Immune Clonal Selection Algorithm for Multiuser Detection in DS-CDMA Systems

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Abstract. Based on the Antibody Clonal Selection Theory of immunology, we put forward a novel artificial immune system algorithm, Immune Clonal Selection Algorithm for Multiuser Detection in DS-CDMA Systems. The performance of the new detector, named by ICSMUD, is evaluated via computer simulations. When compared with Optimal Multiuser detection, ICSMUD can reduce the computational complexity significantly. When compared with detectors based on Standard Genetic Algorithm and A Novel Genetic Algorithm, ICSMUD has the best performance in eliminating multiple-access interference and "near-far" resistance and performs quite well even when the number of active users and the packet length are considerably large.

1 Introduction

In recent years, Direct-Sequence Code-division multiple-access(DS-CDMA) systems have emerged as one of prime multiple-access solutions for 3G. In the DS-CDMA framework, multiple-access interference (MAI) existing at the received signal creates "near-far" effects. Multiuser detection (MUD) techniques can efficiently suppress MAI and substantially increase the capacity of CDMA systems, so it has gained significant research interest since the Optimal MUD (OMD) was proposed by Verdu[1]. Reference [2] to [4] respective proposed their multiuser detectors based on BP Neural Network, Hopfield Neural Network and genetic algorithm. All of them can reduce the computational complexity significantly and get good performances. They provided new ideas and techniques for solving MUD. Antibody Clonal Selection Theory is very important for the immunology. Some new algorithms based on Clonal Selection Theory have been proposed successively[5][6][7].

A novel clonal selection algorithm for MUD based on Antibody Clonal Selection Theory, named by ICSMUD, is presented in this paper. The performances of ICSMUD is evaluated via computer simulations and compared with that of SGA and A Novel Genetic Algorithm based on Immunity[8] as well as with that of the OMD and Conventional Detector in asynchronous DS-CDMA systems.

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2 Problem Statements

Consider a base-band digital DS-CDMA network with K active users operating with a coherent BPSK modulation format. The signal received at the output of the sensor is:

$$\boldsymbol{r}(t) = \sum_{i=0}^{M-1}\sum_{k=1}^{K} A_k b_k(i) s_k(t - iT_{\mathrm{b}}) + \boldsymbol{n}(t) = \boldsymbol{S}(t, \boldsymbol{b}) + \boldsymbol{n}(t) \tag{1}$$

here $\boldsymbol{n}(t)$ is the additive white noise vector whose standard deviation is σ, T_{b} is the symbol interval, M is the packet length, A_k is the signal's amplitude of the k^{th} user, $b_k(m)$ is the m^{th} coded modulated symbol of the k^{th} user and $b_k(m) \in \{\pm 1\}$, $s_k(t)$ is the k^{th} user's signature sequence.

The matched filter output corresponding to the m^{th} bit of the k^{th} user is given by:

$$y_k(m) = \int_{-\infty}^{\infty} \boldsymbol{r}(t) s_k(t - mT_b - \tau_k) dt \tag{2}$$

If set $\boldsymbol{y}(m) = [y_1(m), y_2(m)\cdots, y_K(m)]^{\mathrm{T}}$, $\boldsymbol{b}(m) = [b_1(m), b_2(m), \ldots, b_K(m)]^{\mathrm{T}}$, $\boldsymbol{A}(m) = \mathrm{diag}(\boldsymbol{A}_1, \boldsymbol{A}_2, ..., \boldsymbol{A}_K)$, $\boldsymbol{n}(m) = [n_1(m), n_2(m), \ldots, n_K(m)]^{\mathrm{T}}$ and $\boldsymbol{R}(q) = (\rho_{kl}(q))_{K\times K}$, where $\rho_{kl}(q) = \int_{\tau_k}^{T+\tau_k} s_k(t-\tau_k) s_l(t+qT-\tau_l)dt$ then

$$\boldsymbol{y} = \boldsymbol{RAb} + \boldsymbol{n} \tag{3}$$

where $\boldsymbol{y} = [\boldsymbol{y}(m), \boldsymbol{y}(m+1)\cdots, \boldsymbol{y}(m+M-1)]^{\mathrm{T}}$, $\boldsymbol{b} = [\boldsymbol{b}(m), \boldsymbol{b}(m+1), \ldots, \boldsymbol{b}(m+M-1)]^{\mathrm{T}}$, $\boldsymbol{A} = diag(\boldsymbol{A}(m), \boldsymbol{A}(m+1), ..., \boldsymbol{A}(m+M-1))$ and $\boldsymbol{n} = [\boldsymbol{n}(m), \boldsymbol{n}(m+1), \ldots, \boldsymbol{n}(m+M-1)]^{\mathrm{T}}$.

The OMD produces an estimate for the information vector transmitted at the discrete-time instant m. In the asynchronous systems it holds that

$$\hat{\boldsymbol{b}}_{\text{optimal}} = \arg \max_{\substack{b_k^{(m)} \in \{-1,1\} \\ 1\le k\le K,\, 1\le m\le M}} \left\{ 2\boldsymbol{b}^{\mathrm{T}} \boldsymbol{Ay} - \boldsymbol{b}^{\mathrm{T}} \boldsymbol{ARAb} \right\} \tag{4}$$

Note that, if solved by Viterbi algorithm, its computational complexity will increase exponentially with the number of users and the packet length.

3 Immune Clonal Selection Algorithm for Multiuser Detection

The Antibody Clonal Selection Theory (F. M. Burnet, 1959) was proposed as the basic features of an immune response to an antigenic stimulus[9]. Inspired by the Antibody Clonal Selection Theory, we proposed a novel clonal selection algorithm for multiuser detection.

Assume that K active users share the same channel and the packet length is M, then the question (4) can be described as a combination optimization problem as

$$\text{(P)}: \max\left\{ f(\boldsymbol{b}) = 2\boldsymbol{b}^{\mathrm{T}}\boldsymbol{Ay} - \boldsymbol{b}^{\mathrm{T}}\boldsymbol{ARAb} : \boldsymbol{b} \in \boldsymbol{I} \right\} \tag{5}$$

where $\boldsymbol{b}=\left\{\ [b_1^{(1)},b_2^{(1)}\cdots,b_K^{(1)}]\ ,\cdots,\ [b_1^{(M)},b_2^{(M)}\cdots,b_K^{(M)}]\ \right\}$, $b_k^{(m)}\in\{-1\ ,\ 1\}$ is the variants to be optimized, $\boldsymbol{I}$ denotes the antibody space. Set the antigen f as an objective function, and set $\boldsymbol{I}^n$ denotes the antibody population space as

$$\boldsymbol{I}^n=\{\boldsymbol{B}:\boldsymbol{B}=(\boldsymbol{b}_1,\boldsymbol{b}_2,\cdots,\boldsymbol{b}_n),\ \ \boldsymbol{b}_k\in\boldsymbol{I},\ \ 1\le k\le n\} \tag{6}$$

in which $\boldsymbol{B}=\{\boldsymbol{b}_1,\boldsymbol{b}_2,\cdots,\boldsymbol{b}_n\}$ is the antibody population, n is the size of the antibody population, and antibody $\boldsymbol{b}_i=\left\{\ [b_{1i}^{(1)},b_{2i}^{(1)}\cdots,b_{Ki}^{(1)}]\ ,\cdots,\ [b_{1i}^{(M)},b_{2i}^{(M)}\cdots,b_{Ki}^{(M)}]\ \right\}$. Then the novel clonal selection algorithm can be implemented as Fig 1.

Immune Clonal Selection Algorithm for Multiuser Detection (ICSMUD)
begin
  $k := 0$;
  initialize $\boldsymbol{B}(k)$ and algorithm parameters;
  calculate affinity of $\boldsymbol{B}(k)$: $\{f(\boldsymbol{B}(k))\}=\{f(\boldsymbol{b}_1(k)),f(\boldsymbol{b}_2(k)),\cdots f(\boldsymbol{b}_n(k))\}$;
  while not finished **do**
    $k := k + 1$;
    generate $\boldsymbol{B}(k)$ from $\boldsymbol{B}(k-1)$ by the Clonal Selection Operator including Clonal Operating $T_{\mathrm{c}}^{\mathrm{C}}$, Clonal Mutation Operating $T_{\mathrm{m}}^{\mathrm{C}}$, Clonal Selection Operating $T_{\mathrm{s}}^{\mathrm{C}}$ and Clonal Death Operating $T_{\mathrm{d}}^{\mathrm{C}}$;
    calculate the affinity of $\boldsymbol{B}(k)$, namely, evaluate $\boldsymbol{B}(k)$;
  end
end

Fig. 1. The Immune Clonal Selection Algorithm for Multiuser Detection

The major elements of Clonal Selection Operator are presented as follows.

Clonal Operating $T_{\mathrm{c}}^{\mathrm{C}}$ **:** Define

$$\boldsymbol{Y}(k)=T_{\mathrm{c}}^{\mathrm{C}}(\boldsymbol{B}(k))=[T_{\mathrm{c}}^{\mathrm{C}}(\boldsymbol{b}_1(k))\quad T_{\mathrm{c}}^{\mathrm{C}}(\boldsymbol{b}_2(k)),\quad\cdots,\quad T_{\mathrm{c}}^{\mathrm{C}}(\boldsymbol{b}_n(k))]^{\mathrm{T}} \tag{7}$$

where $\boldsymbol{Y}_i(k)=T_{\mathrm{c}}^{\mathrm{C}}(\boldsymbol{b}_i(k))=I_i\times\boldsymbol{b}_i(k),\quad i=1,2,\cdots,n$, I_i is q_i dimension row vector and

$$q_i(k)=g(N_{\mathrm{c}},f(\boldsymbol{b}_i(k))) \tag{8}$$

$N_{\mathrm{c}}>n$ is a given value relating to the clone scale. After clone, the population becomes:

$$\boldsymbol{Y}(k)=\{\boldsymbol{Y}_1(k),\boldsymbol{Y}_2(k),\cdots,\boldsymbol{Y}_n(k)\} \tag{9}$$

where $\boldsymbol{Y}_i(k)=\{\boldsymbol{y}_{ij}(k)\}=\{\boldsymbol{y}_{i1}(k),\boldsymbol{y}_{i2}(k),\cdots,\boldsymbol{y}_{iq_i}(k)\}$ and $\boldsymbol{y}_{ij}(k)=\boldsymbol{b}_i(k),\quad j=1,2,\cdots,q_i$.

Clonal Mutation $T_{\mathrm{m}}^{\mathrm{C}}$ **:** According to the mutation probability p_{m}, the cloned antibody populations are mutated as follows:

$$Z_i(k) = \{z_{ij}(k)\} = \{T_{\mathrm{m}}^{\mathrm{C}}(\boldsymbol{y}_{ij}(k))\} = \{(-1)^{random \le p_m} \boldsymbol{y}_{ij}(k)\} \tag{10}$$

$(-1)^{random \le p_m} \boldsymbol{y}_{ij}(k)$ means each number of the antibody $\boldsymbol{y}_{ij}(k)$ multiplies -1 with probability of p_{m}.

Clonal Selection Operating $T_{\mathrm{s}}^{\mathrm{C}}$ **:** $\forall i = 1,2,\cdots n$, if there are mutated antibodies $\boldsymbol{b}_i'(k) = \max\{\boldsymbol{Z}_i(k)\} = \{z_{ij}(k) \mid \max f(z_{ij}(k)) \quad j = 1,2,\cdots,q_i\}$, the probability of $\boldsymbol{b}_i'(k)$ taking place of $\boldsymbol{b}_i(k) \in \boldsymbol{B}(k)$ is:

$$p_{\mathrm{s}}^{\mathrm{k}}\left(\boldsymbol{b}_i(k) = \boldsymbol{b}_i'(k)\right) = \begin{cases} 1 & \text{when } f(\boldsymbol{b}_i(k)) < f(\boldsymbol{b}_i'(k)) \\ 0 & \text{when } f(\boldsymbol{b}_i(k)) \ge f(\boldsymbol{b}_i'(k)) \end{cases} \tag{11}$$

Clonal Death Operating $T_{\mathrm{d}}^{\mathrm{C}}$ **:** After the clonal selection, the new population is:

$$\boldsymbol{B}(k+1) = \{\boldsymbol{b}_1(k+1), \boldsymbol{b}_2(k+1), \cdots, \boldsymbol{b}_i'(k+1), \cdots, \boldsymbol{b}_n(k+1)\} \tag{12}$$

where $\boldsymbol{b}_i'(k+1) = \boldsymbol{b}_j(k+1) \in \boldsymbol{B}(k+1)\ i \ne j$ and $f(\boldsymbol{b}_i'(k+1)) = f(\boldsymbol{b}_j(k+1))$, in which $\boldsymbol{b}_j(k+1)$ is one of the best antibodies in $\boldsymbol{B}(k+1)$. Whether $\boldsymbol{b}_i'(k+1)$ should be canceled or not depends on the clonal death proportion *T%*.

We have proved that the algorithm of ICSMUD is convergent with probability of 1 based on Markov Chain.

In this contribution, we succeeded in reducing the complexity of the Optimal MUD by employing the sub-optimal ICSMUD, which performs only $O((K \times M)^2)$ search.

4 Simulation Results

In this section, we present some simulation results and comparisons that demonstrate the advantage of our algorithm. The performance of the ICSMUD is evaluated via computer simulations and compared with that of Standard Genetic Algorithm (GAMUD) and A Novel Genetic Algorithm based on Immunity [8] (IAMUD) as well as with that of Optimal Multiuser Detector (OMD) and conventional Matched Filters Detector (MFD) in asynchronous DS-CDMA systems.

It is assumed that the number of users is *K* and the packet length is *M*, Gold sequences of length 31 are used as code sequences. The signal to noise ratio of the k^{th} user is $SNR_k = A_k^2 / \sigma^2$. For ICSMUD, IAMUD and GAMUD, we will terminate the search at the *Y*th generation where $Y = 1.5 \times K \times M$. In GAMUD and IAMUD, the size of population is 25, the selection probability $P_r = 0.4$, the cross probability $P_{\mathrm{c}} = 0.6$

and the mutation probability $p_m = 0.05$. In ICSMUD, the size of population is 5, clonal scale is 5, $T\% = 50\%$ and $P_m = 1/(K \times M)$. We take all the experiments based on 10000 bits signals. Our performance metric is the average Bit Error Ratio (BER).

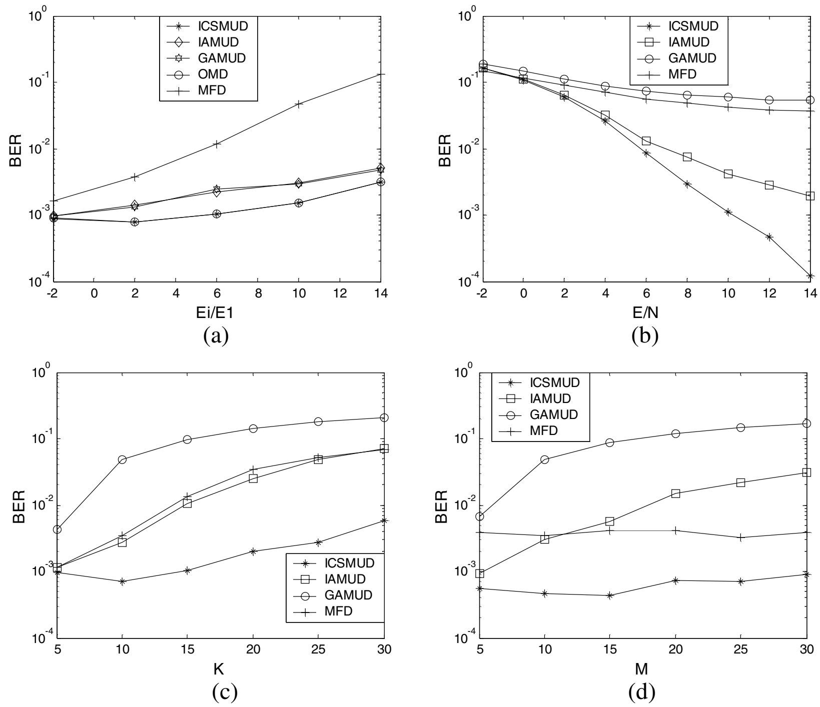

Fig. 2. The simulation results. (a) The performances in 'near-far' resistance; (b) The performances in eliminating noise's disturbing; (c) The performances in accommodating users; (d) The performances in accommodating packet length

A. In order to gain the results of the OMD, we assumed that K=3, M=3, SNR=10 dB. The first user is the desired user while other users are disturbing users and all users have the same power. The ratio of power between disturbing users and desired user denotes the ratio of 'near-far'. The performances in 'near-far' resistance of mentioned receivers are shown in Fig 2(a).
B. It is assumed that K=10, M=10. All users have the same power. Changing the value of SNR from -2 dB to 14 dB. The performances in eliminating noise's disturbing of mentioned receivers are shown in Fig 2(b).
C. It is assumed that M=10, SNR=10 dB, the number of users is changed from 5 to 30, all users have the same power. The performances in accommodating users of mentioned receivers are shown in Fig 2(c).

D. It is assumed that SNR=10 dB, K=10, the packet length is changed from 5 to 30, all users have the same power. The performances in accommodating packet length of mentioned receivers are shown in Fig 2(d).

As we can see from Fig 2(a), the conventional detector produces the receivable estimate only when powers of the users are close to each other. The GAMUD and IAMUD are better than conventional detector. But their performances are unacceptable either when powers of disturbing users are much larger than that of desired user. As we expect, ICSMUD exhibits the best performance and seldom fails to produce the correct estimate for the transmitted symbols, so its performance is almost the same good as the OMD. When the cumulative BER is evaluated versus the value of the SNR of all the users, from Fig 2(b) we can see that ICSMUD receiver achieves acceptable performance, whereas the performances of conventional detector, GAMUD and IAMUD are very poor. When the number of users or the transmitted packet length is relatively large, the advantage of ICSMUD can be seen in Fig 2(c) and Fig 2(d). The simulations suggest that, ICSMUD detector still performs quite well when K and M are relatively large.

5 Conclusions

In this paper, a novel multiuser detection receiver based on Immune Clonal Selection Algorithm was proposed. Monte Carlo simulations show that the new algorithm could significantly reduce the computational complexity and achieve better performance in eliminating MAI and “near-far” resistance over other algorithms such as the conventional detection, SGA and improved GA. It greatly improves the system capacity in acceptable computational cost for practical implementation in CDMA systems.

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