Species-based Differential Evolution with Switching Search Strategies for Multimodal Function Optimization

Miyuki Shibasaka, Akira Hara, Takumi Ichimura, and Tetsuyuki Takahama

Abstract—In multimodal optimization problems, the objective is not only to find one global optimal solution, but also to find various global optimal solutions. For this purpose, the Species-based Differential Evolution (SDE) has been proposed previously. In this method, the population is divided into multiple subpopulations by using speciation, and each species focuses its search for one optimal solution. By this way, multiple optimal solutions can be discovered simultaneously. However, this algorithm takes a long time for complicated problems to acquire global optima. In this paper, we propose SDE with switching search strategies, which selects global search by the population or local search in each species according to the search situation. The experimental results show that the SDE with switching search strategies outperforms the conventional SDE in a complicated function problem.

I. INTRODUCTION

In multimodal function optimization problems, which have multiple global optimal solutions, it is important to find not only one global optimum but also various global optima.

Some meta-heuristics such as Genetic Algorithms (GA)[1][2] and Particle Swarm Optimization (PSO)[3] have been proposed for solving function optimization problems. GA searches solutions by applying genetic operations such as crossover, mutation and selection to the population. On the other hand, PSO is conceived based on swarming behavior of birds. A swarm of particles moves around in the search space in PSO. Each particle has a memory to store its own best position and a global best position of all particles obtained through communication. Each particle moves to the next position by using the information.

GA and PSO show good performance to the unimodal function optimization problems. When these methods are applied to the multimodal function optimization problems, however, they can not find all global optima. Because all individuals or particles are apt to be attracted by the fittest individual and to converge on a local optimum. As one technique for solving multimodal function problems, we could repeat trials for finding one global optimum until all optima are discovered. However, this technique is inefficient because different solutions are not necessarily acquired in respective trials, and a large number of trials are needed. So it is important to develop the search algorithm which can find all global optima by a single run.

For this purpose, several methods which can find various global optima simultaneously have been proposed.

Species-based GA [4] and Particle Swarm Algorithm with speciation[5][6] use speciation mechanism in order to divide the individuals or particles into some species. In [5][6], each particle employs not only the global best position but also the best position in its species for its next move. In Tabu-GA[7], some mechanisms such as preservation of superior individuals, restraint of convergence, and maintenance of diversity have been introduced by using multiple tabu-lists. In addition, niche method for evolutionary algorithm[8] and niche method for genetic algorithm[9] have been proposed for reducing inferior individuals in fitness. In [8][9], each individual is compared with other individuals within the predefined range, and worse individuals are penalized. Superior individuals can survive in selection. These methods can find various global optima simultaneously. However, these algorithms have the problems such as insufficient accuracy or enormous computing time.

In this study, we take another meta-heuristic method, Differential Evolution (DE)[10]. As well as GA and PSO, there are several extensions of DE[11][12] for multimodal function optimization. In the Species-based Differential Evolution (SDE) by Xiaodong Li[13], speciation mechanism is used, and each species searches a solution locally. As a result, multiple optima are acquired simultaneously by the respective species. However, SDE takes a long time for complicated problems to acquire all global optima. In order to solve the problem, we propose a new method, SDE with switching search strategies. This method switches search strategies according to the search situation. The practicable search strategies are global search by all individuals and local search in respective species. We apply this method to five benchmark multimodal test functions and examine the effectiveness of this method.

This paper is structured as follows. Section II describes the basic DE and SDE. Section III presents the proposed species-based DE with switching search strategies. Section IV describes experimental settings. Section V provides experimental results on test functions. Finally, Section VI gives conclusions and future work.

II. SPECIES-BASED DIFFERENTIAL EVOLUTION

A. Differential Evolution

Differential Evolution has been proposed as the continuous function optimization algorithm by Storn and Price in 1995[10]. The structure of the algorithm is quite similar to GA. However, the processes to generate offspring and to replace the parents with the offspring are different from those of GA.
For \( n \)-dimensional function \( f \), each individual in DE is represented by \( n \)-dimensional vector, \( x = (x_1, x_2, ..., x_n) \). At initial population, each individual is generated by random values uniformly distributed between the lower and upper bounds of the respective variables’ ranges. The function value, \( f(x) = f(x_1, x_2, ..., x_n) \), is used as fitness of the individual.

In GA, an offspring is generated by crossover operation between two parents. On the other hand, in DE, an offspring \( x_{\text{child}} \) is generated by crossover between the parent \( x^{\text{IG}} \) and a trial-vector. The trial-vector is generated as follows:

\[
v = x^{s_1} + F \cdot (x^{s_2} - x^{s_3}),
\]

where, \( x^{s_1} \) is a base-vector, and \( (x^{s_2} - x^{s_3}) \) is a difference-vector. These vectors \( x^{s_1}, x^{s_2} \) and \( x^{s_3} \) are chosen randomly from the population on the condition, \( x^{\text{IG}} \neq x^{s_1} \neq x^{s_2} \neq x^{s_3} \). Fig.1 shows procedures for generating an offspring. In the procedures, \( U[0,k] \) is an uniformly distributed number in \( [0,k] \). \( CR, F, \) and \( L \) are user-specified control parameters. \( CR \) is the crossover rate, which is in \([0,1]\). \( F \) is a scaling factor for adjusting the amplification of the difference-vector. \( L \) is a variable for counting the number of genes, which have already been applied crossover. The type of crossover as shown in Fig.1 is called “exponential crossover”. DE’s replacement operation is simple. If the offspring fitness \( f(x^{\text{child}}) \) is better than the parent fitness \( f(x^{\text{IG}}) \), the parent is replaced with the offspring.

### B. Species-based Differential Evolution

In nature, a species is defined as a collection of similar individuals, and speciation is the differentiation of the population into several species in the evolutionary process. The occurrence of the reproductive process is restricted within the same species. Therefore, individuals resemble their parents, and various species can be maintained independently. Since DE works with a population of solutions, the concept of natural speciation mechanisms can be implemented to allow formation of multiple subpopulations. Each species searches for one optimal solution in its own territory. By this way, multiple optimal solutions can be discovered simultaneously.

Species-based Differential Evolution (SDE)[13] is one of the extensions of DE for multimodal optimization problems. This algorithm introduced the speciation mechanism into the conventional DE. The algorithm of SDE is as follows:

1) Generate an initial population.
2) Calculate each individual’s fitness.
3) Form species.
4) Generate an offspring for each parental individual.
   a) Select \( x^{s_1}/x^{s_2}/x^{s_3} \) from the parent’s species.
   b) Generate a trial-vector using selected vectors.
   c) Crossover between the parent and the trial-vector.
5) Replace the offspring with the parent.
6) Return to the 2), if the terminal condition is not satisfied.

The procedures for the formation of species are as follows: The individual with better fitness than neighbors becomes the species seed. Each species seed makes its own territory with radius \( R \). If an individual with lower fitness is in the territory of the species seed, it belongs to the species. Thus, the species seeds are decided in order of fitness in the population. Fig.2 shows a situation, where the individual A has the best fitness and the individual B has the next best fitness. In this case, the individuals A, B and C becomes species seeds. The individual which is in two or more territories belongs to the species of the fittest seed. In this figure, the individual P belongs to the species of individual A, because \( f(x^A) > f(x^B) > f(x^C) \). Each individual belongs to the only one species.

The Euclidean distance is used for the distance between two individuals. That is, the condition for judging whether the individual \( x^i \) is in the territory of the species seed \( x^s \) is as follows:

\[
d_{is} = \sqrt{\sum_{j=1}^{n} (x^i_j - x^s_j)^2} < R.
\]

In DE, \( x^{s_1}, x^{s_2} \) and \( x^{s_3} \), which are used for generating a trial-vector, are chosen at random from the population. On the other hand, in SDE, in order for the respective species to perform local search, \( x^{s_1}, x^{s_2} \) and \( x^{s_3} \) are chosen from the same species of the parent \( x^{\text{IG}} \). In this procedure, at least four individuals are needed in the species to satisfy the
condition of $x^{1G} \neq x^{r1} \neq x^{r2} \neq x^{r3}$. In the process of speciation, however, the number of individuals in a species may be less than four. To cope with this situation, the parameter $SMIN$, the minimum number of individuals in a species, is defined. If the number of individuals in a species is less than $SMIN$, new individuals are generated at random in the species territory till the number of members reaches to $SMIN$. Thus the condition for selection is satisfied, and the individuals for base and difference vectors are chosen from them. The individuals which are generated at random in the species territory are used only for the selection of $x^{r1}$, $x^{r2}$ and $x^{r3}$. They do not reproduce their offspring for the next generation. Fig.3 shows an image of selection in the case of $SMIN = 10$.

In addition, in SDE, the replacement procedure is modified so as not to generate the redundant individuals. In original DE, if an offspring is better than the parent, the parent is replaced with the offspring. Moreover, in SDE, if the offspring has the same fitness as that of its species seed, the offspring is regarded as a redundant individual, and the offspring is replaced with a randomly generated new individual.

III. SDE WITH SWITCHING SEARCH STRATEGIES

SDE is an effective search method for multimodal function optimization, but it takes a long time for optimization due to the search only in the species. In order to solve this problem, we propose SDE with switching search strategies. In this method, individuals search solutions globally till the switching point of search strategies, and after that the global search or local search in respective species is used according to the situations.

Basically, the algorithm of SDE with switching search strategies is the same as SDE. However, the selection method for $x^{r1}$, $x^{r2}$ and $x^{r3}$, which are used to generate the offspring, is modified.

A. Judgment for Switching Point

Switching search strategies means that the search strategy shifts from the only global search to the combination use of the global and local search. The switching point is the time when the change of the number of species becomes stable.

Fig. 4 shows the procedure of the judgment for the switching point. At each generation $t$, we calculate $A_t$, the average of the number of species for the past $SWNUM$ generations. Then, we make comparisons of the current generation’s average $A_t$ and respective averages of the past generations’ $A_{t-i}$ ($i = 1, \ldots, COMP$). If all of the differences are smaller than 0.1, the change of the number of species is considered to be stable, and the switching of search strategy is enabled.

Fig.5 shows an example of the changes of the number of species $sp_{num}$ (i.e. $a_t$ in Fig.4) and the average of the number of species $sp_{ave}$ (i.e. $A_t$ in Fig.4). These are results of an experiment using the function $F4$ in Section IV. In this experiment, the switching parameter $SWNUM$ is 20 and $COMP$ is 10. Switching was enabled at the 212 generation in this trial.

B. Switching of Search Strategies

$x^{r3}$ is a base-vector, which is used for generating a trial-vector. In SDE, the base-vector is chosen at random from the species of the parent individual. On the other hand, in our proposed method, the base-vector is chosen at random
For generating a trial-vector for the parent \(x\),
Before Switching Point:
global search
After Switching Point:
\[
  \text{if} \quad (||\text{species}(x)|| < SMIN')
  \quad \text{local search}
\else
  \quad \text{global search}
\]

Fig. 6. Proposed selection method for \(x^{r2}\) and \(x^{r3}\).

from the superior individuals in the species. The number of superior individuals (i.e. candidates for a base-vector) is defined as the parameter \(SPNUM\). Therefore, more effective and rapid search is performed, since the search is based on the superior individual.

\(x^{r2}\) and \(x^{r3}\) are used for a difference-vector in the trial-vector. These vectors are selected at random from the population in DE, and are selected at random from the same species in SDE. The both selection methods may cause some problems on species search.

If \(x^{r2}\) and \(x^{r3}\) are chosen at random from the population, individuals far apart from the parent’s species may be chosen. In this case, the difference between the parent and the offspring may become large. As a result, offspring are apt to jump out of their species and belong to another species. If a species has few individuals and all of them move to other species accidentally, the original species disappears. Even if the species was near an optimal solution before the disappearance, there is little possibility that the species will appear again. Therefore, the optimum may remain lost sight of in the run.

By contrast, if \(x^{r2}\) and \(x^{r3}\) are chosen at random from the same species, the difference between the parent and the offspring becomes small. As a result, the change of the distribution of individuals is small at alternation of generations. This is efficient for local search. However, if individuals do not exist around a optimal solution at the beginning of search unfortunately, it takes a long time to find the solution.

Therefore we propose a selection method for \(x^{r2}\) and \(x^{r3}\) in order to prevent the extinction of the species and the stagnation of evolution. Fig.6 shows the procedure of the method. In this figure, global search means the random selection of \(x^{r2}\) and \(x^{r3}\) from the population, and local search means the random selection from the species. \(||\text{species}(x)||\) is the number of individuals in the species of \(x\). If the number is less than the parameter \(SMIN'\), the species seems to be in danger of extinction. The search is performed globally until the condition for switching point is satisfied. After the switching, the extinction of the species are prevented by the local search, and the stagnation of evolution is prevented by the global search.

IV. EXPERIMENTS

A. Performance Measurements

In this study, we used the following performance measurements: accuracy, convergence speed and the number of found solutions. Accuracy and convergence speed have been introduced in [13].

1) Accuracy: An algorithm is run for a fixed number of iteration steps, and accuracy is recorded in the final step. Accuracy is calculated by taking the average of the fitness differences between all known global optima \(opt_i\) and their closest species seeds \(seed_i\). The definition of accuracy is as follows:

\[
  \text{Accuracy} = \frac{1}{||opts||} \sum_{i=1}^{||opts||} |f(opt_i) - f(seed_i)| \quad (3)
\]

where \(||opts||\) is the number of known global optima.

2) Convergence speed: The judgment whether the search converges or not is performed every step. The fitness difference between each known global optimum \(opt_i\) and the closest species seed \(seed_i\) is calculated, and it is compared with the pre-defined accuracy level \(\epsilon\). If all differences become less than \(\epsilon\), the step is regarded as the convergence step. The definition of the judgment is as follows:

\[
  \forall x \in S_{opt}, \exists y \in S_{seed}:
  \min |x - y| \land |f(x) - f(y)| \leq \epsilon
  \quad (0 < \epsilon \leq 1), \quad (4)
\]

where \(S_{opt}\) is a set of all known global optima of the multimodal function, and \(S_{seed}\) is a set of species seeds. \(\epsilon\) is defined for each test function. Convergence speed is calculated by the equation (5).

\[
  \text{ConvergenceSpeed} = \text{ConvergenceStep} \times \text{pop.size} \quad (5)
\]

3) The number of found solutions: The number of found solutions is recorded in the final step as well as the accuracy. The Euclidean distance between each known global optimum \(opt_i\) and the closest species seed \(seed_i\) is calculated by the equation (6). If the distance is less than the parameter \(RANGE\), it is considered that the global optimum is acquired by the run. The definitions of the number of found solutions are as follows:

\[
  \text{distance}_i = \sqrt{\sum_{j=1}^{n} (\text{opt}_{ij} - \text{seed}_{ij})^2} \quad (6)
\]

\[
  \text{found}_i = \left\{
  \begin{array}{ll}
  1 & \text{if distance}_i < \text{RANGE} \\
  0 & \text{otherwise}
  \end{array}
  \right. \quad (7)
\]

\[
  \text{TheNumberofFoundSolutions} = \sum_{i=1}^{||opts||} \text{found}_i \quad (8)
\]
B. Test Functions

In this research, to compare the performance of our proposed SDE with switching search strategies and the conventional SDE, we apply these methods to the four test functions. They are 2-dimensional multimodal test functions and minimization problems.

1) Himmelblau Function (F1): Himmelblau function has four global optima. The value of every global optimum is -200. \( \epsilon \) is set to 0.0001 as described in [13].

\[
f_1(x_1, x_2) = -1 \ast (200 - (x^2 + y - 11)^2 - (x + y^2 - 7)^2)
\]

\[-6 \leq x_1 \leq 6, \quad -6 \leq x_2 \leq 6 \tag{9}\]

2) Six-Hump Camel Back Function (F2): Six-Hump Camel Back function has two global optima. The value of every global optimum is -0.88. \( \epsilon \) is set to 0.0001 as described in [13].

\[
f_2(x_1, x_2) = 4[(4 - 2.1x^2 + x^4/3) \cdot x^2
\]

\[+ xy - (4 - 4y^2) \cdot y^2]

\[-1.9 \leq x_1 \leq 1.9, \quad -1.1 \leq x_2 \leq 1.1 \tag{10}\]

3) Brainin RCOS Function (F3): Brainin RCOS function has three global optima. The value of every global optimum is 0.397887. \( \epsilon \) is set to 0.0001 as described in [13].

\[
f_3(x_1, x_2) = (x_2 - 5.1 \cdot x_1^2 + 5 \cdot 1/\pi \cdot x_1 - 6)^2
\]

\[+ 10 \cdot (1 - 1/8 \pi) \cdot \cos(x_1) + 10]

\[-5 \leq x_1 \leq 10, \quad 0 \leq x_2 \leq 15 \tag{11}\]

4) Shubert Function (F4): Shubert function has 760 local optima including 18 global optima. The value of every global optimum is -186.730909. The closest distance between any two global optima is 0.88. Fig.7 shows the landscape of the function F4. \( \epsilon \) is set to 0.1 as described in [13].

\[
f_4(x_1, x_2) = \left( \sum_{i=1}^{5} i \cos[(i + 1)x_1 + i] \right) \times
\]

\[\left( \sum_{i=1}^{5} i \cos[(i + 1)x_2 + i] \right)
\]

\[-10 \leq x_1 \leq 10 \tag{12}\]

Moreover, in order to examine the performance for problems with more than two variables, we also use the following multi-dimensional function.

5) Original Multi-dimensional Function (F5):

\[
f_5(x_1, ..., x_n) = 1 - \sum_{j=1}^{n} e^{-\sum_{i=1}^{n} (x_i - a_i)^2}
\]

\[\sum_{i=1}^{n} x_i^2 \tag{13}\]

\[-2 \leq x_i \leq 2, \quad ((a_1, a_2, a_3) = (-1, 0, 1), \sigma = 0.3)\]

This function has three optima for any \( n \). In our experiments, \( n \) is set to 2, 3, 5 and 10. Fig.8 shows the landscape of the function in the case of \( n = 2 \).

C. Parameter Settings

We performed 50 runs in each function, and calculated an average and a standard deviation for each performance measurement. In addition, we calculate success rate, the rate of the trials in which the accuracy is less than the predefined level. The levels for respective functions are 0.0001 for functions F1, F2 and F3, and 0.1 for function F4.

The other parameter settings are as follows: The population size is 100, and maximum iteration step \( \text{MAX} \) is 500. The parameter \( F \) is 0.5, \( CR \) is 0.9, and \( SMIN \) is 10. The parameter SWNUM and COMP for switching search strategies are 20 and 10 respectively. The parameter \( SMIN' \) for selecting the local search is 2. The parameter RANGE for the number of found solutions is 0.001.

In addition, we also use the linear decreasing radius method for F4 and F5. This method has been used in the Particle Swarm algorithm with speciation[5], though species radius \( R \) is fixed to 0.5 in the SDE. In this case, radius \( R \) at iteration \( itr \) is defined as follows:

\[
R = (R_{int} - R_{fin}) \times (\text{MAX} - itr)/\text{MAX} + R_{fin}, \tag{14}\]

where \( R_{int} \) and \( R_{fin} \) represent the initial and final radius respectively. \( \text{MAX} \) is the maximum number of generations.
V. Results

A. Effect of the selection method for $x^r$

In our proposed method, the base-vector $x^r$ is chosen from $SPNUM$ individuals, which are superior ones in the species of the parent. It is considered that the smaller the value of $SPNUM$ is, the stronger the degree of greedy search is. We examine the effect of varying the parameter $SPNUM$ on search performance. We performed experiments, where the parameter $SPNUM$ was set to 1 or 5. The parameter $SMIN^o$ was set to 2 in the experiments. Table I shows the results for the four test functions above. As shown in this table, $SPNUM = 1$ shows better convergence speed than $SPNUM = 5$ for any functions. In addition, according to the results of $F3$ and $F4$, $SPNUM = 1$ is superior to $SPNUM = 5$ in accuracy and the number of found optimal solutions. $SPNUM = 1$ means that the species seed is always used as the base-vector. Though this is a strong greedy method, the trial-vector can keep diversity by the effect of difference-vector generated through the global search strategy. Therefore, the search with $SPNUM = 1$ shows a good performance. In the following experiments, $SPNUM$ is set to 1.

B. Performance for $F1, F2$ and $F3$

Table II and Table III show the comparison of the results between the proposed method and the conventional SDE for the functions $F1, F2$ and $F3$ respectively. The results for the conventional SDE are taken from [13]. The territory radius $R$ is fixed to 0.5 in the both methods.

We can not see the definite difference of the performance between our proposed method and the conventional SDE from these tables. Moreover, the both methods achieved 100% success rate. It is considered that the both methods have good performance to the functions $F1, F2$ and $F3$.

C. Performance for $F4$

Table IV, V and VI are the results of accuracy, convergence speed, and the number of found solutions for the function $F4$ respectively. Two types of the territory radius $R$ are used for this function. One is the fixed radius, 0.5, and the other is linear decreasing radius. In the case of the linear decrease radius, the initial radius $R_{int}$ is 1.0 and final radius $R_{fin}$ is 0.4. Table VI also shows the number of successful runs, where accuracy becomes less than 0.1.

These results show that the performance of the proposed method is better than that of the SDE on any three measurements. In the SDE, all solutions are not acquired. On the other hand, in the proposed method, all 18 global optima are acquired in most runs.

Fig.9 and Fig.10 show that the snapshots in the last step of the conventional SDE and our proposed method respectively. The circles in these figures represent the territory of existing species, and the crosses represent the locations of solutions for the function $F4$. As shown in Fig.9, there are several solutions not discovered by species. Moreover, many species could not reach an optimum by the stagnation of evolution. By contrast, as shown in Fig.10, all solutions are discovered by the respective species in the proposed method.

In addition, the method using the linear decreasing radius has better performance than the method using fixed radius. In the method using the linear decreasing radius, individuals can search for solutions more globally at the beginning of search, and they can search locally at the end of search. Thus, the decreasing radius also may helps the switch of the search strategy. In addition, the fixed radius 0.5 may be somewhat large, because the closest distance between the global optima is 0.88. This fixed radius may cause overlap of the search space between the closest global optima. In this case, either species may be extinguished by the territorial struggle.

Moreover, in order to examine the effects of switching search strategies, we counted the individuals which exist in each circle with center at a global optimum and with radius $R$. Fig.11 shows the changes of the number of individuals around the 18 global optima in a trial. In the trial, the switching is performed at the 131 generation. After the switching, the extinction of a species does not occur, since the species which is composed of the only one individual is protected by the local search strategy. The switching of the search strategies is useful for preventing the extinction.
TABLE IV
ACCURACY FOR THE FUNCTION \( F_4 \).

<table>
<thead>
<tr>
<th>( R )</th>
<th>SDE with switching strategies</th>
<th>SDE</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fixed</td>
<td>2.81e-01±9.52e-01</td>
<td>1.14e+00±1.76e+00</td>
</tr>
<tr>
<td>Decreasing</td>
<td>1.99e-07±3.66e-13</td>
<td>5.91e-01±1.34e+00</td>
</tr>
</tbody>
</table>

TABLE V
CONVERGENCE SPEED FOR THE FUNCTION \( F_4 \).

<table>
<thead>
<tr>
<th>( R )</th>
<th>SDE with switching strategies</th>
<th>SDE</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fixed</td>
<td>2.33e+04±3.61e+03</td>
<td>—</td>
</tr>
<tr>
<td>Decreasing</td>
<td>1.63e+04±2.32e+03</td>
<td>—</td>
</tr>
</tbody>
</table>

TABLE VI
THE NUMBER OF FOUND SOLUTIONS FOR THE FUNCTION \( F_4 \).

<table>
<thead>
<tr>
<th>( R )</th>
<th>SDE with switching strategies</th>
<th>SDE</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fixed</td>
<td>17.92±0.27 (46/50)</td>
<td>1.52±0.04 (0/50)</td>
</tr>
<tr>
<td>Decreasing</td>
<td>17.96±0.20 (50/50)</td>
<td>5.70±1.36 (0/50)</td>
</tr>
</tbody>
</table>

Fig. 9. A snapshot in the last step of SDE on \( F_4 \).

Fig. 10. A snapshot in the last step of SDE with switching search strategies on \( F_4 \).

Fig. 11. The number of individuals in the around of each global optimum.

of species and for the stabilization of the number of species.

D. Performance for \( F_5 \)

As described above, our proposed method shows good results for several two-dimensional problems. In order to examine the applicability with regard to dimensionality, we apply our proposed method to the multi-dimensional function \( F_5 \). Initial radius \( R_{int} \) for speciation is set to \( 0.1 \times \) diagonal length of the domain, and \( R_{fin} \) is set to the half of \( R_{int} \). For example, \( R_{int} \) is 0.28 and \( R_{fin} \) is 0.14 for \( n = 2 \). The other parameter settings are the same as for the function \( F_4 \).

Table VII shows accuracy, convergence speed and the number of found optimal solutions for each \( n \). We can see from the results on convergence speed that as the dimensionality \( n \) increases, it takes more time to search solutions. In the case of \( n = 10 \), performance on the accuracy and the number of found solutions also becomes worse slightly. However, all three optimal solutions were acquired successfully in most trials. Thus, our proposed method is applicable to multidimensional problems.

VI. CONCLUSION

In this paper, in order to solve the multimodal optimization problems, we introduced the switching search strategies mechanism into the SDE. This method switches global search and local search so that the species will not be extinguished and the stagnation of evolution will not occur. The switching is realized by the new selection method of individuals \((x_{r1}, x_{r2}, x_{r3})\) for a trial-vector.

For the test functions with a small number of solutions, the proposed method has the same performance as the conventional SDE. However, for the test function with a large number of solutions, the proposed method is superior to the SDE.
In our proposed method, when the number of individuals in the species is less than the parameter $SMIN'$, the search strategy is switched from global search to local search. However, the extinction of the species is observed occasionally, though the most species can survive by this switching. Even if two or more individuals are in the species, all of them may move to the outside of the species territory simultaneously by the crossover operation in the global search strategy. This accidental replacement causes the extinction of the species. From now on, we have to examine how to decide the appropriate value of $SMIN'$ for balancing the local search and the global search. In addition, we will have to compare our proposed method with other state-of-the-art multimodal optimization algorithms as well as the SDE algorithm.

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