Reduced-order Multiuser Detection in Multi-rate DS-UWB Communications

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***Abstract*— In ultra-wideband (UWB) systems, the ultra-wide bandwidth and abundant multipath components can provide great spreading gain and diversity gain, but will also induce complicated interference suppression algorithm because of the requirements of very high sampling rate and large number of filter taps. A reduced-order multi-user detector (R-MUD) is proposed in this paper which can significantly reduce the sampling rate thus the computational burden by down-sampling the received multipath signal at appropriate locations, where the energy of the desired user can be effectively captured and the interferences from other users can be dramatically suppressed. The superior performance of the R-MUD is justified by computer simulations.**

I. Introduction

The immense system capacity, super multipath resolution and other attractive features make UWB techniques draw considerable attention in communications. Nevertheless, the highly dispersive UWB channel which may comprise hundreds of multipath components leads to the difficulty of receiver design. The overlayed narrow-band systems, which usually have several tens dB higher power spectrum density than UWB systems, will bring severe jam and interference. The coexistent users will also interfere with each other because of the near-far effect, especially in the asynchronous, multi-rate networks which are eagerly demanded for various extended applications.

The selective-Rake and partial-Rake receivers can be employed in UWB multipath environment to combine the dispersive paths [1]. Since Rake receiver is an optimal matched filter only under additive white noise circumstance, it will suffer considerable performance degradation when the signal is disturbed by narrow-band and multi-user interferences [2]. Conventional multi-user detection (MUD) algorithms can cope with these interferences but require very high sampling rate and complexity [3]–[5]. In some killer applications such as sensor networks, these requirements can not be afforded and simple interference resistant schemes are called for [6]–[8].

An effective way to simplify the implementations of UWB systems is to reduce the sampling rate. [9] developed a frame-rate MUD algorithm, which correlates the received signal with an analog reference signal, say a noise template, and samples the output at frame intervals. The MUD is then performed using this frame-rate signal. This algorithm requires long and high resolution delay lines, which will raise the hardware cost. Moreover, since this algorithm relies on the spreading sequences to combat the multi-user interference, it is not favorable to accommodate the multi-rate systems. [10] studied a low sampling rate narrow-band interference suppression algorithm, which selects a group of down-sampling locations according to the maximal first arrival paths of the desired user, then detects the down-sampled signal with the minimum mean square error (MMSE) filter. This partial sampling MMSE filter can approach the performance of the full sampling MMSE filter with much less filter taps. Unfortunately, a partial sampling MUD (P-MUD) algorithm with the same idea is ineffective to combat the multi-user interference, since the locations where involve the maximal paths of the desired user may also involve the paths of the interfered users with higher magnitudes, or having strong dependence with that of the desired user.

This paper proposes a novel down-sampling algorithm for multi-user detector aimed at significantly reducing the receiver complexity with least expense of the performance degradation comparing to the full sampling MUD (F-MUD). It uses iterative one dimensional searching to select the locations that make the mean square error of an order-recursive filter minimal. To accommodate the multi-rate multi-user systems, the down-sampled signals are detected at each frame duration, so that, unlike in CDMA systems, the capability of suppressing the multi-user interferences comes from the distinction of the channel response of different users. [11] had presented a reduced-rank transmitter adaptation scheme for the reverse link of a DS-CDMA system in which the transmitted signature is constrained to line in a lower dimensional subspace and is optimized to avoid the multiple access interference. While the reduced-rank processing is related, we confront new signaling format and channel environment in UWB communications and concentrate on the problem of sampling rate reducing.

The rest of this paper is organized as follows. Section II introduces the modulation and multi-access scheme, multipath channel response and received signal model. Section III studies the criterion of optimal down-sampling and the suboptimal iterative implementation. Performance of the R-MUD algorithm and comparison with the F-MUD and P-MUD are shown in section IV, and conclusions are provided in the last section.

II. System Description

Consider a DS-UWB communication system with K users, which have identical pulse repetition time (PRT) but different data rates due to different spreading factors. The

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spreading factor of the kth user is $N_k = T_b/T_f$, where T_b is the bit duration and T_f is the frame duration. The transmitted signal of the kth user is

$$s_k(t) = \sum_{j=-\infty}^{\infty} \sqrt{\mathcal{E}_k} a_k(\lfloor j/N_k \rfloor) c_k(j) p_{tr}(t - jT_f), \quad (1)$$

where $\mathcal{E}_k$ represents the energy of the kth user's transmitted pulse, $a_k(i)$ is the pulse amplitude modulated (PAM) polarity of the ith bit, $\lfloor x \rfloor$ is the largest integer less than x, $c_k(j)$ is the kth user's spreading code which repeats every N_k times, p_{tr} is the transmitted pulse waveform with pulse width $T_p \ll T_f$ and energy normalized to $\int_{-\infty}^{\infty} p_{tr}^2(t) = 1$.

Define the impulse response of the kth user's multipath channel as

$$h_k(t) = \sum_{l=0}^{L-1} \alpha_{k,l} \delta(t - \tau_{k,l}), \quad (2)$$

where $\alpha_{k,l}$ and $\tau_{k,l}$ represent the amplitude and delay of the lth path, respectively. Assume the maximal delay $\tau_{k,L-1} < T_f$, then the inter-pulse interference can be avoided.

Due to the differential effect of the UWB antenna, the received pulse waveform becomes $p_{rec}(t)$. Then after matched filter in the receiver front-end, the equivalent composite channel of the kth user is $\tilde{h}_k(t) = p_{rec}(t) * h_k(t) * p_{rec}(t)$. Consider the asynchronous networks, where the kth user has a delay τ_k, then the received signal after matched filter is

$$r(t) = \sum_{k=1}^{K} \sum_{j=-\infty}^{\infty} \sqrt{\mathcal{E}_k} a_k(\lfloor j/N_k \rfloor) c_k(j) \tilde{h}_k(t - jT_f - \tau_k) + n(t), \quad (3)$$

where $n(t)$ is zero mean Gaussian noise with variance σ_n^2.

Define $D_k = \lceil \tau_k/T_p \rceil$ is the smallest integer not less than τ_k/T_p, $N = T_f/T_p$, and

$$\bar{\boldsymbol{h}}_k = [\bar{h}_k(0), \bar{h}_k(1), \cdots, \bar{h}_k(N-1)]^T, \quad (4)$$

$$\bar{\boldsymbol{h}}_k^+ = [0, \cdots, 0, \bar{h}_k(0), \cdots, \bar{h}_k(N - D_k - 1)]^T, \quad (5)$$

$$\bar{\boldsymbol{h}}_k^- = [\bar{h}_k(N - D_k), \cdots, \bar{h}_k(N-1), 0, \cdots, 0]^T, \quad (6)$$

where $\bar{h}_k(m) = \tilde{h}_k[(m+1)T_p]$ is the mth discrete sample from channel response $\tilde{h}_k(t)$ and $\|\bar{\boldsymbol{h}}_k\|$ is assumed to 1. Then the samples of the jth received frame can be expressed as the following matrix form,

$$\boldsymbol{r}(j) = \boldsymbol{S}\boldsymbol{A}\boldsymbol{b} + \boldsymbol{n}, \quad (7)$$

where

$$\boldsymbol{S} = [\bar{\boldsymbol{h}}_1^+, \cdots, \bar{\boldsymbol{h}}_K^+, \bar{\boldsymbol{h}}_1^-, \cdots, \bar{\boldsymbol{h}}_K^-], \quad (8)$$

$$\boldsymbol{A} = diag([\sqrt{\mathcal{E}_1}, \cdots, \sqrt{\mathcal{E}_K} \sqrt{\mathcal{E}_1}, \cdots, \sqrt{\mathcal{E}_K}]^T), \quad (9)$$

$$\begin{aligned} \boldsymbol{b} = [&a_1(\lfloor j/N_1 \rfloor) c_1(j), \cdots, a_K(\lfloor j/N_K \rfloor) c_K(j), \\ &a_1(\lfloor (j-1)/N_1 \rfloor) c_1(j-1), \cdots, \\ &a_K(\lfloor (j-1)/N_K \rfloor) c_K(j-1)]^T, \end{aligned} \quad (10)$$

where $diag(\cdot)$ is a diagonal matrix, and $\boldsymbol{n}$ is the sample vector of $n(t)$ with covariance matrix $\boldsymbol{R}_n = \sigma^2 \boldsymbol{I}_N$.

Assume that the first user is the desired user and its signal has been synchronized, that means $\tau_1 = 0$ and $\boldsymbol{h}_1^- = \boldsymbol{0}$. Detect the received signals with a linear transversal filter $\boldsymbol{w}$ and despread afterwards. The estimation of the transmitted signal is then obtained as

$$\hat{a}_1(i) = sign\left\{ \sum_{j=iN_1}^{(i+1)N_1 - 1} c_1(j) \boldsymbol{w}^T \boldsymbol{r}(j) \right\}, \quad (11)$$

where $\boldsymbol{w}$ can be a filter directly derived from the MMSE criterion, or can be a filter developed from various reduced-rank algorithms, or the reduced-order filter we will present next section.

III. Reduced-order MUD

A. Reduced-rank MUD

In CDMA systems, the reduced-rank linear multi-user detector projects the N dimensional received signal onto a lower M dimensional subspace by a projection matrix $\boldsymbol{P} \in \mathbb{C}^{N \times M}$,

$$\tilde{\boldsymbol{r}} = \boldsymbol{P}^H \boldsymbol{r}, \quad (12)$$

then uses some optimal detector such as MMSE-MUD to process the lower dimensional signals. Define the covariance matrix of the original received signal vector $\boldsymbol{r}$ as $\boldsymbol{R} = E[\boldsymbol{r}\boldsymbol{r}^H]$, the cross correlation matrix of the desired response d and the received signal vector $\boldsymbol{r}$ as $\boldsymbol{\rho} = E[\boldsymbol{r}d^*]$. Then the covariance matrix of the reduced-rank signal is $\tilde{\boldsymbol{R}} = \boldsymbol{P}^H \boldsymbol{R} \boldsymbol{P}$, the cross correlation of the desired response and the reduced-rank signal is $\tilde{\boldsymbol{\rho}} = \boldsymbol{P}^H \boldsymbol{\rho}$. According to the MMSE criterion, the weighting vector of the detector for processing the reduced-rank signal is

$$\tilde{\boldsymbol{w}}_{mmse} = \tilde{\boldsymbol{R}}^{-1} \tilde{\boldsymbol{\rho}}. \quad (13)$$

The critical part of the reduced-rank algorithm is to design the projection matrix. For example, in the multiple stage Wiener filter, auxiliary vector filter and Cayley-Hamilton method, their equivalent projection matrix is [12]

$$\boldsymbol{P} = \left[\bar{\boldsymbol{h}}_1, \boldsymbol{R}\bar{\boldsymbol{h}}_1, \cdots, \boldsymbol{R}^{M-1}\bar{\boldsymbol{h}}_1 \right], \quad (14)$$

where $\bar{\boldsymbol{h}}_1 = \boldsymbol{\rho}/\|\boldsymbol{\rho}\|$.

B. Optimal Down-sampling Criterion

In the reduced-rank algorithms, the rank of the projected signal subspace depends on the number of users. When few users exist, the number of taps of $\tilde{\boldsymbol{w}}_{mmse}$ can be very small, but from the detection process we can see that the estimation of the desired response is

$$\hat{d} = \tilde{\boldsymbol{w}}_{mmse}^H \boldsymbol{P}^H \boldsymbol{r} = \boldsymbol{w}^H \boldsymbol{r}, \quad (15)$$

i.e., the tap number of the transversal filter $\boldsymbol{w}$ is still N.

In the UWB systems we hope that the tap number can be dramatically reduced, thus we will investigate a reduced-order multi-user detector by down-sampling in the following.

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Consider a class of constraint projection matrix

$$\boldsymbol{P} = [\boldsymbol{e}_0, \boldsymbol{e}_1, \cdots, \boldsymbol{e}_{M-1}], \tag{16}$$

where $\boldsymbol{e}_m$ is a column vector with its p_mth element equals to 1 and all others 0. Without loss of generality, we assume $p_0 < p_1 < \cdots < p_{M-1}$.

According to the signal model in last section, we first project the received signal vector $\boldsymbol{r}$ onto the subspace spanned by $\boldsymbol{P}$, then compute the weighting vector of the detector based on the MMSE criterion.

Note that this projection operation is actually a down-sampling process. Instead of finding a general form of the projection matrix as in the usual reduced-rank detectors, the projection matrix with such a special constraint which representing the down-sampling locations p_m will be determined. The rank of the signal reduced through this way depends on M, in stead of the number of users.

Because user 1 is the desired user and $\|\bar{\boldsymbol{h}}_1\| = 1$, the normalized cross correlation between the desired response and the received signal vector is $\boldsymbol{\rho}/\|\boldsymbol{\rho}\| = \bar{\boldsymbol{h}}_1$. Then after projecting operation the weighting vector of the MMSE filter is

$$\tilde{\boldsymbol{w}}_{mmse} = \left(\boldsymbol{P}^H \boldsymbol{R} \boldsymbol{P}\right)^{-1} \boldsymbol{P}^H \bar{\boldsymbol{h}}_1. \tag{17}$$

The mean square error of the filter's output is

$$J_M = 1 - \bar{\boldsymbol{h}}_1^H \boldsymbol{P} \left(\boldsymbol{P}^H \boldsymbol{R} \boldsymbol{P}\right)^{-1} \boldsymbol{P}^H \bar{\boldsymbol{h}}_1. \tag{18}$$

Therefore, select the optimal down-sampling locations is to select a matrix $\boldsymbol{P}$ which can make the mean square error J minimal, that is

$$\boldsymbol{P} = \arg\min_{\boldsymbol{P}} J = \arg\min_{p_0, \cdots, p_{M-1}} J_M. \tag{19}$$

Apparently, this is a multi-dimensional joint searching problem, the computation of which will become unaffordable with the increasing of down-sampling locations.

C. Iterative Implementation of the Reduced-order MUD

To facilitate the implementation of the reduced-order algorithm, we design a suboptimal iterative searching method. The main idea is gradually determining the M down-sampling locations, the $(m+1)$th down-sampling location p_m is selected based on the determined locations $p_0, p_1, \cdots, p_{m-1}$ and MMSE criterion, that is

$$p_m = \arg\min_{p_m} J_{m+1}(p_m | p_0, p_1, \cdots, p_{m-1}). \tag{20}$$

Then the M-dimensional joint searching problem is simplified to a linear searching problem.

Define the signal vector sampled at locations $p_0, p_1, \cdots, p_{m-1}$ as $\boldsymbol{r}_m$, the channel coefficient vector of the desired user sampled at these locations as $\boldsymbol{h}_m$, then the covariance matrix of the down-sampled signal is $\boldsymbol{R}_m = E[\boldsymbol{r}_m \boldsymbol{r}_m^H]$, the weighting vector of the detector is obtained as $\boldsymbol{w}_m = \boldsymbol{R}_m^{-1} \boldsymbol{h}_m$, and the minimal mean square error of the detector is $J_m = 1 - \boldsymbol{h}_m^H \boldsymbol{R}_m^{-1} \boldsymbol{h}_m$.

Define the received signal sampled at the location p_m to be determined as r_{m+1}, the channel coefficient at the corresponding location is h_{m+1}, then the $(m+1)$-dimension received signal vector is $\boldsymbol{r}_{m+1} = [\boldsymbol{r}_m^H, r_{m+1}^*]^H$, channel coefficient vector is $\boldsymbol{h}_{m+1} = [\boldsymbol{h}_m^H, h_{m+1}^*]^H$. Define a vector $\boldsymbol{v} = E[\boldsymbol{r}_m r_{m+1}^*]$ as the cross correlation between the previously selected m samples and the $(m+1)$th new sample, then the relationship between the covariance matrix $\boldsymbol{R}_{m+1} = E[\boldsymbol{r}_{m+1} \boldsymbol{r}_{m+1}^H]$ and $\boldsymbol{R}_m$ is

$$\boldsymbol{R}_{m+1} = \begin{bmatrix} \boldsymbol{R}_m & \boldsymbol{v} \\ \boldsymbol{v}^H & \alpha \end{bmatrix}, \tag{21}$$

where $\alpha = E[\|r_{m+1}\|^2]$.

Employing the matrix inversion lemma of the partitioned matrices [13], the inversion of $\boldsymbol{R}_{m+1}$ can be derived from the inversion of $\boldsymbol{R}_m$ as,

$$\boldsymbol{R}_{m+1}^{-1} = \begin{bmatrix} \boldsymbol{R}_m^{-1} + \beta \boldsymbol{R}_m^{-1} \boldsymbol{v} \boldsymbol{v}^H \boldsymbol{R}_m^{-1} & -\beta \boldsymbol{R}_m^{-1} \boldsymbol{v} \\ -\beta \boldsymbol{v}^H \boldsymbol{R}_m^{-1} & \beta \end{bmatrix}, \tag{22}$$

where $\beta = (\alpha - \boldsymbol{v}^H \boldsymbol{R}_m^{-1} \boldsymbol{v})^{-1}$.

From (22), the reduction of the minimal mean square error after adding one sample can be derived as

$$J_m - J_{m+1} = \beta \|h_{m+1}^* - \boldsymbol{w}_m^H \boldsymbol{v}\|^2. \tag{23}$$

Thus the searching problem of the $(m+1)$th down-sampling location becomes

$$p_m = \arg\max_{p_m} \left\{ \frac{\|h_{m+1}^* - \boldsymbol{w}_m^H \boldsymbol{v}\|^2}{\alpha - \boldsymbol{v}^H \boldsymbol{R}_m^{-1} \boldsymbol{v}} \right\}, \tag{24}$$

where $\boldsymbol{w}_m$ and $\boldsymbol{R}_m^{-1}$ have been obtained in the mth iteration and do not change their values in the linear searching process.

So far, we have completed the development of the iterative linear searching algorithm. However, by observing from a different point of view we will gain some other insight from (24).

Consider the problem of predicting r_{m+1} from $\boldsymbol{r}_m$. If the MMSE criterion is applied, the cross correlation between the desired response and the received signal vector is just $\boldsymbol{v}$, the weighting vector of the predictor is $\boldsymbol{f} = \boldsymbol{R}_m^{-1} \boldsymbol{v}$, and the denominator of (24) is the mean square error of the predictor output. Substitute $\boldsymbol{w}_m = \boldsymbol{R}_m^{-1} \boldsymbol{h}_m$ into the numerator, we can get

$$\|h_{m+1}^* - \boldsymbol{w}_m^H \boldsymbol{v}\|^2 = \|h_{m+1} - \boldsymbol{f}^H \boldsymbol{h}_m\|^2. \tag{25}$$

This is the square error of the prediction of h_{m+1} from $\boldsymbol{h}_m$. Consequently, (24) can be written as

$$p_m = \arg\max_{p_m} \left\{ \frac{\|h_{m+1} - \boldsymbol{f}^H \boldsymbol{h}_m\|^2}{E\left[\|r_{m+1} - \boldsymbol{f}^H \boldsymbol{r}_m\|^2\right]} \right\}. \tag{26}$$

This expression implies that when we make the choice of p_m, we need to select a most distinct $\boldsymbol{h}_{m+1}$ relative to $\boldsymbol{r}_{m+1}$ based on $p_0, p_1, \cdots, p_{m-1}$. Then the error of predicting h_{m+1} with filter $\boldsymbol{f}$ can be maximal. It is sure that the information of $\boldsymbol{h}_{m+1}$ is also involved in $\boldsymbol{r}_{m+1}$, but only if the down-sampled channel responses of the other users are least dependent on $\boldsymbol{h}_{m+1}$, can the system achieves the best performance.

An order-iterative adaptive filter based on least square criterion is introduced in [14]. It adaptively generates the filter weights both in time and in orders and is able to approach the convergence rate of the RLS algorithm with a complexity linear to the order. However, the focus of the order-iterative adaptive filter is to calculate the filter weights, while our focus is to select the down-sampling locations.

It can be seen that the knowledge of the number of user is not required in this scheme, neither is the channel state information of other users. When the M locations from the N possibilities have been determined, the sampling rate can decrease to M/N of the original rate since only M-dimensional signal vector is applied to detect the desired user. All the samples of the received signal are still necessary before down-sampling, whereas these samples can be obtained by serial sampling in the training sequence field when the system possesses M frame-rate ADCs.

IV. Simulation Results

In this section we will study the performance of the reduced-order multi-user detector through computer simulations in various signal-to-noise ratio (SNR), signal-to-interference ratio (SIR), filter taps after down-sampling, the number of users and training sequence length conditions. We will also compare the reduced-order algorithm with the F-MUD and P-MUD algorithms. In our simulations the users are independent on each other, which means that each user has independent random delay and experiences independent multipath channel, as in the asynchronous networks. Because the algorithms will work in the multi-rate environments, which means the transmitted signal may have variable spreading factor, we simulate here the worst scenario that the desired user does not spread. The multi-user interferences are suppressed by the channel response differences.

In the simulation tests, the channel model we applied is given by IEEE802.15.4a low-rate WPAN task group and is based on the practical measurement data in the indoor office environments [15], where 3-28m, 2-8GHz is measured and line-of-sight exists. In this model, the multipath arrives in clusters and the arrival time of the cluster subjects to Poisson distribution, the arrival time of each path in the cluster is modelled by a mixture of two Poisson process. The amplitude of each path has a Nakagami-m distribution and the parameter m subjects to another log-normal distribution, the mean and standard derivation of m depend on the arrival time of that path. The power delay profile of the channel is exponentially declined and the rms delay spread is about $10ns$.

Suppose that each user has the same PRT as $100ns$ and pulse width as $1ns$, each transmitted pulse carries one bit modulated by bipolar PAM. Hence the average power of the signal is $P_s = E_b/T_f$ and the $SNR = P_s/P_n = E_b/N_0 - 20dB$. The maximal delay spread of the channel impulse response is about $50ns$. In the subsequent figures, each result is obtained by an average over 1000 channel realizations, and in each test 1000 bits are transmitted for each user. There is a training sequence before the data stream, which is utilized to estimate the channel response of the desired user and the covariance matrix of the received signal. 50 taps are used for the F-MUD algorithm.

Figure 1 shows the bit error rate (BER) of the three detectors varying with the SNR. There are one desired user and seven interference users in the system. The number of taps used in R-MUD and P-MUD are both 8, and 100 bits of training sequence are deployed. It can be seen that the R-MUD algorithm can approach the performance of the F-MUD and is superior to the P-MUD algorithm. Figure 2 illustrates the BER versus SIR, the SNR is fixed to be -5dB and other conditions are identical to that of figure 1. It is shown that the F-MUD is near-far resistant, but both R-MUD and P-MUD suffer performance degradation with the increasing of the interference power. However, the R-MUD algorithm can resist over 10dB more interference than the P-MUD. Figure 2 also exhibits the BER along with different number of users. It can be observed that the performance of all the three detectors will deteriorate with more users, but the performance of F-MUD can be approached to or even be exceeded by the R-MUD algorithm when the interference power and number of users decrease.

Figure 3 and 4 address the impact of the number of filter taps and length of training sequence. In the tests the number of taps of the F-MUD algorithm remains to be 50, and the SNR and SIR are -5dB and -20dB, respectively. In figure 3 the length of training sequence is 100 bits. It shows that 12 taps are enough for R-MUD to approximate the F-MUD algorithm, with more taps R-MUD outperforms F-MUD. This is due to the estimation error of the covariance matrix and the cross correlation matrix without enough training sequence. From figure 4 we can observe this phenomena clearly, where 8 users are simulated. When the length of training sequence becomes longer, the F-MUD will be the best again. However, since the training sequence consumes the system resources as well in the communications, it is favorable to shorten its length if possible, just as using the reduced-order multi-user detector.

V. Conclusion

In this paper we addressed the approach to reduce the sampling rate thus the implementation complexity of the interference suppressing algorithms in multi-rate multi-user DS-UWB systems. A reduced-order multi-user detector is proposed, and by down-sampling the received signal at the appropriate locations it can approach the performance of a full sampling multi-user detector, yet with much less filter taps. The optimal down-sampling criterion is presented, and an order-iterative one-dimensional searching algorithm is developed to select the down-sampling locations. The iterative procedure only entails matrix multiplication operations. In the future works, the spreading information of the users may also be combined with the channel response information when computing the down-sampling locations, and this will further improve the interference suppressing capabilities.

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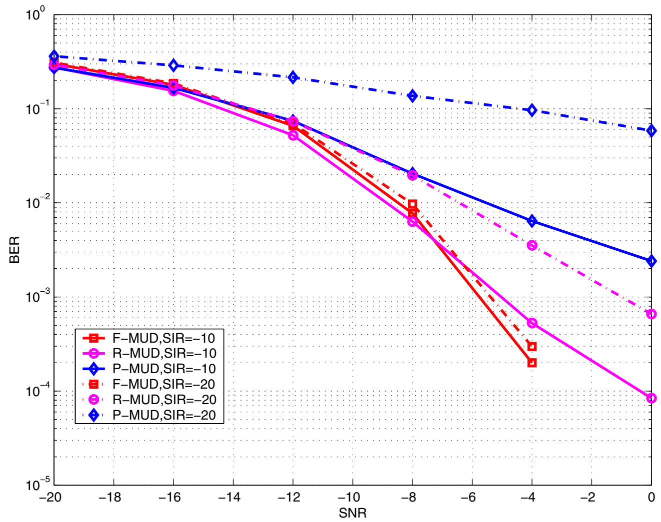

Fig. 1. BER ∼ SNR (8 users, 8 taps filter, 100 bits training sequence)

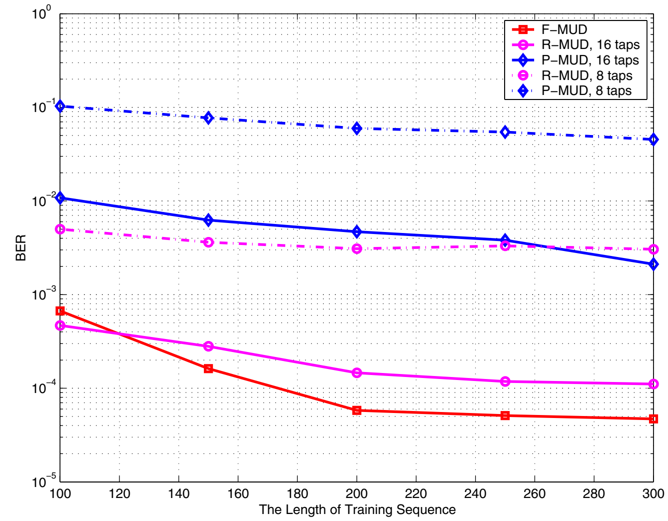

Fig. 2. BER ∼ SIR (SNR=-5dB, 8 taps filter, 100 bits training sequence)

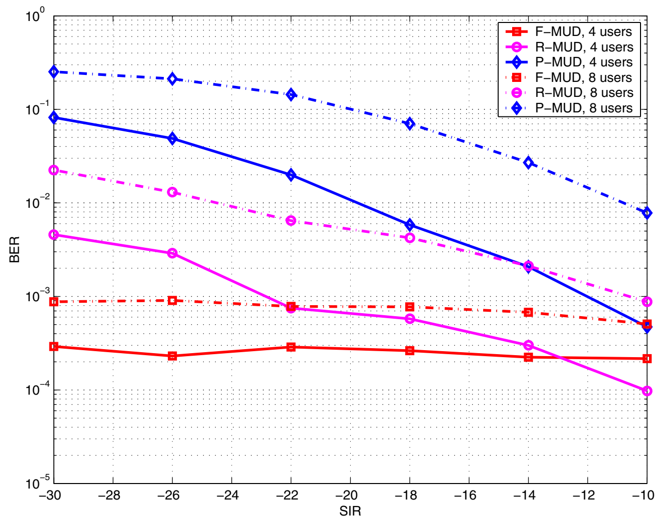

Fig. 3. BER ∼ The Number of Taps (SNR=-5dB, SIR=-20dB)

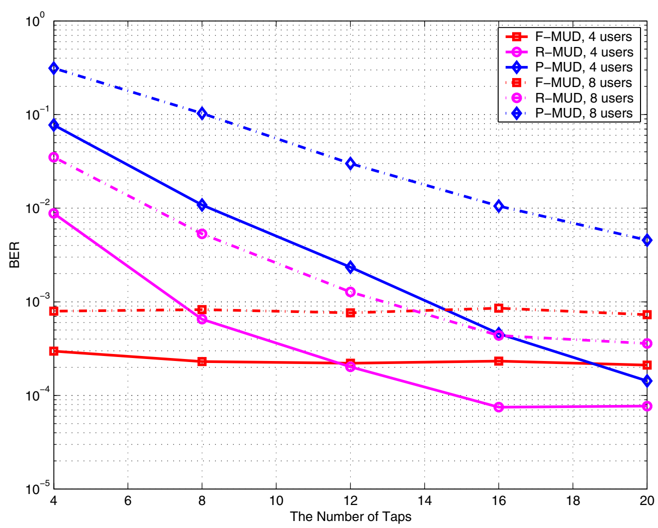

Fig. 4. BER ∼ Training Sequence Length (SNR=-5dB, SIR=-20dB, 8 users)

References

[1] D. Cassioli, M.Z. Win, F. Vatalaro, and A.F. Molisch, "Performance of low-complexity RAKE reception in a realistic UWB channel," *IEEE International Conference on Communications*, vol. 2, pp. 763-767, May 2002.

[2] J. R. Foerster, "The performance of a direct-sequence spread ultrawideband system in the presence of multipath, narrowband interference, and multiuser interference," *IEEE Conference on Ultra Wideband Systems and Technologies*, pp. 87-91, May 2002.

[3] S. Verdu, *Multiuser Detection.* Cambridge Univ. Press, 1998.

[4] Y. C. Yoon and R. Kohno, "Optimum multi-user detection in ultra-wideband (UWB) multiple-access communication systems," *IEEE International Conference on Communications*, vol. 2, pp. 812-816, May 2002.

[5] Q. Li and L. A. Rusch, "Multiuser detection for DS-CDMA UWB in the home environment," *IEEE Journal on Selected Areas in Communications*, vol. 20, pp. 1701-1711, Dec. 2002.

[6] H. Arslan, "Multiaccess interference cancellation receiver for time-hopping ultrawideband communication," *IEEE International Conference on Communications*, vol. 6, pp. 3394-3398, June 2004.

[7] Im Sungbin and E. J. Powers, "An iterative decorrelating receiver for DS-UWB multiple access systems using biphase modulation," *IEEE Workshop on Signal Processing Systems*, pp. 59-64, 2004.

[8] E. Fishler and H. V. Poor, "Low-complexity multiuser detectors for time-hopping impulse-radio systems," *IEEE Transactions on Signal Processing*, vol. 52, pp. 2561-2571, Sept. 2004.

[9] Z. Tian, H. Ge, and L. L. Scharf, "Low-Complexity Multiuser Detection and Reduced-Rank Wiener Filters for Ultra-Wideband Multiple Access," *IEEE International Conference on Acoustics, Speech, and Signal Processing*, vol. 3, pp. 621-624, March 2005.

[10] N. Boubaker and K. B. Letaief, "A low complexity MMSE-RAKE receiver in a realistic UWB channel and in the presence of NBI," *IEEE Wireless Communications and Networking Conference*, vol. 1, pp. 233-237, March 2003.

[11] G. S. Rajappan and M. L. Honig, "Signature sequence adaptation for DS-CDMA with multipath," *IEEE Journal on Selected Areas in Communications*, vol. 20, pp. 384-395, Feb. 2002.

[12] W. Chen, U. Mitra, and P. Schniter, "On the equivalence of three reduced rank linear estimators with applications to DS-CDMA," *IEEE Transactions on Information Theory*, vol. 48, pp. 2609-2614, Sept. 2002.

[13] H. L. Van Trees, *Optimum Array Processing. Part IV of Detection, Estimation, and Modulation Theory.* John Wiley & Sons, Inc., 2002.

[14] S. Haykin, *Adaptive Filter Theory, Chapter 15.* Third Edition, Prentice-Hall, 1996.

[15] A. F. Molisch, *et al.* "IEEE 802.15.4a channel model - final report," http://www.ieee802.org/15/pub/TG4a.html.

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