Blind Channel Estimation in Aperiodic Time Hopping Ultra-Wideband Systems

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***Abstract*— In a traditional pulse position modulation (PPM) time hopping ultra-wideband (UWB) communication system, each user is assigned a distinct time-hopping sequence, either periodic short sequence or aperiodic long sequence. This paper focuses on blind multiuser channel estimation in aperiodic time hopping UWB systems, using both the least squares method and the correlation matching method. After we formulate the PPM UWB signal to a pulse-rate discrete-time linear model, instantaneous estimate of the mean or correlation of received signals can be explored to estimate the channel. We also introduce corresponding single user variants of both methods. The estimation performance is evaluated by simulations in the end.** [1]

Index Terms - **Ultra wideband, aperiodic time hopping, pulse position modulation, channel estimation, moment matching.**

I. Introduction

Ultra-wideband (UWB) impulse radio is shown to be an attractive spread spectrum technique in short range wireless communications [1]. In a conventional UWB system, trains of ultra-short pulses in the order of sub-nanosecond are transmitted to achieve wide-spread spectrum and low power spectral density. Pulse position modulation (PPM) or pulse amplitude modulation (PAM) can be used to carry information symbols. Multiple access is enabled by assigning a pseudorandom (PN) time hopping (TH) sequence to each user. The TH sequence adds an additional time shift to each pulse in the pulse train.

Most of current work only concentrates on periodic TH codes for multiple access UWB systems. Recently, some studies on power spectral density properties have begun to consider aperiodic TH codes because the latter may bring some benefits over the former [2], [3]. Although the authors in [3] claim the period of TH sequence has little effect in terms of increasing maximum transmission power under FCC regulations, it is believed that the spectrum will be smoothed when increasing the length and randomness of TH sequence [2]. In addition, it has been found that performance of current UWB communication systems is dependent on specific realization of a periodic TH sequence. Aperiodic sequence thus can improve system performance by avoiding periodic use of bad codes. Furthermore, in a fading channel, aperiodic sequence will help to explore channel diversity. In fact, long code techniques have been applied and well studied in CDMA systems [4], [5].

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To achieve reliable detection performance, UWB receivers, including single user receivers [6] and multiuser receivers [7], [8], need to know channel parameters. However, in a dense multipath wireless environment, channel information is not known *a priori*. Single-user maximum likelihood (ML) methods are first applied in estimation of channels [9], [10]. Blind channel estimation methods, which use only up to the second order statistics of channel outputs and specifically take into account multiple access interference (MAI) structure, are proposed in [11], [12]. However, discussions in these work are confined to periodic TH codes only. If aperiodic TH codes are used, channel estimation becomes a more complicated task. In this paper, we will apply both least squares (LS) method and correlation matching (CM) method to address this problem. In particular, we first develop a pulse-rate discrete-time channel model, similar to [7], to linearize PPM TH-UWB signals. A unique code matrix related to TH codes will be formulated during this step. Then we can define a rank-one channel dependent matrix for each user [13]. Finally, channel parameters can be obtained by exploring instantaneous estimate of received signal's second order statistics (SOS) and using the LS or CM method.

Notations: Following common practice, we denote Kronecker product by $\otimes$, transpose by ^{T}, inverse by $^{-1}$. $E\{\cdot\}$ represents expectation of a random variable, $\boldsymbol{I}_a$ an identity matrix of degree a whose ith column is denoted by $\boldsymbol{e}_{a,i}$. $\mathbf{1}_a$ is a vector of length a with all elements equal to one. An estimate of a quantity (scalar, vector or matrix) is denoted by putting a $\widehat{}$ over it, such as $\widehat{\boldsymbol{x}}$.

II. System Model

Consider a multiple access (MA) TH UWB system with K users. The transmitted baseband UWB signal from user k can be described by [1]

$$\alpha_k(t) = \sqrt{\mathcal{P}_k} \sum_{i=-\infty}^{\infty} w(t - iT_f - c_k(i)T_c - \tau_{I_k(\lfloor i/N_f \rfloor)}) \quad (1)$$

where $\mathcal{P}_k$ is the kth user's transmission power, $w(t)$ is the baseband monopulse, T_f is the frame duration, N_f is the number of frames over which an M-ary PPM symbol repeats, $\{c_k(i) \in [0, N_c - 1]\}$ is a pseudorandom time hopping sequence. Each chip has duration T_c. $I_k(\lfloor i/N_f \rfloor) \in [0, M-1]$ is the kth user's information bearing symbol during the ith frame, $\tau_{I_k(\lfloor i/N_f \rfloor)} = I_k(\lfloor i/N_f \rfloor)\sigma$ is the corresponding modulation delay in a multiples of σ seconds. Assume $T_f = N_c T_c$ and $T_c = M\sigma$. If we define $w_m(t) \triangleq w(t - m\sigma)$ where $m = 0, \cdots, M-1$ and $s_{k,m}(\lfloor i/N_f \rfloor) = \delta\Big(I_k(\lfloor i/N_f \rfloor) - m\Big)$, then (1) may be expressed by linear modulation in a chip rate as [7]

$$\alpha_k(t) = \sqrt{\mathcal{P}_k} \sum_{i=-\infty}^{\infty} \sum_{m=0}^{M-1} u_{k,m}(i) w_m(t - iT_c) \tag{2}$$

where chip index has replaced frame index in (1),

$$u_{k,m}(i) = s_{k,m}\Big(\lfloor i/(N_c N_f)\rfloor\Big)\widetilde{c}_k(i),$$

$$\widetilde{c}_k(i) = \delta\Big(\lfloor i/N_c\rfloor N_c + c_k(\lfloor i/N_c\rfloor) - i\Big).$$

It is clear according to (2) that input $u_{k,m}(i)$ is modulated by waveform $w_m(t)$ at a chip rate. The transmitted signal $\alpha_k(t)$ propagates through a multipath channel with impulse response $\bar{g}_k(t)$. At the receiver, the channel output is first passed through a matched filter matched to the monopulse $w(t)$. We can define a front-end effective channel including effects from modulated pulse at the transmitter, propagation channel and matched filter at the receiver by $g_{k,m}(t) = \sqrt{\mathcal{P}_k} w_m(t) \star \bar{g}_k(t) \star w(-t)$ where $\star$ denotes convolution. Considering additive white Gaussian noise (AWGN) $v(t)$ and propagation delay d_k for user k, the output of the matched filter becomes

$$y(t) = \sum_{k,i_1,m} u_{k,m}(i_1) g_{k,m}(t - i_1 T_c - d_k) + v(t). \tag{3}$$

Assume each effective channel has length $q\sigma$. Then $y(t)$ is sampled every σ seconds to yield a discrete-time output $y(n) = y(t)|_{t=n\sigma}$. Using the discrete-time version of the effective channel and invoking $T_c = M\sigma$, we obtain a pulse-rate model

$$y(n) = \sum_{k,m} \sum_{i_2=0}^{q} u_{k,m}(\frac{n - i_2}{M}) g_{k,m}(i_2) + v(n). \tag{4}$$

Consider P symbol intervals of data samples with corresponding time instants $nMN_cN_f + p$ for $p = 1, \cdots, \nu$ and collect them in a big vector $\boldsymbol{y}_n$ of length $\nu = MPN_cN_f$. After noticing our definition of $u_{k,m}(i)$, a vector form data model follows [12]

$$\boldsymbol{y}_n = \sum_{k,m,l} \boldsymbol{C}_{n,k,l} \boldsymbol{T}_m \boldsymbol{g}_k s_{k,m}(n + l) + \boldsymbol{v}_n \tag{5}$$

where symbol index l takes all integers $-\lceil q/(MN_cN_f)\rceil$, $\cdots, P-1$, $\boldsymbol{g}_k$ is an unknown channel vector for user k which contains channel coefficients at the pulse rate and power factor $\sqrt{\mathcal{P}_k}$, $\boldsymbol{T}_m = [\boldsymbol{0}, \boldsymbol{I}_q, \boldsymbol{0}]^T$ is a tall selection matrix in order to obtain the mth subchannel from $\boldsymbol{g}_k$ (delayed in $m\sigma$ seconds or equivalently downshifted by m elements), $\boldsymbol{C}_{n,k,l}$ is a matrix constructed from corresponding $\widetilde{c}_k(i)$ and is uniquely determined by the TH sequence. It consists of only zeros and ones. We want to underline here, different from [12], this code matrix is dependent on symbol index n because of the aperiodic nature of TH sequence. This model can be further expressed in a compact form

$$\boldsymbol{y}_n = \sum_{k,l} \boldsymbol{H}_{n,k,l} \boldsymbol{s}_{k,n,l} + \boldsymbol{v}_n = \boldsymbol{H}_n \boldsymbol{s}_n + \boldsymbol{v}_n \tag{6}$$

after collecting M inputs in a vector

$$\boldsymbol{s}_{k,n,l} = [s_{k,0}(n + l), \cdots, s_{k,M-1}(n + l)]^T$$

defining a corresponding effective channel matrix

$$\boldsymbol{H}_{n,k,l} = [\boldsymbol{C}_{n,k,l}\boldsymbol{T}_0\boldsymbol{g}_k, \cdots, \boldsymbol{C}_{n,k,l}\boldsymbol{T}_{M-1}\boldsymbol{g}_k]$$

and successively stacking such matrices (or vectors) in $\boldsymbol{H}_n$ (or $\boldsymbol{s}_n$). The total number of symbols from K users is denoted by $L = K(P + \lceil q/(MN_cN_f)\rceil)$. By employing data model (5), all channels can be estimated based on the statistics (mean or correlation) of $\boldsymbol{y}_n$.

III. Blind Channel Estimation

It is observed that all $\boldsymbol{g}_k$ are embedded in the statistics of the data vector. However, because TH sequence is aperiodic and $C_{n,k,l}$ is dependent on n, the received signal (6) is not cyclostationary. Its mean or correlation cannot be easily estimated. But if we utilize instantaneous estimate of mean or correlation matrix, channel estimate can still be obtained, yielding LS or CM method accordingly.

A. LS approach

Let us denote the time-varying mean of $\boldsymbol{y}_n$ as $\bar{\boldsymbol{y}}_n$. From our definition, the mean of $\boldsymbol{s}_{k,n,l}$ is easily found to be $\frac{1}{M}\boldsymbol{1}_M$. Since noise has zero mean even after the matched filter, we have

$$\bar{\boldsymbol{y}}_n = \frac{1}{M} \sum_{k,m,l} \boldsymbol{C}_{n,k,l} \boldsymbol{T}_m \boldsymbol{g}_k = \sum_k \mathcal{C}_{n,k} \boldsymbol{g}_k = \mathcal{C}_n \boldsymbol{g} \tag{7}$$

where all channel vectors are stacked in a big vector $\boldsymbol{g}$. If we approximate $\boldsymbol{y}_n$ as an estimate of $\bar{\boldsymbol{y}}$, then a LS criterion can be applied to estimate $\boldsymbol{g}$ from N data vectors as follows

$$\widehat{\boldsymbol{g}} = \arg\min \frac{1}{N} \sum_n ||\bar{\boldsymbol{y}}_n - \boldsymbol{y}_n||^2. \tag{8}$$

Invoking (7), the solution to (8) has the following form

$$\widehat{\boldsymbol{g}} = (\frac{1}{N} \sum_n {\mathcal{C}_n}^T \mathcal{C}_n)^{-1} (\frac{1}{N} \sum_n {\mathcal{C}_n}^T \boldsymbol{y}_n). \tag{9}$$

Then the estimate of $\boldsymbol{g}_k$ can be obtained from the corresponding subvector of $\widehat{\boldsymbol{g}}$ as $\widehat{\boldsymbol{g}}_k = (\boldsymbol{e}_{K,k}^T \otimes \boldsymbol{I}_q)\widehat{\boldsymbol{g}}$.

B. CM approach

Since $\boldsymbol{s}_{k,n,l}$ has non-zero mean, the time-dependent autocorrelation matrix of $\boldsymbol{y}_n$ includes cross terms $\boldsymbol{G}_{k_1,k_2} = \boldsymbol{g}_{k_1}\boldsymbol{g}_{k_2}^T$ of two generic users k_1 and k_2:

$$\begin{aligned} \boldsymbol{R}_n &= \sum \boldsymbol{C}_{k_1,n,l_1} \boldsymbol{T}_{m_1} \boldsymbol{G}_{k_1,k_2} \boldsymbol{T}_{m_2}^T \boldsymbol{C}_{k_2,n,l_2}^T \gamma_{k_1,k_2,m_1,m_2,l_1,l_2} \\ &+ \sigma_v^2 \boldsymbol{I}. \end{aligned} \tag{10}$$

Here, summation is over $k_1, k_2, m_1, m_2, l_1, l_2$ and $\gamma_{k_1,k_2,m_1,m_2,l_1,l_2}$ is the correlation of inputs $s_{k_1,m_1}(n + l_1)$ and $s_{k_2,m_2}(n + l_2)$

$$\begin{aligned} \gamma_{k_1,k_2,m_1,m_2,l_1,l_2} &= \frac{1}{M}\delta(m_1 - m_2)\delta(l_1 - l_2)\delta(k_1 - k_2) \\ &+ \frac{1}{M^2}\left[1 - \delta(l_1 - l_2)\delta(k_1 - k_2)\right]. \end{aligned}$$

As in [13], vectored form is convenient to handle in the CM context. Define a new vector $\boldsymbol{x}$ which has entries of all possible $vec(\boldsymbol{g}_{k_1}\boldsymbol{g}_{k_2}^T)$ and σ_v^2 as follows

$$\boldsymbol{x} = [vec(\boldsymbol{G}_{1,1})^T, vec(\boldsymbol{G}_{1,2})^T, \cdots, vec(\boldsymbol{G}_{K,K})^T, \sigma_v^2]^T. \tag{11}$$

Using the property of vec [14], we obtain vectorized correlation $\boldsymbol{r}_n = vec(\boldsymbol{R}_n)$

$$\boldsymbol{r}_n = \boldsymbol{S}_n\boldsymbol{x}, \quad \boldsymbol{S}_n = [\boldsymbol{S}_{n,1,1}, \boldsymbol{S}_{n,1,2}, \cdots, \boldsymbol{S}_{n,K,K}, vec(\boldsymbol{I}_\nu)],$$

$$\begin{aligned}\boldsymbol{S}_{n,k_1,k_2} &= \sum_{m_1,m_2,l_1,l_2} \gamma_{k_1,k_2,m_1,m_2,l_1,l_2} \\ &\times (\boldsymbol{C}_{n,k_2,l_2}\boldsymbol{T}_{m_2}) \otimes (\boldsymbol{C}_{n,k_1,l_1}\boldsymbol{T}_{m_1}). \end{aligned} \tag{12}$$

Therefore, $\boldsymbol{r}_n$ can be matched with its instantaneous estimate $\widehat{\boldsymbol{r}}_n = vec(\boldsymbol{y}_n\boldsymbol{y}_n^T)$ in a vector form

$$\widehat{\boldsymbol{x}} = \arg\min \frac{1}{N}\sum_n ||\boldsymbol{r}_n - \widehat{\boldsymbol{r}}_n||^2. \tag{13}$$

Considering (12), the solution to (13) is given by

$$\widehat{\boldsymbol{x}} = (\frac{1}{N}\sum_n \boldsymbol{S}_n^T\boldsymbol{S}_n)^{-1}(\frac{1}{N}\sum_n \boldsymbol{S}_n^T\widehat{\boldsymbol{r}}_n). \tag{14}$$

Once $\boldsymbol{x}$ is estimated, entries corresponding to $\boldsymbol{G}_{k_1,k_2}$ $(k_1 = k_2 = k)$ can be extracted. Then $\boldsymbol{G}_{k,k}$ is reconstructed by the reverse vec operation. These operations can be described by

$$\widehat{\boldsymbol{G}}_{k,k} = [(\boldsymbol{e}_{q,1}^T \otimes \boldsymbol{I}_q)\widehat{\boldsymbol{x}}_k, \cdots, (\boldsymbol{e}_{q,q}^T \otimes \boldsymbol{I}_q)\widehat{\boldsymbol{x}}_k] \tag{15}$$

$$\widehat{\boldsymbol{x}}_k = [\boldsymbol{e}_{K^2,(k-1)K+1}^T \otimes \boldsymbol{I}_{q^2}, \boldsymbol{0}_{q^2\times 1}]\widehat{\boldsymbol{x}}. \tag{16}$$

Once $\widehat{\boldsymbol{G}}_{k,k}$ is obtained, channel vector $\boldsymbol{g}_k$ can be estimated from its singular value decomposition (SVD) by finding the singular vector corresponding to its maximum singular value. That singular vector becomes an estimate of $\boldsymbol{g}_k$ up to a multiplicative scalar.

IV. Single User Estimator

So far we have successfully obtained channel parameters using the LS and CM methods. However, we have to know all users' TH codes in the above discussions. It is often desirable to estimate the channel with only the desired user's TH codes available. Our main objective in this section is to find corresponding single user counterparts for both methods. Additionally, as we will see later, this effort brings some extra benefits in the CM context by reducing complexity. Because more unknowns (cross-products of channel vectors) are introduced in the CM method, complexity increases compared with the periodic TH scenario [12]. Thus, low complexity solution is of importance.

A. LS Approach

Without loss of generality, we assume user one is the desired user. Then we can break down the received signal (5) into the desired signal, interference signal and noise:

$$\boldsymbol{y}_n = \sum_{1,m,l} \boldsymbol{C}_{n,1,l}\boldsymbol{T}_m\boldsymbol{g}_1 s_{1,m}(n+l) + \boldsymbol{y}_{int,n} + \boldsymbol{v}_n. \tag{17}$$

Here, the total effect of MAI from all other $K-1$ users $\boldsymbol{y}_{int,n}$ is approximated as a stationary process with unknown mean $\boldsymbol{b}_{int}$ and unknown autocorrelation $\boldsymbol{R}_{int}$. As a result, the time-varying mean (7) becomes

$$\bar{\boldsymbol{y}}_n = \mathcal{C}_{n,1}\boldsymbol{g}_1 + \boldsymbol{b}_{int}. \tag{18}$$

Using the LS criterion as in (8), we can obtain the estimate of $\boldsymbol{b}_{int}$ first

$$\widehat{\boldsymbol{b}}_{int} = -\frac{1}{N}\sum_n(\mathcal{C}_{n,1}\boldsymbol{g}_1 - \boldsymbol{y}_n). \tag{19}$$

When we back substitute the above result into (18), the least-squares criterion (8) will lead to channel estimate:

$$\widehat{\boldsymbol{g}}_1 = \left(\frac{1}{N}\sum_n \Delta\mathcal{C}_{n,1}^T\Delta\mathcal{C}_{n,1}\right)^{-1}\left(\frac{1}{N}\sum_n \Delta\mathcal{C}_{n,1}^T\widetilde{\boldsymbol{y}}_n\right),$$

$$\Delta\mathcal{C}_{n,1} = \mathcal{C}_{n,1} - \frac{1}{N}\sum_n \mathcal{C}_{n,1}, \quad \widetilde{\boldsymbol{y}}_n = \boldsymbol{y}_n - \frac{1}{N}\sum_n \boldsymbol{y}_n. \tag{20}$$

B. CM Approach

If we start from (17), we can rewrite the autocorrelation matrix (10) as

$$\begin{aligned}\boldsymbol{R}_n &= \sum_{m_1,m_2,l_1,l_2} \boldsymbol{C}_{1,n,l_1}\boldsymbol{T}_{m_1}\boldsymbol{G}_{1,1}\boldsymbol{T}_{m_2}^T\boldsymbol{C}_{1,n,l_2}^T\gamma_{1,1,m_1,m_2,l_1,l_2} \\ &+ \frac{1}{M}\sum_{m,l}(\boldsymbol{C}_{1,n,l}\boldsymbol{T}_m\boldsymbol{Q}_1 + \boldsymbol{Q}_1^T\boldsymbol{T}_m^T\boldsymbol{C}_{1,n,l}^T) + \widetilde{\boldsymbol{R}}_{int} \end{aligned} \tag{21}$$

where $\boldsymbol{Q}_1 = \boldsymbol{g}_1\boldsymbol{b}_{int}^T$, $\widetilde{\boldsymbol{R}}_{int} = \boldsymbol{R}_{int} + \sigma_v^2\boldsymbol{I}$. Let us define $\boldsymbol{z}_1 = vec(\boldsymbol{Q}_1)$, and $\widetilde{\boldsymbol{r}}_{int} = vec(\widetilde{\boldsymbol{R}}_{int})$. After we take vec operation, (21) becomes

$$\boldsymbol{r}_n = \boldsymbol{S}_{n,1,1}\boldsymbol{x}_1 + (\boldsymbol{D}_{1,n} + \boldsymbol{\Gamma}\boldsymbol{D}_{1,n})\boldsymbol{z}_1 + \widetilde{\boldsymbol{r}}_{int} \tag{22}$$

Here, $\boldsymbol{D}_{1,n} = 1/M\boldsymbol{I}_\nu \otimes \mathcal{C}_{n,1}$, $\boldsymbol{\Gamma} = [\boldsymbol{I}_\nu \otimes \boldsymbol{e}_{\nu,1}, \cdots, \boldsymbol{I}_\nu \otimes \boldsymbol{e}_{\nu,\nu}]^T$ and we use the property of vec operation that for any matrix $\boldsymbol{A}$, $vec(\boldsymbol{A}^T) = \boldsymbol{\Gamma}vec(\boldsymbol{A})$.

Following similar procedures as in LS method, we first find an estimate for $\widetilde{\boldsymbol{r}}_{int}$ from the criterion (13)

$$\widehat{\widetilde{\boldsymbol{r}}}_{int} = -\frac{1}{N}\sum_n(\boldsymbol{S}_{n,1,1}\boldsymbol{x}_1 + \widetilde{\boldsymbol{D}}_{1,n}\boldsymbol{z}_1 - \widehat{\boldsymbol{r}}_n) \tag{23}$$

where $\widetilde{\boldsymbol{D}}_{1,n} = \boldsymbol{D}_{1,n} + \boldsymbol{\Gamma}\boldsymbol{D}_{1,n}$. After back substitution and optimization of (13), we obtain an estimate of all entries in $\widetilde{\boldsymbol{x}} = [\boldsymbol{x}_1^T, \boldsymbol{z}_1^T]^T$ as

$$\widehat{\widetilde{\boldsymbol{x}}} = \left(\frac{1}{N}\sum_n \boldsymbol{W}_n^T\boldsymbol{W}_n\right)^{-1}\left(\frac{1}{N}\sum_n \boldsymbol{W}_n^T\widehat{\widetilde{\boldsymbol{r}}}_n\right) \tag{24}$$

where

$$\widehat{\widetilde{\boldsymbol{r}}}_n = \widehat{\boldsymbol{r}}_n - \frac{1}{N}\sum_n \widehat{\boldsymbol{r}}_n,$$

$$\boldsymbol{W}_n = [\Delta\boldsymbol{S}_{n,1,1}, \Delta\widetilde{\boldsymbol{D}}_{1,n}],$$

$$\Delta\boldsymbol{S}_{n,1,1} = \boldsymbol{S}_{n,1,1} - \frac{1}{N}\sum_n \boldsymbol{S}_{n,1,1},$$

$$\Delta \widetilde{\boldsymbol{D}}_{1,n} = \widetilde{\boldsymbol{D}}_{1,n} - \frac{1}{N} \sum_n \widetilde{\boldsymbol{D}}_{1,n}.$$

Then we can extract $\boldsymbol{x}_1$ from $\widetilde{\boldsymbol{x}}$, construct $\boldsymbol{G}_{1,1}$ and use SVD to get $\widehat{\boldsymbol{g}}_1$, similar to (15)-(16).

Performance of the above methods will be studied elsewhere due to lack of space.

V. Simulation

In this section, we examine the performance of our proposed channel estimators by simulations. The system adopts binary PPM modulation with $N_c = 4$, $N_f = 4$ and four users with equal transmitting power. The monocycle pulse is chosen as normalized second derivative of the Gaussian pulse with pulse duration $D_g = 0.7ns$. Modulation delay parameter is set to be $\sigma = D_g$. A randomly generated 4-path channel has time delay resolution of D_g. Path gains for different users are modeled as independent Gaussian random variables and weighted by linearly decreasing weights [12]. $P = 1$ is used in the above methods.

Averaged channel estimation errors with respect to data length N over 100 independent realizations are illustrated in Fig. 1. Four curves corresponding to the multiuser LS estimator (MU-LS), single-user LS estimator (SU-LS), multiuser CM estimator (MU-CM), and single-user CM estimator (SU-CM) are plotted. All of them decrease almost inverse proportionally with increase of N. When N is above 400, MSEs of all estimators are less than 10^{-2}. CM estimator is found to be consistently better than the LS estimator while both multiuser LS and CM estimators outperform their single-user counterparts. However, the difference is not very big. In Fig. 2, we study the effect of SNR on MSE with $N = 200$. Both CM estimators perform better than LS estimators for all SNR and all curves decrease monotonically with increase of SNR. But these curves show a trend of MSE floor because of the finite data length N we use in our simulations. [2]

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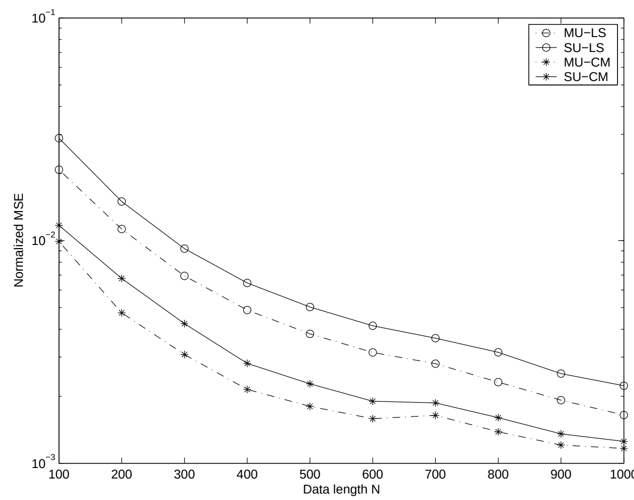

Fig. 1. Channel estimation error under SNR=15dB.

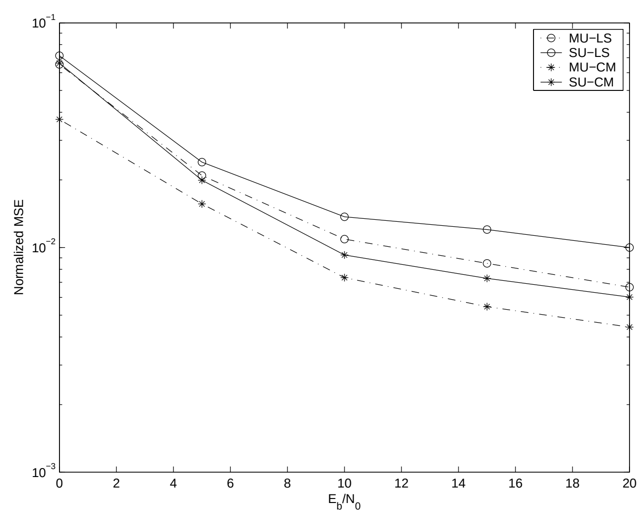

Fig. 2. Channel estimation error with respect to SNR.