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EFFICIENT CHANNEL ESTIMATION FOR WCDMA SYSTEMS

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ABSTRACT

Third generation (3G) cellular communication standards are based on Wideband Code Division Multiple Access (WCDMA). The wideband signals experience frequency-selective fading due to multi-path propagation, hence increasing the Multiple Access Interference (MAI). To combat this effect, an efficient channel estimation algorithm, based on the Maximum Likelihood (ML) approach is derived. The algorithm handles the situation of multi-user, and multi-path by estimating a composite Channel Impulse Response (CIR). This estimation is performed in the reverse link, for each user, without needs of estimating each individual channel parameters. This has the achievement of reducing the computational complexity. The efficiency of the proposed channel estimator is measured in terms of Mean Squared Error (MSE), handling capacity, loss due to estimation, as well as resistance to MAI.

KEYWORDS

WCDMA, channel estimation, multi-path.

1. INTRODUCTION

The multiple access technology selected for today's standards of third generation (3G) wireless communications is the Direct Sequence Code Division Multiple Access (DS-CDMA) [1]. It is also likely that future wireless systems (sometimes referred to as 4G systems) will retain a CDMA component [2].

In a CDMA communication system, a communication channel with a given bandwidth is accessed by all the users simultaneously. The different users are distinguished at the base station receiver by the unique spreading code assigned to the users to modulate their signals. Hence, the CDMA signal transmitted by each user consists of that user's data which modulates the unique spreading code assigned to that user, which in turn modulates a carrier using any well-known modulation scheme such as Binary Phase Shift Keying (BPSK). The receiver receives a linear superposition of the signals transmitted by all the users, attenuated by arbitrary factors and delayed by an arbitrary amount. The goal of channel parameter estimation is to determine these unknowns and time varying attenuation factors and delays

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by processing the received signal, to facilitate recovery of the data transmitted by each user.

Channel estimation is one of the major problems in radio communications particularly when the mobile system is subject to multi-path fading, as in the WCDMA systems. In this case, the transmission channel consists of more than one distinct propagation path for each user's signal. Moreover, when the CDMA technique is used to allow multiple users access to a single channel, the system is susceptible to the near-far effect. The near-far problem arises when the signals from the different users arrive at the receiver with widely varying power levels. The near far problem has been shown to severely degrade the performance of standard single user detection techniques (e.g., matched filters, correlators, etc.) in conventional CDMA systems.

Conventional CDMA systems try to limit the near-far problem with power control. However, even a small amount of the near-far effect can drastically degrade the performance of conventional receivers. For many years this was thought to be an inherent limitation of CDMA until Verd´u developed the optimum multi-user detector [3]. Verd´u's work was followed by many suboptimal schemes of lower computational complexity [4], all of which are near-far resistant. However, these methods deal only with detection and assume that the timing of the spreading waveforms is known.

When studying the different algorithms for the estimation of the channel complex coefficients, most authors usually assume that perfect knowledge about the path delays is available at the receiver, [5], [6]. However, in a realistic CDMA receiver both channel coefficient estimation and delay estimation tasks should be performed, either in a joint or in a decoupled manner. Most of the initial work done on timing acquisition for CDMA systems focused on jointly estimating the necessary parameters for all users [7], [8]. While these techniques produce excellent results, they can be computationally intense since they involve solving a multidimensional optimization problem for a large number of parameters. Joint channel estimation approaches based on ML theory had been described by different authors [9], [10] with the high complexity as a common feature. In [11], the authors give a comprehensive review of the CDMA delay estimation techniques proposed in the literature so far.

In this paper we focus on a reduced complexity joint ML approach that decomposes the multi-user problem into a series of single user ones. The algorithm draws upon certain computationally elegant features of the maximum likelihood approach presented in [12]. The main contribution of this paper is the development of an algorithm which can work in a multi-path environment and estimate a composite channel impulse response, which represents the delays and amplitudes of all the significant propagation paths of all the users in a computationally efficient manner.

The algorithm assumes the transmission of training sequences by all the users being acquired. The delays are estimated modulo N, where N is the length of each spreading code. The additive noise is assumed to be a circularly complex zero mean Gaussian random vector, but no *a priori* assumption is made on its covariance. The paper is organized into the following sections. Section 2 presents the WCDMA system under study and a model for the multi-path channel. In Section 3 we describe the maximum likelihood algorithm. Section 4 analyzes the complexity and Section 5 presents the results of the simulations. The main conclusions of the paper are summarized in Section 6 with directions for future research.

2. SYSTEM MODEL

In this section, we develop a system model that treats the effect of multi-path in an efficient manner. The model doesn't assume chip synchronization, that is, the delays of the signals, introduced by the channel are not integer multiples of chips.

Assume a K-user direct sequence CDMA system with BPSK modulation. Each user transmits a zero mean stationary bit sequence with independent identically distributed components and the different users are independent of each other.

The complex base-band representation of the k^{th} user's transmitted signal is given by

$$s_k(t) = \sqrt{E_k}\sum_{i=1}^{L} b_{k,i} c_k(t - iT) \tag{1}$$

where E_k is the transmitted power, $b_{k,i} \in \{+1,-1\}$ is the i^{th} transmitted bit and $c_k(t)$ is the spreading waveform. The spreading code waveform is composed of N chips and if we assume BPSK for the spreading modulation we have $c_k(t) = \sum_{n=0}^{N-1} c_{k,n} \prod(t - nT_c)$, where $c_{k,n} \in \{+1,-1\}$ and the chip pulse waveform $\prod(t)$ is a rectangular pulse of duration T_c. It is assumed that the extent of the spreading code is one bit period and hence we have $T = N\,T_c$, where T is the symbol period.

It is also assumed that the channel for each user consists of P distinct and resolvable paths [13]. The impulse response $h_k(t)$ of the channel seen by user k is given by:

$$h_k(t) = \sum_{p=1}^{P} \omega_{k,p} \partial\left(t - \tau_{k,p}\right) \tag{2}$$

where, $\omega_{k,p}$ is the complex amplitude with which the p^{th} path of the k^{th} user is received and includes contributions from the channel attenuation and the phase offset and $\tau_{k,p}$ is the relative delay with respect to a reference at the receiver. The multi-path delay spread of the channel T_m is the maximum difference between propagation delays, that is, $T_m = \max_{p,l} \left|\tau_{k,p} - \tau_{k,l}\right|$. In our model, we assume that the delay spread is less than half the symbol period $(T_m < T/2)$. The delay is not constrained to be in multiples of chip. The channel parameters are assumed to be unknown but constant in the time taken to estimate them.

Accordingly, the received signal at the base station is a superposition of attenuated and delayed signals transmitted by all the K users and is given by

$$r(t) = \sum_{k=1}^{K}\sum_{p=1}^{P} w_{k,p} s_k(t - \tau_{k,p}) + \nu(t) \tag{3}$$

The noise component $v(t)$ is assumed to be Gaussian with zero-mean and double sided spectral density of $N_o/2$.

The continuous time signal at the receiver is discretized, by sampling the output of a chip-matched filter at the chip rate [13]. The chip matched filtering is a simple integrate and dump operation, over a time interval equal to the chip period

$$r(n) = \frac{1}{T_c}\int_{nT_c}^{(n+1)T_c} r(t)dt \qquad (4)$$

The observation vector at time i, $\mathbf{r}_i \in C^N$, is then formed by collecting N successive outputs together $r(n)$. Hence, each observation vector corresponds to a time interval equal to the bit period. Since each spreading vector is periodic with period N, $r[n]$ is wide sense cyclostationary, and the observation vectors $\mathbf{r}_i$ are wide-sense stationary. The observation vector $\mathbf{r}_i \in C^N$ at time i is

$$\mathbf{r}_i = \left[r(i), r(i+1), \ldots, r(i+N-1)\right]^T \qquad (5)$$

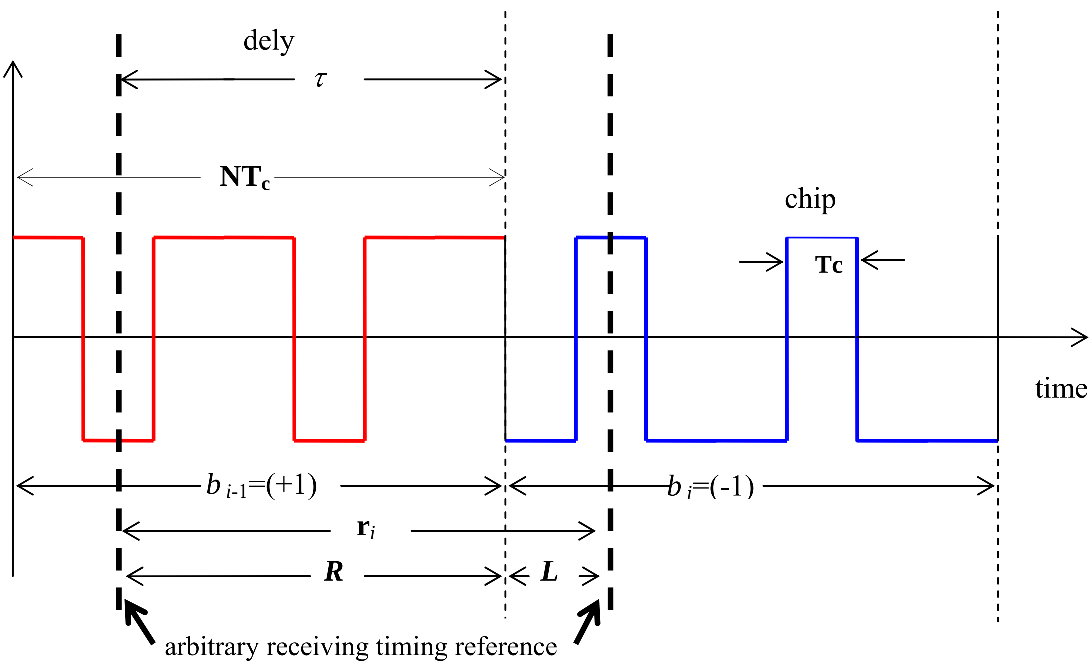


Figure 1: System model-received signal

The system is asynchronous and the receiver has an arbitrary timing reference that will not be aligned to actual transmitted bit boundaries. Hence each observation vector can be viewed as a linear combination of $2K$ signal vectors, two components from each user, due to the past and current bits as shown in Fig.1. In Fig.1, the received vector $\mathbf{r}_i$ overlaps the two adjacent transmitted bits b_{i-1} and b_i. So the contribution of the spreading code of the user to vector $\mathbf{r}_i$ appears in two parts, the right part (shown as R) of bit $\mathbf{b}_{i-1}$ and the left part (shown as L) of bit $\mathbf{b}_i$ We can now write $\mathbf{r}_i$ as :

$$\mathbf{r}_i = \mathbf{AW}\,\mathbf{b}_i + \nu_i \;; \qquad \nu_i \sim N(\mathbf{0}, \mathbf{K}) \tag{6}$$

where **A** is the matrix of the "signal vectors" which depend only on the spreading codes (known) and delays (unknown) of the users, **W** is a diagonal matrix of complex amplitudes (unknown), $\mathbf{b}_i$ contain the users' data bits, and **K** is the unknown noise covariance.
W is a $2K \times 2K$ diagonal matrix of the form:

$$\mathbf{W} = diag\left[w_1, w_1, \ldots\; w_K, w_K\right] \tag{7}$$

and the $2K$ length vector $\mathbf{b}_i$ is of the form

$$\mathbf{b}_i = \left[b_{1,i-1}, b_{1,i}, \ldots, b_{K,i-1}, b_{K,i}\right]^T \tag{8}$$

where $b_{k,i}$ is the i^{th} bit of the k^{th} user. The code response matrix $\mathbf{A} \in C^{N\text{x}2K}$ has columns corresponding to two adjacent bits of each user:

$$\mathbf{A} = \left[\mathbf{a}_1^R\;\mathbf{a}_1^L\;\ldots\;\mathbf{a}_K^R\;\mathbf{a}_K^L\right] \tag{9}$$

Each of the columns $\mathbf{a}_k^R$ and $\mathbf{a}_k^L$ for each user k is function of the corresponding delays ($\tau_{k,1}$ to $\tau_{k,P}$), and attenuation factors ($w_{k,1}$ to $w_{k,P}$).
If T_c is the chip period, let $\tau_{k,p}/T_c = q + \gamma,\; q \in \{0,1,\ldots,N-1\}, \gamma \in [0,1)$ we have [14]

$$\begin{aligned} \mathbf{a}_k^R(\tau_k) &= (1-\gamma)\mathbf{c}_k^R[q] + \gamma\mathbf{c}_k^R[q+1] \\ \mathbf{a}_k^L(\tau_k) &= (1-\gamma)c_k^L[q] + \gamma c_k^L[q+1] \end{aligned} \tag{10}$$

where $\mathbf{c}_k^R[q]$ and $\mathbf{c}_k^L[q]$ are the spreading codes shifted by integer (multiples of chips) delays.

$$\begin{aligned} \mathbf{c}_k^R[q] &= [c_{k,N-q}\ldots c_{k,N-1}\,0\ldots 0]^T \\ \mathbf{c}_k^L[q] &= [0\ldots 0\; c_{k,0},\;\ldots, c_{k,N-q-1}]^T \end{aligned} \tag{11}$$

In order to efficiently model the multi-path effect we will rearrange (6). We write the product of matrices **A** and **W** as:

$$\begin{aligned} \mathbf{AW} &= \left[w_1\mathbf{a}_1^R\quad w_1\mathbf{a}_1^L\;\ldots\; w_K\mathbf{a}_K^R\quad w_K\mathbf{a}_K^L\right] \\ &= \left[\mathbf{u}_1^R\quad \mathbf{u}_1^L\ldots\mathbf{u}_K^R\quad \mathbf{u}_K^L\right] \end{aligned} \tag{12}$$

where

$$\begin{aligned} \mathbf{u}_k^R &= w_k\left\{(1-\gamma)\mathbf{c}_k^R[q] + \gamma\mathbf{c}_k^R[q+1]\right\} \\ \mathbf{u}_k^L &= w_k\left\{(1-\gamma)\mathbf{c}_k^L[q] + \gamma\mathbf{c}_k^L[q+1]\right\} \end{aligned} \tag{13}$$

So the $\mathbf{u}_k$-s can be rewritten as the product of a matrix ($\mathbf{U}_k$) containing all possible $\mathbf{c}_k[q]$-s, or spreading codes shifted by all possible integer delays between 0 and (N-1) and a vector ($\mathbf{h}_k$) which provides the appropriate weights:

$$\mathbf{u}_k^R = \mathbf{U}_k^R \mathbf{h}_k \,,\ \mathbf{u}_k^L = \mathbf{U}_k^L \mathbf{h}_k \,,\ \mathbf{U}_k \in C^{N \times N}, \mathbf{h}_k \in C^{N \times 1}$$

$$\mathbf{U}_k^{(R)} = \left[\mathbf{c}_k^{(R)}[0] \ldots \mathbf{c}_k^{(R)}[N-1]\right]$$

$$\mathbf{U}_k^{(L)} = \left[\mathbf{c}_k^{(L)}[0] \ldots \mathbf{c}_k^{(L)}[N-1]\right]$$

$$\mathbf{h}_k = \begin{bmatrix} 0 \\ . \\ . \\ . \\ w_k(1-\gamma) \\ w_k\gamma \\ . \\ . \\ . \\ 0 \end{bmatrix} \tag{14}$$

Rewriting matrix

$$\mathbf{AW} = [\mathbf{u}_1^R \ \mathbf{u}_1^L \ \ldots \ \mathbf{u}_K^R \ \mathbf{u}_K^L]$$
$$= [\mathbf{U}_1^R \mathbf{h}_1 \ \mathbf{U}_1^L \mathbf{h}_1 \ . \ . \ . \ \mathbf{U}_K^R \mathbf{h}_K \ \mathbf{U}_K^L \mathbf{h}_K],$$

Hence we can write

$\mathbf{AW} = \mathbf{UH}$, $\mathbf{U} \in C^{N\mathrm{x}2K}$, $\mathbf{H} \in C^{2NK\mathrm{x}2K}$:

$$\mathbf{U} = [\mathbf{U}_1^R \ \ \mathbf{U}_1^L \ \ . \ . \ . \ \mathbf{U}_K^R \ \ \mathbf{U}_K^L];$$
$$\mathbf{H} = diag(\mathbf{h}_1, \mathbf{h}_1, \ldots, \mathbf{h}_K, \mathbf{h}_K)$$

This allows us to rewrite equation (6) as:

$$\mathbf{r}_i = \mathbf{UH}\,\mathbf{b}_i + \nu_i \tag{15}$$

where **U** is a known matrix of spreading codes and **H** has all the unknown parameters of all users. The goal of this paper is to estimate the matrix **H** so that individual user channels can be obtained and used after that in the detection process.

The advantage to be gained from expressing $\mathbf{r}_i$ as (15) is that it allows us to easily model the multiple propagation paths without increasing the size of any of the matrices involved. Increasing the sizes of the matrices involved is directly related to the computational complexity of the algorithm. In equation (6), as the number of paths, P, increases, the size of matrices **A** and **W** also increases. However in equation (15), the size of matrices **U** and **H** does not increase, as P increases; instead matrix **H** becomes more dense, as shown in (16).

Let each user have P paths, with corresponding delays and amplitudes of where q is the integer part and γ is the fractional part of the delay. The multiple paths can now be incorporated in the channel impulse response vector $\mathbf{h}_k$, of user k as in (16)

Now **H** has all the unknown parameters of all the paths of all the users and will be estimated from the observations $\mathbf{r}_i$-s, the known sequence of transmitted bits (preamble), and the knowledge of the spreading codes of the different users.

$$\mathbf{h}_k = \begin{bmatrix} 0 \\ . \\ . \\ . \\ w_{k,1}\left(1-\gamma_{k,1}\right) \\ w_{k,1}\gamma_{k,1} \\ . \\ . \\ . \\ w_{k,P}\left(1-\gamma_{k,P}\right) \\ w_{k,P}\gamma_{k,P} \\ . \\ . \\ . \\ 0 \end{bmatrix} \tag{16}$$

3. PROPOSED CHANNEL ESTIMATION ALGORITHM

In this section, a ML-based technique for estimating the composite CIR vector for each user is developed. When an observation vector $\mathbf{r}_i$ depends on a parameter vector ξ, that is either deterministic but unknown or whose a priori statistics are unknown, the maximum likelihood estimate of the parameter ξ is often used. It is given by [15]

$$\hat{\xi}_{ML} = \arg\max_{\xi}\, p(\mathbf{r}_i \,|\, \xi) \tag{17}$$

In the considered problem, $\mathbf{r}_i$ is a function of the channel vectors $\mathbf{h}_k$, the noise covariance matrix **K**, which is assumed unknown, and the transmitted bits $\mathbf{b}_i$. We assume that the bits $\mathbf{b}_i$ are known, since other wise the maximization of the likelihood functions as a function of all the above unknowns is an ill-posed problem. This is accomplished in the acquisition phase by requiring that all the users transmit training sequences or in the tracking phase by the receiver operating in the decision-directed mode.

Given L observations $\mathbf{r}_1, \mathbf{r}_2, \ldots, \mathbf{r}_L$, these are conditionally independent given, $\mathbf{b} = \left[\mathbf{b}_{\mathbf{o}}^T, \mathbf{b}_1^T, \ldots, \mathbf{b}_L^T\right]^T$, the transmitted bits. We form their joint conditional probability density function as

$$p(\mathbf{r}_1, \mathbf{r}_2, \ldots \mathbf{r}_L \,|\, \mathbf{U}, \mathbf{H}, \mathbf{b}, \mathbf{K}) = \frac{1}{\pi^{NL}\left|\mathbf{K}\right|^{L}} \times \exp\left\{-\sum_{i=1}^{L}\left(\mathbf{r}_i - \mathbf{U}\mathbf{H}\mathbf{b}_i\right)\mathbf{K}^{-1}\left(\mathbf{r}_i - \mathbf{U}\mathbf{H}\mathbf{b}_i\right)^{H}\right\} \tag{18}$$

where | . | represents the determinant operator. The corresponding log-likelihood function Λ, ignoring the constant is

$$\begin{aligned}\Lambda &= -\ln(|\mathbf{K}|) - \mathrm{tr}\left\{\frac{1}{L}\sum_{i=1}^{L}\left(\mathbf{r}_i - \mathbf{UHb}_i\right)^H \mathbf{K}^{-1}\left(\mathbf{r}_i - \mathbf{UHb}_i\right)\right\} \\ &= -\ln(|\mathbf{K}|) - \mathrm{tr}\left\{\mathbf{K}^{-1}\frac{1}{L}\sum_{i=1}^{L}\left(\mathbf{r}_i - \mathbf{UHb}_i\right)\left(\mathbf{r}_i - \mathbf{UHb}_i\right)^H\right\}\end{aligned} \quad (19)$$

where tr(.) represents the trace operator.

As the first step, maximization of the log-likelihood function is to be carried out with respect to **K.** The maximum is achieved by the following value of **K** [15].

$$\hat{\mathbf{K}}(\mathbf{U},\mathbf{H}) = \frac{1}{L}\sum_{i=1}^{L}\left(\mathbf{r}_i - \mathbf{UHb}_i\right)\left(\mathbf{r}_i - \mathbf{UHb}_i\right)^H \quad (20)$$

Substituting this into (19), in the next step, we find that we need to maximize $-\ln|\hat{\mathbf{K}}|$ or minimize $|\hat{\mathbf{K}}|$ over all {**H**}. The cost function that we have to minimize with respect to **H** is now

$$\ell = \left|\hat{\mathbf{K}}\right| = \left|\frac{1}{L}\sum_{i=1}^{L}\left(\mathbf{r}_i - \mathbf{UHb}_i\right)\left(\mathbf{r}_i - \mathbf{UHb}_i\right)^H\right| \quad (21)$$

Details regarding the derivation of the cost function (21) by maximizing the likelihood function (19) with respect to **K** can be found in [12].

Direct minimization of (25) with respect to **H** is rather intractable and hence, it is carried out indirectly in the following two steps:

i) Capture the effect of all the unknowns in a single N x $2K$ complex matrix $\boldsymbol{Y} = \mathbf{UH}$. Form the unconstrained ML estimate of $\boldsymbol{Y}$, given by $\hat{y}$.

ii) Having obtained $\hat{y}$, obtain the estimates $\mathbf{h}_k$ by minimizing the weighted least squares fit between $\boldsymbol{Y} = \mathbf{UH}$ and its unstructured estimate, $\hat{y}$.

Step 1: Covariance Approximation

Let us define correlation matrices:

$$\hat{\mathbf{R}}_{rr} = \frac{1}{L}\sum_{i=1}^{L}\mathbf{r}_i\mathbf{r}_i^H \ ,$$

$$\hat{\mathbf{R}}_{br} = \frac{1}{L}\sum_{i=1}^{L}\mathbf{b}_i\mathbf{r}_i^H \ ,$$

$$\hat{\mathbf{R}}_{bb} = \frac{1}{L}\sum_{i=1}^{L}\mathbf{b}_i\mathbf{b}_i^T \quad (22)$$

In terms of the sample correlation matrices, $\hat{\mathbf{K}}(y)$ can be written as:

$$\hat{\mathbf{K}}(y) = \hat{\mathbf{R}}_{rr} - y\,\hat{\mathbf{R}}_{rb}^H - \hat{\mathbf{R}}_{rb}\,y^H + y\,\hat{\mathbf{R}}_{bb}\,y^H \quad (23)$$

So, $\hat{y}$, the ML estimate of Y is:

$$\hat{y} = \arg\min_{y}\left|\hat{\mathbf{R}}_{rr} - y\,\hat{\mathbf{R}}\hat{\mathbf{R}}_{rb}^H - \hat{\mathbf{R}}_{rb}\,y^H + y\,\hat{\mathbf{R}}_{bb}\,y^H\right| \quad (24)$$

This can be shown to be:

$$\hat{y} = \hat{\mathbf{R}}_{rb}\,\hat{\mathbf{R}}_{bb}^{-1} \quad (25)$$

Substituting back,

$$\hat{\mathbf{K}}(\hat{y}) = \hat{\mathbf{R}}_{rr} - \hat{y}\,\hat{\mathbf{R}}_{rb}^H \quad (26)$$

Now, the cost function can be written using expressions for $\hat{y}$ and $\hat{\mathbf{K}}$.

Step 2: Channel Impulse Response Estimation

Substituting the expressions for $\hat{y}$ (25) and $\hat{\mathbf{K}}$ (26), in the cost function (21), the modified cost function is the optimized with respect to **H.** After some simple algebraic steps, this can be shown to be ($\hat{y} = \mathbf{U}\hat{\mathbf{H}}$):

$$\hat{\mathbf{H}} = \arg\min_{\mathbf{H}}\left\{\hat{\mathbf{R}}_{bb}(y-\hat{y})^H\mathbf{K}^{-1}(y-\hat{y})\right\} \quad (27)$$

Since the received signals of the different users are "uncorrelated", $\hat{\mathbf{R}}_{bb}$ is block diagonal for large L. This diagonal form helps to dramatically separate the estimation process of each user. So, we can estimate the k^{th} user's channel impulse response to be:

$$\hat{\mathbf{h}}_k = \arg\min_{\mathbf{h}_k}\left[\left(\mathbf{y}_{2k-1}-\hat{\mathbf{y}}_{2k-1}\right)^H\mathbf{K}^{-1}\left(\mathbf{y}_{2k-1}-\hat{\mathbf{y}}_{2k-1}\right)+\left(\mathbf{y}_{2k}-\hat{\mathbf{y}}_{2k}\right)^H\mathbf{K}^{-1}\left(\mathbf{y}_{2k}-\hat{\mathbf{y}}_{2k}\right)\right] \quad (28)$$

For each user we have contributions for right and left signal vectors, i.e., the 2 k^{th} and $(2k-1)^{th}$ columns of Ψ. Let us recall that the columns of Ψ are the $\mathbf{u}_k$-s in equation (15):

$$\mathbf{y}_{2k-1} = \mathbf{u}_k^R = \mathbf{U}_k^R\mathbf{h}_k\,,\quad \mathbf{y}_{2k} = \mathbf{u}_k^L = \mathbf{U}_k^L\mathbf{h}_k \quad (29)$$

Hence, the estimate of $\mathbf{h}_k$ is:

$$\hat{\mathbf{h}}_k = \arg\min_{\mathbf{h}_k}\left[\left(\mathbf{U}_k^R\mathbf{h}_k - \hat{\mathbf{y}}_{2k-1}\right)^H \mathbf{K}^{-1}\left(\mathbf{U}_k^R\mathbf{h}_k - \hat{\mathbf{y}}_{2k-1}\right) + \left(\mathbf{U}_k^L\mathbf{h}_k - \hat{\mathbf{y}}_{2k}\right)^H \mathbf{K}^{-1}\left(\mathbf{U}_k^L\mathbf{h}_k - \hat{\mathbf{y}}_{2k}\right)\right] \quad (30)$$

This can be shown to be:

$$\hat{\mathbf{h}}_k^H = \left(\hat{\mathbf{y}}_{2k-1}^H \hat{\mathbf{K}}^{-1} \mathbf{U}_k^R + \hat{\mathbf{y}}_{2k}^H \hat{\mathbf{K}}^{-1} \mathbf{U}_k^L\right)\left(\mathbf{U}_k^{R^H} \hat{\mathbf{K}}^{-1} \mathbf{U}_k^R + \mathbf{U}_k^{L^H} \hat{\mathbf{K}}^{-1} \mathbf{U}_k^L\right)^{-1} \quad (31)$$

So, a closed-form expression for the composite CIR vector $\hat{\mathbf{h}}_k$ for each user is obtained.

4. COMPUTATIONAL COMPLEXITY

The computational complexities of the various steps of the algorithm are:
i) Covariance approximation

Calculation of sample correlation matrices, $\hat{\mathbf{R}}_{rr}$, $\hat{\mathbf{R}}_{br}$, and $\hat{\mathbf{R}}_{bb}$ in (22)-$O(N^2)$, $O(NK)$, $O(K^2)$.

Calculation of $\hat{y}$, $\hat{\mathbf{K}}$ in (25) and (26) -$O(K^3)$, $O(N K^2)$, $O(KN^2)$

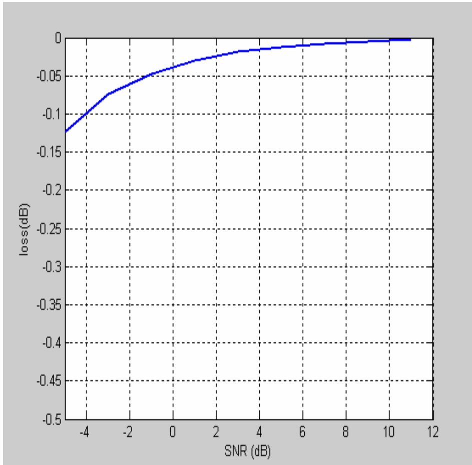
ii) Channel impulse response estimation in (31) $O(N^3)$

From the list of complexity of all the steps in the algorithm, shown above, it is evident that the overall complexity of the algorithm is $O(N^3)$. However the complexity can be reduced further if $\hat{\mathbf{K}}$ is assumed to be identity (the noise being additive white Gaussian) instead of explicitly calculating it. This whiteness assumption is practical not only because thermal noise is assumed Gaussian but also because the residual noise due to other-cell interference can be considered spatially and temporally white.

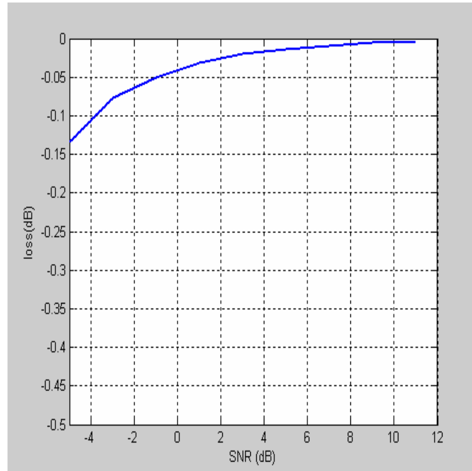
Other than eliminating the computation of $\hat{\mathbf{K}}$, this will also reduce the complexity of the channel impulse response estimation step to $O(N^2)$. The inverse of $\hat{\mathbf{R}}_{bb}$ can be estimated using matrix inversion update algorithms $O(K^2)$, or can be pre-calculated as the preamble is a known sequence of bits. Also the various matrix multiplications in the algorithm can benefit greatly using well-known parallelization techniques on a number of processors [16].

5. SIMULATION RESULTS

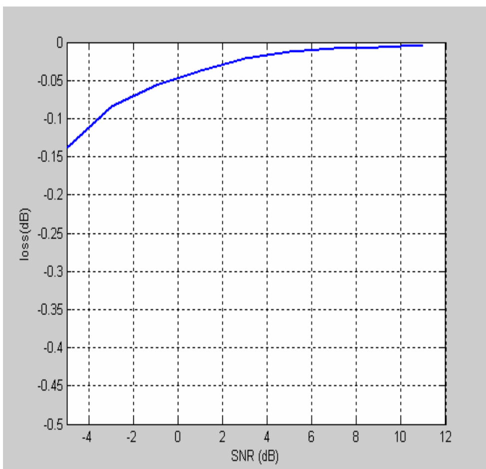
We briefly describe the preliminary simulations that we conducted to evaluate the performance of the proposed estimator. A code length of N = 31 was used in all the simulations. The delays of all the users were assumed uniformly distributed in [1:31) chips. The multiple access interference presented by each interferer, which is the ratio of the



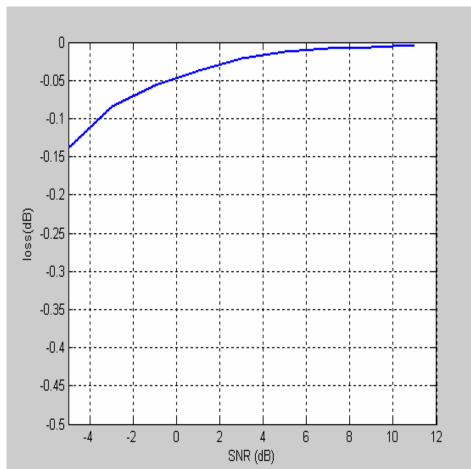
a) 5 users



b) 10 users



c) 15 user



d) 20 user

Fig.2 Loss in the estimated composite channel vector equation (32) versus Signal to Noise Ratio for different numbers of users: a) 5 users, b) 10 users, 15 user, and d) 20 user

interferer's and desired user's received energies, was uniformly distributed in [0:MAI]dB. Unless stated, the values of the system parameters are: the number of observations is L = 200, MAI = 10dB, the signal-to-noise ratio of the background noise is SNR = 10dB and the number of users is K = 5. The number of paths P for each user is taken to be three. Each point in our plots corresponds to 1000 Monte-Carlo trials.

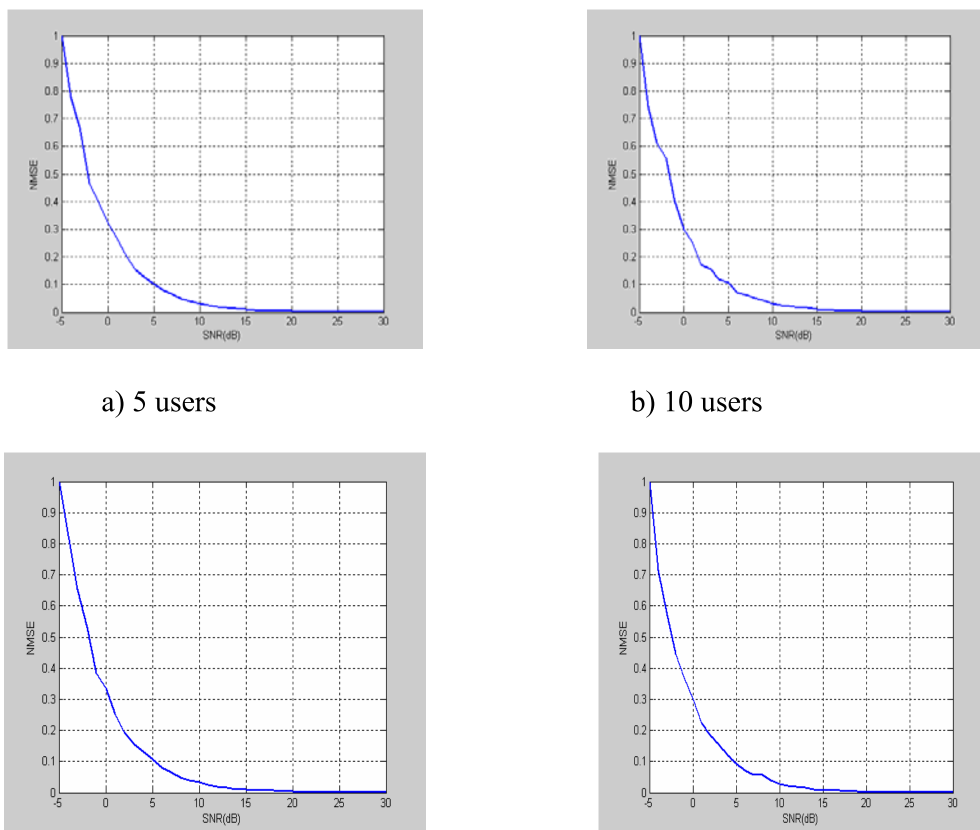
Since a large number of interdependent parameters are to be estimated, it is not very revealing to look at the estimation error of each individual parameter. Instead, the channel impulse response is constructed equation (16) using the actual parameters and the estimated ones and the 'loss' due to the estimation procedure is calculated as:

$$loss = \left(\frac{\mathbf{h}_k}{\left\|\mathbf{h}_k\right\|}\right)^T \left(\frac{\hat{\mathbf{h}}_k}{\left\|\hat{\mathbf{h}}_k\right\|}\right) \tag{32}$$

In Fig.2, it is quite obvious that the MSE of the composite CIR estimate is almost the same for different numbers of users, indicating that the estimator can handle large numbers in an efficient manner.

Fig.3 shows the loss in the composite CIR due to estimation for different values of SNR. It is clear that the loss is negligible [0 : -0.2] dB.

The last plot Fig.4 demonstrates the near-far resistant capability of the algorithm, by showing that the mean squared error doesn't vary with an increase in the MAI power.



a) 5 users b) 10 users

c) 15 users d) 20 users

Fig. 3 Normalized Mean Squared Error of the estimated composite channel vector versus Signal to Noise Ratio for different number of users: a) 5 users, b) 10 users, c) 15 users, d) 20 users

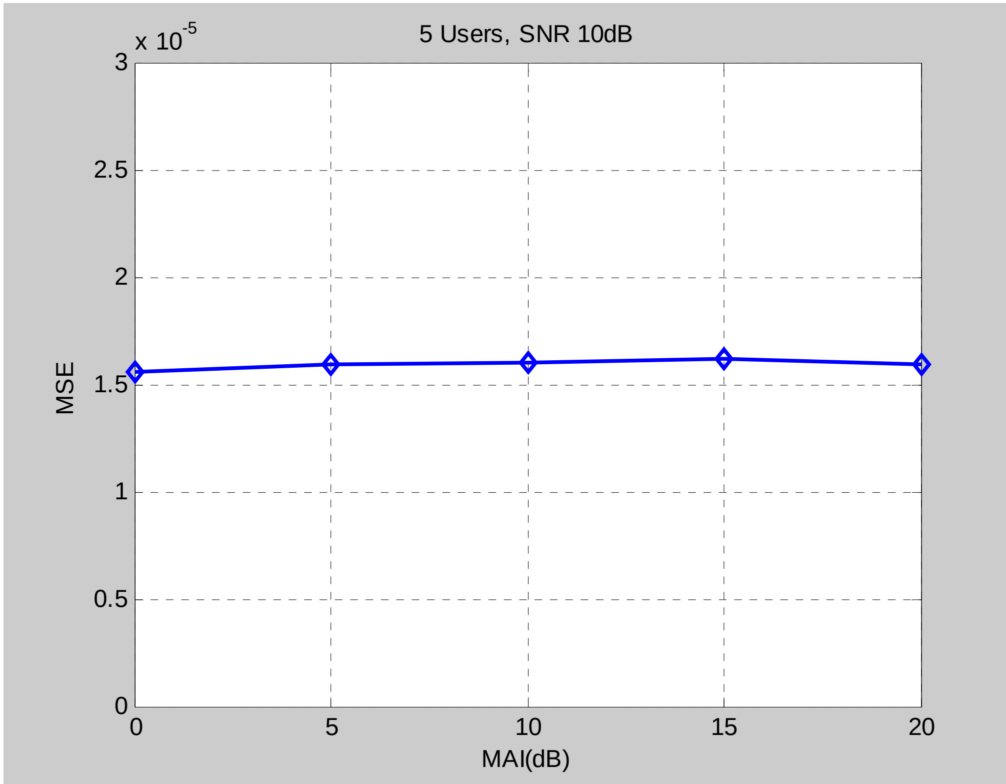


Fig.4 MSE of the estimated composite channel vector versus MAI for a five users system at 10 dB SNR.

6. CONCLUSIONS

A ML algorithm for multi-path composite CIR estimation has been developed. The algorithm considers a set of transmitting users in the reverse link of a wireless WCDMA communication system. The algorithm generalizes a single path model based ML algorithm presented in [12] to include handling of multiple propagation paths without increasing the sizes of the matrices involved, and hence without significantly increasing the computational load. The algorithm elegantly decomposes the multi-user problem into a series of single-user ones.

The additive noise in the system is assumed to be zero mean, Gaussian but no assumption is made on its covariance, which is estimated within the algorithm. Our simulations verify that the algorithm is near-far resistant. Also, the estimators are not dimensionally limited; making it ideal for acquisition of a large number of users. Furthermore, the preamble required is not prohibitively large, good results obtained with 150-200 bits preamble. A direction for future research is to investigate behavior of different detection techniques using the estimator output. Also it could be extension of this algorithm to handle signals from multiple antennas at the receiving terminal.

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