Paper

An adaptive iterative receiver for space-time coding MIMO systems

Chakree Teekapakvisit, Van Dong Pham, and Branka Vucetic

Abstract—An adaptive iterative receiver for layered space-time coded (LSTC) systems is proposed. The proposed receiver, based on a joint adaptive iterative detection and decoding algorithm, adaptively suppresses and cancels co-channel interference. The LMS algorithm and maximum a posteriori (MAP) algorithm are utilized in the receiver structure. A partially filtered gradient LMS (PFGLMS) algorithm is also applied to improve the convergence speed and tracking ability of the adaptive detector with a slight increase in complexity. The proposed receiver is analysed in a slow and fast Rayleigh fading channels in multiple input multiple output (MIMO) systems.

Keywords— adaptive equalizer, iterative detection, layered space-time coding, LMS, PFGLMS.

1. Introduction

Multiple input multiple output (MIMO) systems have recently emerged as one of the most significant technical advances in modern communications. This technology promises to solve the capacity bottleneck in wireless communication systems [1]. It was shown in [2] that a Diagonal Bell Laboratories Layered Space-Time (DBLAST) MIMO system using a combination of forward error control (FEC) codes can exploit spatial diversity to asymptotically achieve outage capacity. El Gamal *et al.* [3] proposed a threaded layered space-time code (TLSTC) structure, which has an improved bandwidth efficiency compared to the DBLAST structure.

In layered space-time coded (LSTC) systems, co-channel interference from adjacent layers limits the system performance. To reduce co-channel interference, two iterative receivers with combined detection and decoding are proposed in [3] and [4], based on the turbo principle. The first scheme implements minimum mean square error (MMSE) detection with soft-output Viterbi algorithm (SOVA) decoding in the iterative receiver. The second approach proposes a combination of parallel interference cancellation (PIC) detection with maximum a posteriori (MAP) decoding. Both approaches depend on additional channel estimation, and exhibit near interference-free single user performance for certain ranges of the signal to noise ratio (SNR) under the assumption of perfect channel state information (CSI) at the receiver. Recently, an adaptive co-channel interference cancellation scheme for an STC system was proposed in [5]. However, the adaptive receiver design is based on linear detection, which could suffer a performance degradation in a high interference environment. Therefore, a non-linear adaptive detection is necessary for improving the performance of the receiver.

In this paper, a new adaptive iterative TLSTC receiver is proposed based on a joint adaptive iterative detection and decoding algorithm. The proposed receiver does not require channel state information as the non-adaptive iterative receivers in [3] and [4]. Therefore, the proposed receiver does not require a matrix inversion process in the system. As a result, the complexity of the proposed receiver is less than that of the non-adaptive iterative receiver. Moreover, this adaptive iterative receiver has the advantage of combining co-channel interference suppression and cancellation. In this paper, we are mainly concerned with the performance gain due to interference cancellation and tracking ability of the adaptive iterative structures. We show that the adaptive iterative receiver provides a significant performance improvement compared to a single iteration linear adaptive receiver.

The paper is organized as follow: Section 2 describes the LSTC systems and channel models as well as the proposed adaptive iterative receiver structure. The simulation results are discussed in Section 3, followed by the conclusion in Section 4.

2. System model

A threaded layered space-time coded transmitter structure for a single user is shown in Fig. 1. A structure consisting of N transmit and M receive antennas is considered throughout this paper. The binary information stream is converted by a serial to parallel converter and encoded by a convolutional encoder to produce a coded data stream for each layer, corresponding to each of the N transmit antennas. The layered coded data streams are then modulated and fed into a spatial interleaver to distribute a coded stream for all layers among N transmit antennas. After time interleaving, the coded symbols of each layer are simultaneously and synchronously transmitted from the N transmit

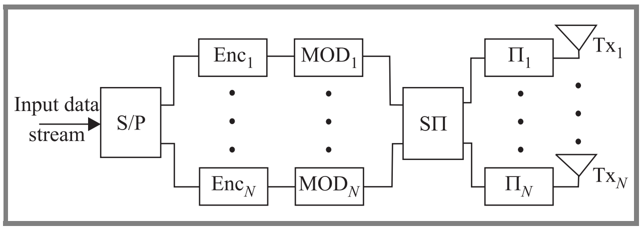

Fig. 1. Layered space-time transmitter structure.

antennas through the MIMO channel. The received signal at each of the M receive antennas can be considered as a superposition of all N transmitted symbols and additive white Gaussian noise (AWGN). The received signal vector, denoted by $\mathbf{r}$, can be represented as

$$\mathbf{r} = \mathbf{H}\mathbf{x} + \mathbf{n}, \tag{1}$$

where $\mathbf{r}$ is an $M \times 1$ column vector of the received signals across the M receive antennas, $\mathbf{H}$ is an $M \times N$ complex channel matrix gain, $\mathbf{x}$ is an $N \times 1$ vector of the transmitted symbols across the N transmit antennas and $\mathbf{n}$ is an $M \times 1$ vector of the AWGN noise with a zero mean and the noise variance of σ^2.

The iterative LSTC receiver structure is shown in Fig. 2. It consists of two stages: a soft-input soft-output (SISO) detector followed by N parallel SISO channel decoders. Time and spatial deinteleavers and spatial and time interleavers separate the two stages. The SISO detector employs an iterative MMSE interference canceller consisting of a feed-forward filter and a feedback filter.

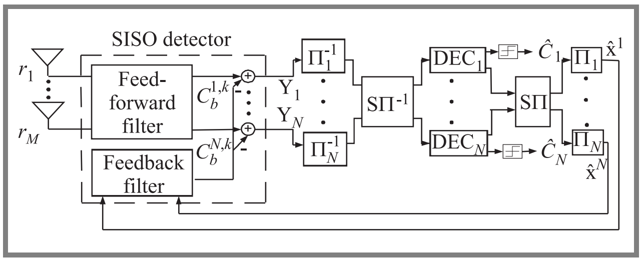

Fig. 2. Block diagram of iterative LST receiver.

In the first iteration, the feed-forward filter performs interference suppression without the interference cancellation process because there are no estimated symbols from the output of the MAP decoder. After the first iteration, the feedback filter is included into the detection process. The estimated symbols from the output of the decoder are fed back to the feedback filter to cancel the interference from other antennas in the detection process. The detected symbol obtained at the output of the MMSE detector in the kth iteration at time t, for layer i, denoted by $y_t^{i,k}$, is given by

$$y_t^{i,k} = \mathbf{w}_f^{i,k^T}\mathbf{r} + \mathbf{w}_b^{i,k^T}\underline{\hat{\mathbf{x}}}^{i,k}, \tag{2}$$

where $\mathbf{w}_j^{i,k}$ is an $M \times 1$ feed-forward coefficient vector, represented as $\mathbf{w}_f = \left[w_{f,0}, w_{f,1}, \ldots, w_{f,M-1}\right]^T$ and $\mathbf{w}_b^{i,k}$ is an $(N-1) \times 1$ feedback coefficient vector, that can be written in the form $\mathbf{w}_b = \left[w_{b,0}, w_{b,1}, w_{b,i-1}\, w_{b,j+1}, \ldots, w_{b,N-1}\right]^T$, and $\underline{\hat{\mathbf{x}}}^{i,k}$ is an $(N-1) \times 1$ vector of the estimated symbols from the output of the SISO MAP decoders at the kth iteration for other antennas, given as

$$\underline{\hat{\mathbf{x}}}^{i,k} = \left(\hat{x}_t^{1,k}, \hat{x}_i^{2,k}, \ldots, \hat{x}_t^{i-1,k}, \hat{x}_t^{i+1,k}, \ldots, \hat{x}_t^{N,k}\right). \tag{3}$$

The second term in Eq. (2) represents the cancelled interference, denoted by a scalar feedback coefficient $c_b^{i,k}$ and given by

$$c_b^{i,k} = \mathbf{w}_b^{i,k^T}\underline{\hat{\mathbf{x}}}^{i,k}. \tag{4}$$

The values of $\mathbf{w}_j^{i,k}$ and $c_b^{i,k}$ are calculated by minimizing the mean square error between the transmitted symbol and its estimate, given by

$$e = E\left[\left|y_t^{i,k} - x_t^{i,k}\right|^2\right]. \tag{5}$$

Let us assume that there is a perfect knowledge of the channel coefficients matrix $\mathbf{H}$. Define $\mathbf{H}_i$ as the ith column of the channel matrix $\mathbf{H}$, representing an $M \times 1$ vector of the complex channel gains for the ith transmit antenna, $\mathbf{H}_i^{\mathbf{H}}$ is a conjugate transpose of $\mathbf{H}_i$ and $\underline{\mathbf{H}}^i$ is an $M \times (N-1)$ matrix composed of the complex channel gains for the other $(N-1)$ transmit antennas. Also define

$$\mathbf{A} = \mathbf{H}_i\mathbf{H}_i^{\mathbf{H}}, \tag{6}$$

$$\mathbf{B} = \underline{\mathbf{H}}^i\left[\mathbf{I}_{N-1} - diag\left(\underline{\hat{\mathbf{x}}}^{i,k}\underline{\hat{\mathbf{x}}}^{i,k^T}\right) + \underline{\hat{\mathbf{x}}}^{i,k}\underline{\hat{\mathbf{x}}}^{i,k^T}\right]\underline{\mathbf{H}}^{i\mathbf{H}}, \tag{7}$$

$$\mathbf{D} = \underline{\mathbf{H}}^i\underline{\hat{\mathbf{x}}}^{i,k}, \tag{8}$$

$$\mathbf{R} = \sigma^2\mathbf{I}_M, \tag{9}$$

where $\mathbf{I}_{N-1}$ and $\mathbf{I}_M$ are $(N-1) \times (N-1)$ and $M \times M$ identity matrices, respectively. The optimum feed-forward and feedback coefficients are given by [6]

$$\mathbf{w}_j^{i,k^T} = \mathbf{H}_i^H\left(\mathbf{A} + \mathbf{B} + \mathbf{R} - \mathbf{D}\mathbf{D}^H\right)^{-1}, \tag{10}$$

$$c_b^{i,k^T} = -\mathbf{w}_j^{i,k^T}\mathbf{D}. \tag{11}$$

From Eq. (10), the complexity of computing an $M \times M$ inverse matrix is approximately in the order of M^3 [7]. Therefore, an adaptive algorithm is utilized in this paper to reduce a high computation complexity. The feed-forward coefficient vector $\mathbf{w}_j^{i,k}$ and feedback coefficient vector $\mathbf{w}_b^{i,k}$ defined in Eq. (2) are determined recursively by an adaptive least mean square (LMS) algorithm [8]. By using Eq. (2) to calculate the coefficients $\mathbf{w}_j^{i,k}(t)$ and $\mathbf{w}_b^{i,k}(t)$ adaptively for a particular time instant t, the mean squared error in Eq. (5) is given by

$$e(t) = E\left[\left|\mathbf{w}_j^{i,k^T}(t)\,\mathbf{r} + \mathbf{w}_b^{i,k^T}(t)\,\underline{\hat{\mathbf{x}}}^{i,k} - x_i^{i,k}\right|^2\right], \tag{12}$$

where

$$\mathbf{w}_j^{i,k}(t+1) = \mathbf{w}_j^{i,k}(t) + \mu_f e(t)\,\mathbf{r}(t), \tag{13}$$

$$\mathbf{w}_b^{i,k}(t+1) = \mathbf{w}_b^{i,k}(t) + \mu_b e(t)\,\underline{\hat{\mathbf{x}}}(t), \tag{14}$$

μ_f and μ_b are the step sizes for the feed-forward and feedback adaptations, respectively. As the LMS algorithm has a slow convergence, the partially filtered gradient LMS (PFGLMS) [9] algorithm based on an exponentially weighted least square error is used to improve the convergence speed of the LMS algorithm with a slight increase in complexity.

The conventional LMS algorithm requires $2M+1$ multiplications and the same number of additions for each received data symbol. However, the PFGLMS algorithm requires $4M+1$ multiplications and the same number of additions for each received data symbol. Therefore, the computation complexity is approximately in the order of M for both LMS and PFGLMS algorithm.

The modified feed-forward and feedback coefficients of the PFGLMS algorithm for MIMO systems are given by

$$\mathbf{w}_j^{i,k}(t+1) = \mathbf{w}_j^{i,k}(t) + \mu_f e(t)\,\mathbf{g}_j^{i,k}(t), \tag{15}$$

$$\mathbf{w}_b^{i,k}(t+1) = \mathbf{w}_b^{i,k}(t) + \mu_b e(t)\,\mathbf{g}^{i,k}(t), \tag{16}$$

where

$$\left.\begin{aligned} \mathbf{g}_f^{i,k}(t) &= e(t)\,\mathbf{x}(t) + \hat{\mathbf{g}}_f^{i,k}(t) \\ \hat{\mathbf{g}}_f^{i,k}(t) &= \lambda_f \hat{\mathbf{g}}_f^{i,k}(t-1) + \gamma_f e(t)\,\mathbf{x}(t) \end{aligned}\right\}, \tag{17}$$

$$\left.\begin{aligned} \mathbf{g}_b^{i,k}(t) &= e(t)\,\mathbf{x}(t) + \hat{\mathbf{g}}_b^{i,k}(t) \\ \hat{\mathbf{g}}_b^{i,k}(t) &= \lambda_b \hat{\mathbf{g}}_b^{i,k}(t-1) + \gamma_b e(t)\,\mathbf{x}(t) \end{aligned}\right\}, \tag{18}$$

where (λ_f,λ_b) and (γ_f,γ_b) are the forgetting factors and the scaling factors, respectively, and $\hat{\mathbf{g}}_f^{i,k}(0) = \hat{\mathbf{g}}_b^{i,k}(0) = 0$. In the proposed receiver structure, the well-known SISO MAP decoder takes the detection output of the detector, $y_t^{i,k}$, as a soft-input to the decoder.

The soft-output from the decoder is used to calculate the interference, which is subtracted for the decoder input in the next iteration. This iterative detection/decoding process is performed until the symbol estimate converges to the optimal performance. The soft-output from the decoder in the last iteration is then fed into a decision device to produce a decision. A BPSK modulation scheme is used.

The likelihood functions for the transmitted modulated symbols 1 and -1 can be written as [10]

$$P\left(y_t^{i,k} \middle| x_t^{i,k} = \pm 1\right) = \frac{1}{\sqrt{2\pi\sigma^2}} \exp \frac{-\left(y_t^{i,k} \mp 1\right)^2}{2\sigma^2}. \tag{19}$$

The log-likelihood ratios (LLR) determined in the kth iteration for the ith transmit layer, denoted by $\lambda_i^{i,k}$, are given by

$$\lambda_i^{i,k} = \log\left(\frac{P\left(x_t^{i,k}=1 \middle| y_t^{i,k}\right)}{P\left(x_t^{i,k}=-1 \middle| y_t^{i,k}\right)}\right). \tag{20}$$

The symbol a posteriori probabilities (APP) $P(x_t^{i,k} = q | y_t^{i,k}$, $q = 1,-1)$ conditioned on the output variable $y_t^{i,k}$ can then be obtained as

$$P\left(x_t^{i,k} = 1 \middle| y_t^{i,k}\right) = \frac{e^{\lambda_t^{i,k}}}{e^{\lambda_t^{i,k}+1}}, \tag{21}$$

$$P\left(x_t^{i,k} = -1 \middle| y_t^{i,k}\right) = \frac{1}{e^{\lambda_t^{i,k}+1}}. \tag{22}$$

The soft-output symbols estimate in the ith layer and kth iteration can be determined as

$$x_t^{i,k} = \frac{e^{\lambda_t^{i,k}} - 1}{e^{\lambda_t^{i,k}} + 1}. \tag{23}$$

3. Performance results

This section presents simulation results for the LSTC non-adaptive and adaptive iterative receivers with BPSK modulation in slow and fast Rayleigh fading channels. The slow fading channel is modelled as a quasi-static fading channel, where each fading coefficient is constant within a frame, but changes from one frame to another and for each sub-channel. The system operates in the training mode until the mean square error (MSE) approaches the minimum mean square error, then it switches to the decision directed mode. The constituent codes are nonsystematic convolutional codes with the code rate R of 1/2, memory order of 3, and the generating polynomial $g_1 = 15_8$ and $g_2 = 17_8$. The proposed system is simulated with 2 transmit and 2 receive antennas, i.e., a 2×2 MIMO system, with 260 information bits in each frame. After serial to parallel conversion, each layer of the LSTC system consists of 130 information bits, followed by 266 encoded symbols per layer. The data rate is 1 Mb/s at the carrier frequency, f_c, of 2 GHz. The simulation results are represented in terms of the average bit error rate (BER) versus the ratio of the averaged energy per bit, denoted by E_b, to the power spectral density of the AWGN, denoted by N_0.

3.1. Slow fading channel

The average BER of the non-adaptive iterative MMSE receiver for various numbers of iterations under the perfect channel knowledge assumption is shown in Fig. 3. The system performance is significantly improved for the second iteration compared to the first iteration and gradually increases for higher iterations. The BER curves also show that the performance converges to a steady state after the 3rd iteration. The performance of the adaptive iterative receiver based on the LMS algorithm and the non-adaptive iterative MMSE receiver are shown in Fig. 3.

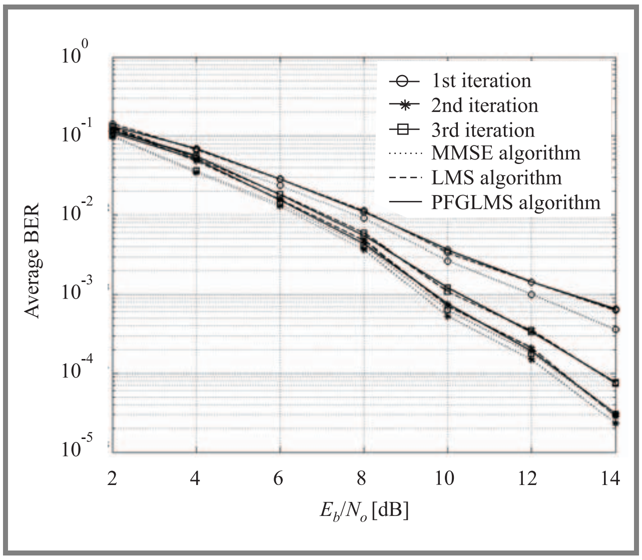

Fig. 3. Performance between the non-adaptive iterative MMSE algorithm and adaptive (LMS and PFGLMS) iterative algorithm in a quasi-static Rayleigh fading channel.

The results show that the average BER of the adaptive iterative structure approaches the performance results of the non-adaptive iterative MMSE receiver.

Figure 4 presents a comparison of the convergence speeds of the LMS and PFGLMS receiver at the 1st iteration. The figure shows that the convergence speed of the PFGLMS receiver outperforms that of the conventional LMS receiver.

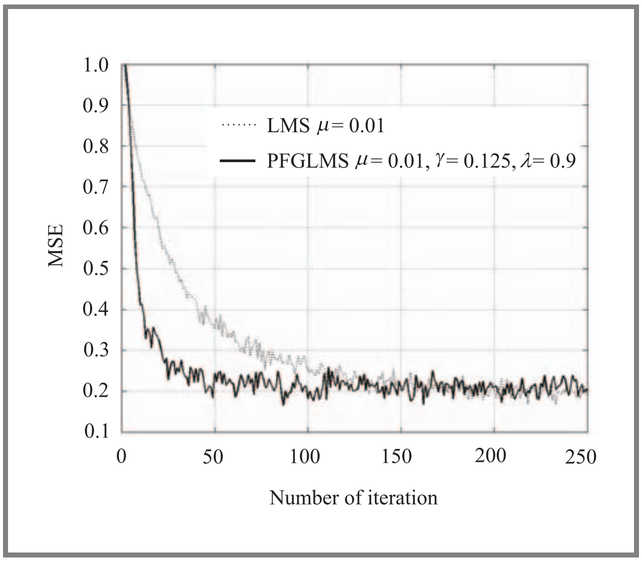

Fig. 4. The convergence speed of the conventional LMS and PFGLMS algorithm at $E_b/N_0 = 10$ dB.

The convergence rate of PFGLMS algorithm is about three times faster than that of the conventional LMS algorithm. However, the average BER of both structures is the same, as the average mean square error of the receivers is the same in a quasi-static fading channel.

3.2. Fast fading channel

The performance of the proposed receiver with the perfect knowledge of CSI at various fading rates is shown in Fig. 5. The figure shows that the average BER decreases when the fading rate is increased, since the MAP decoder performance is sensitive to the fade rates. When the fade

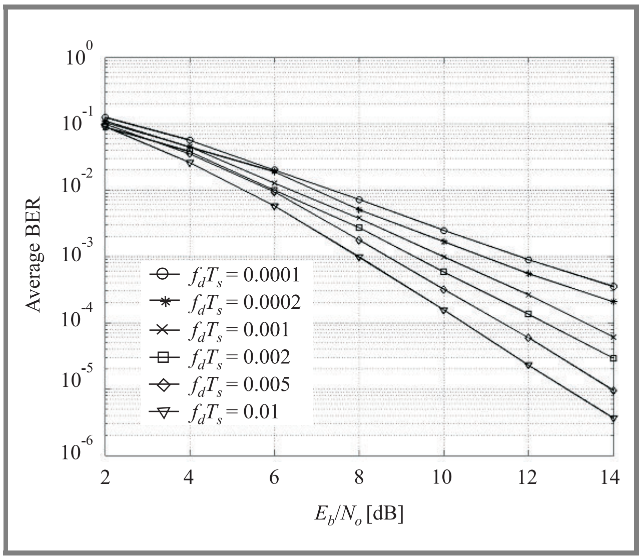

Fig. 5. Performance of the non-adaptive iterative MMSE receiver in various normalized fading rate with perfect channel knowledge.

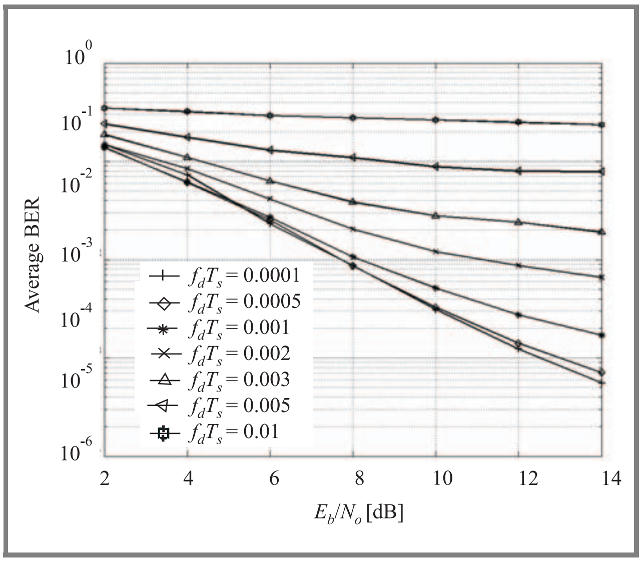

Fig. 6. Performance of the LMS adaptive iterative receiver in various normalized fading rate with imperfect channel knowledge.

rate is increased the inputs to the MAP decoder are less correlated and the decoder has a better performance. On the other hand, the LMS adaptive detector is sensitive to the channel estimation accuracy [11]. Therefore the average BER of the LMS adaptive iterative receiver is increased because of inaccurate channel estimation in fast fading channel. Therefore, the average BER of the LMS receiver increases when the fade rate is increased as shown in Fig. 6.

Figure 7 presents the comparison of the MMSE, LMS and PFGLMS receivers at the normalized fading rate of 0.0002.

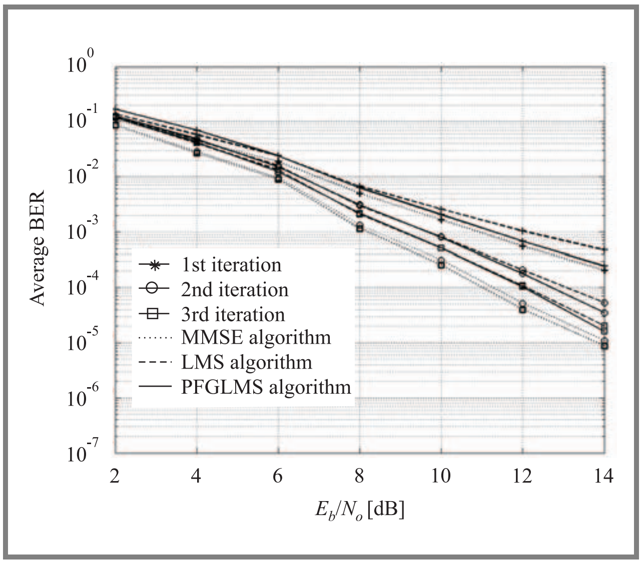

Fig. 7. Comparison between the non-adaptive iterative MMSE algorithm and adaptive (LMS and PFGLMS) iterative algorithm at the 0.0002 normalizes fading rate.

The result shows that the PFGLMS algorithm has a good tracking ability compared to the LMS algorithm on a fast fading channel. The average BER of the PFGLMS receiver is close to the average BER of MMSE receiver in the first iteration. Therefore, the PFGLMS receiver is more convenient for the fast fading channels.

4. Conclusion

A new adaptive iterative receiver for MIMO systems has been developed based on a joint adaptive iterative detection and decoding structure. The adaptive iterative receiver reduces co-channel interference by interference suppression and cancellation techniques. The comparison of the complexity is also consider only in the detector. The complexity of the proposed receiver is lower than that of the non-adaptive receiver because there is no matrix inversion. The complexity is reduced from the order of M^3 in non-adaptive receiver to the order of M in adaptive receiver in each received data symbol. However, there is a need for transmission of training sequences at the beginning of each simulation. Moreover, the proposed receiver based on the PFGLMS algorithm has a faster convergence speed and better tracking ability compared to the LMS receiver in fast fading channels with a slight increase in the complexity in term of the number of multiplier and adder. Therefore the PFGLMS receiver needs a shorter trainning period than that of LMS receiver. The performance of the proposed receiver approaches the one of non-adaptive iterative receiver.

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