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Research Article

Joint Adaptive Blind Channel Estimation and Data Detection for MIMO-OFDM Systems

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In order to track a changing channel in multiple-input multiple-output orthogonal frequency division multiplexing (MIMO-OFDM) systems, it is a priority to estimate channel impulse response adaptively. In this paper, we propose an adaptive blind channel estimation method based on parallel factor analysis (PARAFAC). We used an exponential window to weigh the past observations; thus, the cost function can be constructed via a weighted least squares criterion. The minimization of the cost function is equivalent to the decomposition of a third-order tensor, which consists of the weighted OFDM data symbols. By preserving the Khatri-Rao product, we used a recursive least squares solution to update the estimated subspace at each time instant, then the channel parameters can be estimated adaptively, and the algorithm achieves superior convergence performance. Simulation results validate the effectiveness of the proposed algorithm.

1. Introduction

The combination of MIMO with the OFDM technique has become the most promising broadband wireless access scheme due to a large system capacity and high data rates without any extra consumption of bandwidth and power [1]. In a MIMO-OFDM system, the channel needs to be estimated accurately, and then the transmitted signal can be obtained by channel equalization. Thus, an exact estimation of the changing channel impulse is necessary [2–5].

In past decades, a number of channel estimation methods were proposed for MIMO-OFDM systems and they were grouped into two categories. The first category is called pilot tone-based channel estimation. By using the training sequence from a transmitted signal, channel information can be estimated. In fact, by periodically transmitting a training sequence which is known to the receiver, an Adaptive Channel Estimation (ACE) process can be done in digital communication systems [6–13]. Linear channel estimation methods in Ref. [14, 15] use an adaptive filter to estimate channel information. Due to less computational complexity, linear channel estimation methods such as least squares (LS) algorithms are relatively simple to implement. The Least Mean Square (LMS) algorithm is one of the ACE methods with relatively low computational complexity, but the mean squared error (MSE) performance is poor [14]. Furthermore, simplified LMS algorithms like the Sign Data NLMS (SDNLMS) algorithm [15] can be used to decrease the complexity of the LMS algorithm. Sparse channel estimation [16–20] commonly uses the technique of compressive sensing. However, these methods have great dependence on the number of nonzero taps. The second category is the semiblind or blind channel estimation [21, 22]. Here, training sequences and knowledge of noise statistics are not necessary; channel impulse response can be estimated only by the received signals. Therefore, blind channel estimation methods have attracted wide attention due to its improved spectral efficiency. Blind channel estimation methods usually use the statistical properties of received signals, and the channel is considered static during the receiving time. When the ACE process is concerned, existing blind OFDM channel estimation methods are not suitable for online applications.

Parallel factor (PARAFAC) analysis has been widely used to solve the problem of parameter estimation and signal detection. For OFDM systems, tensor decompositions have been exploited for blind channel estimation [23–26].

Reference [24] proposed a TALS algorithm to estimate channel parameters for SIMO-OFDM systems with Carrier Frequency Offset (CFO). However, the extension on MIMO-OFDM systems is missed. The TALS method can obtain good MSE, but it has high computational complexity and poor convergence rate. The DEBRE algorithm uses the received signal to form a 4-way tensor for MIMO-OFDM systems in the frequency domain, then the loading matrix of the model is estimated via an ALS algorithm [25]. Similar with the TALS algorithm, the DEBRE method can obtain good MSE, but it has high computational complexity and poor convergence rate. The LS-KRF algorithm and the S-CFP algorithm are established based on the tensor model for the Tucker decomposition [26], and they achieve very similar performance with extra pilot overhead at high SNR conditions. While the mentioned algorithms on PARAFAC are suitable for a stationary channel environment, the computational complexity of the whole new tensor decomposition at each sampling instant is too high to suit online applications.

In this paper, we proposed an online adaptive blind channel estimation method using recursive least squares tracking. We used an exponential window to weigh past observations; thus, the cost function can be constructed via a weighted least squares criterion. The minimization of the cost function is equivalent to the decomposition of a third-order tensor which consists of the weighted OFDM data symbols. The main contribution of this paper is briefly summarized as follows. (i) We propose a PARAFAC model for time-varying MIMO-OFDM systems in the time domain, where time is measured in OFDM symbols. For one OFDM symbol, by reshaping the received signal vector of all antennas and letting the reshaped matrix be the lateral slice matrix one by one, we establish a third-order tensor model for time-varying MIMO-OFDM systems. (ii) We develop an adaptive channel estimation algorithm using recursive least squares tracking (ABCE-RLST). Here, training sequences and knowledge of noise statistics are not necessary, and channel impulse response can be estimated adaptively only by the received signals. In addition, our algorithm is a recursive update solution; the computation complexity is very low compared to other PARAFAC decomposition counterparts. (iii) We compare the performance of our proposed algorithms with other existing channel estimation approaches. Simulation results show that the proposed algorithms significantly improve the channel estimation performance of time-varying systems under different conditions compared to the SDNLMS and ASCE-NLMS algorithms.

1.1. Notation. The notational conventions are as follows. Scalars are denoted by lower case italic letters $(a, b, \cdots)$, vectors by lower case boldface letters $(\mathbf{a}, \mathbf{b}, \cdots)$, and matrices by boldface capitals $(\mathbf{A}, \mathbf{B}, \cdots)$. Italic capitals are used to denote index upper bound $(k = 1, \cdots, K)$. The entry with row index i and column index j in a matrix $\mathbf{A}$, i.e., $[\mathbf{A}]_{ij}$, is symbolized by a_{ij}. The columns of a matrix, say $\mathbf{A}$, are denoted by $\mathbf{a}_1, \mathbf{a}_2, \cdots$ generically. The superscripts $\cdot^T$, $\cdot^H$, $\cdot^{-1}$ and $\cdot^\dagger$ denote the transpose, conjugate transpose, inverse operators, and pseudoinverse, respectively. $\mathbf{I}_N$ denote the $N \times N$ identity matrix, and $\|\cdot\|_2$ denotes the Euclid norm. $\odot$ denote the Khatri-Rao product. $E[\cdot]$ denotes the expectation operator. The operator diag $(\cdot)$ may either form a diagonal matrix by a vector or form a vector by collecting the diagonal entries of a matrix.

2. System Model

In this section, we describe the MIMO-OFDM system model with M_t transmitters and M_r receivers in this paper. Specially, if $M_t = M_r = 1$, it reduces to a SISO-OFDM system. In each OFDM block, N symbols are transmitted, so the k th modulated information of the ith transmitter is $\mathbf{s}_i(k) = [s_i(k, 0), \cdots, s_i(k, N-1)]^T$. Suppose all the $M_t \times M_r$ channel paths have the memory upper bounded by L, and let $\tilde{\mathbf{h}}_{ij}^T = [\tilde{h}_{ij}(1), \tilde{h}_{ij}(2), \cdots, \tilde{h}_{ij}(L-1)]$ denote the equivalent discrete channel response from the ith transmitter to the jth receiver. So the N-point DFT of the channel vector is $\mathbf{h}_{ij}^T = [h_{ij}(1), h_{ij}(2), \cdots, h_{ij}(N)]$. The received signal vector from the jth receiver antenna by the ith transformer is then represented as

$$\mathbf{x}_{ij}(k) = \mathbf{F}^H \operatorname{diag}\left(\mathbf{h}_{ij}\right)\mathbf{s}_i(k), , \tag{1}$$

where $\mathbf{F}$ is the $N \times N$ normalized discrete Fourier transform matrix with its (m, q)-th entry given by $(1/\sqrt{N})$ $e^{-j2\pi(m-1)(q-1)}$.

Let

$$\mathbf{H} = \begin{bmatrix} \mathbf{h}_{11}^T & \mathbf{h}_{21}^T & \cdots & \mathbf{h}_{M_t 1}^T \\ \mathbf{h}_{12}^T & \mathbf{h}_{22}^T & \cdots & \mathbf{h}_{M_t 2}^T \\ \vdots & \vdots & \ddots & \vdots \\ \mathbf{h}_{1M_r}^T & \mathbf{h}_{2M_r}^T & \cdots & \mathbf{h}_{M_t M_r}^T \end{bmatrix} \in \mathbb{C}^{M_r \times M_t N}, \tag{2}$$

which denote the overall frequency-domain channel matrix. Therefore, the received symbol vector $\mathbf{x}_j(k) = \sum_{i=1}^{M_t} \mathbf{x}_{ij}(k)$ from the jth receiver antenna is

$$\mathbf{x}_j(k) = \sum_{i=1}^{M_t} \mathbf{F}^H \operatorname{diag}\left(\mathbf{h}_{ij}\right)\mathbf{s}_i(k). \tag{3}$$

Constructing the matrix $\boldsymbol{\Gamma} = [\mathbf{I}_N\, \mathbf{I}_N\, \cdots\, \mathbf{I}_N] \in \mathbb{C}^{N \times NM_t}$, $\mathbf{x}_j(k)$ can be represented as

$$\mathbf{x}_j(k) = \mathbf{F}^H \boldsymbol{\Gamma} \boldsymbol{D}_j(\mathbf{H})\mathbf{s}(k), \tag{4}$$

where $\mathbf{s}(k) = \left[\mathbf{s}_1(k)^T, \mathbf{s}_2(k)^T, \cdots, \mathbf{s}_{M_t}(k)^T\right]^T \in \mathbb{C}^{NM_t \times 1}$, $\boldsymbol{D}_j(\mathbf{H})$ denotes the diagonal matrix with its entries from the jth row of the frequency-domain channel matrix $\mathbf{H}$. Now, we consider a time-varying MIMO-OFDM system. Suppose that the channel parameters stay unchanged during one OFDM symbol and vary for different OFDM symbols. Therefore, we define the channel matrix at the kth symbols as $\mathbf{H}(k)$.

Considering all the M_r receiver antennas, the received signal vector of all antennas $\mathbf{x}(k) = [\mathbf{x}_1(k)^T, \mathbf{x}_2(k)^T, \cdots, \mathbf{x}_{M_r}(k)^T]^T \in \mathbb{C}^{NM_r \times 1}$ is then represented as

$$\mathbf{x}(k) = \left[\mathbf{H}(k) \odot \left(\mathbf{F}^H \boldsymbol{\Gamma}\right)\right] \mathbf{s}(k). \tag{5}$$

As Figure 1 shows, if we reshape $\mathbf{x}(k)$ to be a $N \times M_r$ matrix, then we stack up corresponding matrices of $J(k)$ OFDM symbols, a third-order tensor $\mathcal{X}(k) \in \mathbb{C}^{N \times J(k) \times M_r}$ can be obtained, which is composed by all the received symbols. Therefore, the matrix representation of the tensor decomposition of $\mathcal{X}(k)$ can be written as

$$\mathbf{X}(k) = \left[\mathbf{H}(k) \odot \left(\mathbf{F}^H \boldsymbol{\Gamma}\right)\right] \mathbf{S}(k), \tag{6}$$

where $\mathbf{X}(k) = [\mathbf{x}(1), \cdots, \mathbf{x}(J(k))] \in \mathbb{C}^{NM_r \times J(k)}$, $\mathbf{S}(k) = [\mathbf{s}(1), \cdots, \mathbf{s}(J(k))]$ denote the continuous $J(k)$ transmit symbols. Since the matrices $\mathbf{F}$ and $\boldsymbol{\Gamma}$ are both constant, we define $\mathbf{A} = \mathbf{F}^H \boldsymbol{\Gamma}$ for derivation clarity, then (6) can be rewritten as $\mathbf{X}(k) = [\mathbf{H}(k) \odot \mathbf{A}]\mathbf{S}(k)$. Thus, the loading matrices are $\mathbf{H}(k) \in \mathbb{C}^{M_r \times NM_t}$, $\mathbf{S}(k) \in \mathbb{C}^{NM_t \times J(k)}$, and $\mathbf{A} \in \mathbb{C}^{N \times NM_t}$, respectively. Therefore, we can obtain the channel information by solving the loading matrices of the tensor.

3. Blind Adaptive Channel Estimation Algorithm

3.1. Uniqueness Analysis. The CP decomposition of a tensor is unique up to scaling and permutation ambiguities under a mild condition [27, 28]. It is well known that the following theorem can guarantee the essential uniqueness of the CP decomposition:

Theorem 1. *The CP decomposition of a third-order tensor $\mathcal{X} \in \mathbb{C}^{I \times J \times K}$ is unique, if*

$$\begin{gathered} R \leq K, \\ R(R-1) \leq \frac{I(I-1)J(J-1)}{2}, \end{gathered} \tag{7}$$

where R is the rank of the tensor.

According to Theorem 1, we can obtain the similar Lemma 1 about the CP decomposition of the tensor for MIMO-OFDM systems.

Lemma 1. *Assume that $\mathbf{A}$ and $\mathbf{H}(k)$ are full rank, and $\mathbf{S}(k)$ is full column rank. The CP decomposition in (10) is essentially unique if*

$$NM_t(NM_t - 1) \leq \frac{N(N-1)J(k)(J(k)-1)}{2}. \tag{8}$$

The above assumptions are generically satisfied in our signal model. On one hand, the normalized discrete Fourier transform matrix is full rank, and then the channel matrix is completely full rank surely. On the other hand, all the transmit signals are assumed to have independent continuous distribution, thus the symbols matrix $\mathbf{S}(k)$ is full column rank, which practically satisfies Lemma 1.

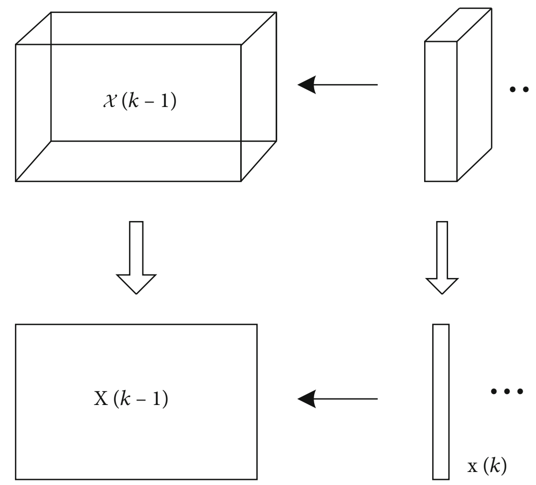

Figure 1: Adaptive third-order tensor model and its equivalent matrix form.

3.2. Algorithm Derivation. We use the first $J(k)$ receiving ymbols to build the initial observed tensor $\mathcal{X}(k)$. Let $\mathcal{X}(k+1) \in \mathbb{C}^{N \times J(k+1) \times M_r}$ be the new observation obtained from $\mathcal{X}(k)$ after appending a new observed tensor slice in the second dimension, which means $J(k+1) = J(k) + 1$. Thus, an estimate of the PARAFAC decomposition of $\mathcal{X}(k+1)$ is

$$\mathbf{X}(k+1) \cong \mathbf{G}(k+1)\mathbf{S}(k+1), \tag{9}$$

where $\mathbf{G}(k+1) = \mathbf{H}(k+1) \odot \mathbf{A}$. In fact, the alternating least squares (ALS) algorithm can be used to do PARAFAC decomposition of $\mathcal{X}(k+1)$ [25] to estimate the new loading matrices $\mathbf{S}(k+1)$ and $\mathbf{H}(k+1)$. However, the ALS algorithm needs a pseudoinverse operation three times at each iteration, and the convergence speed is very slow even with a proper initialization. The computation complexity of the whole new tensor decomposition at each sampling instant is too high to suit the online applications.

Let $\mathbf{x}(k+1) \in \mathbb{C}^{NM_r \times 1}$ be the new received signal vector of all antennas, such that $\mathbf{X}(k+1) = [\,\mathbf{X}(k) \quad \mathbf{x}(k+1)\,]$. Suppose that there is a smooth variation of channel parameters between k to $k+1$, which means $\mathbf{H}(k) \simeq \mathbf{H}(k+1)$. So the initial estimate of $\mathbf{s}(k+1)$ can be given in the least squares sense by

$$\widehat{\mathbf{s}}(k+1) = \mathbf{G}^{\dagger}(k)\mathbf{x}(k+1). \tag{10}$$

To track the channel in a time-varying MIMO-OFDM system, the sufficient statistic data in (5) should be gradually forgotten and a proper window can be used so as to weigh past observations. In this paper, we use the following exponential window least squares criterion to equal the decomposition of the third-order tensor:

$$\min_{\{\mathbf{G}(k+1),\mathbf{S}(k+1)\}} \left(\sum_{\tau=1}^{k+1} \lambda^{k+1-\tau} \|\mathbf{x}(\tau) - \mathbf{G}(k+1)\mathbf{s}(\tau)\|^2 \right), \quad (11)$$

where $0 < \lambda < 1$ is the forgetting factor. Thus, the direction at the maximum rate of change of a function $\phi(k+1) = \sum_{\tau=1}^{k+1} \lambda^{k+1-\tau} \|\mathbf{x}(\tau) - \mathbf{G}(k+1)\mathbf{s}(\tau)\|^2$ with respect to $\mathbf{s}$ is given as

$$\nabla\phi(k+1) = 2\sum_{\tau=1}^{k+1} \lambda^{k+1-\tau} \left(\mathbf{X}(\tau) - \mathbf{G}(k+1)\mathbf{s}(\tau)\mathbf{s}^H(\tau)\right). \quad (12)$$

Thus, we can obtain

$$\mathbf{G}(k+1) = \mathbf{R}(k+1)\mathbf{P}^{-1}(k+1), \quad (13)$$

where $\mathbf{R}(k+1) = \sum_{\tau=1}^{k+1} \lambda^{k+1-\tau}\mathbf{X}(\tau)\mathbf{s}^H(\tau)$, $\mathbf{P}(k+1) = \sum_{\tau=1}^{k+1} \lambda^{k+1-\tau}\mathbf{s}(\tau)\mathbf{s}^H(\tau)$. So the computation of $\mathbf{R}(k+1)$ and $\mathbf{P}(k+1)$ can be written as

$$\mathbf{R}(k+1) = \lambda\mathbf{R}(k) + \mathbf{X}(k+1)\mathbf{s}^H(k+1), \quad (14)$$

$$\mathbf{P}(k+1) = \lambda\mathbf{P}(k) + \mathbf{s}(k+1)\mathbf{s}^H(k+1). \quad (15)$$

To avoid the explicit computation of the pseudoinverse of $\mathbf{P}$, the derivation of the recursive updates of $\mathbf{P}^{-1}$ should be taken into consideration; thus, we define $\mathbf{Q} = \mathbf{P}^{-1}$. From the matrix inversion lemma for rank-one updates [27], we have

$$\mathbf{Q}(k+1) = \lambda^{-1}\mathbf{Q}(k) - \frac{\lambda^{-2}\mathbf{Q}(k)\mathbf{s}(k+1)\mathbf{s}^H(k+1)\mathbf{Q}(k)}{1 + \lambda^{-1}\mathbf{s}^H(k+1)\mathbf{Q}(k)\mathbf{s}(k+1)}. \quad (16)$$

As the definition of $\mathbf{G}(k+1) = \mathbf{R}(k+1)\mathbf{Q}(k+1)$, we can obtain $\mathbf{G}(k+1)$. Let $\widehat{\mathbf{H}}(k+1) = [\mathbf{h}_1(k+1), \mathbf{h}_2(k+1), \cdots, \mathbf{h}_R(k+1)]$ as the estimation matrix of the channel, where $R = NM_t$. Due to the Khatri-Rao product $\mathbf{G}(k+1) = \mathbf{H}(k+1) \odot \mathbf{A}$, we can obtain the following equation

$$\mathbf{g}_r(k+1) = \mathbf{h}_r(k+1) \otimes \mathbf{a}_r, \quad r = 1, \cdots R, \quad (17)$$

where $\mathbf{g}_r(k+1)$ denotes the rth column of $\mathbf{G}(k+1)$, $\mathbf{a}_r$ denotes the rth column of $\mathbf{A}$. We define the rank-one matrices $\mathbf{G}_r(k+1) = \mathrm{unvec}_{M_r \times N}(\mathbf{g}_r(k+1))$, $r = 1, 2, \cdots R$, as

$$\mathbf{G}_r(k+1) = \mathbf{a}_r\mathbf{h}_r^T(k+1), \quad (18)$$

since the normalized discrete Fourier transform matrix $\mathbf{F}$ and the correlation coefficient matrix $\boldsymbol{\Gamma}$ are constant, it is easy to obtain $\mathbf{h}_r(k+1) = \mathbf{G}_r^T(k+1)\mathbf{a}_r$.

On the other hand, by substituting (13) into (10), we can obtain the computation of $\widehat{\mathbf{s}}(k+1)$ as

$$\widehat{\mathbf{s}}(k+1) = \mathbf{P}(k+1)\mathbf{R}^\dagger(k+1)\mathbf{x}(k+1). \quad (19)$$

Similar to $\mathbf{P}^{-1}$, the computation of $\mathbf{R}^\dagger$ can be written as

$$\mathbf{Z}(k+1) = \lambda^{-1}\mathbf{Z}(k) - \frac{\lambda^{-2}\mathbf{Z}(k)\mathbf{X}(k+1)\mathbf{s}^H(k+1)\mathbf{Z}(k)}{1 + \lambda^{-1}\mathbf{s}^H(k+1)\mathbf{Z}(k)\mathbf{X}(k+1)}. \quad (20)$$

Thus, the estimation of transmit signals is $\mathbf{S}(k+1) = [\,\mathbf{S}(k) \quad \widehat{\mathbf{s}}(k+1)\,]$. We present the pseudocode of the proposed adaptive channel estimation algorithm for MIMO-OFDM systems in Algorithm 1.

4. Simulation Results and Discussions

In this section, we evaluate the performance of the proposed method. We provide results under two different simulation environments. In the first simulation, we consider a stationary environment exhibiting abrupt changes, while in the second, we consider a more realistic case of a slowly changing environment. In all cases, we consider the mean square error as a measure of performance. The MSE is defined as

$$\mathrm{MSE}(k) = E\left\{ \left\| \mathbf{H}(k) - \widehat{\mathbf{H}}(k) \right\|_2^2 \right\}, \quad (21)$$

where $\mathbf{H}(k)$ and $\widehat{\mathbf{H}}(k)$ are actual channel vectors and their estimates. The kth received signal at the jth antenna writes $\tilde{\mathbf{X}}_j(k) = \mathbf{F}^H\boldsymbol{\Gamma}\boldsymbol{D}_j(\mathbf{H})\mathbf{s}(k) + \mathbf{n}_j(k)$ in a noisy environment, where $\mathbf{n}_j(k)$ represents the additive noise in the jth antenna. Then SNR is defined as

$$\mathrm{SNR} = 10\log_{10}\frac{\sum_{j=1}^{M_r}\left\|\mathbf{F}^H\boldsymbol{\Gamma}\boldsymbol{D}_j(\mathbf{H})\mathbf{s}\right\|_F^2}{\sum_{j=1}^{M_r}\left\|\mathbf{n}_j\right\|_F^2}\,\mathrm{dB}. \quad (22)$$

We drop the dependency of the SNR with k in the definition, which is because we use the same SNR for all OFDM symbols.

4.1. Abruptly Changing Environment. In this section, we use a MIMO-OFDM system with 2×3 antennas, and the number of subcarriers is set to 32. The modulation scheme used is 16QAM. AWGN noise is added to the simulated MIMO-OFDM system and SNR = 10 dB. We use $N_s = 200$ symbols to construct the initial received symbols. The forgetting factor λ is 0.5.

We compare the channel estimation performance of the proposed ABCE-RLST algorithm with the methods in [15, 20] with received symbols varying from 200 to 1200, which can be seen in Figure 2. The step-size μ_s of the SDNLMS algorithm in [15] and that of the ASCE-NLMS algorithm in [20] are both set to 0.5. We use the IEEE 802.11 model in the simulation. The simulated channel consists of three equal power taps. To test the convergence capability of the channel estimation algorithms to the new channel impulse response, we performed the following. Firstly, we can obtain a random channel response by the simulated channel model. We start with the channel response, and at iteration 501, we abruptly switch to a new response obtained by the simulated channel model. Time is measured in OFDM symbols, and

Input: Old estimations: $\mathbf{S}(k)$, $\mathbf{P}(k)$, $\mathbf{R}(k)$, $\mathbf{Q}(k)$ and $\mathbf{Z}(k)$
Observations: $\mathbf{X}(k)$ and $\mathbf{X}(k+1) = [\mathbf{X}(k), \mathbf{x}(k+1)]$
1: Initial estimation for $\mathbf{s}(k+1)$
$\mathbf{s}(k+1) = \mathbf{G}^{\dagger}(k)\mathbf{x}(k+1)$.
2: Updates $\mathbf{P}(k)$, $\mathbf{R}(k)$, $\mathbf{Q}(k)$ **and** $\mathbf{Z}(k)$
$\mathbf{P}(k+1) = \lambda\mathbf{P}(k) + \mathbf{s}(k+1)\mathbf{s}^H(k+1)$
$\mathbf{R}(k+1) = \lambda\mathbf{R}(k) + \mathbf{X}(k+1)\mathbf{s}^H(k+1)$
$\mathbf{Q}(k+1) = \lambda^{-1}\mathbf{Q}(k) - \lambda^{-2}\mathbf{Q}(k)\mathbf{s}(k+1)\mathbf{s}^H(k+1)\mathbf{Q}(k)/1 + \lambda^{-1}\mathbf{s}^H(k+1)\mathbf{Q}(k)\mathbf{s}(k+1)$
$\mathbf{Z}(k+1) = \lambda^{-1}\mathbf{Z}(k) - \lambda^{-2}\mathbf{Z}(k)\mathbf{X}(k+1)\mathbf{s}^H(k+1)\mathbf{Z}(k)/1 + \lambda^{-1}\mathbf{s}^H(k+1)\mathbf{Z}(k)\mathbf{X}(k+1)$
3: Update H
$\mathbf{G}(k+1) = \mathbf{R}(k+1)\mathbf{Q}(k+1)$
$\mathbf{A} = \mathbf{F}^H\boldsymbol{\Gamma}$
$R = NM_t$
For $r = 1 \cdots R$ Do
$\mathbf{G}_r(k+1) = \mathrm{unvec}_{M_r \times N}([\mathbf{G}(k+1)]_{:,r})$
$\mathbf{h}_r(k+1) = \mathbf{G}_r(k+1)\mathbf{a}_r$
End
$\widehat{\mathbf{H}}(k+1) = [\mathbf{h}_1(k+1), \mathbf{h}_2(k+1), \cdots, \mathbf{h}_R(k+1)]$
4: Update $\widehat{\mathbf{s}}(k+1)$ **and** $\mathbf{S}(k+1)$
$\widehat{\mathbf{s}}(k+1) = \mathbf{P}(k+1)\mathbf{Z}(k+1)\mathbf{x}(k+1)$
$\widehat{\mathbf{S}}(k+1) = [\mathbf{S}(k), \widehat{\mathbf{s}}(k+1)]$
Output: Matrices $\widehat{\mathbf{H}}(k+1)$ and $\widehat{\mathbf{S}}(k+1)$ now stand for estimates of the channel and signals, respectively.

Algorithm 1: Proposed ABCE-RLST algorithm.

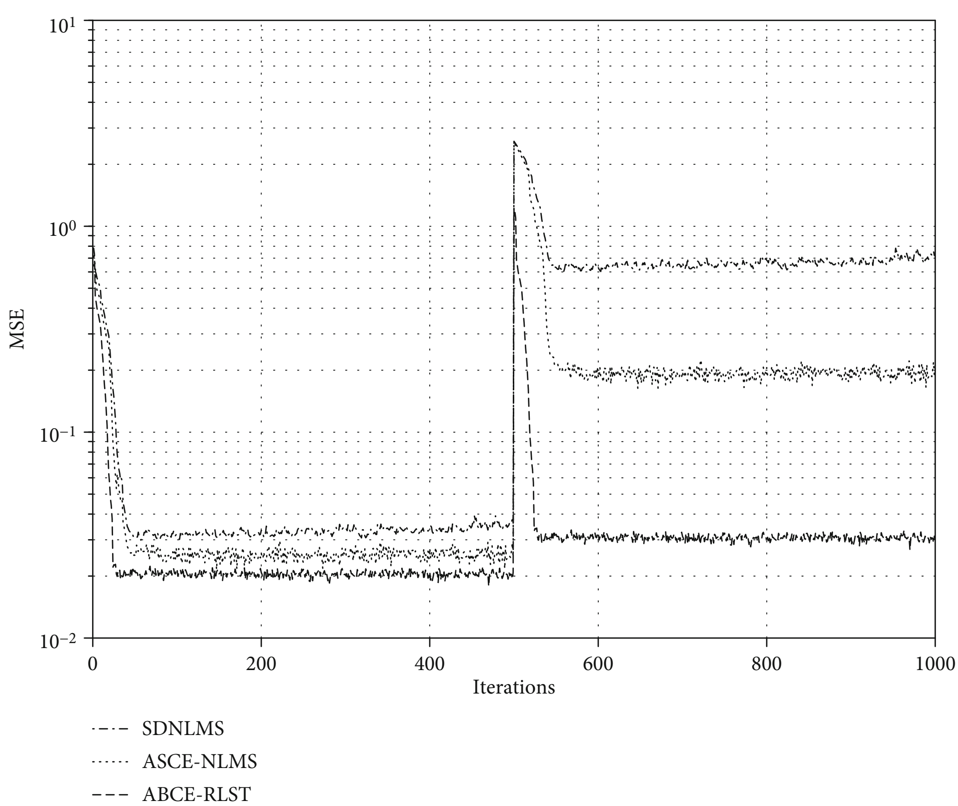

Figure 2: Channel tracking performances with an abruptly changing environment.

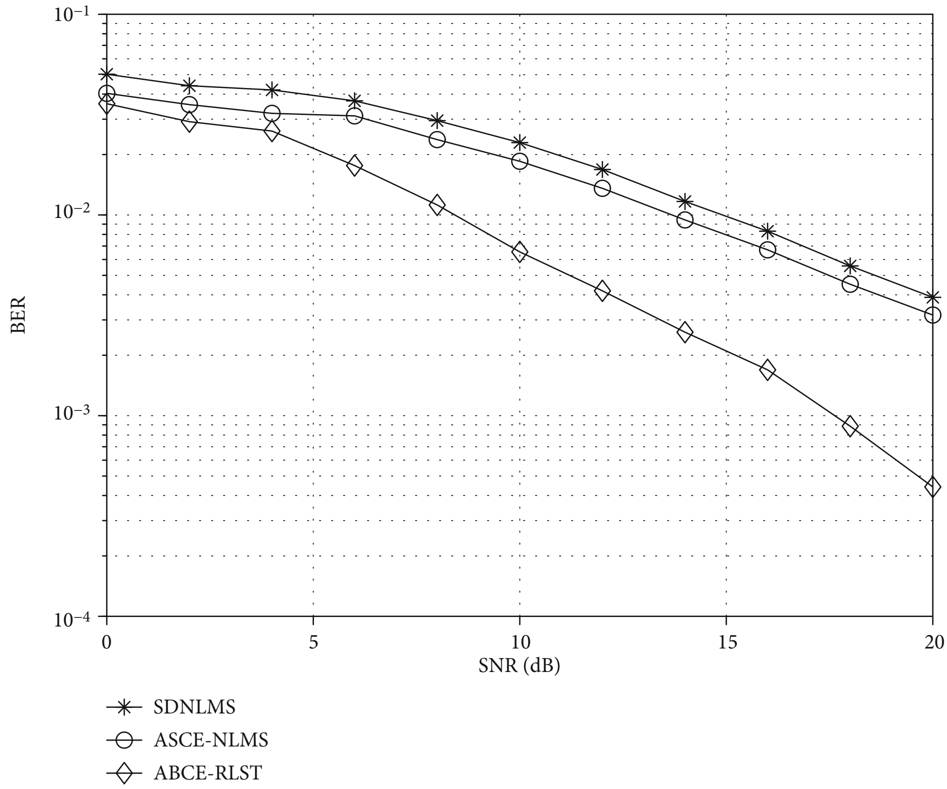

FIGURE 3: BER performances with an abruptly changing environment.

we let the channel remain static during the intervals $[0 \quad 500]$ and $[501 \quad 1000]$.

Figure 2 presents the estimation performance of the proposed ABCE-RLST algorithm, the SDNLMS algorithm, and the ASCE-NLMS algorithm. Obviously, the proposed ABCE-RLST method has a higher MSE than the other two methods at first, but it can achieve better performance soon, and it provides faster convergence. This is because the two competitors use a training sequence to obtain the initial channel information, whereas the proposed method is blind. The window we used makes full use of all previously observed slices with different weights, which can speed up the convergence at low error. The other two algorithms only rely on the last observations, and more symbols are needed to achieve convergence. The complexities of ABCE-RLST, SDSELMS, and ASCE-NLMS for one iteration are $O(N^3M_r^2)$, $O(2N^3 M_r^3 + 2NM_r)$, and $O(3N^3M_r^3 + 3NM_r)$, respectively. Obviously, the proposed algorithm needs the least computational load compared to the other two methods. After the tracking process gets stable, it can be seen that the three algorithms have a stable MSE with the iterations. When we abruptly change parameters of the channel response, the SDNLMS and ASCE-NLMS algorithms obtain poorer MSE performance than the ABCE-RLST algorithm and they need more iterations to converge; even when the tracking process gets stable, the MSE of the two methods still keep a higher value.

In order to shed light on the entire system performance in terms of error probability, after the channel can be tracked, Figure 3 illustrates the averaged BER performance of the three algorithms over 100 independent trials. We can obtain the BER of three competitors that decrease with the growth of SNR, and the proposed ABCE-RLST algorithm achieves better BER performance than the other two competitors.

In fact, we also evaluated the performances of our algorithm under pure additive white Gaussian noise and pure multipath situations independently; the results are similar to those shown in Figures 2 and 3. This further verifies the robustness of our algorithm against the channel multipath effect and noise.

4.2. Slowly Changing Environment. Now, we consider a more realistic scenario of a slowly changing environment. A Jakes-like model is used to simulate the Rayleigh fading; Doppler-frequency is 100 Hz and the communication frequency carrier is at 5 Ghz, with the data rate and receiver speed at 2 Mbits/sec and 3 m/sec, respectively. The simulated channel consists of three equal power taps, and the power delay spectrum obeys negative exponential distribution. The transmitting antennas $M_t = 2$ and the receiver antennas $M_r = 3$, with the number of subcarriers set to 32. We also use $N_s = 200$ symbols to construct the initial receive symbols. The modulation scheme used is 16QAM. The forgetting factor λ is 0.5. The signal-to-noise ratio SNR = 10 dB, and additive white Gaussian noise is used in simulation.

In Figure 4, we plot the MSE of the proposed algorithm versus the SDNLMS and ASCE-NLMS methods under the linear changed channel over 100 independent trials. The step size of the two competitors are both set as $\mu_s = 0.5$. It can be

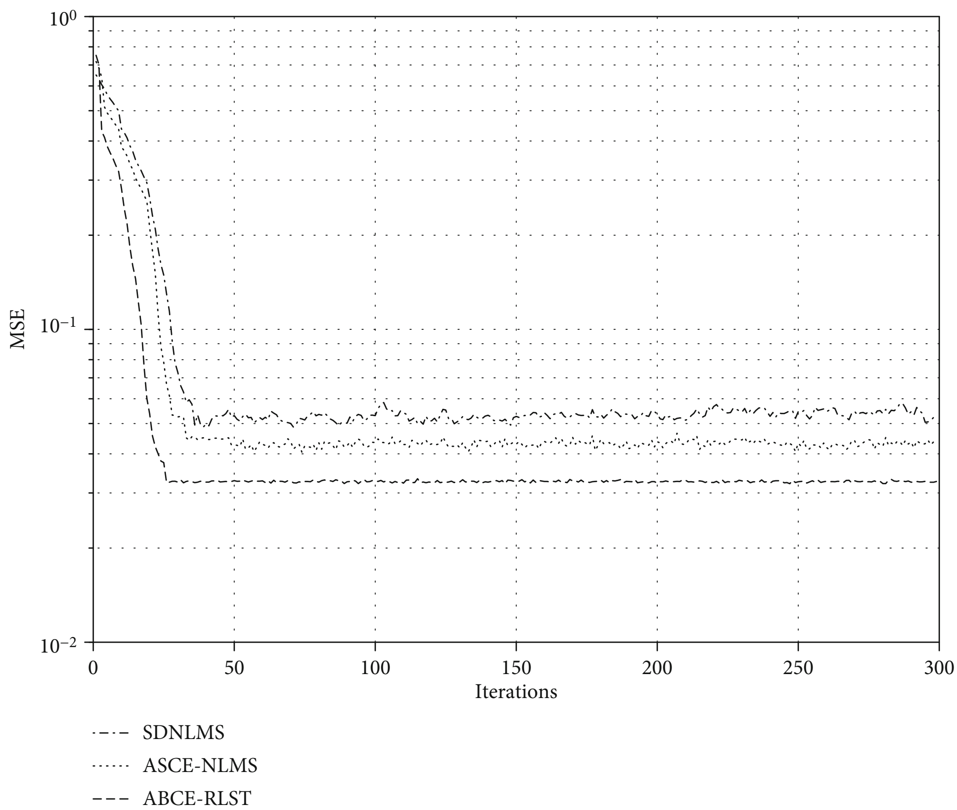

Figure 4: Channel tracking performances under a fading channel.

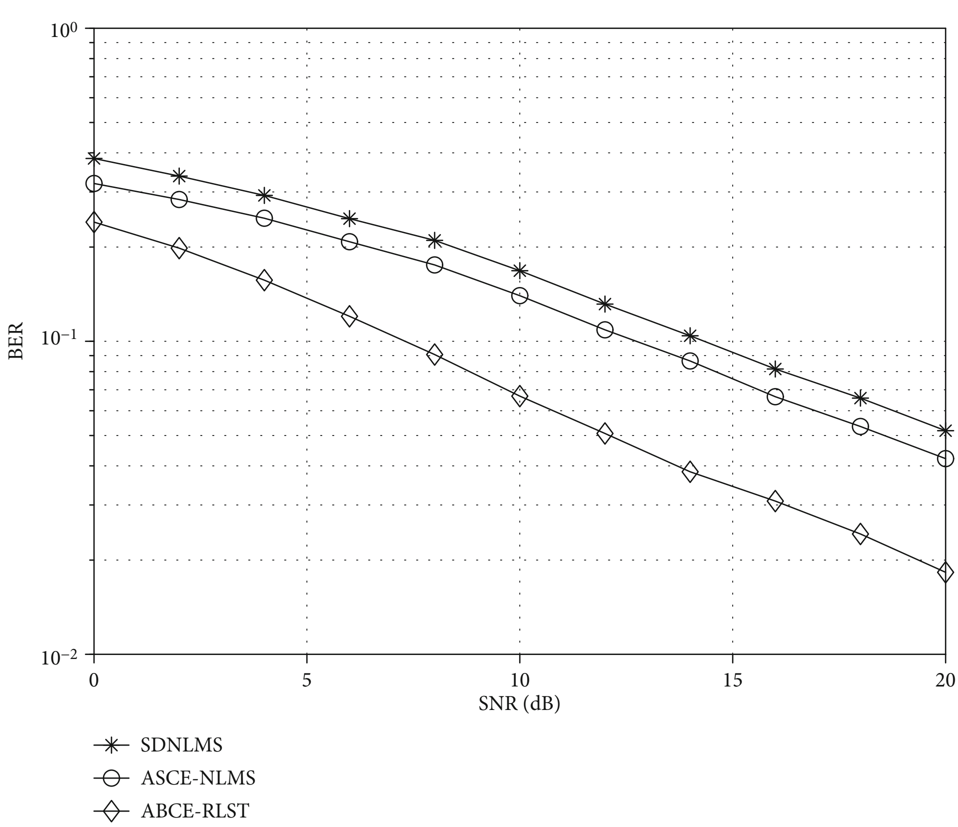

Figure 5: BER performances under a fading channel.

seen that the proposed method has a higher MSE than the other two methods at first, but it can achieve better performance soon, and it provides faster convergence, which is close to the stationary environment. This is because the window we used makes full use of all previously observed slices with different weights, while the other two algorithms only rely on the last observations. It can also be observed that the two existing algorithms perform at a much higher fluctuation after the channel can be tracked. Figure 5 represents the corresponding BER performance of the three algorithms. It can be seen that with the growth of SNR, the BER of the three competitors decrease. As Figure 5 shows, due to a lower estimation error, the proposed algorithm achieves better BER performance than the other two algorithms.

5. Conclusion

The adaptive channel estimation problem is one of the key technical issues to track the channel under wireless random time varying conditions in MIMO-OFDM systems. In this paper, the channel estimation problem is equivalent to the decomposition of a third-order tensor. An exponential window is used to weigh the past observations; thus, the cost function can be constructed by the minimization of the weighted least squares criterion. We used a recursive least squares solution to update the estimated subspace at each time instant, then the channel parameters can be estimated adaptively after appending a new slice in the "symbol" dimension. Moreover, the algorithm achieves superior convergence performance. Computer simulations verify the effectiveness of the proposed algorithm under diverse signalling conditions.

Data Availability

The data used to support the fundings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest regarding the publication of this paper.

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