Application of Wavelet Transform To Denoise Noisy Blind Signal Separation

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Abstract— **Blind Signal Separation (BSS) techniques is a vast field with many successful algorithms and numerous applications. Most rely on the noise free model and carry part of noise in extracted signals when Signal to Noise Ratio (SNR) is low. In view of this situation the solution is to de-noise the mixtures of additive white gaussian noise first and then use the BSS algorithms to separate the signals. This paper proposes Wavelet Transform de-noising approach to de-noise mixtures with strong noise. Solution based on Wavelet Transform proved more effective for noise removal of signals and their superiority against conventional filtering techniques. Simulation results show that the proposed approach has better de-noising performance and can remarkably enhance the separation performance of BSS algorithms, especially when the signal SNR is low. In this paper we evaluated the performance of three prominent BSS algorithms namely FastICA, JADETD and SOBI on simulated noisy signals.**

Index Terms—**Signal de-noising, Wavelet Transform, Noisy Blind Signal Separation, Signal Mean Square Error, Separation Performance**

I. INTRODUCTION

Over the last two decades Blind Signal Separation (BSS) has become large topic of intense research in signal processing and machine learning community. The goal of BSS is to recover independent signals, given only sensor observations without knowing the source signals and their mixing process. A lot of BSS models such as instantaneous mixtures and convolutive mixtures are have been presented in some publications [1],[2],[3] and some prominent BSS algorithms with good performance , such as Fast ICA [3], JADE[13], SOBI[15] etc., have been widely applied to Telecommunications, Speech and Medical signal processing.

However, the best performances of these methods are obtained for the ideal BSS model and their effectiveness is definitely decreased with observations corrupted by additive noise. In order to solve the problem of the BSS with additive noise, i.e. Noisy BSS, a good solution is to apply a powerful de-noising processing before separation. At present, the de-noising techniques mainly include Kalman filtering, particle filtering, wavelet de-noising, etc. As for the Noisy BSS, for lack of any a priori information about the observed mixtures, we cannot build the exact model. Wavelet de-noising based on Wavelet Transform (WT) is simple and wavelet thresholding has been the dominant technique in the area of non-parametric signal de-noising for many years. Thus, wavelet de-noising is suitable for Noisy BSS.

The remainder of this paper is organized as follows : firstly we introduce the noisy BSS model. Then in section III we explain Discrete Wavelet Transform theory and its de-noising principle; while in section IV we analyze the de-noising approach and finally in section V we apply this de-noising approach to Noisy BSS and evaluate performances of BSS algorithms. A short summary concludes this paper in section VI.

II. .NOISY BSS MODEL

A. Noisy BSS Model

Consider a linear instantaneous problem of blind source separation, and the unknown source signals and the observed mixtures are related to:

y(t)=As(t)+v(t)=x(t)+v(t) .... (1)

in which $y(t)=[y_1(t),y_2(t)......y_m(t)]^T$ is the vector of *m* observed mixtures , and $s(t)=[s_1(t),s_2(t0,...........s_n(t)]^T$ is the vector of *n* source signals which are assumed to be mutually and statistically independent. **A** is an unknown full rank m x n mixing matrix and v(t) is an additive noise. This paper focuses on the signals with white Gaussian noise. We call this model Noisy BSS model (Fig. 1).

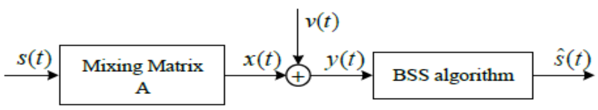

Fig.1 Noisy Blind source separation model.

In BSS model without noise , we can find a - matrix B so that By(t)=Ŝ (t)≈s(t), i.e BA≈I and this de-mixing matrix B is optimum . But in noisy BSS, even if we can get B, the result of de-mixing is By(t)=BAs(t)+Bv(t)≈s(t)+Bv(t) which is the mixture of the source signals and the noise. In practice we can not find the optimum de-mixing matrix B in noisy BSS at all. Therefore generally , noisy BSS is much more difficult to deal with than noise free normal BSS.

B. The Solution for Noisy BSS

A solution of noisy BSS based on wavelet de-noising is proposed in [10]. The idea of this solution is to transform Noisy BSS into normal BSS without noise, i.e. to de-noise the observed mixtures before BSS, and then directly use normal BSS algorithms without noise (Fig. 2).

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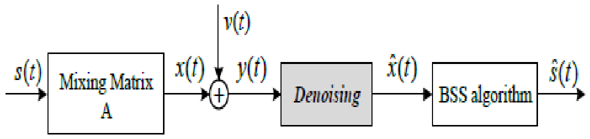

Fig 2. Noisy BSS de-noising method

Discrete Wavelet Transform is used to de-noise the observed mixtures. Wavelet Transform is one of the most widely used de-noising technique and is very efficient. Denoising refers to manipulation of wavelet coefficients for noise reduction in which coefficient values not exceeding a carefully selected threshold level are replaced by zero followed by an inverse transform of modified coefficients to recover de-noised signal. De-noising by thresholding of wavelet coefficients is therefore a nonlinear (local) operation. Thresholding can be done globally in which a single threshold level is applied across all scales, or it can be scale-dependent where each scale is treated separately. It can also be 'zonal' in which the given function is divided into several segments(zones) and at each segment different threshold level is applied.

C. *The BSS Problem of noise free Signals*

A method for solving BSS problem is to find a linear transformation of the measured signals x(t) such that the resulting source signals are as statistically independent from each other as possible. The model used considers the number of unknown sources "m" equal to the number of observations "n". The ideal separation is obtained when $B=A^{-1}$ and y is a (noisy) estimate of s. As it is pointed out by different authors [10,11], obtaining the exact inverse of the "A" matrix is in most of the cases impossible. Therefore, BSS algorithms search a "B" matrix such as the product "BA" is a permuted diagonal and scaled matrix. Consequently sources can be recovered up to their order (permutation) and their amplitude (scale).

Many different algorithms are available and they can be summarized by the following fundamental approaches, depending on the objective or cost functions minimized to find the separation matrix B:

- The most popular approach exploits as cost function some measure of signals statistical independence, non-gaussianity or sparseness. When original signals are assumed to statistically independent regardless of their temporal structure the Higher Order Statistics (HOS) are essentially to solve the BSS problem. In such case the method does not allow more than one Gaussian signal[10].
- If signals have temporal structures, then each signal has non-vanishing temporal correlation and less restrictive conditions than statistical independence can be used namely Second Order Statistics (SOS) are often sufficient to estimate the mixing matrix and the signals. As these algorithms exploit temporal correlations, SOS methods do not allow the separation of signals with identical power spectra shapes or Independent and identically distributed (i.i.d) signals.

Most of BSS algorithms (HOS and SOS) include a SOS only pre-processing step as spatial de-correlation or whitening. The conventional whitening exploits the equal time correlation matrix of the data x, which often considered as necessary criterion, but not sufficient for the independence. The whitening of x consists of the de-correlation and normalization of its components. The idea is to find whitening matrix "W" such as,

$$\mathbf{x_w = Wx} \text{ --(2)}$$

with covariance matrix of x_w equal to identity matrix : $Rx_w= I$. One can show that the whitening matrix W can be written as :

$$\mathbf{W = \in V^T} \quad \text{---------------------------------------(3)}$$

Where ∈ is diagonal matrix and V an orthogonal matrix obtained from the eigen decomposition of Rx, the covariance matrix of the data.

Independent estimates of the source signals will be obtained from the whitening signals x_w by a second transformation:

$$\mathbf{y = Jx_w = J\,Wx} \quad \text{-------------------------------------- (4)}$$

As the estimated signals are independent so uncorrelated , J is necessarily an orthogonal matrix. The minimization of the cost functions leads to this matrix. Another whitening method is robust whitening based on time-delayed correlation of matrices.

The THREE algorithms compared in this work are:

1. FAST ICA: FastICA algorithm [3] is a fixed-point iteration scheme for finding a maximum of the non-Gaussanity. It uses kurtosis and computations can be performed either in batch mode or in a semi-adaptive manner. It uses deflation approach to update the columns of separating matrix W and to find the independent components one at a time. More recent versions are using hyperbolic tangent, exponential or cubic functions as contrast function.
2. JADE-TD: Joint Approximate Diagonalization of Eigen matrices with Time Delays,uses a combination of source separation algorithms of second order time structure (TDSEP)[12] and high order cumulant information JADE[13].In principle it is able to separate simultaneously time correlated and non-gaussian signals[14].
3. SOBI: Second Order Blind Identification is an algorithm adapted for temporally correlated sources. It is based on the joint diagonalization [15] of an arbitrary set of covariance matrices and relies only on second order statistics of the received signals. It allows separation of Gaussian sources.

III. DISCRETE WAVELET TRANSFORM THEORY

The wavelet transform is very useful tool in the analysis of noisy signals particularly non stationary signals. The theory and methods of wavelet analysis are detailed in books[4],[5].In this paper, discrete wavelet analysis is used instead of the continuous wavelet analysis. The discrete wavelet analysis is based on the concept of Multi-resolution analysis (MRA) introduced by Mallat [6].With the MRA, a signal is decomposed recursively in to sum of details and approximations at different levels of resolution as shown in Fig. 3.

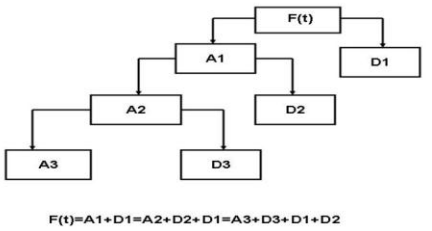

Fig.3. Decomposition tree of signal f(t), D_i and A_i are details and approximation components at level i.

The details represent the high frequency components while the approximations represent the low frequency components of the signal. The decomposition algorithm is fully recursive. At each stage of MRA the signal is passed through a High pass filter called scaling filter, denoted as G and a Low pass filter called the wavelet filter, denoted as H.

These filters are quadrature mirror filters that satisfy the orthogonality conditions; HG*=GH*=0 and H*H+G*G=I ; where I is the identity operator. The filters H and G are the decomposition filters , while the filters H* and G* are the reconstruction filters.

The coefficients of the filters H and G depend on the particular wavelet used for the decomposition[7].The process of decomposing a signal f(t) and reconstructing the approximations Ai and Di is shown in Fig. 4.

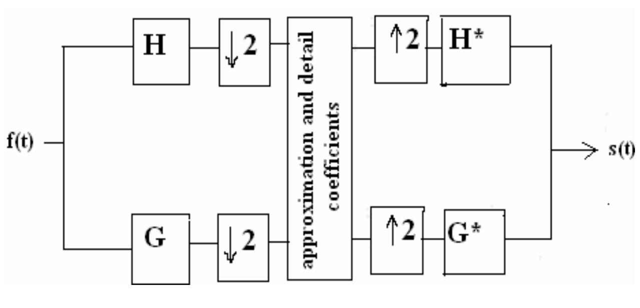

Fig. 4. The process of decomposition and reconstruction of approximations (Ai) and details (Di)(level i).Symbols $\downarrow 2$ $\uparrow$ 2represent dyadic down-sampling and up-sampling.

As shown in Fig. 4, the discrete wavelet transform (DWT) analyzes the signal at different frequency bands and with different resolutions by decomposing the signal in to coarse approximation and detail information. The approximation components are obtained by passing the signal through the low pass filter H, which removes the high frequency components. At this stage, the resolution is halved but the scale remains unchanged .Then, the signal is sub-sampled, thereby removing half the redundant samples. It should be noted that this process does not affect the resolution but affects the scale, which is doubled. Similarly the detailed coefficients are obtained by passing the signal through the high pass filter G. This constitutes one level of de-composition. The wavelet coefficients thus obtained can then be used for the purposes of signal de-noising and compression [8].

1 . WAVELET BASED DENOISING

The general wavelet de-nosing procedure is as follows :

- Apply wavelet transform to the noisy signal to produce the noisy wavelet coefficients to the level which we can properly distinguish the reflection occurrence.
- Select appropriate threshold limit at each level and threshold method (hard or soft thresholding) to best remove the noises.
- Inverse wavelet transform of the thresholded wavelet coefficients to obtain a de-noised signal.

1.1. Wavelet selection

To best characterize the noisy signal, we should select wavelet carefully to better approximate and capture the noise of the original signal. Wavelet will not only determine how well we estimate the original signal in terms of the shape , but also, it will affect the frequency spectrum of the de-noised signal. The choice of mother wavelet can be based on eyeball inspection of the signal with noise , or it can be selected based on correlation γ between the signal of interest and the wavelet de-noised signal , or based on the cumulative energy over some interval where noise will occur.

We choose to select the wavelet based on the inspection of the noise present in the signal and found that the Sym7 wavelet of level 4 for this paper.

1.2. Threshold limits

Thresholding modifies empirical coefficients (coefficients belonging to the given signal) in an attempt to reconstruct a replica of the true signal. Reconstruction of the signal is aimed to achieve a 'best' estimate of the true (noise-free) signal. 'Best estimate' is defined in accordance with a particular criteria chosen for threshold selection. Several criteria are considered for thresholding.The simplest thresholding technique is the hard thresholding, where the new values of the details coefficients *d(t)* are found according to the following:

$$\hat{d}(t) = \begin{cases} d(t) & if d(t) \triangleright \theta \\ 0 & if d(t) \le \theta \end{cases} \quad \text{---------------------- (5)}$$

Where ***d(t)*** are detailed coefficients and θ is the threshold
Another method of thresholding is the soft thresholding, where the new details coefficients are given by the following:

$$\hat{d}(t) = \begin{cases} sign(d(t))(d(t) - 0) & if d(t) \triangleright \theta \\ 0 & if d(t) \le \theta \end{cases} \quad \text{-------(6)}$$

The threshold θ can be estimated as follows:

$$\theta = \sigma\sqrt{2\log(N)} \quad \text{------------------------------------(7)}$$

Where N is the length of threshold coefficients and σ characterizes the noise level.

Hard thresholding can be described as the usual process of setting to zero the elements whose absolute values are lower than the threshold. Soft thresholding is an extension of hard thresholding, first setting to zero the elements whose absolute values are lower than the threshold, and then shrinking the nonzero coefficients towards 0.

1.3 Thresholding Algorithms

The choice of threshold is a fundamental issue[9] . A very large threshold cuts too many coefficients, resulting in an over smoothing. Conversely, a too small threshold value allows many coefficients to be included in reconstruction, giving a wiggly, under smoothed estimate. The proper choice of threshold involves a careful balance of these principles. Most of the work is mainly due to Donoho and Johnstone. A variety of threshold choosing methods can be mainly divided into two categories: global thresholding and level−dependent thresholding. The former chooses a single value of θ to be applied globally to all empirical wavelet coefficients, while the later chooses different threshold value θ_j for each wavelet level j.

A. Universal Thresholding - 'sqtwolog'

This type of global thresholding method was proposed by Donoho and Johnstone. This is also called "sqtwolog" method. The threshold value is given in equation (7) , where N is the number of data points, and σ is an estimate of the noise level. Donoho and Johnstone proposed an estimate of σ that is based only on the empirical wavelet coefficients at the highest resolution level j -1 because they consist most of noise. Most of the function information except the finest details is in lower level coefficients. The median of absolute deviation (MAD) estimator is expressed in equation (8) as

$$\frac{median(|w_{J-1,k} - median(w_{J-1,k})|)}{0.6475} \quad \text{............ (8)}$$

The universal thresholding removes the noise efficiently. The fitted regression curve is often very smooth and hence visually appealing. If $z_1 \dots z_n$ represent the wavelet coefficients of the noise with *idd* $N(0, \sigma^2)$, then it is expressed in equation (9) as

$$\lim_{n\to\infty} P(z_i \le \hat{\sigma}\sqrt{2\log n}) = 1 \quad \text{....................... (9)}$$

This means that the probability of all noise being shrunk to zero is very high for large samples. Since the universal thresholding procedure is based on this asymptotic result, it sometimes does not perform well in small sample situations.

B. Minimaxi Thresholding

Minimaxi is another global thresholding method developed by Donoho and John stone .
Minimaxi threshold is also fixed threshold and it yields minmax performance for Signal Mean Square Error (SMSE) against an ideal procedures. Because the signal required the denoising can be seen similar to the estimation of unknown regression function, this extreme value estimator can realize minimized of maximum mean square error for a given function.

$$W_{tm} = \begin{cases} 0.3936 + 0.1829 * (\log(n)/\log(2)), |n| \rhd 32 \\ ---------0---------, |n| \le 0 \end{cases} \quad \text{-(10)}$$

In this method, the threshold value will be selected by obtaining a minimum error between wavelet coefficient of noise signal and original signal. Compared with universal threshold, the minimaxi thresholding is more conservative and is more proper when small details of function lie in the noise range.

C. Sure Shrink – 'rigrsure'

Sure Shrink chooses a threshold by minimizing the Stein Unbiased Risk Estimate (SURE) for each wavelet level . It is also considered as "rigrsure" method.

Let μ=(μ_i :i=1,....d) be a length d vector, and let x={xi} with x_i distributed as N(μ_i,1) be multivariate normal observations with mean vector μ.Let $\hat{\mu} = \hat{\mu}(x)$ be an fixed estimate of μ based on the observations x. SURE is a method for estimating the loss $\|\hat{\mu} - \mu\|^2$ in an unbiased fashion.

In case of $\hat{\mu}$ is the soft threshold estimator $\hat{\mu}_i^{(t)}(x) = \eta_t(x_i)$. We apply Stein's result to get an unbiased estimate of the risk $E\left\|\hat{\mu}^{(t)}(x) - \mu\right\|^2$:

$$SURE(t;x) = d - 2.\#\{i : |x_i| \lhd T\} + \sum_{i=1}^{d} \min(|x_i|, t)2 \quad \text{---(11)}$$

For an observed vector x which is a set of noisy wavelet coefficients in a sub band, to find the threshold ts that minimizes SURE (t;x) i.e

$$t^s = \arg\min_t SURE(t;x) \quad \text{.............................. (12)}$$

The above optimization problem is computationally straightforward. Without loss of generality, x can be reordered in the order of increasing $|X_i|$ Then on intervals of t that lie between two values of $|X_i|$, SURE(t) is strictly increasing. Therefore the minimum value of t^S is one of the data values $|X_i|$. There are only d values and the threshold can be obtained using $O(d\log(d))$ computations.

D. 'heursure' method

SureShrink does not perform well in certain cases that the wavelet representation at any level is very sparse, i.e.,when the vast majority of coefficients are essentially zeros. Thus, Donoho suggest a mixture of universal threshold and

SureShrink. If the set of coefficients is sparse, then the universal threshold is used; otherwise, SURE is applied. We call this hybrid method as Heursure.

1.4. *Level of Decomposition*

It is known that the wavelet transform is constituted by different levels. The maximum level to apply the wavelet transform depends on how many data points contain in a data set, since there is a down-sampling by 2 operation from one level to the next one. One factor that affects the number of level we can reach to achieve the satisfactory noise removal results is the signal-to-noise ratio (SNR) in the original signal. Generally, the measured signals from the sensors have low SNR So to process the data, we need more level of wavelet transform say 4 or more to remove most of its noise.

1.5. De-noised Signal Reconstruction

Because of the amplitude based muting (based on thresholds) wavelet-transform based filters are in general nonlinear and can be readily applied to non-stationary signals. Wavelet filters are efficient for filtering several types of noise in data at the same time. Reconstruction or synthesis is the process of assembling those components back into the signal .The mathematical manipulation that affects synthesis is called: the *inverse discrete wavelet transforms* (IDWT).In order to get the de-noised signal, the new details coefficients, $\hat{d}(t)$ are used in signal construction process instead of original coefficients *d(t).* The de-noised procedure is summarized in Fig 5.

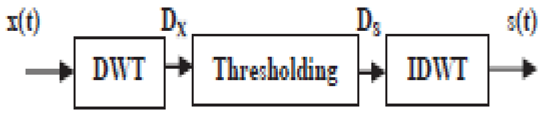

Fig. 5. DWT de-noising procedure.

IV. ANALYSIS OF WAVELET TRANSFORM APPROACH

In this section, we analyze the decomposition results of Wavelet Transform at different SNR levels. The signal " Bumps" is obtained using MATLAB software and is corrupted by white Gaussian noise, and the SNR levels are 15dB and 0dB respectively as shown in fig. 6 .The sample size of signal is N=1000.

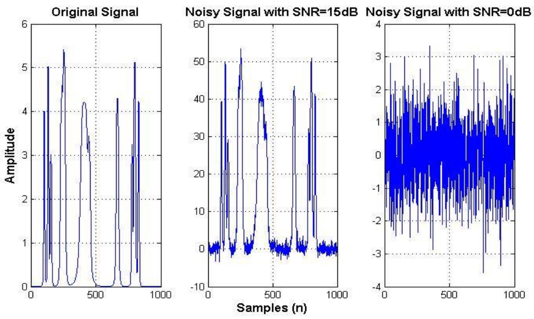

Fig. 6 The signal "Bumps" at different SNR levels

The parameters of Wavelet transform are set as follows: The wavelet basis function chosen is "sym7" and the number of decomposition level selected is 4.The decomposition results of Wavelet Transform are depicted in Fig 7.

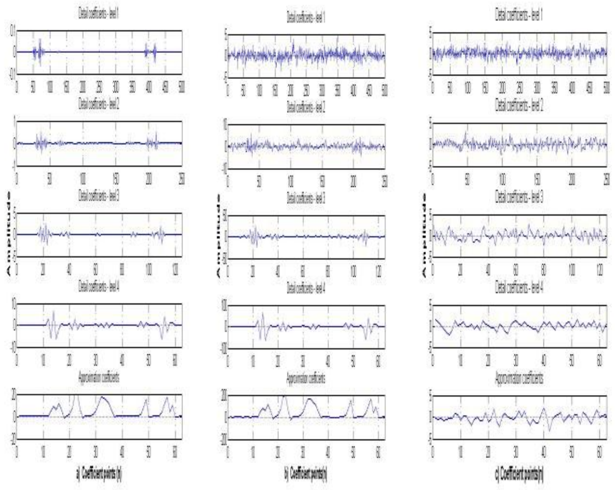

Fig. 7 Decomposition results of WT: a) Original signal, b) Noisy signal with SNR=15dB, c) Noisy signal with SNR=0dB

V. EXPERIMENTAL RESULTS

The experimental analysis of this section aims at objectively evaluating the de-noising performance of de-noising algorithms namely sqtwolog, minimax, sureshrink and rigsure and the separation performance of BSS algorithms namely FastICA ,JADETD and SOBI after de-noising preprocessing. In order to precisely describe the performance of the denoise algorithms, we employ **signal mean square error** (SMSE), a contrast-independent criterion defined as

$$SMSE=1/N\ E\{|x-x_j|^2\} \quad \textbf{..................................(13)}$$

Where x is the source signal or the noise free signal, x_j is estimated signal, and N is sample number of the signal. The performance is better when the value of SMSE is smaller.

In order to precisely assess the BSS performance for the Three prominent BSS algorithms namely FastICA , JADETD and SOBI the following evaluation criteria is employed.

A. Denoising Experiment

In order to test the performance of denoising algorithms – namely "rigrsur" "heursur" "sqtwolog " and "minimax", we performed numerical simulations for TWO test signals:"Heavysine" and "Bumps" signals noise free and noisy signals obtained using MATLAB software are shown in Fig 8. The sample size of the signals is N=1000.The Denoising performance for both soft threshold and hard threshold (white noise) of the four methods is evaluated for "Heavisine" test Signal as shown in Table-I and III and for "Bumps" test signals as shown in Table-II and IV. Denoised signal's performance is compared based on signal mean square error computed. Fig 9 displays the results of applying the four denoising methods to the Two test signals.This is implemented using Matlab tool box, which is widely used for high performance numerical computation and visualization. The wavelet used is Sym7.

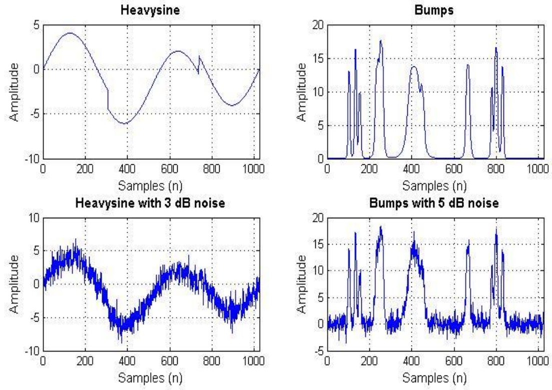

Fig 8. Test signals with N=1000 and Noisy signals (Heavysine: SNR=5dB and Bumps: SNR=3dB).

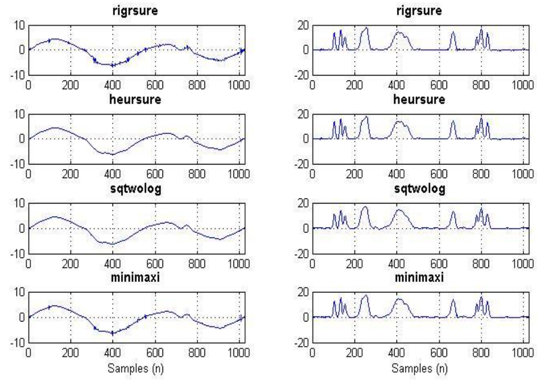

Fig. 9. Denoising results of the Four Approaches. The noise free signals and the reconstructed signals (Heavysine: SNR=5dB and Bumps: SNR=3dB).

TABLE I: SOFT THRESHOLD DENOISING RESULTS OF "HEAVYSINE" SIGNAL AT DIFFERENT SNR LEVELS

SNR (dB)	-10	-8	-6	-4	-2	0	2	4	6	8	10
rigrsur	0.1317	0.1235	0.1109	0.0947	0.0833	0.0903	0.0804	0.0958	0.1091	0.1205	0.1299
heursur	0.1499	0.1280	0.1040	0.0824	0.0679	0.0734	0.0679	0.0810	0.1052	0.1278	0.1460
sqtwlog	0.1642	0.1360	0.1080	0.0827	0.0658	0.0745	0.0674	0.0807	0.1068	0.1356	0.1666
minimax	0.1272	0.1157	0.1011	0.0845	0.0748	0.0781	0.0730	0.0845	0.1015	0.1155	0.1276

TABLE II: SOFT THRESHOLD DENOISING RESULTS OF "BUMPS" SIGNAL AT DIFFERENT SNR LEVELS

SNR (dB)	-10	-8	-6	-4	-2	0	2	4	6	8	10
rigrsur	0.2486	0.2387	0.2149	0.1902	0.1546	0.0786	0.1544	0.1881	0.2160	0.2366	0.2567
heursur	0.2678	0.2337	0.2063	0.2015	0.1613	0.0621	0.1624	0.1956	0.2068	0.2351	0.2638
sqtwlog	0.8345	0.7240	0.6125	0.4771	0.2707	0.0642	0.2700	0.4815	0.6112	0.6112	0.8629
minimax	0.4505	0.4082	0.3480	0.2862	0.1944	0.0689	0.1908	0.2896	0.3471	0.3471	0.4499

TABLE III: HARD THRESHOLD DENOISING RESULTS OF "HEAVYSINE" SIGNAL AT DIFFERENT SNR LEVELS

SNR (dB)	-10	-8	-6	-4	-2	0	2	4	6	8	10
rigrsur	0.3265	0.3171	0.2630	0.2360	0.2347	0.2159	0.2315	0.2526	0.2772	0.2973	0.3115
heursur	0.1249	0.1248	0.1125	0.0939	0.0777	0.0740	0.0787	0.0932	0.1116	0.1216	0.1231
sqtwlog	0.1379	0.1279	0.1077	0.0832	0.0696	0.0671	0.0698	0.0851	0.1076	0.1279	0.1359
minimaxi	0.2492	0.2463	0.2518	0.2435	0.2292	0.2255	0.2352	0.2428	0.2573	0.2568	0.2528

TABLE IV: HARD THRESHOLS DENOISING RESULTS OF "BUMPS" SIGNAL AT DIFFERENT SNR LEVELS

SNR (dB)	-10	-8	-6	-4	-2	0	2	4	6	8	10
rigrsur	0.4530	0.4196	0.4033	0.3695	0.3174	0.2258	0.3262	0.3469	0.3816	0.4366	0.4434
heursur	0.3094	0.2956	0.2669	0.2403	0.1827	0.0714	0.1822	0.2408	0.2723	0.2919	0.3058
sqtwlog	0.3476	0.3171	0.2749	0.2487	0.1896	0.0678	0.1904	0.2548	0.2743	0.3103	0.3561
minimax	0.3810	0.3675	0.3538	0.3234	0.3020	0.2265	0.3069	0.3229	0.3439	0.3624	0.3786

Matlab command 'wden' is used for one dimensional de-noising function which performs automatic de-noising using wavelets and returns XD de-noised version of input signal X obtained by thresholding the wavelet coefficients as shown in equation 14.

[XD]= wden (X, TPTR, SORH, SCAL, N, 'wname') **-- (14)**

TPTR string contains the threshold selection rule: 'rigrsure' / 'heursure' /'sqtwolog'/ 'minimaxi'. SORH ('s' or 'h') is for soft or hard thresholding.
SCAL defines multiplicative threshold rescaling:'one' for no rescaling, 'sln' for rescaling using a single estimation of level noise based on first-level coefficients and 'mln' for rescaling done using level-dependent estimation of level noise. Wavelet decomposition is performed at level N and 'wname' is a string containing the name of the desired orthogonal wavelet.

Denoised signal's performance is compared based on Signal Mean Square Error computed and it is found there is not much difference between Soft and hard threshold for level-1 white noise removal. It is observed that the performance of 'minimax' and 'heursure' is better than that of 'sqtwlog'.

B. BSS Experiment

In the following the case of Two original source signals $x_1(n)$ and $x_2(n)$, n=1,2,3,4......10000 mixed by a 2x2 mixing matrix is considered. Assuming that the mixed source signals are corrupted by additive white Gaussian noise.

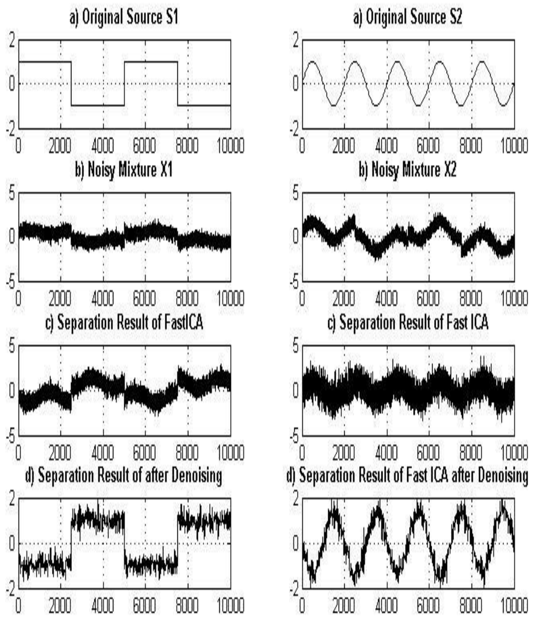

Fig 10. Comparison of separation results (SNR=10dB): (a) Original sources, (b)Noisy mixtures, (c) Separation results of FastICA only, (d) Separation results of FastICA with de-noising preprocessing.

In order visualize the performance improvement in restoring the original source waveforms, the three original source waveforms, the noisy mixture of SNR=10dB and the estimated sources from denoising mixtures with Fast ICA are shown in Fig 10. It can be shown that the separation waveforms without Wavelet Transform de-noising preprocessing almost not be recognized compared with original sources and the de-noising preprocessing provides better waveforms for the estimated sources.

Then the de-noising preprocessing using minimax, heursure, rigsure and sqtwolog approaches proposed are performed individually for each noisy mixture. The parameters selected are Minimax for threshold selection, Wavelet is Sym7 with Decomposition level set to four same as in Section A. And then the separation performances of THREE prominent BSS algorithms: FastICA , JADETD and SOBI are evaluated. Assuming different SNR levels for the observed mixtures, for each SNR level the performance criteria SMSE are averaged over 100 Monte Carlo simulations. The comparison of separation performance is depicted in Fig. 11,12 and 13.

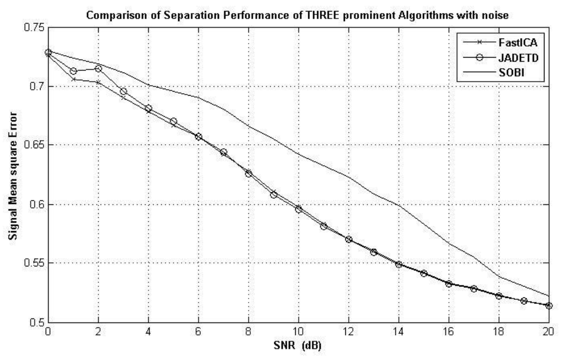

Fig. 11 Comparison of separation performance of three prominent BSS algorithms without preprocessing approach.

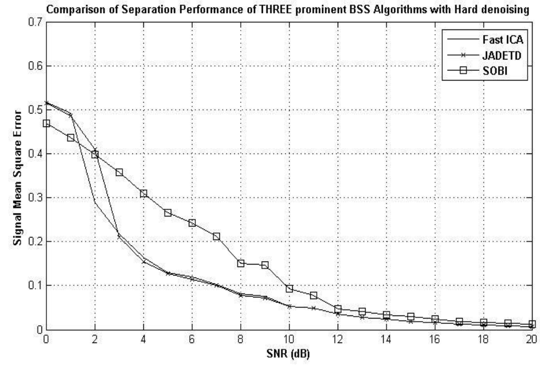

Fig. 12 Comparison of separation performance of three prominent BSS algorithms with hard threshold de-noising preprocessing approach.

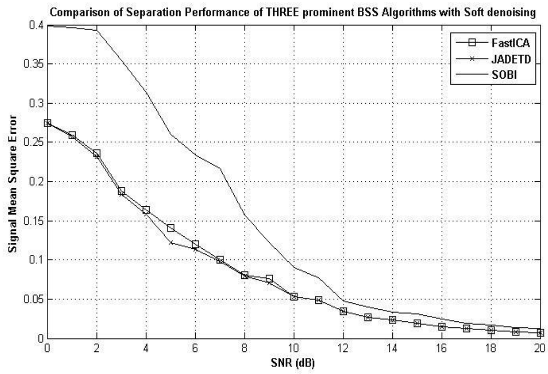

Fig. 13 Comparison of separation performance of three prominent BSS algorithms with soft threshold de-noising preprocessing approach.

As indicated in Fig. 11,12 and 13 de-noising preprocessing is very efficient for improving the performance of BSS algorithms in the presence of strong noise. Moreover Wavelet Transform threshold level algorithm based on minimaxi de-noising preprocessing improves Signal Mean Square Error, especially in the cases where the signal SNR is low.

VI. CONCLUSIONS

Noise strongly reduces the separation performance of BSS algorithms, which is known as Noisy BSS problem. A direct and simple solution is to de-noise the noisy mixtures before BSS. In this paper, signal de-noising approach called wavelet transform de-noising is proposed. This de-noising scheme, based on minimax, is simple and fully data-driven approach exhibits an enhanced performance by reducing SMSE compared to without preprocessing in the cases where the signal SNR is low. Simulation results show that de-noising preprocessing before BSS is an efficient solution, especially for strong noisy mixtures. De-noising the noisy mixtures as preprocessing step of Noisy BSS will improve the performance of CDMA communication systems increasing the capacity of wireless channels and made EEG signals towards easier interpretation for the physicians by elimination of artifacts and noise that the EEG signals present.

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