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A Globally DiversifiedIsland ModelPGA for Multimodal Optimization

Li Feng Zhang, Rong He
School of Information, Renmin University of China
59, Zhongguancun Street, Haidian, Beijing
P.R.China,100872
Lifeng.zhang@hotmail.co.uk

***Abstract*—Multimodal optimization aims to find multipleglobal and local optima as opposed to only the best optimum. Parallel genetic algorithms (PGAs) provide a natural advantage for dealing with this issue, since they are multi-population based searching methodologies. For single population based evolutionary algorithms, a number of niching and multimodal optimization techniques have been proposed and successfully applied to cope with this problem. However, these approaches are definitely not applicable for PGAs, since due to communicational and computational costs it is very always impossible to obtain and compute global information of all the sub-populations during massive parallel evolution procedure.In this study, a new island model PGA, called local competitionmodel (LCM), is developed to cope with this issue. The new method only uses local information received from a few neighbouring subpopulations to reach a global diversification in which all the subpopulations are automatically allocated to differentareas of searching space so that they canconverge to multiple optima including both global optima and local optima.Finally, experimental studies on both real number optimization and combinatorial optimization are implemented to illustrate the performance of the new PGA model.**

Keywords-Parallel genetic algorithm; Island model; Niching; Multimodal optimization

I. INTRODUCTION

In real applications, it may bedesirable to find multiple global and local optimaof an optimization problemin a single run. Multimodal optimization aims to find multipleglobal and local optima as opposed to only one best solution.On one hand, it may provide a better understandingofthe solution space landscape.On the other hand, the users can easily choose the most proper solution in his/her problem domainfrom the found optima without worrying about the performance of solution.

Unfortunately, the natural tendency of genetic algorithms (GAs) is to converge to only one best solution because of the global selection scheme used.How to detect and maintain multiple optima are two challenges of solving multimodal optimization problems [4]. To overcome this problem, numbers of niching techniques had been proposed to prevent GAs from premature convergence to a single optimum, such as clearing, sharing, crowding, speciation, and other methods such as locally informedparticle swarm (LIPS), attraction basins estimating GA, and ring topology PSO [4], [5], [20].

In recent years, parallel computing is rapidly becoming a beneficial tooland a prominent technology in many fields that need to tacklecomplex problems.ParallelGAs (PGAs),which are extensions of traditional GAs, can benefit significantly from thistrend since evolutionary algorithms can be parallelized anddistributed straightforwardly, andhave been demonstrated to be effective and robust in searching large and complex spaces in a wide range of applications [1], [2]. Generally, PGA models can be classified into four basic types, master-slave model, fine-grained model (also refer to as cellular model), island model (also named distributed GA or coarse-grained model), and hierarchical models [3].Fine-grained and master-slave models consist of only a single population. Island model is a type of multi-population model that consists of a number of subpopulations distributed on the different processors called islands. The subpopulations distributed on each island execute as simple GAs independently, and exchange individuals periodically called migrationmechanism.Hierarchical PGA mixes the other three kinds of models and develops into a hierarchical structure, so it also called the multi-layered parallel model. Island model PGAs are particularly well-suited for parallel computing environments such as cloudcomputing and grid computing due to thelow communication costs.They have been widely acknowledgedto speed up the searching process and to obtain higher qualitysolutions to large scale and complex optimization problems [11], [12].

Island model PGA is also benefit for preventing the problem of premature convergenceto some extent due to thesemi-isolation of the subpopulations. Nevertheless, Migration in PGA can be viewed as a special global elitist strategy, since the best individuals move from one subpopulation to the others every time migration happens until a super best individual capture the entire populations.Therefore, it could not essentiallymaintain the diversity of entire populations, and detecting and maintaining multiple optima arestill challenges of the design of island models.

Obviously the niching techniques which are designed for single population Gas could not directly applied to cope withisland model PGAs. For multi-population based PGAs, various PGA models have been proposed to overcome this problem by the use of heterogeneous PGA settings, hierarchical models, dynamic or adaptive migration schemes[6], [7], [8], [9]. More straightforwardly, [13] developed a new method to create subpopulations within the niches defined by the multi-optima. [10] usesa master node to sendsbiased seeds to slave nodesfor guiding subpopulation initializationand searching in biasedareas in the entire solution space. [14] introduces a speciating island model to exploit new species when they arise by allocating them to new search processes executing on other islands. In [15], a multi-population algorithm was developed to perform migration between subpopulations where individuals are redistributed to new subpopulations based on a speciation tree which places similar individuals together. In addition, clustering techniques have been also incorporated in PGA to locate multiple optimal or sub-optimal solutions, and find better solutions in shorter computational time [16], [17].

Nevertheless, these methods still have drawbacks. In order to perform well, they always require global information about all thesubpopulations, prior knowledge of optimization problem, and much morecomputational and communicationalexpenses. Furthermore, most of the previous approaches are designed only for improving the diversity and exploration capability of PGA, and will finally locatea single best solution, while fail to maintainmore optima even though they are with very good performance. As aforementioned it might be desirable to obtain both global and excellent local optima simultaneously. To cope with this problem, [18] proposed a self-organised islandmodel which achieves a global diversification of PGA by the use of the topological information of island interconnections to guide the evolutionary search of each subpopulation.

In the present study an alternativeisland model PGA model is developed. The basic idea behind the new method is that a set of connected island can be viewed as a local competition environment, and may contend for a limited number of dummy living resources. When most neighbouring subpopulations converge into the same searching area in solution space, theassociatedresourcewill become insufficient and some of the subpopulations will be driven away from the overcrowded area. Through using the new method, island modelis able to automatically allocate different searching regions to local GAs to maintain the diversity between subpopulations. The advantages of the new modelcan be summarized as the follows.

- Firstly, each island only uses local information obtained from a few neighbouring subpopulations but not global information about the entire population, and therefore it only needs small communicational and computational costs.
- Secondly, in the newmethodthe only two parametersfor adjusting the power of diversification are a multiplier and a percentile value which are much easier to be selected.
- Finally, the new method automatically allocatessubpopulations to different regions of solution spaceso that itis able to find multiple optima including both global optima and sub optima, and maintains these optimalsolutions until the end of aevolution.

The present study is organised as follows. In section 2, a brief introduction to island model topology is presented, and the principles of new model are introduced. Section 3 presents the computational procedure of the new method. In section 4, two case studies are employed to examine the performance of the new method. Finally, in Section 5 conclusions are drawn to summarise the study.

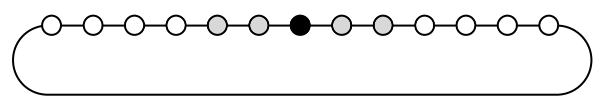
II. LOCAL COMPETITION MODEL (LCM) PGA

In this study, a new PGA model called local competition model (LCM) is proposed to maintain the diversity of subpopulations in PGA procedure for multimodal optimization. As the new method is developed on the basis of traditional distributed PGA, relevant PGA models will be also briefly revisited in the following subsection.

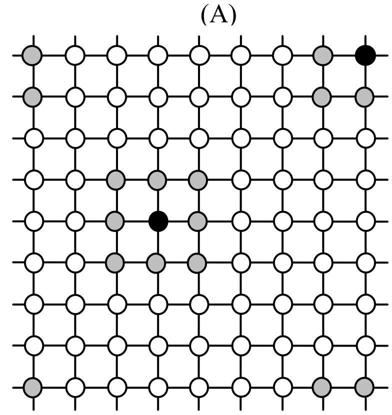
A. Island Model PGA

Island model is the most widely used PGA model and may be implemented easily on parallelhardware. It is a type of multi-population model that consists of a number of subpopulations distributed on the different islands. These subpopulations execute as simple GAs independently, and exchange representative individuals occasionally. This exchange mechanism is called migration.Migration interval and migration rate specifies how often and how many individuals need to be exchanged. Representative selection and replacement schemes choose individuals from each subpopulation to execute the migration [19]. Finally, island model topology and neighbourhood shape determine the routes of exchanging individuals.

Consider an island model PGA with M subpopulations $\{\mathbf{P}_i \mid 1 \le i \le M\}$ .Each subpopulation consists of N individuals $\{s_j \mid 1 \le j \le N\}$, and directly connects with K neighbours. As shown in Fig 1, two widely-used PGA models i.e. ring (4 neighbours) and grid (8 neighbours) connection topologies are adopted in this study.



(A)



(B)

Fig 1.Island model PGA: (A) is ring connection topology; and (B) is grid connection topology with Moore neighbourhood: each circles presentsa subpopulation (island) interconnected with its neighbours, black circle present host subpopulations; grey circles present the neighbours connected to the host subpopulations

B. Local competition model

Searching radius of subpopulation: In most niching algorithms, such as fitness sharing, niche radius is a measure of distance for disorganising whether two individuals surround the same modal, nevertheless, it is always difficult to select niche radius since optimization problems are many and varied. In this study, a new distance measure, called searching radius of subpopulation, is proposed to substitute for the traditional niche radius.

Firstly, at the last generation before migration a distance parameter D_i is computed as follows.

$$D_i = \max(\mathbf{d}_{rep}) \quad (1)$$

where $\mathbf{d}_{rep} = \{d_{rep,j} \mid 1 \le j \le N\}$, and $d_{rep,j}$ denotes the distance between s_i^{rep} and $s_j \in \mathbf{P}_i$. s_i^{rep} is the representative individual.Then, searching radius $r_i^{(t)}$ is derived as follows.

$$r_i = \alpha \text{median}\{D_i, D_{n1}, ..., D_{nK}\} \quad (2)$$

It should be noted that r_i is a median which could make theradiusvalueuniform, and prevent the influence of extreme subpopulations. Moreover, $\alpha > 0$ is a parameter to modify the power of diversification in whichthe diversity of entire population will become higher as α increases.

***Grouping of representatives*:**It is quite possible that the searching area of the two subpopulations overlap when the distance between their representatives is smaller than subpopulation radius. In other words, two local GAs can be viewed as searching around the same area in solution space if the two representatives are close to each other. Based on this principle, the new method divides the representativesinto groups that each group indicates a distinctive searching area.

Consider a host subpopulation $\mathbf{P}_i$, once migration occurs representatives $\mathbf{S}^{i,rep} = \{s_i^{rep}, s_{n1}^{rep}, ..., s_{nK}^{rep}\}$ including boththe native and immigrantscan be classified into a number of groups $\{\mathbf{G}_i \mid 1 \le i \le Kg\}$ where $\mathbf{G}_1 \cap \mathbf{G}_2, ..., \mathbf{G}_{Kg} = \mathbf{s}^{i,rep}$ and $\mathbf{G}_i \cap \mathbf{G}_j = \varnothing$. In this study, the definition of a group is based on the notation of reachability. A representative s_p^{rep} is called directly reachable from another representative s_q^{rep} if it is not farther away than $r_i^{(t)}$. s_p^{rep} is also reachable from the s_q^{rep} if there is a chain of representatives $s_1^{rep}, ..., s_k^{rep}$ where $s_1^{rep} = s_p^{rep}$ and $s_k^{rep} = s_q^{rep}$ such that each s_{j+1}^{rep} is directly reachable from s_j^{rep}. Then, all the representatives which are mutually reachable with respect to r_i are classified into the same group. Fig 2 shows the sketch plot of representative grouping.

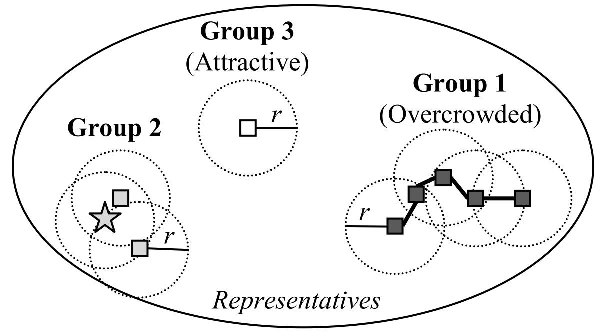


Fig 2.Sketch plot of representative grouping: squares present the immigrated representatives; star presents the native representative.

***Local competition*:** The basic idea of local competition mechanism is that a set of neighbouring subpopulations forms a local competition environment, and contend for a limited number of dummy living resources. Similar subpopulations, in which their representatives are classified into the same group, split up a single resource.Three rules of resource constraint are proposed as follows.

- If there are too many subpopulations share the same resource, the resource will become insufficient, hence, only better subpopulations can survive, and the other ones have to move to other areas for finding new resources.
- If there are few subpopulations share the resource, since the resource is sufficient the corresponding searching region is very attractive to other subpopulations.
- When a proper number of representatives converge intoa searching area, the area is neither overcrowded nor attractive.

Let $L_{\min}$ and $L_{\max}$ respectively denote the limitations of group size that perform attractive and overcrowded. It should be noted that, in the present studystudy $[L_{\min}, L_{\max}]$ are fixed to be [1,3] for ring topology, and [2,4] for grid topology.

Subsequently attractive representatives $\mathbf{S}^A$ and overcrowded representatives $\mathbf{S}^O$ are extracted from $\mathbf{S}^{i,rep}$ as follows.

Selection procedure of $\mathbf{S}^A$ and $\mathbf{S}^O$

Begin
$k = 1$, $\mathbf{S}^A = \varnothing$, and $\mathbf{S}^O = \varnothing$
While $k \le Kg$
n = the size of group $\mathbf{G}_k$
If $n \le L_{\min}$
$m = L_{\max}$-n-1 , $\mathbf{G}_k$ = copy $\mathbf{G}_k$ m times
$\mathbf{S}^A = \mathbf{S}^A \cup \mathbf{G}_k$
Elseif $n \ge L_{\max}$
If ($s_i^{rep} \in \mathbf{G}_k$ and s_i^{rep} is not the best $L_{\max} - 1$ representatives in $\mathbf{G}_k$) or $s_i^{rep} \notin \mathbf{G}_k$

$\mathbf{S}^O = \mathbf{S}^O \cup \mathbf{G}_k$

End If

End If

$k = k + 1$

End While

End Begin

C. Rejection operation

$\mathbf{S}^O$ indicates the searching areas of insufficient recourse, therefore, host subpopulation should avoid these areas as much as possible. This process is named rejection operation which is achieved through reducing the fitness of the native individuals. There are two conditions may arise in the use of rejection operation, as depicted inFig 3.

- Condition 1: When host subpopulation overlaps the overcrowded area, all the nearby native individuals are rejected in order to force host subpopulation escape from the region.
- Condition 2: When host subpopulation is isolated from the representatives, some of the native individuals are also rejected even they are outside the overcrowded region, for the sake of driving host subpopulation way from the area.

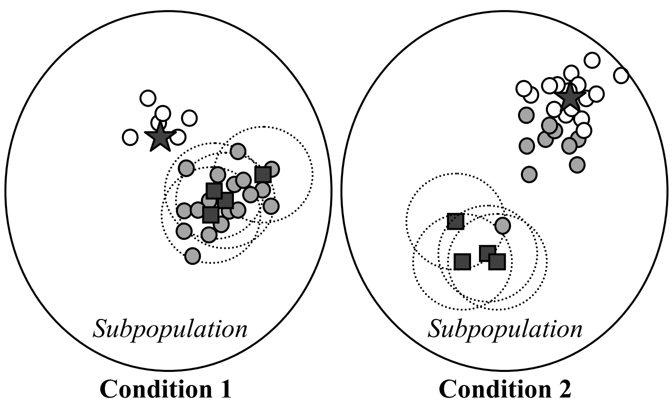


Fig 3.Sketch plot of rejection process: circles denote the individuals in these two subpopulations; black squares present the immigrated representatives selected for implementing rejection; black star present the native representative generated after rejection operation; grey circles present the native individuals which is rejected; white circles present the other native individuals.

The computational procedure of rejection operation is formulated as follows. First, threshold R_{ik} with respect to a particular $s_k^{rep} \in \mathbf{S}^O$ is derived as follows.

$$R_{ik} = \max(r_i, d_{k,\beta\%}) \tag{3}$$

where $d_{j,\beta\%}$ is the β percentile of the distances $\{d_{jk} \mid 1 \le j \le N\}$ between s_k^{rep} and $\mathbf{P}_i$. β is the parameter for adjusting the power of rejection, i.e. the larger α the higherrejection power.

Host subpopulation rejects an individual through decreasing its survival probability. Then, for individual s_j the reassignment of fitness is derived as follows.

$$\varepsilon_{ijk} = \begin{cases} \dfrac{R_{ik} - d_{jk}}{R_{ik}}, & d_{jk} \le R_{ik} \\ 0, & d_{jk} > R_{ik} \end{cases} \tag{4}$$

$$f_j^{\circ} = f_j - (\max(\mathbf{f}) - \min(\mathbf{f})) \sum_{\mathbf{s}^{reject}} \varepsilon_{ijk} \tag{5}$$

where f_j and f_j° respectively denote the raw and reassigned fitness values.It is clear that $f_j^{\circ} < f_j$ if d_{jk} is smaller than the threshold, otherwise $f_j^{\circ} = f_j$.

III. COMPUTATIONAL PROCEDURE OF THE NEW METHOD

The new PGA procedure differs from traditional island model in four aspects surmised as follows.

Two subpopulations on each island:On each island at generation t, besides subpopulation $\mathbf{P}_i^{(t)}$, a rejection pool $\mathbf{Q}_i^{(t)}$ is also formed to keep $\mathbf{S}^O$. It is obviously that $\mathbf{Q}_i^{(t)}$ is empty at the beginning of evolution procedure, and will be updated every time migration occurs.

Enlarged selection after every migration: Once migration takes place, $\mathbf{S}^A$ are picked up and passed onto host subpopulation straightforwardly. Roulette selection, then, are adopted to select individuals from the enlarged $\mathbf{P}_i^{(t)}$ to construct $\mathbf{P}_i^{(t+1)}$.

Fitness reassigningand representative selection: At each generation, rejection operation is implemented to reassign fitness values f_j° to all the individuals through the use of (5) for computing survival probability.In addition, for each island the individual with the largest f_j° is selected as representative, and will be chosen as emigrant to send copies to the other islands.

Since new subpopulation is selected according to f_j°, then representatives and the nearby individuals are most likely to survive during the evolution procedure. Representatives can be considered as the centres of diversified searching areas of local GAs so that selection process will automatically direct the subpopulations to different regions in solution space.

Local elitist strategy: Elite preserving technique is also employed in the new method. The best individual with the f_j° will be directly passed onto new generation to ensure the local best individual wouldn't be lost during parallel evolution procedure. At the same time, the global best individual, which is the best one of the local bests found so far, will be also preserved.

The computational procedure of the new PGA model is presented as follows.

LCM PGA

Begin

$t \leftarrow 0$

Initialize $\mathbf{P}_i^{(0)}$, $\mathbf{Q}_i^{(0)} = \varnothing$, and $r_i^{(0)} = 0$, where $1 \le i \le M$

While Termination condition is not met

Do in parallel for each island

If Migration condition is met

Exchange representatives s_i^{rep} and D_i with neighbouringsubpopulations

Divide $\mathbf{S}^{i,rep}$ into groups, and select $\mathbf{S}^A$ and $\mathbf{S}^O$

Pass $\mathbf{S}^A$ onto $\mathbf{P}_i^{(t)}$ directly, update $\mathbf{Q}_i^{(t+1)} = \mathbf{S}^O$, and calculate r_i

Else

$\mathbf{Q}_i^{(t+1)} \leftarrow \mathbf{Q}_i^{(t)}$, and $r_i^{(t+1)} = r_i^{(t)}$

End If

Evaluate $\mathbf{P}_i^{(t)}$ to assign raw fitness values f_j

If $\mathbf{Q}_i^{(t+1)} \ne \varnothing$

Perform rejection operation to reassign fitness values f_j°

Else

$f_j^{\circ} \leftarrow f_j$

End If

Compute survival probabilities for $\mathbf{P}_i^{(t)}$

Select individuals from $\mathbf{P}_i^{(t)}$ to construct $\mathbf{P}_i^{(t+1)}$

Perform crossover, mutation, and elitist strategies

End Do in parallel

$t \leftarrow t+1$

End While

End Begin

I. EXPERIMENTAL STUDIES

Experiments on both real numberoptimization and combinatorial optimizationare conducted to illustrate the proposed method under the situation of multimodal, the PGA performances of locating multi optima are observed under different island connection topologies.

A. Real number optimization

Two multimodal benchmark test functions, Rastrigin function and Ripple function, are employedin this study to test the new method. It is noted that these two functions display different and typical multimodal properties that Rastrigin function has a finite number of isolated local optima in its feasible solution space, contrarily, Ripple function has infinite numbers of optima continuously distributed on several circles. In this study, the dimension of the two functions was set to be 2 in order to visually investigate the distributions of subpopulations. The two test functions are given as follows.

$$\begin{cases} f_2(x) = \sum_{i=1}^{n} \left(x_i^2 - 10\cos(2\pi x_i) + 10 \right) \\ -5.12 \le x_i \le 5.12 \end{cases} \tag{6}$$

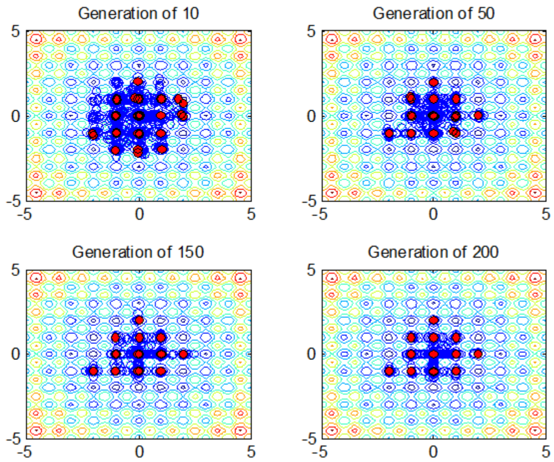
$$\begin{cases} f\ (x) = 0.5 + \dfrac{\left(\sin\sqrt{\sum_{i=1}^{n} x_i^2} \right)^2 - 0.5}{\left(1 + 0.001\sum_{i=1}^{n} x_i^2 \right)^2} \\ -10 \le x_i \le 10 \end{cases} \tag{7}$$

In these experiments, all the initial subpopulations were generated at random, and rank selection was adopted to compute survival probability for implementing roulette wheel selection. Convex crossover and Gaussian mutation with standard deviation of 0.2 were employed as genetic variations. Crossover and mutation rates were set as 0.6 and 0.1. For island model PGA, migration interval was set to be 10, the size of subpopulation was fixed as 20, in addition $\alpha = 1$ and $\beta = 30\%$. Ring topology with 50 subpopulations and grid topology with400 subpopulations were employed to implement the new PGA model. The maximum (termination) generation number was set to be 200.

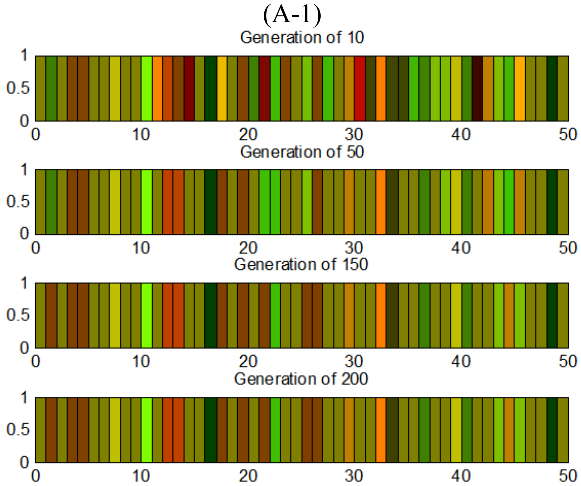
Figs 4 (A-1) to (D-1) show the contour maps of the objective function values, and the subpopulations distribution obtained during the PGA procedures for (6) and (7) respectively. The figures clearly suggest that the new method successfully locate both global optimum and numbers of sub-optima simultaneously. All subpopulations converge to the optima, particularly the representative individuals achieve the optimal or sub-optimal points exactly. Actually, these subpopulations are already stable, and their distribution would not change significantly even though they evolve for more generations. Moreover, Figs 4 (C-1) and (D-1) clearly suggests that with grid topology and more subpopulations the new island model could locate even more optima. Especially for Ripple function that the obtained optima evenly spread on the first sub-optimal circle.

For the sake of visually displaying the diversification performance of the subpopulations, RGB images, also referred to as true-colour images, are adopted to illustrate the subpopulation distribution correspond to the island model topology. Firstly, twodimensional individuals (solutions) are normalized into the range of [0 1]. Then, the normalized values are used as the components of red and green colour, and the blue colour component is fixed to be 0. Finally the colour representation of each individual is determined by the combination of the red, green, and blue intensities. It is clear that a similar colour indicates a similar solution. Moreover, it is noted that in these plots, each lattice presents a representative individual which represents the searching region of subpopulation, and ordered according to the interconnection topology of island model.

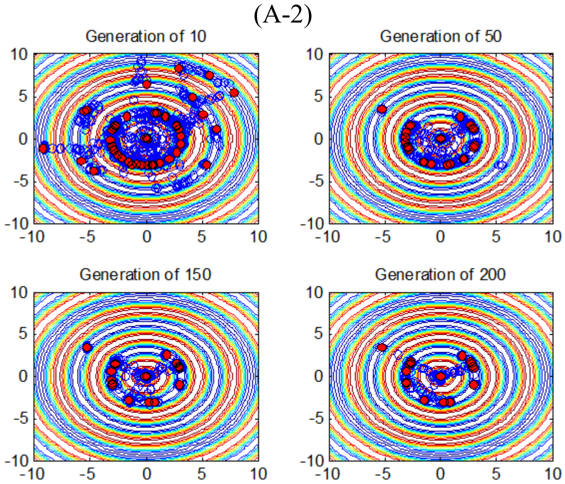
Figs 4 (A-2) to (D-2) present the RGB images for cases (6) and (7). As can be seen from the figures, at the beginning of evolution, subpopulations distribute randomly, and at the end of evolution they exhibit a regular distribution. First, similar representative individuals are grouped and linked together, which means that neighbouring islands always tend to locate similar optima by the means of migration operation. Second, according to the local competition mechanism different representatives appear alternatelyin every local region of the connection topologies so that it will avoid convergence to a single solution.



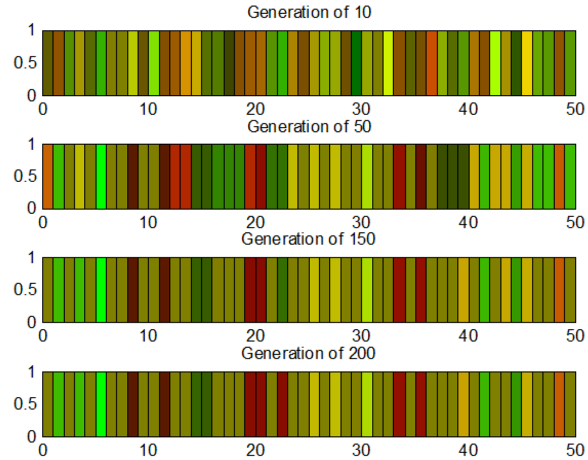
(A-1)



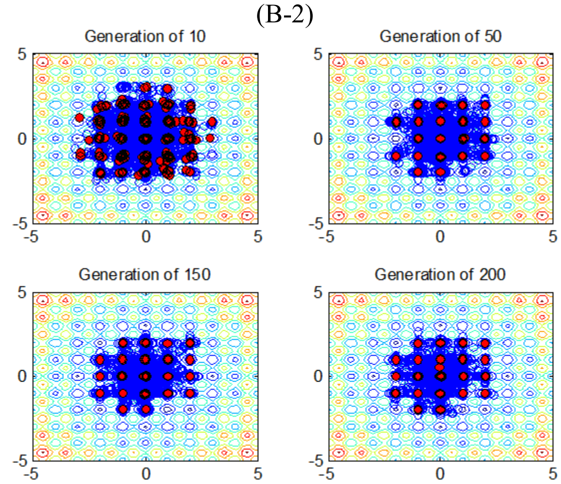
(A-2)



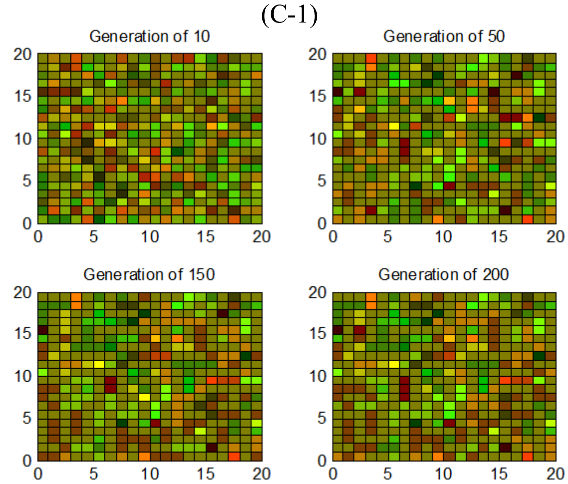
(B-1)



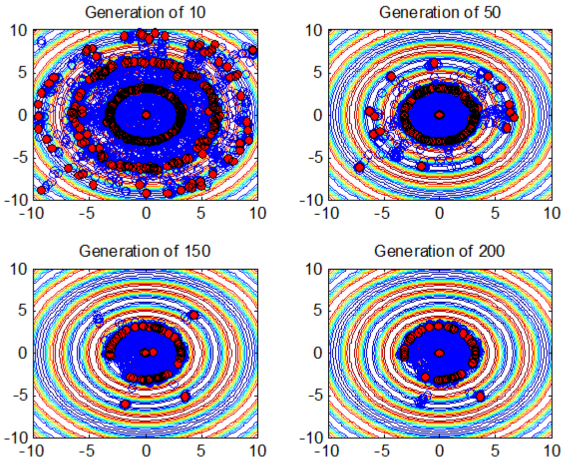
(B-2)



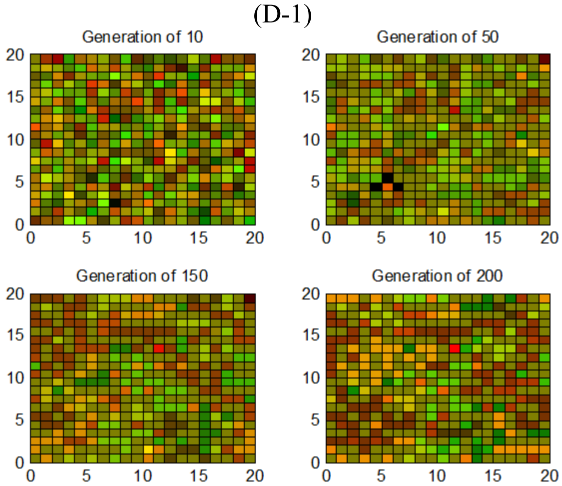
(C-1)



(C-2)



(D-1)



(D-2)

Fig.4. Experimental results for real number optimization: (A-1) to (D-1) show the subpopulation distributions (green solid circles present the representatives, and blue hollow circles present the other individuals),and (A-2) to (D-2) are RGB images; (A) and (C), (B) and (D) arethe results for functions (6) and (7) respectively; (A) and (B), (C) and (D) are obtained from the use of ring and grid topologies respectively.

B. Combinatorial optimization

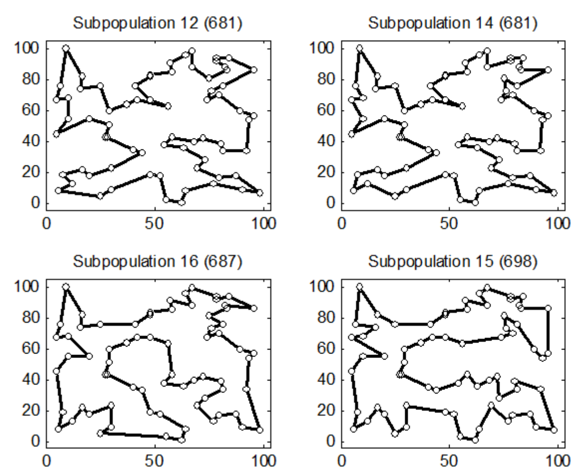
In this subsection, experiments on integer coded GA for solving well-known travel salesman problem (TSP) was conducted to demonstrate the performance of the new method. TSP is a typical combinatorial optimization problem which can be characterized by a finite number of discontinuous feasible solutions. It also can be viewed as a multimodal problem since a TSP problem always has a number ofoptimal solutions.Two benchmark problems, St70 andEil76, are selected from TSPLIB (http://elib.zib.de/pub/Packages/mp-testdata/tsp/tsplib/tsp/). OX crossover and Inversion mutation were employed, and crossover and mutation rates were set to be 0.5 and 0.3 respectively. For PGA, migration interval was set to be 20. The size of subpopulation was also fixed as 20.Ring topology with20 subpopulations and grid topology with100 subpopulations wereused here. Finally, $\alpha = 2$, $\beta = 20\%$, and the maximum generation number was set to be 3000. It should be noted that in this study the distance for TSP problem is measured as $d_{ij} = N_{diff} / N_{total}$ where N_{diff} is the number of different edges between twoTSP cycles, and N_{total} is the total edge number of a cycle.

The new method was implemented for each problem and each connection topology only once. Figs 5 (A-1) to (D-1) show the selected TSP solutions for the two problems obtained at the end of evolution procedure. Actually numbers of different optima were maintained at the generation of 3000 in these experiments. Here, only four typical solutions which are very different from each other are chosento display for each case. The figures clearly suggest that even with a single run the new PGA method is able to successfully locate different optima.

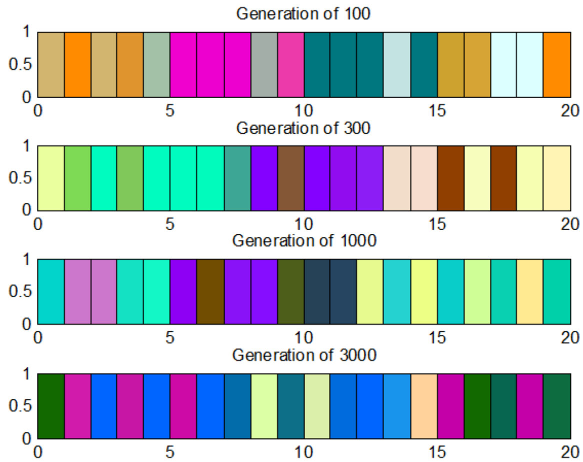
TSP is a typical combinatorial optimization problem, and therefore it is impossible to directly display TSP solution by RGB images. In this study a new conversion process is proposedand used to transfer a set of TSP solutions to three dimension real numbers.

- First the distance matrix is computed as $\mathbf{D} = [\mathbf{d}_1,\ldots,\mathbf{d}_M]$ where $\mathbf{d}_i = [d_{1i},\ldots,d_{Mi}]^T$.
- Second, principle component analysis (PCA) is used to reduce the dimension of $\mathbf{D}$ and three principle components are generated.
- Finally, these principle components are normalized into the range from zero to one, and used as the components of red, green, and blue colours for plotting RGB images.

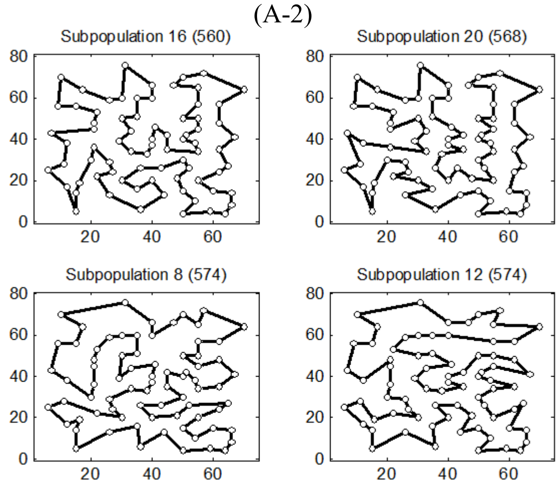
It is clearly that this method could not accurately describe TSP cycles in solution space, however, it can roughly position each TSP solution in a three-dimensional space, that is, similar solutions should display similar colours, and different colours indicate different solutions. Figs 5 (A-2) and (D-2) show the RGB images that the diversity of subpopulations is also clear and evident. Similar representatives are grouped together, and regularly distributed inaccordancewith the connection topologies.Many different optimum solutions have been found and kept until the end of PGA evolution.



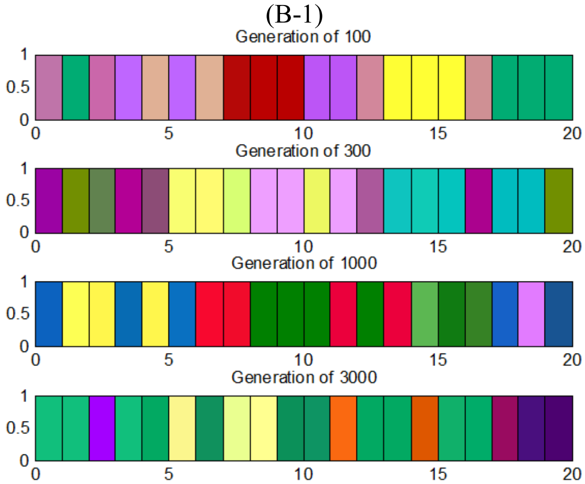
(A-1)



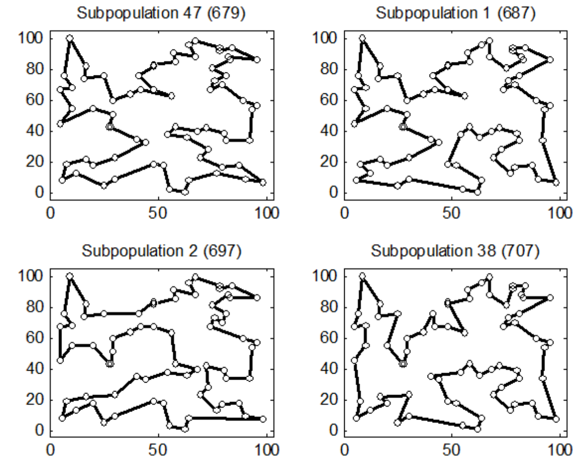
(A-2)



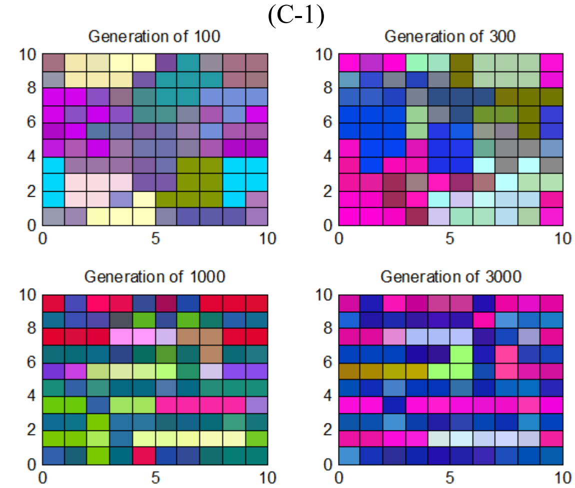
(B-1)



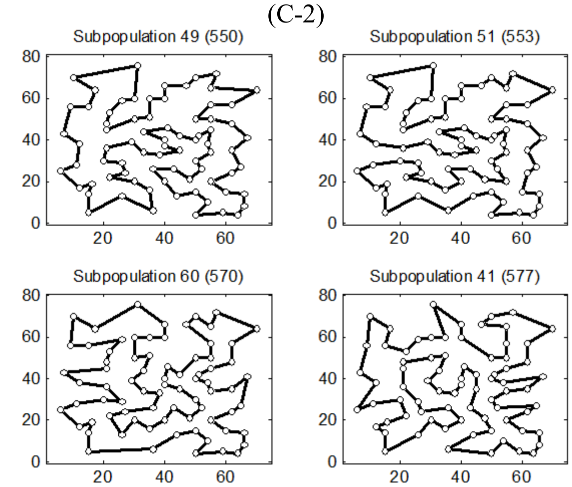
(B-2)



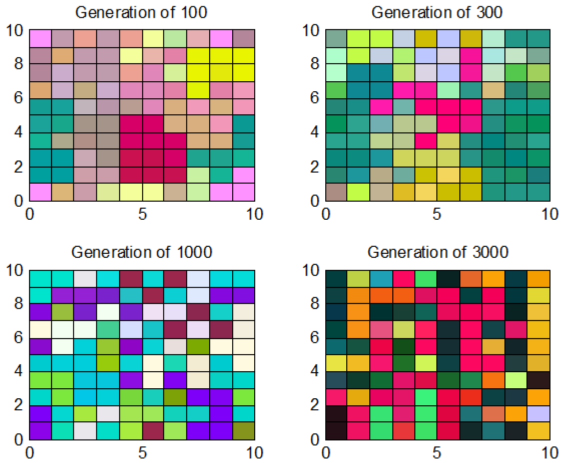
(C-1)



(C-2)



(D-1)



(D-2)

Fig.5. Experimental results for TSP optimization: (A-1) to (D-1) show optimal solutions (the title of each subfigure indicates the subpopulation number and objective function value) maintained at the last generation, and (A-2) to (D-2) are RGB images; (A) and (C), (B) and (D) are the results for St70 and Eil76 respectively; (A) and (B), (C) and (D) are obtained from the use of ring and grid topologies respectively.

II. Conclusions

In this study, a novel islandmodel PGA named LCM has been proposed to realizemultimodal optimization. The new method maintains the diversity of entire population of PGA by the use of onlylocal information exchanged from a few neighbouring subpopulations. It is able to locate multiple optimal solutions in a single run, and maintains these found optimasimultaneously until the end of evolution. Moreover itonlyhas two parameters which can be set easily as oppose to the specification of niching distance, or the number of optima.In the new model, without manualintervention, subpopulations are automatically guided in searching different regions of the solution space. Finally, it does not significantly enhance the communication and computational costs of island model PGA as only local information is utilized for conducting the new method. Empirical studies on both real number and integer number coded PGA have been implemented to illustrated the performance of the new method. Experiment results clearly suggest that the new model successfully locates numbers of optimal solutions, and these optima evenly distributed in the solution spaces. Furthermore, similar subpopulations are grouped together, regularly distributed inaccordancewith the connection topologies of islands.

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