Research Article

Efficient DS-UWB MUD Algorithm Using Code Mapping and RVM

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A hybrid multiuser detection (MUD) using code mapping and a wrong code recognition based on relevance vector machine (RVM) for direct sequence ultra wide band (DS-UWB) system is developed to cope with the multiple access interference (MAI) and the computational efficiency. A new MAI suppression mechanism is studied in the following steps: firstly, code mapping, an optimal decision function, is constructed and the output candidate code of the matched filter is mapped to a feature space by the function. In the feature space, simulation results show that the error codes caused by MAI and the single user mapped codes can be classified by a threshold which is related to SNR of the receiver. Then, on the base of code mapping, use RVM to distinguish the wrong codes from the right ones and finally correct them. Compared with the traditional MUD approaches, the proposed method can considerably improve the bit error ratio (BER) performance due to its special MAI suppression mechanism. Simulation results also show that the proposed method can approximately achieve the BER performance of optimal multiuser detection (OMD) and the computational complexity approximately equals the matched filter. Moreover, the proposed method is less sensitive to the number of users.

1. Introduction

Ultra wide band (UWB) is an attractive wireless communication technology for its characteristics of high data transmission rate, low power density, high interference resistance, strong multipath resolution, and so on [1–3]. The application range of UWB has been broadened to Wireless Local Area Networks (WLAN), Wireless Sensor Networks (WSN), radar detection, and high-speed communications of indoor and outdoor applications [4–6].

There are mainly two standard schemes of UWB formulated by IEEE 802.15.3a, that is, the multiband-based orthogonal frequency division multiplexing (MB-OFDM) and impulse-radio-based direct sequence UWB (DS-UWB) [7]. Compared with MB-OFDM scheme, DS-UWB has many attractive advantages such as low peak-to-average power ratio, significant ability of information hidden, and less sensitivity to multipath fading [8, 9]. In a sense, the multiple access scheme of DS-UWB is similar to code division multiple access (CDMA) systems; both of them use pseudorandom (PN) codes to distinguish different users. However, as in conventional CDMA systems, DS-UWB systems also suffer from the multiple access interference (MAI). The optimal multiuser detector (OMD) proposed by Verdu [10] could achieve the single user's BER performance, but it had a very high computational complexity and was too expensive to handle [11]. Therefore, suboptimal detectors which may approximate OMD's BER performance with an acceptable computational complexity have become a focus of research. In recent years, artificial swarm algorithms are widely used in multiuser detection (MUD). Literature [12] investigates an efficient multiuser detector by selection of initial states based on code mapping for the artificial bee colony algorithm. A complexity-performance-balanced MUD method based on artificial fish swarm algorithm for DS-UWB is introduced in [13]; the BER performance of these methods can approximate the performance of OMD while these artificial swarm algorithms need iterated operation.

A multiuser frequency-domain turbo detector was employed which combines FD turbo equalization schemes with soft interference cancellation [14]. A code-aided interference suppression method was introduced for narrow band interference restriction in DS-UWB systems [15]. Adaptive MUD methods using the recursive least square (RLS) principles were studied in [16, 17]. In [18], a low-complexity approximate SISO MUD using soft interference cancellation and linear minimum mean square error (MMSE) filtering for coded CDMA system was introduced. However, few studies were reported that can approximate OMD's BER performance with a computational complexity approximates to linear MUD.

In this paper, a novel MUD algorithm which combines a code mapping method and a wrong code recognition based on RVM is proposed to achieve a BER performance approximate to OMD method with a very low complexity which almost equals the complexity of matched filter.

The remainder of this paper is organized as follows. In Section 2, the DS-UWB system models are introduced. And in Section 3, the principles of the proposed algorithm are described, respectively. In Section 4, simulation results that compare the performance of the proposed algorithm and other approaches are illustrated and discussed, followed by conclusions given in Section 5.

2. System Models

Consider a K-user asynchronous DS-UWB system in additive white Gaussian noise (AWGN) channel, and assume that each user employs the binary phase-shift key (BPSK) modulation. In this paper, Scholtz's monocycle is used as the UWB pulse waveform, which is approximated to the second derivation of Gaussian pulse. And the expression of Scholtz's monocycle is [19]

$$p(t) = A\left[1 - 4\pi\left(\frac{t - t_d}{\tau_m}\right)^2\right]\exp\left[-2\pi\left(\frac{t - t_d}{\tau_m}\right)^2\right], \quad (1)$$

where t_d and τ_m are the pulse center and the pulse shape parameter, respectively. At the transmitter k ($k = 1, 2, \ldots, K$), BPSK symbols $b_k(i) \in \{-1, 1\}_{i=1}^M$ are spread with the specific PN codes $c_k(t)$, which are the binary bit stream valued only by -1 or 1, and M is the length of bits per packet. The symbol duration is denoted by T_s. We consider that each BPSK symbol can be divided into N_c chips each with duration T_c, where N_c equals T_s/T_c. In each chip, a monocycle $p(t)$ is transmitted with the duration of T_p to represent the sign of the chip. Practically, the duration of a chip is much longer than the duration of a UWB pulse; that is, $T_c \gg T_p$. The kth user's transmission signal can be written as

$$x_k(t) = \sum_{i=1}^{M}\sum_{j=0}^{N_c-1} b_k(i)c_k(t - (i-1)T_s) \\ \cdot p(t - (i-1)T_s - jT_c - \tau_k), \quad (2)$$

where τ_k represents the random delay of the kth transmitter's monocycle, $0 \le \tau_k < T_c$.

Assume that each transmitter uses a time-invariant multipath channel in the same band. Let $h(t)$ represent the impulse response of the transmission channel. Furthermore, suppose that UWB signals reach the receiving antenna by L different paths. The channel impulse response can be written as [20]

$$h(t) = \sum_{l=1}^{L} \alpha_l \delta(t - \tau_l). \quad (3)$$

The received signal that is transmitted from the kth user is given by

$$v_k(t) = x_k(t) * h(t), \quad (4)$$

where $*$ denotes convolution operator.

The total received signal can be written as

$$r(t) = v(t) + n(t) = \sum_{k=1}^{K} x_k(t) * h(t) + n(t), \quad (5)$$

where $n(t)$ is zero-mean additive white Gaussian noise (AWGN) with the unilateral power spectral density of N_0.

In the receiver, the traditional receiver of a DS-UWB system consists of a pulse demodulator and a set of matched filters corresponding to each user. Regard signal $r(t)$ as the input of the group of matched filters. Furthermore, the inter symbol interference (ISI) can be ignored when the base-band signal transmission rate is much lower than the UWB pulse rate.

Let vector $\mathbf{y} = [y_1, y_2, \ldots, y_K]^T$ represent the output of the matched filter group, and let vector $\mathbf{b} = [b_1, b_2, \ldots, b_K]^T$ represent the output of sign detectors, so the output of the matched filters can be represented as follows:

$$\mathbf{y} = \mathbf{RAd} + \mathbf{n}, \quad (6)$$

$$\mathbf{b} = \text{sgn}(\mathbf{y}), \quad (7)$$

where the vector $\mathbf{d} = [d_1, d_2, \ldots, d_K]^T$ denotes the correct bits of each user and the vector $\mathbf{n} = [n_1, n_2, \ldots, n_K]^T$ denotes the output of the AWGN from each user's corresponding matched filter, while the random variable n_k is normally distributed and $E[n_k] = 0$ and $D[n_k] = N_0 N_c/2$, $\mathbf{R} = (r_{ij})_{K \times K}$ denotes the cross-correlation matrix, where $r_{ij} = \sum_{l=0}^{N_c-1} c_i(l)c_j(l)$ (what is more, $r_{ii} = N_c$) and $\mathbf{A} = \text{diag}(A_1, A_2, \ldots, A_K)$, in which the diagonal element A_k ($k \in [1, K]$, $k \in N$) represents the signal amplitude of the kth user.

3. The Proposed Hybrid Multiuser Detection

The main purpose of the proposed method is to pick out the error codes among the received signals and correct them. Firstly, the received codes are mapped into a feature space to make the error codes and the right ones different in some properties which can be easily distinguished. Secondly, identify and pick out the wrong codes by using some approaches in the feature space. Figure 1 shows the diagram of the algorithm. The first stage is corresponding to the
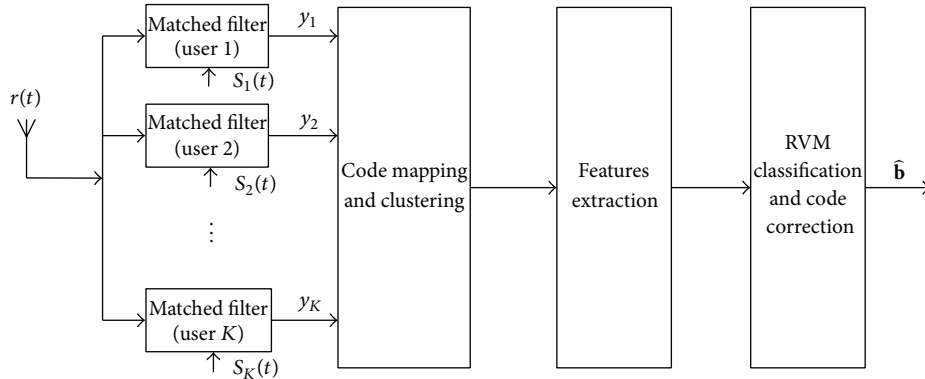
Figure 1: The block diagram of the receiver.

code mapping, the second stage is corresponding to features extraction for RVM, and the third stage is corresponding to classification of the codes based on RVM and correcting the wrong codes.

3.1. Code Mapping. Here, a mapping function is constructed to map the output codes set of the matched filter to a one-dimensional feature space [21].

According to the theory of optimal multiuser detection described in [22], optimal multiuser detection computes the likehood function

$$\Lambda(\mathbf{b}) = \int_0^T \left(r(t) - \sum_{k=1}^K A_k b_k c_k(t) \right)^2 dt$$

$$= \int_0^T r(t)^2 dt + \int_0^T \left(\sum_{k=1}^K A_k b_k c_k(t) \right)^2 dt \quad (8)$$

$$- \int_0^T 2r(t) \left(\sum_{k=1}^K A_k b_k c_k(t) \right) dt$$

and selects the sequence $\{b_k, 1 \le k \le K\}$ that minimizes $\Lambda(\mathbf{b})$. Thus the output of OMD can be expressed as

$$\widehat{\mathbf{b}}_{\text{OMD}} = \arg \left\{ \max_{b \in \{-1,1\}} \left(2\mathbf{b}^T \mathbf{A} \mathbf{y} - \mathbf{b}^T \mathbf{A} \mathbf{R} \mathbf{A} \mathbf{b} \right) \right\}. \quad (9)$$

It can be easily seen that (9) needs 2^K trials to get the expected $\mathbf{b}$. The computational complexity of OMD is too high. Thus other methods need to be explored to suppress the multiple access interference. Let

$$F(\mathbf{b}) = \frac{1}{2} \mathbf{b}^T \mathbf{A} \mathbf{R} \mathbf{A} \mathbf{b} - \mathbf{b}^T \mathbf{A} \mathbf{y}. \quad (10)$$

According to (9), it can be seen that when the value of function $F(\mathbf{b})$ achieves the minimum, the optimal $\mathbf{b}$ can be obtained. By expanding (10), we get

$$F(\mathbf{b}) = F(b_1, b_2, \dots, b_K)$$

$$= \frac{1}{2} \sum_{i=1}^K \sum_{j=1}^K A_i A_j r_{ij} b_i b_j - \sum_{i=1}^K b_i A_i y_i. \quad (11)$$

From (10) and (11), it is clear that function $F(\mathbf{b})$ is a quadratic form of vector $\mathbf{b}$, which means this is a nonlinear equation with the order of two. And it is not easy to solve the minimum of $F(\mathbf{b})$ and the corresponding value of $\mathbf{b}$. In addition, the function $F(\mathbf{b})$ embraces cross-component $b_i b_j$ $(i, j = 1, 2, \dots, K, i \neq j)$, and we cannot judge a code independently by $F(\mathbf{b})$. Hence, it is not appropriate for function $F(\mathbf{b})$ to be the mapping function.

In this case, it is better to calculate the derivative of function $F(\mathbf{b})$ to decrease the order of mapping function. Making the partial derivation of (10), we get

$$\frac{\partial F}{\partial \mathbf{b}} = \mathbf{A} \mathbf{R} \mathbf{A} \mathbf{b} - \mathbf{A} \mathbf{y}. \quad (12)$$

By expanding (12), we get Kth-order linear equations given as follows:

$$\frac{\partial F}{\partial b_1} = \sum_{j=1}^K A_1 A_j r_{1j} b_j - A_1 y_1$$

$$\frac{\partial F}{\partial b_2} = \sum_{j=1}^K A_2 A_j r_{2j} b_j - A_2 y_2$$

$$\vdots \quad (13)$$

$$\frac{\partial F}{\partial b_K} = \sum_{j=1}^K A_K A_j r_{Kj} b_j - A_K y_K.$$

Because $F(\mathbf{b})$ is a discrete equation, we cannot just set the partial derivative described above equal to 0 and get the stationary point of $F(\mathbf{b})$. Let $L(b_i) = \sum_{j=1}^K A_i A_j r_{ij} b_j - A_i y_i$, $i = 1, 2, \dots, K$. Substituting the candidate sequence $\mathbf{b}$ into (13) (the output of matched filter as shown in (7) or results of other conventional suboptimal multiuser detectors can be employed as the candidate sequence $\mathbf{b}$), there will be two situations as discussed below.

(1) No Wrong Code in $\mathbf{b}$. Based on the theory of extreme value, if MAI is the only interference resource without AWGN and the elements in $\mathbf{b}$ are all correct, the result of (13) strictly

equals **0**. And in the condition of high SNR, substituting (6) into $L(b_k)$, we can see that $L(b_k) = -A_k n_k \sim N(0, A_k^2 N_c N_0/2)$ ($k = 1, 2, \ldots, K$) when there is no error bit in the candidate codes set **b**.

(2) Wrong Codes Exist in **b**. Suppose that b_i ($i \in [1, K]$, $i \in N$) is the wrong code (in other words, $-b_i$ is the correct code); the other codes are correct. Substituting it to the ith equation of (13), we get

$$
\begin{aligned}
L(b_i) &= \sum_{\substack{j=1 \\ j \neq i}}^{K} A_i A_j r_{ij} b_j - A_i y_i + A_i^2 r_{ii} b_i \\
&= \sum_{\substack{j=1 \\ j \neq i}}^{K} A_i A_j r_{ij} b_j - A_i y_i + A_i^2 r_{ii} (-b_i) + 2A_i^2 r_{ii} b_i \\
&= 2A_i^2 N_c b_i - A_i n_i.
\end{aligned}
\tag{14}
$$

As for k which is not equal to i, we get

$$
L(b_k) = 2A_i A_k r_{ik} b_i - A_k n_k, \quad k = 1, 2, \ldots, K, \ k \neq i. \tag{15}
$$

According to (14) and (15), we can see when the ith user's code is wrong; then we get $|L(b_i)| \gg |L(b_k)|$, $k = 1, 2, \ldots, K$, $k \neq i$. Therefore, the function $L(\mathbf{b})$ can obviously differentiate the wrong codes and the right codes through the absolute value of it. In addition, $L(\mathbf{b})$ is Kth-order linear equations which can get the result of $L(\mathbf{b})$ without complex computations. In conclusion, it is appropriate to set $|L(\mathbf{b})|$ as the optimal decision function in the hybrid MUD algorithm.

It is accessible to map **b** into a one-dimension feature space $|L(\mathbf{b})|$ to identify the wrong codes in the candidate set. Figure 2 shows an example of the feature space mapping in the scenario of 10 users, with 6 dB signal-to-noise ratio (SNR). $|L(\mathbf{b})|$ of 3200 codes are shown in this figure (candidate **b** is selected from the result of matched filter as in (7)).

According to Figure 2, it is clear that the wrong codes and the right ones have a significant difference in the feature space mapped by $|L(\mathbf{b})|$.

3.2. Code Classification and Correction

3.2.1. Theory of RVM.
Tipping proposed the relevance vector machine (RVM) in [23], a sparse Bayesian modeling approach, which enables sparse classification and regression functions to be obtained by linearly weighting a small number of fixed basis functions from a large dictionary of potential candidates. And a significant advantage to support vector machine is that the kernel function of RVM avoids satisfying Mercer's condition [24–26].

In classification, the output function $y(x)$ is defined by

$$
y(x, \boldsymbol{\omega}) = \sigma\left(\boldsymbol{\omega}^T \phi(x)\right), \tag{16}
$$

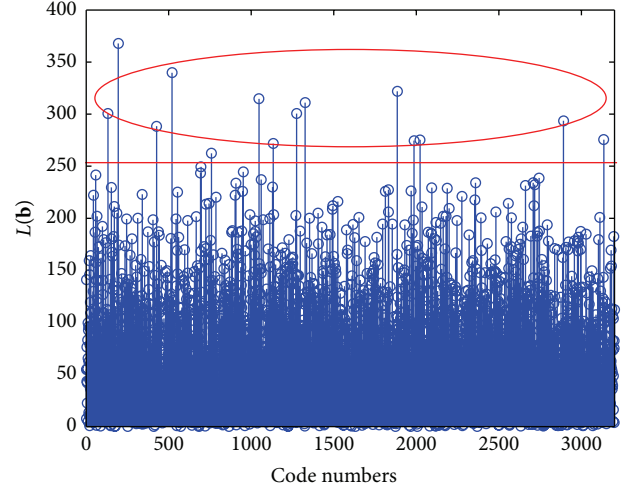where $\sigma(z) = 1/(1 + e^{-z})$ and $\boldsymbol{\omega}$ denotes the weight matrix.

FIGURE 2: Relationship between code numbers and mapping function $|L(b_k)|$.

Suppose $\boldsymbol{\omega}$ is a Gaussian conditional probability [27], with the 0 expectation and variance α_i^{-1}. For two classes' classification, the likelihood function is defined by

$$
P(\mathbf{t} \mid \boldsymbol{\omega}) = \prod_{n-1}^{N} \sigma\left\{y(x_n, \boldsymbol{\omega})\right\}^{t_n} \left[1 - \sigma\left\{y(x_n, \boldsymbol{\omega})\right\}\right]^{1-t_n}, \tag{17}
$$

where $t_n \in (0, 1)$ denote the target value.

Seeking the maximum posterior probability estimation is equivalent to seeking the mode point of the Gaussian function, namely, μ_{MP}.

Due to the fact that

$$
P(\boldsymbol{\omega} \mid \mathbf{t}, \alpha) = \frac{P(\mathbf{t} \mid \boldsymbol{\omega}) P(\boldsymbol{\omega} \mid \alpha)}{P(\mathbf{t} \mid \alpha)}, \tag{18}
$$

the maximum posterior probability estimation according to $\boldsymbol{\omega}$ is equivalent to maximize

$$
\begin{aligned}
\log\{P(\boldsymbol{\omega} \mid \mathbf{t}, \alpha)\} &= \log\{P(\mathbf{t} \mid \boldsymbol{\omega})\} + \log\{P(\boldsymbol{\omega} \mid \alpha)\} \\
&\quad - \log\{P(\mathbf{t} \mid \alpha)\} \\
&= \sum_{n=1}^{N} \left[t_n \log y_n + (1 - t_n) \log(-y_n)\right] \\
&\quad - \frac{1}{2}\boldsymbol{\omega}^T \mathbf{A}\boldsymbol{\omega} + C,
\end{aligned}
\tag{19}
$$

where $y_n = \sigma\{y(x_n, \boldsymbol{\omega})\}$ and C denotes a constant. Similarly, the marginal likelihood function can be given by

$$
\begin{aligned}
P(\boldsymbol{\omega} \mid \mathbf{t}, \alpha) &= \int P(\mathbf{t} \mid \boldsymbol{\omega}) P(\boldsymbol{\omega} \mid \alpha) \, d\boldsymbol{\omega} P(\mathbf{t} \mid \boldsymbol{\omega}_{\text{MP}}) \\
&\quad \cdot P(\boldsymbol{\omega}_{\text{MP}} \mid \alpha) (2\pi)^{M/2} |\Sigma|^{1/2}.
\end{aligned}
\tag{20}
$$

Suppose $\widehat{\mathbf{t}} = \Phi_{\boldsymbol{\omega}_{\text{MP}}} + \mathbf{B}^{-1}(\mathbf{t} - \mathbf{y})$, the approximation of the Gaussian posterior distribution; that is, $\mu_{\text{MP}} = \Sigma\Phi^T \mathbf{B}\widehat{\mathbf{t}}$,

with the variance $\Sigma = (\Phi^T \mathbf{B} \Phi + \mathbf{A})^{-1}$. The logarithm of the approximate marginal likelihood function is given by

$$\log P(\mathbf{t} \mid \alpha) = -\frac{1}{2} \left\{ N \log(2\pi) + \log |\mathbf{C}| + \widehat{\mathbf{t}}^T \mathbf{C}^{-1} \widehat{\mathbf{t}} \right\}, \quad (21)$$

where $\mathbf{C} = \mathbf{B} + \Phi \mathbf{A}^{-1} \Phi^T$.

Reference [28] proposed fast marginal likelihood maximization for sparse Bayesian models, which can reduce the learning time of RVM effectively. To simplify forthcoming expressions, it is defined that

$$\begin{aligned} s_i &= \phi_i^T \mathbf{C}_{-i}^{-1} \phi_i, \\ q_i &= \phi_i^T \mathbf{C}_{-i}^{-1} \mathbf{t}. \end{aligned} \quad (22)$$

It is showed that (20) has a unique maximum with respect to α_i:

$$\begin{aligned} \alpha_i &= \frac{s_i^2}{q_i^2 - s_i}, \quad \text{if } q_i^2 > s_i, \\ \alpha_i &= \infty, \quad \text{if } q_i^2 \le s_i. \end{aligned} \quad (23)$$

3.2.2. Wrong Codes Recognition Using RVM. We use RVM clustering approach to classify the candidate codes into right bits and wrong ones. Firstly, get the output of the matched filters by (6) and (7), the output of the matched filter group is $\mathbf{y}$, and the output of sign detectors is $\mathbf{b}$. Secondly compared with the vector $\mathbf{b}$ and the correct bits vector $\mathbf{d}$, we can classify the candidate codes into right set m_1 and wrong set m_2; let m_1 and m_2 be the training samples to train the RVM. Thirdly two useful feature parameters of the training samples can be extracted below: $\mathbf{y}$ and $|L(\mathbf{b})|$. Fourthly use the training samples m_1 and m_2 to train the RVM. Fifthly use the trained RVM clustering approach to classify the candidate codes into right bits and wrong ones.

4. Results and Discussions

In this section, simulation results are presented in order to show the superiority of the hybrid multiuser detector using code mapping based on relevance vector machine with respect to both system performance improvement and computational complexity reduction.

We present simulation results for the performance of a DS-UWB system with four types of multiuser detector: (1) the matched filter detector; (2) the MMSE multiuser detector; (3) the OMD; and (4) the proposed hybrid multiuser detector. Set the chip transmission rate as 2.55 GHz with the UWB transmission bandwidth 4~8 GHz and use length 255 Kasami spreading codes for the transmitters. Assume that the signal was transmitted in two typical channels: one is AWGN channel without ISI and the other is IEEE 802.15.3a multipath channel and the multipath signal is processed by a selective-RAKE (SRAKE) receiver with 8 branches and using MRC (Maximal Ratio Combining) rule. Our main objective was to examine a receiver's BER which directly bases the performance of the receiver on the condition of different SNR environments. In addition, we can check the recognition rate to identify the SNR in this scenario.

4.1. Results of Experiment 1: BER Performance versus SNR. First, consider the AWGN channel environment and IEEE 802.15.3a channel model (without loss of generality, CM2 channel is studied in the simulation experiment). There are four kinds of detectors to be simulated: matched filter detector, MMSE detector, OMD, and the proposed hybrid multiuser detector. The number of transmitters is set to 10, the spread spectrum gain N_c equals 255, and the range of SNR output from the receiver is 0 dB~12 dB. The curves of BER performance versus SNR are depicted in Figure 3.

As shown in Figure 3, on the whole, the BER performance of the hybrid multiuser detector is superior to that of the matched filter detector and the MMSE detector in both AWGN channel and the IEEE 802.15.3a multipath CM2 channel. Especially in conditions of high SNR (greater than 8 dB), the detection performance of the hybrid multiuser detector is much better than that of the other two detectors (approximately 1~3 orders of magnitude higher). Hence, what is more important is that the BER performance of the hybrid multiuser detector is very close to that of OMD. In theory, the OMD can completely eliminate the MAI and can arrive at the lower limit of BER in the condition of multiple users. This means that the hybrid multiuser detector can correct almost all the wrong codes caused by MAI. Another experiment was carried out to study the BER performance of the proposed hybrid MUD method in different IEEE 802.15.3a channel models, which is presented in Figure 4. Seen from Figure 4, the proposed method is sensitive to channel environments; the performance trend worsened with the deterioration of the channel environment.

4.2. Results of Experiment 2: User Capacity of System. Furthermore, consider another situation with different number of transmitters under the same SNR condition. To make the comparison apparent, the algorithms of matched filter detector MMSE and hybrid multiuser detector are simulated. The simulation results are shown in Figure 5 with the SNR of 4 dB, 6 dB, 8 dB, and 10 dB; the other simulation environments yield the same results as BER performance.

Based on the results in Figure 5, it can be seen that the BER performance of the hybrid multiuser detector remains nearly unchanged with an increase in the number of transmitters compared with that of the matched filter receiver. This shows that the hybrid multiuser detection can suppress multiaccess interference. Therefore, under the stated specific SNR conditions, the hybrid multiuser detector is still able to give a superior detection performance when there are many transmitters occupying the same channel simultaneously, which indicates that the BER performance of the hybrid multiuser detector is not sensitive to the channel capacity. This is one of the great advantages of this type of detector.

4.3. Results of Experiment 3: The Near-Far Effect (NFE) Resistant Capability. Due to the spatial distribution of terminals, NFE is one of the outcomes in Multiple Address (MA) systems, which is discussed in this simulation in both AWGN channel and IEEE 802.15.3a CM2 channel. In this experiment, the number of users was set as 10; the first user received
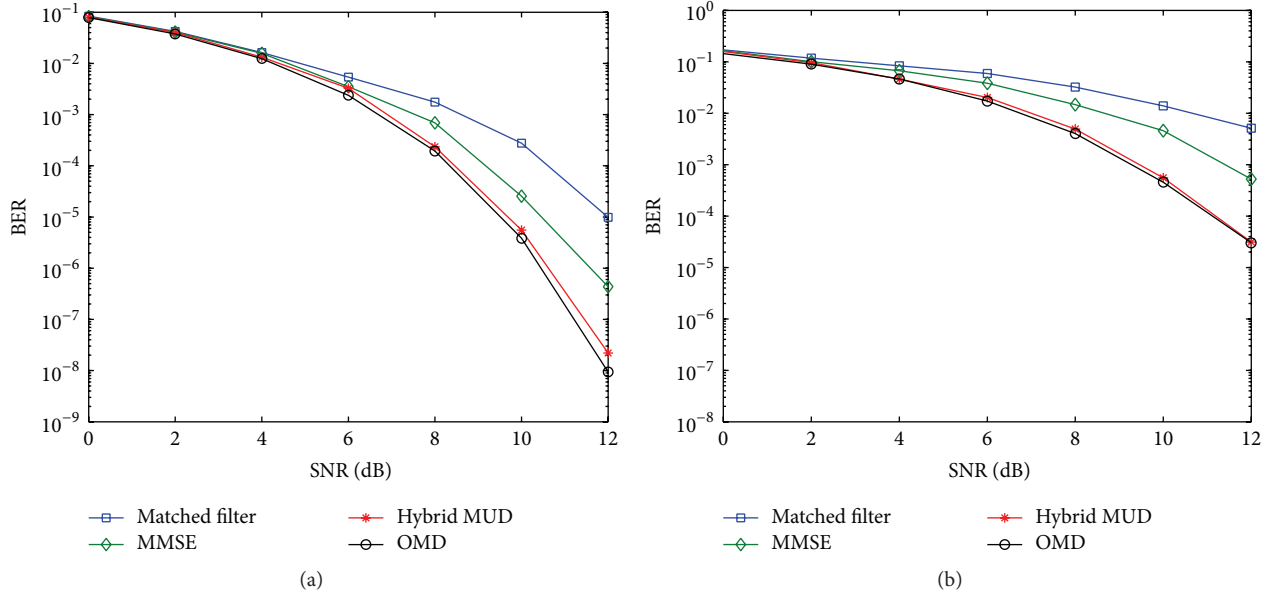
FIGURE 3: (a) BER performance versus SNR in 10-user condition for AWGN channel. (b) BER performance versus SNR in 10-user condition for multipath CM2 channel.
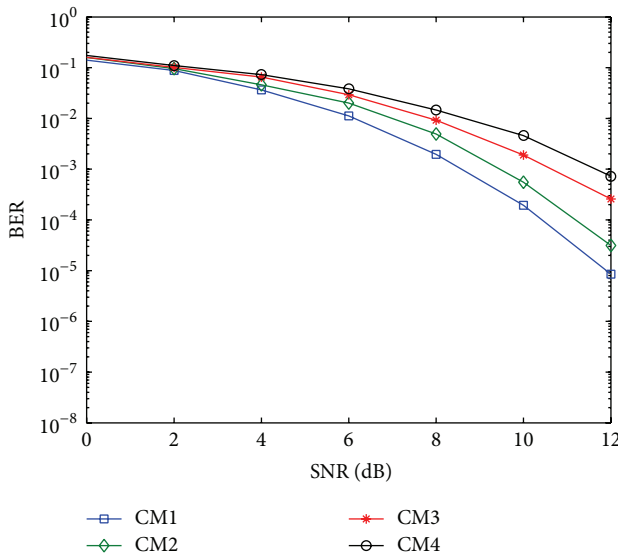

FIGURE 4: BER performance of the proposed method in 4 IEEE 802.15.3a channels.

signal with the stationary SNR of 6 dB, while in that of other users, SNR varies from 0 to 12 dB synchronously. And other parameters are the same as those in the former experiments.

The near-far effect resistant abilities of different multiuser detector in both AWGN channel and IEEE 802.15.3a CM2 channel are shown in Figure 6. It is evident that the matched filter detector has the worst NFE resistance ability, and both the proposed hybrid multiuser detector and the MMSE have the stronger NFE resistant ability compared to matched filter detector. However, considering the BER performance of them, hybrid MUD is the best.

TABLE 1: The relative execution time of different multiuser detectors.

Multiuser detectors	Matched filter	MMSE	OMD	Hybrid MUD
Relative execution time	1	1.41	58.7	1.26

4.4. Results of Experiment 4: Computational Complexity. OMD can obtain the best BER performance. However, as is shown in (8), in OMD the value of $(2\mathbf{b}^T \mathbf{A} \mathbf{y} - \mathbf{b}^T \mathbf{A} \mathbf{R} \mathbf{A} \mathbf{b})$ needs 2^K computations to find the maximum one (K is the number of users). The multiuser proposed in this paper computes the mapping function $|L(b_k)|$ and employs RVM to distinguish the wrong codes and then correct them. Let the execution time of matched filter normalize to 1. In an environment of 10-user AWGN channel, Table 1 lists the relative execution time of matched filter, MMSE, OMD, and the proposed hybrid MUD.

From Table 1, it can be seen that the computational complexity of the proposed hybrid multiuser detector is much lower than that of OMD. And it is in the same order of magnitude to matched filter and MMSE. Thus the proposed multiuser detector based on code mapping and RVM can get good BER performance with computational complexity.

5. Conclusions

In this paper, a new MAI suppression mechanism is proposed for multiuser detection of DS-UWB system. The algorithm embraces three steps. First, as the output of matched filters, the candidate codes set is mapped into a one-dimensional feature space by the optimal decision function. The purpose is to make the right codes and wrong codes easy to be
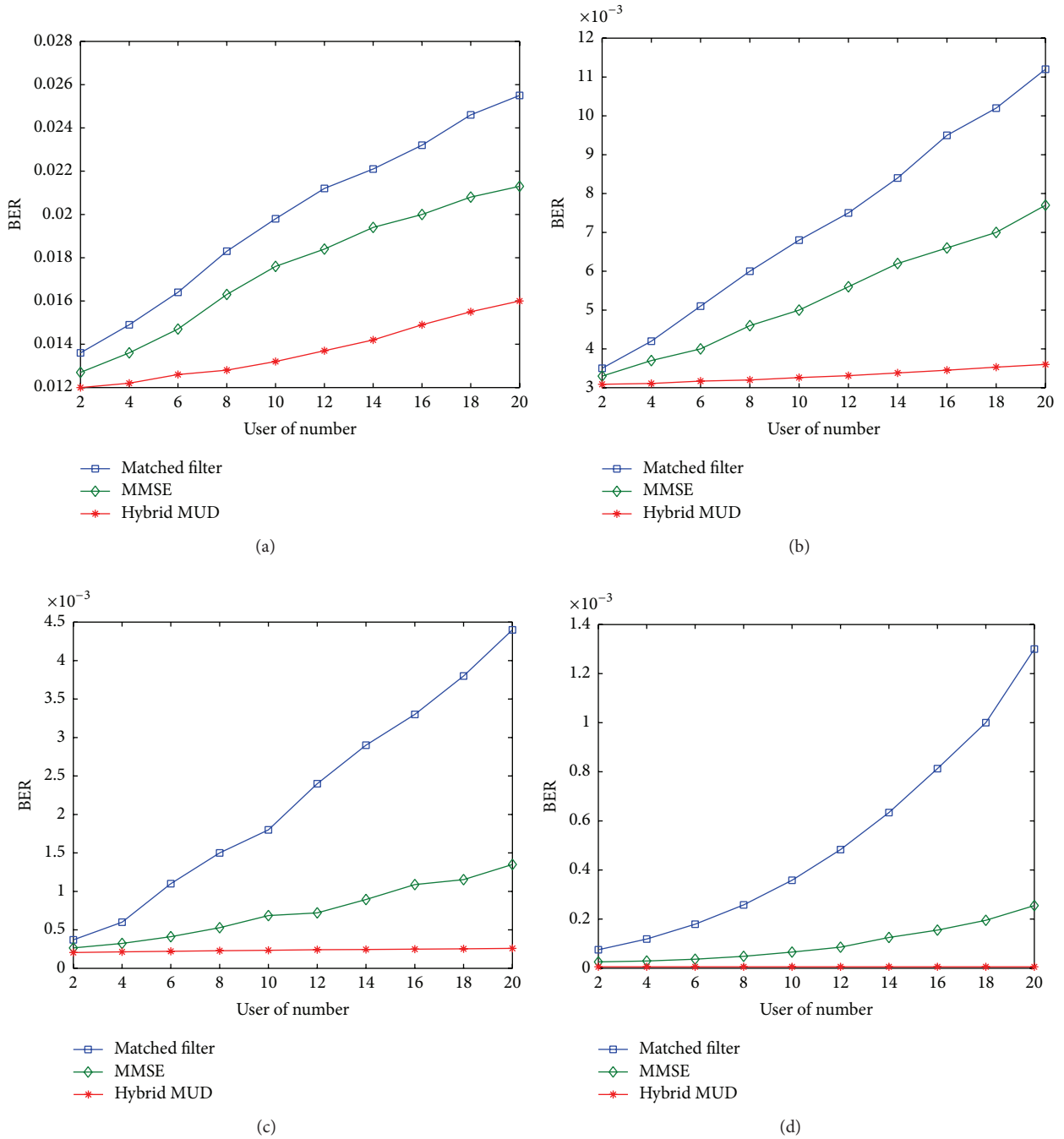
Figure 5: BER performance versus the number of users in specific SNR condition. (a) SNR = 4 dB, (b) SNR = 6 dB, (c) SNR = 8 dB, and (d) SNR = 10 dB.

distinguished. Second, calculate the statistical characteristics of the codes in the feature space. Third, use RVM classifier to classify the receiver multiuser function mapping characteristic value, and then correct the wrong codes by sign reversal. The simulation results show that the BER performance and the near-far effect resistant abilities of the new MAI suppression mechanism are superior to those of the matched filter detector and the MMSE detector in both AWGN channel and IEEE 802.15.3a channel, especially when the output SNR is greater than 8 dB. Its performance is very

close to that of OMD. Compared to the OMD, the new MAI suppression mechanism has lower computational complexity that increases linearly with the number of users. Hence, we conclude that the new MAI suppression mechanism can give an admirable detection performance under high SNR and large number of users, which is very useful for practical applications. Furthermore, the performance of the new MAI suppression mechanism can hardly be influenced by changes in numbers of users, which means that this hybrid approach for multiuser detection will be an efficient method to solve
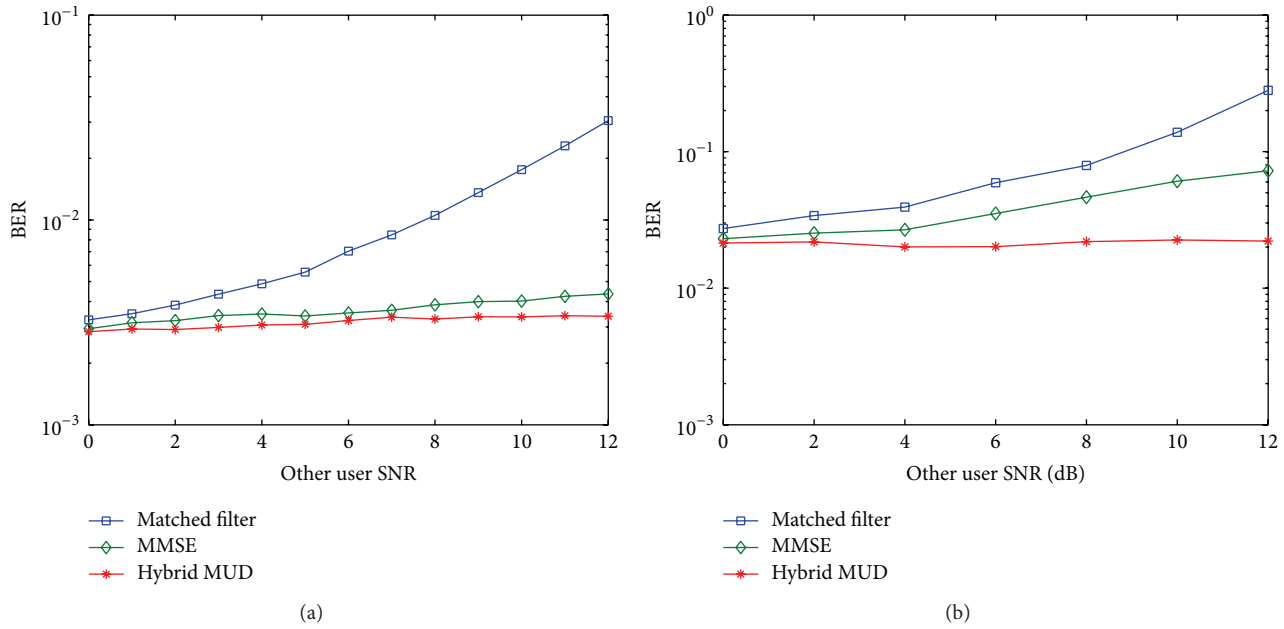
FIGURE 6: (a) The near-far effect resistant abilities of different MUD methods in AWGN channel. (b) The near-far effect resistant abilities of different MUD methods in CM2 channel.

interference problems when there are large quantities of transmitters occupying the same channel simultaneously.

Conflict of Interests

The authors declare that there is no conflict of interests regarding the publication of this paper.

Acknowledgments

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