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言語: eng
出版者: 
公開日: 2007-11-14
キーワード (Ja): 
キーワード (En): 
作成者: MAEDA, Yoichiro, ISHITA, Masahide, LI, Qiang
メールアドレス: 
所属: 
URL http://hdl.handle.net/10098/1164
Fuzzy Adaptive Search Method for Parallel Genetic Algorithm with Island Combination Process

Yoichiro Maeda\textsuperscript{a} Masahide Ishita\textsuperscript{b} Qiang Li\textsuperscript{b}

\textsuperscript{a}Dept. of Human and Artificial Intelligent Systems, Faculty of Engineering, Univ. of Fukui
\textsuperscript{b}Dept. of Human and Artificial Intelligent Systems, Graduate School of Engineering, Univ. of Fukui
3-9-1, Bunkyo, Fukui, 910-8507 Japan

Abstract

Genetic algorithms (GAs) pose several problems. Probably, the most important one is that the search ability of ordinary GAs is not always optimal in the early and final stages of the search because of fixed GA parameters. To solve this problem, we proposed the fuzzy adaptive search method for genetic algorithms (FASGA) that is able to tune the genetic parameters according to the search stage by the fuzzy reasoning. In this paper, a fuzzy adaptive search method for parallel genetic algorithms (FASPGA) is proposed, in which the high-speed search ability of fuzzy adaptive tuning by FASGA is combined with the high-quality solution finding capacity of parallel genetic algorithms. The proposed method offers improved search performance, and produces high-quality solutions. Moreover, we also propose FASPGA with an operation of combining dynamically sub-populations (C-FASPGA) which combines two elite islands in the final stage of the evolution to find a better solution as early as possible. Simulations are performed to confirm the efficiency of the proposed method, which is shown to be superior to both ordinary and parallel genetic algorithms.

Key words: Parallel Genetic Algorithm, Fuzzy Reasoning, Adaptive Search, Migration Rate

1 Introduction

Genetic algorithms are search algorithms based on the mechanics of natural selection and natural genetics [Goldberg(1989),Holland(1992)]. GAs can be applied to several types of optimization problems by encoding design variables...
to individuals. However, the use of GAs also poses several problems, the most important of which is that the search ability of ordinary GAs is not always optimal. This is particularly important in the early and final stages of the search, and is due to the fixed GA parameters (crossover rate, mutation rate etc.). The large number of iterations required to find a solution using GAs also limits their utility. Thus, many types of modified GAs have been proposed in an attempt to improve the performance of this potentially useful technique.

Lee et al. [Lee(1993)] proposed a method of dynamic control of GA parameters based on fuzzy logic techniques. In this method, the population sizes, and crossover and mutation rates are decided from average and maximum fitness values and differentials of the fitness value by fuzzy reasoning. Herrera et al. [Herrera(1996)] have reviewed many aspects of the adaptation of GA parameters based on Fuzzy logic controller. In our laboratory, a fuzzy adaptive search method for genetic algorithms (FASGA) has been developed as a modified GA [Maeda(1996),Maeda(1999)]. By this method, efficient searching is realized by using fuzzy inference rules to tune the GA parameters (crossover and mutation rates) based on maximum and average fitness values according to the search stage.

Parallel GA methods have also been proposed as effective methods for finding high-quality solutions using GAs [Nang(1994)]. In parallel methods, the total population is divided into independent sub-populations called islands. Three distribution models have been proposed: a master-slave model, a coarse-grained model (island model) [Pettey(1987)], and a fine-grained model (cellular model) [Manderick(1989)]. In the present research, the island model is employed so as to avoid the propagation of local minimum solutions in a whole population, thereby yielding a high-quality solution. After a predetermined number of generations (the migration interval), genes are moved to another island at a predetermined migration rate defined as the number of genes migrating per migration event. Although the population size of each island is smaller than that of the ordinary GA, the existence of islands and the operation of migration ensure that the variety of solutions is kept comparatively high in this type of parallel genetic algorithm (PGA). Generally, PGAs are therefore capable of higher-quality solutions than ordinary GAs.

The disadvantage of PGAs is that parallel processing cannot always be used effectively because the migration rate of PGA is a constant. Many modified methods have been proposed to overcome this problem, including a distributed GA with a randomized migration rate method [Hiroyasu(1999)], PGA with distributed environment scheme [Miki(1999)] and PGA with dual individuals in each island [Hiroyasu(2000)], and PGA with the master/slave particle swarm optimizers [Belal(2004)] and so on.

In the present study, a fuzzy adaptive search method for parallel genetic algo-
rithms (FASPGA) is proposed, combining FASGA with an island-model PGA. It is expected that this FASPGA method will overcome both of these problems, the sub-optimality of GA search, and the effective utilization of parallel processing [Maeda(2003)]. FASPGA is a PGA method that offers both fast search ability and high-quality solutions. Tuning is not only defined by the crossover and mutation rates but also by the migration rate that is determined via fuzzy reasoning. The main characteristic feature of this method is the fuzzy adaptive control of the migration rate of the PGA by evaluating the evolutionary degree for each island. Furthermore, in this paper, we also propose the FASPGA with the island combination process (C-FASPGA) which combines two elite islands in the final stage of the evolution to find a better solution as early as possible [Maeda(2004)].

Section 2 summarizes the general concept of FASGA and FASPGA with genetic parameters tuned by the fuzzy reasoning. Section 3 describes a proposal of C-FASPGA with the island combination process. In section 4, computer simulations of the optimization of the Rastrigin function to confirm the efficiency of the FASPGA and C-FASPGA approach are presented and the results are analyzed. Section 5 concludes the paper.

2 The FASPGA Method

The proposed method combines FASGA, which allows the genetic parameters to be tuned according to the search stage using fuzzy inference rules, with a PGA, which produces high-quality solutions. FASPGA uses fuzzy inference rules to improve both the search performance of each sub-population (tuning the genetic parameters in each sub-population in every generation), and the search performance of the whole population (tuning the migration rate). The FASPGA method is therefore expected to do faster searches and achieve higher-quality solutions.

2.1 General Concept of FASGA

The setting of genetic parameters and crossover and mutation rates influences the behavior and performance of GAs greatly. These parameters relate directly to the performance of the algorithm: the higher the crossover rate, the faster the production of new individuals, but the more easily the genetic schema is broken, causing the construction of individuals with high fitness value to fail quickly. If the crossover rate is too low, the search will be so slow to become stationary. Similarly, if the mutation rate is too small, the production of new individuals will be difficult. However, a high mutation rate causes the GA to
become a pure stochastic search algorithm. Finding robust genetic operators and parameter settings that avoid the premature convergence in any problem is not a trivial task. This is so because the interaction of these settings with the GA performance is complex and optimal values are often problem-dependent.

Many adaptive techniques have been suggested in order to adjust the genetic parameters associated with GA performance. The FASGA method proposed by our laboratory is such an adaptive technique, in which the genetic parameters, including the crossover and mutation rates, are tuned according to the search stage using fuzzy reasoning. In the early stage, the crossover rate should be small and the mutation rate should be large to maintain the species diversity. On the contrary, in the final stage, the mutation rate should be small in order to avoid breaking the schema of excellent individuals, and the crossover rate should be large for obtaining good individuals quickly.

2.2 Tuning of Genetic Parameters by Fuzzy Reasoning

The membership functions in the antecedent part and the singletons in the consequent part of the fuzzy rules used in the simulation of this research are shown in Fig.1. All genetic parameters of FASPGA including the crossover rate \( r_{c_i} \), the mutation rate \( r_{m_i} \), and the migration degree \( E_i \) to decide the migration rate \( r_{e_i} \) are decided by fuzzy reasoning. In this research, membership functions in the antecedent part of the fuzzy inference rule in FASPGA are almost same as FASGA. However, the migration degree \( E_i \) is an additional parameter in the consequent part in FASPGA. The fuzzy inference rule is based on two variables, the average fitness value \( f_{a_i} \) and the difference between the maximum and the average fitness value \( (f_{m_i} - f_{a_i}) \) in each island \( i \). By checking these two variables, we are able to recognize the evolutionary conditions of each island in every search stages. The fuzzy inference rule controls three genetic parameters (crossover, mutation and migration rates) according to these two values \( f_{a_i} \) and \( (f_{m_i} - f_{a_i}) \).

2.3 Individual Migration Process

This method also uses the so-called random ring typed migration process. In this migration method, an arrival island where to migrate some individuals is decided at random. To our knowledge, it is difficult to decide the migration rate properly, but it is very important because it concerns the performance of PGA directly. Generally, individuals of migration are some of the best individuals in each subpopulation. So if the migration process is frequent, an advantage is that it spreads the most advanced individuals in all populations and improves the speed of convergence. However, at the same time it causes the decrease of
population diversity, and thus a disadvantage is that avoids the exploration of different regions of the search space.

The migration rate is a constant in ordinary PGA. In other words, individuals of each sub-population are migrated in the same size. Regardless of sub-populations with the different evolutionary condition, this process is performed every time. This is not obviously effective by using parallel processing.

In the proposed method, the migration process is performed in every migration interval as shown in the following rule expression. We call the migration interval $Mig_{Span}$, that means a time tag from a migration to the next migration. The number of migration individuals is decided according to the migration degree in each island $E_i$ ($i$: island number, $i = 1, 2, \ldots, n$) by fuzzy reasoning. Therefore, in this method, the migration process is not performed in case of $E_i = 0$.

\[ IF \ (Generation \mod Mig_{Span} = 0) \ and \ (E_i \neq 0) \]
The concept of the migration process in FASPGA is shown in Fig.2. In this figure, some individuals (a proportion of $E_i$) are migrated to an island selected at random for each migration interval $Mig_{-}Span$. Therefore, the island with a migration degree $E_i = 0$ escapes the migration process. However, even if the migration process is not executed in a certain island, the next island is checked the migration process to maintain the Random ring chain.

![Fig. 2. Migration Process of FASPGA](https://via.placeholder.com/150)

In the process of migration, some individuals in a sub-population with an advanced evolutionary condition are easy to be spread in all populations. On the contrary, some individuals in sub-population with delayed evolutionary condition are difficult to be spread in the whole population under the tuning of fuzzy inference rule. So the fuzzy inference rule plays a good part in guiding the evolutional direction for improving the quality of solution effectively.

In this method, the migration rate $r_{e_i}$ is decided in proportion to the migration degree in each sub-population $E_i$ as shown in Equation (1) where $k$ shows a constant value. We used the tournament selection as the selection method for migration individuals. The number of migration individuals $M_i$ is decided by the equation (2) where $P_{initial}$ shows the number of individuals in the initial sub-population (island) and $M_i$ is obtained as the nearest integer number.

\[
r_{e_i} = k \cdot E_i \quad (1)
\]

\[
M_i = r_{e_i} \cdot P_{initial} \quad (2)
\]
3 Proposal of C-FASPGA

Next, we explain about our additional proposal of Fuzzy Adaptive Search method for Parallel GA with the island combination process (C-FASPGA). Since C-FASPGA has almost the same algorithm as FASPGA, we focus on the island combination process as this is the characteristic feature that is not included in the FASPGA algorithm.

3.1 Basic Algorithm of C-FASPGA

At first, the initial individuals are generated at random. Then the fitness value of each individual is calculated. Next, the initial population is divided into $n$ sub-populations (islands). In the beginning of a learning process, the average fitness value $f_{a_i}$ and the maximum fitness value $f_{m_i}$ are calculated in each sub-population ($i=1, 2, ..., n$). After the selection, the island evaluation for obtaining the average fitness value of all individuals in each island is executed and we evaluate which island should be combined with another island together. This is explained in detail in section 3.2.

After the combination process, the fitness values for each individual are calculated again. Using an estimation of the progress degree of the evolution with the average fitness value $f_{a_i}$ and the difference between the maximum and average fitness value ($f_{m_i} - f_{a_i}$), the migration degree $E_i$ in each sub-population is decided by fuzzy reasoning. The migration rate $r_e$ is calculated from the migration degree $E_i$. The migration process is executed with the Random ring model. Before the operation of crossover and mutation, $f_{a_i}$ and $f_{m_i}$ are recalculated once again. Because the fuzzy inference rule depends on current $f_{a_i}$ and ($f_{m_i} - f_{a_i}$), the crossover rate $r_c$ and mutation rate $r_m$ must be successfully tuned.

Finally, after the elite selection, the termination condition of the evolution is checked. If it is satisfied then the evolution terminally finishes, if not the system returns to the selection and executes once again the same process. We can regard this process as the FASGA algorithm applied to each sub-population.

The algorithm flowchart of C-FASPGA proposed in this paper is shown in Fig.3. Tuning processes of the crossover rate, mutation rate and migration degree in each island by fuzzy reasoning are executed in the dotted line area.
3.2 The Island Combination Process

In C-FASPGA, the island combination process is evaluated in every combination intervals $Com_{Span}$. This process is executed when $f_{a_1}$, the average fitness value of the island with highest average fitness value, exceeds the constant value $Com_{Start}$ as shown in the following rule expression. However, the island number in the combination process must be greater or equal than the constant limitation of island numbers $Is_{Limit}$. If these preconditions are satisfied at the same time, then the two top islands (the ones with first and second average fitness value $I_{a_1}, I_{a_2}$) are combined together. Fig.4 shows an outline of the island combination process in this proposed method.

\[
IF \ (f_{a_1} > Com_{Start}) \ and \ (Generation \ mod \ Com_{Span} = 0) \ and \ (N \geq Is_{Limit}) \ THEN \ Combine \ I_{a_1} \ & \ I_{a_2}
\]

Fig. 3. Flowchart of C-FASPGA
4 Simulation

A computer simulation was performed to confirm the efficiency of FASPGA and C-FASPGA proposed in this paper. We report the precondition and simulation results for FASPGA and C-FASPGA in this section.

4.1 Precondition of Simulation

In this simulation, we used the Rastrigin function as a test function to confirm the efficiency of FASPGA and C-FASPGA. The Rastrigin function is a $n$-dimensional function with multiple peaks as shown in Equation (3). The function has Lattice-shaped semi-optimum solutions around an optimum solution and there is no dependence between design parameters. The simplest example, the 2-dimensional Rastrigin function, is shown in Fig.5.

$$F_{\text{Rastrigin}}(x) = 10n + \sum_{i=1}^{n} \{x_i^2 - 10 \cos(2\pi x_i)\}$$

$$(-5.12 \leq x_i < 5.12)$$

$$\min(F_{\text{Rastrigin}}(x)) = F(0, 0, \ldots, 0) = 0$$

Fig. 4. Island Combination Process of C-FASPGA
Fig. 5. Overview of the 2-Dimensional Rastrigin Function

For example in Fig.5, the Rastrigin function has two design parameters which are shown as the two horizontal axes. the function to be used as the fitness value in our systems is represented in the vertical axis. The optimum solution in this function is a point with zero fitness value, that is, a bottom of the valley in the origin of Fig.5. In this simulation, we used $n = 20$ design parameters and gray coding.

An elitist strategy is exploited in GA, PGA, FASPGA and C-FASPGA with one elite. The way of selecting the elite is that it selects the fittest individual in the island as the elitist individual and the way of returning elite is that it replaces the worst individual in the island.

4.2 Simulation Results of FASPGA

The value of default parameters in GA, PGA and FASPGA are shown in Table 1. In this simulation, we used the PGA approach with the island model proposed by Miki et al. [Miki(1999)]. The parameters of the fuzzy reasoning in FASPGA are shown in Fig.1. In this section, there are two simulations that are experimented in GA, PGA and FASPGA with the different population size and the island size. Individuals in each island are equally divided from the total population. The simulations are carried out in a partial fashion, exploring the effect of varying one parameter while fixing the other at their default values.

In the first simulation (Sim1), we compare the results of simulation with GA, PGA and FASPGA in different population sizes. This is needed in order to confirm the performance of FASPGA subject to different population size. The second simulation (Sim2) is performed in a small population size with GA, PGA and FASPGA. The purpose of this simulation is confirming the performance of FASPGA in any cases. In this simulation we have to utilize small individuals size or short generations to obtain the optimum solution in short time.
### Table 1
Default Parameters for Simulation

<table>
<thead>
<tr>
<th>Parameters</th>
<th>GA</th>
<th>PGA</th>
<th>FASPGA</th>
</tr>
</thead>
<tbody>
<tr>
<td>Population Size</td>
<td>Sim1: 400, 600, 800, 1000</td>
<td>Sim1: 400, 600, 800, 1000</td>
<td>Sim1: 400, 600, 800, 1000</td>
</tr>
<tr>
<td></td>
<td>Sim2: 100</td>
<td>Sim2: 100</td>
<td>Sim2: 100</td>
</tr>
<tr>
<td>Generations</td>
<td>1000</td>
<td>1000</td>
<td>1000</td>
</tr>
<tr>
<td>Chromosome Length (L)</td>
<td>200</td>
<td>200</td>
<td>200</td>
</tr>
<tr>
<td>Selection Method</td>
<td>Roulette Wheel</td>
<td>Roulette Wheel</td>
<td>Roulette Wheel</td>
</tr>
<tr>
<td>Crossover Rate</td>
<td>0.6 (Single Point Crossover)</td>
<td>0.6 (Single Point Crossover)</td>
<td>Tuned by Fuzzy Reasoning</td>
</tr>
<tr>
<td>Mutation Rate</td>
<td>1/L</td>
<td>1/L</td>
<td>Tuned by Fuzzy Reasoning</td>
</tr>
<tr>
<td>Island Size</td>
<td>–</td>
<td>Sim1: 20</td>
<td>Sim1: 20</td>
</tr>
<tr>
<td></td>
<td>–</td>
<td>Sim2: 5, 10</td>
<td>Sim2: 5, 10</td>
</tr>
<tr>
<td>Migration Method</td>
<td>–</td>
<td>Random Ring</td>
<td>Random Ring</td>
</tr>
<tr>
<td>Migration Rate</td>
<td>–</td>
<td>0.5</td>
<td>Tuned by Fuzzy Reasoning</td>
</tr>
<tr>
<td>Migration Interval</td>
<td>–</td>
<td>5 (generations)</td>
<td>Changed</td>
</tr>
</tbody>
</table>

We performed the optimization simulation using the Rastrigin function and compared the result of simulation based on maximum fitness value. All figures display the maximum fitness on the y-axis, and the generations on the x-axis. The Rastrigin function with 20-dimensions in Equation (3) is used in this simulation. The maximum value of this function is 810 and minimum value (the optimum solution) is 0. In order to make easy to find the optimum solution, we modified the Rastrigin function value $F_{\text{Rastrigin}}$ to $F_{\text{max-fitness}}$ in this simulation.

$$F_{\text{max-fitness}} = 810 - \min(F_{\text{Rastrigin}})$$

The results of Sim1 are shown in Fig.6 (a) to (d). These figures show the maximum fitness values based on $F_{\text{max-fitness}}$ in case of 400, 600, 800 and 1000 individuals, and the island size is 20 islands. From these figures, we confirmed that the performance of FASPGA is the best, and that GA is the worst. On the search capability of the early search stage, FASPGA is almost the best in populations of any size. However, there are only tiny differences between PGA and FASPGA in the final search stage, but in the case of 1000 individuals, only FASPGA has already obtained the best solution in about 400 generations.

Fig.6 (e) and (f) show the results of Sim2. In this simulation, we have that the population size is fixed in 100 individuals and the island size is fixed either to 5 or 10. The performance of GA is also the worst in this simulation. And FASPGA has slightly better performance than PGA in the early search stage in case of 5, 10 islands. In case of 10 islands, FASPGA has a better solution in the final stage than PGA. However, in case of 5 islands, it is the opposite case and the PGA is better than the FASPGA in the final search stage. After all, there is no clear difference in the final search stage. In addition, we could also find that the difference between PGA and FASPGA becomes small along with the island size becoming small.
4.3 Simulation Results of C-FASPGA

Next, we performed another simulation using Rastrigin function to confirm the efficiency of C-FASPGA. In this simulation, we compared the results of simulation with PGA, FASPGA and C-FASPGA. Fig. 7 (a) to (d) show simulation results based on the maximum fitness value using $F_{\text{Rastrigin}}$. These results were obtained by the average of 20 simulation trials with different random seeds when the initial population size is 400 and the initial island size is 10.

In Fig.7(a), PGA has the best performance in the early search stage, but the performance of FASPGA and C-FASPGA is better than that of PGA after 70 generations. In the final search stage, C-FASPGA could find the best individual in about 150 generations and FASPGA after about 350 generations. In this simulation, we used $\text{Com}_\text{Start} = -30$, $\text{Is}_\text{Limit} = 4$, $\text{Com}_\text{Span} = 5$ as initial parameters.

In the next three figures, we show the performance of C-FASPGA with different initial parameters. Fig. 7(b) shows the result for different combination of the start period $\text{Com}_\text{Start}$, Fig.7(c) for different island limitation $\text{Is}_\text{Limit}$ and Fig.7(d) for different combination interval $\text{Com}_\text{Span}$. After all, we confirmed that the best value for the initial parameters of C-FASPGA is $\text{Com}_\text{Start} = -30$, $\text{Is}_\text{Limit} = 4$, $\text{Com}_\text{Span} = 5$. These are the same values used in Fig.7(a).

4.4 Remarks for Simulation Results

Furthermore, in the first simulation, FASPGA finally obtained the high-quality solution as compared with PGA. We think this performance was obtained by maintaining a high variety of sub-populations tuning migration parameters in each search stage by fuzzy reasoning. In addition, FASPGA seems to be able to achieve a better performance in larger population sizes. As a result, totally, we could confirm that the FASPGA method is able to obtain the optimum solution faster and with higher quality than PGA in case of large population size.

However, the difference between FASPGA and PGA became small in the case of a small population size, even when FASPGA is worse than PGA. We consider that a reason of causing this state is that the sub-population size in each island also decreased because the population size decreased. This lead the tuning capability of fuzzy inference rule in the migration rate to be weakened, because the size of individuals in each island is too small to find obvious difference in the migration individual size between large and small migration rate.
In the simulations for C-FASPGA, FASPGA and C-FASPGA, they obtained the optimum solution in an earlier search stage than the PGA. Moreover, in Fig.7(a), we confirmed that the C-FASPGA has the best performance to obtain the best solution because the combination process is very efficient to increase the variety of individuals in each island in the final search stage.

5 Conclusions

A fuzzy adaptive search method for parallel genetic algorithms was proposed, in which the genetic parameters are adaptively tuned by fuzzy rules in accordance with the search stage. This method combines the fast search ability of a fuzzy adaptive search method with the capacity of parallel genetic algorithms. The FASPGA method therefore offers improved search efficiency and higher-quality solutions. Furthermore, we also proposed FASPGA with the operation of dynamically combining sub-populations (C-FASPGA) which combines two elite islands in the final stage of the evolution to find a better solution.

The performance of FASPGA and C-FASPGA was evaluated through optimization using the Rastrigin function with a range of parameter settings and comparing their results with the results obtained by an ordinary GA and PGA. The FASPGA method was confirmed to reach the optimum solution faster and to produce higher-quality solutions than the PGA in the case of a large population size. These results suggest that large number of individuals are required to obtain good solutions. In the case of small populations, FASPGA also provided good performance in the early search stage, but offered no improvements in the final search stage using a small island population and small island size. This result demonstrates that the island population size and the number of islands have a substantial effect on the performance of FASPGA when the total population size is small.

Furthermore, we confirmed that the FASPGA and the C-FASPGA method are able to obtain the optimum solution faster than the PGA. By simulation results, we also confirmed that the C-FASPGA has a slightly better performance on obtaining the best solution than the FASPGA because the island combination process increased the variety of individuals in each island in the final search stage. This method is very useful to find higher quality solutions in the final search stage.

Future work will include further research to confirm the performance of C-FASPGA using other testing functions, and the consideration of new optimum parameters. The FASPGA and C-FASPGA method are currently being investigated for application to motion learning for a robot manipulator and an autonomous mobile robot.
References


Fig. 6. Simulation Results of FASPGA
(a) Comparison of total performance  
(b) Comparison of \( \text{Com}_\text{Start} \)

(c) Comparison of \( \text{Is}_\text{Limit} \)  
(d) Comparison of \( \text{Com}_\text{Span} \)

Fig. 7. Simulation Results of C-FASPGA