Cognitive radio resource allocation based on coupled chaotic genetic algorithm*

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A coupled chaotic genetic algorithm for cognitive radio resource allocation which is based on genetic algorithm and coupled Logistic map is proposed. A fitness function for cognitive radio resource allocation is provided. Simulations are conducted for cognitive radio resource allocation by using the coupled chaotic genetic algorithm, simple genetic algorithm and dynamic allocation algorithm respectively. The simulation results show that, compared with simple genetic and dynamic allocation algorithm, coupled chaotic genetic algorithm reduces the total transmission power and bit error rate in cognitive radio system, and has faster convergence speed.

Keywords: cognitive radio, chaotic genetic algorithm, resource allocation, coupled Logistic map

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1. Introduction

Cognitive radio is an intelligent communication system which can perceive the external communication environment. It can study and adapt the changes of the wireless communication environment in real time, and achieve adaptive resource allocation and the dynamic spectrum sharing by changing the transmit power, carrier frequency and modulation mode. With the rapid development of wireless communication technology, spectrum resources has become more and more precious, more and more users access to the wireless networks through the non-authorised frequency bands. In order to improve spectral efficiency and reduce power consumption of the system, new allocation algorithms for cognitive radio resource allocation are need to be investigated.

Currently, most of the cognitive radio resource management algorithms are mainly focused on adaptive subcarrier-bit allocation and power control, which proposed for multiuser systems in Refs. [1]–[5]. An adaptive dynamic subcarrier and bit allocation algorithm for cognitive radio system has been presented in Ref. [6]. The transmission power reduction is expected by using the algorithm for multiuser modulation and subcarrier allocation, but the algorithm which has slow convergence rate can not meet the requirements of real-time. The allocation algorithm in Ref. [7] which uses the genetic algorithm gives nearly optimal performance, but does not take into account the conditions under which primary user occupies channel. The resource allocation algorithm in Ref. [8] assigns each user a fixed communication flow, and dynamically allocates channel, but it does not consider the user's communication load demand. A suboptimal adaptive modulation algorithm which is close to the lower bound is given in Ref. [9], since its computational complexity is too high, it is hard to use in practical system.

This study proposes a coupled chaotic genetic algorithm for cognitive radio resource allocation, which is based on genetic algorithm and coupled Logistic map. The proposed algorithm takes full advantages of chaotic characteristics of coupled Logistic map.[10−12] Coupled Logistic chaotic map is used in the whole process of the proposed algorithm, such as population generation, crossover and mutation. The algorithm runs crossover and mutation at the same time, which will save the run time and reduce the computational complexity. Meanwhile, parameters of the proposed algorithm are also dynamically adjusted by using adaptive technology. The search space is the whole solution space, which reduces the similarity of individuals in the same population. Simulation results show that, compared with dynamic allocation algo-

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rithm and simple genetic algorithm, coupled chaotic genetic algorithm reduces the transmit power and bit error rate. Meanwhile, the computational complexity is decreased.

2. Coupled chaotic genetic algorithm

Chaotic refers to the phenomenon with uncertain and aperiodic behaviour which happens in a deterministic system. Chaotic theory is widely used in long-term weather forecasting, confidential communication, neural network, economics, and so on.[13−17] The genetic algorithm which combines with chaotic operator has a lot of advantages, such as fast convergence speed, low similarity among individuals, large search space, global convergence, and so on. However, most of the combination of genetic algorithm with chaotic operator is used for generating the initial population of genetic algorithm and doing the chaotic disturbances of population. Furthermore, most of them use the one-dimensional Logistic map,[18−23] which did not take full advantages of the global and the random character of chaotic systems.

We define the coupled chaotic genetic algorithm as the combination of coupled Logistic chaotic map[24−27] and the genetic algorithm. Traditional genetic algorithm has some shortcomings, such as the small search space, fixed parameters of algorithm, and it can easily converge to a local optimal solution. In coupled chaotic genetic algorithm initial population is generated through coupled chaotic mapping, crossover and mutation are done at the same time by the chaotic sequence, which can effectively improve the global search ability, prevent premature convergence, enhance the computational efficiency and shorten the computing time.

The key steps of coupled chaotic genetic algorithm are: establishing the coupled Logistic chaotic sequences, population coding, using coupled chaotic sequence to initialise population, adaptive adjusting the algorithm parameters, running crossover and mutation using chaotic sequences, etc.

2.1. Establishment of the coupled Logistic chaotic sequence

Logistic mapping is first proposed in an overview written by May. Expression of one-dimensional Logistic map is as follows.

$$x_{n+1} = \mu \cdot x_n \cdot (1 - x_n). \tag{1}$$

This equation is widely used in the generation of one-dimensional chaotic sequence,[28−33] as well as ecology research. Logistic map has several characteristics, such as sensitive to the initial value, aperiodic, non-convergence and so on.

We extend the Logistic map to coupled Logistic map. The coupled Logistic map equation is as follows:

$$\begin{aligned} x_{n+1} &= 4\lambda_1 x_n(1 - x_n) + \gamma y_n, \\ y_{n+1} &= 4\lambda_2 y_n(1 - y_n) + \gamma x_n, \end{aligned} \tag{2}$$

where $\lambda_1, \lambda_2, \gamma$ are the control parameters. When $\gamma = 0.1$, $\lambda_1 = 0.89, \lambda_2 = 0.89$ the system is in a chaotic state. In order to generate uniform random points, map is amended as formula (3) after each iteration.

$$\begin{aligned} x &= \mathrm{mod}(\nu_1 \cdot \arccos x, 1), \\ y &= \mathrm{mod}(\nu_2 \cdot \arccos y, 1), \end{aligned} \tag{3}$$

where the operator mod(, 1) represents taking the fractional part of a number. When the system takes the initial point (0.10,0.11), $\nu_1 = 23, \nu_2 = 23$, the distribution of the chaotic sequence points is highly random and uniform. A generated coupled Logistic chaotic sequence is as follows after n iteration

$$L = \{(x_1, y_1), (x_2, y_2), \ldots, (x_i, y_i), \ldots, (x_n, y_n)\}. \tag{4}$$

2.2. Population coding

In order to facilitate crossover and mutation, the chromosome encoding takes the form of matrix and is shown in formula 5

$$\boldsymbol{D} = \begin{bmatrix} d_{1,1} & d_{1,2} & \ldots & d_{1,N-1} & d_{1,N} \\ d_{2,1} & d_{2,2} & \ldots & d_{2,N-1} & d_{2,N} \\ \vdots & & d_{k,n} & & \vdots \\ d_{K-1,1} & d_{K-1,2} & \ldots & d_{K-1,N-1} & d_{K-1,N} \\ d_{K,1} & d_{K,2} & \ldots & d_{K,N-1} & d_{K,N} \end{bmatrix}, \tag{5}$$

where $\boldsymbol{D}$ is the individual matrix, $d_{k,n}$ represents the modulation method of the kth user in the nth subcarrier, N is the quantity of subcarrier in cognitive radio system, K is the number of users. Each element's value in matrix $\boldsymbol{D}$ ranges from 0 to m, and m is the maximum modulation mode allowed by the system.

In matrix $\boldsymbol{D}$ each column has only one non-zero element which means that each subcarrier can only be assigned to one user.

The aim of this algorithm is to find the optimal subcarrier allocation users and modulation type according to the constraints and the changes of wireless environment.

2.3. Initialise population using chaotic sequence

In order to generate the initial population randomly and ensure that the initial population is uniformly distributed in the solution space, we use formula (2) and formula (3) to generate the coupled Logistic map chaotic sequence, and then use this chaotic sequence to generate initial population. In each individual matrix of the initial population, the location of the non-zero element at column n is determined by y_n in the chaotic sequence

$$r = \lceil K \cdot y_n \rceil , \tag{6}$$

where y_n is the value of the element in the chaotic sequence. Equation (6) is a ceiling function which maps a real number to the smallest following integer. The value of non-zero elements $d_{k,n}$ is determined by x_n which corresponds with y_n as shown in formula (7):

$$\begin{aligned} d_{k,n} &= \lceil m \cdot x_n \rceil \quad (k = r), \\ d_{k,n} &= 0 \quad (k \neq r). \end{aligned} \tag{7}$$

An initial population $\{D_1, \ldots, D_n\}$ which is composed by n individuals is gotten by assigning the values of the chaotic sequences to the corresponding individuals. In this way the individuals in the initial population is uniformly and randomly distributed in the whole solution space.

2.4. Adaptive adjustment of algorithm parameters

In traditional genetic algorithm crossover probability P_{cross} and mutation probability P_{mutation} are constants, so appropriate P_{cross} and P_{mutation} are need to be pre-selected before running the algorithm. The larger P_{cross} and P_{mutation} are, the faster the speed of generating new individual will be. However, if P_{cross} and P_{mutation} are too large, the algorithm will degenerate into a completely random search algorithm.

Fitness of population will change with the running of algorithm in actual systems. If the fitness of individuals approach to the same level, the pre-selected P_{cross} and P_{mutation} are often too small, which leads the solution population can not get away from the local optimum value. If the distribution of individuals fitness is dispersive, the pre-selected P_{cross} and P_{mutation} are often too large to preserve the higher fitness individuals. Therefore the high fitness individuals should give a relatively low crossover probability and mutation probability so that they can smoothly go into the next generation. The crossover probability and mutation probability of the low fitness individuals should be risen. Similarly, in order to avoid the high fitness individuals to do crossover repeatedly, which will lead stagnation of population evolution, the crossover probability and mutation probability should be dynamically adjusted according to the vector distance between individuals.

An adaptive adjustment method is developed in this work according to the vector distance and fitness. P_{cross} and P_{mutation} are as follows.

$$P_{\text{cross}} = \begin{cases} k_1 \dfrac{r_{ij}(f_{\max} - f_{\text{high}})}{r_{\max}(f_{\max} - f_{\text{avg}})}, & f_{\text{high}} > f_{\text{avg}}, \\ k_2 \dfrac{r_{ij}}{r_{\max}}, & f_{\text{high}} \leq f_{\text{avg}}, \end{cases} \tag{8}$$

$$P_{\text{mutation}} = \begin{cases} k_3 \dfrac{(r_{\max} - r_{ij})(f_{\max} - f)}{r_{\max}(f_{\max} - f_{\text{avg}})}, & f > f_{\text{avg}}, \\ k_4 \dfrac{(r_{\max} - r_{ij})}{r_{\max}}, & f \leq f_{\text{avg}}. \end{cases} \tag{9}$$

P_{cross} and P_{mutation} represent the crossover probability and mutation probability of the two selected individuals. $f_{\max}$ is the largest fitness value in the whole population, and f_{avg} is the average fitness value of the population. f is the fitness value of the individual, and f_{high} is fitness value of the higher fitness individual in the two individuals which are selected to do crossover. When an individual fitness value is lower

than the average fitness value, the greater crossover and mutation probabilities are given to this individual so as to promote the improvement of its fitness. When an individual fitness is higher than the average, the smaller individual crossover and mutation probabilities are given, so the individual can be preserved to the next generation.

Similarly, when the hamming distance between two individuals is too small, the crossover probability of the two individuals should be reduced, so as to avoid crossover between the individuals which have a higher similarity. Meanwhile, a higher mutation probability is given to the individual which has lower fitness in the two individuals mentioned above, so as to ensure that it can generate new individuals and maintain the population diversity. r_{ij} in formulas (8) and (9) represents the hamming distance between two individuals, and $r_{\max}$ is the maximum hamming distance between individuals. The hamming distance between two individuals is shown in formula (10).

$$\begin{aligned} r_{ij} &= \|\boldsymbol{D}_i - \boldsymbol{D}_j\| \\ &= \sqrt{\sum_{k=1}^{K}\sum_{n=1}^{N}(d_{k,n}^{(i)} - d_{k,n}^{(j)})^2}, \\ &\quad \begin{pmatrix} i = 1, 2, \ldots, M-1 \\ j = i+1, i+2, \ldots, M \end{pmatrix}, \end{aligned} \tag{10}$$

where M is the number of individuals within a population, $K \times N$ is the number of elements in each individual matrix which shown in formula (5). $d_{k,n}^{(i)}$ and $d_{k,n}^{(j)}$ are the element's value of k row n column in matrix $\boldsymbol{D}_i$ and $\boldsymbol{D}_j$ respectively. If the hamming distance is too small, namely individuals are too similar to each other, so the probability for crossover of the similar individuals will be reduced according to formula (8), and the mutation probability of these lower fitness individuals will be improved according to formula (9), meanwhile preserving these higher fitness individuals retained in the population to improve the efficiency of the algorithm.

2.5. Use chaotic sequences to do crossover and mutation

When using genetic algorithms to allocate subcarrier of cognitive radio system, crossover between two individual matrixes will generate two new subcarrier distribution methods. Traditional genetic algorithm uses the single-point crossover, that is, to use the roulette wheel to select crossover location randomly. However, in the subcarrier allocation of cognitive radio system crossover means the exchange of subcarrier allocation method. Because the amount of subcarrier in cognitive radio systems is very large, the chromosome coding of an individual is long. These populations using single-point crossover will updates slowly, that results in slow convergence. Mutation means the sudden change of user's subcarrier allocation method. New subcarrier allocation will be generated by using the mutation operator. Traditional mutation would produce a number of non-zero elements in a column, which leads to that one subcarrier is distributed to multiple users and may generate infeasible solution. Also, because the crossover and mutation in traditional algorithm were divided into two separate processes, the computation efficiency is low.

Coupled chaotic genetic algorithm uses two parallel coupled Logistic maps to generate chaotic sequences and complete the crossover and mutation of individuals. As shown in Fig. 1, crossover of chromosome uses two-point crossover. Meanwhile, two adjacent gene sequences exchange and two coupled Logistic map iteration is done. After the nth iterations the following two chaotic sequences are generated: $\{(x_{11}, y_{12}), \ldots, (x_{1n}, y_{1n})\}$ and $\{(x_{21}, y_{21}), \ldots, (x_{2n}, y_{2n})\}$. The crossover position$(p,q)$ of these two points are determined by the following formulas:

$$\begin{aligned} p &= [(N+1) \cdot x_{1n}], \\ q &= [(N+1) \cdot x_{2n}], \end{aligned} \tag{11}$$

where N is the number of subcarrier in cognitive radio system. The Eq. (11) is a floor function which maps a real number to the largest previous integer.

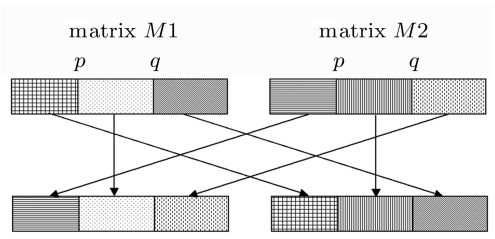


Fig. 1. Crossover.

Mutation of individual matrix is done by exchanging two rows so as to ensure that there is only one non-zero element in each column. As shown in Fig. 2, two rows i and j in the individual matrix are selected according to the following formula

$$i = [(K+1) \cdot y_{1n}],$$

$$j = [(K+1) \cdot y_{2n}], \tag{12}$$

where K is the number of users in cognitive radio system. As the amount of subcarrier is large, two-point crossover promotes the generation of new individuals in the population and increases the convergence speed of the algorithm. As mentioned above, the mutation method exchanging two rows can ensure that each subcarrier is only distributed to one user and all individuals generated by mutation meet the constraints. Coupled chaotic genetic algorithm completes the crossover and mutation at the same time, which reduces the time of the algorithm running and improves the operation efficiency of the algorithm.

$$\begin{bmatrix} \vdots & \cdots & \vdots \\ d_{i,1} & d_{i,2}\cdots & d_{i,N} \\ \vdots & \cdots & \vdots \\ d_{j,1} & d_{j,2}\cdots & d_{j,N} \\ \vdots & \cdots & \vdots \end{bmatrix} \rightarrow \begin{bmatrix} \vdots & \cdots & \vdots \\ d_{j,1} & d_{j,2}\cdots & d_{j,N} \\ \vdots & \cdots & \vdots \\ d_{i,1} & d_{i,2}\cdots & d_{i,N} \\ \vdots & \cdots & \vdots \end{bmatrix}$$

Fig. 2. Mutation.

2.6. Flowchart of coupled chaotic genetic algorithm

Flowchart of coupled chaotic genetic algorithm is shown in Fig. 3. After initialising the population by coupled Logistic map chaotic sequence, we use chaotic sequences which will be continuously generated later to do crossover and mutation to individuals. The crossover probability and mutation probability are determined dynamically and adaptively by the individual fitness value and hamming distance between individuals as mentioned in formula (8) and formula (9). Our goal is to find individual with highest fitness. When the algorithm has arrived at its designated iteration number or has achieved the target of the problem, this algorithm will stop running. For the subcarrier allocation issue of cognitive radio, the target is to minimize the transmit power under the constraints of reaching the minimum transmission rate which users need, and BER must be under a certain value.

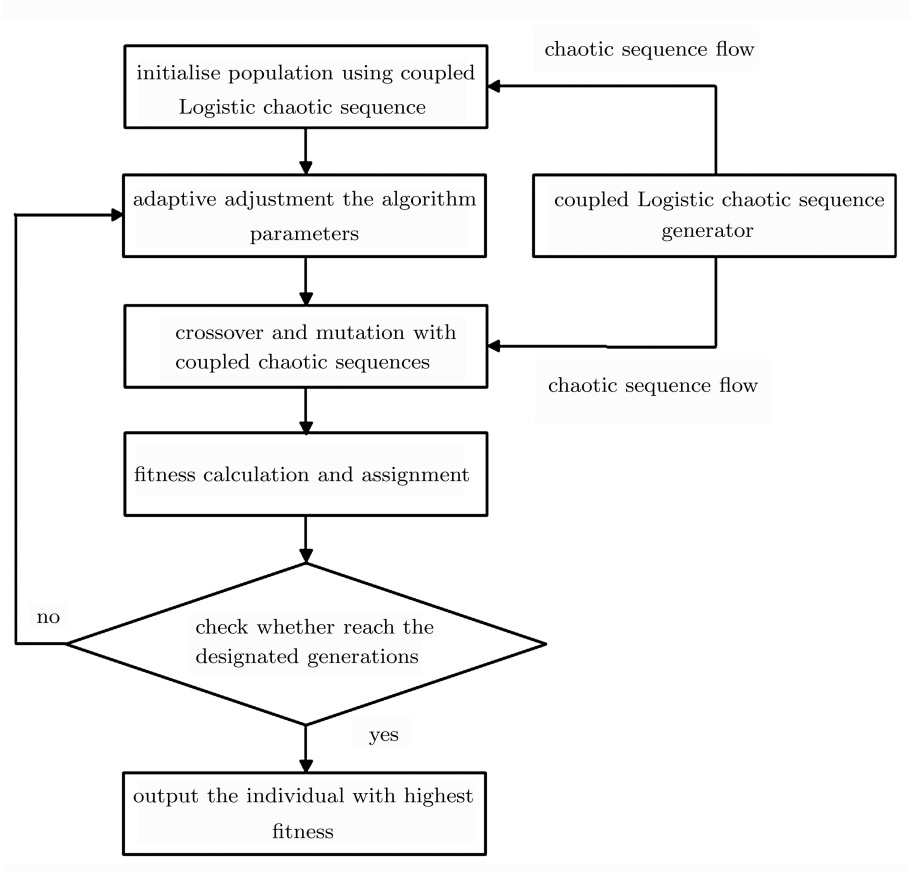


Fig. 3. Flowchart of coupled chaotic genetic algorithm.

3. Cognitive radio resource allocation based on coupled chaotic genetic algorithm

3.1. Mathematical model of cognitive radio resource allocation

In cognitive radio systems different users usually have different transmission rate requirements, transmission power restrictions and BER restrictions. As all users will share the available idle spectrums, all idle spectrums can be collected to a spectrum pool and classified orthogonal subcarriers. Each user can be assigned appropriate subcarrier according its transmission rate requirement, transmission power restriction and BER restriction. At the same time, corresponding dynamic modulation on subcarrier must be completed.

The goal of optimal subcarrier allocation is to minimise the total transmission power of multi-user cognitive radio system under the premise of reaching the user's transmission rate requirement and BER restriction. Assume that there are N available idle subcarriers in the idle spectrum pool and K users, then the expression of total transmission power is shown by formula (13)

$$\min V(D) = \sum_{k=1}^{K} \sum_{n=1}^{N} \frac{f_{k,n}(d_{k,n}, P_{\mathrm{e}})}{a_{k,n}^2}, \tag{13}$$

where $V(D)$ is the total downlink transmission power, $f(d_{k,n}, P_{\mathrm{e}}) = (N_0/3)[Q^{-1}(P_{\mathrm{e}}/4)]^2(2^{d_{k,n}} - 1)$ is the transmission power of the kth user with modulation mode $d_{k,n}$ on nth subcarrier, $a_{k,n}$ is the channel gain of the kth user on the nth subcarrier, P_{e} is the BER limit, and $Q(x) = (1/\sqrt{2\pi}) \int_x^{\infty} \mathrm{e}^{-t^2/2} \mathrm{d}t$ is the normal distribution integral function. The fitness function is shown by formula (14), where $V_{\max}$ is the limit of transmission power

$$\mathrm{Fit}(D) = V_{\max} - V(D). \tag{14}$$

Considering different transmission rate requirement of each user, the base station's downlink transmission rate for each user must meet formula (15), which is the first constraint.

$$B \sum_{n=1}^{N} d_{k,n} \geq R_k, \tag{15}$$

where B represents subcarrier bandwidth, $d_{k,n}$ is the modulation mode of modulation matrix $\boldsymbol{D}$, and R_k is the transmission rate requirement of the kth user.

If the base station has restriction on transmitting power for each user it is necessary to add the second constraint as shown in formula (16)

$$\sum_{n=1}^{N} \frac{f_{k,n}(d_{k,n}, P_{\mathrm{e}})}{a_{k,n}^2} \leq P_k, \tag{16}$$

where P_k is the kth user's transmission power limit.

3.2. Resource allocation of cognitive radio based on coupled chaotic genetic algorithm

Resource allocation of cognitive radio is to minimise the total transmission power under the constraints of formula (15) and formula (16).

Matrix $\boldsymbol{D}$ in formula (5) is the individual matrix of coupled chaotic genetic algorithm. $\boldsymbol{D}$ represents subcarrier distribution and adaptive modulation mode in cognitive radio system which has N subcarriers and K users. After iterative computation the generated individual which satisfies the user's transmission rate and minimum transmission power is the solution.

In summary, the steps of this coupled chaotic genetic algorithm used for cognitive radio resource allocation are described as follows:

(1) To generate fitness function according to channel gain, the user's demand of transmission rate, and transmission power constraints shown in formulas (14), (15) and (16).

(2) To establish the coupled Logistic chaotic map generator, generate chaotic sequence, and initialise the individuals in population using chaotic sequence.

(3) To select the individuals for crossover and mutation using two parallel chaotic sequences.

(4) To calculate the hamming distance of individuals and to obtain the crossover probability P_{cross} and mutation probability P_{mutation} according to the method shown in Subsection 2.4.

(5) To perform crossover and mutation operations according to the method shown in Subsection 2.5.

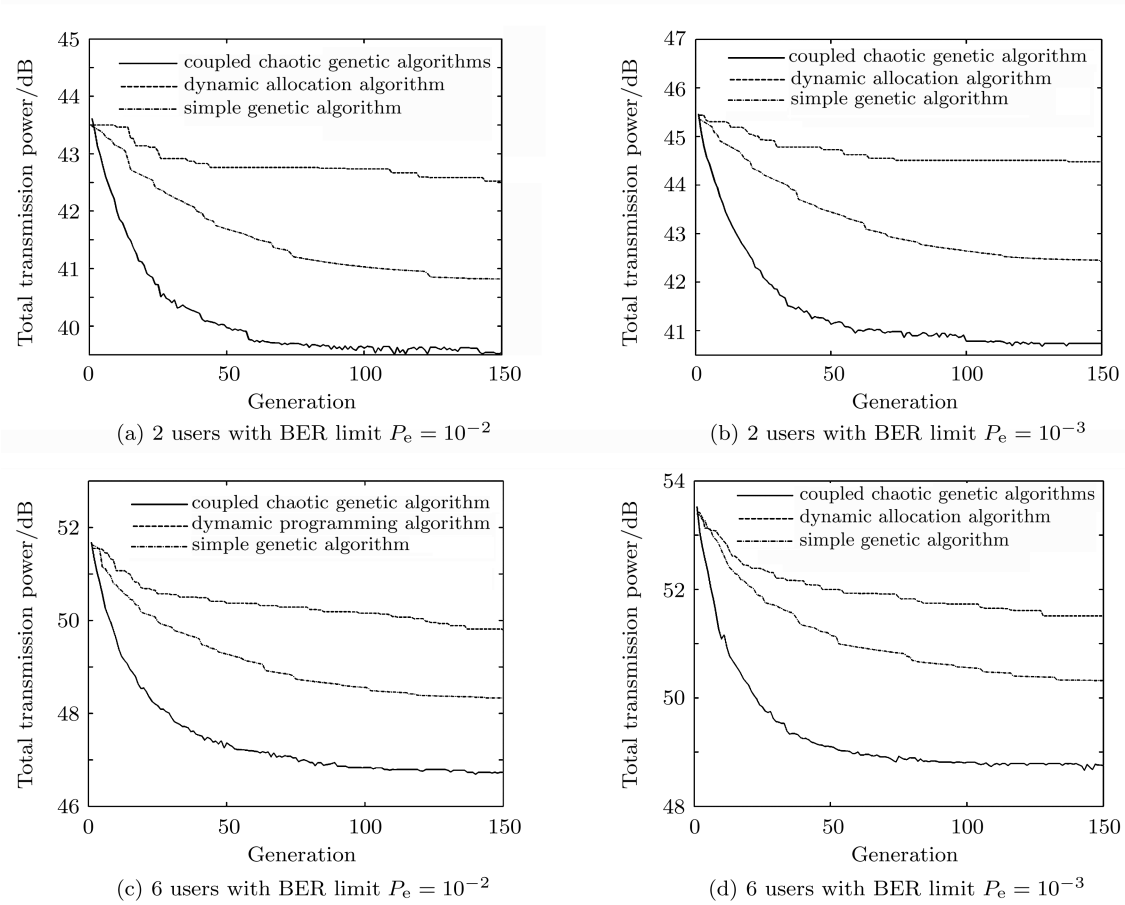
(6) To calculate the individual fitness according to the method shown in Subsection 3.1, and dynamically adjust the individual fitness according to the constraints (15) and (16).

(7) To check if the algorithm has reached the designated generations. The individual with best fitness will be output if the designated generation has reached, otherwise, continue the iteration of algorithm from step (3) until reach the designated generation.

4. Simulation results and analysis

In the simulation, suppose that channel estimation is accurate, the single-sideband power spectral density of additive Gaussian noise is $N_0 = 1$, the total bandwidth of idle spectrum in the spectrum pool is 10 MHz, the number of subcarrier is 1024, the bandwidth of each subcarrier is 10 kHz, the total amount of individuals in the population is 100, the dynamic modulation mode is 0–8 bit/(s/Hz).

Figure 4 shows the changes of the total transmit power with the iteration of algorithms with the conditions that the transmission rate demand of each user is 5 MHz, the number of users is 2 or 6, and the bit error rate limits are $P_e = 10^{-2}$ and $P_e = 10^{-3}$ respectively. The coupled chaotic genetic algorithm, simple genetic algorithm and dynamic allocation algorithm are compared for the decline of the total transmit power with the growth of the generation, as shown in Fig. 4. The decline is the fastest for the coupled chaotic genetic algorithm, slower for the simple genetic algorithm, and the slowest for the dynamic allocation algorithm. The dynamic allocation algorithm allocates multiple subcarriers at each time, which results in a low fitness initial allocation and comes into stagnation after certain evolutionary, and finally converges in a sub-optimal solution. The coupled chaotic genetic algorithm can avoid highly similar individuals to fill the population and preserve species diversity by dynamically adjusting the crossover and mutation probability. At the same time, it can maintain the continuing evolution of population by using chaotic sequences to do crossover and mutation. So the coupled chaotic genetic algorithm has the best performance and faster convergence speed.



(a) 2 users with BER limit $P_e = 10^{-2}$

(b) 2 users with BER limit $P_e = 10^{-3}$

(c) 6 users with BER limit $P_e = 10^{-2}$

(d) 6 users with BER limit $P_e = 10^{-3}$

Fig. 4. Total transmission power.

In Fig. 5 the relationship of the average bit SNR and BER is compared for coupled chaotic genetic algorithm, simple genetic algorithm and dynamic allocation algorithm. As shown in Fig. 5, compared with simple genetic and dynamic allocation algorithm, the required SNR is reduced 1.5 dB and 3 dB respectively by using the coupled chaotic genetic algorithm for the same bit error rates. So the system's transmission power reduces at the same BER limit and the BER reduces for the same average bit SNR.

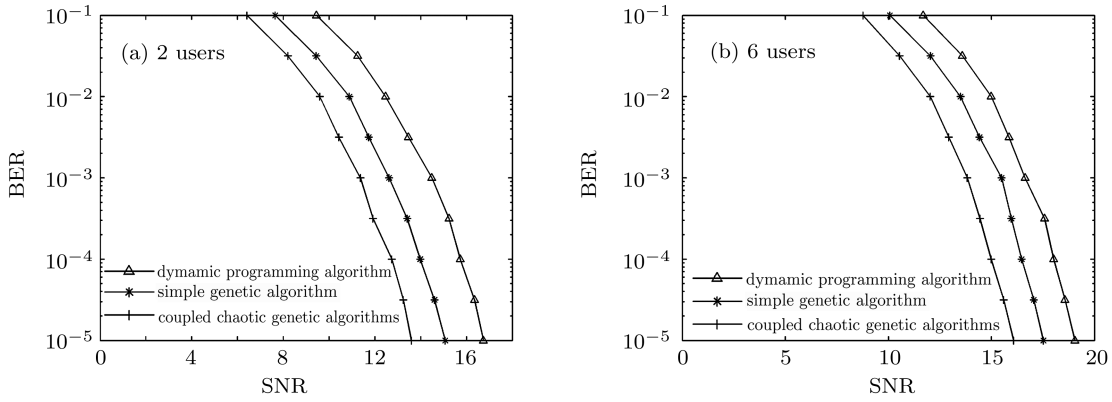


Fig. 5. SNR to BER.

5. Conclusions

This study focuses on the issue of how to reduce the transmission power with the constraints of multi-user's transmission rates requirement and limited BER. This is a common and important issue of the cognitive radio resource allocation. A coupled chaotic genetic algorithm which is based on genetic algorithm and coupled Logistic map is proposed, and a fitness function for cognitive radio resource allocation is provided. By simulation it is clearly shown that the coupled chaotic genetic algorithm can effectively reduce system's transmission power and bit error rate, and speed up the convergence compared with simple genetic algorithm and dynamic allocation algorithm.

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