Maximum Likelihood Multipath Channel Parameter Estimation in CDMA Systems Using Antenna Arrays

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ABSTRACT

The problem addressed in this paper is the estimation of the channel parameters in a Code Division Multiple Access (CDMA) communication system, in the presence of multipath effects and multiple sensors at the base station receiver. The algorithm presented in this paper solves the problem by estimating a composite channel impulse response of each user, which can be directly used in the detection process to appropriately modify the spreading code of the user. In addition, the algorithm combines the benefit of spatial processing in the form of an antenna array at the receiver to gain an increase in performance of the system.

I. INTRODUCTION

In a *Code Division Multiple Access (CDMA)* communication system, a communication channel with a given bandwidth is accessed by all the users simultaneously. The different mobile users are distinguished at the base station receiver by the unique *spreading code* assigned to the users to modulate their signals. 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 unknown and time varying attenuation factors and delays by processing the received signal, to facilitate recovery of the data transmitted by each user.

Most of the initial work done on near-far resistant timing acquisition for CDMA systems focused on jointly estimating the necessary parameters for all users [1, 2]. 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. Recently, more computationally efficient near-far resistant algorithms have been proposed for multipath [3, 4] as well as single path, multiple sensors [5] scenarios.

It has been shown before [5] that the use of a number of sensors at the receiver dramatically improves the performance of channel estimators as well as linear detectors. However the problem of using multiple sensors to detect multipath channel parameters, is mathematically complex, as it involves the estimation of a large number of parameters. Most of the existing literature deals with the single path case when studying the multiple sensor scenario.

This paper presents an algorithm based on the maximum likelihood (ML) approach [5] that estimates the channel impulse response of a *multipath channel* in the presence of an *antenna array* at the receiving base station. In addition, it also outlines how this estimated channel impulse response can be directly used in the detection process to appropriately modify the spreading code of the user. The resulting algorithm is computationally efficient and performs well in the presence of multiple paths, high multiple access interference and low signal-to-noise ratio scenarios.

The algorithm assumes the transmission of training sequences by all the users being acquired. The algorithm makes no assumption whatsoever on the individual delays or on the array structure. The additive noise is assumed to be a circularly complex zero mean Gaussian random vector, but no assumption is made on its covariance.

II. CDMA SYSTEM MODEL

We assume a K-user narrow band direct sequence CDMA system with BPSK (Binary Phase Shift Keying) modulation with each transmitted signal selected from a binary alphabet and limited to $[0, T]$, where T is the symbol period. Each user transmits a zero mean stationary bit sequence with i.i.d. components and different users are independent of each other.

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

$$s_k(t) = \sqrt{P_k} \sum_i b_{k,i} c_k(t - iT) \; , \tag{1}$$

where P_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 or code waveform is composed of N chips and if we assume BPSK for the spreading modulation we have
$c_k(t) = \sum_{n=0}^{N-1} c_{k,n} \Pi(t - nT_c)$, where $c_{k,n} \in \{+1, \; -1\}$ and the chip pulse waveform $\Pi(t)$ is a rectangular pulse of duration T_c.

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We will assume that the extent of the spreading code is one bit period and hence we have $T = NT_c$.

The frontend of the receiver consists of an antenna array of M sensors arranged in a specific geometry. The corresponding array response vector, which is the response to a propagating plane wave impinging on the array at an angle θ, with the vertical is :

$$[\rho^{(1)}(\theta), \cdots, \rho^{(m)}(\theta), \cdots, \rho^{(M)}(\theta)]. \tag{2}$$

and is determined by the geometry of the array. It is assumed that the time taken by the signal to traverse the physical array is much smaller than the message bandwidth and hence, the envelope characteristics of the signal do not vary across the array.

The received signal at the base station is a superposition of P copies of attenuated and delayed signals transmitted by all the K users. Therefore, the signal at the m^{th} sensor is given by:

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

where $w_{k,p}$ is the complex amplitude with which the p^{th} path of the k^{th} user is received, $\tau_{k,p}$ is the relative delay of the same path, and $\theta_{k,p}$ is its direction of arrival. The additive Gaussian noise is assumed to have some correlation across the array and is not necessarily white.

The continuous time signal at the receiver is discretized by sampling the output of a chip-matched filter at the chip rate. The observation vector at time i at the m^{th} sensor, $\mathbf{r}_i^{(m)} \in \mathbb{C}^N$, is then formed by collecting N such outputs together:

$$\mathbf{r}_i^{(m)} = \mathbf{A}^{(m)}\mathbf{b}_i + \boldsymbol{\nu}_i^{(m)}, \quad \boldsymbol{\nu}_i^{(m)} \sim \mathcal{N}(\mathbf{0}, \mathbf{K}^{(m)}). \tag{4}$$

The $2K$ length vector $\mathbf{b}_i$ is of the form :
$\mathbf{b}_i = [b_{1,i-1}, b_{1,i}, \ldots, b_{k,i-1}, b_{k,i}, \ldots, b_{K,i-1}, b_{K,i}]^T$, where $b_{k,i}$ is the i^{th} bit of the k^{th} user.

Let us consider the columns of the matrix $\mathbf{A}^{(m)}$. Since the system is asynchronous, this matrix has columns corresponding to two adjacent bits of each user denoted by the superscripts R and L.

$$\mathbf{A}^{(m)} = [\mathbf{a}_1^R \quad \mathbf{a}_1^L \quad \cdots \quad \mathbf{a}_K^R \quad \mathbf{a}_K^L]. \tag{5}$$

If T_c is the chip period, let $\tau_{k,p}/T_c = q + \gamma$, $q \in \{0, 1, \cdots, N-1\}, \gamma \in [0, 1)$, we have [3]:

$$\begin{aligned}\mathbf{a}_k^R &= \sum_{p=1}^{P}[w_{k,p}\{(1-\gamma)\mathbf{c}_k^R[q] + \gamma\mathbf{c}_k^R[q+1]\}\rho_{k,p}^{(m)}]\\ \mathbf{a}_k^L &= \sum_{p=1}^{P}[w_{k,p}\{(1-\gamma)\mathbf{c}_k^L[q] + \gamma\mathbf{c}_k^L[q+1]\}\rho_{k,p}^{(m)}]\end{aligned} \tag{6}$$

where $\rho_{k,p}^{(m)} = \rho^{(m)}(\theta_{k,p})$ and $\mathbf{c}_K^R[q]$ and $\mathbf{c}_K^L[q]$ are the spreading codes shifted by integer (multiples of chips) delays.

$$\begin{aligned}\mathbf{c}_k^R[q] &= [c_{k,N-q} \cdots c_{k,N-1}\, 0 \cdots 0]^T\\ \mathbf{c}_k^L[q] &= [0 \cdots 0\; c_{k,0} \cdots c_{k,N-q-1}]^T\end{aligned} \tag{7}$$

Note that (5) and (6) show that the columns of $\mathbf{A}^{(m)}$ are linear combinations of $\mathbf{c}_k[q]$'s. Let $\mathbf{U}_k^R \in \mathbb{C}^{N\times N}$ and $\mathbf{U}_k^L \in \mathbb{C}^{N\times N}$ be matrices formed from the spreading codes, delayed by all possible integer delays. Let $\mathbf{z}_k^{(m)} \in \mathbb{C}^{N\times 1}$ be the composite channel impulse response vector corresponding to the m^{th} sensor, consisting of the weight vectors in the linear combinations of the $\mathbf{c}_K[q]$'s, expressed in (6). Hence, we can write $\mathbf{U}_k^R$, $\mathbf{U}_k^L$, and $\mathbf{z}_k^{(m)}$ as:

$$\begin{aligned}\mathbf{U}_k^{(R)} &= [\mathbf{c}_k^{(R)}[0] \cdots \mathbf{c}_k^{(R)}[N-1]],\\ \mathbf{U}_k^{(L)} &= [\mathbf{c}_k^{(L)}[0] \cdots \mathbf{c}_k^{(L)}[N-1]], \qquad (8)\\ \mathbf{z}_k^{(m)} &= \mathbf{p}_k^{(m)} \circ \mathbf{h}_k, \qquad (9)\end{aligned}$$

$$\mathbf{h}_k = \begin{bmatrix} 0 \\ \vdots \\ w_{k,1}(1-\gamma_{k,1}) \\ w_{k,1}\gamma_{k,1} \\ \vdots \\ w_{k,P}(1-\gamma_{k,P}) \\ w_{k,P}\gamma_{k,P} \\ \vdots \\ 0 \end{bmatrix} \begin{array}{l} \\ \\ \leftarrow \quad q_{k,1}^{th} element \\ \leftarrow \quad (q_{k,1}+1)^{th} element \\ \\ \leftarrow \quad q_{k,P}^{th} element \\ \leftarrow \quad (q_{k,P}+1)^{th} element \\ \\ \\ \end{array} \tag{10}$$

$$\mathbf{p}_k^{(m)} = \begin{bmatrix} 0 \\ \vdots \\ \rho_{k,1}^{(m)} \\ \rho_{k,1}^{(m)} \\ \vdots \\ \rho_{k,P}^{(m)} \\ \rho_{k,P}^{(m)} \\ \vdots \\ 0 \end{bmatrix} \begin{array}{l} \\ \\ \leftarrow \quad q_{k,1}^{th} element \\ \leftarrow \quad (q_{k,1}+1)^{th} element \\ \\ \leftarrow \quad q_{k,P}^{th} element \\ \leftarrow \quad (q_{k,P}+1)^{th} element \\ \\ \\ \end{array} \tag{11}$$

Here the operator '$\circ$' denotes the element-wise multiplication of the two vector operands. The parameters $q_{k,p}$ and $\gamma_{k,p}$ are the integer and fractional parts of the delay $\tau_{k,p}$. Now, the columns of $\mathbf{A}^{(m)}$ can be expressed in terms of $\mathbf{U}_k^R$, $\mathbf{U}_k^L$, and $\mathbf{z}_k^{(m)}$ as:

$$\mathbf{a}_k^R = \mathbf{U}_k^R\mathbf{z}_k^{(m)}, \qquad \mathbf{a}_k^L = \mathbf{U}_k^L\mathbf{z}_k^{(m)}. \tag{12}$$

Hence, the observation vector $\mathbf{r}_i$, of length MN, across the array: $\mathbf{r}_i = [\mathbf{r}_i^{(1)^T}, \cdots \mathbf{r}_i^{(k)^T}, \cdots \mathbf{r}_i^{(K)^T}]^T$ is:

$$\mathbf{r}_i = \begin{bmatrix} \mathbf{U}_1^R\mathbf{z}_1^{(1)} & \mathbf{U}_1^L\mathbf{z}_1^{(1)} \cdots \mathbf{U}_K^R\mathbf{z}_K^{(1)} & \mathbf{U}_K^L\mathbf{z}_K^{(1)} \\ & \vdots & \\ \mathbf{U}_1^R\mathbf{z}_1^{(M)} & \mathbf{U}_1^L\mathbf{z}_1^{(M)} \cdots \mathbf{U}_K^L\mathbf{z}_K^{(M)} & \mathbf{U}_K^L\mathbf{z}_K^{(M)} \end{bmatrix} \mathbf{b}_i + \boldsymbol{\nu}_i. \tag{13}$$

where the noise vector $\boldsymbol{\nu}_i$ is formed from the components $\boldsymbol{\nu}_i^{(m)}$ and is assumed to have an unknown covariance of $\mathbf{K}$.

The columns of the combined code and channel matrix in the expression for $\mathbf{r}_i$ above are written as: $\mathcal{U}_k^R\mathbf{z}_k$ and $\mathcal{U}_k^L\mathbf{z}_k$, where, $\mathcal{U}_k^R = I_M \otimes \mathbf{U}_k^R$, $\mathcal{U}_k^L = I_M \otimes \mathbf{U}_k^L$, $\mathcal{U}_k^R, \mathcal{U}_k^L \in \mathbb{C}^{MN\times MN}$, $\mathbf{z}_k = [\mathbf{z}_k^{(1)^T}, \cdots, \mathbf{z}_k^{(m)^T}, \cdots, \mathbf{z}_k^{(M)^T}]^T$, $\mathbf{z}_k \in \mathbb{C}^{MN\times 1}$. Here the operator '$\otimes$' represents the Kronecker product of two matrices. This helps us to rewrite the expression for $\mathbf{r}_i$ as:

$$\mathbf{r}_i = [\mathcal{U}_1^R\mathbf{z}_1 \quad \mathcal{U}_1^L\mathbf{z}_1 \cdots \mathcal{U}_K^R\mathbf{z}_K \quad \mathcal{U}_K^L\mathbf{z}_K]\mathbf{b}_i + \boldsymbol{\nu}_i$$

$$\mathbf{r}_i = \mathcal{U}\mathbf{Z}\mathbf{b}_i + \boldsymbol{\nu}_i \tag{14}$$

where, $\mathcal{U} = [\mathcal{U}_1^R \;\; \mathcal{U}_1^L \c{d}ots \mathcal{U}_k^R \;\; \mathcal{U}_k^L \cdots \mathcal{U}_K^R \;\; \mathcal{U}_K^L]$ and $\mathbf{Z} = diag(\mathbf{z}_1, \mathbf{z}_1, \cdots, \mathbf{z}_K, \mathbf{z}_K)$.

Now $\mathbf{Z}$ has all the unknown parameters of all the paths of all the users from all the sensors 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.

III. PROPOSED CHANNEL ESTIMATION ALGORITHM

Given L observations $\mathbf{r}_1, \mathbf{r}_2, \ldots, \mathbf{r}_L$ the log-likelihood function of these observations can be expressed as

$$\Lambda = -\ln|\mathbf{K}| - \operatorname{tr}\left\{\frac{1}{L}\sum_{i=1}^{L}(\mathbf{r}_i - \mathcal{U}\mathbf{Z}\mathbf{b}_i)^H\mathbf{K}^{-1}(\mathbf{r}_i - \mathcal{U}\mathbf{Z}\mathbf{b}_i)\right\} \tag{15}$$

where $|\cdot|$ represents the determinant operator and $\operatorname{tr}(\cdot)$, the trace operator. Maximization of the log-likelihood function is to be carried out with respect to $\{\mathbf{Z}, \mathbf{K}\}$. This problem is ill-defined if $\mathbf{b}_1, \ldots, \mathbf{b}_L$ are unknown and hence the need for training sequences or preamble. The maximum with respect to $\mathbf{K}$ is easily found to be

$$\widehat{\mathbf{K}}(\mathcal{U}, \mathbf{Z}) = \frac{1}{L}\sum_{i=1}^{L}(\mathbf{r}_i - \mathcal{U}\mathbf{Z}\mathbf{b}_i)(\mathbf{r}_i - \mathcal{U}\mathbf{Z}\mathbf{b}_i)^H. \tag{16}$$

Substituting this into equation 15, we find that we need to maximize $-\ln|\widehat{\mathbf{K}}|$ or minimize $|\widehat{\mathbf{K}}|$ over all $\{\mathbf{Z}\}$. Direct minimization of $|\widehat{\mathbf{K}}|$ with respect to $\{\mathbf{Z}\}$ is rather intractable and hence, it is carried out in two steps [5]:

(i) Capture the effect of all the unknowns in a single complex matrix $\mathcal{Y} \triangleq \mathcal{U}\mathbf{Z}$. Form the unconstrained ML estimate of $\mathcal{Y}$, given by $\widehat{\mathcal{Y}}$.

(ii) Obtain the estimates $\hat{\mathbf{z}_k}$ by minimizing the weighted least squares fit between $\mathcal{Y} = \mathcal{U}\mathbf{Z}$ and its estimate, $\widehat{\mathcal{Y}}$.

A. Step 1: Covariance approximation

Let us define correlation matrices: $\widehat{\mathbf{R}}_{rr} = \frac{1}{L}\sum_{i=1}^{L}\mathbf{r}_i\mathbf{r}_i^H$, $\widehat{\mathbf{R}}_{br} = \frac{1}{L}\sum_{i=1}^{L}\mathbf{b}_i\mathbf{r}_i^H$, $\widehat{\mathbf{R}}_{bb} = \frac{1}{L}\sum_{i=1}^{L}\mathbf{b}_i\mathbf{b}_i^H$. In terms of the sample correlation matrices, the estimated values of $\widehat{\mathcal{Y}}$ and $\widehat{\mathbf{K}}(\mathcal{Y})$ obtained by minimizing our cost function is:

$$\widehat{\mathcal{Y}} = \widehat{\mathbf{R}}_{rb}\widehat{\mathbf{R}}_{bb}^{-1}, \qquad \widehat{\mathbf{K}}(\widehat{\mathcal{Y}}) = \widehat{\mathbf{R}}_{rr} - \widehat{\mathcal{Y}}\widehat{\mathbf{R}}_{rb}^H \tag{17}$$

Now we can rewrite the cost function using expressions for $\widehat{\mathcal{Y}}$ and $\widehat{\mathbf{K}}$.

B. Step 2: Channel impulse response estimation

Using expressions for $\widehat{\mathcal{Y}}$ and $\widehat{\mathbf{K}}$ in the cost function, the estimate of the k^{th} user's channel impulse response is obtained [5]:

$$\widehat{\mathbf{z}_k} = \arg\min_{\mathbf{z}_k}\Big[(\mathbf{y}_{2k-1} - \hat{\mathbf{y}}_{2k-1})^H\widehat{\mathbf{K}}^{-1}(\mathbf{y}_{2k-1} - \hat{\mathbf{y}}_{2k-1}) + (\mathbf{y}_{2k} - \hat{\mathbf{y}}_{2k})^H\widehat{\mathbf{K}}^{-1}(\mathbf{y}_{2k} - \hat{\mathbf{y}}_{2k})\Big] \tag{18}$$

For each user we have contributions for right and left signal vectors, i.e., the $2k^{th}$ and $(2k-1)^{th}$ columns of $\mathcal{Y}$. Let us recall that the columns of $\mathcal{Y}$ are nothing else but the columns of matrix $\mathcal{U}\mathbf{Z}$ (14): $\mathbf{y}_{2k-1} = \mathcal{U}_k^R\mathbf{z}_k$, $\mathbf{y}_{2k} = \mathcal{U}_k^L\mathbf{z}_k$. Using this information and some algebraic manipulation:

$$\widehat{\mathbf{z}_k}^H = (\hat{\mathbf{y}}_{2k-1}^H\widehat{\mathbf{K}}^{-1}\mathcal{U}_k^R + \hat{\mathbf{y}}_{2k}^H\widehat{\mathbf{K}}^{-1}\mathcal{U}_k^L)(\mathcal{U}_k^{R^H}\widehat{\mathbf{K}}^{-1}\mathcal{U}_k^R + \mathcal{U}_k^{L^H}\widehat{\mathbf{K}}^{-1}\mathcal{U}_k^L)^{-1} \tag{19}$$

Most of the work that has been done on channel parameter estimation focuses on estimating each individual parameter for each user, such as, time delay, amplitudes, and direction of arrival. For multipath channel parameter estimation with a single sensor using maximum likelihood techniques, the authors have previously proposed a method [6] to efficiently extract the individual channel parameters from the composite channel impulse response.

However when multiple sensors are used, and the various multipath components arrive at the receiver from different directions, the problem of fitting the estimate $\hat{\mathbf{z}_k}$ to the parametric model described in the previous section, is much more complex. To simplify the computation, in this paper, we propose to use the estimate $\hat{\mathbf{z}_k}$ directly in detection algorithms. Using this approach it will be possible to exploit the benefits of spatial diversity from using multiple sensors, without having to extract the individual delays, amplitudes, and directions of arrival of all the paths of each user.

IV. USE OF CHANNEL IMPULSE RESPONSE IN DETECTION

In this section, we examine the possibility of using the composite channel impulse response, from the multiple sensors, in linear multiuser detection. We restrict ourselves to *single-shot* detectors; however the gains from using multiple sensors in this case can also be extended to sequence detection.

For a single sensor, the matched filter receiver, matched to multipath components, is usually implemented using the channel parameters as:

$$\mathbf{y}_k^{(1)}(i) = \sum_P\int_{(i-1)T}^{iT}\mathrm{w}_{k,p}r^{(1)}(t)c_k(t - iT - \tau_{k,p})dt, \tag{20}$$

where $\mathbf{y}_k^{(1)}(i)$ is the matched filter output at a single sensor for the k^{th} user at the i^{th} bit period. In [6], it has been shown that the discretized version of the received signal, for a single sensor, can be written as $\mathbf{r}_i^{(1)} = \mathbf{UHb}_i + \boldsymbol{\nu}_i$ where $\mathbf{U}$ and $\mathbf{H}$ is the same as $\mathcal{U}$ and $\mathbf{Z}$ when $M = 1$.

Using this discretized signal model the equation for the matched filter can be rewritten as :

$$\mathbf{y}_{k}{}_i^{(1)} = (\mathbf{UH})^T \mathbf{r}_i^{(1)} \tag{21}$$

This is similar to the use of the notion of *received effective signature waveform*, described in [7]. The received effective signature waveform is the spreading code of a user modified with the corresponding channel parameters, which is exactly the result of $\mathbf{UH}$, for all the users.

Extending this to multiple sensors, the combined output of a matched filter receiver at each of the sensors, for all the users, is:

$$\mathbf{y}_i = (\mathcal{U}\mathbf{Z})^T \mathbf{r}_i. \tag{22}$$

where $\mathbf{y}_i \in \mathbb{C}^K$ Since all the delay as well as the angle of arrival information is captured in $\mathbf{Z}$, this can be interpreted as a code matched filter operation at each sensor, followed by an 'angle-matched filter' or conventional beamformer.

Extending this idea to linear multiuser *single-shot* detectors, with multiple sensors [8], the vector of decision statistics for all the users, from a linear detector, $G \in \mathbb{C}^{K \times K}$, is given by :

$$z_i = G\mathbf{y}_i = G(\mathcal{U}\mathbf{Z})^T \mathbf{r}_i. \tag{23}$$

The required bit estimate is then, $\hat{\mathbf{b}}_i = sign(z_i)$. Now, according to our system model, $\mathbf{b}_i$ contains consecutive bits of each user. Hence the decision statistic for each user will consist of two *soft* estimates for each bit of the user. The two *soft* estimates can be combined such that the output signal-to-interference ratio is maximized [8], to obtain a *hard* decision for each bit.

For a decorrelating detector, it follows that $G = ((\mathcal{U}\mathbf{Z})^T(\mathcal{U}\mathbf{Z}))^{-1}$. In the next section, we will show the performance of such a detector.

V. SIMULATION RESULTS

In this section, we describe the simulations that we conducted to evaluate the performance of the proposed estimators. 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 interferer's and desired user's received energies, was uniformly distributed in $[0, MAI]$dB. The signal-to-noise ratio of the background noise is denoted by SNR.

The results (Figure 1) from the matched filter receiver show that the performance actually improves if the channel impulse response is directly used in the detector as in equation 21 (plot labeled 'z directly, M=1') instead of first extracting the individual parameters from the composite channel impulse response and then using them as in equation 20 (plot labeled 'parameters, M=1'). Also, the performance improves dramatically as the number of sensors are increased.

Figure 2 shows the performance of the decorrelating detector using multiple sensors and compares it to the matched filter. The matched filter performs worse than in the previous figure due to the higher MAI, even though its performance still improves when multiple sensors are used.

VI. CONCLUSION

We have developed a maximum likelihood algorithm for multipath channel estimation for a set of transmitting users in the reverse link of a wireless CDMA communication system, when an antenna array is used at the receiver. The algorithm estimates the channel impulse response encapsulating all the channel parameters which was then directly used in the detection process. Our simulations show that considerable performance benefits can be obtained by using multiple sensors at the receiver, in the presence of multipath effects and multiple access interference.

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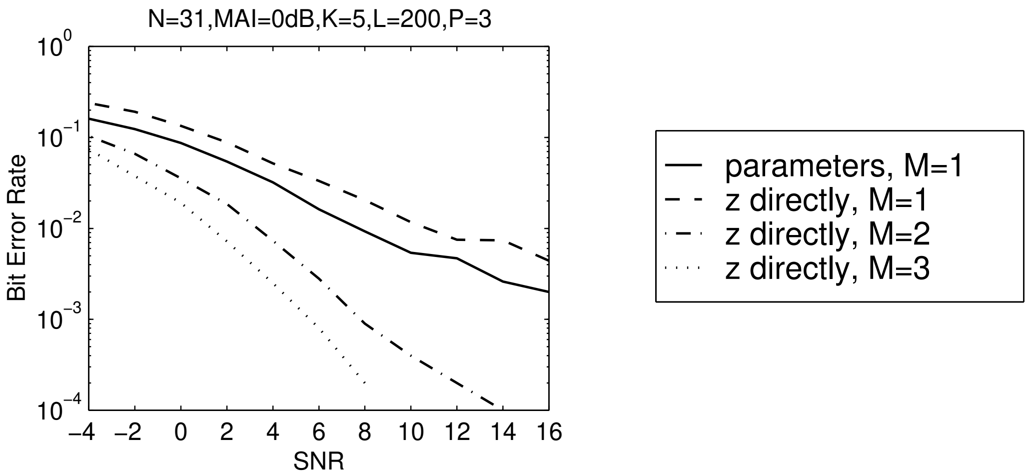

Figure 1: BER from a matched filter receiver using composite channel impulse response ($\hat{\mathbf{z}_k}$) and multiple sensors (M)

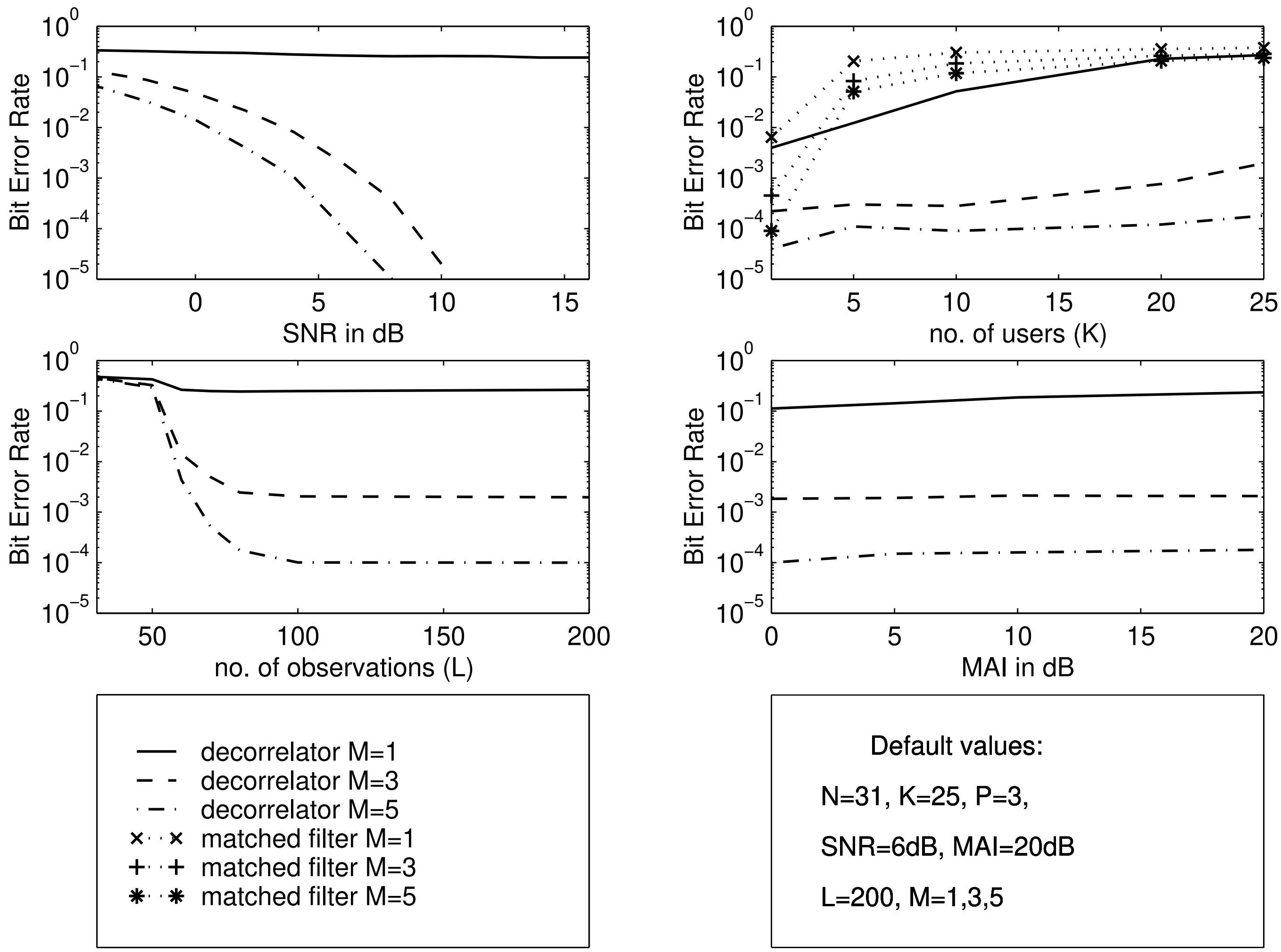

Figure 2: BER from a *one-shot* decorrelating detector using composite channel impulse response ($\hat{\mathbf{z}_k}$) and multiple sensors (M)