Joint estimation of correlated multi-carrier DS-CDMA mobile fading channels based on optimal filters

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Abstract: This paper deals with the joint estimation of rapidly time-varying and correlated Rayleigh fading channels in synchronous multi-carrier direct-sequence code-division-multiple-access (MC-DS-CDMA) systems. Usually, when the multiple carrier fading channels are modelled by autoregressive (AR) processes, they can be estimated separately by means of an optimal Kalman filter. However, a loss in performance can be expected when the channels are correlated. To take into account these correlations, the multiple carrier fading processes are stored in a vector, modelled as vector AR process, and estimated jointly by means of an optimal Kalman filter. Nevertheless, this requires the simultaneous estimation of the AR parameter matrices in the vector AR process. To avoid a non-linear approach such as the extended Kalman filter (EKF), this estimation issue can be solved by using dual Kalman filters.

A comparative study on channel estimation is carried out between the proposed joint estimation scheme, the separate estimation counterpart and the standard least mean square (LMS) based estimator.

Keywords: multi-carrier; DS-CDMA; correlated fading channels; joint estimation; autoregressive models; separate estimation; optimal filters; dual Kalman filters.


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1 Introduction

There has been a great deal of recent interest in multi-carrier direct-sequence code-division-multiple-access (MC-DS-CDMA) systems (Jamoos, 2009) due to their
potentials for high data rate transmission, high bandwidth efficiency, fading resilience and interference suppression capability. Thus, MC-DS-CDMA has been adopted as an option for the down-link transmission in the CDMA2000 third generation cellular standard (CDMA2000, 2001).

When considering the conventional MC-DS-CDMA receiver (Kondo and Milstein, 1996), which consists of a correlator along each carrier followed by a maximal ratio combiner (MRC), the channel is assumed to be perfectly known. However, this approach cannot eliminate the multiple access interference (MAI). Besides, in real cases, the channel is usually unknown and, hence, should be estimated. To avoid these drawbacks, a first approach consists in designing a minimum mean square error (MMSE) receiver where the Wiener filtering is performed based on the least-square estimated channel fading processes (Miller and Rainbolt, 2000). In the framework of MC-CDMA, Kalofonos et al. (2003) study the performance of MMSE detection schemes with adaptive estimation of the fading processes based on the least mean square (LMS) and recursive least square (RLS) algorithms. Moreover, the authors examine the relevance of Kalman filtering for channel estimation, by modelling it as a first order autoregressive (AR) process. Nevertheless, perfect knowledge of the AR parameters is assumed.

In Chen and Liao (2007), a channel estimator based on multiple channel model, which includes several possible channel models based on different ranges of Doppler frequencies, is proposed for MC-CDMA systems. The estimated channel coefficients are then employed in a MMSE equaliser for symbol detection. However, the estimation of the channel coefficients is carried out in the frequency domain.

In Jamoos et al. (2005), we have proposed to combine the decorrelation multi-user detection for MAI suppression with an adaptive channel estimation based on two cross coupled Kalman filters. One Kalman filter is used to estimate the channel fading process along each carrier while the second one makes it possible to estimate the corresponding AR parameters from the estimated fading process. In this study, using a second order AR model provides significant results over the model independent LMS and RLS estimators, especially when dealing with high Doppler rates channels. However, the estimation issue is addressed separately along each carrier.

Separate estimation is optimal when the multiple carrier fading channels are uncorrelated. Nevertheless, this is not the case in practice, where channel correlation might arise due to the existence of a significant Doppler spread for instance. In that case, joint estimation of the correlated channels based on vector AR process can improve the estimation quality by exploiting these correlations. Several methods dealing with the joint estimation of correlated fading channels based on Kalman filtering have been already proposed in the literature. Thus, Tsatsanis et al. (1996) focus their attention on the estimation and the equalisation of time-varying frequency selective fading channels in single user single carrier systems. The AR parameter matrices are estimated by means of a Yule-Walker estimator. However, this method results in high estimation error especially at low signal-to-noise ratio (SNR). In addition, Gao et al. (2003) investigate the estimation of multiple time-varying and correlated fading paths in single-carrier DS-CDMA systems. The parameter matrices of the vector AR model are estimated by means of an expectation maximisation (EM) algorithm involving a Kalman smoothing. However, only first order vector AR process is used.

In this paper, we propose to jointly estimate the correlated MC-DS-CDMA mobile fading channels and their AR parameter matrices based on dual optimal Kalman filters. In addition, we study the relevance of first and second order vector AR processes, under
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realistic Jakes’ model for correlated Rayleigh fading channels with different delay spread scenarios.

The remainder of the paper is organised as follows. Section 2 recalls the synchronous MC-DS-CDMA system model and the receiver structure proposed in Jamoos et al. (2005). The proposed joint estimation approach is introduced in Section 3. Simulation results are reported in Section 4. Conclusions are drawn in Section 5.

2 MC-DS-CDMA system model

2.1 System model

A synchronous MC-DS-CDMA system with binary phase shift keying (BPSK) modulation is considered based on $M$ carriers and involving $K$ users. The transmitted signal at the $m$th carrier can be expressed as follows:

$$S_m(t) = \text{Re} \left[ \sum_{n=-\infty}^{\infty} \sum_{k=1}^{K} \sqrt{E_b} b_k(n)c_k(t-nT_b) e^{j2\pi f_{m}t} \right]$$

(1)

where $E_b$ is the bit energy of the $k$th user, $b_k(n) \in \{-1, 1\}$ is the $n$th data bit of the $k$th user, $T_b$ is the bit duration and $f_m$ is the $m$th carrier frequency. In addition, the spreading waveform of the $k$th user is given by:

$$c_k(t) = \sum_{i=0}^{N-1} s_k(i)\psi(t-iT_c)$$

(2)

where $T_c$ is the chip duration, $N = T_b / T_c$ is the processing gain, $s_k(i) \in \{\pm 1 / \sqrt{N}\}$ with $i = 0, 1, \ldots, N-1$ is the normalised spreading sequence and $\psi(t)$ is the chip pulse shape, assigned to 1 over the interval $[0, T_c]$ and 0 otherwise.

The transmitted MC-DS-CDMA signal goes through a frequency-selective Rayleigh fading channel having a maximum delay spread of $T_m$ and a coherence bandwidth $B_c$, which are related as follows:

$$B_c \approx 1/T_m$$

(3)

If the spacing between two adjacent carrier frequencies is assigned to $2 / T_c$, there is no overlap between the main lobes of the carriers. In addition, according to Kondo and Milstein (1996), the number $M$ of carriers is chosen to meet two conditions:

1. Each carrier undergoes frequency non-selective fading. Thus, the normalised delay spread $T_m / T_c$ satisfies:

$$\frac{T_m}{T_c} \leq 1$$

(4)

2. All carriers are subject to independent fading, implying that $2 / T_c \geq B_c$. Given (3), this leads to the following inequality:
In this paper, the second condition is relaxed to account for the case of correlated channels (i.e., $0 \leq \frac{T_m}{T_c} < 0.5$).

In addition to the fading, the transmitted signal at the $m^{th}$ carrier is corrupted by a zero-mean additive white Gaussian noise (AWGN) process $\eta_m(t)$. The noise processes $\{\eta_m(t)\}_{m=1,\ldots,M}$ are assumed to be mutually independent and identically distributed, with equal variance $\sigma^2_\eta$. Hence, the continuous time received signal at the $m^{th}$ carrier in its complex analytic form is given by:

$$r_m(t) = \sum_{n=-\infty}^{+\infty} \sum_{k=1}^{K} \sqrt{E_{b_k}} b_k(n)c_k(t-nT_b)h_m(n)e^{j2\pi f_d t} + \eta_m(t)$$

where the channel fading coefficients $\{h_m(n)\}_{m=1,\ldots,M}$ are assumed to be correlated complex Gaussian random processes, each with zero-mean and unit variance.

### 2.2 Receiver structure

To retrieve the desired symbol sequence of the first user $b_1(n)$, from the received signals $\{r_m(t)\}_{m=1,\ldots,M}$, we recall the receiver structure proposed in Jamoos et al. (2005). In that case, the received signal at the $m^{th}$ carrier is firstly demodulated and then processed with a chip-matched filter, which consists of an integrator with duration $T_c$. The samples are then stored during one bit interval, resulting in the following $N \times 1$ vector:

$$x_m(n) = \sum_{k=1}^{K} \sqrt{E_{b_k}} b_k(n)h_m(n)s_k + \eta_m(n)$$

where $s_k = [s_k(0) \ s_k(1) \ \cdots \ s_k(N-1)]^T$ denotes the normalised spreading vector of the $k^{th}$ user and $\eta_m(n)$ is an $N \times 1$ vector of independent AWGN samples with zero-mean and covariance matrix $\sigma^2_\eta I_N$.

The received vector at the $m^{th}$ carrier is then processed by the near-far resistant decorrelating filter (Verdu, 1998), which can be written in the following form for user 1:

$$y_1(n) = w_1^T x_1(n) = \sqrt{E_{b_1}} b_1(n)h_m(n) + \xi_m(n)$$

where $\xi_m(n)$ is a zero-mean Gaussian noise with variance $\sigma^2_\xi = \sigma^2_\eta [R^{-1}]_{11}$. 

$$w_1 = \sum_{k=1}^{K} [R^{-1}]_{1k} s_k$$
Finally, MRC makes it possible to provide the estimated data symbol of the desired user as follows:

\[
\hat{s}_m(n) = \text{sgn} \left( \text{Re} \left( \sum_{m=1}^{M} h_m(n) y_m(n) \right) \right)
\]

(10)

As \( \{h_m(n)\}_{m=1}^{M} \) are unknown, we propose to investigate their joint estimation in Section 3 by modelling them as a vector AR process.

3 Proposed joint estimation scheme

3.1 Vector AR modelling of the correlated channels

The multiple carrier fading processes \( \{h_m(n)\}_{m=1}^{M} \) are assumed to be correlated across carriers as well as time according to the Jakes’ (1974, pp.45–54) model as follows:

\[
R_{h_m,h_l}(\tau) = E \left[ h_m(n) h_l^*(n-\tau) \right] = J_0 \left( 2\pi f_d T_b \tau \right) \frac{1 - j 2\pi (m-l)(T_m/T_c)}{1 + \left[ 2\pi (m-l)(T_m/T_c) \right]^2}, \quad m, l = 1, \ldots, M
\]

(11)

where \( J_0(.) \) denotes the zero-order Bessel function of the first kind, \( f_d \) is the maximum Doppler frequency and \( f_d T_b \) denotes the Doppler rate. It should be noted that the above correlation functions exhibit two separable parts:

1. a temporal correlation part given by the Bessel function and governed by the Doppler rate \( f_d T_b \)
2. an inter-carrier correlation part defined by the cross correlation factor given after the Bessel function and governed by the normalised delay spread \( T_m / T_c \).

By defining \( \mathbf{h}(n) = [h_1(n) \ldots h_M(n)]^T \) as the fading processes vector, the channel autocorrelation matrix \( \mathbf{R}_{\mathbf{h}\mathbf{h}}(\tau) = E[\mathbf{h}(n)\mathbf{h}^H(n-\tau)] \) is an \( M \times M \) matrix whose \( (m, l)^{th} \) entry is defined in (11). Thus, the dynamics of \( \mathbf{h}(n) \) can be modelled by a \( p^{th} \) order multi-channel AR process, AR\( (p) \), as follows (Baddour and Beaulieu, 2004):

\[
\mathbf{h}(n) = - \sum_{i=1}^{p} \Phi_i \mathbf{h}(n-i) + \mathbf{u}(n)
\]

(12)

where \( \{\Phi_i\}_{i=1}^{p} \) are \( M \times M \) matrices involving the AR parameters. In addition, \( \mathbf{u}(n) = [u_1(n) \ldots u_M(n)]^T \) is a zero-mean complex Gaussian driving vector with covariance matrix \( \mathbf{Q}_u = E[\mathbf{u}(n)\mathbf{u}^H(n)] \).

Figure 1 shows the autocorrelation function (ACF) \( R_{\mathbf{h}\mathbf{h}}(\tau) = J_0 \left( 2\pi f_d T_b \tau \right) \) of the theoretical Jakes model and that of the fitted AR(1) and AR(2) models. According to Figure 1, the AR(2) autocorrelation matches the theoretical Jakes autocorrelation well for lags less than 8, whereas for AR(1) the matching is satisfactory only for the first two lags. Indeed, increasing the AR model order leads to a better fit between the statistics of the
resulting AR process and that of the theoretical Jakes channel (Baddour and Beaulieu, 2004). However, the higher the AR model order, the higher the computational complexity of the resulting estimation algorithm. Therefore, a compromise had to be found.

Figure 1  Autocorrelation function of the theoretical Jakes model and that of the fitted AR(1) and AR(2) models

Notes: $f_d = 150$ Hz and $f_d T_b = 0.05$.

It should be noted that the unknown model parameter matrices $\{\Phi_i\}_{i=1,\ldots,p}$ and $Q_u$ can be obtained by solving the following multi-channel Yule-Walker equations (Kay, 1988):

\[
\begin{bmatrix}
R_{hh}(0) & \cdots & R_{hh}(-p+1) \\
\vdots & \ddots & \vdots \\
R_{hh}(p-1) & \cdots & R_{hh}(0)
\end{bmatrix}
\begin{bmatrix}
\Phi_i^{-H} \\
\vdots \\
\Phi_i^{-H}
\end{bmatrix}
= 
\begin{bmatrix}
R_{hh}(1) \\
\vdots \\
R_{hh}(p)
\end{bmatrix}
\]  \hspace{1cm} (13)

Consequently, the covariance matrix of the driving vector $u(n)$ can be computed as follows:

\[
Q_u = R_{hh}(0) + \sum_{i=1}^{p} R_{hh}(-i)\Phi_i^{-H}
\]  \hspace{1cm} (14)

When solving equations (13) and (14) given (11), we notice that the resulting AR parameter matrices are diagonal and the driving process covariance matrix is non-diagonal with Toeplitz structure corresponding to correlated fading channels. This is
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Due to the fact that the Jakes’ correlation function in (11) has a separable time and inter-carrier components.

However, equations (13) and (14) can be used providing the Doppler frequency $f_d$ and the delay spread $T_m$ have been previously estimated. In the following, the approach we present makes it possible to complete the simultaneous estimations of $h(n)$, $\{\Phi_i\}_{i=1,\ldots,p}$ and $Q_u$, by means of dual Kalman filtering algorithm.

3.2 Joint estimation of the correlated channels

By stacking (9) in a vector form, for $M$ carriers, one has the following measurement vector:

$$y(n) = \sqrt{E_b} h(n) h(n) + \xi(n)$$

(15)

where $y(n) = [y_1(n) \cdots y_M(n)]^T$ and $\xi(n) = [\xi_1(n) \cdots \xi_M(n)]^T$ is a zero-mean Gaussian noise vector with covariance matrix $R_\xi = \sigma_\xi^2 I_M$.

Given equations (12) and (15), estimating $h(n)$ can be recursively obtained by means of Kalman filtering. To this end, let us first define the following state vector whose dimension is $Mp$,

$$\underline{h}(n) = [h^T(n) \cdots h^T(n-p+1)]^T$$

(16)

Then, equation (12) can be written in state space form as follows:

$$\begin{bmatrix}
    -\Phi_1 & -\Phi_2 & \cdots & -\Phi_p \\
    I_M & 0_M & \cdots & 0_M \\
    \vdots & \vdots & \ddots & \vdots \\
    0_M & 0_M & \cdots & I_M
\end{bmatrix}
\begin{bmatrix}
    u(n) \\
    0_M \\
    \vdots \\
    0_M
\end{bmatrix}
+ \Theta(n) \underline{h}(n-1) + \Gamma u(n)$$

(17)

where $\Gamma = [I_M \ 0_M \cdots \ 0_M]^T$ and $I_M$ is the $M \times M$ identity matrix.

Moreover, the vector (15) can be re-written as:

$$y(n) = B(n) \underline{h}(n) + \xi(n)$$

(18)

where $B(n) = \sqrt{E_b} h(n) [I_M \ 0_M \cdots \ 0_M]$.

Hence, equations (17) and (18) define a state space representation of the multi-channel system (12) and (15), for which a standard Kalman algorithm can be carried out to recursively estimate the state vector $\underline{h}(n)$ as follows:

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

$$\alpha(n) = y(n) - B(n) \Theta(n) \underline{h}(n-1) / n - 1$$

(19)

- Its covariance matrix is then defined:

$$C(n) = E[\alpha(n)\alpha^H(n)] = B(n)P(n / n-1)B^T(n) + R_\xi$$

(20)
where \( P(n / n - 1) \) denotes the so-called a priori error covariance matrix:
\[
P(n / n - 1) = \Theta(n)P(n-1 / n - 1)\Theta^T(n) + \Gamma Q_\alpha \Gamma^T
\] (21)

- The Kalman gain is calculated in the following manner:
\[
K(n) = P(n / n - 1)B^T(n)C^{-1}(n)
\] (22)

- The update of the state vector \( \mathbf{h}(n / n) \) and the channel vector \( \mathbf{h}(n / n) \) are respectively given by:
\[
\mathbf{h}(n / n) = \Theta(n)\mathbf{h}(n-1 / n - 1) + K(n)\alpha(n)
\] (23)
\[
\mathbf{h}(n / n) = \Gamma^T \mathbf{h}(n / n)
\] (24)

- The error covariance matrix is updated as follows:
\[
P(n / n) = P(n / n - 1) - K(n)B(n)P(n / n - 1)
\] (25)

This approach can be carried out if the AR parameter matrices that are involved in the transition matrix \( \Theta \) and the driving vector covariance matrix \( Q_\alpha \) are available. They will be estimated following the method presented in the next subsections.

### 3.3 Estimation of the AR parameter matrices

Equations (23) and (24) are firstly combined to express the estimated channel vector \( \hat{\mathbf{h}}(n / n) \) as a function of the AR parameter matrices \( \{\Phi_i\}_{i=1,...,p} \) as follows:
\[
\hat{\mathbf{h}}(n / n) = \Gamma^T \Theta(n)\mathbf{h}(n-1 / n - 1) + \Gamma^T K(n)\alpha(n)
\] (26)
\[
[- \Phi_1 \quad \Phi_2 \quad \cdots \quad \Phi_p] \mathbf{h}(n-1 / n - 1) + \nu(n)
\]
where \( \nu(n) = \Gamma^T K(n)\alpha(n) \) with covariance matrix equal to \( Q_\nu = \Gamma^T K(n)C(n)K^H(n)\Gamma \).

To make use of the Kalman algorithm, the AR parameters matrices in the above equation are first rearranged in a vector form by using the so-called ‘vec-operator’, which stacks the columns of a matrix on top of each other. Hence, equation (26) can be rewritten as follows:
\[
\hat{\mathbf{h}}(n / n) = -\mathbf{H}(n-1 / n - 1)\mathbf{a}(n) + \nu(n)
\] (27)

where
\[
\mathbf{a}(n) = \text{vec}\left(\left(\Phi_1 \quad \Phi_2 \quad \cdots \quad \Phi_p\right)^T\right)
\] (28)
\[
\mathbf{H}(n-1 / n - 1) = \mathbf{I}_{M} \otimes \mathbf{h}^T(n-1 / n - 1)
\] (29)

When the channels are assumed stationary, the AR parameters are time-invariant and, hence, satisfy the following relationship:
\[
\mathbf{a}(n) = \mathbf{a}(n-1)
\] (30)
Equations (27) and (30) hence define a state space representation for the estimation of the AR parameters. A second Kalman filter is then used to recursively estimate \( \text{AR parameters} \). By inverting the ‘vec-operator’ we get the estimation of the AR parameter matrices \( \{ \Phi_i \}_i = 1, \ldots, p \). Therefore, the proposed dual Kalman filter based channel estimator operates as follows: during the so-called training mode, the first Kalman filter (19) to (25) uses the training sequence \( b_1(n) \), the observation \( y(n) \) and the latest estimated AR parameter matrices \( \{ \hat{\Phi}_i \}_i = 1, \ldots, p \) to estimate the channel vector \( h(n) \); while the second Kalman filter uses the estimated channel vector \( \hat{h}(n) \) to update the AR parameters matrices. At the end of the training period, the receiver stores the estimated AR parameter matrices and uses them in conjunction with the observation \( y(n) \) and the decision \( \hat{b}_1(n) \) given by (10) to predict \( h(n + 1) \) in a decision directed manner. It should be noted that a prediction version of the Kalman filtering algorithm (19) to (25) must be used in the decision directed mode.

### 3.4 Estimation of driving process covariance matrix

To estimate the driving process covariance matrix \( Q_u \), the so-called Riccati equation is first obtained by inserting (21) into (25) as follows:

\[
P(n / n) = \Theta(n)P(n - 1 / n - 1)\Theta^H(n) + \Gamma Q_u \Gamma^T - K(n)B(n)P(n / n - 1)
\]  

(31)

Taking into account that \( P(n / n - 1) \) is a symmetric Hermitian matrix, one can rewrite the Kalman filter gain equation (22) in the following manner:

\[
B(n)P(n / n - 1) = C(n)K^H(n)
\]  

(32)

By combining (31) and (32), \( Q_u \) can be expressed as follows:

\[
\hat{Q}_u(n) = F \left[ P(n / n) - \Theta(n)P(n - 1 / n - 1)\Theta^H(n) + K(n)C(n)K^H(n) \right] F^T
\]  

(33)

where \( F = [\Gamma^T \Gamma]^{-1} \Gamma^T = [I_M \ 0_M \ \cdots \ 0_M] \) is the pseudo-inverse of \( \Gamma \).

Thus, we propose to estimate \( Q_u \) recursively as follows:

\[
\hat{Q}_u(n) = \lambda \hat{Q}_u(n - 1) + (1 - \lambda) F \left[ P(n / n) - \Theta(n)P(n - 1 / n - 1)\Theta^H(n) + K(n)C(n)K^H(n) \right] F^T
\]  

(34)

where the covariance matrix of the innovation process \( C(n) \) is replaced by \( a(n)a^H(n) \) and \( \lambda \) is the forgetting factor.

### 4 Simulation results

In this section, a comparative study on channel estimation is carried out between three methods:

1. the proposed joint estimation scheme
2. the separate estimation counterpart proposed in Jamoos et al. (2005)
3. the standard LMS based channel estimator.
We consider a system of $K = 10$ multiple-access active users, each using a gold code of length $N = 31$. The fading channel coefficients $\{h_m(n)\}_{m=1,2,...,M}$ are generated according to the modified Jakes’ model (Dent et al., 1993) where Walsh-Hadamard code words are used to insure that these fading coefficients are uncorrelated. Based on (11), correlated fading coefficients are obtained from the uncorrelated ones by using the zero-time shift cross-correlation matrix $R_{hh}(0)$. For $M = 3$ and $T_m / T_c = 0.05$, this correlation matrix is given by:

$$R_{hh}(0) = \begin{bmatrix}
1 & 0.91 + j0.29 & 0.72 + j0.45 \\
0.91 - j0.29 & 1 & 0.91 + j0.29 \\
0.72 - j0.45 & 0.91 - j0.29 & 1
\end{bmatrix}$$ (35)

From Figure 2, one can notice that the joint estimation scheme provides a little bit error rate (BER) performance gain over the separate estimation counterpart. This comparable performance between the two schemes is not surprising because the Jakes correlation functions in (11) exhibits separable time and inter-carrier components. In addition, it is noticed that channel estimators using AR(2) model performs much better than that using AR(1), especially at high SNR. Furthermore, it is clear that the Kalman filter based estimators with either AR(1) or AR(2) outperforms the LMS based one with the performance difference increases as the SNR increases. Therefore, exploiting the channel statistics by using AR(1) or AR(2) models in a Kalman filter based estimators results in significant performance improvement over the model-independent LMS estimator, but at the expense of increased computational complexity and storage.

**Figure 2** BER performance versus SNR with the various channel estimators

![Figure 2](image-url)

Notes: $M = 3, f_b T_b = 0.05$ and $T_m / T_b = 0.05$. 

**Figure 3** BER versus the normalised delay spread $T_m/T_c$ with the various channel estimators

![Graph showing BER versus the normalised delay spread with various channel estimators.](image)

Notes: $M = 3$, $f_bT_b = 0.05$ and SNR = 15 dB.

**Figure 4** Real and imaginary parts of the estimated AR(2) parameters

![Graphs showing the real and imaginary parts of the estimated AR(2) parameters.](image)

Notes: True AR(2) parameter matrices are $\Phi_1 = a_1I_M$ with $a_1 = -1.9389$ and $\Phi_2 = a_2I_M$ with $a_2 = 0.9876$. $M = 3$, $f_bT_b = 0.05$ and $T_m/T_b = 0.05$. 

According to Figure 3, increasing the normalised delay spread will decrease the BER and vice versa. This can be explained from the fact that increasing the normalised delay spread results in decreasing the correlation between the channels and, hence, increasing the diversity gain. For $T_m / T_c \geq 0.05$, the cross correlation is negligible and therefore the BER provided by the joint estimation scheme come close to that of the separate estimation one.

The recursive estimates of the real and imaginary parts of the AR(2) parameters are shown in Figure 4 for SNR = 40 dB. One can notice that the estimated parameters converge close to the true values after approximately 500 symbols.

5 Conclusions

This paper investigates the estimation of rapidly time-varying and correlated MC-DS-CDMA mobile fading channels. A method based on dual optimal Kalman filters is proposed for the joint estimation of multiple carrier fading channels and their corresponding AR parameter matrices. The comparative simulation study we carried out with existing methods shows that the proposed joint estimation scheme outperforms the separate estimation counterpart.

References


Notes

1 Although we deal only with BPSK modulation for the sake of simplicity, the method we presented in this paper can also work with other modulation techniques such as QPSK, 16-PSK, QAM, etc.