Binary Quantum Elite Particle Swarm Optimization Algorithm for Spectrum Allocation in Cognitive Wireless Medical Sensor Network

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Abstract. Cognitive wireless medical sensor network (CWMSN) is a new development direction of the wireless sensor network (WSN) in recent years. The requirements of CWMSN are multifaceted such as optimized utilization of resources, energy efficiency and channel sharing. However, CWMSN also faces the problem of limited energy and spectrum. For this reason, this paper proposes a spectrum allocation model. Moreover, a new binary quantum-behaved elite particle swarm optimization algorithm (BQEPSO) based on the combination of quantum operator, elite operator and binary particle swarm optimization (BPSO) is proposed to solve the spectrum allocation problem in CWMSN. The algorithm can enable the conflict-free use of spectrum resources in CWMSN and maximize the efficiency of spectrum allocation. The BQEPSO is compared with the genetic algorithm (GA) and traditional particle swarm optimization (PSO) under the same experimental conditions. The simulation results indicate that the performance of BQEPSO is better than the other two algorithms. And BQEPSO can maintain the total throughput of the CWMSN. What’s more, BQEPSO has a high network reward and throughput.

Keywords. Cognitive wireless medical sensor network, quantum particle swarm optimization, spectrum allocation

1. Introduction

With the development of telecommunications technology, wireless sensor networks (WSNs) are receiving a lot of attention from the healthcare field[1, 2]. The consequence is an increase in demand for wireless communication services. There are still many problems, such as optimum utilization of resources, energy efficiency and channel sharing. Solving the problem of spectrum resources shortage is the key method of resolving these problems. Therefore, the Cognitive Radio (CR) technology was issued[3]. The Cognitive Wireless Medical Sensor Network (CWMSN) based on this concept is composed of some wireless sensors for data transmission. Each sensor has certain calculation, storage and data transmission capabilities to realize the remote transmission and monitoring of medical information between individuals and hospitals. This technology can use radio spectrum resources
intelligently, efficiently and reasonably, and can realize spectrum resource sharing for improving the spectrum utilization rate.

Generally speaking, each data packet transmitted through a wireless sensor network is extremely important in the medical industry for the reason that it may contain critical information. However, the wireless sensor devices that exist in CWMSN are generally small in size, and their communication capabilities are extremely limited. At the same time, according to the traditional static spectrum management method, all wireless sensor devices communicate under a single channel, which is more likely cause data loss[4, 5], mutual interference between devices, and overhearing of content in the channel in WSN. CWMSN introduces cognitive radio (CR) nodes into the network to support multi-channel access and facilitate channel reuse. In this way, different device can be assigned to different channels, and the total revenue of CWMSN is the sum of all channel revenues.

In spectrum resource allocation, dynamic spectrum allocation is one of the important technologies to maximize the use of spectrum[6]. According to the surrounding spectrum environment, the right to use the spectrum can be dynamically adjusted, so that the limited spectrum resources can be used efficiently, so as to maximize the network benefit.

To deal with the problem of spectrum resource allocation in CWMSN for maximizing network benefits, we propose a new binary quantum-behaved elite particle swarm algorithm (BQEPSO). Based on the spectrum allocation scheme, compared with the traditional GA and PSO, it has the advantage to achieve the goal of ideal network revenue and improving the efficiency of spectrum allocation in CWMSN.

2. System Model
In this section, the spectrum allocation problem is regarded as a graph colouring problem, and we use an undirected graph to denotes the network. Suppose a CWMSN system with U cognitive users and C channels in the spectrum allocation model, the correlation matrices are defined as follow:

The non-occupied matrix \( T = \{ t_{u,c} \mid t_{u,c} \in \{0,1\} \} \) is a binary matrix with U rows and C columns, which is used to indicate channel availability, and judge whether \( u \) cognitive user can occupy \( c \) channel. If \( t_{u,c} = 1 \), it represents that the \( c \) channel is not occupied by neighbour primary users, and it is available to \( u \) user. If \( t_{u,c} = 0 \), it means that \( c \) channel is unavailable.

The interference constraint matrix is \( G = \{ g_{u,k,c} \mid g_{u,k,c} \in \{0,1\} \} \). This matrix describes the relationship between the \( u \) user, the \( k \) user, and the \( c \) channel. We set \( g_{u,k,c} = 1 \) if \( u \) and \( k \) user would interfere with each other when they use \( c \) channel simultaneously. And if \( g_{u,k,c} = 0 \), it indicates that \( c \) channel can be assigned to the \( u \) user and the \( k \) user simultaneously. Especially, when \( g_{u,k,c} = 1 - t_{u,c} \) and \( u = k \), the interference matrix \( G \) is only related to the available matrix \( T \).

The channel reward matrix \( R = \{ r_{u,c} \mid r > 0 \} \) is set to calculate the channel reward, where \( r_{u,c} \) is the reward that obtained by the \( u \) user using the \( c \) channel.

The spectrum allocation matrix \( E = \{ e_{u,c} \mid e_{u,c} \in \{0,1\} \} \) represents the channel assignment. When \( e_{u,c} = 1 \) it suggests that \( c \) channel is allocated to \( u \) cognitive user, and every element in matrix \( E \) is required to satisfy the non-interference constraint in interference matrix \( G \).

The benefits of all \( U \) cognitive users can be represented by matrix \( B = \{ b_u = \sum_{c=1}^{C} e_{u,c} \cdot r_{u,c} \} \). Let \( A(T,G) \) be the set of non-conflicting channel assignment. The spectrum allocation’s purpose is to maximize network profit \( U(B) \). Therefore, the spectrum allocation problem can be expressed by formula (1)

\[
E^* = \arg \max_{A \in A(T,G)} U(B)
\]

where \( E^* \) is the optimal non-interference spectrum allocation matrix. Here, we use the definition of network reward that is given in[7], thus, the network benefit function can be defined by formula (2).
\[ F_1 = \text{max}(U(B)) = \sum_{u=1}^{U} b_u = \sum_{u=1}^{U} \sum_{c=1}^{C} e_{u,c} \cdot b_{u,c} \]  

(2)

3. BQEPSO for Spectrum Allocation in CWMSN

Particle swarm optimization (PSO) was proposed by the American social psychologist Kennedy and electrical engineer Eberhart, its basic thought comes from the study of bird colony behavior. In each round of iterative process, the particles in the particle swarm update their location by tracking two "extreme points". The specific update formulas for speed and position are as follows:

\[ V_{t+1} = \alpha \cdot V_t + \eta_1 \cdot \epsilon \cdot (p_{best_t} - L_t) + \eta_2 \cdot \epsilon \cdot (g_{best} - L_t) \]  

(3)

\[ L_{t+1} = L_t + V_{t+1} \]  

(4)

Where \( \alpha \) is the inertia weight; \( \eta_1 \) and \( \eta_2 \) are called the learning factors; \( V \) indicates the moving speed of particles; \( p_{best} \) is the personal best of particles, and \( g_{best} \) is the global best in particle swarm; \( t \) is the number of current iterations; \( L \) is the particle’s location; \( \epsilon \) is a random number between 0 and 1.

To improve the search performance of PSO, the quantum particle swarm optimization algorithm (QPSO) is proposed. Compared with PSO, there is only one displacement update formula in QPSO. And the QPSO effectively simplifies the complexity of the algorithm and improves the calculation efficiency and convergence speed of the algorithm. The related formulas are described as follows:

\[ q_i = u \cdot p_{best_i} + (1 - u) \cdot g_{best} \]  

\[ m_{best} = \frac{\sum_{n=1}^{N} p_{best_n}}{N} = \left( \frac{\sum_{n=1}^{N} p_{best_{n,1}}}{N}, \frac{\sum_{n=1}^{N} p_{best_{n,2}}}{N}, \ldots, \frac{\sum_{n=1}^{N} p_{best_{n,N}}}{N} \right) \]  

(5)

\[ L_{t+1} = q_i \pm \varphi \cdot m_{best} - L_t \times \ln \left( \frac{1}{U} \right) \]  

(6)

Where the \( \epsilon \) is a random number between 0 and 1; \( q_i \) is the local attraction factor of the \( i^{th} \) particle, which is determined by the personal best \( p_{best_i} \), and the global best \( g_{best} \); \( m_{best} \) is called the mean best; \( \varphi \) is the contraction/expansion factor, and it is used to control the particles’ convergence speed; \( L \) is the location of the particles; \( N \) is the number of particles in the particle swarm. In the iterative process, there is a random \( r \), when it is greater than 0.5, the sign of formula (6) is negative, otherwise, the sign is positive.

In this research, we use a new Binary Quantum-behaved Elite Particle Swarm Optimization (BQEPSO) algorithm to solve the spectrum allocation problem in CWMSN. In the standard PSO, the condition of a particle is influenced by its location and velocity, and they decide jointly the particle’s flight trajectory. Since the velocity of a particle is always finite, the search space of a particle in the search process is a finite region that cannot cover the whole feasible space [8, 9]. QPSO combines related concepts of quantum mechanics with PSO, so that the particle can search in the whole feasible solution space. For BQEPSO, it introduces the concept of binary coding in QPSO, and combines the elite operator which makes QPSO adapt to the discrete search space of spectrum allocation. Compared with ordinary PSO, BQEPSO has the characteristics of global convergence, less control parameters and strong optimization ability.

In the BQEPSO algorithm, the initial particle swarm should be set first. Then, in the evolution process, the particles update their position with a certain probability, thereby generate a new particle swarm. Finally, the best solution is found by comparing the personal best and the global best of the particle. The primary process of BQEPSO to deal with the spectrum allocation problem in CWMSN are as follows:

A) Coding and initialization.
B) Initialize the particle location \( L_i \), and set the personal best location \( p_{best_i} \) for \( L_i \).
C) Calculate each particle’s mean best \( m_{best} \).
D) Calculate the fitness value of the current particle, and compare it with the personal best and global best of the previous generation. If \( f(L_u) > f(p_{best_u}) \), then \( p_{best_u} = L_u \), and if \( f(L_u) > f(g_{best}) \), then \( g_{best} = L_u \).
E) Each particle through cross-behaviour to generate a local attractor \( q_i \) and calculates the mutation rate \( p_r \), and then updates the position \( L_u \) of the particle according to \( P_r \).

F) Repeat step B to E until the iteration termination condition is reached.

3.1. Initialize the particle swarm
According to the system model description, we use the binary coding method to code the population, and randomly generate the initial population. We initialize the population into a \( P \times Q \) binary matrix, where \( P \) means there are \( P \) particles in the population, and \( Q \) is the product of cognitive users’ number \( U \) and channel numbers \( C \), in our model the number of the channel is equal to primary users. The location of each particle is a solution in spectrum allocation in CWMSN.

3.2. Calculate \( m_{best} \)
There is no velocity vector in BQEPSO algorithm, but there are the concepts of location and distance, In BQEPSO, a binary character string is used to represent the location of the particle, and we use the Hamming distance to represent the distance between the two locations of particle \( L_1 \) and \( L_2 \).

\[
\text{Dis}(L_1, L_2) = \text{sum}(L_1 \oplus L_2)
\]  
(7)

Where, the function \( \text{sum}() \) is used to calculate the number of bits with the value of 1 in the XOR result.

In BQEPSO, the \( j^{th} \) value of \( m_{best} \) is determined by the \( j^{th} \) value of all particles’ \( p_{best} \). When the particle takes 1 more than 0 at the \( j^{th} \) position, then the \( j^{th} \) bit of \( m_{best} \) is set to 1, otherwise, it is set to 0. Moreover, if the occurrence number of 1 is the same as 0, then take 0 or 1 in equal probability.

3.3. Compare and update \( p_{best_u} \) and \( g_{best} \)
Calculate each particle’s fitness value \( f(L_u) \) according to the fitness function, then compare it with the \( p_{best} \) value \( f(p_{best_u}) \) of last generation, if \( f(L_u) > f(p_{best_u}) \), then \( p_{best_u} = L_u \), and meanwhile compare it with the global best \( g_{best} \), if \( f(L_u) > f(g_{best}) \), then \( g_{best} = L_u \), otherwise, remain constant.

3.4. Calculate local attraction factor \( q_u \)
In BQEPSO, \( q_u \) is calculated by \( p_{best_u} \) and \( g_{best} \) through single-point crossover or multi-point crossover strategy, its purpose is to reduce the difference and play a certain role in local search. Each bit of the particle location \( L_u \) of BQEPSO can be obtained by mutating every bit of the local attractor \( q_u \), the variation rate \( p_r \) is determined by \( b \), and the expression is set as follow:

\[
b = \gamma \ast \text{Dis}(L_u, m_{best}) \ast \ln \left( \frac{1}{r} \right)
\]  
(8)

\[
p_r = \begin{cases} 
\frac{b}{l} & b > 1 \\
1 & b \leq 1
\end{cases}
\]  
(9)

Where \( l \) is the binary bit length of the particles dimension, \( \gamma \) is the coefficient of BQEPSO algorithm, \( r \) is a random number within \([0,1]\).

3.5. Update the particle’s location \( L_u \)
\( L_u \) is updated through the function \( T() \):

\[
L_u = T(q_u, p_r)
\]  
(10)

In function \( T() \), there is a random number \( r \) between 0 and 1, when \( r > p_r \), each bit of \( q_u \) is inverted, otherwise the corresponding bit of \( L_u \) is equal to \( q_i \).

4. Simulation and Results
In this section, the BQEPSO algorithm is compared with the PSO and GA in optimizing the spectrum allocation problem of CWMSN. Then, we show the optimization performance of BQEPSO through
algorithm simulations. The hardware platform we use for experiments is a Ryzen5 3500X machine with 16 GB RAM and the software platform is MATLAB. Under this condition, the objective function is used to evaluate the network reward in CWMSN. The objective function applied in the experiments is presented in formula (2).

In this study, the three algorithms all terminated after 100 iterations, to ensure the specified quality of the solution, we set the population size to 80, and we set the variation rate to 0.08 in GA. In PSO, the learning factor $\eta_1 = \eta_2$, inertia weight $\alpha$, and maximum velocity $v_{max}$ are set to 2.05, 1.2, 10, respectively.

Figures 1 and 2 respectively show the convergence of BQEPSO, GA, and PSO with two different conditions of 15 channels with 30 cognitive users, 20 channels with 40 cognitive users. Obviously, the BQEPSO achieves better network reward than GA and PSO. From these two figures, it shows that PSO eventually falls into a local optimum with the iteration of the algorithm, due to the lack of diversity. While GA requires extensive functional evaluation, resulting in convergence speed always can't obtain the desired effect.

In figures 3 and 4, the network rewards of the three algorithms are compared under two other different conditions. In figure 3, it shows three cases where the number of channels is 5, and the numbers of cognitive users are 20, 25, and 30 respectively. And the figure 4 shows the network rewards of these three algorithms when the number of cognitive users is 40 and the number of channels is set to 5, 10 and 15 respectively. From the comparison results, it is clear that the network rewards optimized by BQEPSO are always higher than GA and traditional PSO. It is obvious that the BQEPSO has more advantages in solving the spectrum allocation problem in CWMSN.

5. Conclusion
In this study, we proposed a new Binary Quantum-behaved Elite Particle Swarm Optimization (BQEPSO) algorithm to optimize the spectrum allocation problem in CWMSN. We design a mathematical model for the spectrum allocation problem. Then, we used BQEPSO, GA and PSO to carried out the simulations. Results show that BQEPSO has more advantages than GA and traditional PSO in maximizing network revenue and improving the efficiency of spectrum allocation.

Figure 1: 15 channels and 30 cognitive users
Figure 2: 20 channels and 40 cognitive users
Acknowledgments
This paper was funded by the Corps innovative talents plan, grant number 2020CB001, the project of Youth and Middleaged Scientific and Techno-logical Innovation Leading Talents Program of the Corps, grant number 2018CB006, the China Postdoctoral Science Foundation, grant number 220531, Funding Project for High Level Talents Research in Shihezi University, grant number RCZK2018C38, Project of Shihezi University, grant number ZZZC201915B.

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