A New Quantum Clone Genetic Algorithm Based Multi-user Detection for CDMA System

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Abstract

Quantum intelligent computation has been widely drawing the attention of many researchers. Quantum clone genetic algorithm, which is based on quantum genetic algorithm and clone algorithm, is a new quantum intelligent algorithm with good performance. In order to overcome the shortcomings such as low efficiency, poor population diversity, slow convergence speed, easy to trap in local minimums, and blindness in global optimal searching direction etc, a new quantum clone genetic algorithm (NQCGA) is proposed in this paper. Results of optimization experiment about the function extreme demonstrate that NQCGA have many merits: (1) Adopting nicking probability division initialization strategy, the population diversity is enhanced; (2) Introducing quantum whole interference crossover, the information is spread in the whole population, so it helps to avoid trapping in local minimums, and accelerates convergence speed; (3) Making use of adaptation strategy in quantum rotate gate updating, the searching speed for optimal solution is accelerated; (4) Adopting the superior individual whole crossover quantum catastrophe strategy, it helps the algorithm to avoid premature and evolution stagnation, and helps the population to search the objective solution in different directions. Finally, a new multi-user detection based on NQCGA for CDMA system is put forward in this paper. Simulation results prove that the given multi-user detection has lower bit error, rapider converge speed, better resisting MAI ability, better Near-far Resistance ability and larger system capacity than other multi-user detections based on quantum clone genetic algorithm and classical genetic algorithms obviously.

Keywords: Multi-User Detector, Quantum Clone Genetic Algorithm, Quantum Whole Crossover

1. Introduction

CDMA system is an Interference limited system, MAI impacts serious on the system. Multi-user detection is a key technology to resist MAI. The initial work on multi-user detection is the optimal multi-user detector proposed by Verdu [1], which has a potential improvement in capacity and near-far resistance. The optimal multi-user detection for CDMA systems can be characterized as an NP-hard optimization problem. However, computational complexity of optimal maximum likelihood multi-user detection (OMD) grows exponentially with the number of users and the length of the bit sequence; therefore, it is unfeasible for implementation. The sub-optimal multi-user detection reduces computational complexity, but the performance of sub-optimal multi-user detection is not optimal. Multi-user detection based on intelligence optimal algorithm can get closer to the performance of optimal maximum likelihood multi-user detection, and can reduce the computational complexity efficiently. So multi-user detection based on intelligence optimization algorithm has arouses intense interests recently. There are many intelligence computation algorithms have been deployed to multi-user detection, such as Genetic Algorithm (GA), Particle Swarm Optimization algorithm (PSO), Ant Colony Optimization algorithm (ACO), Immune Algorithm (IA), Quantum Evolution algorithm (QE) and Artificial Neural Network (ANN) etc. Quantum intelligent computing comprises the high efficiency of quantum parallel calculation and the advantages of traditional intelligent algorithms, so it has better performance than traditional intelligent algorithms. Many quantum intelligent computing algorithms have been put forward to solve the complicated problems as NP-hard problem in the applications. Quantum genetic algorithm is a probability optimization algorithm which is fused by quantum calculation and genetic algorithm. This algorithm has many advantages: good population diversity, whole optimal searching and parallel searching. However, there are many drawbacks: low
convergence speed; easy to trap in local minimums and high calculation complexity. Therefore, in order to realize the balance between global search and local search, enhance the performance, expand the application scope and reduce calculate complexity, many improved quantum genetic algorithms have been proposed.

Numerous quantum intelligent computing algorithms have been used to develop the sub-optimal multi-user detection in the last few years. Many new detections with near-optimal performance and lower complexity, such as Genetic algorithm based multi-user detection (GA-MUD)\cite{15}, Quantum genetic algorithm based multi-user detection\cite{16} (QGA-MUD), Quantum clone genetic algorithm based multi-user detection (QCGA-MUD)\cite{17} and so on, have been proposed. However, the complexity of the detections is still too high to be implemented. Therefore, the improved multi-user detection based on new quantum intelligent computing algorithm with better performance and lower calculation complexity should be investigated.

As a novel genetic algorithm, Quantum clone genetic algorithm (QCGA)\cite{3} builds on the quantum encode of quantum calculation and the idea of traditional genetic algorithm, and makes use of the immune operator of immune clone strategy, This algorithm utilizes the concept of quantum theory, which is based on quantum vectors, representing chromosome by quit coding, and updating chromosome by quantum rotation gate and quantum not gate. QCGA uses quantum bit encode as probabilistic representation, which is defined as the smallest unit of information. Quantum individual carries the information of multiple individuals, preceding evolutional operation for quantum individuals, so the overhead of the program is decreased and QCGA can acquire high efficiency. Furthermore, with quantum bit tends to 1 or 0, quantum bit then converges to single state, so QCGA could achieve better convergence while the diversity vanishes.

In order to avoid degenerating and premature, QCGA makes use of useful information to guide evolution, introduces immune clone strategy and then extends the proportion of superior individuals. Immune clone strategy contains clone, clone mutation and clone selection. Because QCGA combines evolution search and random search, global search and local search, which performs clone, mutation, selection on candidate solutions, so it can obtain the global optimal solution quickly. Furthermore, QCGA uses quantum rotate gate to precede quantum mutation, which makes it converge to superior individual quickly.

However, the performance promotion of the algorithm is achieved at the cost of expanding the searching scope, sacrificing the computational complexity, and increasing calculating time. Furthermore, the mutation strategy of quantum rotate gate is designed according to quantum superposition and the quantum transition, but the global optimal searching direction of quantum gate is blindness and randomness. In order to overcome the defects and improve the performance, a new quantum clone genetic algorithm (NQCGA) is proposed in this paper. NQCGA adopts nicking probability division initialization strategy\cite{6} to initialize the quantum population, uses quantum whole interference crossover and superior individual whole crossover, makes use of adaptation quantum rotate gate update strategy and exploits quantum catastrophe strategy. Simulation results demonstrate the feasibility and effectiveness of NQCGA based multi-user detection.

2. A New Quantum Clone Genetic Algorithm (NQCGA)

2.1. Operation strategy

2.1.1. Quantum whole interference crossover strategy

Quantum whole interference crossover is developed by quantum superposition state coherence. The number of selected individuals is random in the crossover, whereas all selected individuals perform crossover. The newly formed individual carries the information of multiple parent individuals, so that species information is fully fused to overcome premature and evolution stagnation. When quantum whole interference crossover is carried out, some individuals are selected from the population according to crossover rate $P_c$ and will be put in a crossover pool, and then a crossover array is formed, the new individual is generated according to diagonal permutation renewedly.
2.1.2. Quantum rotate gate adaptive updating strategy

The improved quantum rotate gate updating strategy using in NQCGA is defined as follows:

\[ \theta_i = \text{sign}(\langle x'_i - b'_j \rangle \cdot (f(x'_i) - f(b'_j)) \cdot \alpha'_i \cdot \beta'_i) \cdot \Delta \theta_i \]  

(1)

Where \( \theta_i \) denotes rotate gate; \( \text{sign} \) is symbol function; \( x'_i \) and \( b'_j \) are both the \( x'_j \) solution and the \( i \) th of the present optimal solution \( b'_j \) respectively; \( f(x'_i) \) and \( f(b'_j) \) are fitness value respectively; \( \alpha'_i \cdot \beta'_i \) is the \( i \)th generation pairs of the \( j \)th chromosome in the population; \( \Delta \theta_i \) is the angle of quantum bit rotate to control consequence speed, and it will be adjusted as generation evolves, the value can be calculated as follows:

\[ \Delta \theta = 0.05 \pi - 0.05 \pi / (\max t + 1) \]  

(2)

Here, \( \max t \) is evolution termination times, \( t \) is the present evolution times, in initial phase of the algorithm, search speed is becoming faster as \( \Delta \theta \) increases, while in later phase of the algorithm, is becoming smaller; precise search is implementing while \( \Delta \theta \) is decreased.

2.1.3. Superior individual whole interference crossover quantum catastrophe strategy

In superior individual whole interference crossover quantum catastrophe strategy, new quantum chromosomes are generated renewedly by whole interference crossover while the optimal individual is reserved. Operation is defined as follows: probability selecting one or several larger fitness individuals in every population, implementing the quantum whole interference crossover, and then allocating the new generated individual to population in original proportion, which will inject vigor to population while the new individuals participating in population quantum calculation.

The operation strategy allocates the new individual to every population, which is generated by the individuals with the larger fitness value after completing whole interference crossover. This helps to exchange information within superior individuals, and guide the evolution direction of the population and make the population search the optimal solution in different directions. All in all, it enhances the local optimal searching ability, avoids trapping in local minimums, weakens the influence of inferior individuals and accelerates efficiency. So this strategy acquires the balance of avoiding evolution stagnation, maintaining population diversity and computation efficiency.

2.2. NQCGA

2.2.1. Initialization phase

Step1: Let evolution generation \( t = 0 \), quantum catastrophe counter \( k = 0 \), population size \( N \), population \( Q(t) = \{q_1, q_2, \ldots, q_N\} \) by nicking probability division initialization strategy.

Step2: Evaluate the initialization quantum individuals, obtain a group of states \( R(t) \).

Step3: Calculate the fitness value of quantum individual in population \( Q(t) \).

Step 4: Select N individuals which have larger fitness value, record their states and fitness values, save to \( B(t) \) furthermore, record the status and fitness value of the individual with larger fitness value to \( B(t) \), save to \( b(t) \).

2.2.2. Iteration evolution phase

Iteration evolution phase starts when the termination condition could not be satisfied.

Step5: Update the population by quantum whole interference crossover, obtain the new generation \( Q(t) \)
Step 6: Evaluate the population \( Q_t(t) \), obtain a group of status \( R(t) \).

Step 7: If the optimal individual fitness value in \( Q_t(t) \) and \( B(t-1) \) is better than \( b(t-1) \), then replace \( b(t-1) \) and get \( b(t) \).

Step 8: Select \( m \) larger fitness individuals of \( Q_t(t) \) and \( B(t-1) \) According to the given clone size, do clone, and form the temporary clone population \( C \).

Step 9: Do quantum mutation strategy by adaptation quantum rotate gate updating strategy in the sub-population of population \( C \), and obtain mutation population \( c_1 \).

Step 10: Do immune selection in \( c_1 \), form the new population \( c_2 \), and calculate the fitness value. Select the larger individuals in \( c_2 \) to replace the weaker individuals in \( B(t-1) \), then obtain \( B(t) \). If the optimal individual of \( B(t) \) is better than \( b(t) \), replace and save it, otherwise invariable.

Step 11: If evolution is continued after \( k \) generations, go to Step 5, let \( k = k+1 \); otherwise, let \( k = 0 \), then implement superior individual whole interference crossover quantum catastrophe strategy, generate new population \( Q(t+1) \), and calculate its fitness value; Select the larger individuals in \( Q(t) \) to replace the weaker individuals in \( B(t-1) \) then obtain \( B(t) \). If the optimal individual of \( B(t) \) is better than \( b(t) \), replace and save it, otherwise invariable.

Step 12: If the termination condition is satisfied, output \( b(t) \); if not, let \( t = t+1 \), go to Step 5 and re-operate.

2.2.3. Performance of NQCGA

In order to test the optimization ability and the convergence speed, NQCGA is compared against three state-of-the-art algorithms. Three other algorithms are listed below: Quantum clone genetic algorithm (QCGA)[3]; Quantum genetic algorithm[15, Genetic algorithm[15].

The five typical test functions are as follows: Simple quadratic function; De Jong function; Schaffer function; Six peak value humpback function and Griewank function.

<table>
<thead>
<tr>
<th>Function</th>
<th>NQCGA</th>
<th>QCGA</th>
<th>QGA</th>
<th>GA</th>
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</thead>
<tbody>
<tr>
<td></td>
<td>a</td>
<td>w</td>
<td>t</td>
<td>a</td>
</tr>
<tr>
<td>( f_1 )</td>
<td>0</td>
<td>411,3</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>( f_2 )</td>
<td>0</td>
<td>6132</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>( f_3 )</td>
<td>10.3 \times 10^6</td>
<td>6015</td>
<td>3</td>
<td>2.14 \times 10^4</td>
</tr>
<tr>
<td>( f_4 )</td>
<td>1 \times 10^5</td>
<td>5986</td>
<td>5</td>
<td>0.911213</td>
</tr>
<tr>
<td>( f_5 )</td>
<td>2.57 \times 10^4</td>
<td>25708</td>
<td>6</td>
<td>5.36 \times 10^4</td>
</tr>
</tbody>
</table>

In simulation experiments, parameter sets is as follows: population size 100, maximum termination generation 1500, calculation precision \( 10^{-5} \), mutation 0.05, crossover probability 0.95, QCGA mutation population 10, QCGA mutation population 10, Four kinds of algorithms run 50 times independently to searching the optimal solution of the above-mentioned functions. All experiments are conducted on a Lenovo computer, which is equipped with an Intel Core2 (2.7 GHz) CPU and 2 GB internal memory. The proposed algorithm has been coded with MATLAB7.1 under Windows XP. Table 1 is the statistical results of 50 times independent experiments.
As shown in Table 1, NQCGA can converge to optimal solution with high precision in less generation than other three algorithms( QCGA,QGA and GA), its calculation precision and convergence speed both have superiority. Furthermore, NQCGA has less times to fall into local minimums. NCQGA yields superior results as compared to other three algorithms. It can be concluded to five points: Good global search ability, Rapid convergence speed, Good local search ability, . Good stability, High calculation precision.

3. Applying NQCGA on Multi-user Detection

Suppose that there are \( k \) users and \( N \) carriers in DS-CDMA system, signal \( r(t) \) received by Basic Station is defined as

\[
r(t) = \sum_{i=1}^{P} \sum_{i=1}^{K} A_i b_i^{(i)} S_i(t - iT_k - \tau_i) + n(t)
\]

Where, \( P \) is transferred bit size; \( T_k \) is bit element interval of emission signals; \( A_k \) is signal amplitude of the kth user; \( b_i^{(i)} \in \{-1,1\} \) is the ith transferred bit of the kth user; \( \tau_i \in [0,T_k) \) is the time delay of the \( k \)th user; \( n(t) \) is the Gaussian white noise with the power spectral density \( N_0/2 \). The spread signature \( S_i(t) \) of the kth user can expressed as:

\[
S_i(t) = \sum_{l=1}^{L-1} a_i^{(l)} P\tau_i(t - lT_k)
\]

Where, \( P \) is the square wave with duration \( T_i \); \( T_i \) is the duration of spread spectrum signal chip; \( a_i^{(l)} \) is the lth bit of the spreading sequence of the \( k \)th user. The received signals are performed coherent processing through \( K \) matcher filter respectively, and the corresponding observation data

\[
y^{(i)} = \left[ y_1^{(i)}, y_2^{(i)}, \ldots, y_k^{(i)} \right] \text{ of the } k \text{th user will be obtained which is defined as}
\]

\[
y_k^{(i)} = \int_{T_i + \tau_i}^{T_i + \tau_i + T_k} r(t) S_i(t - iT_k - \tau_i) dt
\]

Usually, the matched filter’s output vectors of the \( k \) users is:

\[
y = RAb + n
\]

Where, A is a \( PK \times PK \) dimension diagonal matrix which is formed by the signal amplitude; \( b \) is a \( PK \) dimension signal column vector and \( n \) is a noise column vector with \( PK \) dimension ; \( R \) is a \( PK \times PK \) dimension Toeplitz array which is composed by \( R(v) \), \( v \in \{-1,0,1\} \), the elements of \( R(v) \) can be expressed as:

\[
\rho_{v}^{(k)}(v) = \int_{T_i + \tau_i}^{T_i + \tau_i + T_k} S_i(t - \tau_i) S_i(t + vT_k + \tau_i) dt
\]

Where, \( 1 \leq k \leq K \), \( \rho_{v}^{(k)}(v) = 1 \). In the synchronization condition, for a user \( i \), \( P = 1 \), \( R = R(0) \), \( \tau_i = 0 \). NQCGA-MUD(new quantum clone genetic algorithm based multi-user detection) is based on NQCGA ,and consists of initialization evolution stage and iteration evolution stage, its algorithm model is described as follows:

\[
\begin{align*}
\text{Max} & : C(b) = 2b^T Ay - b^T Hb \\
\text{subject to} & : b_k \in \{-1,1\} \text{ for all } (k = 1,2,\ldots,K)
\end{align*}
\]

Where, \( C(b) \) is the fitness function, \( H = ARA \).

In order to acquire better performance, the non-negative fitness function is constructed by the selected positive number \( Z \) as follows.

\[
M(b) = C(b) + Z = (2b^T Ay - b^T Hb) + Z
\]

4. Simulation Results
In order to test the performance, NQCGA-MUD is compared against four state-of-the-art detectors, four other detectors are listed below: QC-GA-MUD, QGA-MUD, GA-MUD, OMD [2].

For comparison, the population of all QC-GA, QGA and GA are supposed to be equal. Initial input of QC-GA, QGA and GA is identical. Set the quantum catastrophe generation condition 100.

4.1. Bit error (BER)

In order to evaluate the performance of NQCGA-MUD, a ten users DS-CDMA modulated by QPSK in AWGN is considered, and the 1st user is the desired user, its SNR is 4 dB, the other nine users are interfered users (suppose the ratio the signal energy of the interfered users and desired user 1th is E_i / E_1), the spread spectrum code is the Gold code of 31 bits, the maximum normalized cross-correlation is 9/31, the scale of population is 50, the maximum evolution generation is 300. The different interference can be obtained while the user changing his condition.

It can be seen from Figure 1, BER is reducing with SNR enhancing in four detectors. In low SNR condition, all four detectors’ BER is very close, but in high SNR, BER of NQCGA-MUD is obviously lower than GA-MUD’s, QGA-MUD’s and QC-GA-Mud’s. We can draw a conclusion that NQCGA-MUD enhances searching ability and searching precision, and significantly reduces BER, its solution gets more close to the optimal solution.

<table>
<thead>
<tr>
<th>BER</th>
<th>OMD</th>
<th>NQCGA-MUD</th>
<th>QCGA-MUD</th>
<th>QGA-MUD</th>
<th>GA-MUD</th>
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<tr>
<td>SNR (dB)</td>
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<td>10</td>
<td>0.01</td>
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Figure 1 BER versus SNR

4.2. Convergence speed

In Figure 2 and Figure 3, we investigate the convergence speed of NQCGA-MUD under MAI effect and Near-far effect. We consider a ten users DS-CDMA modulated by QPSK in AWGN. Furthermore, the 1st user is the desired user, the other nine users are interfered users (suppose the ratio the signal energy of the interfered users and desired user 1th is E_i / E_1), the spread spectrum code is the Gold code of 31 bits, the maximum normalized cross-correlation is 9/31, the scale of population is 50, the maximum evolution generation is 300. The different interference can be obtained while the user changing his condition.

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Figure 2 Convergence Speed under MAI

Figure 3 Convergence Speed under Near-far

Figure 4 MAI Resistance Ability
The convergence speed of five multi-user detectors with \( R_{SN} = 8 \) under MAI is showed in Figure 2. \( E_i \) of all 10 users are equal. It can be seen that BER of five multi-user detector is reducing gradually with iteration times increasing. Moreover, BER of OMD is almost constant, and BER of other detections is approaching constant till it tends to complete convergence when the iteration times increases to a definite value. So, the convergence speed of NQCGA-MUD and OMD is obviously faster than QCGA-MUD’s, QGA-MUD’s and GA-MUD’s. We can draw a conclusion that NQCGA-MUD has stronger global and local searching ability than QCGA-MUD, it can search the optimal solution more quickly.

The convergence speed of five multi-user detectors with \( R_{SN} = 8 \) under Near-far is showed in Figure 3. \( E_i \) is invariable, and SNR is 4 dB. It can be seen that BER of five multi-user detector is reducing with iteration times increasing. Furthermore, BER is almost constant till it tends to complete convergence when the iteration times increases to a definite value. The convergence speed of NQCGA-MUD and OMD is faster than QCGA-MUD’s, QGA-MUD’s and GA-MUD’s. So NQCGA-MUD has stronger global and local searching ability than QCGA-MUD, which means that NQCGA-MUD can search the optimal solution more quickly.

### 4.3. MAI resistance ability

To examine the MAI resistance ability, we select a ten users DS-CDMA modulated by QPSK in AWGN. In the DS-CDMA system, the \( i \)th user is the desired user, its SNR is 4 dB, the other nine users are interfered users (suppose the ratio the signal energy of the interfered users and desired user \( i \)th is \( E_i / E_1 \)), the spread spectrum code is the Gold code of 31 bits, the maximum normalized cross-correlation is \( 9 / 31 \), the scale of population is 50, the maximum evolution generation is 300. The different interference can be obtained while the user changing his condition.

The relation between BER and MAI resisting ability is showed in Figure 4. When SNR of interfered users increases, MAI resistance ability of NQCGA-MUD is obviously superior to GA-MUD’s, QGA-MUD’s and QCGA-MUD’s, and more close to OMD’s. From above we can reach the conclusion that NQCGA-MUD has better MAI resistance ability.

### 4.4. Near-far resistance ability

To compare the Near-far resistance ability, a ten users DS-CDMA modulated by QPSK in AWGN is considered. In this case, the \( i \)th user is the desired user, its SNR is 4 dB, the other nine users are interfered users (suppose the ratio the signal energy of the interfered users and desired user \( i \)th is \( E_i / E_1 \)), the spread spectrum code is the Gold code of 31 bits, the maximum normalized cross-correlation is \( 9 / 31 \), the scale of population is 50, the maximum evolution generation is 300. The different interference can be obtained while the user changing his condition.

Curve graph of BER and near-far resistance ability is showed in Figure 5. With the interference users’ power increasing, near-far resistance ability of NQCGA-MUD is superior to GA-MUD’s, QGA-
MUD’s and QCGA-MUD’s, and it closes to OMD’s. So NQCGA-MUD has better near-far resistance ability than GA-MUD, QGA-MUD and QCGA-MUD.

4.5. System capacity

To evaluate the system capacity, a $n$ users DS-CDMA modulated by QPSK in AWGN is considered. In this system, the 1th user is the desired user, its SNR is 4 dB, the other users are interfered users (suppose the ratio the signal energy of the interfered users and desired user 1th is $E_i / E_1$, $E_i / E_1$ is 8dB), the spread spectrum code is the Gold code of 31 bits, the maximum normalized cross-correlation is $9 / 31$, the scale of population is 50, the maximum evolution generation is 300. The different interference can be obtained while the number of users increasing.

Curve graph of BER and number of users is showed in Figure 6. With the number of users increasing, BER of NQCGA-MUD is smaller than GA-MUD’s, QGA-MUD’s and QCGA-MUD’s. Furthermore, with the number of users increasing, BER of NQCGA-MUD closes to OMD’s, so NQCGA-MUD has larger system capacity.

5. Conclusion

Quantum clone genetic algorithm has many shortcomings such as: low efficiency, poor population diversity, slow convergence speed, easy to trap into the local minimum and blind global optimal searching direction, many improvements aimed at the population initialization of initial evolution phase, population information transferring and rotate gate updating of middle evolution phase, premature and evolution stagnation of later evolution phase is putted forward in this paper, and a novel quantum clone genetic algorithm based multi-user detection is proposed, simulation results show that it has low BER, rapid convergence speed, good MAI resistance ability, excellent near-far resistance ability and larger system capacity. However, BER, MAI resistance ability and near-far resistance ability of the proposed multi-user detection is superior to GA-MUD’s QCGA-MUD’s and QGA-MUD’s, but worse than OMD’s. So multi-user detection based on quantum intelligence calculation still need further research.

6. References