Estimation of OFDM Time-Varying Fading Channels Based on Two-Cross-Coupled Kalman Filters

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***Abstract*—This paper deals with the estimation of rapidly time-varying Rayleigh fading channels in Orthogonal Frequency Division Multiplexing (OFDM) mobile wireless systems. When the fading channel is approximated by an Autoregressive (AR) process, it can be estimated by means of Kalman filtering. Nevertheless, the AR model order has to be selected. In addition, the AR parameters must be estimated. One standard solution to obtain the AR parameters consists in first fitting the AR process autocorrelation function to the theoretical Jakes one and then solving the resulting Yule-Walker Equations (YWE). However, this approach requires the Doppler frequency which is usually unknown. To avoid the estimation of the Doppler frequency, the joint estimation of both the channel and its AR parameters can be addressed. Instead of using the Expectation-Maximization (EM) algorithm which results in large storage requirements and high computational cost, we propose to consider a structure based on two-cross-coupled Kalman filters. It should be noted that the Kalman filters are all the more interactive as the variance of the innovation of the first filter is used to drive the Kalman gain of the second. Simulation results show the effectiveness of this approach especially in high Doppler rate environments.**

***Index Terms*—Autoregressive processes, Rayleigh fading channels, Jakes model, Kalman filters, OFDM.**

I. INTRODUCTION

Orthogonal Frequency Division Multiplexing (OFDM) is a parallel data transmission scheme in which high data rates can be achieved by the simultaneous transmission over many orthogonal carriers [1][2]. This multi-carrier transmission scheme makes it possible to convert the severe wide-band frequency-selective fading channel into many narrow-band frequency non-selective flat fading sub-channels, which are free from Inter-Symbol Interference (ISI). Due to the various advantages of OFDM, it has been adopted in many wide-band digital communication systems such as digital audio and video broadcasting, Asynchronous Digital Subscriber Lines (ADSL), IEEE 802.11 a/g Wireless Local Area Networks (WLAN), etc. [3].

In OFDM systems, due to user mobility, each carrier is subject to Doppler shifts resulting in time-varying fading. Thus, the estimation of the fading process over each carrier is essential to achieve coherent symbol detection at the receiver. In that case, training sequence/pilot aided techniques and blind techniques are two basic families for channel estimation [4]. In this paper, as blind techniques require longer observation window and have higher complexity than training based techniques, we will focus our attention on training based channel estimation techniques.

The time-varying Rayleigh fading channels are usually modeled as zero-mean wide-sense stationary circular complex Gaussian processes, whose stochastic properties depend on the maximum Doppler frequency denoted by f_d . According to the Jakes model [5], the theoretical Power Spectrum Density (PSD) associated with either the in-phase or quadrature portion of the fading process, is band-limited and U-shaped. Moreover, it exhibits twin peaks at $\pm f_d$. This key information about channel statistics cannot be however exploited when directly estimating the fading processes by means of the Least Mean Square (LMS) and the Recursive Least Square (RLS) algorithms as in [6]. Alternatively, Kalman filtering combined with an Autoregressive (AR) model to describe the time evolution of the fading processes is shown to provide superior Bit Error Rate (BER) performance over the LMS and RLS based channel estimators [6] [7]. Nevertheless, the AR model order has to be selected. In addition, the AR model parameters are unknown and, hence, must be estimated.

On the one hand, several authors (e.g., [7][8][9][10]) have expressed the AR parameters by first fitting a low-order AR process autocorrelation function to the theoretical Jakes one and then solving the resulting Yule-Walker Equations (YWE). However, this requires the preliminary estimation of the maximum Doppler frequency, which is not necessarily a trivial task [11].

On the other hand, the AR parameters can be estimated from the received noisy signal. Among the existing methods, Tsatsanis *et al.* [12] have proposed to estimate the AR parameters from estimates of the channel covariance function, by means of a standard Yule-Walker estimator. However, this method results in biased AR parameter estimates. In [13], Cai *et al.* have proposed a channel estimation scheme for OFDM wireless systems based on two-serially-connected Kalman or H_∞ filters. The first one is used for AR parameter estimation and the second one for fading process estimation. Nevertheless, the AR parameter estimates are biased since they are estimated directly from the noisy data. This might result in poor estimation of the fading process. To avoid this drawback, one can look at other approaches proposed in other fields than mobile communications. Thus, the Expectation-Maximization (EM) algorithm which often implies a Kalman smoothing could be used [14]. Nevertheless, since it operates repeatedly on a batch of data, it results in large storage requirements and high computational cost. In addition, its success depends on the initial conditions. As an alternative, two recursive filters could be cross-coupled to solve the so-called dual estimation issue [15], i.e. the estimations of both the AR process and its parameters. Each time a new observation is available, the first filter uses the latest estimated AR parameters to estimate the signal, while the second filter

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uses the estimated signal to update the AR parameters. According to Gannot [16], this dual filtering approach can be viewed as a sequential version of the EM algorithm. Recently, a variant [17] based on two-cross-coupled Kalman filters has been developed in which the variance of the innovation process in the first filter is used to define the gain of the second filter. As this solution can be seen as a recursive instrumental variable technique, consistent estimates of the AR parameters are obtained. Meanwhile, we have analyzed the relevance of this approach to estimate Multi-Carrier Direct-Sequence Code Division Multiple Access (MC-DS-CDMA) fading channels in [18].

In this paper, we propose to take advantage of the two-cross-coupled Kalman filters for the joint estimation of time-varying OFDM fading channels and their corresponding AR parameters. See Fig. 1. In addition, both low and high order AR models are investigated.

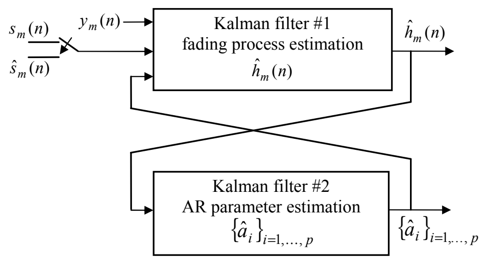

Fig. 1. Two-cross-coupled Kalman filter based structure for the joint estimation of the fading process and its AR parameters along the m^{th} carrier.

The remainder of the paper is organized as follows. In section II, we recall the OFDM system model. The estimation of the fading channels based on two-cross-coupled Kalman filters with high-order AR models is introduced in section III. Simulation results are reported in section IV. Conclusion remarks are drawn in section V.

II. OFDM System Model

Let us consider a standard OFDM system as shown in Fig. 2. In this system, the input serial data stream is firstly converted into parallel data blocks. An Inverse Fast Fourier Transform (IFFT) is performed on each block and a guard interval to eliminate the Inter-Symbol Interference (ISI) is then added before they are transmitted through the channel. The transmitted OFDM signal is assumed to go through a rapidly time-varying frequency-selective Rayleigh fading channel. At the receiver, the FFT is performed on each received OFDM symbol after the guard interval being removed. Thus, with proper selection of the guard interval and perfect carrier synchronization, the received signal sample over the m^{th} carrier for the n^{th} OFDM symbol can be written in the following manner

$$y_m(n) = h_m(n)s_m(n) + w_m(n), \qquad m = 1, 2, \ldots, M \tag{1}$$

where $s_m(n)$ is the m^{th} information symbol of the n^{th} OFDM symbol, $h_m(n)$ is the fading process over the m^{th} carrier during the n^{th} OFDM symbol, $w_m(n)$ is an Additive White Gaussian Noise (AWGN) process, and N is the total number of carriers. The information symbols $s_m(n)$ are assumed to be drawn from Quadrature Phase shift Keying (QPSK) constellation $\{1, -1, j, -j\}$ independently for different *m* and *n*. The noise processes $\{w_m(n)\}_{m=1,\ldots,M}$ are assumed to be mutually independent and identically distributed zero-mean complex Gaussian processes, with equal variance σ_w^2. The fading process over the m^{th} carrier $h_m(n) = \beta_m(n)e^{j\theta_m(n)}$ is assumed to be a zero-mean complex Gaussian process with uniformly distributed phase $\theta_m(n)$ on $[0, 2\pi[$ and a Rayleigh distributed envelop $\beta_m(n)$. The variances of the fading processes $\{h_m(n)\}_{m=1,\ldots,M}$ are all assumed equal to σ_h^2.

The stochastic characteristics of the m^{th} carrier fading process $h_m(n)$ depend on the maximum Doppler frequency:

$$f_d = v f_c / c \tag{2}$$

where v is the mobile speed, f_c is the central carrier frequency and c is the light speed.

According to [5], the theoretical Power Spectral Density (PSD) associated with either the in-phase or quadrature portion of the fading process $h_m(n)$ is band-limited and U-shaped. Moreover, it exhibits two peaks at $\pm f_d$ as follows:

$$\Psi_{hh}(f) = \begin{cases} \dfrac{1}{\pi f_d \sqrt{1-(f/f_d)^2}}, & |f| \le f_d \\ 0, & \text{else where} \end{cases} \tag{3}$$

Its corresponding normalized discrete-time Autocorrelation Function (ACF) hence satisfies:

$$R_{hh}(n) = J_0\left(2\pi f_d T_s |n|\right) \tag{4}$$

where $J_0(.)$ is the zero-order Bessel function of the first kind, T_s is the symbol period, and $f_d T_s$ denotes the Doppler rate.

III. Kalman Filtering based Channel Estimation

A. AR Modeling of Rayleigh Fading Channels

To exploit the statistical properties of the fading channel given by its PSD and ACF, the fading process over the m^{th} carrier can be modeled by a p^{th} order AR process, denoted by AR(*p*) and defined as follows [7][19]:

$$h_m(n) = -\sum_{i=1}^{p} a_i h_m(n-i) + u_m(n) \tag{5}$$

where $\{a_i\}_{i=1,\ldots,p}$ are the AR model parameters and $u_m(n)$ denotes the zero-mean complex white Gaussian driving process with equal variance σ_u^2 over all carriers.

However, selecting a low-order AR model for the channel is debatable. Some authors [7][12] choose first or second order AR process, as it is simple and the corresponding computational cost is low. Nevertheless, a deterministic model should be used for the channel due to the band-limited nature of its PSD according to Kolmogoroff-Szego formula [20]:

$$\sigma_u^2 = \exp\left(\frac{1}{2\pi}\int_{-\pi}^{\pi} \ln\left(\Psi_{hh}(\omega)\right) d\omega\right) \tag{6}$$

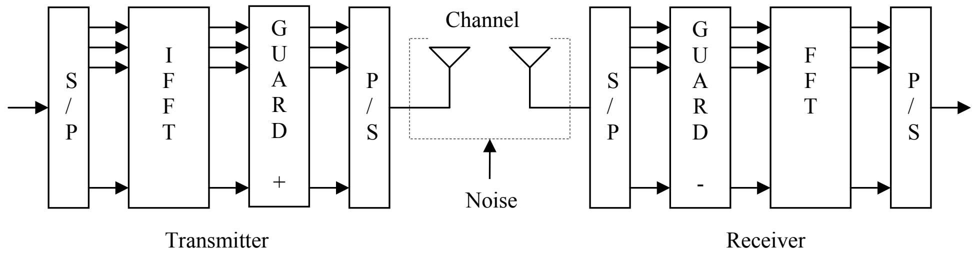

Fig.2: OFDM System.

where $\Psi_{hh}(\omega)$ denotes the PSD of the AR process that fits the theoretical Jakes spectrum. Meanwhile, alternative solutions have been also studied. Firstly, a sub-sampled AR Moving Average (ARMA) process followed by a multistage interpolator has been used by Schafhuber *et al.* [21] in the framework of channel simulation. Nevertheless, only a very high down-sampling factor leads to a PSD which is never equal to 0. Secondly, Baddour *et al.* [19] use high-order AR processes (e.g. $p \geq 50$) when they simulate the channel. For this purpose, they modify the properties of the channel by considering the sum of the theoretical fading process and a zero-mean white process whose variance ε very small (e.g., $\varepsilon = 10^{-7}$ for $f_d T_s = 0.01$). Then, the AR parameters are estimated with the Yule-Walker (YW) equations based on the modified autocorrelation function

$$R_{hh}^{\text{mod}}(n) = J_0\left(2\pi f_d T_s |n|\right) + \varepsilon\delta(n) \tag{7}$$

Taking into account the above discussion, we propose in this paper to use an AR model whose order is high enough to approximate the channel. Fig. 3 and Fig. 4 show, respectively, the autocorrelation function and the power spectrum density of the Jakes model and that of the fitted AR process whose order is 1, 2, 5 and 20.

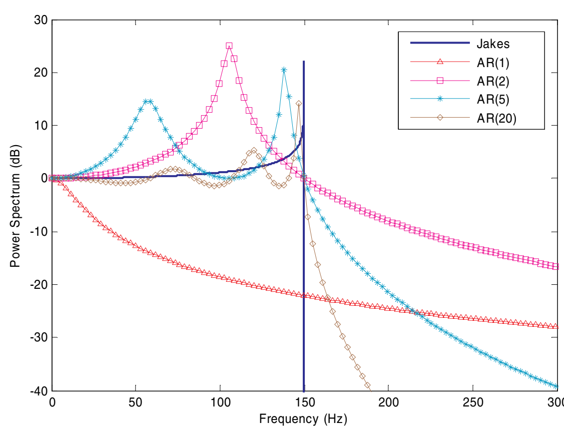

Fig. 3. Power spectral density of the Jakes model and that of the fitted AR (p) process with p=1, 2, 5, and 20. $f_d = 150\,\text{Hz}$ and $f_d T_s = 0.05$.

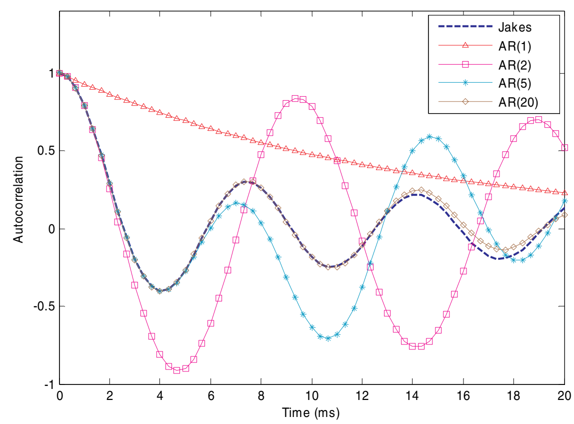

Fig. 4. Autocorrelation function of the Jakes model and that of the fitted AR (p) process with p=1, 2, 5, and 20. $f_d = 150\,\text{Hz}$ and $f_d T_s = 0.05$.

In the following, as $R_{hh}(n)$ is usually unknown, we propose to complete the joint estimation of the fading process $h_m(n)$ and its AR parameters.

A. *Estimation of the Fading Processes*

To estimate the fading process $h_m(n)$ along the m^{th} carrier, let us define the state vector as follows:

$$\mathbf{h}(n) = \left[h(n) \quad h(n-1) \quad \Lambda \quad h(n-p+1)\right]^T \tag{8}$$

Note that, for the sake of simplicity and clarity of presentation, the carrier subscript is dropped. Then, equation (5) can be written in the following state space form:

$$\mathbf{h}(n) = \mathbf{\Phi}\,\mathbf{h}(n-1) + \mathbf{g}\,u(n) \tag{9}$$

where:

$$\mathbf{\Phi} = \begin{bmatrix} -a_1 & -a_2 & \dots & -a_p \\ 1 & 0 & \dots & 0 \\ & \ddots & & \vdots \\ 0 & \dots & 1 & 0 \end{bmatrix} \text{ and } \mathbf{g} = \begin{bmatrix}1 & 0 & \cdots & 0\end{bmatrix}^T \tag{10}$$

In addition, given (1) and (8), one has:

$$y(n) = \mathbf{s}^T(n)\mathbf{h}(n) + w(n) \tag{11}$$

where $\mathbf{s}(n) = \left[s(n) \quad 0 \quad \cdots \quad 0\right]^T$.

Hence, equations (9) and (11) define the state space representation dedicated to the one-carrier fading channel system (1) and (5). At that stage, a standard Kalman filtering algorithm can be carried out to provide the estimation $\hat{\mathbf{h}}(n/n)$ of the state vector $\mathbf{h}(n)$ given the set of observations $\{y(i)\}_{i=1,\dots,n}$ as listed below:

The so-called innovation process $\alpha(n)$ is first obtained:

$$\alpha(n)=y(n)-\mathbf{s}^T(n)\mathbf{\Phi}\hat{\mathbf{h}}(n-1/n-1) \tag{12}$$

Its variance is then defined:

$$C(n)=E[\alpha(n)\alpha^*(n)]=\mathbf{s}^T(n)\mathbf{P}(n/n-1)\mathbf{s}(n)+\sigma_w^2 \tag{13}$$

where the so-called *a priori* error covariance matrix $\mathbf{P}(n/n-1)$ can be recursively obtained as follows:

$$\mathbf{P}(n/n-1)=\mathbf{\Phi}\mathbf{P}(n-1/n-1)\mathbf{\Phi}^H+\mathbf{g}\sigma_u^2\mathbf{g}^T \tag{14}$$

The Kalman gain is calculated in the following manner:

$$\mathbf{K}(n)=\mathbf{P}(n/n-1)\mathbf{b}(n)C^{-1}(n) \tag{15}$$

The *a posteriori* estimate of the state vector and the fading process are respectively given by:

$$\hat{\mathbf{h}}(n/n)=\mathbf{\Phi}\hat{\mathbf{h}}(n-1/n-1)+\mathbf{K}(n)\alpha(n) \tag{16}$$

and

$$\hat{h}(n/n)=\mathbf{g}^T\hat{\mathbf{h}}(n/n) \tag{17}$$

The error covariance matrix is updated as follows:

$$\mathbf{P}(n/n)=\mathbf{P}(n/n-1)-\mathbf{K}(n)\mathbf{s}^T(n)\mathbf{P}(n/n-1) \tag{18}$$

It should be noted that the state vector and the error covariance matrix are initially assigned to zero vector and identity matrix respectively, i.e. $\hat{\mathbf{h}}(0/0)=\mathbf{0}$ and $\mathbf{P}(0/0)=\mathbf{I}_p$.

However, equations (12)-(18) can be carried out providing the AR parameters that are involved in the transition matrix $\mathbf{\Phi}$ and the driving process variance σ_u^2 are available. They will be estimated in the next two subsections.

B. Estimation of the AR Parameters

To estimate the AR parameters from the estimated fading process $\hat{h}(n)$, equations (16) and (17) are firstly combined to express the estimated fading process as a function of the AR parameters:

$$\begin{aligned}\hat{h}(n)&=\mathbf{g}^T\mathbf{\Phi}\hat{\mathbf{h}}(n-1)+\mathbf{g}^T\mathbf{K}(n)\alpha(n)\\&=\hat{\mathbf{h}}^T(n-1)\mathbf{a}(n)+\upsilon(n)\end{aligned} \tag{19}$$

where $\hat{\mathbf{h}}(n-1)=[\hat{h}(n-1)\quad \hat{h}(n-2)\quad \cdots\quad \hat{h}(n-p)]^T$ and $\mathbf{a}(n)=[-a_1\quad -a_2\quad \cdots\quad -a_p]^T$. In addition, the variance of the process $\upsilon(n)=\mathbf{g}^T\mathbf{K}(n)\alpha(n)$ is given by:

$$\sigma_\upsilon^2(n)=\mathbf{g}^T\,\mathbf{K}(n)C(n)\,\mathbf{K}^H(n)\mathbf{g} \tag{20}$$

When the channel is assumed stationary, the AR parameters are time-invariant and satisfy the following relationship:

$$\mathbf{a}(n)=\mathbf{a}(n-1) \tag{21}$$

As (19) and (21) define a state space representation for the estimation of the AR parameters, a second Kalman filter can be used to recursively estimate $\mathbf{a}(n)$ as follows:

$$\hat{\mathbf{a}}(n)=\hat{\mathbf{a}}(n-1)+\mathbf{K_a}(n)\left(\hat{h}(n)-\hat{\mathbf{h}}^T(n-1)\hat{\mathbf{a}}(n-1)\right) \tag{22}$$

where the Kalman gain $\mathbf{K_a}(n)$ and the update of the error covariance matrix $\mathbf{P_a}(n)$ are respectively given by:

$$\mathbf{K_a}(n)=\mathbf{P_a}(n-1)\hat{\mathbf{h}}^*(n-1)\left(\hat{\mathbf{h}}^H(n-1)\mathbf{P_a}(n-1)\hat{\mathbf{h}}(n-1)+\sigma_\upsilon^2(n)\right)^{-1} \tag{23}$$

$$\mathbf{P_a}(n)=\mathbf{P_a}(n-1)-\mathbf{K_a}(n)\hat{\mathbf{h}}^T(n-1)\mathbf{P_a}(n-1) \tag{24}$$

with initial conditions $\hat{\mathbf{a}}(0)=\mathbf{0}$ and $\mathbf{P_a}(0)=\mathbf{I}_p$.

It should be noted that according to (20) and (23), the variance of the innovation process of the first Kalman filter is used to drive the Kalman gain of the second.

C. Estimation of the Driving Process Variance

To estimate the driving process variance σ_u^2, the Riccati equation is first obtained by inserting (14) in (18) as follows:

$$\mathbf{P}(n/n)=\mathbf{\Phi}\mathbf{P}(n-1/n-1)\mathbf{\Phi}^H+\mathbf{g}\sigma_u^2\mathbf{g}^T-\mathbf{K}(n)\mathbf{s}^T(n)\mathbf{P}(n/n-1) \tag{25}$$

Taking into account that $\mathbf{P}(n/n-1)$ is a symmetric Hermitian matrix, one can rewrite (15) in the following manner:

$$\mathbf{b}^T(n)\mathbf{P}(n/n-1)=C(n)\mathbf{K}^H(n) \tag{26}$$

By combining (25) and (26), σ_u^2 can be expressed as follows:

$$\sigma_u^2=\mathbf{f}[\mathbf{P}(n/n)-\mathbf{\Phi}\mathbf{P}(n-1/n-1)\mathbf{\Phi}^H+\mathbf{K}(n)C(n)\mathbf{K}^H(n)]\,\mathbf{f}^T \tag{27}$$

where $\mathbf{f}=[\mathbf{g}^T\mathbf{g}]^{-1}\mathbf{g}^T=\mathbf{g}^T$ is the pseudo-inverse of $\mathbf{g}$.

Thus, we propose to estimate σ_u^2 recursively as follows:

$$\begin{aligned}\hat{\sigma}_u^2(n)=\lambda\hat{\sigma}_u^2(n-1)+(1-\lambda)\mathbf{f}[\mathbf{P}(n/n)-\mathbf{\Phi}\mathbf{P}(n-1/n-1)\mathbf{\Phi}^H\\+\mathbf{K}(n)|\alpha(n)|^2\mathbf{K}^H(n)]\,\mathbf{f}^T\end{aligned} \tag{28}$$

where the variance of the innovation process $C(n)$ is replaced by its instantaneous value $|\alpha(n)|^2$ and λ is the forgetting factor. It should be noted that λ can be either constant or time-varying (e.g., $\lambda(n)=(n-1)/n$).

D. Operation of the Channel Estimator

During the so-called training mode, the first Kalman filter in Fig. 1 uses the training sequence $s_m(n)$, the observation $y_m(n)$ and the latest estimated AR parameters $\{\hat{a}_i\}_{i=1,\dots,p}$ to estimate the fading process $h_m(n)$; while the second Kalman filter uses the estimated fading process $\hat{h}_m(n)$ to update the AR parameters. At the end of the training period, the receiver stores the estimated AR parameters and uses them in conjunction with the observation $y_m(n)$ and the decision $\hat{s}_m(n)$ to predict $h_m(n+1)$ in a decision directed manner. It should be noted that a prediction version of the Kalman filtering algorithm (12)-(18) must be used in the decision directed mode.

At the receiver, the received signal is multiplied by the conjugate of the channel estimate to compensate for the phase offset introduced by the fading channel, and the data symbols are recovered by coherent detection.

IV. Simulation Results

A. Simulation Protocols

In this section, we carry out a comparative simulation study on the estimation of OFDM fading channels between the proposed two-cross-coupled Kalman filter based channel estimator and other estimators based on LMS or RLS algorithms [6]. We consider an OFDM system with QPSK modulation, 52 carriers, and a central carrier frequency of 1900 MHz. The transmitted frame size over each carrier is assumed to be 256 symbols. The fading processes $\{h_m(n)\}_{m=1,\ldots,M}$ are generated according to the modified Jakes model [22] with 16 distinct oscillators and Doppler rate $f_d T_s = 0.097$. They are normalized to have a unit variance, i.e. $\sigma_h^2 = 1$. The average Signal-to-Noise Ratio (SNR) per carrier is defined by:

$$\mathrm{SNR} = 10\log_{10}(\sigma_h^2 / \sigma_w^2) = 10\log_{10}(1/\sigma_w^2) \tag{29}$$

B. Results and Comments

Fig. 5 illustrates the on-line estimation of the AR(2) parameters, for high Doppler rate scenario of $f_d T_b = 0.097$ and SNR=30 dB. One can notice that the estimated real and imaginary parts of the AR(2) parameters converge to the true values after approximately 100 symbols.

Fig. 6 and 7 show, respectively, the Mean Square Error (MSE) of the estimated fading process and the BER performance of the OFDM system when using the various channel estimators. Thus, exploiting the channel statistics by using AR models in the proposed two-cross-coupled Kalman filter based channel estimator results in significant performance improvement over the LMS and RLS based ones. In addition, increasing the AR model order will improve the performance of the system with the amount of improvement decreases as the model order increases. While the amount of improvement between AR(1) and AR(2) is significant, the amount of improvement beyond AR(5) is not so much. Although high-order AR models (e.g., AR(20)) can provide better modeling approximation than low-order AR models (see Fig. 3 and 4), the amount of performance improvement in that case is small compared with the resulting computational cost $O(p^3)$ of the estimation algorithm. Therefore, to reduce the computational cost, an AR(5) is recommended.

V. Conclusion

This paper investigates the estimation of rapidly time-varying OFDM fading channels. A scheme based on two-cross-coupled Kalman filters is proposed for the joint estimation of the fading process and the corresponding AR parameters over each carrier. The comparative simulation study we have carried out with the conventional LMS and RLS channel estimators shows that the two-cross-coupled Kalman filter based channel estimator can provide significant results over the LMS and RLS ones. In addition, an AR(5) model can provide a trade-off between the accuracy of the model, the computational cost of the estimation algorithm and the system performance.

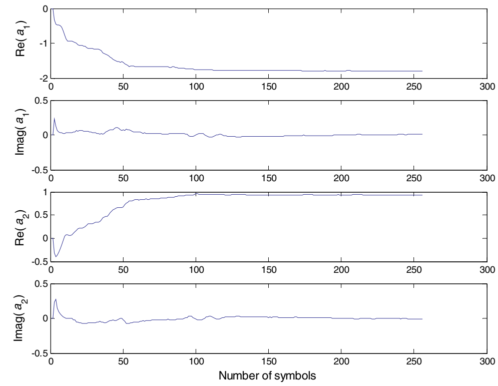

Fig. 5. Real and imaginary parts of the estimated AR(2) parameters of the fading process along the first carrier. True AR(2) parameter values are $a_1 = -1.7627$ and $a_2 = 0.9503$.

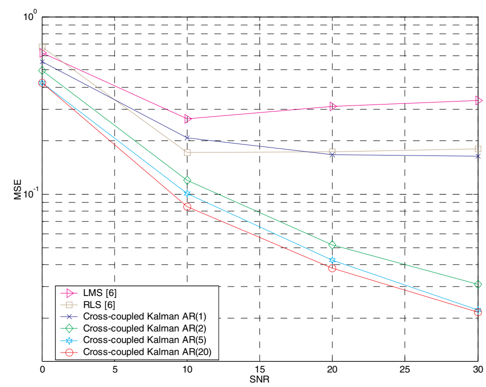

Fig. 6. MSE versus SNR of the OFDM system with the various channel estimators.

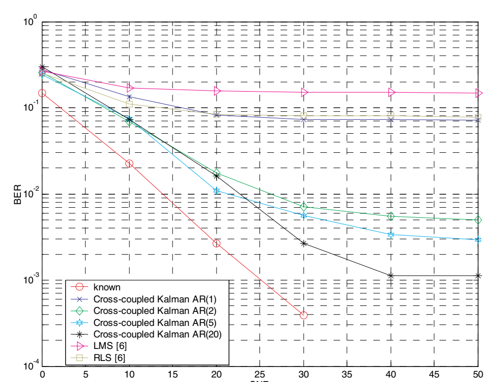

Fig. 7. BER performance versus SNR of the OFDM system with the various channel estimators.

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