Bee System: Finding Solution by a Concentrated Search

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Abstract

In this paper we propose an improved genetic algorithm named *Bee System*. The concept of the *Bee System* comes from behavior of bees: first, a bee finds feed and then it notifies the information to the other many bees by dance to work together. In the proposed *Bee System*, each chromosome tries to find good solution individually. When some chromosome is regarded as superior one, other chromosomes try to find solution around there using multiple populations. Such a procedure is repeated. The *Bee System* employs some new operations such as *concentrated crossover*, and *Pseudo-Simplex Method*. By computer simulations it is confirmed that the *Bee System* has better performance than the conventional genetic algorithm.

1 Introduction

Nowadays many kinds of systems have been becoming more and more complicated. Adjustment of the parameters in such a system is a very important problem. It can be regarded as an optimization problem of multivariate functions. Traditional optimization methods[1] such as Quasi-Newton method have some shortcomings.

- They tend to suffer from excessively slow convergence.
- Many of them require some special information such as gradient of the objective function.
- If they fall into a local optimum, it is difficult to escape from the point.

Genetic Algorithms (GAs) have recently attracted much attention as a new optimization technique. Many applications using GAs have been proposed. For example, gas pipeline control, design planning of airplane, image pattern matching and so on[2]-[9]. Techniques combining GAs with neural networks or fuzzy systems have been also studied[2][11]. Thus it is thought that GAs are ones of the very important optimization methods.

It is certain that GAs have good global search ability, however, they lack the local search ability [2]-[9][14][15][19]. To improve this problem several methods have been proposed before.

- Combining GA with Quasi-Newton method[15]: One of the shortcomings of this method is that it requires gradient of the objective function.
- Forking GA[16]: One of the shortcomings of this method is complexity of the algorithms to obtain superior schemata.
- GAMAS[14]: The idea of GAMAS is very interesting, however, a little improvement is reported for local search.

It is thought that these studies are not sufficient to overcome the shortcoming.

Artificial Life, which is considered as a larger framework of GAs, also has been studied actively[12]. For instance, Marco Dorigo *et al.* proposed *Ant System* which originated from an analogy with cooperative work of ants[10]. We believe that observation of natural system can be an invaluable source of inspiration[10].

In this paper, we propose an improved GA inspired by the bee colony's function. We call it *Bee System*. The bee colony's function which we refer is as follows. First, each bee belonging to a colony looks for the feed individually. When a bee finds feed, then it notifies the information to the other many bees by dance, and they engage in a job to carry the feed. When they finish the work, each bee tries to find new one individually again.

In the proposed *Bee System*, global search is done first, and some chromosomes with pretty high fitness are obtained using the simple GA. These chromosomes are called superior chromosomes. Second, many chromosomes obtain the information of superior chromosomes by the concentrated crossover, and they search intensively around there using multiple populations. In addition, we modify the Simplex Method[17] which is popular as one of the optimization techniques and combine it with the *Bee System*.

The features of the *Bee System* are as follows:

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- Probability of falling into a local optimum is low because of the combination of local search and global search.

- Proposed concentrated crossover can concentrate many chromosomes on the areas where the global optimum might exist.

- Modified Simplex Method named Pseudo-Simplex Method contributes to enhance the local search ability of the *Bee System*.

The remainder of this paper is organized as follows: Section 2 reviews Genetic Algorithms; Section 3 provides details of the *Bee System*; Section 4 shows the results of computer simulations.

2 Genetic Algorithms

GAs are the effective algorithms for search and optimization problems based on an analogy with the processes of evolution and adaptation of natural life.

Fig.1 shows a flowchart of the conventional GAs. In GAs each candidate for solution for the problem is encoded into a linear list of the symbols, which is called chromosome. The GA generates a group of chromosomes called population, and three basic operations, selection, crossover, and mutation are applied to it. Selection is a process to keep chromosomes with high fitness value. Crossover is a process for exchanging genes of two chromosomes to create higher fit ones. Mutation is the occasional alternation of some gene values in chromosomes.

Compared with the other optimization methods, GAs have the following features[13]:

- Since GAs work in parallel on a number of search points, they are not easily caught in a local optimum.

- GAs do not need derivative of the objective function but only need to evaluate each candidate for solution.

For these features, it is possible to find the most suitable values or near suitable values for various problems effectively.

It is said that, however, the disadvantage of GAs is their lack of the local search ability. The reasons are thought as follows:

- Since the search is based on bit strings represented as chromosomes, the search points are not necessarily proximal each other on the actual search space.

- Generally speaking, since the local search ability conflicts with the global search ability, the global search ability degrades if we try to improve the local search ability without consideration of the balance.

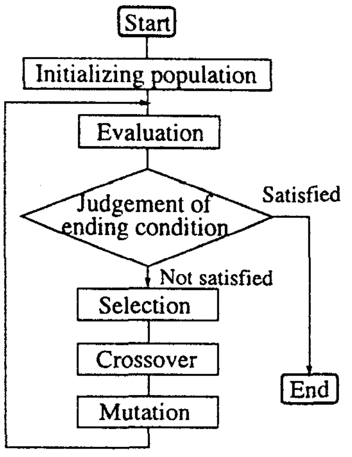

Figure 1: Genetic Algorithm.

We should consider these points to improve the local search ability.

3 Bee System

As we mentioned above, the *Bee System* is based on the functions of bee's colony. The purpose of the *Bee System* is to improve the local search ability of GAs without degrading the global search ability.

The *Bee System* uses multiple populations as shown in Fig.2; one *pop_G* for global search, and some $pop\_L_i (i = 1, \ldots n)$ for local search. First, global search is done by using *pop_G*. If one chromosome which is regarded to have pretty high fitness value is found, it is kept for local search as *Superior Chromosome*. It corresponds to a bee which finds feed. After finding n Superior Chromosomes ($SC_1 \sim SC_n$), local search starts. In the local search, all of the chromosomes in pop_L_k try to search around the SC_k intensively. To realize this concentrated search, we introduce *concentrated crossover* corresponding to bee's dance. Basically multiple populations ($pop\_L_1 - pop\_L_n$) work independently, but a little exchange is desired for multiple population models [14]. Thus we apply *Migration* to *pop_L*. We also introduce *Pseudo-Simplex Method* to enhance the local search ability. When the search around SCs is over, the best solution found is judged whether it satisfies the predetermined conditions or not. If not, the *Bee System* returns to the global search mode again.

Now we explain details of *Superior Chromosome*, *concentrated crossover*, *Migration*, and *Pseudo-Simplex Method*.

3.1 Superior Chromosome

In the *Bee System*, first global search is done by *pop_G*. The purpose is to search as widely as possible to avoid falling into a local optimum. In the *pop_G*, simple GA is applied in every generations.

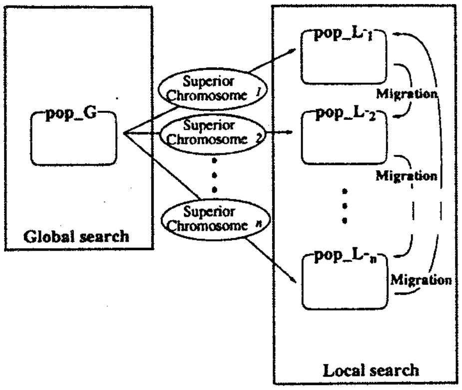

Figure 2: Bee System.

If one chromosome is the best for successive G_{sc} generations, it is considered as very good one around which there may be the global optimum. We call it *Superior Chromosome* (SC), and keep it for local search. If one chromosome is regarded as SC, *pop_G* is initialized and the search begins again. Such a procedure is repeated n times. Fig.3 shows the flowchart of global search, where m_{sc} is the counter representing the number of generations in which max fitness did not change, and k is the counter representing the number of *Superior Chromosomes* saved already.

In *pop_G*, in order to keep variety of genes, mutation rate is set at comparatively high value and the elitist strategy[13] is not employed.

3.2 Concentrated crossover

At the beginning of local search, all of the chromosomes in *pop_L*$_k$ make couple with SC_k and crossover operation is applied. In the conventional crossover each pair is made randomly, while in this concentrated crossover all of the chromosomes make pair with SC_k. This concentrated crossover transmits information about the kth Superior Chromosome SC_k to all of the chromosomes in the kth population *pop_L*$_k$. So *pop_L*$_k$ can try to search concentratedly around SC_k.

3.3 Migration

As we mentioned above, basically all of the populations are independent each other. But it is more effective to communicate with other populations. The *Bee System* selects one individual per predetermined generation G_{mig}, and transfers it to the neighboring population. It is called *Migration*. For this Migration, each population tries to search independently and cooperatively.

3.4 Pseudo-Simplex Method

For more effective search, a simplified Simplex Method named Pseudo-Simplex Method is introduced. Here we briefly explain the Simplex Method first. The geometrical figure formed by a set of $n+1$

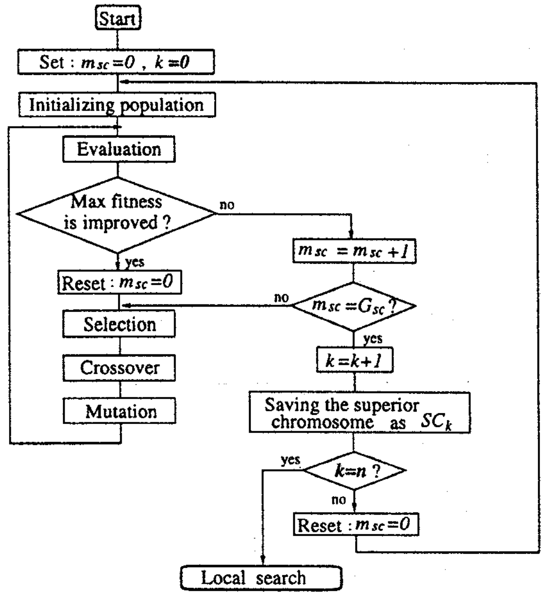

Figure 3: Flowchart of global search.

points in the n-dimensional space is called a simplex. In the two-dimensional case, the simplex becomes a triangle. The basic idea of the Simplex Method is to move the simplex gradually toward the optimum point by an iterative process using three operations: *reflection, expansion,* and *contraction.* One of the most attractive features of the Simplex Method is that it does not require derivative of the objective function[17].

For the sake of simplicity in the proposed Pseudo-Simplex Method, we always use just 3 points even if the dimensions of the objective function are higher than 2. One of the authors proposed a GA combined with a simplified Simplex Method[19]. Since it considered only *reflection*, however, it might go pass the optimum point. On the other hand, the proposed Pseudo-Simplex Method utilizes not only *reflection* but also *contraction* for more effective search.

In every generation, the following algorithm is applied. Fig.4 shows the schematic expression of the proposed Pseudo-Simplex Method in a two-dimensional case.

1) Pick up the best three chromosomes, and name them C_1, C_2, and C_3 in order of fitness.

2) Translate them into vectors; $\boldsymbol{X}_1, \boldsymbol{X}_2$, and $\boldsymbol{X}_3$, respectively.

3) Calculate the middle point of $\boldsymbol{X}_1$ and $\boldsymbol{X}_2$, and make $\boldsymbol{X}_0$ as follows:

$$\boldsymbol{X}_0 = \frac{\boldsymbol{X}_1 + \boldsymbol{X}_2}{2}. \tag{1}$$

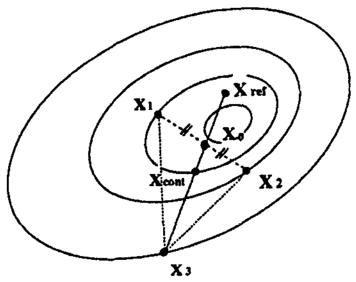

Figure 4: Pseudo-Simplex Method in a two dimensional case. ($\alpha = 0.5, \beta = 0.3$)

4) Calculate $\boldsymbol{X}_{ref}$ as follows:

$$\boldsymbol{X}_{ref} = (1+\alpha)\boldsymbol{X}_0 - \alpha \boldsymbol{X}_3. \tag{2}$$

This step corresponds to *reflection*. Where α is a constant which represents the reflection ratio.

$$\alpha = \frac{|\boldsymbol{X}_{ref} - \boldsymbol{X}_0|}{|\boldsymbol{X}_3 - \boldsymbol{X}_0|} \tag{3}$$

5) Calculate $\boldsymbol{X}_{cont}$ as follows:

$$\boldsymbol{X}_{cont} = (1-\beta)\boldsymbol{X}_0 + \beta \boldsymbol{X}_3. \tag{4}$$

This step corresponds to *contraction*. Where β is a constant which represents the contraction ratio.

$$\beta = \frac{|\boldsymbol{X}_{cont} - \boldsymbol{X}_0|}{|\boldsymbol{X}_3 - \boldsymbol{X}_0|} \tag{5}$$

6) Exchange $\boldsymbol{X}_{ref}$ and $\boldsymbol{X}_{cont}$ into chromosomes and make them C_{ref} and C_{cont}, respectively.

7) Introduce C_1, C_{ref} and C_{cont} to the original population to which crossover and mutation have already applied.

3.5 Return to global search

After passing the predetermined generations, the local search stops. If the best solution found so far does not suffice the ending condition, the global search starts again and the algorithm is repeated.

The flowchart of the local search is summarized in Fig.5.

4 Simulations

We have done a series of computer simulations to confirm the validity of the *Bee System*. We compared it with the conventional GA. In addition, we examined the effects of the concentrated crossover and the Pseudo-Simplex Method.

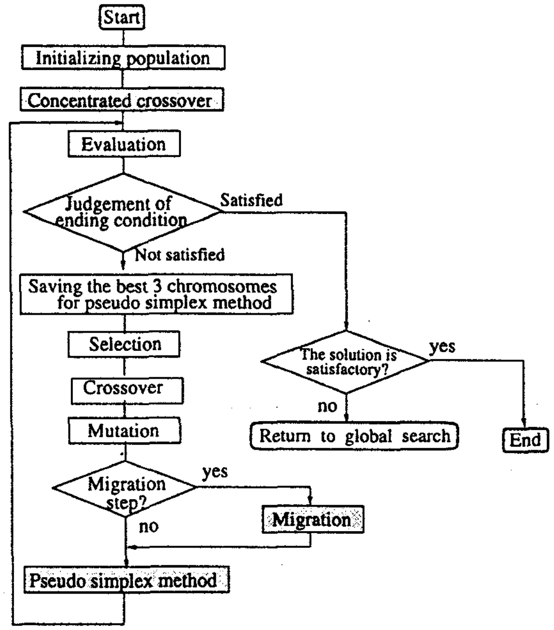

Figure 5: Flowchart of local search.

Table 1: Parameters used in simulations.

Mutation rate	*pop_G*	0.05
	pop_L	0.005
G_{mig}		5
G_{sc}		20
number of pop_L : n		3
parameters for PSM	α	0.4
	β	0.4

4.1 Simulation conditions

We used gray-code coding, two-point crossover and proportionate selection in both the *Bee System* and the conventional GA. Mutation rate was 0.005, and the elitist strategy was employed in the conventional GA. Other parameters used in the *Bee System* are summarized in Table 1. These parameters were determined by preliminary simulations, they are not necessarily the best. For each function, twenty trials were done to obtain averaged data.

We used nine test functions f1–f9, which are summarized in Table 2. They are widely used in GAs community[18][19][20].

To compare the performance of the *Bee System* with the one of the conventional GA fairly, chromosomes were evaluated total 15000 times per one trial for f1–f5, and total 50000 times per one trial for f6–f9, in both the *Bee System* and the conventional GA. For the same purpose, the *Bee System* did not return to a global search mode again, that is, only one cycle was executed in each trial.

Table 2: Test functions used in simulations.

Functions	Range	Dimension
$f_1(x_i) = \sum_{i=1}^{3} x_i^2$	$-5.12 \leq x_i < 5.12$	3
$f_2(x_i) = 100(x_1^2 - x_2)^2 + (1 - x_1)^2$	$-2.048 \leq x_i < 2.048$	2
$f_3(x_i) = \sum_{i=1}^{5} \text{integer}(x_i)$	$-5.12 \leq x_i < 5.12$	5
$f_4(x_i) = \sum_{i=1}^{30} i x_i^4 + Gauss(0,1)$	$-1.28 \leq x_i < 1.28$	30
$\frac{1}{f_5(x_i)} = 0.002 + \sum_{j=1}^{25} \frac{1}{j+\sum_{i=1}^{2}(x_i - a_{ij})^6}$	$-65.536 \leq x_i < 65.536$	2
$f_6(x,y) = 0.5 - \frac{\sin^2\sqrt{x^2+y^2} - 0.5}{(1+0.001(x^2+y^2))^2}$	$-100 \leq x, y < 100$	2
$f_7(x_i) = 20 + \sum_{i=1}^{20}(x_i^2 - \cos(2\pi x_i))$	$-5.12 \leq x_i < 5.12$	20
$f_8(x_i) = \sum_{i=1}^{10} -x_i \sin(\sqrt{\lvert x_i \rvert})$	$-500 \leq x_i < 500$	10
$f_9(x_i) = \sum_{i=1}^{10} x_i^2/4000 - \prod_{i=1}^{10} \cos(x_i/\sqrt{i}) + 1$	$-600 \leq x_i < 600$	10

$$[a_{ij}] = \begin{bmatrix} -32 & -16 & 0 & 16 & 32 & -32 & -16 & \cdots & 0 & 16 & 32 \\ -32 & -32 & -32 & -32 & -32 & -16 & -16 & \cdots & 32 & 32 & 32 \end{bmatrix}$$

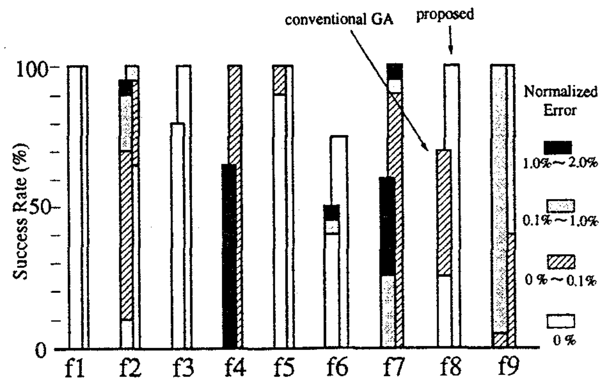

Figure 6: Simulation Results. (For each function, the left bar shows the result by the conventional GA and the right bar shows the one by the proposed *Bee System*.)

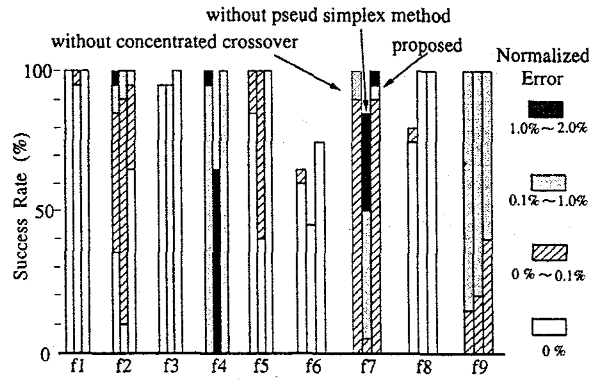

Figure 7: Effect of the concentrated crossover and the Pseudo-Simplex method. (For each function, the left bar shows the result by the *Bee System* without the concentrated crossover, the center bar shows the one by the *Bee System* without the Pseudo-Simplex Method, and the right bar shows the one by the complete *Bee System*.)

We introduce the *Normalized error* to evaluate their performances. When the number of chromosome evaluations reaches the predetermined number, we calculate the normalized error E_n of the best solution as follows:

$$E_n = \frac{x - O_t}{I_{ave} - O_t} \times 100\ (\%). \tag{6}$$

Where x is the best solution found in the trial, O_t is the Theoretical Optimum, and I_{ave} is the Averaged best solution in the Initial population. By the normalizing if the theoretical optimum is found, the normalized error E_n becomes 0%.

4.2 Simulation results

Fig.6 compares the *Bee System* with the conventional GA in respect of the success rate. For every function, the proposed *Bee System* shows better performance than the conventional GA. Let us take f8, for example, about 30% of the trials by the conventional GA could not find a solution whose normalized error was within 2.0%. And the optimum solution, whose normalized error was 0%, was found in only 25% of the trials. While the proposed *Bee System* could find the optimum solution in all of the trials under the same conditions.

Since f1 is a very simple function, however, the conventional GA shows the same performance as the *Bee System*. It is thought that the proposed *Bee System* is more effective especially for highly complex multivariate functions.

In order to examine the effect of the concentrated crossover and the Pseudo-Simplex Method, we tried the *Bee System* without using each of them. We compared the results with the complete *Bee System*. Fig.7 shows the results. It can be seen that the *Bee System* without either the concentrated crossover or the Pseudo-Simplex Method, has lower ability than the complete system. Thus we could verify their effectiveness.

5 Conclusion

In this paper we have proposed an improved Genetic Algorithm named *Bee System*. It is based on the bee's colony function. In the proposed *Bee System*, first pretty good chromosomes are found by using a population for the global search, then the concentrated search around them is carried out by using some populations for the local search. If the solution found by one cycle is not satisfactory, the global search is repeated. We have introduced new operations: the concentrated crossover and the Pseudo-Simplex Method. Because of these techniques and good balance between global search and local search, the proposed *Bee System* can obtain high ability for local search without degrading the global search ability.

We have confirmed the validity of the proposed *Bee System* by computer simulations. It is found that the *Bee System* is more effective especially for highly complex multivariate functions.

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References

[1] T.Ibaraki and M.Fukushima: "*Optimizatin Methods*", Kyoritsushupan, 1993. (in Japanese)

[2] M.Hagiwara: "*Neuro, Fuzzy, and Genetic Algorithms*", Sangyotosho, 1994. (in Japanese)

[3] H.Kitano: "*Genetic Algorithms*", Sangyotosho, 1993. (in Japanese)

[4] H.Kitano: "*Genetic Algorithms 2*", Sangyotosho, 1995. (in Japanese)

[5] T.Agui and T.Nagao: "*Genetic Algorithms*", Shokodo, 1993. (in Japanese)

[6] L.Davis: "*Handbook of Genetic Algorithms*", Morikitashuppan, 1994. (in Japanese)

[7] Y.Davidor: "*Genetic Algorighms and robotics*", Baifukan, 1996. (in Japanese)

[8] Y.Yonezawa: "*Genetic Algorithms*", Morikitashuppan, 1993. (in Japanese)

[9] H.Kawanishi and M.Hagiwara: "A Shape Detection Method using Improved Genetic Algorithm", *Trans. IEE of Japan*, vol.116-C, No.8, pp.891-897, Aug. 1996.

[10] M.Dorigo, V.Maniezzo, and A.Colorni: "Ant System: Optimization by a Colony of Cooperating Agents", *IEEE Trans. Syst., Man, and Cybern. PartB: Cybern.*, vol.26, No.1, pp.29-41, Feb. 1996.

[11] H.Ishiuchi, K.Nozaki, N.Yamamoto, and H.Tanaka: "Selectiong Fuzzy If-Then Rules for Classification Problems Using Genetic Algorithms", *IEEE Trans. Fuzzy Systems*, vol.3, No.3, pp.260-270, Aug. 1995.

[12] K.Hattori: "*The world of artificial life*", Ohmsha, 1994. (in Japanese)

[13] D.E.Goldberg: "Genetic Algorithms in Search, Optimization & Machine Learning", Addison Wesley, 1989.

[14] J.C.Potts, T.D.Giddens, and S.B.Yadav: "The Development and Evaluation of an Improved Genetic Algorighm Based on Migration and Artificial Selection", *IEEE Trans.on Syst.,Man,and Cybern.*,vol.24, pp.73-86, Jan.1994.

[15] J.M.Renders and S.P.Flasse: "Hybrid Methods Using Genetic Algorithms for Global Optimization", *IEEE Trans. Syst., Man, and Cybern. PartB: Cybern.*, vol.26, No.2, pp.243-258, Apr.1996.

[16] S.Tsutsui and K.Fujimoto: "Forking GA", *Journal of Japanese Society for Artificial Intelligence*, vol.9, No.5, pp.741-747, 1994.

[17] S.S.Rao: "Optimization theory and applications (second edition)", John Wiley & Sons, pp.292-300, 1984.

[18] K.A.De Jong: "Analysis of the behavior of a class of genetic adaptive systems", Technical Report No.185, Department of Computer and Communication Sciences, University of Michigan, 1975.

[19] M.Hagiwara: "Pseudo-Hill Climbing Genetic Algorithm (PHGA) for Funcion Optimization", *Proceedings of 1993 International Joint Conference on Neural Networks.* vol.1, pp.713-716, 1993.

[20] H.Mühlenbein, M.Schomisch, and J.Born: "The Parallel Genetic Algorithm as Function Optimizer", *Proceedings of the fourth international conference on Genetic Algorithms,* pp.271-278, 1991.