Blind Channel Estimation Using Wavelet Denoising of Independent Component Analysis for LTE System

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Abstract: - A new blind channel estimation method for long term evaluation (LTE) based on combining advantages of denoising property of wavelet transform (WT) with blind estimation capability of independent component analysis (ICA) called wavelet denoising of ICA (WD-ICA) is presented. This new method increases the spectral efficiency compared to training based methods, and provides considerable performance enhancement over conventional ICA methods. The conventional blind channel estimation methods based on ICA is performed individually for each orthogonal frequency division multiplexing (OFDM) subcarrier. To reduce complexity of implementation of WD-ICA method, channel interpolation is used. This method is presented for multiple-input-multiple-output (MIMO) downlink LTE system. WD-ICA method is compared to conventional ICA methods and the Performance is evaluated by calculating normalized mean square error (NMSE) and bit error rate (BER). WD-ICA method as compared to the other known ICA channel estimation methods has lower complexity, lower value of NMSE, and lower value of BER, which indicates the superiority of the proposed method.

Key-Words: -LTE, Blind channel estimation, WT, ICA, OFDM, MIMO.

1 Introduction

The demand for fast and reliable wireless mobile communication systems has been increased constantly. Since the system bandwidth is limited, the desired high data rates must be achieved through higher spectral efficiency. MIMO systems result in significant spectral efficiency increase due to the spatial multiplexing of parallel data stream. The transmission of modulated signal over wireless communication in wideband communication systems results in inter-symbol interference (ISI), due to that, the wireless channel is time varying and frequency selective with randomly changing impulse response, which usually corrupts the received signal. We mitigate the ISI caused by the multipath fading of high data rate communication system by using OFDM. The major challenging in MIMO-OFDM is to design a good channel estimation method with less computational complexity and lower value of BER, to estimate the channel impulse response.

There are two types of channel estimation approaches that are commonly used in wireless communications, training based methods, and blind methods. Transmitting training signals (pilots) reduces the spectral efficiency, especially in wireless communication systems with very scarce bandwidth resource. On the other hand, the pure blind methods increase the computational complexity, particularly at the receiver. Blind channel estimation methods recover the source data directly from the structure and statistics of the received signals without extra bandwidth and power for training needed. Blind channel estimation methods can be classified into methods employing second order statistics (SOS) and methods using higher order statistics (HOS). The HOS is more against the Gaussian noise, but the SOS is sensitive to the Gaussian noise [1-2]. ICA, which is an efficient HOS based blind source separation technique by maximizing non-Gaussianity of the ICA output signals, has been applied to wireless communications, including blind multiuser detection, blind channel estimation and blind equalization. ICA is a class of blind source separation (BSS) methods for separating linear mixtures of signals into independent components. ICA can recover signals from a mixture, up to certain ambiguities, if the signals are statistically independent and non-Gaussian. ICA can also be viewed as a solution to the blind channel estimation problem, when the MIMO channel is frequency-flat and time-invariant. When OFDM is employed, the frequency selective channel is converted into a set of independent flat channels at each orthogonal subcarrier. Then the original BSS problem is transformed into a set of standard ICA problems. Each ICA problem is associated with one of the orthogonal subcarriers. Then ICA methods for instantaneous linear mixtures can be applied directly to MIMO-OFDM systems on a per subcarrier basis [3-5].

WT is a mathematical tool which generally used for the analysis of non-stationary signals. Wavelets allow complex information to be decomposed into elementary forms at different positions and scales and subsequently reconstructed with high precision. Wavelets are a powerful statistical tool which can be used for a wide range of applications. One of the applications of wavelets is the signal de-noising in wireless communication systems. In This paper we use wavelets for denoising received signals in LTE system [6-9].

The application of ICA algorithms in wireless communication is investigated by a number of researchers. In [10], two ICA algorithms: FAST-ICA and JADE applied to 2x4 MIMO wireless systems and the comparison of them shows that JADE shows a better performance than FAST-ICA. In [11] FAST-ICA and JADE algorithms are proposed for detection of DS-CDMA signals. Simulation results show that JADE algorithm has lower bit error rate (BER) compared to FAST-ICA algorithm also as the signal to noise ratio (SNR) is increased, ICA algorithms is performing well. The approach in [12] proposes a novel blind receiver structure for MIMO-OFDM systems based on ICA and reduces complexity of implementation using channel interpolation which enhances BER performance. The ICA method in [3] incorporate ICA with channel interpolation and LSFE for MIMO-OFDM system and the achieved performance in the tested scenarios is good. Paper [9] proposes multi-scale independent component analysis (MS-ICA) method for OFDM channel estimation and equalization. Simulation results established the fact that the proposed method is superior as compared to other established methods. However, much work is still required to reduce the complexity and increase the spectral efficiency of ICA blind estimation. In this paper, we propose a new blind channel estimation method called wavelet denoising of ICA (WD-ICA) for LTE system to estimate the channel. This method combines advantages of denoising property of WT with ICA and uses channel interpolation to reduce complexity of implementation and enhance system performance. WD-ICA method is shown to offer considerable performance improvements and reduced complexity over conventional ICA methods.

This paper is organized as follows: section II describes system model for ICA. Section III investigates ICA pre-processing, FAST-ICA and JADE algorithms. Section IV describes WD-ICA method. Simulation results are provided in Section V. Section VI presents the conclusion.

2 System Model

The whole model for the MIMO-OFDM system with ICA can be illustrated by figure1.

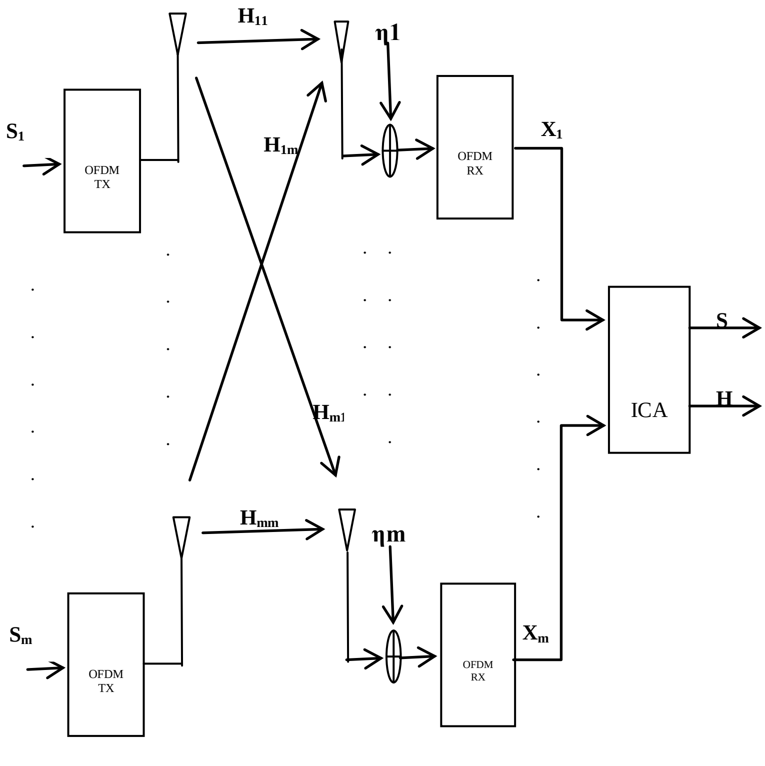


Fig.1: MIMO-OFDM System Model with ICA

We consider a frequency selective MIMO wireless system with N_t transmit and N_r receive antennas. Each antenna transmits a stream of OFDM signals. The channel impulse response (CIR) of length $L_c = L + 1$, between every transmit and receive antenna is a frequency selective described by the vector

$$h_{n,m} = [h_{n,m}(0), \ldots, h_{n,m}(L)]^T \tag{1}$$

Assuming the same channel order L for all channels, and we suppose block fading channel model [10].

ICA requires the number of observed mixtures to be at least equal to the number of ICs, as a consequence, applying ICA to frequency selective MIMO systems requires number of receive antennas to be at least equal to number of transmit antennas [5]. In figure1 the number of transmitters and receivers are the same, so that there are *m* independent sources, observations and outputs. This makes the MIMO channel a square matrix with the same number of sources and outputs. This can now be put into the ICA framework. We have a set of source signals *S* which are assumed to be statistically independent and non-gaussian. The mixing matrix *H* that represents the wireless channel effect in communication applications is achieved through a frequency-selective channel. At each receiving antenna, the received signal is a mixture of source signals, each of them passing through different spatial channels. The total received signal *X* per subcarrier *k* can be expressed as [4-5]

$$X^{(k)} = H^{(k)} S^{(k)} + \eta^{(k)} \tag{2}$$

or in matrix form

$$\begin{bmatrix} X_1^{(k)} \\ \vdots \\ X_m^{(k)} \end{bmatrix} = \begin{bmatrix} H_{11}^{(k)} \cdots H_{1m}^{(k)} \\ \vdots \ddots \ddots \ddots \ddots \vdots \\ H_{m1}^{(k)} \cdots H_{mm}^{(k)} \end{bmatrix} \begin{bmatrix} S_1^{(k)} \\ \vdots \\ S_m^{(k)} \end{bmatrix} + \begin{bmatrix} \eta_1^{(k)} \\ \vdots \\ \eta_m^{(k)} \end{bmatrix} \tag{3}$$

Where η represents an additive white gaussian noise (AWGN) term.

Given the observation frequency symbol vector *X(k)* at the *k*-th frequency, the estimates of the transmitted streams and the MIMO channel can be obtained by applying ICA in each subcarrier to the received signal [12].We seek a mixing matrix *W(k)* at the *k*-th frequency such that the elements of *Y(k)* are statistically independent and approximate that of *S(k)*. The mixing matrix *W* represents the channel response. Mathematically,

$$Y^{(k)} = (W^{(k)})^H X^{(K)} \approx S^{(k)} \tag{4}$$

Applying this demixing model to each subcarrier frequency results in a set of matrices *W(k)* which reconstructs the sources from knowledge of the mixtures only. ICA algorithm is applied to estimate the channel matrix *H* and thus can separate the source signals. We use fixed-point FAST-ICA algorithm and JADE algorithm for estimating the de-mixing matrix. FAST-ICA algorithm has rapid convergence properties; it is a gradient based technique that can be used in both on-line and off-line applications. While JADE algorithm requires shorter data sequences than other ICA algorithms and it can be used only off-line, after the whole data is acquired. WD-ICA method is compared to HOS methods such as FAST-ICA and JADE algorithms.

3 ICA Preprocessing and Algorithms

Before applying an ICA algorithm on the data, it is usually very useful to do some preprocessing that make the problem of ICA estimation simpler and better conditioned. Centering and whitening are the standard ICA preprocessing steps. Such preprocessing is done individually for each frequency sub-band [13].

Centering the observable variables means subtracting their sample mean. This means that the original mixtures are preprocessed by

$$X \leftarrow X - E\{X\} \tag{5}$$

Whitening is done before the application of the ICA algorithm (and after centering), which transform the observed vector *X* linearly so that we obtain a new vector $\overline{X}$ which is white, i.e., its components are uncorrelated and their variances equal unity. In other words, the covariance matrix of $\overline{X}$ equals the identity matrix [4-5]

$$E\{\overline{X}\,\overline{X}^T\} = I \tag{6}$$

One popular method for whitening is to use the eigenvalue decomposition (EVD) of the covariance matrix

$$E\{XX^T\} = EDE^T \tag{7}$$

Where E is the orthogonal matrix of eigenvectors of $E\{XX^T\}$ and D is the diagonal matrix of its eigenvalues. Whitening can now be done by

$$\overline{X} = ED^{-1/2}E^T X \tag{8}$$

Then put $X \leftarrow \overline{X}$ (9)

The related and more general problem of ICA consist of obtaining from a set of component (mixtures in BSS), another set as statistically independent as possible. An ICA algorithm is an optimization algorithm that search for extremum points of some suitable non-linear real valued function depending on observed data. These suitable functions often called as contrast functions. Contrast functions are cost functions whose optimization yields the solution to the BSS/ICA and are designed such that their extreme points equal to the ICA basis.

3.1 FAST-ICA Algorithm

FAST-ICA algorithm is a fixed-point algorithm which operates on a block of observed data samples. The FAST-ICA algorithm converges fast to extremum points, and assuming that the data is preprocessed by centering and whitening. We start from an arbitrary non-linear contrast function so that its extrema coincide with the independent components [14]. Our contrast function is:

$$J_G(W) = E\{G(|W^H X|^2)\} \tag{10}$$

Where G is a smooth function, W is an m-dimensional complex weight vector and $E\{(|W^H X|^2)\} = 1$. The algorithm searches for the extrema of $E\{G(|W^H X|^2)\}$ [15].

For the choice of G we have three different functions, and its derivatives g.

$$G_1(y) = \sqrt{a_1 + y}, \quad g_1(y) = \frac{1}{2\sqrt{a_1 + y}} \tag{11}$$

$$G_2(y) = \log(a_2 + y), \quad g_2(y) = \frac{1}{a_2 + y} \tag{12}$$

$$G_3(y) = \frac{1}{2} y^2, \quad g_3(y) = y \tag{13}$$

Where a_1 and a_2 are some arbitrary constants with chosen values: $a_1 \approx 0.1$ & $a_2 \approx 0.1$.

The final vector $W(\kappa)$ given by the algorithm equals one of the columns of the orthogonal mixing matrix.

$$W(\kappa) = E\{X(W^H(\kappa-1)X)^* g(|W^H(\kappa-1)X|^2)\} - E\{g(|W^H(\kappa-1)X|^2) + |W^H(\kappa-1)X|^2 g'(|W^H(\kappa-1)X|^2)\}W(\kappa-1) \tag{14}$$

Where κ represents the iteration number and * denotes the complex conjugate.

In the case of blind source separation, $W(\kappa)$ separates one of the non-Gaussian source signals in the sense that $W^H(\kappa)X$ equals one of the source signals [15-16].

To ensure that we estimate each time a different independent component and preventing from converging to the same maxima. We must decorrelate the outputs after every iteration. We only need to add a simple orthogonalizing projection inside the loop. When we have estimated p independent components, or p vectors $W_1,\ldots,W_p$. We run the one-unit fixed-point algorithm for W_{p+1}, and after every iteration step subtract from W_{p+1} the projections of the previously estimated p vectors and then renormalize W_{p+1}.

$$W_{P+1} = W_{P+1} - \sum_{j=1}^{P} W_j W_j^H W_{P+1} \tag{15}$$

$$W_{P+1} = \frac{W_{P+1}}{\|W_{P+1}\|}$$

3.2 JADE Algorithm

JADE (joint approximation diagonalization of eigen matrices) is a well-established batch algorithm based on joint diagonalization of cumulant matrices of the received signals and requires shorter data sequences than other ICA algorithms. JADE diagonalize certain fourth order cumulant matrices to extract the independent components and uses a huge number of cumulant matrices so it is computationally very heavy in high-dimensional cases.

The operation of JADE includes optimization of orthogonal contrast by finding the rotation matrix V such that the cumulant matrices are as diagonal as possible. The JADE algorithm can be summarized as [17-20]:

1. Estimate a whitening matrix $\hat{Wi}$ and set $Z = \hat{Wi}\,X$.
2. Estimate a miximal set $\{\hat{Q}_i^z\}$ of cumulant matrices.
3. The JADE contrast function is:

$$J_{JADE} = \sum_i OFF(V^+ \hat{Q}_i^z V) \tag{16}$$

The objective function of the JADE algorithm is based on minimization the off-diagonal elements of the cumulate matrices. So, find the rotation matrix

$\hat{V}$ such that the cumulant matrices are as diagonal as possible, that is, solve

$$\hat{V} = \arg\min J_{JADE} \tag{17}$$

4. Estimate W as:

$$\hat{W} = \hat{V}\hat{Wi}^{-1} \tag{18}$$

4 Wavelet Denoising of Independent Component Analysis (WD-ICA)

Wavelet analysis consists of breaking up a signal into scaled and shifted versions of the original signal or mother wavelet. Wavelets are family of functions constructed from translations and dilations of a single function called the "mother wavelet" $\psi(t)$. They are defined by:

$$\psi_{a,b}(t) = \frac{1}{\sqrt{|a|}}\psi\left(\frac{t-b}{a}\right), a \neq 0 \tag{19}$$

Where $\psi_{a,b}(t)$ is called Daughter wavelet. The parameter a is the scaling parameter or scale, and it measures the degree of compression. The parameter b is the translation (shift) parameter which determines the time location of the wavelet. The factor $1/\sqrt{|a|}$ is for energy normalization across the different scales. The main challenging issue on Wavelet is the proper selection of mother wavelet function. The accuracy of output is purely based on mother wavelet function [6-8].

Multiresolution Analysis (MRA) is one of the basic wavelet applications that allow the original signal to be built up from lower resolution signals and necessary details. Also Wavelet denoising is one of the most significant applications of wavelets that we apply in this paper. Only the transform values whose magnitudes are greater than a threshold will be kept. Equivalently, we can discard all the transform values whose magnitudes lie below threshold. The general de-noising procedure involves three steps described below [21]:

- *Decomposition*: Choose a wavelet, choose a level N_{WL}. Compute the wavelet decomposition of the signal at level N_{WL}.
- *Thresholding*: For each level from 1 to N_{WL}, select a threshold and apply soft thresholding to the detail coefficients.
- *Reconstruction*: Compute wavelet reconstruction using the original approximate coefficients of level N_{WL} and the modified detail coefficients of levels from 1 to N_{WL}.

The application of ICA to blind MIMO-OFDM system and estimating the transmitted streams and the MIMO channels can be obtained by applying ICA in each subcarrier to the received signal. If the system uses a large number of subcarriers, the complexity will be increased. The complexity can be reduced by using channel interpolation. We estimate the MIMO channel for a small number of n subcarriers. Channel estimation for the remaining subcarriers is obtained by interpolation.

Channel estimation in n subcarriers and interpolation in the remaining subcarriers can reduce complexity of implementation of ICA. Increasing n increases the complexity of the system while reducing n reduces the number of subcarriers with channel estimates available for interpolation, which is expected to have a negative impact on the accuracy of the interpolated channel estimates. Thus, the optimal n is a trade-off between the two requirements [3, 12].

We have the following constraints for choosing n [12, 22]:

1. $n << N$ (where N is the total number of subcarriers).
2. $n \geq L_c$
3. N/n is an integer.
4. Equispaced subcarriers.

Channel interpolation reduces the computational complexity as well as performs denoising on the interpolated channel estimates by forcing the last ($N-Lc$) CIR values to zero.

WD-ICA steps are given as follows

1. After the whole data is received, remove CP from OFDM symbols then perform fast fourier transform (FFT).
2. Apply wavelet denoising.
3. Perform ICA on n subcarriers to estimate the MIMO channel for a small number of n subcarriers.
4. Use interpolation to obtain channel estimation for the remaining subcarriers.

5 Simulation Results

Simulation results in terms of normalized mean square error (NMSE) and bit error probability of WD-ICA method is evaluated for LTE downlink system and compared with FAST-ICA and JADE algorithms. Simulation parameters are shown in table 1.

Table I: Simulation Parameters

Simulation Parameter	value
Modulation Scheme	QPSK
System Bandwidth	1.4 MHZ
Cyclic Prefix (CP) Length L_{cp}	9
FFT/IFFT size	128
Channel Impulse Response Length L_c	9
TX/RX antenna	4x4 MIMO
Total Number of Symbols N_s per Subcarrier	560
Wavelet	Sym2
Wavelet Thresholding Method	Soft
Channel	Rayleigh and Rician fading channel
Number of subcarriers to interpolate n	16
Positions of subcarriers to interpolate	Between: 1 9 17 25 33 41 49 57 65 73 81 90 98 106 114 122.

The quality of estimation was measured using NMSE and BER. No error correcting code is employed. The NMSE was defined as [12]

$$NMSE(k) = \frac{1}{N_t} E\left\{ \sum_{t=0}^{N_t-1} \frac{\left\| \hat{H}_{:,t}(k) - H_{:,t}(k) \right\|^2}{\left\| H_{:,t}(k) \right\|^2} \right\} \quad (20)$$

and the channel averaged NMSE over all subcarriers is

$$NMSE = \frac{1}{N} \sum_{k=0}^{N-1} NMSE(k) \quad (21)$$

Figures 3 and 4 show the NMSE versus SNR for the FAST-ICA algorithm applied to all subcarriers, FAST-ICA algorithm applied to n subcarriers and interpolation is made in between (FAST-ICA with interpolation), FAST-ICA algorithm combined with wavelet denoising (FAST-ICA with Wavelet denoising), and FAST-ICA with interpolation and wavelet denoising (WD-ICA) method for Rayleigh and Rician block fading channel, with Rician factor (ratio of the specular component power and scattering component power) equals -10 dB. The results show that the performance of FAST-ICA algorithm which is applied to all subcarriers in the system is the worst while WD-ICA method is the best. For Rayleigh block fading channel, figure 3, for an average NMSE of 4.5×10^{-1}, a SNR improvement of 13 dB and for Rician block fading channels with Rician factor equals -10 dB, Figure 4, about 15 dB. WD-ICA method has superior performance as compared to FAST-ICA method under Rayleigh and Rician block fading channels, as this method combines the advantages of both channel interpolation and wavelet denoising.

Figures 5 and 6 show the NMSE versus SNR for the JADE algorithm applied to all subcarriers, JADE algorithm applied to n subcarriers and interpolation is made in between (JADE with interpolation), JADE algorithm combined with wavelet denoising (JADE with Wavelet denoising), and JADE with interpolation and wavelet denoising (WD-ICA) method for Rayleigh and Rician block fading channel, with Rician factor equals -10 dB. The results show that the performance of JADE algorithm which is applied to all subcarriers in the system is the worst while WD-ICA method is the best. For Rayleigh block fading channel, figure 5, for an average NMSE of 4.5×10^{-1}, a SNR improvement of 6 dB and for Rician block fading channels with Rician factor equals -10 dB, figure 6, about 9 dB. WD-ICA method has superior performance as compared to JADE method under Rayleigh and Rician block fading channels.

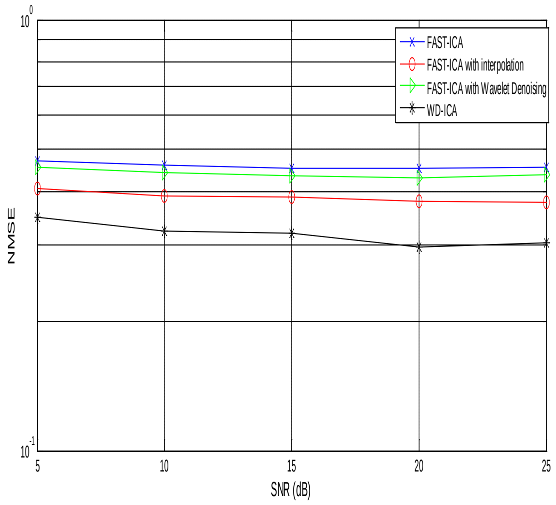


Fig.2: NMSE Performance of FAST-ICA, FAST-ICA with interpolation, FAST-ICA with Wavelet Denoising and WD-ICA with Rayleigh fading channel.

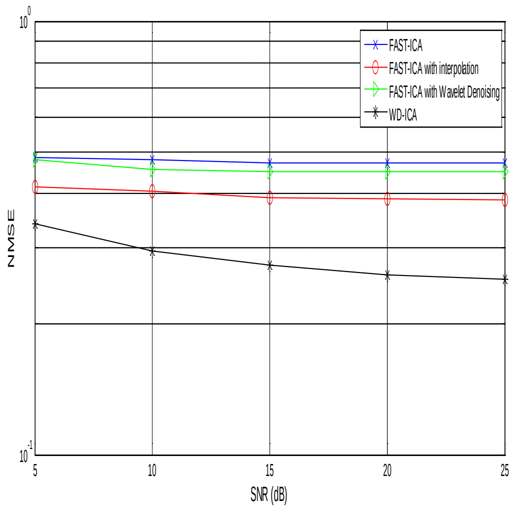
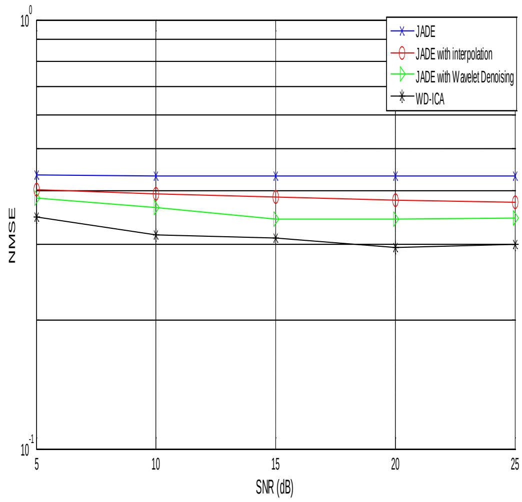


Fig.3: NMSE Performance of FAST-ICA, FAST-ICA with interpolation, FAST-ICA with Wavelet Denoising and WD-ICA with Rician fading channel.

Figures 7 and 8 show the BER versus SNR for FAST-ICA algorithm applied to all subcarriers in the system and WD-ICA method under Rayleigh and Rician block fading channels with Rician factor equals -10 dB. We see that a significant increase in BER performance can be achieved through using WD-ICA method, particularly, in case of Rayleigh fading channel, figure 7, for an average BER of 10^{-2}, an SNR improvement of 10 dB, and for Rician block fading channels with Rician factor equals -10 dB, Figure 8, about 9 dB.



F ig.4: NMSE Performance of JADE, JADE with interpolation, JADE with Wavelet Denoising and WD-ICA with Rayleigh fading channel.

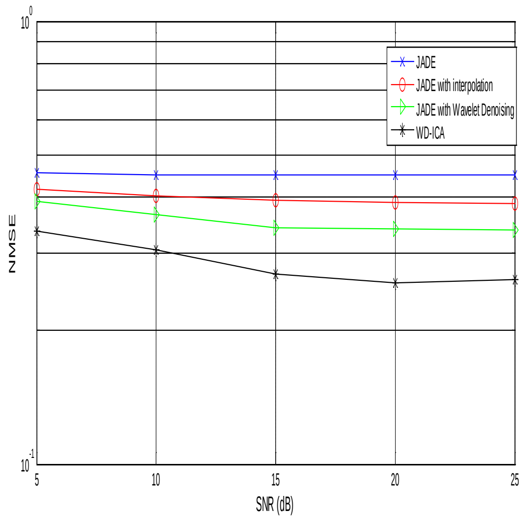


Fig.5: NMSE Performance of JADE, JADE with interpolation, JADE with Wavelet Denoising and WD-ICA with Rician fading channel.

Also, figures 9 and 10 show the BER versus SNR for JADE algorithm applied to all subcarriers in the system and WD-ICA method under Rayleigh and Rician block fading channels with Rician factor equals -10 dB. We see that a significant increase in BRR performance can be achieved through using WD-ICA method, particularly, in case of Rayleigh fading channel, Figure 9, for an average BER of $3x10^{-3}$, an SNR improvement of 11 dB, and for Rician block fading channels with Rician factor equals -10 dB, Figure 10, about 19 dB. The result shows that BER performance of WD-ICA algorithm is better than FAST-ICA and JADE algorithms under Rayleigh and Rician fading channels.

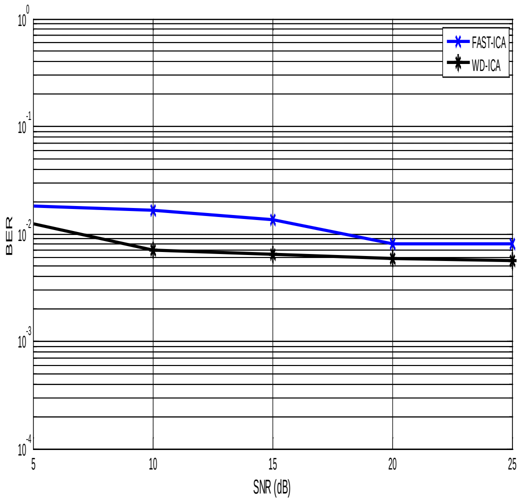


Fig.6: BER Performance of FAST-ICA and WD-ICA with Rayleigh fading channel.

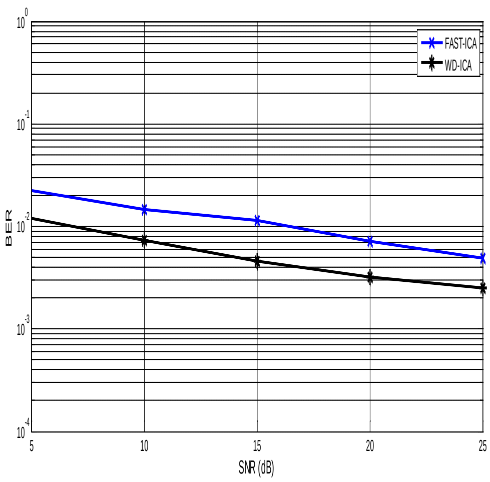


Fig.7: BER Performance of FAST-ICA and WD-ICA with Rician fading channel.

The BER performance of WD-ICA is better than FAST-ICA and JADE algorithms. In our simulation, no error correcting code is employed, so the performance can be improved by using an error correcting code. Also by adding small number of pilots (semi blind approach) the performance can be further improved.

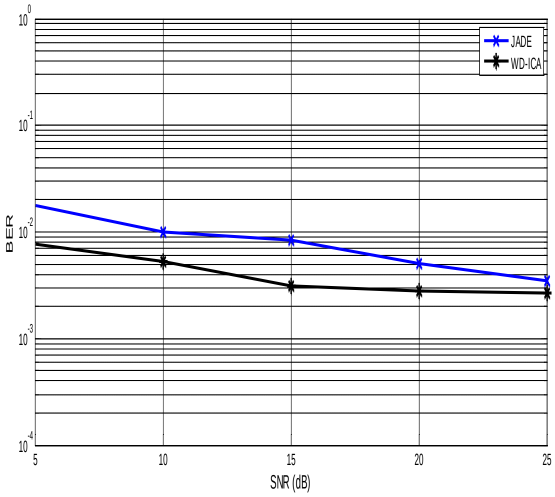


Fig.8: BER Performance of JADE and WD-ICA with Rayleigh fading channel.

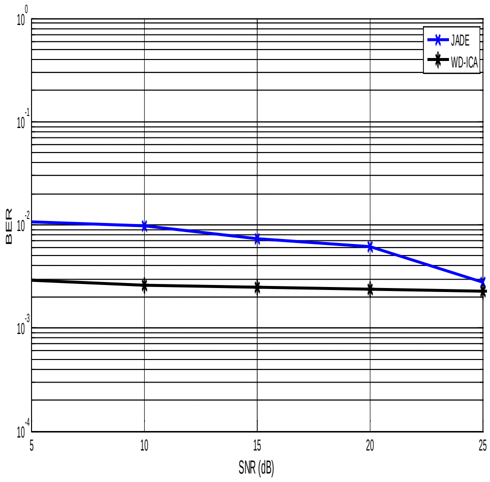


Fig.9: BER Performance of JADE and WD-ICA with Rician fading channel.

6 Conclusion

A new proposal for blind channel estimation method for LTE based on combining the advantages of denoising property of wavelet transform with blind estimation capability of independent component analysis called wavelet denoising ICA (WD-ICA) has been proposed to estimate the LTE channel characteristics. This proposed method increases the spectral efficiency compared to training based methods, and provides considerable performance enhancement over conventional ICA methods. To reduce complexity of implementation of WD-ICA method, channel interpolation is used. The NMSE and BER simulation results show that, the WD-ICA method is superior as compared to other Conventional ICA methods in MIMO-OFDM

Rayleigh and Rician wireless channel. The performance can be improved by using an error correcting code.

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