_{M-1}$.

Finally, interpolate the middle point series $c_2, c_3, \cdots, c_{M-1}$ with the cubic spline to get middle curve. Keep subtracting middle curve from the original curve until the remaining component meet the requirement of IMF, when the first IMF was successfully extracted.

After obtaining the first IMF, subtract the IMF from the original observation. Doing the same magic to the remained signal, and we can get the second and third IMF. Extract all the IMF until there is only monotonous signal left, which is the trend component.

Compared with traditional EMD algorithm, there is only one interpolation needed for directly-mean EMD, and the calculation doesn't involves the side point, so that the algorithm is free from the "side effect" and also eliminated the need for prolongation.

3.2 Independent Component Analysis

Assuming that the directly mean EMD generates K IMFs and one trend component, denoted as $h_1[t], h_2[t], \cdots, h_K[t]$ and $r[t]$. By arranging them into a matrix $\mathbf{Y} = [h_1[t], h_2[t], \cdots, h_K[t], r[t]]^T$, we can now regard $\mathbf{Y}$ as the multi-channel observation mixed from multi-channel sources:

$$\mathbf{Y} = \mathbf{A}\mathbf{x}, \tag{3}$$

where A denotes the mixing matrix, and $\mathbf{x} = [x_1[t], x_2[t], \cdots, x_N[t]]^T$ is the source components. Suppose that matrix $\mathbf{A}$ is full rank, we can use ICA to estimate the unmixed matrix $\mathbf{W} = \mathbf{A}^{-1}$, which in turn yields source estimation.

4 Experimental Results and Analysis

As an illustrative experiment, we adopt the model where there are only two sources, one sine signal and one sawtooth signal, as shown in Fig. 1.

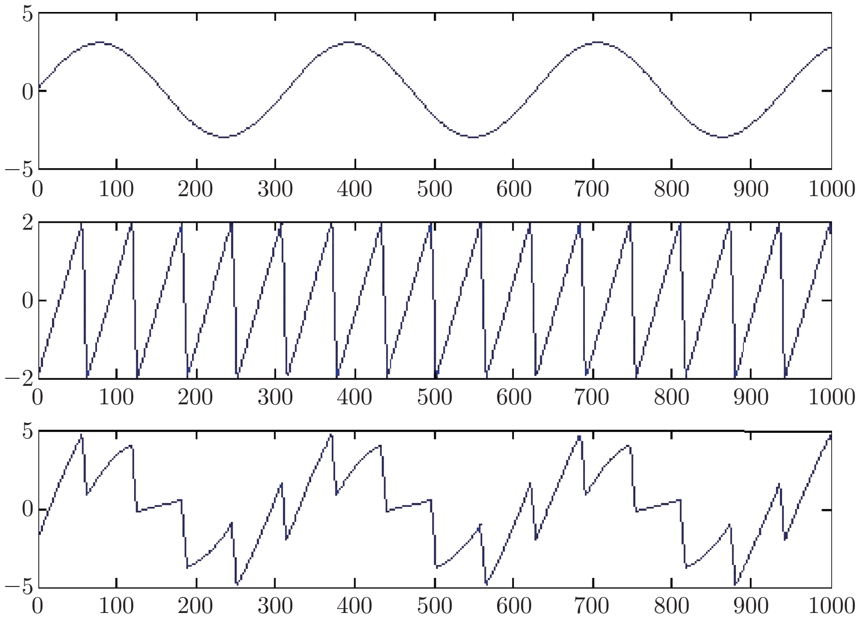

Fig. 1: Source signals (top, middle) and mixed signal (bottom)

We are going to test the performance of signal separating ability of primitive EMD with I-CA, wavelet ICA and our directly-mean EMD with ICA. The ICA algorithm employed in the experiment is FastICA.

4.1 Primitive EMD with ICA

Using primitive EMD to exploit the observation returned with 6 IMFs and a trend component. Regarding them as the pseudo-multichannel mixture and apply ICA to it, we can get two estimated "independent" sources, which are illustrated in Fig. 2.

We can see from the result that primitive EMD cannot separate sources properly with ICA. The error between estimation and real source is too large. The reason why primitive EMD performs bad is the "side effect" causing the deformation of the signal. For example, the third IMF shown in Fig. 3 is largely influenced by side effect from the right end. Thus, primitive EMD cannot be used to separate single channel mixtures.

4.2 Wavelet ICA

Here we employ binary wavelet transformation with mother wavelet function using "db10". We decomposed the signal into 5 levels, and obtained detail signal from level 1 to 5 and approximate signal level 5. The estimation using wavelet and ICA is given by 4.

From Fig. 4 we can conclude that every signal is almost zero except the fifth approximate signal.

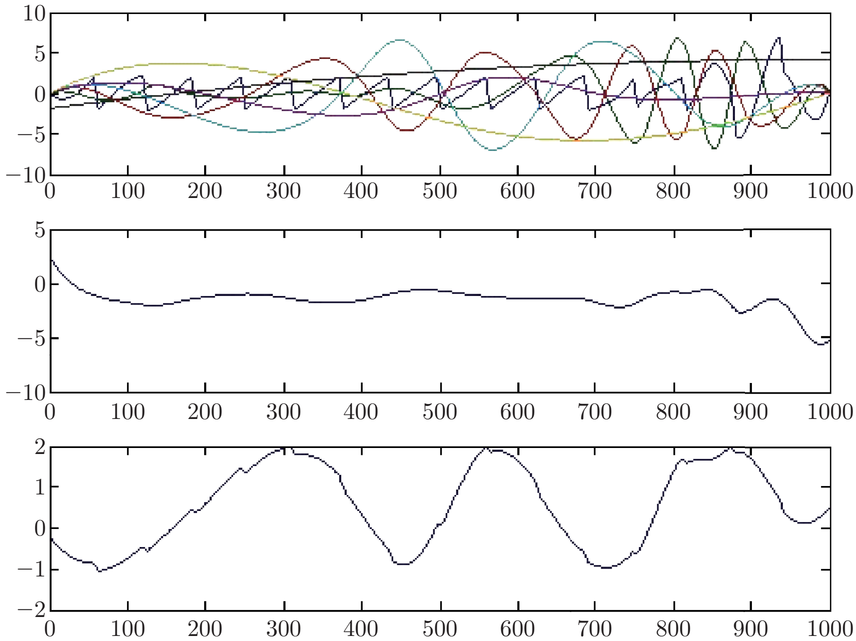

Fig. 2: IMFs and trend component (top) and two estimations (middle, bottom)

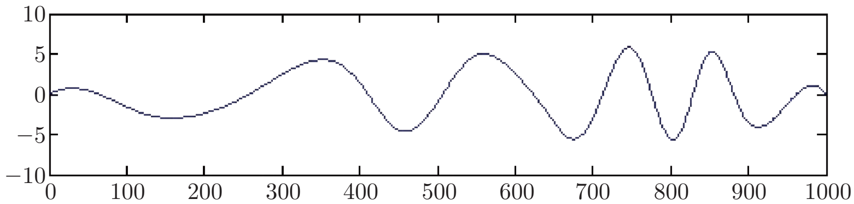

Fig. 3: The third IMF extracted using primitive EMD

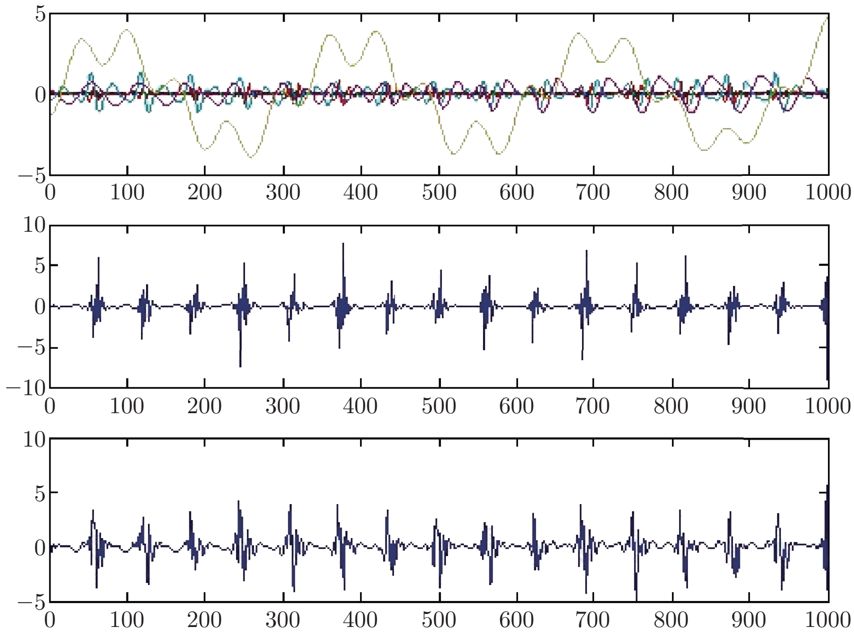

Fig. 4: Decomposed signals using wavelet transformation (top) and estimation from ICA (middle, bottom)

The two source signals we choose have certain difference in its frequency, but still in the same order, which is the reason why wavelet transformation cannot perform well.

4.3 The Proposed Method

We first commit the decomposition using directly-mean EMD and got a series of IMF and one trend component, which is then processed by a primitive ICA algorithm. Two estimations of the sources are generated, and the results are shown in Fig. 5.

From the result, we can get the point that directly-mean EMD with ICA outperforms both the primitive EMD and wavelet transformation. And the estimation is very close to the real source signal.

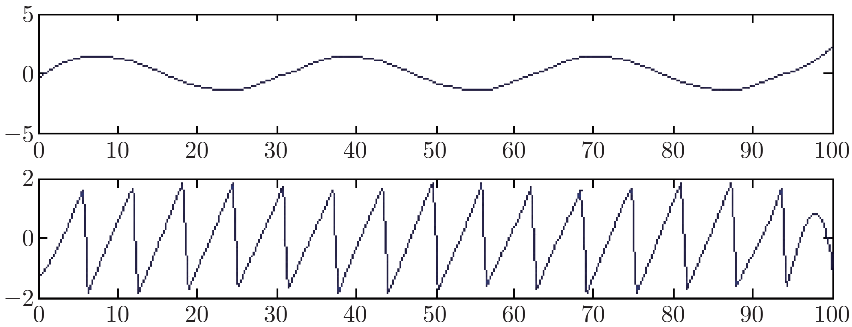

Fig. 5: Source estimations using directly-mean EMD with ICA

5 Conclusions

This paper incorporates the preprocessing stage using directly-mean EMD to the primitive ICA, and achieved the blind separation of single channel mixture. And we demonstrated the effectiveness of the algorithm by experiments.

However, it is clear that there remain some disadvantages of our method. From the experimental results, we can still observe some deformation at the two sides of the signal. Directly-mean EMD discarded the side points to avoid side effect, but it also made the curve dangling since no points could be used to help with the interpolation at the two ends. This problem will remain a consideration in future works.

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