RLS Channel Estimation and Tracking for MIMO-extended IEEE 802.11a WLANs

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Summary

Wireless communication systems based on multiple-input multiple-output (MIMO) technology and orthogonal frequency division multiplexing (OFDM) have the potential to achieve enormous increase in the capacity and link reliability. In order to realize such systems, channel estimation is crucial. In this paper, an adaptive channel estimation and tracking scheme based on recursive least squares (RLS) algorithm is proposed for MIMO OFDM-based wireless local area networks (WLANs). Preamble-aided channel estimation is performed in time-domain (TD). The estimator is then extended to perform decision-directed (DD) channel tracking during data transmission. The channel is assumed to be constant during one OFDM symbol and evolving in time according to the first-order Markov process. Different training rates at different Doppler frequencies were investigated. Simulation results show that the proposed estimation scheme has excellent performance measured in terms of the mean squares error (MSE) and the bit error rate (BER), provided that the forgetting factor of the RLS algorithm is optimally selected.

Key words: MIMO, OFDM, Channel estimation, RLS algorithm.

1. Introduction

Orthogonal frequency division multiplexing (OFDM) is an attractive technique for high data rate transmission over frequency-selective fading channels due to its capability to combat the intersymbol interference (ISI), low complexity, and spectral efficiency [1]. Using multiple-antennas (known as multiple-input multiple-output (MIMO) technology) at both the transmitter and receiver results in further increase in the capacity, provided that the environment is rich scattering [2].

The combination of MIMO and OFDM, referred to as MIMO OFDM, has been proposed as a very promising system for enhancing the capacity and improving the link reliability for future broadband wireless communication [3]. However, to obtain the promised capacity and to achieve maximum diversity gain, MIMO OFDM systems require accurate channel state information (CSI) at the receiver, in order to perform coherent detection, space-time decoding, diversity combining, and spatial interference suppression [4].

In MIMO OFDM systems, channel estimation based on either least squares (LS) or minimum mean squares error (MMSE) methods has been widely explored and several estimation schemes have been proposed [5], [6].

Channel estimation based on adaptive filtering has been proposed as an appropriate solution for estimating and tracking the time-varying channels in mobile environments. For example, in [7], a frequency-domain (FD) adaptive Wiener filter channel estimator for OFDM systems has been proposed, where the normalized least-mean-square (NLMS) and recursive least squared (RLS) algorithms are used to estimate the time-varying channel. In [8], a two-dimensional RLS adaptive channel estimator for OFDM systems that exploit the time-domain (TD) and FD correlations was proposed. In [9], flat-fading MIMO channel tracking based on decision-directed (DD) RLS algorithm was considered.

Channel estimation in TD is attractive over its counterpart in FD due to its lower computational complexity, accuracy, and effective channel impulse response tracking especially when the channel is time-varying [10].

In this paper, adaptive TD channel estimation and tracking, based on exponentially weighted (EW) RLS algorithm, is investigated for MIMO-extended OFDM-based WLAN systems (IEEE 802.11a standard). The estimated channel impulse response (CIR) is Fourier transformed and zero forcing (ZF) equalization is performed in FD. The time evolution of the channel is modeled according to the first-order Markov process, and the time variations of channel estimates are tracked through applying the DD method. The computational complexity is significantly reduced by recursively updating the channel estimates and by applying the matrix inversion lemma.

The rest of this paper is organized as follows. In Section II, MIMO OFDM system model is briefly introduced. In section III, the EW-RLS estimator is derived. In Section IV, first-order Markov process is described. Simulation results are presented for 2×2 MIMO OFDM WLAN system in Section V, and conclusions are drawn in Section VI.

2. System Model

2.1 Wireless Channel Model

Assume sufficient antenna element spacing so that the subchannels between different transmit-receive antenna pairs are spatially uncorrelated, and have impulse responses of equal maximum resolvable paths L. Each subchannel is assumed to be slowly time-varying frequency-selective fading so that it can be considered as a constant during one OFDM symbol. The time-variant complex baseband CIR between the *p*th transmit and the *q*th receive antennas can be described as

$$h_{pq}(\tau,t)=\sum_{l=0}^{L-1}\beta_{pq}(l)\delta(\tau-\tau_l) \qquad (1)$$

where $\beta(l)$ and τ_l represent the gain and the delay of the path *l*, respectively, and $\delta(t)$ is the Dirac delta function. The path gains $\beta(l)$'s are modelled as independent and identically distributed (i.i.d.) wide-sense stationary (WSS) complex Gaussian random variables with zero-mean and variance σ_l^2. They are represented as

$$\beta_{pq}(l)=\alpha_{pq}(l)e^{j(\theta_l+2\pi f_{D,l}t)} \qquad (2)$$

where $\alpha(l)$, θ_l, and $f_{D,l}$ denote the amplitude, the phase, and the Doppler shift of the *l*th path, respectively. Assuming isotropic scattering, the autocorrelation of the path gains is expressed as [11]

$$r_l(\tau)=E\{\beta_l^*(t)\beta_l(t+\tau)\}=\sigma_l^2 J_0(2\pi f_{D\max}\tau) \quad (3)$$

where σ_l^2 is the power of the *l*th path gain, $J_0(x)$ is the Bessel function of the first kind of order 0, and $f_{D\max}$ is the maximum Doppler frequency which is related to the velocity ν of movement and the wavelength λ of the carrier frequency by $f_{D\max}=\nu/\lambda$.

2.2 MIMO OFDM Systems

A typical baseband MIMO OFDM system with M_t transmit antennas, M_r receive antennas, and *K* subcarriers is depicted in Fig. 1. The TD $K\times 1$ received signal $\tilde{\mathbf{y}}_q(m)$ at the *q*th receive antenna at time *m* is a noisy superposition of the transmitted signals from M_t transmit antennas, and can be represented in a matrix-vector form as

$$\tilde{\mathbf{y}}_q(m)=\sum_{p=1}^{M_t}\tilde{\mathbf{X}}_p(m)\mathbf{h}_{pq}(m)+\mathbf{v}_q(m) \qquad (4)$$

where

$$\tilde{\mathbf{X}}_p(m)=[\mathbf{x}_p^H(m,0),\mathbf{x}_p^H(m,1),\cdots,\mathbf{x}_p^H(m,N-1)]^H$$

denotes a $N\times L$ Toeplitz matrix containing delayed versions of the input data sent from the *p*th transmit antenna, in which

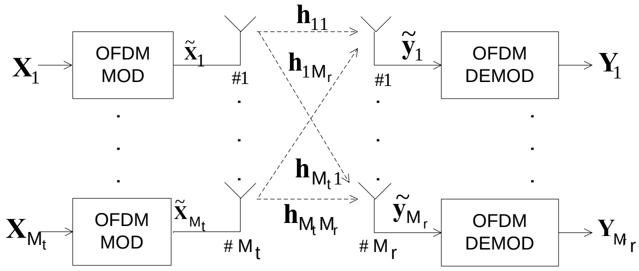

Fig.1. Baseband MIMO OFDM system model

$$\mathbf{x}_p(m,i)=[x_p(m,i),x_p(m,i-1),\cdots,x_p(m,i-L+1)] \;,$$

$$\mathbf{h}_{pq}(m)=[h_{pq}(m,0),h_{pq}(m,1),\ldots,h_{pq}(m,L-1)]^T$$

is an $L\times 1$ CIR between the *p*th transmit and the *q*th receive antennas. The $K\times 1$ vector $\mathbf{v}_q(m)$ represents additive white Gaussian noise (AWGN) at the *q*th receive antenna with complex elements that are independent and identically distributed (i.i.d.) Gaussian with zero mean and variance σ_v^2.

The FD received signal at the *q*th antenna over the *k*th tone at the time *m*, $Y_q(m,k)$, can be expressed as

$$Y_q(m,k)=\sum_{p=1}^{M_t}H_{pq}(m,k)X_p(m,k)+V_q(m,k) \quad (5)$$

where $X_p(m,k)$, $H_{p,q}(m,k)$, and $V_q(m,k)$ denote the *k*th data sample of the transmitted OFDM symbol from the *p*th antenna, the channel coefficient of the *k*th tone between the *p*th transmit and the *q*th receive antennas, and the AWGN at the qth receive antenna on the *k*th tone, respectively.

3. MIMO Channel Estimation and Tracking

In this section, the adaptive EW-RLS estimator is presented. The channel estimates are updated recursively upon receiving new training symbols. Synchronized replicas of the training symbols, locally stored at the receiver will act as references. In the following, the RLS estimator is derived.

3.1 RLS Estimator Derivation

To derive the EW-RLS-based MIMO OFDM channel estimator, first, we define the estimation error, and then the cost function (defined as the weighted sum of error squares) is optimized against the taps of the channel under estimation. Since channel estimation is carried out during the time interval of one OFDM symbol, the time index *m* will be omitted in the following. The *a posteriori* estimation error is defined as the difference between the noisy received signal and its estimate. In TD, it can be expressed in a matrix-vector form as

$$\mathbf{e}_q(n) = \tilde{\mathbf{y}}_q(n) - \hat{\tilde{\mathbf{y}}}_q(n) = \tilde{\mathbf{y}}_q(n) - \tilde{\mathcal{X}}(n)\tilde{\mathbf{h}}_{n,q} \quad (6)$$

where n denotes the observation time index and $\tilde{\mathcal{X}}(n) = [\tilde{\mathbf{X}}(0), \tilde{\mathbf{X}}(1), \cdots, \tilde{\mathbf{X}}(n)]^H$ is an $(n+1) \times M_t L$ input matrix with $\tilde{\mathbf{X}}(i) = [\mathbf{x}_1(i), \mathbf{x}_2(i), \cdots, \mathbf{x}_{M_t}(i)]^H$ representing an $1 \times M_t L$ vector of the relative inputs into the adaptive filter at the instant *i*. The vectors $\mathbf{x}_p(i)$ may written as $\mathbf{x}_p(i) = [x_p(i), x_p(i-1), \ldots, x_p(i-L+1)]$, and $\tilde{\mathbf{h}}_{n,q} = [\mathbf{h}^T_{n,1q}, \mathbf{h}^T_{n,2q}, \cdots, \mathbf{h}^T_{n,M_t q}]^T$ is a $M_t L \times 1$ vector that contains the stacked vectors of the CIRs from the transmit antennas to the *q*th receive antenna, which are under estimate at time instant *n*, with $\mathbf{h}_{n,pq}$ denotes a $L \times 1$ vector of the CIR between the *p*th transmit and *q*th receive antennas, and is defined as $\mathbf{h}_{n,pq} = [h_{n,pq}(0), h_{n,pq}(1), \ldots, h_{n,pq}(L-1)]^T$.

The estimation error $\mathbf{e}_q(n)$ is used to recursively adjust the adaptive filter tap-weight vector $\tilde{\mathbf{h}}_{n,q}$, which corresponds to the taps of the channel under estimation. The optimum channel estimate can be obtained by minimizing the exponentially weighted cost function $J_q(n)$, which is defined as

$$J_q(n) = \mathbf{\Lambda}^2(n)\left|\tilde{\mathbf{y}}_q(n) - \tilde{\mathcal{X}}(n)\tilde{\mathbf{h}}_{n,q}\right|^2 \quad (7)$$

where $\Lambda^2(n) = diag[\lambda^n, \lambda^{n-1}, \cdots, \lambda, 1]$ is an $(n+1) \times (n+1)$ weighting matrix with λ is a positive scalar called forgetting factor ($0 << \lambda < 1$). The optimum estimates of the subchannels, $\mathbf{h}_{n,pq}$, that minimize $J_q(n)$ are found by setting the partial derivatives of $J_q(n)$ with respect to $\tilde{\mathbf{h}}_{n,pq}$ equal to zero. By solving the resulting equations for the optimum $\hat{\mathbf{h}}_{n,pq}$, we have

$$\mathbf{R}(n)\hat{\mathbf{h}}_{n,q} = \mathbf{Z}(n) \quad (8)$$

where $\mathbf{R}(n)$ is an $M_t L \times M_t L$ EW autocorrelation matrix of the inputs $\tilde{\mathbf{X}}(n)$, and is defined as

$$\mathbf{R}(n) = [\mathbf{\Lambda}(n)\tilde{\mathcal{X}}(n)]^H \mathbf{\Lambda}(n)\tilde{\mathcal{X}}(n) = \sum_{i=0}^{n} \lambda^{n-i} \tilde{\mathbf{X}}^H(i)\tilde{\mathbf{X}}(i) \quad (9)$$

and $Z(n)$ is an $M_t L \times 1$ vector of EW cross-correlation between the inputs $\mathbf{X}(n)$ and noisy received signal $y_q(n)$, and is defined as

$$\mathbf{Z}(n) = [\mathbf{\Lambda}(n)\tilde{\mathcal{X}}(n)]^H \mathbf{\Lambda}(n)\tilde{\mathbf{y}}_q(n) = \sum_{i=0}^{n} \lambda^{n-i} \tilde{\mathbf{X}}^H(i) y_q(i) \quad (10)$$

Hence, the channel estimate $\hat{\mathbf{h}}_{n,q}$ can be obtained by solving (8) as

$$\hat{\mathbf{h}}_{n,q} = \mathbf{R}^{-1}(n)\,\mathbf{Z}(n) \quad (11)$$

where $\hat{\mathbf{h}}_{n,q} = [\hat{\mathbf{h}}^T_{n,1q}, \hat{\mathbf{h}}^T_{n,2q}, \cdots, \hat{\mathbf{h}}^T_{n,M_t q}]^T$ is a $M_t L \times 1$ vector of MIMO channel estimate at time instant *n* at the *q*th receive antenna. The computation complexity of (11) is significantly reduced by recursively updating the inverse of the matrices $\mathbf{R}(n)$ and the vectors $\mathbf{Z}(n)$ as

$$\mathbf{R}(n) = \lambda\mathbf{R}(n-1) + \tilde{\mathbf{X}}^H(n)\tilde{\mathbf{X}}(n) \quad (12)$$

$$\mathbf{Z}(n) = \lambda\mathbf{Z}(n-1) + \tilde{\mathbf{X}}^H(n) y_q(n) \quad (13)$$

The inverse of the recursion in (11) can be avoided by invoking the matrix inversion lemma [12], to obtain

$$\mathbf{R}^{-1}(n) = \lambda^{-1}\mathbf{R}^{-1}(n-1) - \lambda^{-1}\mathbf{G}(n)\tilde{\mathbf{X}}^H(n)\mathbf{R}^{-1}(n-1) \quad (14)$$

Finally, the time update of the subchannels estimates $\hat{\mathbf{h}}_{n,q}$, at time *n*, can be easily shown to be given by

$$\hat{\mathbf{h}}_{n,q} = \hat{\mathbf{h}}_{(n-1),q} + \mathbf{G}(n)[y_q(n) - \tilde{\mathbf{X}}(n)\hat{\mathbf{h}}_{(n-1),q}] \quad (15)$$

where $\mathbf{G}(n)$ is referred to as the gain vector and is given by

$$\mathbf{G}(n) = \frac{\lambda^{-1}\mathbf{R}^{-1}(n-1)\tilde{\mathbf{X}}^H(n)}{1 + \lambda^{-1}\tilde{\mathbf{X}}(n)\mathbf{R}^{-1}(n-1)\tilde{\mathbf{X}}^H(n)} \quad (16)$$

3.2 First-order Markov Model

Assuming that the CIR taps are slowly varying and fade at the same Doppler rate, then it may be possible to statistically describe such variations according to the first-order Markov process as follows [13]

$$\mathbf{h}(n+1) = \mathbf{A}\mathbf{h}(n) + \boldsymbol{\omega}(n) \tag{17}$$

where $\mathbf{h}(n)$ is the optimum channel estimate at time n, $\boldsymbol{\omega}(n)$ denotes the process noise vector, $\mathbf{A} = a\mathbf{I}$ is state transition matrix with $a = J_0(2\pi f_{D_{\max}} T_s)$ is a constant parameter which is very close to unity, $f_{D_{\max}}$ denotes maximum Doppler frequency, and T_s is the OFDM symbol duration.

4. Simulation Results

For the simulations, 2×2 MIMO OFDM system with K = 64 subcarriers and a cyclic prefix of length N_{CP} = 8 samples is considered. Channel bandwidth B = 20 MHz and sampling frequency $f_s = 20$ MHz are set as in IEEE 802.11a standard [14]. Quadrature phase-shift keying (QPSK) modulation is used. The CIRs between transmit-receive antenna pairs are assumed to be uncorrelated with maximum length of $L = 8$ taps. The performance is evaluated in terms of the MSE of the channel estimate, which is defined as $MSE = E\{|\mathbf{h}(n) - \hat{\mathbf{h}}(n)|^2\}$, and the system BER, for different Doppler frequencies. The MSE results are obtained by running Monte Carlo simulations on 10000 channel realizations, and the BER performance is measured by averaging over 1000 OFDM blocks. The optimum forgetting factor is selected via simulations to be $\lambda = 0.995$ and perfect synchronization between the transmitter and the receiver is assumed.

The MSE of channel estimates versus SNR are shown in Figs. 2 and 3, while the BER performance versus SNR is shown in Figs. 4 and 5, for different Doppler frequencies and training rates of 10% and 4%, respectively.

From Figs. 2 and 3 we observe that the MSE performance of the estimator is almost the same when the channel is experiencing low Doppler frequencies, regardless of training rate. However, very small degradation in the MSE of the channel estimates is noticed for training rate of 4%, compared to 10%, especially at high SNR and higher Doppler frequencies. This increase in the MSE pertains mainly to the decision errors created during the operation of channel estimator in the DD-mode. In Figs. 4 and 5, the BER performance versus SNR, with DD channel tracking. The BER for perfectly known channel is also demonstrated to give a lower bound for channel tracking performance. As it can be noticed, the BER curves obtained with channel tracking (solid curves) are very close to those obtained with perfect channel (dashed curves), especially at low Doppler frequencies (low mobility) and low SNR. However, small degradation in the BER relative to that of perfectly known channel has occurred at high SNR and higher Doppler frequencies. This degradation is mainly due to the decision error propagation arising when the estimator switches its operation into the DD-mode and also due to the mismatch between the actual time-correlation of the channel taps and the assumed first-order Markov process model used.

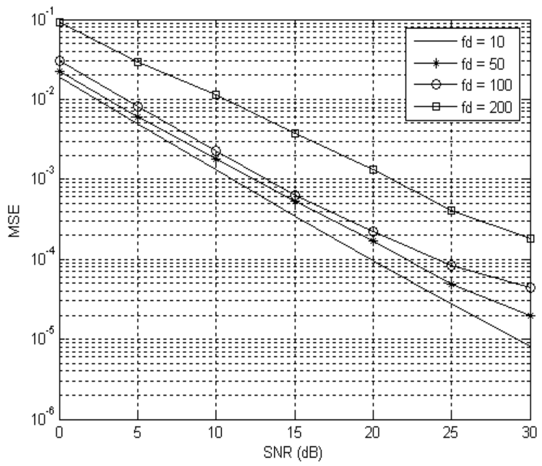

Fig. 2: MSE of channel estimates of the DD EW-RLS estimator with 10% training data.

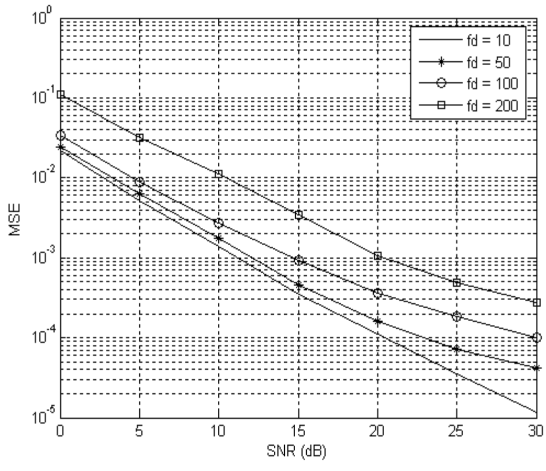

Fig. 3: MSE of channel estimates of the DD EW-RLS estimator with 4% training data.

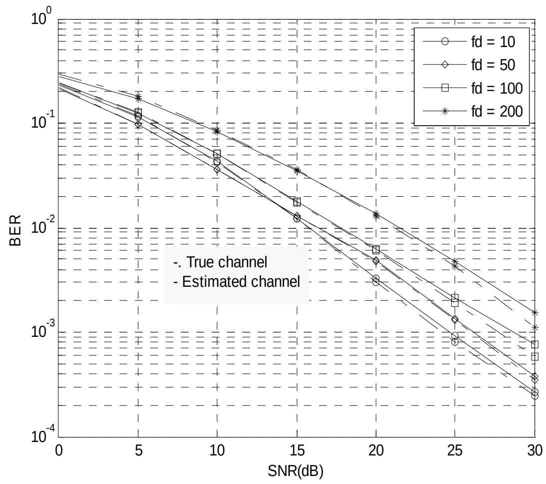

Fig. 4: The BER performance vs. SNR, with DD EW-RLS channel tracking and 10% training data.

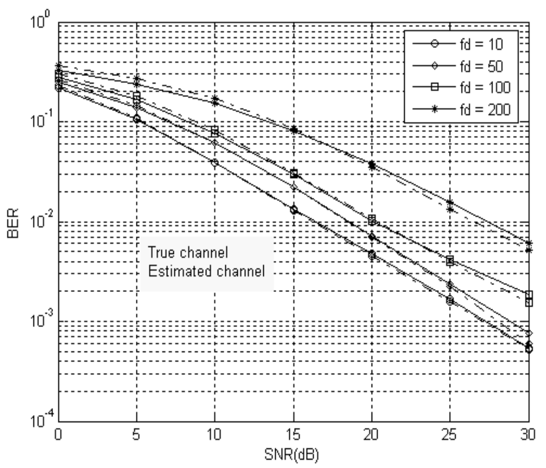

Fig. 5: The BER performance vs. SNR, with DD EW-RLS channel tracking and 4% training data.

5. Conclusion

In this paper, adaptive TD channel estimation and tracking based on EW-RLS algorithm is investigated for MIMO OFDM WLAN systems. The computational complexity is significantly reduced by recursively updating the channel estimates and by applying the matrix inversion lemma. Simulation results show that the proposed estimator has excellent performance (very close to the ideal) over slowly to moderate time-varying channels and at low SNR. In channels where higher Doppler frequencies are experienced, the performance can be improved by increasing the training rates.

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