Independent Component Analysis Assisted Efficient PAPR Reduction and Symbol Recovery in OFDM Systems

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Abstract: In order to coordinate the performance loss and PAPR reduction due to the effect of the conventional PAPR reduction scheme, a new peak-to-average power ratio (PAPR) reduction and symbol recovery scheme in OFDM system is proposed assisted by precoding and independent component analysis (ICA). The proposed scheme is formulated as the model of the mixture of the mutual statistical independence of subcarrier's signals of OFDM, which can use ICA for strengthening the signal recovery capabilities. Simulation results illustrate that the precoding in transmitter combined with ICA based blind equalization not only provides PAPR reduction role, but also has a better bit error rate (BER) performance, which makes a good trade off between bandwidth and energy requirement.

Key-Words: independent component analysis; orthogonal frequency division multiplexing; peak-to-average power ratio; blind equalization

1 Introduction

Orthogonal frequency division multiplexing (OFDM) is an attractive multicarrier technique for high-bit-rate transmission [1]. By dividing wideband frequency selective fading channel into parallel narrowband flat fading sub-channels, OFDM can effectively offer high spectral efficiency and high power efficiency, immune to the multipath delay and frequency selective fading. Due to these merits, OFDM system has various applications including the digital audio, digital TV, and broadband satellite communication, and so on. Particularly, a lot of wireless standards (IEEE 802.11a, LTE and Wi-Max) have adopted OFDM technology as a method to improve wireless communication in the future [1, 2].

However, one of the main drawbacks of OFDM systems is the high peak-to-average power ratio (PAPR) of OFDM signals [1-3]. The transmit signals in OFDM system can have high peak values in the time domain since subcarrier components are added via an inverse fast Fourier transformation (IFFT) operation. In this case the high PAPR problem is caused. The high PAPR is one of the most detrimental aspects in OFDM system as it decreases the signal-to-quantization noise ratio (SQNR) of the analog-digital convertor (ADC) and digital-analog convertor (DAC) while degrading the efficiency of the power amplifier in the transmitter. This gives rise to non-linear distortion which changes the superposition of the signal spectrum resulting in performance degradation. So far, several techniques have been proposed to reduce the PAPR of an OFDM signal, including clipping and filtering, selected mapping (SLM), partial transmit sequences (PTS), tone reservation, tone injection and Reed-Muller codes, etc. These techniques can be organized into three classes [1, 2]: signal distortion, signal scrambling, and block coding.

The signal distortion is the simplest class of techniques to reduce the PAPR, including clipping and peak windows, and peak cancellation, etc. These techniques reduce peaks directly by distorting the signal prior to amplification. To clip the signal, the peak amplitude is limited to some desired maximum level. It can give a good PAPR, but at the expense of some performance degradation, including in-band and out-of-band interference. The second class of techniques is signal scrambing, including SLM and PTS technique. The basic idea of signal scrambling is to introduce some limited redundancy, and to send the OFDM signal with the minimum PAPR. The goal is not to eliminate the peaks, but only to achieve lower probabilistic occurrence of peak values. However, for the SLM and PTS, to recover the data, the used side information must be transmitted to the receiver, resulting in some loss of band efficiency. The third class of techniques is block coding, including typically m-sequences, complementary Golay sequences, and Reed-Muller codes. This class of techniques limits the set of possible signals that can be transmitted, and only those signals with peak amplitude below some threshold are chosen.

However, these techniques have high computations needed and the required exhaustive search for a good code is intractable.

As described in the end, the aforementioned existing conventional method has various degrees of effect on the system performance, such as BER performance and spectral efficiency, and so on. Hence, in order to overcome the detrimental influence of the above-mentioned method on system performance, the new PAPR reduction scheme is developed, including two steps. The heuristic precoding processing is executed for the source signals firstly. Then we conduct a ICA framework model [4-7] for OFDM system for the purpose of blind equalization. The heuristic precoding is carried out in the transmitter for PAPR reduction. The ICA-based blind equalization is implemented for avoiding side information transmission and pilot-sequence used for channel estimation or synchronization.

The remainder of this paper is organized as follows. In section 2, the ICA model is reviewed. In section 3, the ICA-based system model is bulit for OFDM system. Section 4 describes the precoding design for PAPR reduction. The symbol recovery based on ICA equalization is illustrated in Section 5. Section 6 describes the simulation results and conclusions are given in section 7, respectively.

2 Independent Component Analysis

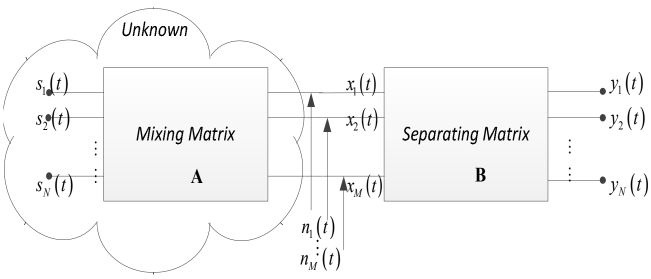


Fig. 1 General framewok for independent component analysis

Independent component analysis (ICA) is a statistical technique which involves the task of computing the mixing projection of a set of components as a linear transformation of statistically independent compnent variables [4-12]. The increasing interest in ICA is mainly due to emerging new practical application areas, where the assumption of independence is both powerful and realistic, which making it possible to find meaningful source signals or independent component from the data to be analyzed in a completely blind manner.Therefore, the main application of ICA is blind source separation (BSS) problem, which has become an appealing blind equalization method for wireless communications system. In the conventional ICA techniques, the data model is described as follows.

Consider a set of M measured signals $\mathbf{x}(t)=\left[x_1(t),x_2(t),\dots,x_M(t)\right]^T$ are instantaneous linear combinations of a set of N mutually independent unknown source signals $\mathbf{s}(t)=\left[s_1(t),s_2(t),\dots,s_N(t)\right]^T$. In its simplest form, the ICA/BSS problem accepts the following matrix model.

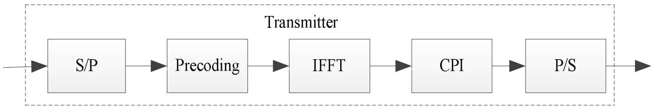
$$\mathbf{x}(t)=\mathbf{As}(t)+\mathbf{n}(t) \tag{1}$$

where $\mathbf{A}$ is an unknown full rank mixing matrix, $\mathbf{n}(t)$ is a realization of a noise process. The goal of ICA is the reconstruction of those unknow sources from the set of mixtures. The mutual independence of the sources is the key to separate them.If the mixing matrix $\mathbf{A}$ is non-singular, $\mathbf{x}(t)$ is a stationary ergodic random sequence, and no more than one Gaussian distributed sources is present in the mixture, forcing the statistical independence of the outputs yields the sources as follows [10]

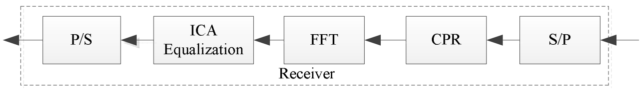
$$\mathbf{y}(t)=\mathbf{Bx}(t)=\mathbf{BAs}(t)+\tilde{\mathbf{n}}(t) \tag{2}$$

where $\tilde{\mathbf{n}}(t)=\mathbf{Bn}(t)$ denotes noise vector. $\mathbf{B}$ is referred to as separation matrix, which means that a set of filters $\mathbf{b}_1,\mathbf{b}_2,\dots$ should be estimated such that the filtered/separated source processes $\mathbf{b}_1^H\mathbf{x}(t),\mathbf{b}_2^H\mathbf{x}(t),\dots$ i.e. $\mathbf{Bx}(t)$ are independent and each of them can be used to represent one of the sources. The ideally matrix $\mathbf{C}=\mathbf{BA}$ should be the identity matrix. However, since the scale and the order of the components of $\mathbf{s}(t)$ do not affect their statistical independence, satisfactory separation is characterized by a global matrix $\mathbf{C}$ with a non-mixing structure, that is, with a single non-null element per row and per column. This is an inherent feature of any ICA method is that the original scaling and arrangement cannot be estimated from the mere independence assumption. Although it is not an important in blind separation problem, it should not be ignored in communication systems. A schematic description of the ICA framework model is shown in Fig. 1.

3 System Model



(a) Precoding based OFDM transmitter



(b) ICA blind equalization based OFDM receiver

Fig.2 System Model：S/P (Serial to Parallel), CPI (Cyclic Prefix Inserted), P/S (Parallel to Serial), CPR (Cyclic Prefix Removed)

In this section, we propose a PAPR adaptive reduction method for OFDM system. As shown in Fig. 2, the proposed method is divided into two parts: firstly, the precoding based OFDM transmitter is proposed, then the ICA blind equalization based OFDM receiver is implemented. The description of the math model is as follows.

Consider an OFDM system communicates through frequency selective fading channels. We assume that the n^{th} OFDM digital modulation symbol is denoted as $\mathbf{s}(n)=\left[s_0(n),s_1(n),\ldots,s_{N-1}(n)\right]^T$, $s_i(n)(i=0,\ldots,N-1)$ comes from the QPSK or 4QAM modulation constellation points, etc. Assume that the precoding matrix is described as $\mathbf{\Theta}$, which is size of $N\times N$. The design detail of the precoding matrix will illustrated in the next section. Then the time-domain OFDM symbol can be obtained with IFFT operation, yielding $\underline{\mathbf{s}}(n)=\left[\underline{s}_0(n),\underline{s}_1(n),\ldots,\underline{s}_{N-1}(n)\right]^T$, i.e.,

$$\underline{\mathbf{s}}(n)=\mathbf{F}_N^H\mathbf{\Theta}\mathbf{s}(n) \tag{3}$$

$$\mathbf{F}_N=\frac{1}{\sqrt{N}}\begin{bmatrix} W^{0.0} & \cdots & W^{0.(N-1)} \\ W^{1.0} & \cdots & W^{1.(N-1)} \\ \vdots & \ddots & \vdots \\ W^{(N-1).0} & \cdots & W^{(N-1)(N-1)} \end{bmatrix} \tag{4}$$

where the number of subcarriers is N, and $W=e^{-j2\pi/N}$. $\mathbf{F}_N$ is the N point fast Fourier transform (FFT) matrix; $\mathbf{F}_N^H$ is the N point IFFT matrix; $(\cdot)^H$ and $(\cdot)^T$ denote Hermitian transpose and transpose respectively. $\mathbf{F}_N^H\mathbf{F}_N=\mathbf{F}_N\mathbf{F}_N^H=\mathbf{I}_N$, $\mathbf{I}_N$ denotes the $N\times N$ identity matrix. Finally, a sufficient long cyclic-prefix (CP) is added at the beginning of each OFDM symbol block, such that interblock interference (IBI) is avioded.

After passing through channel and removing CP at the receiver, the channel convolution matrix is a circulant matrix. The received signal is given by

$$\mathbf{y}(n)=\mathbf{H}\underline{\mathbf{s}}(n)=\begin{bmatrix} h_0 & h_{N-1} & \cdots & h_1 \\ h_1 & h_0 & \cdots & h_2 \\ \vdots & \vdots & \ddots & \vdots \\ h_{N-1} & h_{N-2} & \cdots & h_0 \end{bmatrix}\begin{bmatrix} \underline{s}_0(n) \\ \underline{s}_1(n) \\ \vdots \\ \underline{s}_{N-1}(n) \end{bmatrix} \tag{5}$$

where $\mathbf{H}$ is $N\times N$ circulant channel matrix, with a $N\times 1$ column vector $\mathbf{h}=\left[h_0,h_1,\ldots,h_{L-1},\ldots,h_{N-1}\right]^T$ as the first column and L is the maximum channel delay spread. Namely, the channel is an (at most) L^{th} order FIR channel with impluse reponse h_k staisfying $h_k=0$ for $k<0$ and $k>L$. Notice that the circulant matrix has a important property that it can be diagonalized by FFT matrix [13]. Therefore, the decomposition can be given by $\mathbf{H}=\mathbf{F}_N^H\mathbf{\Lambda}\mathbf{F}_N$, where $\mathbf{\Lambda}$ is a size of $N\times N$ diagonalization matrix. The diagonal elements of $\mathbf{\Lambda}$ is the eigenvalue of the circulant matrix $\mathbf{H}$. The eigenvalue of the matrix $\mathbf{H}$ can be obtained by computing FFT operation of the first column $\mathbf{h}$ in matrix $\mathbf{H}$. Taking into account the additive noise, the received signal vector in time domain is given by

$$\underline{\mathbf{x}}(n)=\mathbf{H}\underline{\mathbf{s}}(n)+\underline{\mathbf{z}}(n) \tag{6}$$

where $\mathbf{z}$ is circularly symmetric white Gaussian noise vector, i.e., $\mathbf{z}\sim CN(0,N_0\mathbf{I})$ and N_0 is the noise variance per complex dimension.

After the N point FFT carried out at the receiver, the output symbol block can be written as

$$\begin{aligned} \mathbf{x}(n) &= \mathbf{F}_N\underline{\mathbf{x}}(n)=\mathbf{F}_N\left(\mathbf{H}\underline{\mathbf{s}}(n)+\underline{\mathbf{z}}(n)\right) \\ &= \mathbf{F}_N\mathbf{F}_N^H\mathbf{\Lambda}\mathbf{F}_N\mathbf{F}_N^H\mathbf{\Theta}\mathbf{s}(n)+\mathbf{F}_N\underline{\mathbf{z}}(n) \\ &= \mathbf{I}_N\mathbf{\Lambda}\mathbf{I}_N\mathbf{\Theta}\mathbf{s}(n)+\mathbf{z}(n) \\ &= \mathbf{\Lambda}\Theta\mathbf{s}(n)+\mathbf{z}(n) \\ &\overset{\mathbf{A}=\mathbf{\Lambda}\mathbf{\Theta}}{=} \mathbf{A}\mathbf{s}(n)+\mathbf{z}(n) \end{aligned} \tag{7}$$

Where $\mathbf{\Lambda}=\mathbf{F}_N\mathbf{H}\mathbf{F}_N^H$ is the frequency channel response and is diagonal with elements $[\mathbf{\Lambda}]_{m,m}=\sum_{n=0}^{N-1}h_n e^{-j2\pi mn/N}$. At last, $\mathbf{z}(n)=\mathbf{F}_N\underline{\mathbf{z}}(n)$ is the noise vector in the frequency domain. The equation (7) is analogous to the blind separation/ ICA model. The matrix $\mathbf{A}=\mathbf{\Lambda}\mathbf{\Theta}$

corresponds to the mixing matrix, which is non-singular. $\mathbf{s}(n)$ is the source signals vector, which is a stationary ergodic random seuqence. Therefore, the source recovery problem can be converted as the blind separation problem. The source signals can be extracted from the observations of mixture based on statistical independence of source. Thus the ICA based blind equalization can recover the original source with no need for extra side information or pilot sequence.

4 Precode Design for PAPR Reduction

According to the aforementioned OFDM system, the PAPR is defined as

$$PAPR = \frac{\max\left|\mathbf{F}_N^H \mathbf{\Theta} \mathbf{s}(n)\right|^2}{E\left[\left|\left|\mathbf{F}_N^H \mathbf{\Theta} \mathbf{s}(n)\right|^2\right|\right]} \tag{8}$$

In order to achieve the purpose of PAPR reduction, the precode matrix $\mathbf{\Theta}$ should possess some properties as follows:

[a]. The column of precode matrix has high autocorrelation;

[b]. The column between of each precode matrix has low cross-correlation;

[c]. The row of each precode matrix has the same module;

[d]. The design of the precode matrix is independent of the modulation data in subcarriers;

In the illustration of the previous-mentioned properties, the properties of the [a] and [b] are to ensure that the received signals in each subcarrier have a high enough signal to noise ratios (SNR); the property of the [b] guarantees to avoid inter-carrier interference; the property of the [c] is to ensure that the operation of the precode matrix has no influence on power-loading and bit-loading in each subcarrier; the property of the [d] denotes the precode matrix is fixed.

The precode matrix is size of $N \times N$,which is defined as

$$\mathbf{\Theta} = \left[\mathbf{\theta}_0, \mathbf{\theta}_1, \ldots, \mathbf{\theta}_{N-1}\right] \tag{9}$$

where the i^{th} column is given by

$$\mathbf{\theta}_i = \left[\theta_{i,0}, \theta_{i.1}, \ldots, \theta_{i,N-1}\right]^T \tag{10}$$

where $i = 0, \ldots, N-1$.

In an ideal case, the properties of the [a] and [b] can be described as

$$\mathbf{\Theta}^H \mathbf{\Theta} = diag\left(\rho_0, \rho_1, \ldots \rho_{N-1}\right) \tag{11}$$

where ρ_i denotes that the power of the i^{th} subcarrier which is allocated by the operation of the precode matrix. Note that the ρ_i $(i = 0, \ldots, N-1)$ should be equivalent according with the property of the [c]. Moreover, The arbitrary two columns of the precode matrix is orthogonal, i.e.,

$$\mathbf{\theta}_p^H \mathbf{\theta}_q = 0, p \neq q, 0 \leq p, q \leq N-1 \tag{12}$$

Based on the previous analysis, that is to say, the column of the precode matrix is the based of subspace spanned by transmitted signals.

According to the design principle of the precode matrix, there are several simple design methods.

(1) This simple design method is to extract the precode matrix from the DFT or IDFT matrix $\mathbf{F}_N$ or $\mathbf{F}_N^H$. The precode matrix is $\mathbf{\Theta} = \mathbf{F}_N$ or $\mathbf{\Theta} = \mathbf{F}_N^H$.

(2) The Kronecker product is used to constructed N-order complex Hadamard matrix $\mathbf{W}_N$ [13]. At first, the 2-order complex Hadamard matrix is defined as

$$\mathbf{W}_2 = \begin{bmatrix} 1 & j \\ 1 & -j \end{bmatrix} \tag{13}$$

The order of matrix is same as the number of subcarriers, which is both the power of 2. The N-order complex Hadamard matrix $\mathbf{W}_N$ can be derived by recursion operation, i.e.,

$$\mathbf{W}_N = \mathbf{W}_{(N/2)\cdot 2} = \mathbf{W}_{N/2} \otimes \mathbf{W}_2 = \ldots = \mathbf{W}_2 \otimes \ldots \otimes \mathbf{W}_2 \tag{14}$$

where “ $\otimes$ ” denotes the Kronecker product.

(3) The arbitrary unitary matrix can be used to construct the precode matrix. For example, to construct a $N \times N$ matrix $\mathbf{V}_N$, in which $(p,n)^{th}$ element is defined as $\left[(p-1)N+n\right]+j\left[(N-p+1)N-n\right]$. The Schur decomposition of $\mathbf{V}_N$ can be arrived at

$$\mathbf{T} = \mathbf{U}^H \mathbf{V}_N \mathbf{U} \tag{15}$$

where $\mathbf{T}$ is a $N \times N$ upper triangular matrix, and $\mathbf{U}$ is a $N \times N$ unitary matrix. The precode matrix $\mathbf{\Theta}$ can be defined as $\mathbf{\Theta} = \mathbf{U}$.

5 Symbol Recovery Based on ICA Equlization

5.1 Conventional equalization method

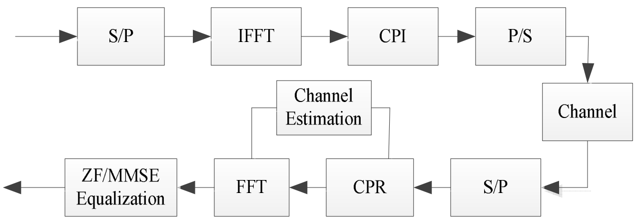


Fig.3 Conventional OFDM system model

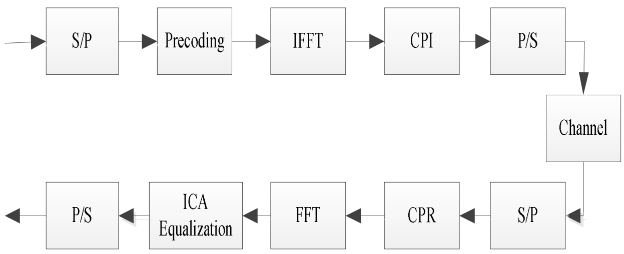


Fig. 4 ICA-based OFDM system model

In order to recover the data signals, the equalization methods need to be carried out in the receiver. As shown in Figure 1, the conventioal scheme needs channel estimation operation for further source recovery. Even if the channel condition is perfectly known, the estimation of the source signal in a noise model is not a trival task. In the source recovery process, the maximun likelihood sequence estimator is the optimal detector, but its computational load can be prohibitive in scenarios involving a large number of user and highly dispersive channels. Trade of complexity for performance, linear receiver are based on the estimation of a linear transformation fulfilling certain suboptimal criterion. According to the equation (7), the data symbols are detected as $\mathbf{s}(n)=\mathbf{B}\mathbf{x}(n)$.The zero forcing (ZF) detectors aim at the joint minimization of ISI and ICI in the absence of noise, and can be thus be expressed as the least-squares problem

$$\mathbf{B}_{ZF}=\arg\min_{\mathbf{B}}\left\|\mathbf{B}\mathbf{A}-\mathbf{I}_N\right\|_F^2 \tag{16}$$

The solution to (16) is readily computed as $\mathbf{B}_{ZF}=\left(\mathbf{A}^H\mathbf{A}\right)^{-1}\mathbf{A}^H=\mathbf{A}^{\dagger}$. The ZF detector can be lead to severe noise amplification in noisy scenarios. This drawback is avioded by the minimum mean square error (MMSE) equalizer

$$\mathbf{B}_{MMSE}=\arg\min_{\mathbf{B}} E\left\{\left\|\mathbf{B}\mathbf{x}(n)-\mathbf{s}(n)\right\|^2\right\} \tag{17}$$

With closed-form solution $\mathbf{B}_{MMSE}=\mathbf{R}_{\mathbf{x}}^{-1}\mathbf{A}$, where $\mathbf{R}_{\mathbf{x}}=E\left\{\mathbf{x}\mathbf{x}^H\right\}$. Due to noise considered in MMSE detector, it can provide enhanced performance compoared with ZF detector. Considering imperfect estimations, e.g. due to finite sample size, in the estimation of channel matrix or the sensor covariance matrix have a negative impact on the detection of the transimitted data symbols. To alleviate this deterimental effect, the satistical independence of the subcarriers' signals can be exploited. At the OFDM receiver, the received signals appear as linear mixed combinationas of the original source signals due to the effect of multipath fading channel which causes the mixing process of the signals. The model (7) corresponds to a problem of blind separation of independent sources in instantaneous linear mixtures. From this perspective, the source estimation can be carried out without previous channel identification by applying an ICA method directly and then using a simple algorithm to identify. The ICA-based scheme is shown in Figure 4. This scheme aviods channel estiamtion operation, which can improve performace becaues of sparing the effect of imperfect estimations.

5.2 ICA-based blind equalization method

In the section 2, the separation processing is mentioned, and the ICA-based blind separation technique depends on independence of source signals to separate or extract latent signals of interest. Combined the equation (2) and the equation (7), the separation process is denoted as

$$\mathbf{y}(n)=\mathbf{B}\mathbf{x}(n)=\mathbf{C}\mathbf{s}(n)+\mathbf{z}'(n) \tag{18}$$

Where $\mathbf{C}=\mathbf{B}\mathbf{A}$ is regarded as a generalized permutation matrix if it has one and only one nonzero element in each row and column. The matrix $\mathbf{B}$ is the separation matrix, which will be sought in the ICA model. The ICA-based blind separation techniques always include two-step process. First step is to choose a principle, based on which a cost function is obtained. Next a suitable method for optimizing the cost function needs to be adopted. In other words, using a cost function converts the blind separation problem into an optimization problem. Usually, high-order statistical information about the source signals is used to build uo the cost function. In this paper, the separation processing is implemented by the adaptive ICA based on the natural gradient for its fast and accurate adaptation behavior. For any suitable smooth gradient-searchable cost function $J(\mathbf{B})$, the natural adaptation is defined as [12]:

$$\mathbf{B}\leftarrow\mathbf{B}-u\nabla J(\mathbf{B})\mathbf{B}^T\mathbf{B} \tag{19}$$

Where u is step size factor. The cost fucntion of ICA problem is usually derived via the maximum likelihood (ML) approach under the independence assumption. The cost function can be established as follows.

$$J(\mathbf{B}) = -\log_2 |\det \mathbf{B}| - \sum_{i=1}^{N} \log_2 p_i(y_i) \quad (20)$$

Where $p_i(\cdot)$ denotes the probability density function (PDF). Since source are supposed to be unknown, and $p_i(\cdot)$ is also unknow and the activation or score function can be used to approximate PDF. The function $\varphi(y_i)$ denotes the activation or score function in the ML approach, which is defined as

$$\varphi(y_i) = -\frac{d \log_2 p_i(y_i)}{dy_i} = -\frac{p_i'(y_i)}{p_i(y_i)} \quad (21)$$

Since sources in digital communcation are always subgaussian signals, this activation function can be chosen as follows [8, 12].

$$\varphi(y_i) = |y_i|^3 \operatorname{sgn}(y_i) \quad (22)$$

Furthermore we can obtain the gradient of the cost function as follows.

$$\nabla J(\mathbf{B}) = \frac{\partial J(\mathbf{B})}{\partial \mathbf{B}} = -\mathbf{B}^{-T} + \varphi(\mathbf{y})\mathbf{x}^T \quad (23)$$

The natural gradient learning law yields

$$\mathbf{B} \leftarrow \mathbf{B} - u\left(\mathbf{I} - \varphi(\mathbf{y})\mathbf{y}^T\right)\mathbf{B} \quad (24)$$

Considering the available prior information, we can use the acquired information to help blind separation assignment. Thus the conventional scheme and ICA-based scheme can be combined together for more performance refinement, called "hybrid scheme" in this paper. The rationale behind ICA-aided conventional scheme detection consists of taking advantage of the available channel estimation as an initial point in the ICA search. Two main benefits can be derived from this combination. Firstly, the exploitation of ICA is expected to mitigate performance drops caused by estimation errors at the channel identification stage. Secondly, if these channel identification errors are moderate, the initialization provided by the channel estimation may already be quite close to the ICA solution, thus improving the rate of convergence and convergence precision. To exploit the source statistical independence, an ICA method can operate on the whitened signals with a separating matrix initialized at the conventional ZF/MMSE detection matrix. Final detection is then performed with separating matrix provided by the ICA algorithm at convergence. The selected natural gradient ICA algorithm has low computational complexity, fast convergence, and equivariant property (resisting ill-conditioned channel) properties. The natural gradient ICA algorithm can be outlined as follows:

Assignment: Estimate the source signal $\mathbf{s}(n)$ from their liner mixture as: $\mathbf{x}(n) = \mathbf{A}\mathbf{s}(n) + \mathbf{z}(n)$

i. Whiten the $\mathbf{x}(n)$ through a linear transform given by:

$$\tilde{\mathbf{x}}(n) = \mathbf{V}\mathbf{x}(n) = \mathbf{D}^{-1/2}\mathbf{E}\mathbf{x}(n)$$

Where $\mathbf{D}$ and $\mathbf{E}$ is the diagonal matrix of eigenvalues and the matrix of the eigenvectors of the covariance matrix $\mathbf{C}_X$, respectively. This operation is named as whitening processing, which has the function of suppressing noise.

ii. Initialize the separation matrix $\tilde{\mathbf{B}}$.

iii. Produce the $\mathbf{y}(n)$ as:

$$\mathbf{y}(n) = \tilde{\mathbf{B}}\mathbf{x}(n)$$

iv. Obtain the nonlinear vector $\varphi(\mathbf{y})$ as:

$$\varphi(\mathbf{y}) = \left[\varphi(y_0(n)), \ldots, \varphi(y_{N-1}(n))\right]^T$$

Where $\varphi(\mathbf{y}) = |\mathbf{y}(n)|^2 \mathbf{y}(n)$ is used for sub-Gaussian signals.

v. Update the separation matrix $\tilde{\mathbf{B}}$ as: (complex signal)

$$\tilde{\mathbf{B}} \leftarrow \tilde{\mathbf{B}} - \mu\left(\mathbf{I} - \varphi(\mathbf{y})\mathbf{y}^H\right)\tilde{\mathbf{B}}$$

vi. Normalize $\tilde{\mathbf{B}}$ using

$$\tilde{\mathbf{B}} \leftarrow \tilde{\mathbf{B}}\left(\tilde{\mathbf{B}}^H\tilde{\mathbf{B}}\right)^{-1/2}$$

vii. Check the convergence of $\tilde{\mathbf{B}}$. If the convergence is not reached go back to 3, otherwise proceed to 8.

viii. The separating matrix corresponding to the mixing matrix $\mathbf{A}$ is given by:

$$\mathbf{B} = \tilde{\mathbf{B}}\mathbf{V}$$

ix. The recovered signal vector is given by

$$\mathbf{s}(n) = \tilde{\mathbf{B}}\mathbf{V}\mathbf{x}(n)$$

5.3 Computational complexity

The computational complexity of the different detectors will then be compared among the ZF detector, the subspace-based MMSE detector, ICA detector, the ZF-ICA detector, and the MMSE-ICA detector. Assume that the number of symbol blocks is M.

In the subspace-based MMSE detector, the EVD of autocorrelation matrix has the complexity of $O(N^2M) + O(N^3)$, and the complexity of the projection of the desired signature waveform onto signal subspace is $O(N^2)$. Thus, the final complexity of the subspace-based MMSE is of order $O(N^2M)+O(N^3)+O(N^2)\approx O(N^2M)(M\gg N)$. Besides, in the MMSE-ICA, the computational complexities of autocorrelation matrix, prior subspace estimation, pre-whitening of the received data, and each unit-gain-based ICA iteration are $O(N^2M)$, $O(N^2)$, and $O(N^2M)$, respectively. Thus, the final complexity of the MMSE-ICA is of order $O(N^2M)$. In the ZF detector, the complexity of inverse of mixing and the projection of the separation desired signal is about $O(N^2M)$. Correspondingly, the complexity of the ZF-ICA detector is of order $O(N^2M)$.

6 Simulations

In this section, we tested the algorithms using simulated OFDM with frequency selective channel. We evaluate the comparative performance of the PAPR under different precoding scheme and ICA-aided equalizers under different simulation conditions, and illustrate the analysis of the previous theoretical exposition. Transmitted symbols are equiprobable and independent QAM symbols. The number of subcarriers is N=32, and the channel impulse response is chosen randomly as follows,

$$h(k)=\{0.5931,-0.5421-0.4391j,0.397j,0.0524-0.0678j\},$$

i.e., L=3. This channel is generated to obtain a significant ICI.

Fig.5 shows the PAPR index under three precoding methods and OFDM without precoding. According to the results in the Fig.3, we can obtain that the threee precoding schemes all can carry out PAPR reduction role, and the DFT precoding has the best performance among the three schemes. Note that the DFT precoding is similar to the function in single carrier frequency division multiple access (SC-FDMA).

Fig. 6 shows the achieved bit-error-rates (BER) for different schemes as a function of SNR. The performance of ZF is quite moderate due to estimation error for channel and effect of noise amplification. Although The MMSE considers the noise compared to ZF, it is affected by the estimation imperfect of the signal subspace or system channel. The ICA method can spare the previous adverse effect due to exploiting the statistical independence of the source signal, thus the performance is improved. For the acquired prior information, the ZF-ICA or MMSE-ICA can use the ZF or MMSE as an initial point in the ICA search, which can improve the rate of convergence and convergence precision. Thus, the performance can be improved more.

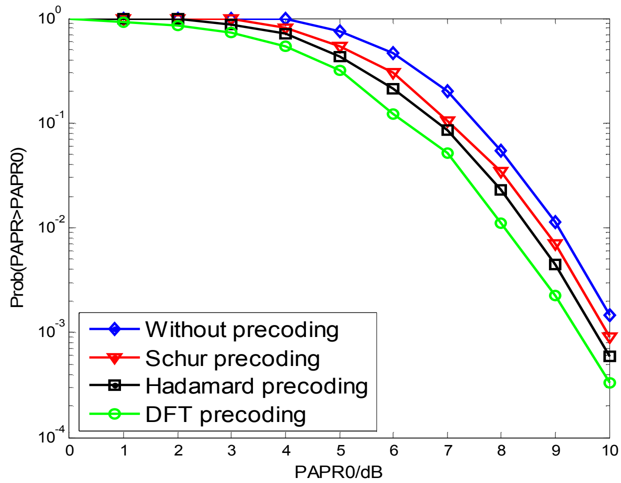


Fig.5 shows the PAPR for the differernt precoding methods as a function of PAPR0.

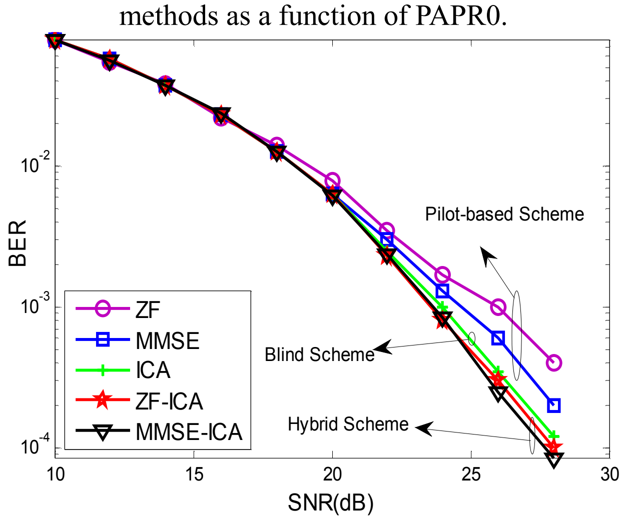


Fig.6 shows the achieved bit-error rates (BER) for the methods as a function of SNR.

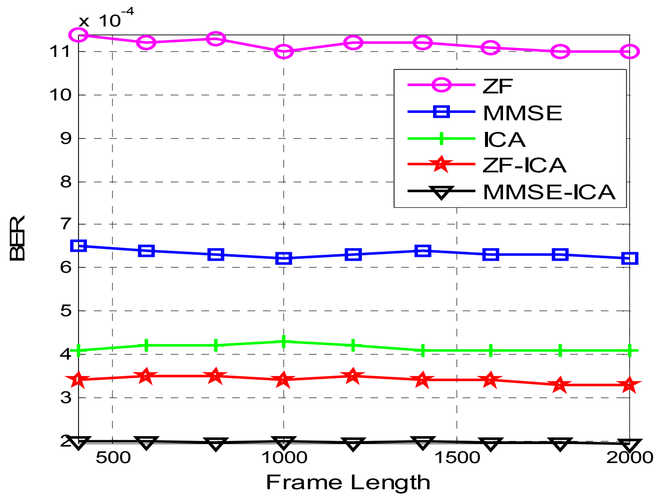


Fig. 7 shows the achieved bit-error-rates (BER) for different methods as a function of frame length (bits)

Fig.7 illustrates the performance comparison of the above-mentioned different schemes in Fig.6 about the effect of the sample length on symbol estimation accuracy at SNR levels of 25 dB. It is obvious that the simulated results conform to the previous analysis. In a word, we can learn that the ICA-aided detector can strengthen the signal detection capabilities.

7 Conclusions

For the purpose of coordinating the efficient PAPR reduction and system performance in OFDM system, the ICA assisted PAPR reduction symbol recovery method is proposed in this paper. The main advantage of the proposed method consistes in the better BER performance and higher spectrum efficiency than the traditional ones such as clipping and filtering, etc.. Hence, the proposed method is fit for the requirement of higher performance in OFDM systems. In addition, as an added advantage of the ICA-based methods, the prior knowlege of system parameters such as extra side information or subcarriers' modulations is spared, with the consequent increase in flexibility. These characteristics make ICA-based techniques very promising not only in future commercial wireless systems, but also in non-cooperative military scenarios. The statistical characteristic based ICA technique may be the next gengeration signal processing solution due to its adaptive signal processing manner.

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