Independent component analysis for single channel source separation using wavelet packet decomposition

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Abstract—(ICA) Independent Component Analysis is recently developed computational method for separating the multiple channel source. Each component of ICA representation is a linear combination of the original variable. The common ICA method cannot be directly applied for single channel mixed signal. A novel method is proposed based on ICA that is Convolution Type Wavelet Packet Decomposition. This method provides new approach for separating the limited source. Convolution Type Wavelet Packet is non down-sampled therefore the sequence in the different levels and frequency sets can be same length as the original signal. Each sub-band sequence is same as the original signal and corresponding to certain frequency division. Different wavelet functions are used for decomposing the signal for example symlet (order8), haar, daubechies(order4) biorthogonal(order 3.5) and coif let (order 3) wavelet function. Using this wavelet functions the signal decomposed into multiple channel mixed signals and that mixed signal can be applied to ICA (Independent component analysis) which gives the separated signal as same as the original signal. Therefore this paper focused on a comparative study of different wavelet functions to find the most convenient wavelet function for getting exact output from the five wavelet functions for mixed sinusoidal signals and motor vibration signals. From analysis values of Signal to noise ratio (SNR), Bit error rate (BER) and Peak signal to noise ratio (PSNR) can be calculated before and after applying wavelet packet transform for each wavelet functions. Daubechies (order 4) and coiflet (order3) wavelet functions performed relatively better separation results when compared to other wavelets. For the purpose of a simulation results, mixed sinusoidal signals series and motor vibration signals are used.

Index Terms— BER, BSS, DWT, PSNR, wavelet functions, wavelet packet transform, SNR.

1 Introduction

THE well known method that independent component analysis (ICA) is an effective statistical and computational method to process the multi dimensional signals.ICA is a field of Blind source separation (BSS), it can effectively extract the higher-order statistics from the one dimensional signal. It is widely used in signal processing, speech enhancement, image processing, and radar signal processing and communication systems. BSS has a much richer class of techniques, however, capable of finding the sources when the classical methods, implicitly or explicitly based on Gaussian models. In many cases, the measurements are given as a set of parallel signals or time series.

Typical examples are mixtures of simultaneous sounds or human voices that have been picked up by several microphones, brain signal measurements from multiple ECG sensors, several radio signals receiving at a portable phone, or multiple parallel time series obtained from some industrial process. Perhaps the best known single methodology in BSS is Independent Component Analysis (ICA), in which the latent variables are non Gaussian and statistically independent. ICA is mainly only one assumption that is number getting or observed signals are more than th8e number of sources. Many cases only one channel mixed signal source is obtained in that case ICA cannot be applied directly, for those cases many researcher proposed many methods which are single-channel ICA algorithm (SCICA) can be used in certain cases to separate the independent components. Zuo [5] uses wavelet transform to preprocess the data collected from the single channel mixed signal. Using those wavelet coefficients applied to ICA for separation. He, Du and Kong [6] proposed new method for future extraction method from one dimensional signal based on ICA. According to the James and Davies proposed a technique that breaks the signal into bunch of blocks. Dong [2] proposed a repeated BSS method based on morphological filtering and singular value decomposition (SVD) to decompose the mixed signals from single-channel signal. Ibrahim Missaouri [4] proposed new blind speech source separation system; it integrates a perceptual filter bank and ICA by using kurtosis criterion. In this method using the un decimated wavelet packet decomposition for increasing the non-Gaussianity of the acoustic signal.

To solve the problem of separation single channel mixed signals BSS with the single channel mixed signal, we proposed method based on convolution type wavelet packet transform. Basically a wavelet packet (WP) can be considered as series of band pass filters and A WPT can be used to pre process the signal which is equivalent to band pass series. Convolution type wavelet packet transform is nothing but keep the decomposed sub–band series always same length as the

ISSN 2229-5518

original signal [9][3].

Therefore, as input one- dimensional signals are applied to convolution type wavelet packet transform of different wavelet functions like symmlet8, haar, daubechies4, bi-orthogonal3.5 and coif let wavelet functions, then by using the WPT coefficients of different levels and scales Can be considered as the multiple inputs for ICA to separation. We have find un mixing matrix mixed signal After reconstructing original signal, considering the values of signal to noise ratio (SNR), Bit error rate (BER)and peak signal to noise ratio(PSNR) if we compare values between without applied wavelet transform and with applied wavelet transform table1 and table2 shown in below. By considering the table values and graphical results, coif let wavelet and daubachies4 wavelet gives better results for retrieving the original signal. The proposed method in this paper is an effective approach for blind source separation when there are a limited number of sources are given in an application.

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Wavelet transforms:

Wavelet transform is represents the technique for non stationary signals. The discrete wavelet transform (DWT) is a multi resolution representation of the signal which decomposes the signal into basis functions. The DWT Filters the input signal into two parts one is H it is a low pass filter and another G is a high pass filter. This leads to two sub-bands called approximations and details coefficients followed by decimated factor by two. This iteration process is only for approximation sub-band decomposition at each level [8]. The wavelet transform decomposition is shown in below figure1.

Wavelet families:

More number of variety wavelet functions is there in digital signal processing. Let's consider some of them, symmlet8, and daubechies4, and haar (db2), bi-orthogonal3.5 and coiflet wavelets to decompose the signal for analyzing purpose. Mainly wavelet consist two sections one is analysis and synthesis.

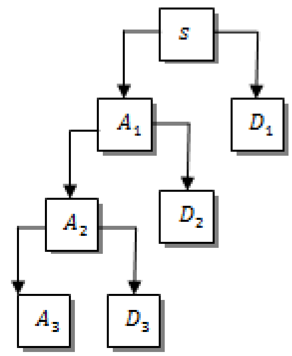

Fig: 1. wavelet transforms tree

$$S=A1+D1$$

$$=A2+D2+D1$$

$$=A3+D3+D2+D1$$

Analysis section used for decomposition and synthesis section is used for reconstruction purpose [7].

Haar wavelet:

Any discussion of wavelets begins with Haar wavelet, the fast and simplest. Haar wavelet is discontinuous wave form, and it is a step function. It represents the same wavelet as Daubechies db1

Daubechies4:

Ingrid Daubechies, one of the most useful wavelet in the world of wavelet research, invented what are called compactly supported orthonormal wavelets, thus making practicable discrete wavelet analysis.

The names of the Daubechies family wavelets are written dbN, where N is the wavelet order, and db the "surname of the wavelet". The db1 wavelet, as mentioned above, db wavelet is the same as Haar wavelet.

Symlets8:

The symlets are nearly symmetrical wavelets proposed by Daubechies as modifications to the db family. The two wavelet families of the properties are similar.

Biorthogonal3.5:

This family of wavelets exhibits the property of linear phase representation, which is needed for reconstruction of signal and image. By using two wavelets, one for decomposition and the other for reconstruction purpose instead of the same single one.

Coiflets2:

Built by Daubechies at the request of researcher R. Coifman . The wavelet function has 2N moments equal to zero and the scaling function has 2N-1 moments equal to zero. The two functions have a length 6N-1.

Wavelet packets transform:

Wavelet packet decomposition is generalization of discrete wavelet transform. The aim is a more complete interpretation of the signal. Here filtering process is applied to both approximation as well as detail coefficients. To provide denser approximation and to preserve the translation invariance non down sampling wavelet packet transform has been introduced. It is similar to the wavelet transform except that the down sampling process after each filtering step suppressed. The only difference between the wavelet transform and wavelet packet transform is that it can decompose the signal into each sub-band of both approximation and details as well

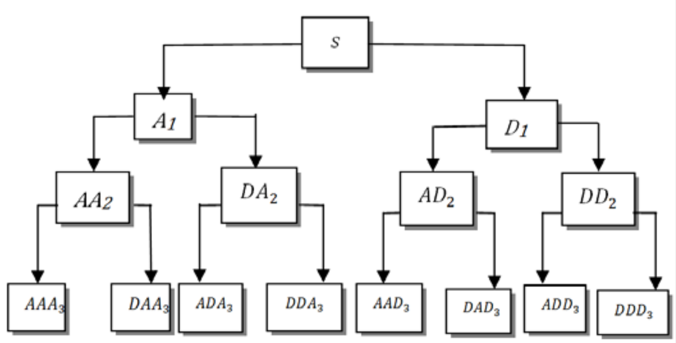

Fig. 2. Wavelet packets transform

2. A CONVOLUTION TYPE WAVELET PACKET TRANSFORM

2.1 The convolution type wavelet packets transform

The wavelet packet decomposition adopted for only iterative algorithm. This algorithm collects only one sample data from every two samples in the iterative decomposition process; after decomposed sequence samples will be reduced to half of the original data [1].

This process would be very difficult if applied to ICA. This paper organized as a convolution type wavelet packet transform is introduced to transformation of the signal length.

Convolution type wavelet packet keeps frequency of the signal as same length as the original signal, here there is no down sampling in the process of transformation [3]. It is well known that, for wavelet transform, besides the inner product was done shown in equation(1), there is another definition, i.e. the convolution WPT definition[3], which is proposed to detect the local singularity of signal for WPT, there is only the inner product definition, whether the convolution definition is suitable for WPT? In this paper the Problem was studied and it's proved that the convolution definition for WPT is also feasible. For this purpose, let's define the Convolution WPT as follows [9]:

For signal x (t) € L2(R), supposing the function series becomes $\{2^{-j/2}\mu_n\,(2^{-jt-k}) \mid k \in Z\}$ make up of the orthonormal bases of Wavelet packet subspace μ_n the convolution WPT can be defined as follows

$$x_p^{n,j} = \frac{1}{2^j}\int_R x(t)\cdot\mu_n\left(\frac{p-t}{2^j}\right)dt = \frac{1}{2^j}\cdot x(t) * \mu_n\left(\frac{t}{2^j}\right),$$

$$0 \le j \le S,\ 0 \le n < 2^s, \qquad (1)$$

Where j is the number of decomposition level, or so-called scale parameter, p is the position parameter, n is the channel Number, S is the maximum decomposition level.

Decomposition algorithm is described as:

$$x_p^{2n,j+1} = \frac{1}{\sqrt{2}}\sum_{k\epsilon Z} h(k)\cdot x_{p-2^j k}^{n,j}$$
$$x_p^{2n+1,j+1} = \frac{1}{\sqrt{2}}\sum_{k\epsilon Z} g(k)\cdot x_{p-2^j k}^{n,j} \qquad (2)$$

h (k) is low pass filter and g (k) is high pass filter[3].

2.2 Frequency division process in wavelet packet transforms:

The wavelet was designed to have a perfect reconstruct condition, which is consider only time domain requirement, if filter bank has an ideal cut of characteristics then each decomposed frequency band signal provides the exact corresponding spectrum information.

3. BSS FOR SINGLE CHANNEL SOURCE:

3.1 ICA algorithm:

The independent component analysis (ICA) is a Statistical technique whose main application is BSS Problem; it can be described as follows

$$x(t)=AS(t) \qquad (3)$$

$x(t)=(x1, x2,\dots, xN)T$

$s(t)=(s1, s2,\dots, sN)T$

where, x(t)=(x1, x2,…, xN)T is a N-dimensional observation vector; s(t)=(s1, s2,…, sN)T is a N-dimensional original source vector having independent components; A is a non-singular N×N mixed matrix. The basic problem of ICA is to find N×N separation matrix W=(w1, w2,…, wN)T without knowing s(t) and A, make y(t)=Wx(t) is the estimation of s(t)[5].

The blind source separation (BSS) is based on the following assumption. First, source vector s(t) is mutually statistics independence, and only one of them is subject to Gaussian distribution; second, the number of observed signals are less than source signals[14].

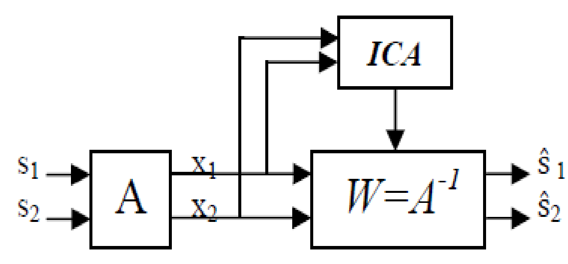

Fig. 3. Block diagram for ICA Algorithm

ISSN 2229-5518

3.1. Un-co relatedness and Independence:

s1 and *s2* are un-co relatedness if their covariance *C*(*s1*,*s2*) is zero.

$$C\,(s1,\, s2) = E\,\{(\mathrm{s1}-\mathrm{ms1})(s2-ms2)\}$$
$$= E\,\{s1s2-s1ms2-s2ms1+ms1ms2\}$$
$$= E\,\{s1s2\} - E\,\{s1\}\,E\,\{s2\} = 0 \qquad (4)$$

Where ms1 is mean of the signal. Hence independent variables are always uncorrelated. But inverse is not true.

3.2. Non-Gaussianity:

Central limit theorem states, that the sum of two independent signals usually has a distribution that is closer to Gaussian than distribution of two original signals. Thus, Gaussian is linear combination of many independent signals. To separate the signals again from their mixtures can be done by making linear signal transformation as non- Gaussian. Non-gaussianity is done when the data is centered (zero mean) and has variance equal to 1[15].

3.3. The sources being considered are statistically independent:

Statistically independence is the feature that enables estimation of the independent components from the observations. It was defined in terms of probability density function of the signals. Consider the joint probability density function (pdf) of s1 and s2 be P (s1, s2). Let the marginal PDF of s1 and s2 be denoted by P1 (s1) and P2 (s2) respectively. s1 and s2 are said to be independent[15].

3.4. The independent components have non-Gaussian distribution

The second assumption is necessary because of the close link between Gaussianity and independence. It is impossible to separate Gaussian sources using the ICA framework because the sum of two or more Gaussian random variable is itself Gaussian [5].

3.5. The mixing matrix is invertible.

The third assumption is if the mixing matrix is not revertible then clearly the un-mixing matrix we seek to estimate does not even exist. If these three assumptions are satisfied, then it is possible to estimate the independent components. Pre-processing technique Before examining specific ICA algorithms, it is instructive to discuss pre-processing steps that are generally carried out before ICA.

3.5.1. Centering

A simple pre-processing steps that is commonly performed is to "centre" the observation vector x by subtracting its mean vector. This step simplifies ICA algorithms by allowing us to assume a zero mean. Once the un-mixing matrix has been estimated using the cantered data, we can obtain the actual estimates of the independent components.

From this point onwards, all the observed vectors will be assumed cantered. The mixing matrix, on the other hand, remains the same after this pre-processing so we can always do this without affecting the estimation of the mixing matrix.

3.5.2. Whitening

Another useful pre-processing strategy in ICA is to first whiten the observed variables. This means that before the application of the ICA algorithm (and after cantering), we transform the observed vector linearly so that we obtain a new vector, which is white i.e. its components are uncorrelated and their variances equal to unity [15].

4. BSS based on the convolution- type wavelet packet transform:

We define the wavelet packet decomposition a series of band pass filter, so

$$W\mathrm{p(t)}=[Wp_1\,(t),\,,Wp_2\,(t),\,Wp_3\,(t),\text{----}\quad]^T \qquad (5)$$

The elements of Wp(t) are considered as sub-band coefficients of the convolution-type wavelet packet decomposition for the observed signal $\mathrm{X_i(t)}$. Next we assume that the original signal s are mapped to the new subspace *Wp(t),*that can be expressed as

$$\boldsymbol{W}\mathbf{p(t)=AS(t)} \qquad (6)$$

Then we have to prove the some properties for that purpose, we can make equation as

$$\mathbf{Z(t)}=\boldsymbol{W_0 W}\mathbf{p(t)} \qquad (7)$$

Where, $\mathrm{W_0=V^{-1/2}U^T}$, U and V are eigenvector and Eigen value of the covariance matrix.

The U always satisfies the equation

$$\mathrm{U^TU=UU^T=1}$$

The (7)[th] equation can be written as:$\wedge$

$$\mathrm{E}\{\mathrm{Z}Z^T\}=\mathrm{E}\{\wedge^{-1/2}U^T W\mathrm{p}Wp^T U\wedge^{-1/2}\}$$
$$= \wedge^{-1/2}U^T E\{\,W\mathrm{p}Wp^T\}\,U\wedge^{-\frac{1}{2}}$$
$$= \wedge^{-1/2}\wedge\wedge^{-1/2}$$
$$= 1 \qquad (7)$$

According to (5) [th] equation with (6)[th] equation

$\mathrm{W_0A} = \breve{\mathrm{A}}$ Wmay be expressed as:

$$\mathrm{Z(t)}= W_0 Wp(t)= W_0\breve{\mathrm{A}}\ \mathrm{s(t)=AS(t)} \qquad (8)$$

$$\mathrm{E}\{\,\mathrm{Z}Z^T\} = \mathrm{E}\{\mathrm{A}SS^T A^T\}$$
$$= \mathrm{AE}\{SS^T\}A^T$$

ISSN 2229-5518

$$= AA^T$$

$$= 1$$

It is clear that a space projection transformation simplifies mixing matrix A into a new orthogonal matrix Ă [1].

If we consider the wavelet packet decomposition as a series of band-pass filters we will obtain the different frequency signals, then these coefficients can be used as a different mixture-signals collected from the same sensor. This multiple mixture-signals are used to input to the ICA algorithm, by using one assumption the mixture signals collected from the sensor is more than that of source signals (m>n);the source can be separated by the ICA algorithm. Shown in below figure

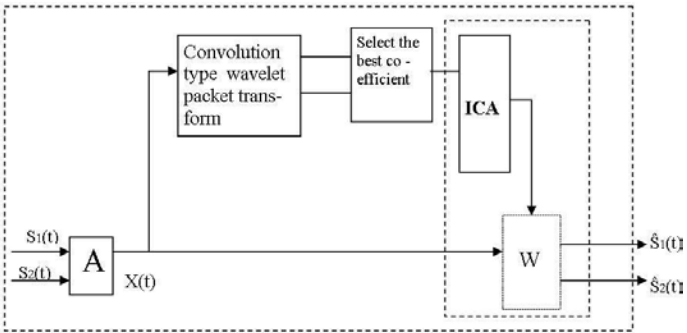

Fig. 4. Block diagram for ICA based on convolution WPT

The above figure shows the proposed method of this paper as follows:

i) Generate the signals and calculated the SNR BER and PSNR of the signal

ii) Decompose the observed signals into wavelet packets

iii) Select the best coefficients from the WPT.

iv)Wavelet packet coefficients were given as input to ICA algorithm for recovering the original signal.

v) Also calculated the SNR, BER and PSNR values of the recovered signal for analysis.

vii) Find the un mixed signal (retrieving the original signals) by using inverse of A[4].

For analyzing tabulations value SNR, BER, PSNR defined by,

Signal-to-Noise Ratio: The signal to noise ratio is the ratio between the wanted signal and the unwanted background noise. The formula for SNR is given by

$$SNR=\frac{P_{signal}}{P_{niose}}$$

It is more usual to see a signal to noise ratio expressed in a logarithmic basis using decibels is given by

$$SNR_{dB} = 10\log_{10}\left(\frac{P_{signal}}{P_{noise}}\right)$$

If all levels are expressed in decibels, then the formula can be given by

$$SNR_{dB} = P_{signal_{dB}} - P_{noise_{dB}}$$

The power levels may be expressed in levels such as dBm (decibels relative to a milliwatt, or to some other standard by which the levels can be compared.

SNR is the ratio of the power of the input signal level to the power of the noise level and is usually expressed in dB. It can also be calculated using the root mean square (RMS) value of the signal amplitude and the noise amplitude. SNR is the ratio of signal to noise power. The best approximation of SNR is using power of the amplitude and noise, but the most accurate calculation uses the RMS quantization of each. When calculating SNR, the bandwidth of the signal should be specified. The larger the SNR specification, the better an instrument differentiates the signal from the noise in measurements and generations. Better definition of the signal of interest means better frequency and AC voltage or current performance and resolution of signals with low energy.

SNR shows how well signal frequency components will stand out from noise in a device's measurements and generations, but does not account for the effects of device spurs.

3.7. Bit error rate:

A bit error rate is defined as the rate at which errors occur in a transmission system. This can be directly translated into the number of errors that occur in a string of a stated number of bits. The definition of bit error rate can be translated into a simple formula is given by

$$\text{Bit Error Rate} = \frac{\text{Number of errors}}{\text{Total number of bits sent}}$$

If the medium between the transmitter and receiver is good and the signal to noise ratio is high, then the bit error rate will be very small - possibly insignificant and having no noticeable effect on the overall system. However if noise can be detected, then there is chance that the bit error rate will need to be considered.

The main reasons for the degradation of a data channel and the corresponding bit error rate, BER is noise and changes to the propagation path (where radio signal paths are used). Both effects have a random element to them, the noise following a Gaussian probability function this means that analysis of the channel characteristics are normally undertaken using statistical analysis techniques.

3.8. Peak signal to niose ratio:

ISSN 2229-5518

Now let's look at peak signal to noise ratio. This definition is given by

$$P_{PSNR} = \frac{\max(s2[n])}{MSE}$$

This definition is really the same as that of PSNR except that the numerator of the ratio is now the maximum squared intensity of the signal, not the average one. This makes this criterion less strict. You can see that PPSNR≤PSNR and It makes sense because the case of SNR we are looking at how strong the signal is to how strong the noise is. In case of PSNR,

We are interested in signal peak because we can be interested in things like the bandwidth of the signal or number of bits we need to represent. This is much more content-specific than pure SNR and can find many reasonable applications, image compression being on of them. Here we're saying that what matters is how well high-intensity regions of the image come through the noise, and we're paying much less attention how

5. Simulated results:

5.1 Simulated sinusoidal signals:

To test the effectiveness of the proposed method, we first constructed a signal to simulate. The frequencies of the source signal were 500 Hz, 600Hz, 700Hz and 800Hz.we set the sampling frequency to be 8000 Hz and sampling point to 128.The sinusoidal signal signals with different frequencies are illustrated in below figures. We use a random function to generate a mixed matrix, then this matrix used to obtain mixed signal [1].

First take the mixed sinusoidal signal then applied to convolution type wavelet packet transform for different wavelets we get de noised spectrogram of each wavelet and decomposition of different layer signal then calculated some properties of the signal that is given to as input to ICA for reconstructed the original signal from decomposed signals

The spectrogram gives you an array of numbers, which are scaled and map to a color palette to produce a color image. It shows the frequency spectrum of the signal and how it changes over time. If the beginning of the signal is white noise (flat spectrum), and the end of the signal is a tone (spiked spectrum), the spectrogram will show how it changed from one spectrum to the other over time. It does this by dividing the signal up into small chunks and calculating the spectrum of each chunk. The resonant frequencies present in that window spectrogram is a graphical representation that shows the spectrum plot over all the frames. This makes it a 3-D figure and the Spectrogram function generates a 2-D projection of this figure. The x-axis represents the time scale (or the corresponding window), the y-axis represents the frequency and the grey stripes you see denote the magnitude of the frequency for that particular window.

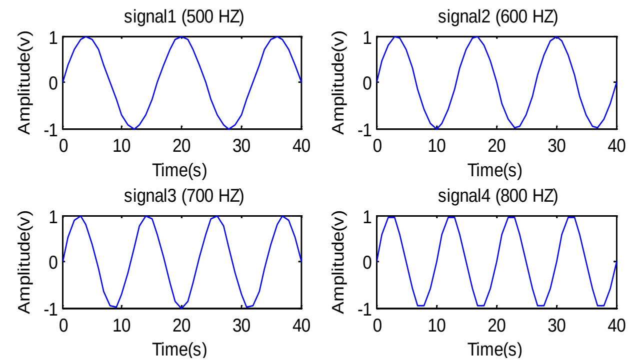

Fig: 5. Different frequencies of sinusoidal signals

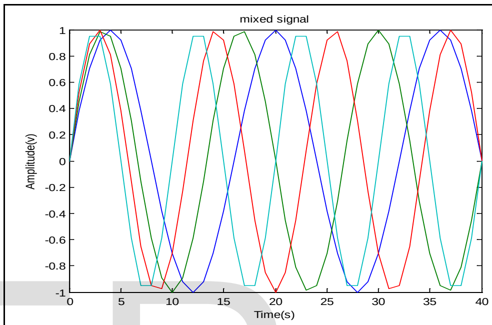

Fig: 6. Mixed sinusoidal signals

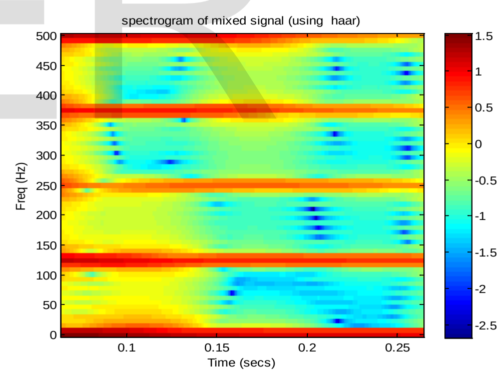

Fig: 7. Spectrogram of mixed signal using convolution type of symlet wavelet

The darker the stripe, greater is the magnitude of the frequency component in that particular window of the signal. When compared to the other wavelets cieflet wavelet function gives the exact results of original signal shown in figure 21. Spectrograms are shown in below Fig. 7,10,13,16 and 19 from these, Fig. 13 is best spectrogram. The decomposed sub-band signals shown in below Fig. are 8,11,14,17 and 20. After applying the ICA algorithm to sub-band signals the recovering signals shown in the following figures 9,12,15,18 and 21. From these fig21 gives good results. And also comparisons of original signal and recovering signal using ICA are shown in below fig22.

ISSN 2229-5518

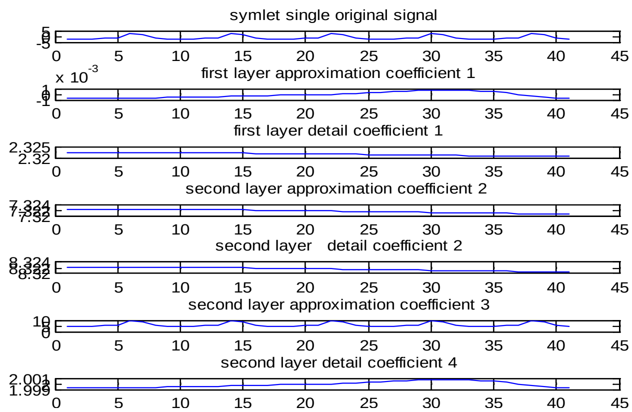

Fig: 8. Sub-band signals of mixed signal decomposed by convolution -type WPT

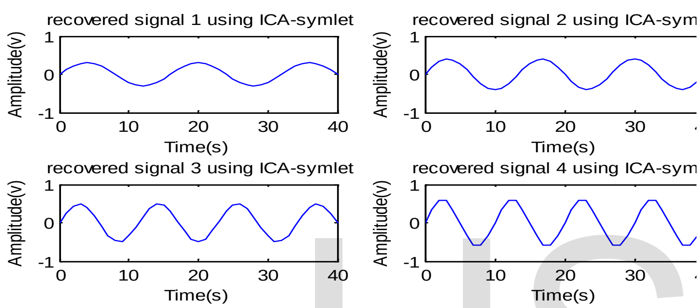

Fig: 9. Separation results using the ICA method presented

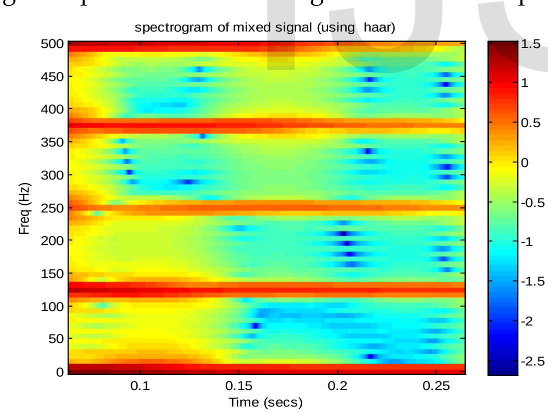

Fig10. Spectrogram of mixed signal using convolution type of haar wavelet

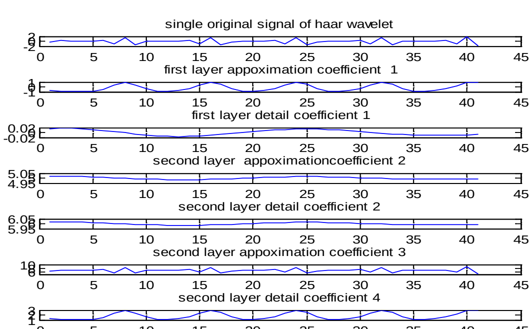

Fig: 11. Sub-band signals of mixed signal decomposed by convolution -type WPT

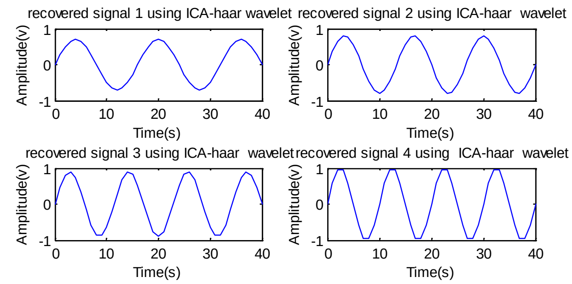

Fig: 12 .Separation results using the ICA method

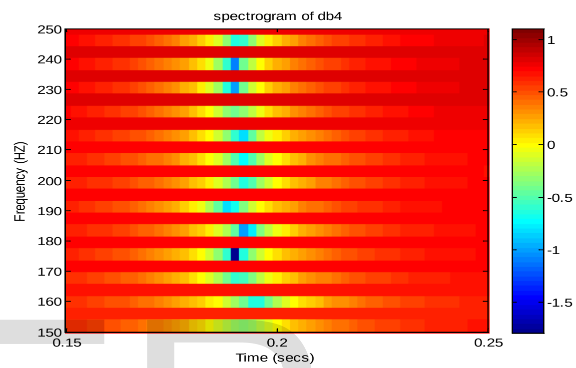

Fig: 13. Spectrogram of mixed signal using convolution type of db4 wavelet

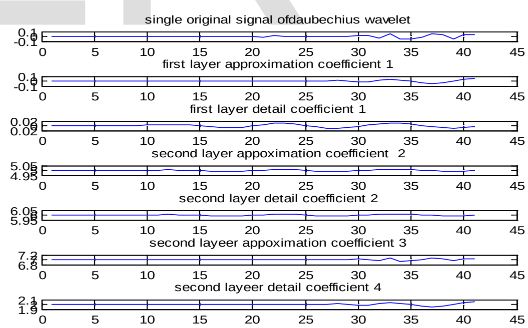

Fig: 14. Sub-band signals of mixed signal decomposed by convolution -type WPT

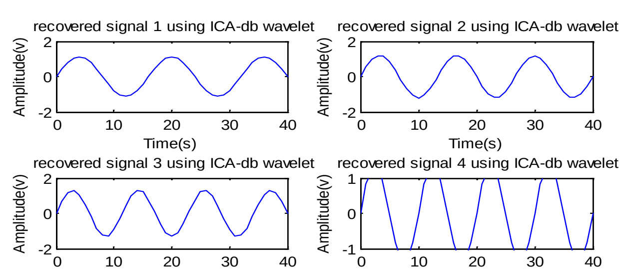

Fig: 15. Separation results using the ICA method

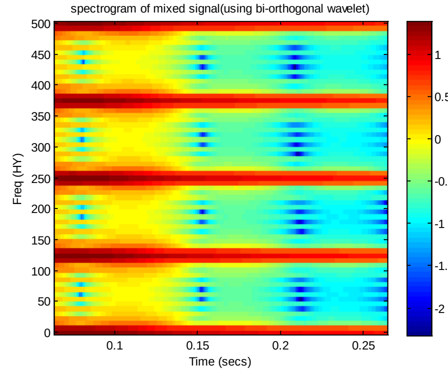

Fig: 16. Spectrogram of mixed signal using convolution type of bi orthogonal wavelet

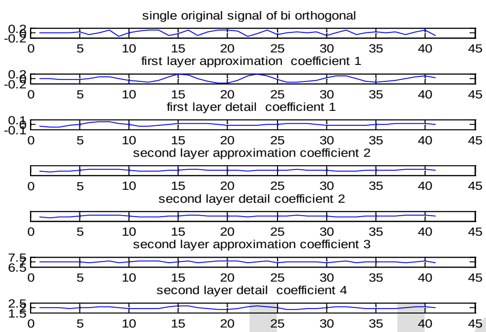

Fig: 17. Sub-band signals of mixed signal decomposed by convolution -type WPT

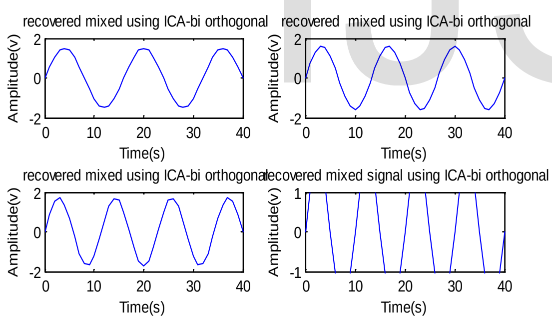

Fig: 18. Separation results using the ICA method

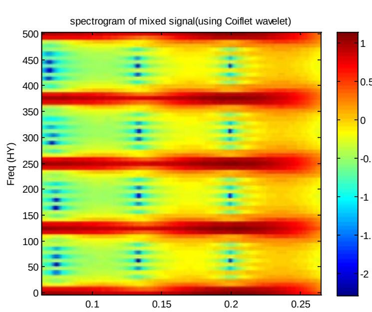

Fig 19. Spectrogram of mixed signal using convolution type of coif let wavelet

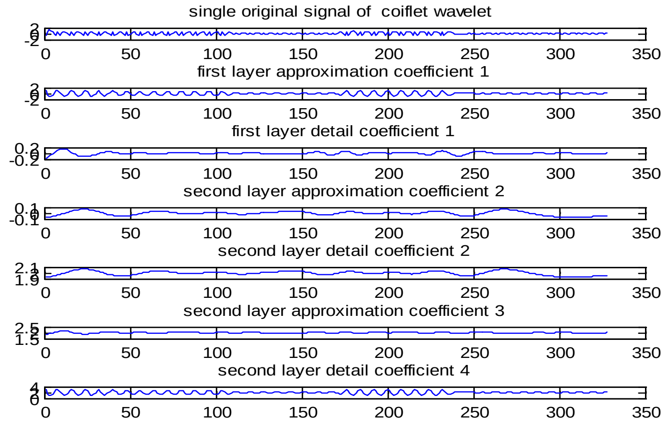

Fig: 20. Sub-band signals of mixed signal decomposed by convolution -type WPT

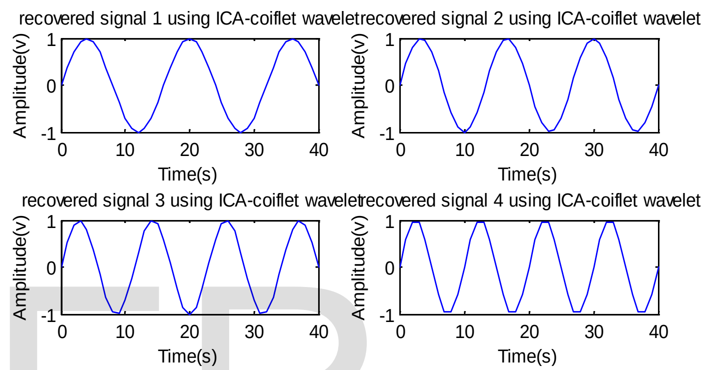

Fig: 21. Separation results using the coiflet function of ICA method

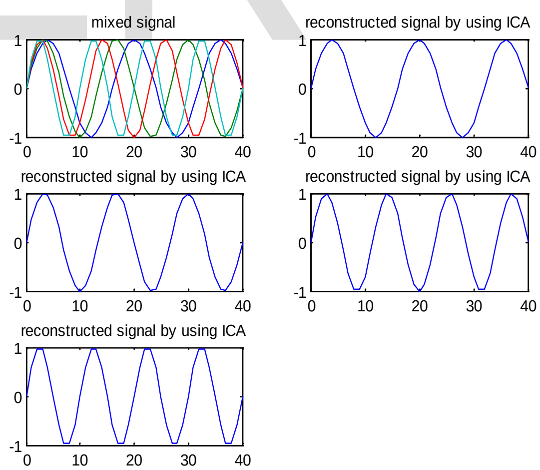

Fig: 22. Recovered original signals by using coiflet wavelet function convolution-type WPT of ICA

5.2. Motor Vibration signal:

We aim to verify the effectiveness of the proposed method to non stationary signals. Real motor vibration signal is generated in the MATLAB. Take 5000samples points and add the AWGN noise to vibration signal taken as input which is given to convolution type of different wavelet functions. We got different spectrograms shown in figures 25,28,31,34and 37 and wavelet decomposition sub-bands of different wavelets functions are shown in figures26,29,32,35and 38.

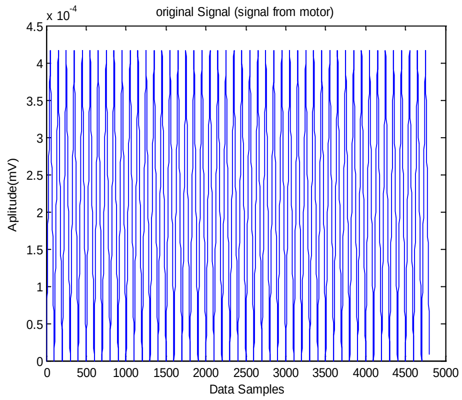

Fig: 23. Original motor vibration signal

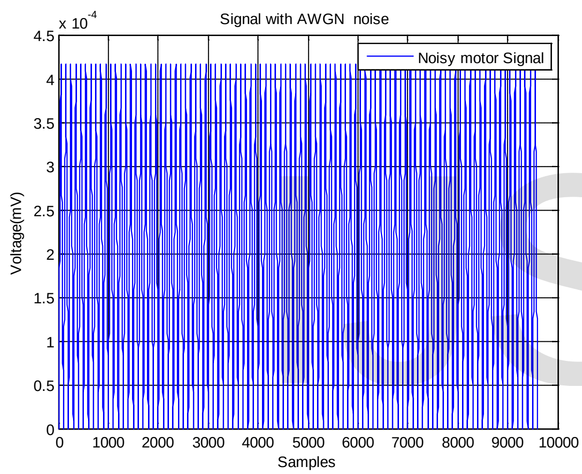

Fig: 24. Motor vibration signal with Awgn signal

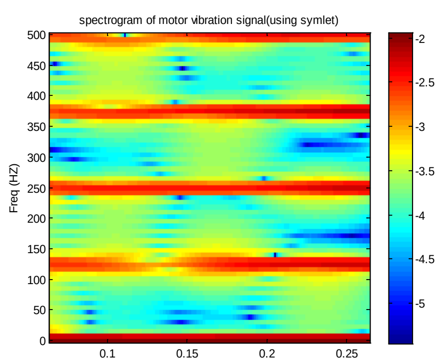

Fig: 25. Spectrogram of motor vibration signal using Convolution type of symlet wavelet

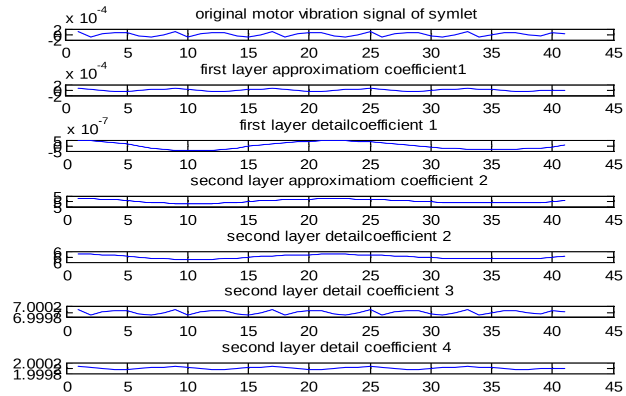

Fig:26. Sub-band signals of motor vibration signal decomposed by convolution type of symlet wavelet

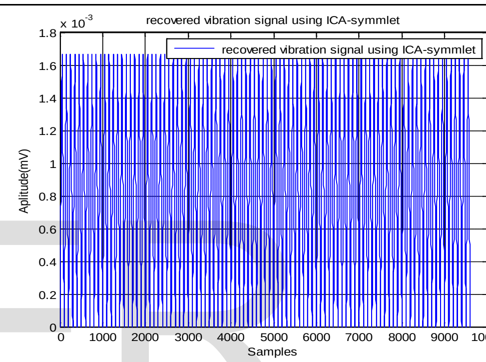

Fig: 27. Recovered Separation results using the ICA algorithm

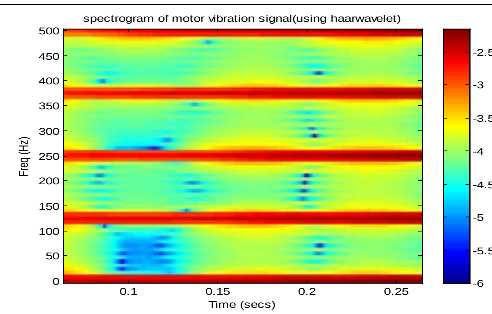

Fig: 28. Spectrogram of motor vibration signal using convolution type of haar wavelet

which is given as input to ICA we got exact original signal by using daubachies4 wavelet for best recovering signal shown in when compared to other figures 27,30,33,36and 39. When compared to the other wavelet functions db4 wavelet gives the good results shown in figure40.SNR, BER and PSNR values are better for Daubauchies4 wavelet function [6].And also comparisons of original signal and recovering signal using ICA are shown in below figure40.

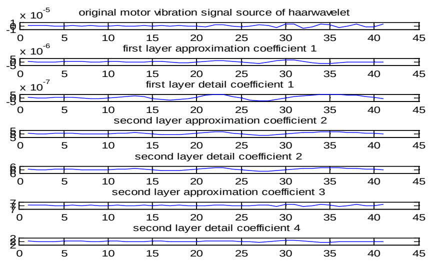

Fig. 29. Sub-band signals of motor vibration signal decomposed by convolution type of haar wavelet

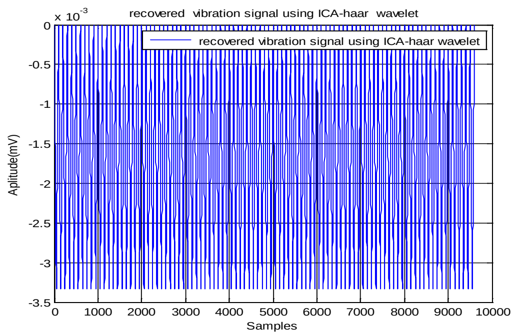

Fig. 30. Recovered Separation results using the ICA algorithm

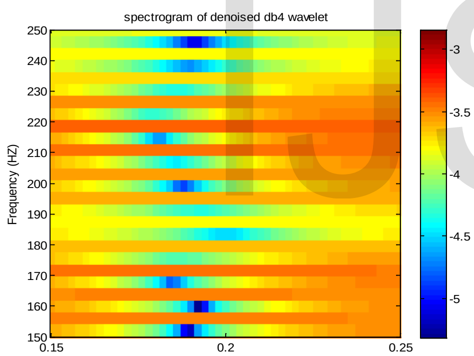

Fig: 31. Spectrogram of motor vibration signal using convolution type of db4 wavelet

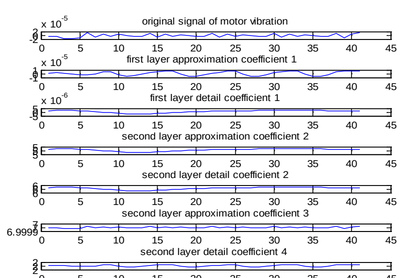

Fig: 32. Sub-band signals of motor vibration signal decomposed by convolution type of db4 wavelet

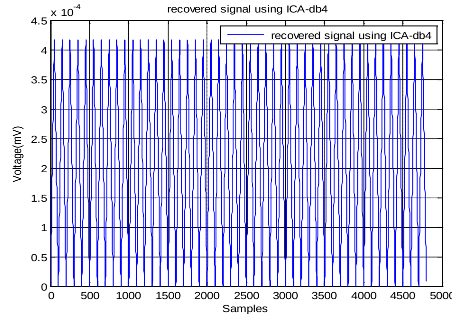

Fig: 33. Recovered Separation results using the ICA algorithm of db4 wavelet

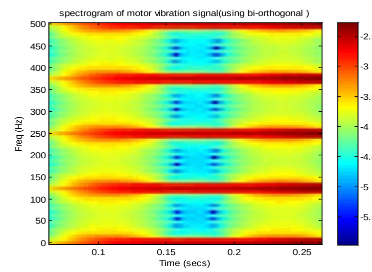

Fig: 34. Spectrogram of motor vibration signal using convolution type of bi orthogonal3.5 wavelet

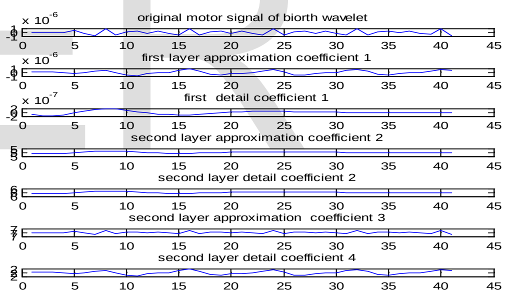

Fig: 35. Sub-band signals of motor vibration signal decomposed by convolution type of bi orthogonal3.5 wavelet

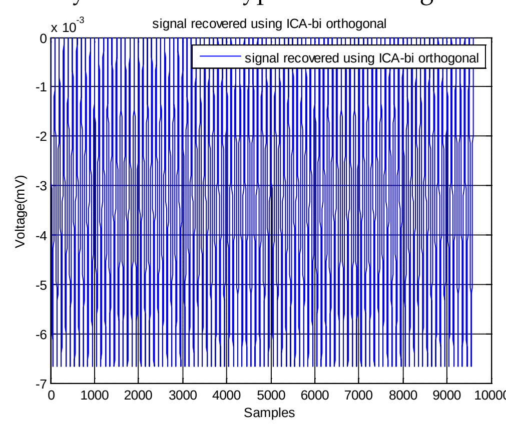

Fig: 36. Recovered Separation results using the ICA algorithm of bi-orthogonal wavelet

ISSN 2229-5518

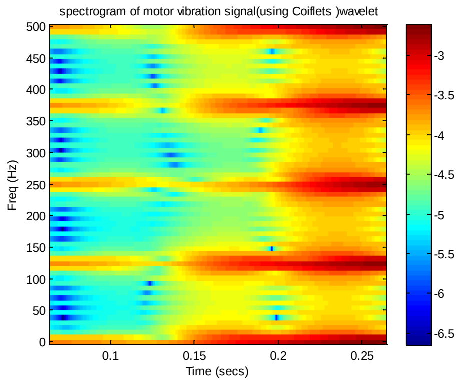

Fig: 37. Pectrogram of motor vibration signal using convolution type of coif let wavelet

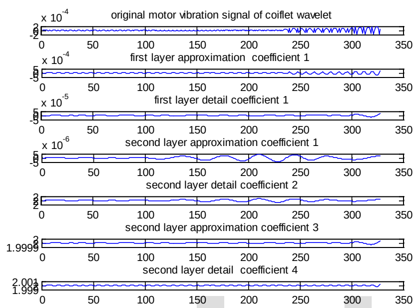

Fig: 38. Sub-band signals of motor vibration signal decomposed by convolution type of coif let wavelet

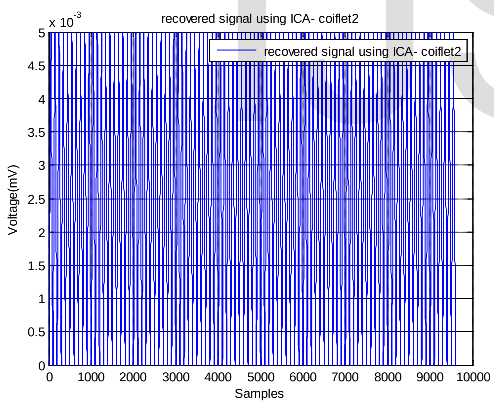

Fig: 39. Recovered Separation results using the ICA algorithm of coif let wavelet

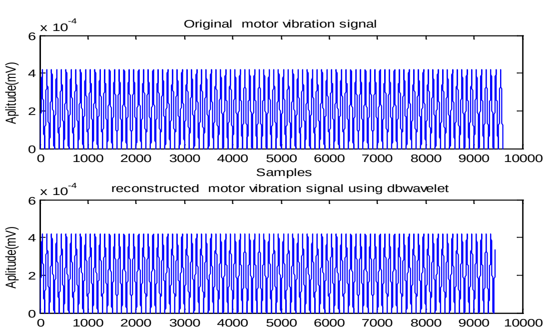

Fig: 40. Recovered original signals by using db4 wavelet using ICA algorithm

6. Analysis of Results

In this paper, a novel method is proposed for separation of single- channel mixed signals, a fast fixed-point ICA algorithm based on the kurtosis is used to separate the group of sinusoidal signals and motor vibration signals for the results AWGN noise is taken into consideration as a pure source signal. This noise signal is added to source signal for better decomposition results. The simulation results are shown above figures and also calculated the properties of the signal SNR, BER and PSNR values. coiflet and db4 wavelets gives better results for table and graphical also .

TABLE 1. Sinusoidal Mixed Signal

Parameters	Without WPT	With WPT				
		Symmlet8	haar	db4	Biorth 3.5	Coif 2
SNR	4.7712	9.2429	1.4291	9.4135	1.2283	10.1146
BER	10	4.0195	13.493	15.9908	2.1225	1.2831
PSNR	54.9045	64.2586	46.991	79.2148	73.4967	84.2339

TABLE 2. Motor Vibration Signal

Parameters	Without WPT	With WPT				
		Symmle-t8	haar	db4	Biorth 3.5	Coif 2
SNR	10.93	-0.4148	3.019	12.9	2.292	7.51
BER	5.1663	2.2345	17.09	12.3	0.199	2.24
PSNR	58.8557	33.8011	32.01	81.4	77.46	53.4

7. Conclusion

ICA is an effective method for separating the multiple channel independent sources which is observed from the multiple sensors. However, when there are a limited number of sources ICA cannot directly worked. In this paper non-down sampled characteristic of Convolution Type Wavelet Packet Transform is used to preprocess the signal channel mixed signal into multiple signal series at different scales. In the Convolution Type Wavelet Packet Transform can uses the five different types of wavelets which are haar, symmlet8, daubachies4, biorthogonal3.5 and coieflets used for decomposition. These decomposed multiple signal series are used to give input to the ICA algorithm. The proposed method in this paper was applied to BSS using simulated sine signal mixed signal series and motor vibration signal. For analyzing purpose the SNR, BER and PSNR values are calculated. By observing of the table values db4 at the level of 2 is the best wavelet for perfect decomposition of the non stationary signals. ICA especially for medical signals used this method for effective achievement of decomposition without loss of information. And thus provides a new and effective way for BSS when the numbers of observed signals were limited.

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