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Joint Multiuser Detection of CD and AFSA in DS-UWB Communication Systems

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Abstract: This study mainly studies the application of Multiuser Detection (MUD) technology in DS-UWB multiple-access communication systems. As the time complexity of Optimum Multiuser Detection (OMUD) ascends quickly when the number of users increases and the BER performance of Correlation Detection (CD) is very poor, we proposed a Joint Multiuser Detection Algorithm of CD and AFSA (CD-AFSA-MUD). The process of OMUD is similar with that of the function's optimization, meanwhile Artificial Fish Swarm Algorithm (AFSA) is good at optimization because it can realize the global convergence. In order to accelerate the speed of global convergence and reduce the number of iteration for AFSA, we use the sub-optimal result of CD and its modified formations as the initial values of Artificial Fishes (AFs), which is a hybrid multiuser detection method. That is, we apply the sub-optimal value to approximate the optimal value. Computer simulation experiments show that the BER performance of CD-AFSA-MUD is much better than those of CD and AFSA-MUD which is also close to that of OMUD; furthermore, its convergence rate and the ability to resist Near-far Effect are superior to those of other MUD algorithms.

Key words: Direct sequence ultra-wideband, correlation detection, Artificial Fish Swarm Algorithm, hybrid multiuser detection

INTRODUCTION

Ultra-wideband (UWB) technology is one of the most promising technologies for high data rate networks over short-range communication (Ramesh and Vaidehi, 2006) and it is regarded as the key technology for the next generation of wireless communication (Siwiak, 2001). UWB technology displays a number of distinct advantages over conventional communication methods (Wenhui and Jiming, 2008). It modulates the baseband information sequences with nanosecond pulses and occupies a bandwidth of more than 25% of a center frequency, or more than 1.5 GHz. UWB signals have lower transmission power spectral density, better hidden ability, less sensitivity to multi-path fading than traditional narrow-band signals. The application of UWB has been broadened since 2002 when Federal Communications Commission (FCC) specified the using rules for UWB equipments. According to these rules, UWB devices' transmission power must be lower than the power limited by Emission Mask (FCC, 2002). Currently, UWB technology has a number of practical applications, such as wireless location, radar detection, high-speed communication, Wireless Local Area Network (WLAN) and so on.

Scholtz firstly proposed the UWB multiple-access communication system by combining UWB technology with Spread Spectrum (SS) technology in 1993 (Scholtz, 1993). Actually there is Multiple Access Interference (MAI) when using CD receivers to detect the received signals, which is because the spreading codes for multiple-access communications are not strictly orthogonal. Particularly, in asynchronous transmission channel and multi-path propagation environment, the effect of MAI is too severe to reduce the capacity and detection performance of multiple-access systems.

MUD is a method to eliminate or weaken the effect of MAI. Verdu provided the Optimum Multiuser Detection (OMUD) algorithm (Verdu, 1986), which makes the BER performance of multiple-access system approximate to that of the single-user system. But its poor real-time characteristic confines its using in engineering. Yoon and Kohno (2002) applied OMUD to UWB multiple-access systems, which could enhance the detection performance greatly. In Fishler and Poor (2004), the authors put forward the Blinking Receiver Multiuser Detection (BR-MUD). When the target user's information pulses don't collide with other users', the output of matched filter will be allowed and sampled; otherwise, the output won't be judged. Li and Rusch (2002) proposed an

adaptive MMSE detection algorithm for DS-CDMA UWB systems, which could reject the multi-path interference and the IEEE 802.11a OFDM narrow-band interference. A new MUD method based on Recurrent Neural Networks (RNN) was advanced in (De Lamare and Sampaio-Neto, 2002), which could keep the approximately minimum BER performance.

In order to possess a good BER performance and a low time complexity, we propose a Joint Multiuser Detection Algorithm of CD and AFSA (CD-AFSA-MUD). This algorithm makes use of the thought of the AFSA's iterative optimization and the result of CD, that is, we can improve the performance of the sub-optimal CD through AFSA. Simulation results show that the BER performance of this algorithm is better than those of CD and AFSA-MUD and even close to that of OMUD. Meanwhile, its ability to reject the Near-far Effect is also superior to those of other MUD algorithms.

At the beginning of this study, we study the model of CD receivers for DS-UWB multi-access communication system. On the basis of this model, we analyze some typical MUD algorithms, such as OMUD and AFSA-MUD. Further, we provide the CD-AFSA-MUD algorithm and make some simulations. The conclusions are given in the end.

REVIEW OF MUD MODELS AND METHODS

The model of correlation receivers for DS-UWB system:

In theory, for the orthonormality of the spreading codes, correlation receivers (or called matched filter receivers) can be used to detect data from different users' signals. Figure 1 is the block diagram of correlation receivers.

In this study, we assume that the channel is a frequency-flat AWGN channel and the DS-UWB system is not subjected to the frequency-selective multi-path. The received signals of DS-UWB system can be expressed as:

$$r(t) = \sum_{k=1}^K A_k(t) b_k(t) S_k(t-jT) + \alpha n(t) \quad (1)$$

where, $t \in [jT, (j+1)T]$ is the duration of the received signal, T is the symbol interval, $n(t)$ is the additive, zero mean and Gaussian white noise with two-sided power spectral density of $N_0/2$, $b_k \in \{-1, +1\}$ is the binary information symbol of the k th user, K is the total number of users in this system, $S_k(t)$ is the deterministic signature waveform assigned to the k th user by Eq. 2 and normalized so as to have unit energy by Eq. 3, $A_k(t)$ is the amplitude of the k th user's received signal, σ^2 is the power of the noise.

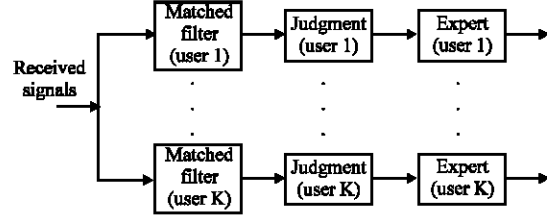


Fig. 1: The block diagram of correlation receivers

$$S_k(t) = \sum_{n=0}^{N_c-1} c_k(n) p(t - nT_c) \quad (2)$$

$$\|S_k\|^2 = \int_0^T S_k(t) dt = 1 \quad (3)$$

where, $\{c_k(n)\} \in \{-1, +1\}$ denotes the spreading code of the k th user, $T_c = T/N_c$ is the chip period and $p(t)$ is the UWB narrow pulse.

For the purpose of analysis, we assume that $j = 0$ and then the received signal turns to:

$$r(t) = \sum_{k=1}^K A_k(t) b_k(t) S_k(t) + \alpha n(t) \quad (4)$$

The output of the k th correlation receiver is as follows:

$$y_k = \frac{1}{T} \int_0^T r(t) S_k(t) dt = A_k b_k + \sum_{i=1, i \neq k}^K A_i b_i \rho_{ik} + n_k \quad (5)$$

where, $A_k b_k$ is the target signal,

$$\sum_{i=1, i \neq k}^K A_i b_i \rho_{ik}$$

is MAI, n_k is the noise interference,

$$\rho_{ik} = \int_0^T S_i(t) S_k(t) dt$$

is the correlation coefficient of the user j and the user k . If the parameter k in Eq. 5 ranges from 1 to K , the model of correlation receivers can be expressed as the following equation:

$$y = RA + n \quad (6)$$

where, $R = S^T S = \{\rho_{ik}\}$ is the normalized cross-correlation matrix:

$$\begin{aligned} \mathbf{y} &= [y_1, \dots, y_K]^T \\ \mathbf{b} &= [b_1, \dots, b_K]^T \\ \mathbf{A} &= \text{diag}\{A_1, \dots, A_K\} \end{aligned}$$

and \mathbf{n} is a zero mean Gaussian random vector with the covariance matrix equal to:

$$E[\mathbf{nn}^T] = \rho^2 \mathbf{R} \quad (7)$$

Optimum multiuser detection (OMUD): On the basis of correlation receivers, OMUD takes advantage of the maximum likelihood sequence detection algorithm to improve the BER performance of detections (Duel-Hallen *et al.*, 1995).

The problem of OMUD is equivalent to the most likely vector \mathbf{b} maximizes (Verdu, 1998):

$$\Omega(\mathbf{b}) = 2\mathbf{b}^T \mathbf{A} \mathbf{y} - \mathbf{b}^T \mathbf{A} \mathbf{R} \mathbf{A} \mathbf{b} \quad (8)$$

The expression Eq. 8 reveals that the selection of optimal \mathbf{b} can be accomplished in 2^K operations, therefore the OMUD algorithm has a time complexity of 2^K .

Artificial Fish Swarm Algorithm (AFSA): The basic Artificial Fish Swarm Algorithm (AFSA) was advanced by Li *et al.* (2002), which is a new bionic optimization algorithm based on the study of fish swarm's intelligence and behaviors in nature. There are four main types of fish behaviors: the fish preying, the fish swarming, the fish following and the fish random behavior. The global optimal value can be reached through the local search of each individual fish; meanwhile the details of the optimization problem are not necessary. The solution space is the environment that AFs belong to. Moreover, each fish has its own environmental state that is influenced by its own activities and other fishes' activities (Ma and Wang, 2009).

The mathematical model of behaviors: Firstly, we give some definitions about this model: $\mathbf{X} = (x_1, x_2, \dots, x_n)$ is the current AF's state, Step is the moving step length of AFs, Visual and δ are the perception range (or called the visual distance) and the crowd factor of Afs, Try_number is the number of random attempts, d_{ij} = distance (X_i, X_j) represents the distance between the state X_i and the state X_j , the concentration of food can be expressed by:

$$Y = f(\mathbf{X}) \quad (9)$$

where, Y is also the value of the objective optimization function.

The basic behaviors of AFs are defined as follows:

- **Preying behavior:** Let us assume that X_i is the AF current state. Within its visual distance, this AF selects a state X_j randomly. If $Y_i < Y_j$, the AF moves from X_i to X_j . Otherwise, select a state X_j randomly again and justify if it satisfies the moving requirement. If there is none fish that can satisfy the condition after Try_number times, we should choose a state randomly no matter what the value of expression Eq. 9 is. This procedure can be expressed as:

$$\mathbf{X}_{next} = \begin{cases} \mathbf{X}_i + \text{Random}(\text{step}) \frac{\mathbf{X}_j - \mathbf{X}_i}{\|\mathbf{X}_j - \mathbf{X}_i\|}, & \text{if } Y_j > Y_i \\ \mathbf{X}_i + \text{Random}(\text{step}) & \text{otherwise} \end{cases} \quad (10)$$

- **Swarming behavior:** The AF will assemble in the center of its partners during the process of preying; in the meantime, they should avoid overcrowding. Let us assume that X_i is the AF's current state, X_c is the center position of its partners in its visual distance and n_f is the number of its partners. If $Y_c/n_f > \delta Y_i$, this AF should go forward a Step to the center of its partners, because the center has more food and the surroundings are not too crowded. Otherwise, enforce the preying behavior. This process can be expressed as:

$$\mathbf{X}_{next} = \begin{cases} \mathbf{X}_i + \text{Random}(\text{step}) \frac{\mathbf{X}_c - \mathbf{X}_i}{\|\mathbf{X}_c - \mathbf{X}_i\|}, & \text{if } Y_c/n_f > \delta Y_i \\ \text{AF-prey} & \text{otherwise} \end{cases} \quad (11)$$

- **Following behavior:** If a certain AF finds food, its partners will follow with it and move to the food position quickly. Let us assume that X_i is the AF current state and then search the state X_j that has the biggest Y_j within the visual distance of X_i . If $Y_j/n_f > \delta Y_i$, which means that the X_j state has more food while its surroundings are not too crowded, this AF moves from X_i to X_j . Otherwise, execute the preying behavior. This process is given by:

$$\mathbf{X}_{next} = \begin{cases} \mathbf{X}_i + \text{Random}(\text{step}) \frac{\mathbf{X}_j - \mathbf{X}_i}{\|\mathbf{X}_j - \mathbf{X}_i\|}, & \text{if } Y_j/n_f > \delta Y_i \\ \text{AF-prey} & \text{otherwise} \end{cases} \quad (12)$$

- **Random behavior:** The AF makes random activities within its visual distance. If this AF finds more food

than its current state, it will move there as soon as possible

- **Notice board:** The notice board is used to record the state and the food concentration of the best AF. Compare the current state of each AF with the record on the notice board after each iteration. If the current state is better, then replace the record with it

The method of behavior selection: Appraise the AF's current environment based on the optimization problem to be solved and then choose a suitable behavior to execute in practice. Generally, we select the behavior that can make the greatest progress or just a little progress.

The procedure of AFSA: The procedure of AFSA is explained as follows:

- **Step 1:** Initialization. Generate the initial fish swarm randomly in the solution space
- **Step 2:** Initialize the notice board. Calculate the function value (the food concentration) Y of each AF and assign the state of the optimal AF to the notice board
- **Step 3:** Behavior selection. Make the following behavior and swarming behavior simulations for each AF, the better of which is the behavior for this AF to execute really. The default behavior is the preying behavior
- **Step 4:** Update the notice board. Compare the function value Y of each AF with the record on the notice board. If Y is better, then replace the value of the notice board by Y
- **Step 5:** Judge whether the termination condition is satisfied. If the value of the notice board is an approximate optimal value or the maximum iteration number has achieved, the procedure is over. Otherwise, go to Step 3
- **Step 6:** Output the value on the notice board

JOINT MULTIUSER DETECTION OF CD AND AFSA (CD-AFSA-MUD)

The discretization of behavior models: The mathematical model of OMUD is considered as a combinatorial optimization problem (Yu *et al.*, 2005). The optimization function for OMUD is shown in the expression Eq. 8, which is a discrete optimization function. For this reason, we should discretize the behavior models of AFSA.

The discretizations are defined as follows:

- Expression of states. The state of each AF is expressed by -1 and +1

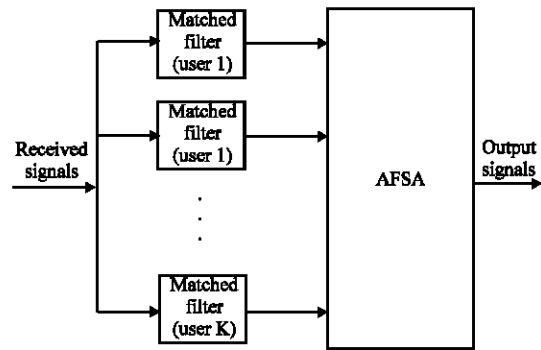


Fig. 2: Block diagram of the detector based on the CD-AFSA-MUD algorithm

- Initialization. The initial state of each AF is selected in the discrete solution space randomly
- Calculation of distance. The number of different elements between state X_i and X_j is the distance d_{ij} . So, XOR operation is used in this algorithm (Yu *et al.*, 2005). For example, if $X_i = (-1, 1, 1, 1, -1)$ and $X_j = (1, -1, 1, 1, -1)$, the distance $d_{ij} = X_i \text{ XOR } X_j = 2$, that is, the distance between state X_i and X_j is 2
- Calculation of the fish swarm's center. X_c is the result by adding up the state vectors of all AFs within the visual distance. If the element of X_c is $x_{ci} > 0$, then assign $x_{ci} = 1$; otherwise, $x_{ci} = -1$

The selection of initial states: AFSA is an iterative optimization algorithm, which means that the selection of initial states has a great effect on the iteration times and the convergence rate. In this study, we choose the result of CD and its variations as initial state values of AFs, which can ensure the AFs gather near the optimal value of the optimization problem because the sub-optimal result of CD is quite close to the optimal value in the solution space. Besides, this selection method of initial states can also reduce the required times of iteration and speed up the convergence rate for optimization. The detector block based on this CD-AFSA-MUD algorithm is given in Fig. 2.

The specific steps of the initial value selection are shown as follows:

- **Step 1:** Execute Correlation Detection (or matched filter detection) at first. Assign the result

$$\bar{b}_{1 \times K} = (b_1, b_2, \dots, b_K)$$

to the first AF as its initial state value, where, $b_i \in \{-1, 1\}$ and $i = 1, 2, \dots, K$

- **Step 2:** Change an element b_i of the result $\bar{b}_{i:k}$ randomly, that is, $\bar{b}_i = b_i \oplus (-1)$. Then assign this new result $\bar{b}_{i:k}$ which is changed from $\bar{b}_{i:k}$ to the second AF as its initial state value
- **Step 3:** Repeat the process of Step 2 and assign these new varied results to other AFs. What is worth noticing is that every new result is based on the result of CD and the varied element is different for each AF
- **Step 4:** If all AFs have been assigned initial state values, the procedure of the initial value selection comes to an end. And then we can start the AFSA to research the optimal value for OMUD.

Simulation and analysis

The comparison of the BER performance: We assume that the DS-UWB system is a synchronous system under the AWGN channel and the signature waveforms are originated from m sequence with the length of 31. And each user has 10000 baseband symbols to send. Moreover, as for AFSA, we fix the number of AFs is 3, the maximum number of iteration is 30, the visual distance is 2 and the number of attempts in this distance is 2. In order to demonstrate the BER performance of CD-AFSA-MUD is better, we choose the AFSA-MUD that has random initial values, OMUD and CD to compare with it.

Figure 3 is the BER performances of these four MUD algorithms in ten-user DS-UWB multi-access system.

It can be seen from Fig. 3 that the BER performance of CD-AFSA-MUD is better than those of AFSA-MUD and CD and even coincides with that of OMUD. The reason is that CD-AFSA-MUD makes full use of the sub-optimal result of CD, so it can research to the optimal value of OMUD much easier than AFSA-MUD.

The comparison of the convergence rate between CD-AFSA-MUD and AFSA-MUD: As iterative optimization algorithms, the convergence rate is as important as the BER performance. The improved BER performance may not deserve the cost of the time consumed sometimes. To compare the convergence rate between CD-AFSA-MUD and AFSA-MUD algorithms, we simulate the BER performances for both algorithms while the number of iterations is 10, 20 and 30, respectively.

Figure 4 and 5 are the convergence rate of CD-AFSA-MUD and AFSA-MUD separately. From them, we can see the convergence rate of CD-AFSA-MUD is much quicker than that of AFSA-MUD. When the number of iterations is lower than 20, their performances are almost the same. If the number increases to 30, the BER performance of CD-AFSA-MUD gets close to that of

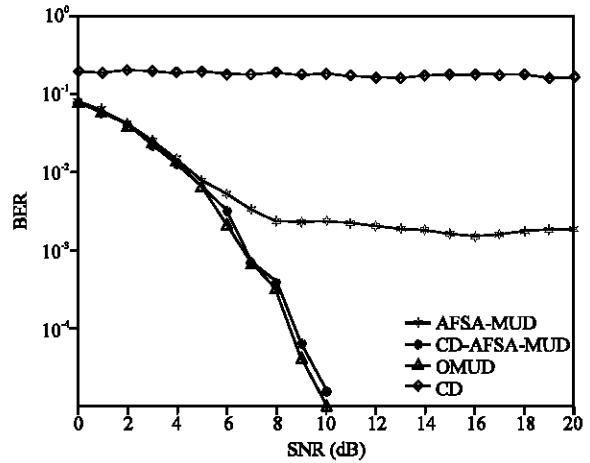


Fig. 3: The comparison of BER performances in ten-user DS-UWB system

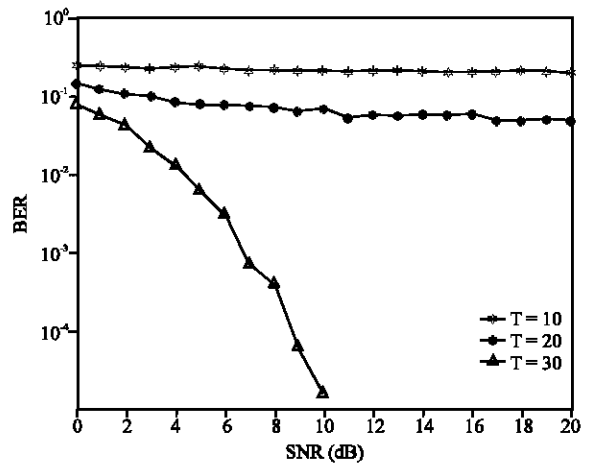


Fig. 4: The convergence rate of CD-AFSA-MUD

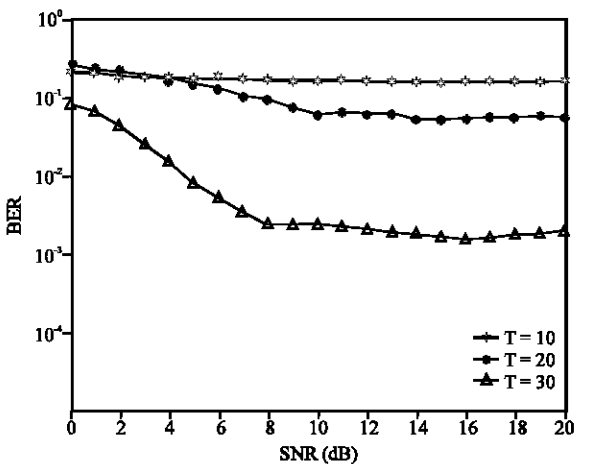


Fig. 5: The convergence rate of AFSA-MUD

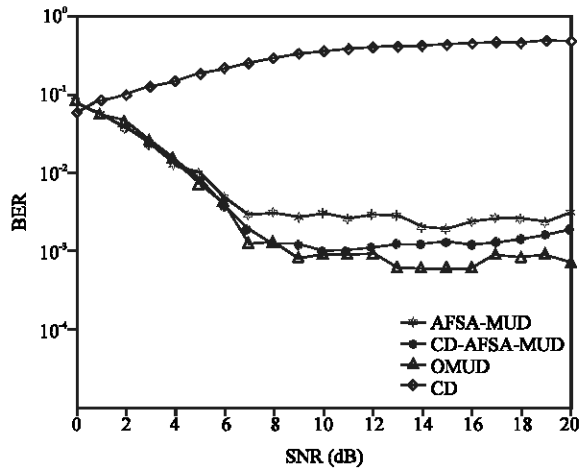


Fig. 6: Near-far effect resistant comparison of different MUD algorithms

OMUD (Fig. 3). Meanwhile, AFSA-MUD only improves its BER performance a little, which is much worse than that of CD-AFSA-MUD at the same iteration times.

The comparison of the Near-far Effect resistant abilities:

In this experiment, we assume that the signal to noise ratio (SNR) of the first user’s received signal is 5 dB which is invariable all the time; while other users with SNR₃₋₁₀ changing from 0 to 20 dB synchronously. Besides, other parameters are set the same as those in the comparison of the BER performance.

Figure 6 is the first user’s BER performances of different MUD algorithms. From it, we can note that OMUD algorithm has the best Near-far Effect resistant ability of all and CD has the worst. Furthermore, CD-AFSA-MUD has a better ability to resistant the Near-far Effect than AFSA-MUD has, that is because CD-AFSA-MUD takes full advantage of the sub-optimal results of CD as the initial values for AFSA and then it can boost the enhancement of its BER performance and Near-far Effect resistant ability easily.

CONCLUSIONS

In this study, MUD technology in DS-UWB multi-access communication systems is studied. On the basis of analyzing the typical MUD algorithms and a combinatorial optimization viewpoint, we propose a joint multiuser detection method of CD and AFSA (CD-AFSA-MUD) that can make full use of the suboptimal results of CD and the advantages of AFSA to research the optimal value in solution space. Simulation results indicate that the BER performance of CD-AFSA-MUD is close to that of OMUD; in the meantime, its convergence rate and Near-far Effect resistant ability are better than AFSA-MUD’s.

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