A Cultural Immune Quantum Evolutionary Algorithm and Its Application

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***Abstract*—This paper proposes to integrate immune quantum evolutionary algorithm into cultural algorithms frame to develop a more efficient cultural immune quantum evolutionary algorithm (CIQEA). The computing model consists of a population space based on quantum-inspired evolutionary algorithm and a belief space based on immune vaccination, the population space and belief space have their own population evolved independently and parallel. The population space contributes vaccines to the belief population periodically, and the belief space continually evolve these vaccines which are used to provide better evolutionary direction to the population space, to constitute the dual-evolution and dual-improvement mechanism that can improve the global optimization abilities and convergence speed greatly. The convergence of CIQEA is proved based on markov random process and its superiority is shown by the experimental results on the knapsack problem.**

***Index Terms*—quantum bit, quantum-inspired evolutionary algorithm(QEA), immune operator, cultural algorithm, knapsack problems**

I. Introduction

Quantum-inspired evolutionary algorithm (QEA) is an unconventional algorithm of evolutionary computation. QEA inherits the structure and probabilistic search way of conventional genetic algorithm (CGA), and some concepts and operations of quantum computing, such as quantum-inspired bit (Q-bit), quantum-inspired gate (Q-gate) and quantum operators including superposition, entanglement, interference and measurement [1], [2]. Up to now, as a better optimization method than CGA, QEA has been developed rapidly and applied in several applications of knapsack problem[2], [3], numerical optimization and other fields[4]. It has gained more attraction for its good global search capability and effectiveness. Therefore, many research efforts in the field of merging evolutionary strategy with QEA have been made to improve QEA since the end of the 90's[5], [6].

In recent years, the study on the cultural algorithms based on novel algorithms has become an active research field. Cultural algorithm (CA) is a novel evolutionary computational frame based on concept of culture of human society, which shows higher intelligence in treating all kinds of complicated problems[7], [8]. It is made of two main components: the population space, and the belief space. The population space consists of a set of possible solutions to the problem, and can be modeled using any population-based techniques. The belief space is an information repository in which the individuals can store their experience for the other individuals to learn them indirectly. Both spaces are linked through a communication protocol, which states the rules about the individuals that can contribute to the belief space with their experience (the acceptance function), and the way the belief space can influence to the new individuals (the influence function). So, cultural algorithm can provide explicit mechanisms for acquiring, storing, refining and reasoning about knowledge obtained during the evolutionary search. The knowledge can be used to guide the search of an evolutionary computation technique by pruning the infeasible individuals in the population space and promoting the exploration of promising regions of the search space [9], [10]. Those interactions are depicted in Fig.1.

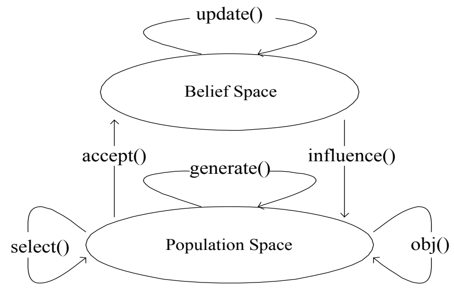

Figure 1. A framework of cultural algorithms

We present a new algorithm, called a cultural immune quantum evolutionary algorithm **(CIQEA)**, which is based on merging cultural algorithm with immune vaccination based quantum evolutionary algorithm. There are three innovation points as follows. Initially, quantum evolutionary algorithm based on immune vaccination is proposed as a population space, from which the good individuals are selected as vaccines into belief space. Secondly, the belief space continually evolve these vaccines parallel then inject the good vaccine into individuals in the population space, so as to improve the searching ability and suppress degeneration happened in

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the evolutionary process. Finally, the convergence of CIQEA is proved based on markov random process and its superiority is shown by the experimental results on the knapsack problem.

The paper is organized as follows. Section II describes the proposed cultural immune quantum evolutionary algorithm. Section III describes evolution of the belief space and interactions of the population space and belief space. Section IV then proves that the novel algorithm is convergence with probability one by using markov chain model. Section Ⅴ presents an application example with CIQEA, QEA[3] and IQEA[6] for knapsack problems, and summarizes the experimental results.

II. The Population Space: Qea Based On Immune Vaccination

A. Quantum-inspired Evolutionary Algorithm

QEA utilizes a new representation, called a Q-bit, for the probabilistic representation that is based on the concept of qubits [3]. A qubit may be in the "1" state, in the "0" state, or in any superposition of the two [11]. The state of a qubit can be represented as

$$|\varphi>=\alpha|0>+\beta|1> \tag{1}$$

where α and β are complex numbers that specify the probability amplitudes of the corresponding states. $|\alpha|^2$ gives the probability that the qubit will be found in '0' state and $|\beta|^2$ gives the probability that the qubit will be found in the '1' state. Normalization of the state to unity always guarantees:

$$|\alpha|^2+|\beta|^2=1 \tag{2}$$

One qubit is defined with a pair of complex numbers(α,β), as $\begin{bmatrix}\alpha\\ \beta\end{bmatrix}$ which is characterized by (1) and (2). And an *m*-qubits representation is defined as

$$\begin{bmatrix}\alpha_1 & \alpha_2 & \cdots & \alpha_m\\ \beta_1 & \beta_2 & \cdots & \beta_m\end{bmatrix} \tag{3}$$

where $|\alpha_i|^2+|\beta_i|^2=1$, *i*=1,2…m.

Q-bit representation has the advantage that it is able to represent a linear superposition of states probabilistically. If there is a system of *m*-qubits, the system can represent 2^m states at the same time. However, in the act of observing a quantum state, it collapses to a single state. The basic structure of QEA is described in the following[3].

```
QEA ()
{ t←0;
  initialize Q(t);
  make P(t) by observing the states of Q(t) ;
  evaluate P(t);
  store the optimal solutions among P(t) ;
  while (not termination-condition) do
    { t=t+1;
      make P(t) by observing the states of Q(t-1);
      evaluate P(t) ;
      update Q(t) using Q-gate U(t);
      store the optimal solutions among P(t) ;
    }
}
```

where *Q*(t) is a population of qubit chromosomes at generation *t*, and *P*(*t*) is a set of binary solutions at generation *t*.

1)In the step of 'initialize *Q*(*t*)', all qubit chromosomes are initialized with the same constant $1/\sqrt{2}$. It means that one qubit chromosome represents the linear superposition of all possible states with the same probability.

2)The next step makes a set of binary solutions, *P(t)*, by observing *Q(t)* states. One binary solution is formed by selecting each bit using the probability of qubit. And then each solution is evaluated to give some measure of its fitness.

3)The initial best solution is then selected and stored among the binary solutions, *P(t)*.

4)In the while loop, a set of binary solutions, *P(t)*, is formed by observing *Q*(*t*-1) states as with the procedure described before, and each binary solution is evaluated to give the fitness value. It should be noted that *P*(*t*) can be formed by multiple observations of *Q*(*t*-1).

5)In the next step—'update Q(*t*)', a set of qubit chromosomes *Q(t)* is updated by applying rotation gate defined below

$$U(\Delta\theta_i)=\begin{bmatrix}COS\ (\Delta\theta_i) & -SIN\ (\Delta\theta_i)\\ SIN\ (\Delta\theta_i) & COS\ (\Delta\theta_i)\end{bmatrix}$$

where $\Delta\theta_i$ is a rotation angle of each Q-bit towards either '0' or '1' state depending on its sign. Fig.2 shows the polar plot of the rotation gate. $\Delta\theta_i$ should be designed in compliance with practical problems. Table I can be used as an angle parameters table for the rotation gate.

The magnitude of $\Delta\theta_i$ has an effect on the speed of convergence, but if it is too big, the solutions may diverge or have a premature convergence to a local optimum. The sign of $\Delta\theta_i$ determines the direction of convergence.

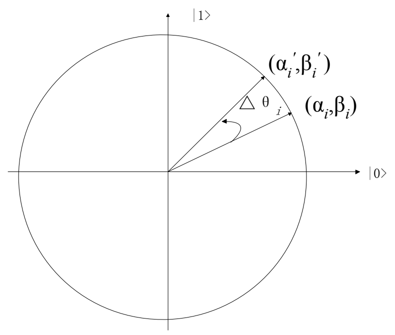


Figure 2. Polar plot of the rotation gate

6)The best solution among *P(t)* is selected, and if the solution is fitter than the stored best solution, the stored solution is replaced by the new one. The binary solutions *P(t)* are discarded at the end of the loop.

TABLE I
LOOKUP TABLE OF $\Delta\theta_i$, WHERE $f(\cdot)$ IS THE FITNESS FUNCTION, b_i AND x_i ARE THE i-th BITS OF THE BEST SOLUTION **b** AND THE BINARY SOLUTION **x**, RESPECTIVELY

x_i	b_i	f(x)≥f(b)	$\Delta\theta_i$
0	0	false	θ_1
0	0	true	θ_2
0	1	false	θ_3
0	1	true	θ_4
1	0	false	θ_5
1	0	true	θ_6
1	1	false	θ_7
1	1	true	θ_8

In a complicated problem, there are many basic and obvious characteristics or knowledge. However, in basic QEA, Q-gate variation operators usually lack the capability of utilizing these characteristics and knowledge. When using basic QEA for solving complicated problems, variation operators may neglect the assistant function of these characteristics or knowledge. And the loss due to the negligence is sometimes considerable. Research has shown that considerable improvement in their performance can be achieved when problem-specific knowledge is used to adapt the problem solving process in order to identify pattern in their performance environment [9], [10].

Therefore we add an immune operator in QEA, the immune operator utilizes the information of vaccines for seeking the ways or patterns of finding the optimal solution. By using the immune operator, the QEA can suppress the degeneration phenomena arising from the evolutionary process, improve the searching ability, and increase the converging speed greatly.

B. Cultural Immune Quantum Evolutionary Algorithm (CIQEA)

The CIQEA is designed with a Q-gate as a variation operator and an immune operator. The immune operator is based on the theory of immunity in biology. And it operates as injecting the good vaccines into a solution, so as to improve the fitness[12], [13]. It can increase the converging speed and make the improvement of the searching ability. The structure of CIQEA is described in the following:

```
CIQEA ()
  { t← 0;
    initialize Q(t) ;
    make P(t) by observing the states of Q(t) ;
    evaluate P(t) ;
    store Q(t) corresponding to the best solutions
    among P(t) as a vaccine V(t) into the belief space;
    while (not termination - condition) do
       { t=t+1;
         make P(t) by observing the states of Q (t-1);
         evaluate P(t) ;
         update Q(t) using Q-gates U(t);
         according to the acceptance function store
         Q(t) corresponding to the best solutions
         among P(t) as vaccines V(t) into the belief
         space;
         according to the influence function,
         implement the immune operator for Q(t)
          {vaccination;
           immune test;
          }
       }
  }
```

In the CIQEA, an immune operator is composed of two operations: vaccination and immune test. These two operations are based on reasonable selecting vaccines. The vaccine contains some basic features of the problem and problem-solving knowledge during the evolutionary search, while antibodies are potential solutions. In other words, a vaccine can be regarded as an estimate on some genes of the optimal antibody.

In our approach, the operation of selecting vaccines is selecting the good individuals as vaccines from the population space. The operation of vaccination is injecting vaccines into the population space for raising the fitness; and that of immune test is testing the effect of vaccination for preventing the degeneration.

1) Vaccine Abstraction. In our study, the operation of constructing vaccines is selecting the best individual as a vaccine from the current population space (via the acceptance function). When an individual is selected as a vaccine, it will be added into the belief space.

2) Vaccination. The vaccination operation is performed as follows: a) select a number of individuals from the current population space according to the proper proportion; b) modifying their genes on some bits, according to a vaccine's scheme, so that individuals have higher probabilities to get higher fitness[14]. The procedure of vaccination is described as below.

Given an individual $q_i=\left(\begin{array}{c|c|c|c}\alpha_{i1} & \alpha_{i2} & ..\alpha_{ij}.. & \alpha_{im} \\ \beta_{i1} & \beta_{i2} & ...\beta_{ij}.. & \beta_{im}\end{array}\right)$, the vaccine is $q_g=\left(\begin{array}{c|c|c|c}\alpha_{g1} & \alpha_{g2} & .\alpha_{gj}... & \alpha_{gm} \\ \beta_{g1} & \beta_{g2} & ..\beta_{gj}. & \beta_{gm}\end{array}\right)$, where $|\alpha_{ij}|^2+|\beta_{ij}|^2=1$, j=1,2……m, $0 \le |\alpha_{ij}| \le 1$, $0 \le |\beta_{ij}| \le 1$.

***Definition* 1**: Assume that $\alpha_{gj} \le \alpha_{ij}$ (else α_{gj} and α_{ij} should be swapped)

$$\alpha_{gj}^* = \begin{cases} \alpha_{ij} + \dfrac{(\alpha_{ij}-\alpha_{gj})(1-\alpha_{ij})}{1+\alpha_{ij}}, & \alpha_{ij} \ne -1 \\ \alpha_{ij} & , \alpha_{ij} = -1 \end{cases}$$

$$\alpha_{ij}^{*}=\begin{cases}\alpha_{gj}-\dfrac{(\alpha_{ij}-\alpha_{gj})*(\alpha_{gj}+1)}{1-\alpha_{gj}}, & \alpha_{gj}\neq 1\\ \alpha_{gj}, & \alpha_{gj}=1\end{cases}$$

It is not difficult to prove: $-1\le\alpha_{ij}^{*}\le\alpha_{gj}\le\alpha_{ij}\le\alpha_{gj}^{*}\le 1$.

Assume that $z_i=\left(\begin{array}{c|c|c|c}\alpha_{i1}^{z} & \alpha_{i2}^{z} & \cdots\cdots & \alpha_{im}^{z}\\ \beta_{i1}^{z} & \beta_{i2}^{z} & \cdots\cdots & \beta_{im}^{z}\end{array}\right)$ is outputted as a vaccinated individual, where

$$\alpha_{ij}^{z}=\begin{cases}(1-\alpha)\alpha_{gj}, & \mathrm{mod}(\theta,4)=0\\ R(\alpha*\alpha_{gj}+(1-\alpha)\alpha_{ij},\alpha*\alpha_{gj}+(1-\alpha)\alpha_{ij}^{*}), & \mathrm{mod}(\theta,4)=1\\ R(\alpha*\alpha_{ij}+(1-\alpha)\alpha_{gj},\alpha*\alpha_{ij}+(1-\alpha)\alpha_{gj}^{*}), & \mathrm{mod}(\theta,4)=2\\ \alpha*\alpha_{ij}+(1-\alpha), & \mathrm{mod}(\theta,4)=3\end{cases},$$

$\beta_{ij}^{z}=\sqrt{1-(\alpha_{ij}^{z})^{2}}$, α is a random positive real with a range between 0 and 1, θ is a random positive integer, $R(x,y)$ is a random selection function, which indicates randomly select one from x and y. It is capable of proof: when mod(θ,4)=0, a new allocation α_{ij}^{z} is generated between -1 and α_{gj}; when mod(θ,4)=1 or mod(θ,4)=2, α_{ij}^{z} is generated between -1 and 1; when mod(θ,4)=3, α_{ij}^{z} is generated between α_{ij} and 1.

The new allocation has great chance to obtain more fitness and has more probability to be the optimal allocation. The operations of vaccination reflect the criterion of our strategy: good individuals should have more chance to be accepted in the allocation than bad individuals.

3) Immune Tests. After vaccination, the vaccinated chromosome needs immune test. If the fitness of the vaccinated chromosome is smaller than that of the original one, which means that degeneration has happened in the process of vaccination, instead of the vaccinated chromosome, the unvaccinated chromosome will participate in the next competition.

III. Design And Influence Of The Belief Space

A. The Evolution of the Belief Space

The population size of the belief space is usually set to 20% of the population space size; all the vaccines of population are involved in the crossover operation. The common crossover operator is limit to between two individuals. By using quantum theory (namely interference characteristic), the quantum crossover—all interference crossover [16] is used in this paper. Let the population size is 5, and the chromosome length is 8 described as the following Table II in detail: take the 1st element of chromosome 1,take the 2nd element of chromosome 2, take 3rd element of chromosome 3, take the 4th element of chromosome 4, etc. After quantum crossover operation, the new population is shown as the following Table III.

Because the population size of the belief space is smaller than that of the population space, quantum crossover can be performed by less computational cost, but it can bring more diverse vaccines among population and avoid prematurity.

TABLE II
CHROMOSOMES BEFORE ALL INTERFERENCE CROSSOVER IS USED

No.	Chromosome
1	A(1) E(2) D(3) C(4) B(5) A(6) E(7) D(8)
2	B(1) A(2) E(3) D(4) C(5) B(6) A(7) E(8)
3	C(1) B(2) A(3) E(4) D(5) C(6) B(7) A(8)
4	D(1) C(2) B(3) A(4) E(5) D(6) C(7) B(8)
5	E(1) D(2) C(3) B(4) A(5) E(6) D(7) C(8)

TABLE III
CHROMOSOMES AFTER ALL INTERFERENCE CROSSOVER IS USED

No.	Chromosome
1	A(1) A(2) A(3) A(4) A(5) A(6) A(7) A(8)
2	B(1) B(2) B(3) B(4) B(5) B(6) B(7) B(8)
3	C(1) C(2) C(3) C(4) C(5) C(6) C(7) C(8)
4	D(1) D(2) D(3) D(4) D(5) D(6) D(7) D(8)
5	E(1) E(2) E(3) E(4) E(5) E(6) E(7) E(8)

B. The Acceptance Function

The *accept*() function selects individuals who can directly impact the formation of current belief space. During evolutionary search of the population space, when every *AcceptStep* generations is completed, the current best individual is selected to replace the worst individual in the belief space, where *AcceptStep* is a parameter given by user, in our study, *AcceptStep* is suggested using 15.

C. The Influence Function

The influence function is responsible for choosing the knowledge source to be applied to the variation operator of the population space evolution. During evolutionary search of the belief space, when every *InfluenceStep* generations is completed, apply roulette wheel selection on the belief space, the individual with higher fitness would has more chance to be chosen as the new vaccine applied in the vaccination operation.

$$InfluenceStep=BaseNum+\frac{EndStep-CurrentStep}{EndStep}*DevNum$$

where *EndStep* is the total amount of the algorithm's iterations, *CurrentStep* is the number of current iterations, *BaseNum* and *DevNum* are constants of 10 and 30 respectively as suggested by this paper. During the whole evolutionary process of the population space, at the beginning, a larger *InfluenceStep* is helpful to accelerate the process, because vaccine in the belief space has less impact on evolutionary search of the population space; while a smaller *InfluenceStep* tends to facilitate global exploration (searching new areas) to fine-tune the current search area, directed by evolving knowledge in the belief space. Suitable selection of *InfluenceStep* can provide a balance between global and local exploration abilities and thus require less iterations on average to find the optimum.

Ⅳ. ALGORITHM CONVERGENCE

Theorem 1: Population sequences of CIQEA $\{A(n), n>=0\}$ are finite stochastic markov chain.

Proof. Population sequence shift may express as the following stochastic states:

$$A(K) \xrightarrow{measure} A^1(K) \xrightarrow{crossover} A^2(K) \xrightarrow{mutation} A^3(K)$$

$$\xrightarrow{vaccination} A^4(K) \xrightarrow{test} A^5(K) \xrightarrow{select} A(K+1)$$

CIQEA uses Q-bit chromosome, *which* is then represented by above (3). α_i and β_i have a limited precision, assume that the precision is ε (ε is 10^{-5} or 10^{-6}), so the dimension of α_i in Q-bit chromosome is $(Qh-Ql)/\varepsilon$, where Qh is the upper bound of α_i , Ql is the lower bound of α_i. For Q-bit, Qh=1, Ql=-1, let $V=(Qh-Ql)/\varepsilon$, therefore $V=2/\varepsilon$. Assume that the length of chromosome is M, the size of population is N, thus the size of population states space is $N^* V^M$, therefore the population sequence is finite.

$A(K+1)=T(A(K))=$ $Ts \circ Tte \circ Tva \circ Tmu \circ Tc \circ Tme(A(K))$, Ts, Tte, Tva Tmu, Tc and Tme are transition matrices of stochastic states, denoting selection operator, test operator, vaccination operator, quantum rotation gate mutation operator, crossover operator and measurement operator, respectively, they have nothing to do with the number of iterations K, thus $A(K+1)$ only have to do with $A(K)$. Therefore $\{A(n), n>=0\}$ are finite stochastic markov chain, which completes the proof.

We assume that S is the feasible solutions space and f^* is the optimal solutions of S, let $A^*=\{A|\max(f(A))=f^*, \forall A\in S\}$.

***Definition* 2**: $\{A(n), n>=0\}$ are stochastic states, $\forall$ $S_0 \in S$, S_0 is the initial solution. If $\lim_{k\to\infty} p\{A(k)\in A^* \mid A(0)=S_0\}=1$, then the stochastic states $\{A(n), n>=0\}$ are called convergence with probability one[15].

Let P_k denote $P\{A(k) \in A^*|A(0)=S_0\}$, then $P_k=\sum_{i\in A^*} P\{A(k)=i\ |A(0)=S_0\}$.

Let $P_i(k)$ denote $P\{A(k)=i\ |A(0)=S_0\}$, then

$$P_k=\sum_{i\in A^*} P_i(k) \tag{4}$$

Let $P_{ij}(k)=P\{A(k)=j\ |A(0)=i\}$.

Under elitist approach (the best individual survives with probability one), we have two special equations [15]:

$$\text{When } i\in A^*, j\notin A^*,\quad P_{ij}(k)=0 \tag{5}$$

$$\text{When } i\in A^*, j\in A^*,\quad P_{ij}(k)=1 \tag{6}$$

Theorem 2:CIQEA is convergence with probability one.

Proof. From the above (4) $P_k=\sum_{i\in A^*} P_i(k)$

$$P_{k+1}=\sum_{i\notin A^*}\sum_{j\in A^*} P_i(k)P_{ij}(1)+\sum_{i\in A^*}\sum_{j\in A^*} P_i(k)\,P_{ij}(1)$$

From $\sum_{j\notin A^*} P_{ij}(1)+\sum_{j\in A^*} P_{ij}(1)=1$

Thus $P_k=\sum_{i\in A^*} P_i(k)=\sum_{i\in A^*} P_i(k)(\sum_{j\notin A^*} P_{ij}(1)+\sum_{j\in A^*} P_{ij}(1))=$ $\sum_{i\in A^*}\sum_{j\in A^*} P_i(k)\,P_{ij}(1)+\sum_{i\in A^*}\sum_{j\notin A^*} P_i(k)\,P_{ij}(1)$

From above (5) $\sum_{i\in A^*}\sum_{j\notin A^*} P_i(k)\ P_{ij}(k)=0$, so $P_k=\sum_{i\in A^*}\sum_{j\in A^*} P_i(k)P_{ij}(1)$

Thus $P_{k+1}=P_k+\sum_{i\notin A^*}\sum_{j\in A^*} P_i(k)\ P_{ij}(1)>P_k$, so that, $1\geq P_{k+1}>P_k>P_{k-1}>P_{k-2}\ldots\ldots\geq 0$, therefore $\lim_{k\to\infty} p_k=1$. By definition 2, CIQEA is convergence with probability one.

Ⅴ. EXPERIMENTAL RESULTS AND ANALYSIS

In this section, the knapsack problem, a kind of combinatorial optimization problem, is used to investigate the characteristics of CIQEA. The knapsack problem can be described as selecting from among various items those items that are most profitable, given that the knapsack has limited capacity. The 0-1-knapsack problem is described as follows. Given a set of m items and a knapsack, select a subset of the items so as to maximize the profit $f(X)$

$$f(X)=\sum_{i=1}^{m} x_i \times p_i$$

$$st.\sum_{i=1}^{m} x_i \times w_i \leq C$$

where $\mathbf{x}=(x_1,x_2,\ldots,x_m)$, x_i is 0 or 1, p_i is the profit of item i, w_i is the weight of item i, and C is the capacity of the knapsack. If x_i=1, the ith item is selected for the knapsack. In all experiments, strongly correlated sets of data were considered as

$$w_i = uniformly\quad random\ [1,10]$$

$$p_i = w_i + 5$$

and the following average knapsack capacity was used:

$$C=\frac{1}{2}\sum_{i=1}^{m} w_i$$

The data were unsorted. Three knapsack problems with 100,250, and 500 items were considered.

In our study, we execute CIQEA to solve these combinatorial optimization problems. The above problems were examined by the QEA in [3] and IQEA in [6]. The existing results reported in [3] and [6] can be used for a direct comparison in Table IV.

The population size of CIQEA was set to 10. The vaccination proportion was 45%. A rotation gate was used for the Q-gate, and the parameter setting of Table I was (0, 0, 0.01π , 0, -0.01π , 0, 0, 0) recommended in[3] and the maximum generation is 10^3.

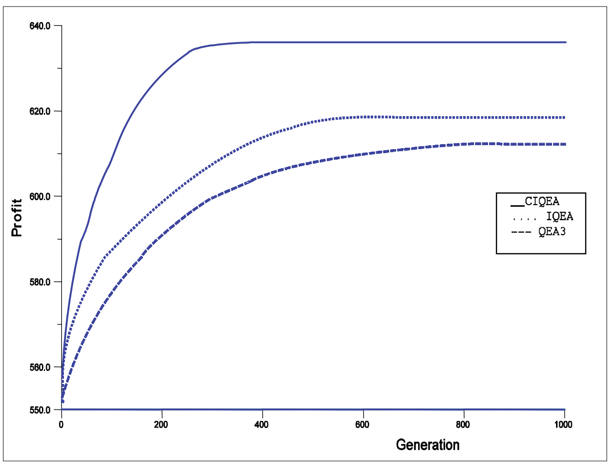
As a performance measure of the algorithms, we performed 30 independent runs for CIQEA on the knapsack problems with 100, 250, and 500 items and recorded in Table IV.

TABLE IV
THE COMPARISON OF QEA(3),IQEA AND CIQEA.(THE PARENTHESIZED VALUES ARE THE POPULATION SIZES.)

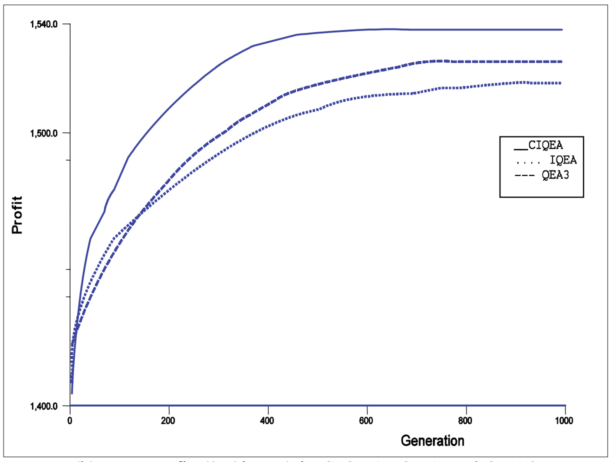
Items	Performance	QEA3 (10)	IQEA (10)	CIQEA (10)
100	best	612.7	617.9	**635.04**
	mean	609.5	614.0	**615.42**
	worst	607.6	585.2	**608.01**
	stdev	2.404	-	**2.23**
250	best	1525.2	1519.5	**1539**
	mean	1518.7	1511.4	**1519.3**
	worst	1515.2	1471.3	**1516.4**
	stdev	2.910	-	**2.65**
500	best	3025.8	3053.4	**3053.9**
	mean	3008.0	3036.5	**3038.1**
	worst	2996.1	2931.7	**2998.4**
	stdev	8.039	-	**7.83**

As Table IV shows, CIQEA performs significantly better than QEA3 and IQEA in term of profit amount, because its population space evolves under guidance of the belief space and has better adjusting direction to the better solution.

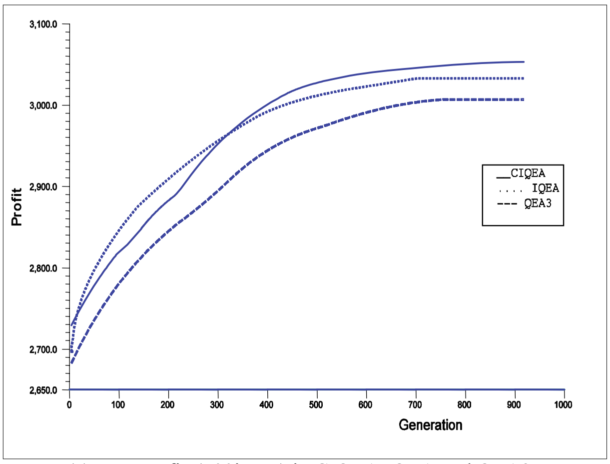
The convergence tendency of CIQEA, IQEA and QEA3 can be shown clearly in Fig. 3. In the cases of 100 and 250 items, the best profit was obtained with CIQEA after 300 and 550 generations respectively, whereas QEAs were able to obtain after 450 and 750 generations, respectively. This certainty of convergence of CIQEA may be attributed to its ability to maintain the population diversity. But, in the cases of 500 items, the improvements are not so remarkable, further research should be investigated.



(a) Best profits(100items) in CIQEA,IQEA and QEA3



(b) Best profits(250items) in CIQEA,IQEA and QEA3



(c) Best profits(500items) in CIQEA,IQEA and QEA3

Figure 3. Convergence comparison of CIQEA, IQEA and QEA3 on the knapsack problem.

VI. CONCLUSIONS AND FUTURE WORK

This paper has proposed a novel dual-evolutionary cultural immune quantum evolutionary algorithm (CIQEA) for a class of combinatorial optimization problem. The balance between exploration and exploitation of solutions within a search space are realized through the integration of the immune vaccination algorithm in the quantum evolutionary algorithm procedure. The belief space accepts a certain number of elite individuals and takes quantum crossover operation for improvement of population diversity and avoiding prematurity. Using the immune operation, the CIQEA is capable of alleviating degeneration phenomenon and greatly accelerate convergence.

The efficiency of the approach has been illustrated by application to combinatorial optimization problem. Simulation results show that compared to previous works, our proposed CIQEA can yield significant improvements in both the convergence rate and solution quality. The further work is exploiting more reasonable vaccination model and different types of influence functions, which may allow a better exploration of the fitness landscape.

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