A Novel Selection Circuit Based on Rough Comparison Method for Genetic Algorithms Hardware

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Genetic algorithm (GA) are search techniques used in computing to find true or approximate solutions to optimization and search problems. GA are a particular class of evolutionary algorithms that use techniques inspired by evolutionary biology such as inheritance, selection, crossover and mutation. GA are categorized as global search heuristics.

Hardware accelerators for GA are required to reduce the execution time. Therefore, many research results for hardware implementation of GA have been reported. In the hardware implementation of GA, a circuit design of roulette wheel selection influences the performance of the GA hardware.

This paper propose a new selection circuit based on Rough Comparison Method (RCM). The RCM selects the larger data included within a certain definite range as selection candidates (SC). Figure 1 illustrates an example of the RCM. In the data ($D_0 \sim D_5$), the high-order several bits which are defined *Range* are used for data comparison. The other bits are considered as a rounding error. When the high-order four bits are compared (i.e. $Range = 4$), the values of D_0 , D_4 and D_5 are 112. Thus, D_1 , D_2 and D_3 is ruled out as SC, because the value of D_1 , D_2 and D_3 is 96, 80 and 16, respectively. The larger data in the data group is selected by this procedure. If there are several data in the SC, only one data is selected at random from the SC. If the fitness values of GA are used to RCM, RCM selects one fitness value from larger fitness values at random. i.e. the individuals which have larger fitness are selected in high probability. Therefore RCM's operation is as good as the ordinary roulette wheel selection scheme.

Figure 2 illustrates the proposed roulette selection circuit based on the RCM. This is a parallel processing circuit. Part (A) searches the individuals of SC. First, shift left registers (*data*) store the fitness values of all the individuals, and *flag* of all cells are set to '1.' Secondly, when at least one of the MSBs is '1,' signal line becomes '0.' Then, the *data* of MSB = 0 is smaller than that of MSB = 1. Therefore, the *flag* of the *data* of MSB = 0 changes to '0.' i.e. the *data* are no longer SC. Finally, *data* is shifted to the left. These operations are repeated *Range* times. The *Range* is the parameter which represents accuracy of the selection. In other words, the *Range* determines the threshold of the fitness. Part (A) takes a lot of SC when the *Range* is small. Part (B) selects only one individual at random from the SC. Only one cell receives $rand_j = 1$, and others '0' at random by the random number generator. When the $rand_j = 1$ and $flag_j = 1$ or $C_{in,j} = 1$ and $flag_j = 1$, win_j changes to '1,' otherwise '0.' i.e. j -th individual is selected as the individual to be used in the next process of GAs. If the $flag_j = 0$ and $rand_j = 1$, the chance to be selected is ceded to the next

cell ($C_{out,j} = 1$).

We designed a GA hardware embedded the proposed new selection circuit based on the RCM. The software simulations results showed that the proposed selection scheme has a performance better than the ordinary roulette wheel selection scheme. The hardware implementation result showed that the proposed circuit has a considerable validity. Moreover, the execution time and circuit size of the proposed circuit can be reduced. Therefore the proposed circuit suits well for the GA hardware.

Fig. 1. An architecture of the rough comparison method; (a) $Range=2$, (b) $Range=4$, (c) $Range=6$

Fig. 2. RCM circuit; part (A) searches the SC, part (B) selects one individual from SC

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Genetic algorithms (GAs) are search algorithms based on the mechanics of natural selection and natural evolution. Due to cost reasons, hardware accelerators for GAs are required to reduce its execution time. In the hardware implementation of GAs, a circuit design of roulette wheel selection influences the performance of the GAs hardware. In this paper, we propose a new selection circuit based on Rough Comparison Method (RCM), and evaluate effects of the proposed circuit in terms of execution time and circuit size. The RCM is a parallel processing circuit. Therefore, the execution time is constant regardless of the increase of number in individuals, and the circuit size of the RCM is reduced than the ordinary parallel roulette selection circuits.

Keywords: genetic algorithm, selection scheme, rough comparison method, digital hardware

1. Introduction

Genetic algorithm (GA) is a search technique used in computing to find true or approximate solutions to optimization and search problems⁽¹⁾⁽²⁾. GA is a particular class of evolutionary algorithm that uses techniques inspired by evolutionary biology such as inheritance, selection, crossover and mutation. GA is categorized as global search heuristic. GA has been applied to many hard optimization problems in computer science, engineering, economics, physics, mathematics and other fields⁽³⁾. They have been recognized as a robust general purpose optimization technique.

However, application of GA to increasingly complex problems can overwhelm software implementations of GA, causing unacceptable delays in the optimization process. This is true of any non-trivial application of GA if the search space is large. It follows that a hardware implementation of GA would be applicable to problems too complex for software-based GA.

In addition, a personal navigation system for tourism⁽⁴⁾ and a high resolution image compression system⁽⁵⁾ are proposed as an application of GA to embed in a portable terminal. A speedup, a miniaturization and a low-power consumption of GA are fundamental to embed these applications in the portable terminal.

Therefore, many research results for hardware implementation of GA have been reported^{(6)–(15)}. Although these hardware accelerate execution of GA over soft-

ware implementations, the speedup and the miniaturization of the circuits are not enough. Because these hardware were embedded of a roulette wheel selection circuit which is a major bottleneck with respect to the execution time and the circuit size.

In this paper, we proposed a new selection circuit based on a rough comparison method (RCM) to improve the performance of the selection circuit on the speedup of the execution time and the downsizing of the circuit size.

This paper is organized into seven sections. Section 2 provides a brief overview of genetic algorithms and extracts problem of previously reported GA hardware. Section 3 describes the rough comparison method. Section 4 discusses software simulations of GA using a proposed selection algorithm. Section 5 describes the GA hardware embedded proposed selection algorithm. Section 6 discusses a *Range* value and a optimization problem. Finally, Section 7 contains some concluding remarks.

2. Genetic Algorithm

2.1 Basic Architecture GA is an optimization technique based on the process of natural selection and evolution⁽¹⁾. A simple genetic algorithm (SGA) is the basis of GA⁽²⁾. The SGA has shown its usefulness for optimization problems requiring the search of large and complex problem spaces from engineering design to combinatorial optimization to control.

The SGA maintains a collection (population) of candidate solutions during the SGA operation. Associated with each candidate is a fitness or measure of its quality. An algorithm of the SGA proceeds by selecting candidates from the current generation to propagate into the next generation. In the process of this propagation the

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Fig. 1. A flow of SGA

algorithm may simply copy the selected candidates to the new generation or it may combine pairs of candidates through a crossover operation, reminiscent of mating in natural systems. In this case, the newly created the candidate solutions have characteristics taken from both parents. The selection of candidates for copy and crossover is randomized but biased toward candidates with higher fitness, thus, more fit individuals are more likely to be used to produce future generations of solutions. As a means of preventing premature convergence to local minima, an operation known as mutation randomly perturbs solutions to yield new ones not otherwise related to existing solutions.

SGA works as follows;

- (1) Randomly generating an initial population P_0
- (2) Computing and saving the fitness f_i for each individual G_i in the current population P_t
- (3) Defining selection probabilities p_i for each individual G_i in P_t so that p_i is proportional to f_i
- (4) Generating P_{t+1} by probabilistically selecting individuals from P_t to produce offspring via genetic operators (crossover, mutation)
- (5) Repeating step 2 to 4 until satisfying solution is obtained.

These steps are summarized in Fig. 1.

2.2 Hardware Implementation of GA A hardware implementation of GA is effective to obtain drastic performance improvement. The structure of GA computation forms a good basis for hardware. There have already been research carried out on hardware for GA, some of which concerned specific problems such as the pattern matching⁽⁶⁾, the scheduling⁽⁷⁾, the traveling salesman problem⁽⁸⁾ and the image filtering⁽⁹⁾, and some of which are a general-purpose hardware^{(10)–(15)}.

GA hardware which we propose belongs to the group of the general-purpose hardware.

2.3 Problems of Previous Works Much GA hardware which was reported previously employs a roulette wheel selection scheme for individual selection operation.

The roulette wheel selection is a representative stochastic selection model which is based on a fitness-proportionate selection strategy. The principle of the roulette wheel selection is a linear search over a roulette wheel with slots weighted in proportion to the individual's fitness value. At first, a sum of the fitness is calculated in Eq. (1), and then, a target value S_t set which is a random proportion of the sum of the fitness values

 Fig. 2. Selection circuits of the ordinary roulette wheel selection⁽⁸⁾ (main parts): (a) serial processing circuit, (b) parallel processing circuit

in the population in Eq. (2). The population is stepped through until the target value is reached. If the best individual is not selected to reproduce or if they're destroyed by crossover or mutation, they will be lost. To solve this problem, an elitist preserving selection is an addition to many selection methods that forces the GA to retain some number of the best individuals at each generation.

Procedure of the roulette wheel selection is as follows;

- (1) Summing up the fitness values of all individuals within the current population.

$$S_N = \sum_{i=1}^N f_i \dots\dots\dots (1)$$

- (2) Generating a random number $rand \in [0, 1]$ and calculating the target value S_t .

$$S_t = rand \times S_N \dots\dots\dots (2)$$

- (3) Examining the individuals in the order in which they appear in the population, and accumulating the fitness values into S_a up to k times where k is number of individuals. The individual under examination is selected when $S_a > S_t$.

$$S_a = \sum_{i=1}^k f_i \geq S_t \dots\dots\dots (3)$$

This method is implemented in two kinds of circuits⁽⁸⁾; serial processing circuit and parallel processing circuit (Fig. 2). However, these circuits (a) and (b) are major bottleneck with respect to the execution time and the circuit size, respectively.

Hence, several studies have focused on the improvement of selection scheme. Asada et al.⁽¹³⁾ suggested "roulette selection with binary search." This selection scheme narrowed the search space of the target individuals in roulette wheel selection by binary search to reduce of execution time. Besides, Yoshida et al.⁽¹⁵⁾ suggested "simplified tournament selection." This selection scheme reduced the execution time by simplification of a tournament selection scheme. This scheme selects two individuals at random, and the better one reproduces to next generation.

We propose a RCM-based selection scheme to improve the performance of the selection circuit on the speedup of execution time and the downsizing of the circuit size. And we will discuss performance comparisons between the RCM and the previous works in Sec. 4 and 5.3.

3. RCM-Based Selection

3.1 RCM The rough comparison method (RCM) selects the larger data included within a certain definite range as selection candidates (SC)⁽¹⁶⁾. Figure 3 illustrates an example of the RCM. In the data ($D_0 \sim D_5$), the high-order several bits which are defined as a *Range* are used for data comparison. The other bits are considered as a rounding error.

As shown in Fig. 3, when the high-order one bit is compared, all data are selected as SC. Because each bit is '0.' When the high-order two bits are compared, the values of every data except for D_3 are 64. At this point, as D_3 is smaller than the other data, D_3 is ruled out as SC. When the high-order four bits are compared, the values of D_0, D_4 and D_5 are 112. Thus, D_1, D_2 and D_3 is ruled out as SC, because the value of D_1, D_2 and D_3 is 96, 80 and 16, respectively. If all bits are compared, the maximum data is selected. The larger data in the data group is selected by this procedure. If there are several data in the SC, only one data is selected at random from the SC.

3.2 Selection Scheme Using RCM As mentioned above, RCM selects the larger data at random. If the fitness values of GA are used to RCM, RCM selects one fitness value from larger fitness values at random. i.e. the individuals which have larger fitness

are selected in high probability from all the individuals. Therefore RCM's operation is as good as the ordinary roulette wheel selection scheme. When it is necessary to select several individuals from the population, the RCM only selects several times from the SC at random. Thus the execution time for selection scheme can be reduced. Moreover, the population of next generation is composed of the individuals which are selected from the SC at random.

The RCM-based roulette wheel selection drastically reduces the execution time. Because this selection scheme takes only *Range* times by selecting one individual although the ordinary roulette wheel selection takes up to number of individuals times. In addition, the bit comparison in the RCM is well suited for a digital hardware implementation.

4. Simulations and Results

4.1 Verification of Effectiveness In order to verify the effectiveness of the proposed selection scheme based on the RCM in SGA, it is applied to four test problems⁽¹⁷⁾⁽¹⁸⁾; Eq. (4) is *parabola*, Eq. (5) is *step function*, Eq. (6) is *Shekel's foxholes* (a_{ij} is parameter) and Eq. (7) is *Rastrigin function*. The sketches of these functions are shown in Fig. 4.

Fig. 3. An architecture of the rough comparison method; (a) *Range*=2, (b) *Range*=4, (c) *Range*=6

Fig. 4. Test functions (two-dimensional version)⁽¹⁷⁾⁽¹⁸⁾; (a) *parabola*, (b) *step function*, (c) *Shekel's foxholes*, (d) *Rastrigin function*

Table 1. GA parameters in software implementation

No. of individuals	64
Precision of individual	(4) 30 bits (5) 50 bits (6) 34 bits (7) 100 bits
Precision of fitness	16 bits
Probability of crossover / mutation	0.3 / 0.05
<i>Range</i> (in proposed method)	10 bits
No. of generations	(4)–(6) 500 (7) 10000

Fig. 5. Comparison of selection schemes in software implementation; (a) *parabola*, (b) *step function*, (c) *Shekel's foxholes* and (d) *Rastrigin function*; these are average of 100 trials of each 500 and 10000 generations

$$f(x) = -\sum_{i=1}^3 x_i^2 \quad (-5.11 \leq x_i \leq 5.12) \dots\dots (4)$$

$$f(x) = -\sum_{i=1}^5 [x_i] \quad (-5.11 \leq x_i \leq 5.12) \dots\dots (5)$$

Fig. 6. Comparison of population diversity; (a) *parabola*, (b) *step function*, (c) *Shekel's foxholes*

$$f(x) = -\left[\frac{1}{500} + \sum_{j=1}^{25} \frac{1}{j + \sum_{i=1}^2 (x_i - a_{ij})^6} \right]^{-1} \quad (-65.535 \leq x_i \leq 65.536) \dots\dots (6)$$

$$f(x) = -\left[100 + \sum_{i=1}^{10} (x_i^2 - 10 \cos(2\pi x_i)) \right] \quad (-5.11 \leq x_i \leq 5.12) \dots\dots\dots (7)$$

The convergence property of the proposed selection was compared with the ordinary roulette wheel selection scheme. We programmed both the proposed selection and the ordinary selection schemes in software implementation. In these simulations, parameters of GA were configured as shown in Table 1.

Figure 5 illustrates the results of simulations. These results are represented as the maximum fitness values of each generation, and are average of 100 trials of each 500 and 10000 generations. As shown in Fig. 5, we confirmed that the convergence property of the proposed selection scheme is better than the ordinary roulette wheel selec-

Fig. 7. The maximum fitness values and the number of generations to the convergence when the *Range* value was set from 1 to 16; (a) a relationship between the maximum fitness value and the *Range*, (b) a relationship between the convergence speed (generations) and the *Range*

tion scheme.

The *Rastrigin function* and the *Shekel's foxholes* are hard problem for SGA. In order to resolve these hard problems, new GA architectures such as a parallel GA⁽²⁾ have been proposed. These GA embedded new architecture for upgrading a searching ability. Yet the ordinary selection scheme such as the roulette wheel selection is used. Thus, the new GA architecture with the RCM-based selection scheme will be able to resolve the hard problem for SGA because the RCM-based selection scheme is better than the ordinary roulette wheel selection scheme.

4.2 Verification of Diversity When only one SC exists in the population, it is quite likely that a population diversity is reduced because the same SC is kept selecting. Figure 6 shows a transition of the population diversity in one trial of each test problem. In these simulations, parameters of GA were configured as shown in Table 1. As shown in Fig. 6, it is certain that the population diversity is maintained by the RCM-based selection scheme.

Therefore, the proposed selection scheme is a valid method for the selection operation of GA.

4.3 How to Set the *Range* Figure 7 illustrates the maximum fitness values and the number of generations to the convergence when the *Range* value was set from 1 to 16. These results are average of 100 trials, where 500 generations are performed for 1 trial.

As shown in Fig. 7(a), the maximum fitness values of the test functions *parabola*, *step function* and

Fig. 8. Block diagram of GA hardware

Table 2. GA parameters in hardware implementation

No. of individuals	32
Precision of individual	16 bits
Precision of fitness	16 bits
Probability of crossover / mutation	0.2 / 0.01
<i>Range</i>	10 bits
No. of generations	10

Shekel's foxholes converges above *Range* = 6, 4 and 10, respectively. Moreover, as shown in Fig. 7(b), the number of generations to the convergence of the test functions *parabola*, *step function* and *Shekel's foxholes* converges above *Range* = 5, 8 and 14, respectively.

Accordingly, we adopted empirically the *Range* = 10 with careful regard to the results in Fig. 7. If we want to speed up the convergence speed, we can set the large *Range* value. Alternatively, the circuit requires a long execution time to select individuals.

5. Digital Hardware Design

5.1 System Architecture We designed a GA hardware embedded the proposed selection algorithm. Figure 8 illustrates a block diagram of a proposed GA hardware. This hardware implements SGA architecture, and consists of a global controller, a population memory, a random number generator, a fitness calculation circuit, a selection circuit, a crossover circuit and a mutation circuit. Table 2 shows the GA parameters in hardware implementation.

Each part of GA hardware is described in the following section.

5.1.1 Random Number Generator⁽¹⁰⁾ The random number generator supplies pseudo-random bit strings to the selection, crossover and mutation circuit.

The random number generator uses a linear cellular automata (CA)⁽²⁰⁾ to generate a sequence of pseudo-random bit strings, and is embedded in some previous GA hardware^{(10) (12) (15)}. The CA used in the random number generator consists of some alternating cells (bits) which change their states according to rules named "90" and "150":

$$\text{Rule 90: } S_i^+ = S_{i-1} \oplus S_{i+1} \dots \dots \dots (8)$$

$$\text{Rule 150: } S_i^+ = S_{i-1} \oplus S_i \oplus S_{i+1} \dots \dots \dots (9)$$

where S_i is the current state of the i -th cell (bits) in the linear cell array (bit string), S_i^+ is the next state for S_i , and $\oplus$ is the exclusive OR operator. Serra et al.⁽²⁰⁾ showed that a 16-cell CA whose cells are updated

Fig. 9. CA-based random number generator

Fig. 10. RCM circuit; part (A) searches the SC, part (B) selects one individual from SC

by the rule sequence “150-150-90-150 ... 90-150” produces a maximum-length cycle, i.e. it cycles through all 2^{16} possible bit patterns except the all 0s pattern. It has also been shown that such a rule sequence has more randomness than a linear feedback shift register (LFSR) of corresponding length⁽²¹⁾. Figure 9 illustrates the random number generator with the above rule sequence.

5.1.2 Fitness Calculation Circuit The fitness calculation circuit computes the fitness values of the randomly generated population during initialization. Also, once a complete new population is generated by the mutation circuit, the fitness calculation circuit generates the fitness values for each of the generated individuals.

5.1.3 Selection Circuit Figure 10 illustrates the proposed selection circuit based on the RCM. This is a parallel processing circuit.

Part (A) searches the individuals of SC. First, shift left registers (*data*) store the fitness values of all the individuals, and *flag* of all cells are set to ‘1.’ Secondly, when at least one of the MSBs is ‘1,’ signal *line* becomes ‘0.’ Then, the *data* of MSB = 0 is smaller than that of MSB = 1. Therefore, the *flag* of the *data* of MSB = 0 changes to ‘0.’ i.e. the *data* are no longer SC. Finally, *data* is shifted to the left. These operations are repeated *Range* times. The *Range* is the parameter which represents accuracy of the selection. In other words, the *Range* determines the threshold of the fitness. Part (A) takes a lot of SC when the *Range* is small.

Part (B) selects only one individual at random from the SC. Only one cell receives $rand_j = 1$, and others ‘0’ at random by the random number generator. When the $rand_j = 1$ and $flag_j = 1$ or $C_{in,j} = 1$ and $flag_j = 1$, win_j changes to ‘1,’ otherwise ‘0.’ i.e. j -th individual is selected as the individual to be used in the next process

 Fig. 11. Crossover circuit⁽¹⁴⁾

 Fig. 12. Mutation circuit⁽¹⁴⁾

Table 3. The performance of GA hardware

Operating frequency	50 MHz
Total gate of design	200K gates

of GAs. If the $flag_j = 0$ and $rand_j = 1$, the chance to be selected is ceded to the next cell ($C_{out,j} = 1$).

5.1.4 Crossover Circuit⁽¹⁴⁾ Figure 11 illustrates the crossover circuit which performs the single-point crossover operation. A crossover point depends on random values sent from the random number generator. When this circuit receives a selected pair of individuals from the selection circuit, it decides whether to perform crossover based on the probability of crossover which sent from the random number generator. When crossover is done, the new individual is sent to the mutation circuit.

5.1.5 Mutation Circuit⁽¹⁴⁾ Figure 12 illustrates the mutation circuit. When this circuit receives the individual from the crossover circuit, it decides whether to perform mutation based on the probability of mutation which sent from the random number generator in each bit. When mutation is done, the new individual is sent to the fitness calculation circuit for evaluation.

5.2 Hardware Simulations The problem in function maximization was applied to investigate the effects of the GA hardware embedded the RCM-based selection algorithm. In this paper, we used the following equation (7) as the evaluation function for simplicity (the sketch is shown in Fig. 13);

$$f(x) = \begin{cases} 2x & (0 \leq x \leq 0.5) \\ -2x + 2 & (0.5 < x \leq 1) \end{cases} \dots \dots \dots (10)$$

Fig. 13. The evaluation function of GA hardware

Fig. 14. The result of hardware simulation; these are average of 5 trials, where 10 generations are performed for 1 trial

We designed the GA hardware described in VHDL, and synthesized using a Mentor Graphics Precision Synthesis 2006 for a Xilinx XC2V6000-5 FPGA. A Xilinx ISE Foundation 8.1i was used for place and route. The hardware simulation using a Mentor Graphics ModelSim SE 6.2 is done. Table 3 shows the performance of the GA hardware embedded the RCM-based selection circuit.

Figure 14 illustrates the result of simulation. This result is represented as the maximum and average fitness values of each generation, and is average of 5 trials, where 10 generations are performed for 1 trial. As shown in Fig. 14, the average of fitness value gradually increased at each alternation of generations. Therefore, the GA hardware embedded the RCM-based selection circuit was considerable validity.

5.3 Performance Comparisons

5.3.1 Execution Time Figure 15 shows the comparison of the execution time for selecting one individual between the proposed RCM circuit and the previous works; the ordinary roulette wheel selection circuit by serial processing (Fig. 2(a), RW-s), the ordinary roulette wheel selection circuit by parallel processing (Fig. 2(b), RW-p), a roulette selection with binary search (BS)⁽¹³⁾⁽¹⁴⁾ and a simplified tournament selection (STS)⁽¹⁵⁾, where the precision of fitness value is 16 bits.

Firstly, the RW-p and BS are parallel processing circuit, and are implemented as the combinational logic circuits. The STS is implemented by only two comparators. Thus, these circuits need no clocks.

Secondly, the execution time of the RCM is much shorter than the RW-s. As mentioned in Sec. 2.3, the RW-s is added the fitness values one by one until go-

Fig. 15. Comparison of the execution time for selecting one individual by increase of individuals, where the fitness value is encoded in 16 bits

Fig. 16. Comparison of the circuit size of the proposed circuit and previous works

ing over the threshold. Therefore, the number of clocks which equal the number of individuals is needed until the individual is selected. Moreover, the execution time increases whenever the number of individuals increases. In contrast, the RCM selects the SC after the *Range* clocks are repeated, and then selects the individual from the SC by the combinational logic circuit. Therefore, the execution time is *Range* clocks, and is not more than the precision of fitness value (in this case, 16 clocks). In addition, the execution time is constant regardless of increase of the number of individuals because the RCM circuit is parallel processing circuit.

5.3.2 Circuit Size Figure 16 shows the comparison of the circuit size between the RCM and the previous works; RW-s, RW-p, BS and STS, where the individual and the fitness value are encoded in 64 bits and 16 bits, respectively.

Firstly, the circuit size of the RCM is much smaller than the RW-p and BS. The RW-p includes as many adders and comparators as the number of individuals (Fig. 2(b)) because this circuit has a parallel structure to expand the loop structure of Fig. 2(a). The BS is also a parallel processing circuit to narrow the search space of the target individuals by binary search. Therefore, the circuit size becomes much larger whenever the number of individuals increases. In contrast, the size of the RCM increases in proportion to the number of individuals as well as the RW-p and BS, yet the increase rate of the circuit size is few because the circuit size for one individual is small.

Table 4. Comparison of the operating frequency

	RWs	RWp	BS	STS	RCM
Operating frequency(MHz)	108	25	54	133	51

Fig. 17. Comparison of the selection schemes in the SGA; (a) parabola, (b) step function, (c) Shekel's foxholes; these are average of 100 trials, where 500 generations are performed for 1 trial

Secondly, the circuit size of the RW-s is considerably smaller than that of the RCM because the RW-s is implemented by an adder, an accumulator and a comparator (Fig. 2(a)). As with the RW-s, the circuit size of the STS is small because the STS is implemented by only two comparators. In addition, the circuit size is constant regardless of increase of the number of individuals because of the serial processing circuit.

5.3.3 Operating Frequency Table 4 shows the comparison of an operating frequency between the RCM and the previous works; RW-s, RW-p, BS and STS, where the fitness value is encoded in 16 bits. As shown in Table 4, the RCM circuit is not always high speed than other circuits. The low operating frequency is due to a chain circuit structure; the *line* signal chain and the *C_{in}* signal chain as shown in Fig. 10.

In order to reduce the delay time of the chain circuit,

Fig. 18. RCM circuit for the SSGA; part (X) selects one individual with smaller fitness value, part (Y) selects one individual with larger fitness value

the RCM circuit is divided into some parts. For example, when the RCM circuit is divided into two parts, the delay time of each chain circuit are reduced to half because each length of the chain circuit is reduced by half. Thus, the operating frequency of the RCM circuit doubles.

5.3.4 Convergence Property The two type simulations were performed to compare the convergence properties between the RCM and the previous works (BS, STS); the simple GA (SGA) and a steady-state GA (SSGA).

SGA Simulation The BS and STS are embedded to the SSGA in original paper. In this section, we evaluated the convergence property by embedding BS and STS to the SGA. In the SGA, all individuals are updated in each generation. Hence these selection schemes are repeated until creating the same number of offspring as the individuals in population. The parameters of SGA were configured as shown in Table 1. And the SGA is applied to three De Jong's test problems (Fig. 4).

Figure 17 illustrates the results of simulations. These results are represented as the maximum fitness values of each generation, and are average of 100 trials, where 500 generations are performed for 1 trial. As shown in Fig. 17, we confirmed that the convergence property of the RCM is better than the other selection schemes.

SSGA Simulation The SSGA⁽²²⁾ is an alternative to the SGA that replaces only a few individuals at a time, rather than an entire generation. In practice, the number of new strings created each generation is usually one or two. The new string(s) replace the string(s) selected from the population according to its fitness value. In this way the SSGA allows both parents and their offspring to coexist in same population.

When the RCM is embedded to SSGA, the RCM

Fig. 19. Comparison of the selection schemes in the SSGA; (a) *parabola*, (b) *step function*, (c) *Shekel's foxholes*; these are average of 100 trials, where 5000 generations are performed for 1 trial

scheme is customized as follows for the SSGA;

- (1) Two individuals with larger fitness values are selected (G_{L1}, G_{L2}).
- (2) Two individuals with smaller fitness values are selected (G_{S1}, G_{S2}).
- (3) The genetic operations are applied to G_{L1} and G_{L2} (G'_{L1}, G'_{L2}).
- (4) G_{S1} and G_{S2} are replaced with G'_{L1} and G'_{L2} .

The RCM circuit customized as shown in Fig. 18 is able to select the individual with smaller fitness value as well as larger fitness value although the circuit size increases somewhat.

The parameters of SSGA were configured as shown in Table 1. And the SSGA is applied to three De Jong's test problems (Fig. 4).

Figure 19 illustrates the results of simulations. In Fig. 19, these results are represented as the maximum fitness values of each generation, and are average of 100 trials, where 5000 generations are performed for 1 trial. As shown in Fig. 19, we confirmed that the convergence

property of the RCM is better than the other selection schemes.

The BS scheme narrowed the search space of the target individuals in roulette wheel selection by binary search to reduce of execution time. Therefore the BS scheme does not always select the individual with larger fitness value. The STS scheme selects two individuals at random, and the better one reproduces to next generation. Thus, as with the BS, the STS scheme does not always select the individual with larger fitness value. In contrast, the RCM scheme certainly selects the individual with larger fitness value. Therefore we considered that the convergence property of the RCM is better than the other selection schemes in both SGA and SSGA. However, it should be considered that the circuit size of the RCM somewhat increases.

6. Discussions

6.1 Variable Range A difference between individuals does not appear within the *Range* bits because there is not so much of the difference of the fitness value between individuals in the final phase of the convergence. In these circumstances, the proposed method operates as a random search. If a suitable *Range* bits for problem can be set in advance, it is possible to search for an optimal solution by the random search.

On the other hand, if the suitable *Range* bits for the problem cannot be set in advance, the other way is that a length of the *Range* is increased in the final phase of the convergence. As a result, the proposed method does not operate as a random search in the final phase, and can search the optimal solution.

6.2 Combinatorial Optimization Three test functions presented in Fig. 4(a)(b)(c) have been firstly proposed by De Jong⁽¹⁷⁾ to measure the performance of GA. The test environment includes functions which are convex (*parabola*), discontinuous (*step function*) and multimodal (*Shekel's foxholes*).

Because the *step function* has a discrete-valued data, the optimal solution is obtained by combining the discrete-valued data. Hence, the *step function* is a combinatorial optimization problem.

In contrast, the *Shekel's foxholes* has a continuous-valued data. However, this function has many local optima, and seems the discrete function. Therefore, the *Shekel's foxholes* as well as the *step function* is considered the combinatorial optimization problem. As we mentioned before, the RCM-based selection method has effectiveness of these test functions. As a result, the RCM-based selection method has effectiveness for not only the functional optimization problem but also the combinatorial optimization problem. i.e. a traveling salesman problem and a knapsack problem.

7. Conclusions

In this paper, we proposed the new selection circuit based on the rough comparison method, and evaluated effects of the proposed circuit in terms of the execution time and circuit size. The software simulations results showed that the proposed selection scheme has a perfor-

mance better than the ordinary roulette wheel selection scheme. The hardware implementation result showed that the proposed circuit has a considerable validity. In considering that the circuit size of the RCM increases somewhat, the convergence property of the proposed selection scheme is better than the other previous works. From what has been discussed above, we can conclude that the proposed circuit suits well for the GA hardware.

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