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Multi-User Detection based on PSO-KICA

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Abstract: Multi-user detection (MUD) is used to reduce multiple access interference (MAI) and promote system performance and capacity, which is one of the core technologies for CDMA system. In this paper, some questions of blind MUD based on independent component analysis (ICA) are introduced firstly, and then a kernel independent component analysis (KICA) algorithm which brings in a new hybrid kernel function is proposed. In addition, the particle swarm optimization (PSO) algorithm is studied and it is devoted to the optimizing process of the KICA algorithm. The improved PSO-KICA algorithm can solve the issues that the objective function falls into the local optimum. The experimental results show that the PSO-KICA algorithm has the smaller bit error rate and good convergent speed than the classical ICA algorithm.

Keywords: Multi-user Detection, Hybrid Kernel Function, PSO-KICA Algorithm

1 Introduction

In recent years, the world has gone almost completely wireless. Particularly, Direct sequence code division multiple access (DS-CDMA) is the most popular technologies in wireless communication systems. In this system, all users transmit information simultaneously by a distinct code waveform. But there are many errors at the detector. These errors due to the multiple access interference (MAI), the inter symbol interference (ISI), the asynchronous behavior of users and the Near-far problem.

Multi-user detection (MUD) is considered as one of the core techniques for the 3rd Generation (3G) mobile communication system. MUD can reduce the MAI and solve the Near-far problem and improve the capacity of the system. The blind MUD does not require training sequences and the interference users information. It only needs the prior knowledge of the signature waveform and the timing of the desired user.

Kernel independent component analysis (KICA) is a new algorithm for ICA [1,2] by making use of the kernel trick. It builds contrast functions which are related to mutual information and have desirable mathematical properties as measures of statistical dependence based on canonical correlations in a reproducing kernel Hilbert space (RKHS) [3].

The particle swarm optimization (PSO) algorithm was first introduced by Kennedy and Eberhart [4]. It is one of the optimization techniques and a kind of evolutionary computation technique. As a global optimization method it is more concise and has a higher efficiency [5].

In this paper, the PSO-KICA is applied for DS-CDMA detection and compared with the classical FastICA and KICA algorithms. The proposed PSO-KICA algorithm can enhance the convergence speed. Sequentially it can improve the multi-user detection performance.

This paper is organized as follows: In section 2, two signal models are given. The improved KICA algorithm is introduced in section 3. The proposed PSO-KICA algorithm is discussed in section 4. In section 5, the simulation of detection for different numbers of users, SNR are given respectively, and the results are analyzed. Finally, the conclusions are given in section 6.

2 System Model

2.1 Signal Model of DS-CDMA

In a DS-CDMA system, several users can share the medium simultaneously by using their own signatures. The simplest DS-CDMA system model is synchronous

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CDMA. The form of the received signal is described as follows:

$$r(t) = \sum_{m=1}^{M}\sum_{k=1}^{K} b_{k,m} \sum_{l=1}^{L} a_{k,l,m} s_k(t) + \sigma n(t), \qquad (1)$$

where $b_{k,m}$ is mth symbol of the kth user, M is the number of symbols per user, K is number of users, L is the number of multi-path spread, $a_{k,l,m}$ is attenuation factor of mth symbol of lth path of kth user. $s_k(t)$ is the spread spectrum waveform of kth user. $n(t)$ denotes the additive white Gaussian noise. σ^2 is the noise power spectral density.

If using matrix form to rewrite Eq. (1), the expression will change to the following Eq. (2):

$$X = RAb + N, \qquad (2)$$

where R is the correlation matrix of spectrum waveform, A is the amplitude and phase of the signal, b is the signal of the user. N is the noise.

2.2 ICA Model

The ICA algorithm is a new method to decompose the statistical independent components. The classical ICA model is as follows:

$$X = AS + N, \qquad (3)$$

where S is the source signal vector with dimension m , X is the observed mixed vector with dimension n , A is the unknown mixing matrix and N is the noise.

The problem now becomes to find out a matrix W, such that the output $Y = WX$ is the estimate of the possible scaled and permutated source vectors.

3 KICA Algorithm Based on Hybrid Kernel Function

3.1 Basic Theory of KICA

The ICA is based on a linear model and it works well in linear space but fails in the case of non-linearity [6]. So the Kernel ICA algorithm was proposed in reference [7]. It is not the "kernelization"of an extant ICA algorithm but a new nonlinear promotion of the ICA algorithm. This algorithm first makes the original data from the input space mapping to a feature space F , through a nonlinear mapping function $\varphi(\cdot)$. Then do independent component analysis in the feature space F. This paper uses the KPCA algorithm [8] to realize the pretreatment firstly, and then makes linear ICA calculation in the KPCA whitening space.

Hypothesis x is nonlinear mixture of random vectors in original space. It through mapping function $x \to \varphi(\cdot) \in F$ to map to a feature space F. Assuming the data by nonlinear mapping in feature space is linearly separable, the goal of KICA algorithm is to find a linear solution mixed matrix W in feature space. Map the vector preprocess using KPCA in the feature space. Assuming the sample data is $X = \{x_1, x_2, ..., x_M\}$ and the data meets $\sum_{j=1}^{N} \varphi(x_j) = 0$. In the F space, the covariance operator is $C^{\phi} = (1/M)\sum_{j=1}^{M} \varphi(x_j)\varphi(x_j)^T$ and also called covariance matrix in finite dimensional feature space. Let $Q = [\varphi(x_1), \varphi(x_2), ..., \varphi(x_M)]$, and then $C^{\phi} = (1/M)QQ^T$. Building a $M \times M$ Gram matrix $R = QQ^T$, and it can be determined by a known kernel function. Defining $V = \{y_1, y_2, ..., y_M\}$, $\Lambda = \{\lambda_1, \lambda_2, ..., \lambda_M\}$ are the characteristic vector and characteristic value of matrix R respectively. The orthogonal eigenvector is $\beta_j = Q\gamma_j/\sqrt{\lambda_j}$. Defining the matrix $B = \{\beta_1, \beta_2, ..., \beta_m\} = QV\Lambda^{-1/2}$, then the whitening matrix is $P = \sqrt{M}QV\Lambda^{-1}$.

Therefore whitening signal Z can be calculated by Eq. (4):

$$Z = P^T \varphi(X) = \sqrt{M}\Lambda^{-1}V^T Q^T \varphi(X) = \sqrt{M}\Lambda^{-1}V^T R. \quad (4)$$

This process is looking for a mixed separable matrix in KPCA whitening space and realizing extraction of independent component. It is also called KICA feature vector transform.

3.2 Hybrid Kernel Function

An algorithm based on kernel function is one of the methods in model's analyses field. Replacing the two vectors with the inner product for non-linear transformation is a significant character of it. Taking advantage of kernel function, it is not necessary to take into account the specific forms of non-linear transformation.

Each kind of kernel function has itself advantages and disadvantages. Currently available kernel functions are divided into two categories: Global kernel function and local kernel function. Global kernel function has the global properties. It allow distant from the data points have influence to kernel function value, while local kernel function is only allowed very close to the data points have influence to kernel function value.

The basic kernel functions are shown as Eq. (5) and Eq. (6):

$$K(x_i, x_j) = [a(x_i, x_j) + b]^q. \qquad (5)$$

$$K(x_i, x_j) = exp(-\|x_i - x_j\|/2\sigma^2). \qquad (6)$$

Eq. (5) is poly kernel function [9] and Eq. (6) is RBF kernel function, where q is Polynomial order variable, σ is width parameter of RBF.

In combination with the two kernel functions structures, the hybrid kernel function can be described as Eq. (7) and Eq. (8):

$$K_{p+R}(x,m) = [((x,m)^d) \cdot exp(-\gamma\|x-m\|^2)], \quad (7)$$

$$K_{p+R}(x,m) = [(x,m)^d + exp(-\gamma\|x-m\|^2)], \quad (8)$$

where d is for freedom, γ is nuclear width, they are all adjustable parameters. It was proved a new function which is multiplied or added by two kernel functions is still a kernel function. So $K_{P\times R}$ and K_{P+R} are also kernel functions.

4 MUD Based on PSO-KICA Algorithm

4.1 Optimization Algorithm

The PSO algorithm is an evolutionary algorithm based on bionics which was proposed in the mid-nineties of last century [10]. It tends gradually to adapt to the optimal objective function by updating the speeds and positions of the particles. It is based on a simple concept. Therefore, the computation time is short and requires few memories. It was originally developed for nonlinear optimization problems with continuous variables.

The speed and position update formulas of PSO model are as follows Eq. (9) and Eq. (10):

$$\begin{aligned} v_{k+1} &= wv_i(k) + c_1 rand()(p_i(k) - x_i(k)) \\ &\quad + c_2 rand()(p_g(k) - x_i(k)), \end{aligned} \quad (9)$$

$$x_i(k+1) = x_i(k) + v_i(k+1), \quad (10)$$

where x_i is the ith particle, p_i indicates the best position that the particles have experienced. p_g means the best position that all particles have experienced. w is the inertia weight. c_1 and c_2 are the acceleration constants with the general value of 2. k is the number of particle evolutionary steps.

Using Eq. (9), the new velocity of the particles, which gradually gets close to and , is calculated.

Using Eq. (10), the position can be modified.

4.2 Proposed PSO-KICA Algorithm

The important part of the PSO algorithm is to look for the fitness function. In the ICA algorithm, many functions can be used for the fitness functions, such as the mutual information minimization, the information maximization, maximum likelihood estimation method and the negentropy.

In this paper, the negentropy is used for the fitness function. The expression of negentropy approximate is as follows Eq. (11):

$$N_g(y) \propto [E\{G(y)\} - E\{G(Y_{gauss})\}]^2. \quad (11)$$

In Eq. (11), $G(\cdot)$ has three function forms: $G_1(y) = (1/a)\log\cosh(ay)$, $G_2(y) = -exp((-ay^2)/2)$ and $G_3(y) = ay^4$, where a is the constant and $1 \leqslant a \leqslant 2$.

In this paper, the fitness function form is as Eq. (12):

$$fitness(y) = E\{-exp(-y^2/2)\}. \quad (12)$$

The steps of PSO-KICA algorithm can be summarized as follows:

1. Center the observed data X to make its mean zero, $X = X - E(X)$, X is the observed mixed vector.
2. Using KPCA to do pretreatment for receiving signals, kernel function is Eq. (7) or Eq. (8).
3. Initialize the particle numbers, including $W_i = [w_{i1}, w_{i2}, ..., w_{iD}]$ and $V_i = [v_{i1}, v_{i2}, ..., v_{iD}]$.
4. Using Eq. (12) to calculate the fitness value of all particles, $y_i = W_i Z = [y_{i1}, y_{i2}, ..., y_{iD}]$.
5. Compare the personal best fitness value and set p_{id} to the better one. Set the global best p_{gd} to the position of the particle with the best within the swarm.
6. Update the speed and the position of each particle according to Eq. (9) and Eq. (10).
7. Do the orthogonalization and normalization according to the following formulas: $W_p = W_p - \sum_{k=1}^{p-1}(W_p W_k)W_k$, $W_p = W_p/\|W_p\|$.
8. Record every global optimum, If maximum iterations or minimum error is attained, stop the evolutions, otherwise go back to the step 4.

5 Simulation Results and Discussion

For simulation, DS-CDMA with BPSK modulation is considered, and spreading codes with Gold code for length 31 is adopted.

The classical FastICA algorithm, classical KICA and PSO-KICA algorithm combined to classical detector and BER simulations are done with various stages of number of users (4, 6, 8, 10, 12, 14). Each user has 300 symbols. At the same time, simulations are done with various values of SNR (0dB, 4dB, 8dB, 12dB, 16dB, 20dB). The curves of the simulation result are showed in Figure 1 and Figure 2 respectively.

Figure 1 shows the simulation results of BER vs. number of users of classical FastICA algorithm, classical KICA algorithm and PSO-KICA algorithm in detection of DS-CDMA when SNR=10dB. It can be observed that PSO-KICA algorithm has lower BER compared to the classical FastICA and classical KICA algorithms.

Figure 2 shows the simulation results of SNR vs. BER curves as four users. This curve shows that with the SNR increasing, PSO-KICA algorithm is performing well

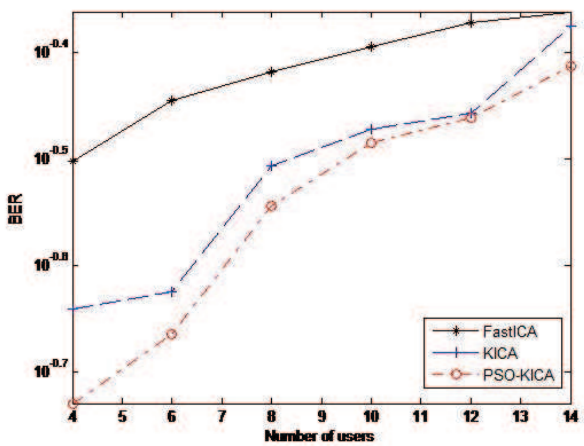

Fig. 1: BER curves with the number of users

compared with the classical FastICA algorithm. In the low SNR bit-error-rate of these three methods have no significant differences, but as the SNR goes on, the PSO-KICA algorithm performs well.

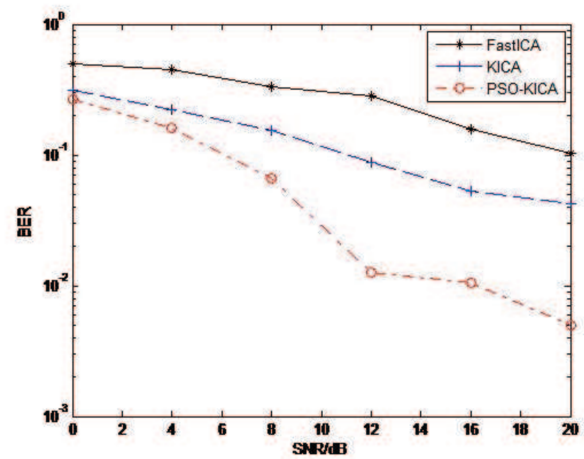

Fig. 2: BER curves with with different SNR

For classical FastICA algorithm, classical KICA and proposed PSO-KICA algorithm, the comparison results of running time are showed in Table 1.

The simulation results indicate that PSO-KICA algorithm has faster convergence than the classical KICA algorithm and FastICA algorithm.

Table 1: Comparison of Running Time

Classes	FastICA	KICA	PSO-KICA
1	0.1147s	0.0336s	0.0193s
2	0.0332s	0.0254s	0.0202s
3	0.0295s	0.0278s	0.0270s
4	0.0512s	0.0385s	0.0345s
5	0.0418s	0.0388s	0.0358s
6	0.1255s	0.0833s	0.0788s
7	0.1403s	0.1125s	0.1122s
8	0.0278s	0.0205s	0.0122s
9	0.0336s	0.0204s	0.0204s
10	0.0261s	0.0155s	0.0122s

6 Conclusions

In this paper, we combine KICA with particle swarm optimization (PSO) successfully in DS-CDMA system firstly. Then we calculate the performance of the classical FastICA algorithm, classical KICA algorithm and PSO-KICA algorithm based on the detection of DS-CDMA. The PSO-KICA algorithm gives better performance in different SNR and different users. In particular, the speed of constringency is better than two other methods.

In a word, PSO-KICA algorithm performs well for detection of DS-CDMA signals.

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