AUTOMATIC ADJUSTMENT FOR LASER SYSTEMS USING A STOCHASTIC BINARY SEARCH ALGORITHM TO COPE WITH NOISY SENSING DATA

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Abstract: For laser systems, the adjustment of the optical axes is crucial. However, it is difficult for conventional methods to adjust the optical axes because they require high-precision positioning with µm resolutions and because laser systems have many adjustment points that have an interdependent relationship. We have proposed an automatic adjustment method using genetic algorithms to overcome this problem. However, there are still two problems that need to be solved: (1) long adjustment times, and (2) adjustment precision due to observational noise. In order to solve these problems, we propose a robust and efficient automatic adjustment method for the optical axes of laser systems using a binary search algorithm. Adjustment experiments for optical axes with 4-DOF demonstrate that the adjustment time could be reduced to half the conventional adjustment time with the genetic algorithm. Adjustment precision was enhanced by 60%.

Index terms: Automatic adjustment, Laser system, Binary search, Genetic Algorithm, Noisy environments

1. Introduction

Laser systems are currently essential in various industrial fields. For laser systems, the adjustment for the optical axes is crucial, because the performance of the laser system deteriorates when the optical axes deviate from their specification settings, due to disturbances such as vibrations. However, it is very difficult to adjust the optical axes, because adjustment requires high-precision positioning settings with µm resolutions and because it is necessary to adjust for multi-degrees-of-freedom (DOF) that have an interdependent relationship. Thus, adjustment costs are a major problem due to the huge amounts of time required for a skilled engineer to adjust the optical axes.

In order to overcome this problem, we have proposed automatic adjustment methods for optical axes using Genetic Algorithms (GA) [1, 2, 3]. For example, our method has been successfully applied to the automatic adjustment of a femto-second laser that has 12-DOF [2]. However, there were two problems with the proposed methods that needed to be solved. First, it has been necessary to reduce the adjustment time to within 10 minutes. Because a laser system should ideally be re-adjusted every time it is used, for practical considerations, adjustment times must be as fast as possible. Secondly, because the adjustment of the optical axes is usually undertaken in very noisy environments, the precision of adjustment can vary widely. In order to overcome these problems, we propose a novel adjustment method. This method has two characteristics:

1. The method adopts a Binary Search Algorithm (BSA) [4].The BSA gradually changes from the exploration phase to the exploitation phase. The exploration phase searches a region that has not previously been searched using a binary search tree. The exploitation phase searches a region around good points.
2. The fitness value adopts a weighted average of sampled fitness values using a search history.

There are two advantages with the proposed method: (1) adjustment time can be reduced. The method does not search in regions that have previously been searched. In addition, it is not necessary to re-evaluate the fitness function to mitigate the influence of noise. (2) It provides robust automatic adjustment. Instances of premature convergence or falling into local solutions do not occur because the adjustment is less influenced by noise. Accordingly, we can realize robust and efficient automatic adjustment systems for the optical axes within laser system by the proposed method. Conducted experiments involving 4-DOF adjustment with the proposed method demonstrate that (1) adjustment time can be reduced to half the conventional adjustment times, and (2) precision can be enhanced by 60%.

This paper is organized as follows: In Section 2, we explain the adjustment system for the optical axes of laser systems and the conventional method of automatic adjustment. Section 3 describes our proposed method, and Section 4 demonstrates the benefits of the proposed method for benchmark problems. Section 5 outlines the automatic adjustment system used in the experiments. In Section 6, we present the experimental results obtained for the proposed method. Finally, a summary of this study and future investigations are provided in Section 7.

2. Adjustment systems for optical axes and automatic adjustment methods

2.1. Adjustment systems for optical axes

For laser systems, the adjustment of the optical axes is crucial because the performance of laser systems deteriorates when the optical axes deviate from their specification settings. Let us explain adjustment systems taking the one in Fig. 1 as an example. This system is a femto-second laser system that consists of seven mirrors and two prisms. A characteristic of femto-second lasers is that the high-peak power is inversely proportional to the short duration of the laser pulses, so they can generate high power levels, over one megawatt, during femto-second (10^{-15} sec) pulses. This system has 12-DOF to be adjusted with μm resolutions. The optical axes are adjusted by moving stepping motors, so that the output power from the laser system is maximized.

In such an adjustment system, there are two sources of observational noise influencing output evaluations. The first is the noise in the detectors that evaluates the output from the laser system. The second source is the precision of the positioning motors. While the positioning motors are moved according to constant displacements, actual axial displacements are not constant. Therefore, the optical axes can deviate from the desired state, even if the motors are moved according to the displacement settings in seeking to adjust to the target state. Thus, the adjustment of optical axes must be carried out by considering these sources of noise. In the system shown in Fig. 1, for example, manual adjustment takes about a week.

2.2. Automatic adjustment methods

We have already demonstrated how it is difficult for a hill climbing method to automatically adjust optical axes [2]. There are two reasons for this. The first reason is that the adjustment becomes trapped by local solutions, because the adjustment points of the laser system have an interdependent relationship. The second reason is that adjustment must be executed in noisy environments. In order to overcome these problems, we have proposed an adjustment method using a GA [1, 2, 3]. In the proposed method, a chromosome is a set of genes, which represent motor displacements, and fitness is the output from the laser system. We have demonstrated the effectiveness of automatic adjustment using GA for the laser system illustrated in Fig. 1. However, there were two problems that needed to be solved. (1) Adjustment took a long time, because the method also performed exploration during the final phase. The time for motor movements, which accounts for nearly all of the adjustment time, increases in proportion to the degree of motor displacement. (2) Robust adjustment is difficult, because search is influenced by the two sources of noise explained in subsection 2.1. Consequently, instances of premature convergence occurred or adjustment became trapped at local solutions, so adjustment precision varied widely.

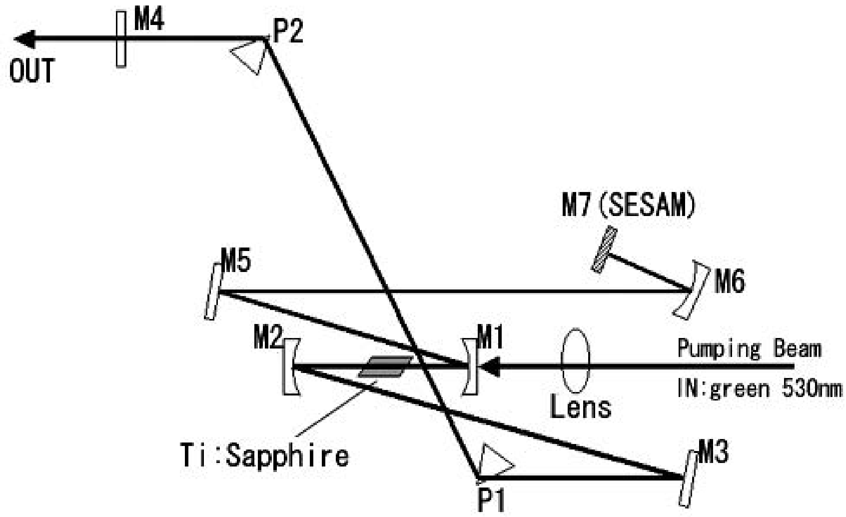

Figure 1: A femto-second laser system.

3. Proposed adjustment method

We propose a robust and efficient automatic adjustment for the optical axes of laser systems using a binary search algorithm (BSA) [4] for noisy environments. The flowchart of the proposed method is shown in Fig. 2. This method utilizes a weighted averaged fitness value in the BSA, as explained in Fig. 2. We refer to the proposed method as BSW. The algorithm is explained in more detail below.

3.1. Stochastic Binary Search Algorithm

The strategy of BSA is to use a binary search tree [4] to divide the search space into empty regions, allowing for the largest empty regions to be approximated. The search tree is constructed by generating a point x_t at random within a chosen hypercube, and then by dividing that hypercube along the dimension that yields the most 'cube-like' subspaces. The basic algorithm for constructing the binary search tree works by repeatedly choosing an exploration or exploitation step:

1. **Exploration:** Next point x_{t+1} is generated within the largest empty region.
2. **Exploitation:** Next point x_{t+1} is generated within the largest empty region that is within a small distance from a 'good point'.

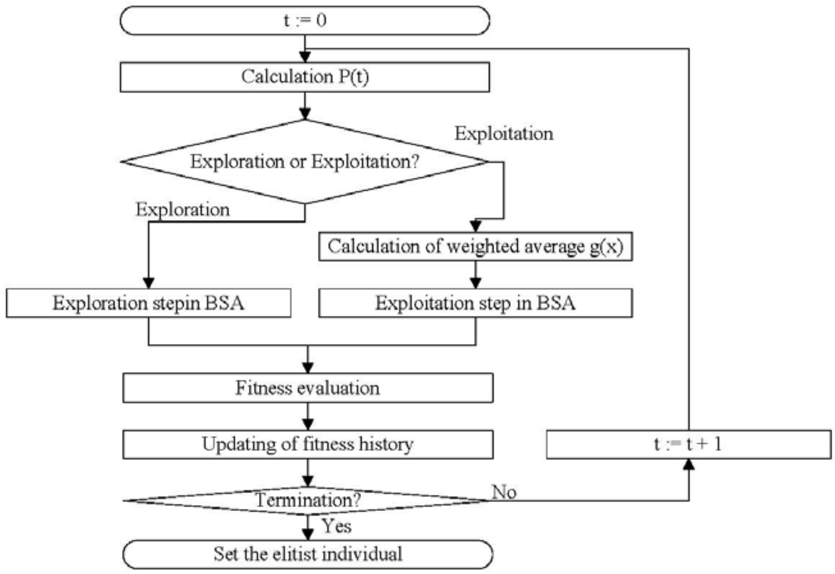

Figure 2: Flowchart for the proposed method.

The coordinates of point x_t and the evaluated value f_t at x_t are stored in a search history *F(t)* represented in Eq. (1).

$$F(t) = \{(x_1, f_1), (x_2, f_2), \cdots, (x_i, f_i), \cdots, (x_t, f_t)\} \tag{1}$$

The characteristics of the BSA are (1) the search phase in the BSA gradually shifts from exploration to exploitation and (2) the BSA stores a complete search history for all regions that have been searched. Based on these characteristics, the BSA can reduce adjustment times, because the BSA does not undertake exploration in the final phase and because the BSA does not search in regions that have previously been searched. The flow is explained in more detail below.

1. Determination of the basic algorithm

   The decision of whether to perform exploration or exploitation is made based on a probability distribution *P(t)* that varies with the number of fitness evaluations. *P(t)*, which is calculated using Eq. (2), is illustrated graphically in Fig. 3.

$$P(t) = (C-1)\frac{\tanh\left(\frac{t/N-K}{\sigma}\right)-\tanh\left(\frac{-K}{\sigma}\right)}{\tanh\left(\frac{1-K}{\sigma}\right)-\tanh\left(\frac{-K}{\sigma}\right)}+1 \tag{2}$$

C is the minimum probability of performing the exploration step, σ is the rate at which the probability of exploration decays. K is the midpoint of the decay and N is the maximum number of trials that are to be performed.

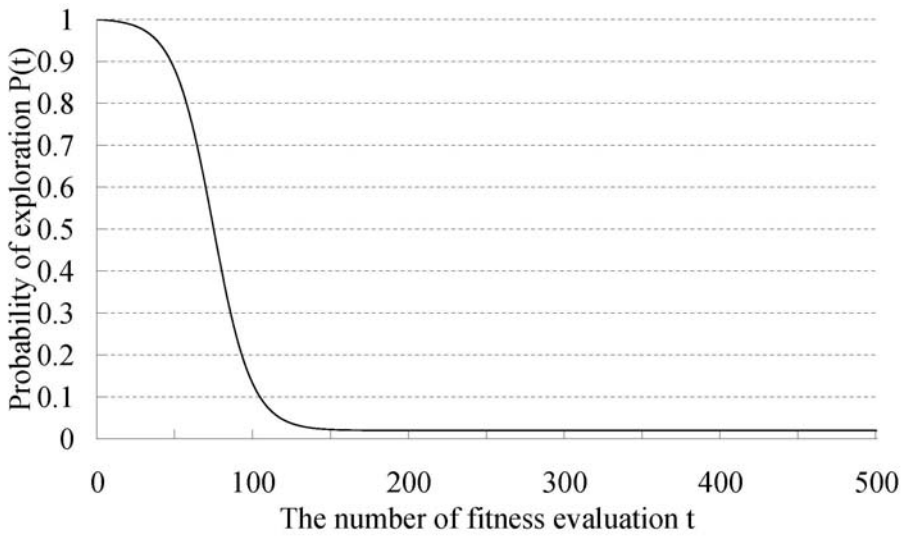

Figure 3: Probability of exploration for C = 0.02, K = 0.1, σ = 0.05 and N = 500.

2. Exploration

   In the beginning, the largest region which has not previously been searched is identified from the search history. A search point x_t is generated randomly within that region. For example, exploration in a two-dimensional search is illustrated in Fig. 4. Within the search region, the region ‘A’ is selected because region ‘A’ is the largest region that has not already been searched. Next, the search point x_t is generated at random in the region ‘A’.

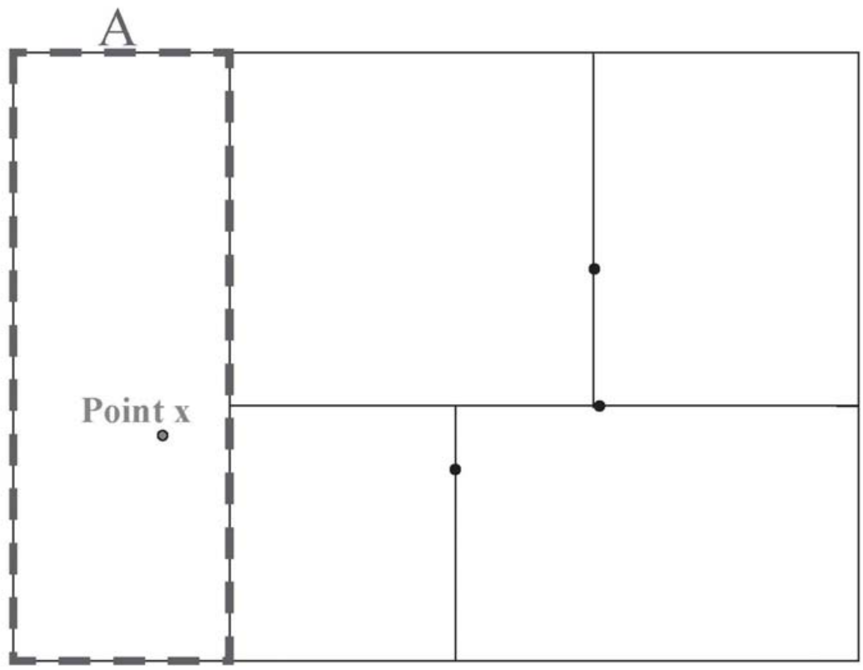

Figure 4: Exploration.

3. Exploitation

   First, N_p points are selected at random from the search history and the weighted averaged fitness, which will be explained in subsection 3.2, is calculated for those points. According to the calculated weighted averaged fitness, non-dominated solutions are chosen from the N_p searched points. A ‘good point’ is selected at random from among these non-dominated solutions. Next, a small offset distance d_p is used to generate a hypercube of interest about the ‘good point’. The small hypercube is placed around the ‘good point’ simply to provide an efficient means of identifying neighboring regions. A search point x_t is generated at random in the largest region that intersects the hypercube. Exploitation in a two-dimensional search is shown in Fig. 5. The small hypercube is placed around the ‘good point’ selected in the search history. Then, the largest region ‘B’ is selected where three regions intersect with the hypercube. The search point x_t is generated at random in the region ‘B’.

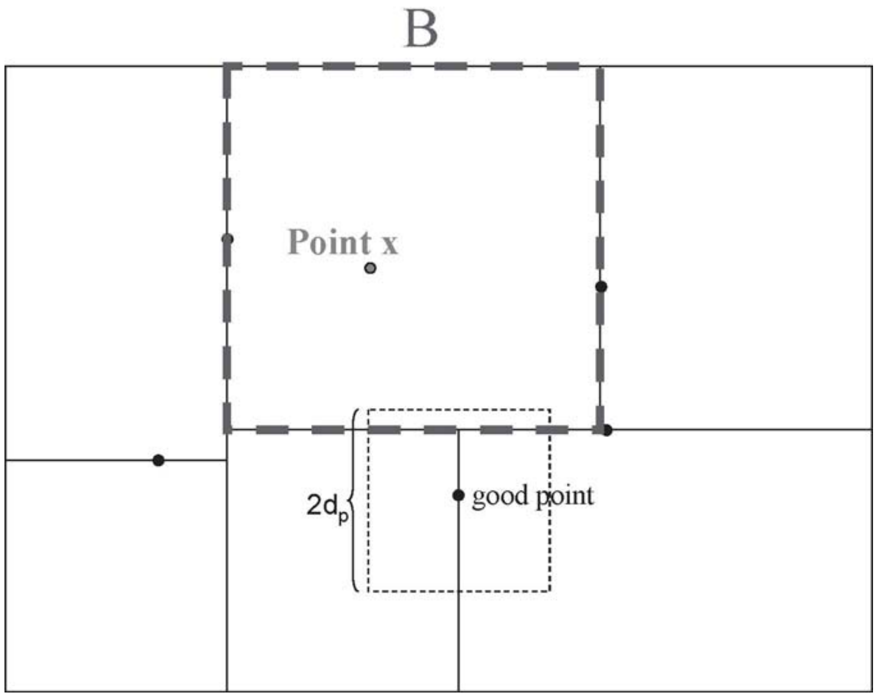

Figure 5: Placement of a small hypercube.

4. Division of the search region

   After generation of the search point x_t, the search region that was selected in either the exploration or exploitation phase is divided to two subspaces along a dimensional axis based on the search point x_t. Then, spaces along a dimensional axis that yields the most 'cube-like' subspaces are selected. The definition of 'cube-like' employed here is the split that minimizes Eq. (3), where d_{max} is the maximum side length for the sides of the two subspaces, and d_{min} is the overall shortest side length. If H is 1, the two subspaces become hypercubes.

$$H = \frac{d_{\max}}{d_{\min}} \tag{3}$$

5. Fitness evaluation

   In this adjustment, the positioning error of the optical axes is obtained after displacement of the positioning motors. The unit for f is μm. This fitness value is calculated from the X-Y coordinates on the front of the optical sensor.

6. Updating of search history

   The search history is updated by adding information about the search point x_t, the fitness values and the two subspaces. Updating of the binary tree as the search history is illustrated in Fig. 6. When the search point was generated in the region marked by node 2 and the region was divided to two subspaces, the information about the search point and the fitness are stored in node 2. Then, the two nodes for the two divided subspace are referred to as child nodes of node 2.

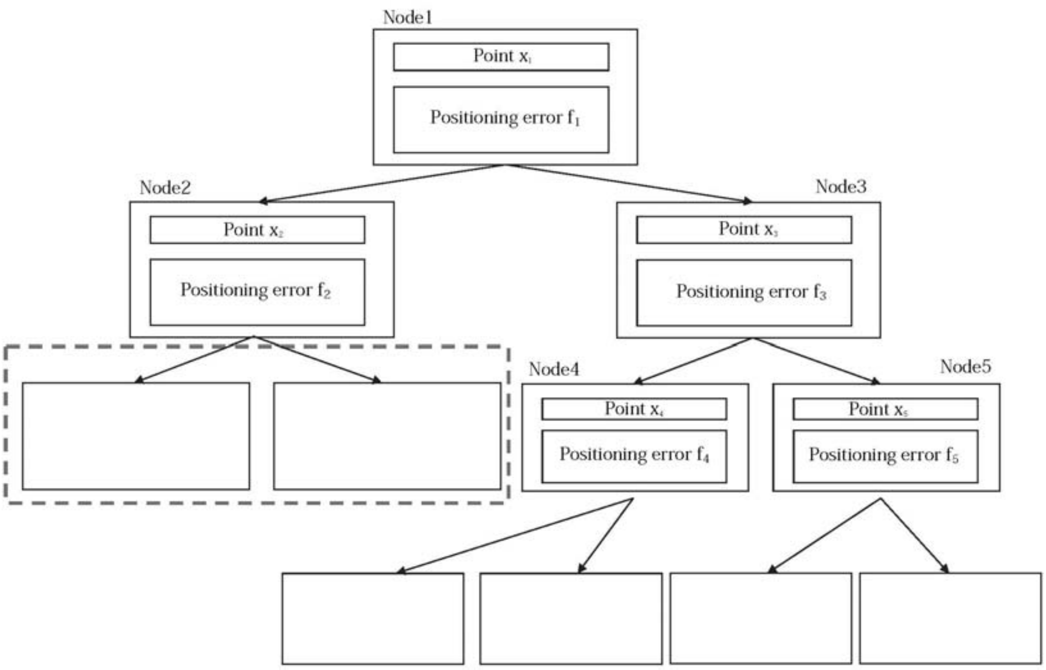

Figure 6: Updating the search history.

The adjustment terminates after N repetitions of the above steps. Fig. 7 presents the termination of a two-dimensional example search, where the optimized solution is at the center of the square area. The red points were generated at the exploration phase, and the blue points were generated at the exploitation phase.

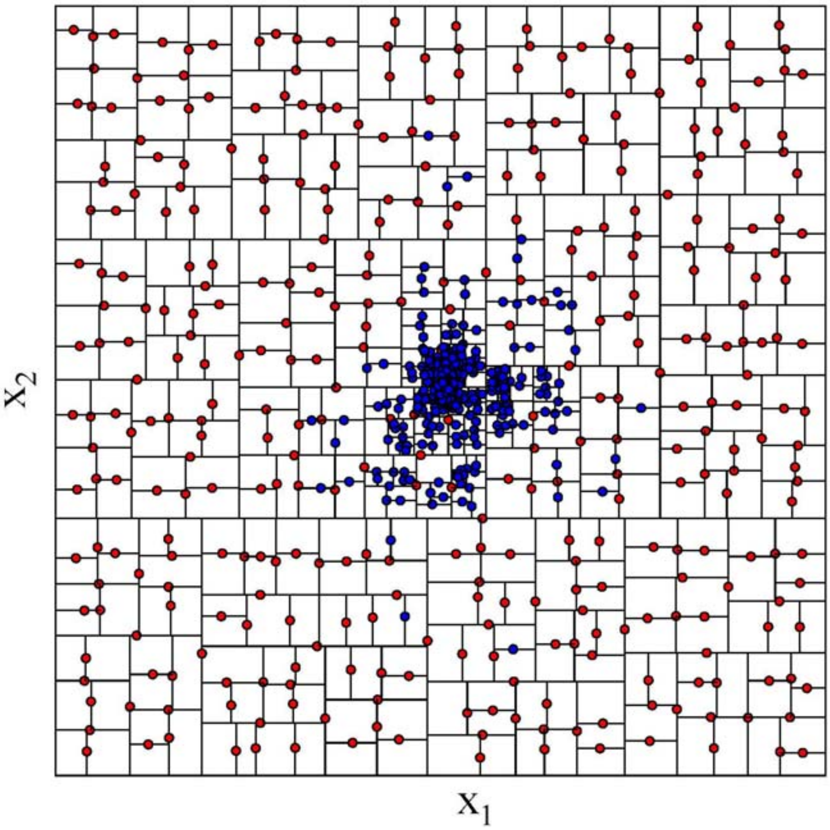

Figure 7: Two-dimensional search result using BSW.

3.2. Weighted averaged fitness

The conventional method of coping with noisy fitness functions is to evaluate the fitness values several times for each individual and to adopt the average of the sampled values [5, 6]. However, adjustment for laser systems by the conventional method is not practical, because adjustment time increases. For example, if moving the motors and detection to obtain a fitness value are performed *N* times, then the adjustment time increases *N*-fold.

In order to solve this problem, a weighted average value, which is calculated from the search history, is used for the fitness value. For the laser system, we assume the detected value f_t at x_t increases or decreases in proportion to the distance d_t from a certain point x to the point x_t and that noise varies according to a normal distribution. The maximum likelihood estimation of $f(x)$ can be obtained as follows:

$$g(x) = \frac{f(x) + \sum_{t=1}^{T-1} \frac{1}{1 + k \times d_t^2} f_t}{1 + \sum_{t=1}^{T-1} \frac{1}{1 + k \times d_t^2}} \qquad (4)$$

$$d_t = \|x - x_t\| \tag{5}$$

where $f(x)$ is the evaluated value with the detector, $f_T = f(x)$, $x_T = x$ and k is the proportional value and d_t is the distance from the sampled points. The 'good point' in the exploitation step of the BSA is decided using this weighted averaged fitness $g(x)$.

There are two advantages of this method. The first is that this method can prevent premature convergence during the exploitation phase due to observational noise. The second advantage is that the number of evaluations is just one time for each individual. Thus, this method is capable of adjusting the optical axes robustly and efficiently in noisy environments.

4. Performance validation of the proposed method using benchmark problems

4.1. Details of the validation approach

Two verification experiments were conducted to evaluate the performance of the proposed method. In these experiments, we compared the proposed BSW method with the conventional method, which is a GA employing the Minimal Generation Gap (MGG) model [7], for two benchmark problems with noise-free fitness evaluations. These test problems are the Rosenbrock function [8] which is a uni-modal function with a strong dependency between its variables, and the Rastrigin function [9] which is a multi-modal function without dependency. For these experiments, the two test models can be defined as four-dimension problems. The parameters were as follows:

1. For the Rosenbrock function.

· GA: The population size was 200. The probabilities for crossover and mutation were 0.7 and 0.01, respectively. The number of fitness evaluations was 50,000.

· BSW: Parameters of $P(t)$ were $C = 0.01$, $K = 0.4$, $\sigma = 0.1$ and $N = 50{,}000$. Parameter for the weighted averaged fitness was $k = \infty$.

2. For the Rastrigin function.

· GA: The population size was 200. The probabilities for crossover and mutation were 0.7 and 0.01, respectively. The number of fitness evaluations was 100,000.

· BSW: Parameters of $P(t)$ were $C = 0.2$ $K = 0.01$, $\sigma = 0.05$ and $N = 100{,}000$. Parameter for the weighted averaged fitness was $k = \infty$.

4.2. Validation results

Fig. 8 presents the comparison results for BSW and GA on the Rosenbrock function. These results show that the BSW identified an optimal solution faster than the GA. This reflects the facts that the BSW does not search again in previously searched regions, and it does not execute exploration in the final phase. Accordingly, the BSW is more efficient than the GA. Fig. 9 presents the comparison results for BSW and GA on the Rastrigin function. The BSW and the GA yielded similar performances for the multi-modal function. Performance for the BSW was better than for the GA after shifting from exploration to exploitation. In the early phase, the BSW was sufficiently required to employ exploration in order to prevent it falling into local solutions. These results show that efficient searching was achieved by the BSW.

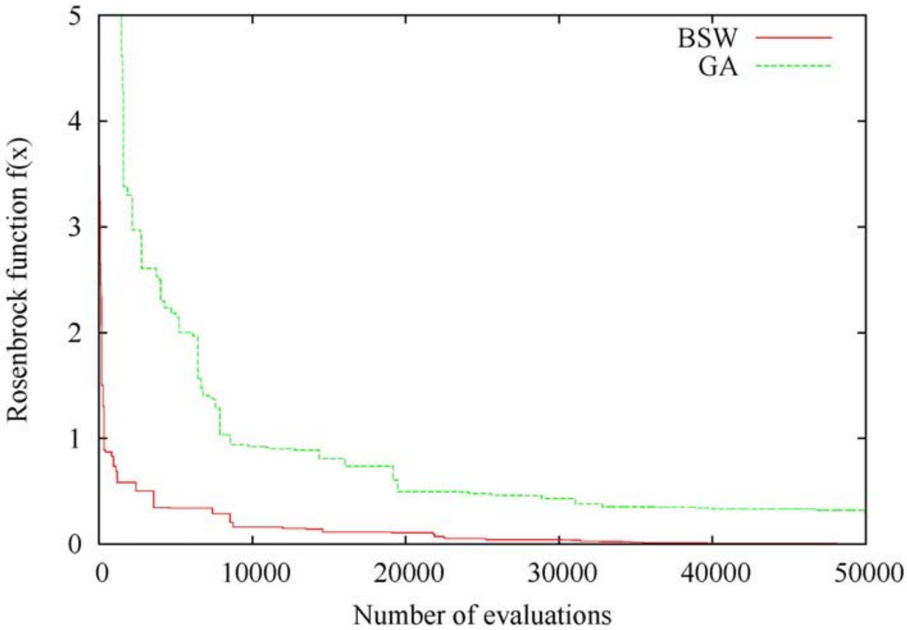

Figure 8: Comparison for BSW and GA on the Rosenbrock function.

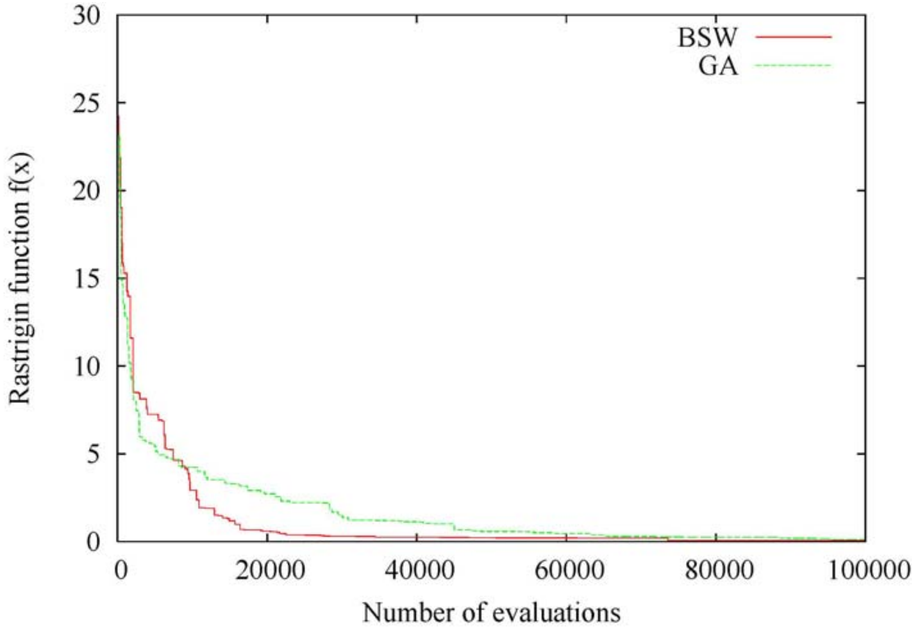

Figure 9: Comparison for BSW and GA on the Rastrigin function.

5. An automatic adjustment system for optical axes

5.1. Configuration of the adjustment system

In this paper, we demonstrate the effectiveness of the proposed method using the most basic adjustment system [3]. The structure of this adjustment system is illustrated in Fig. 10. The adjustment system consists of two mirrors with two stepping motors, an evaluation detector to detect the positioning of the optical axis, a motor controller to control the stepping motor for the mirror and PC to execute the calculations. The mirrors in the system can be adjusted according to 2-DOF to adjust the positioning of the optical axis.

A photograph of the experimental system is shown in Fig. 11. Details for each component in the system are provided below.

1. Motor controller

   The motor controller is a stepping motor driver and the mirror holder system has a resolution of 0.075μm/step. With this controller, the time to move the motors in evaluating each individual is at maximum about 4 seconds.

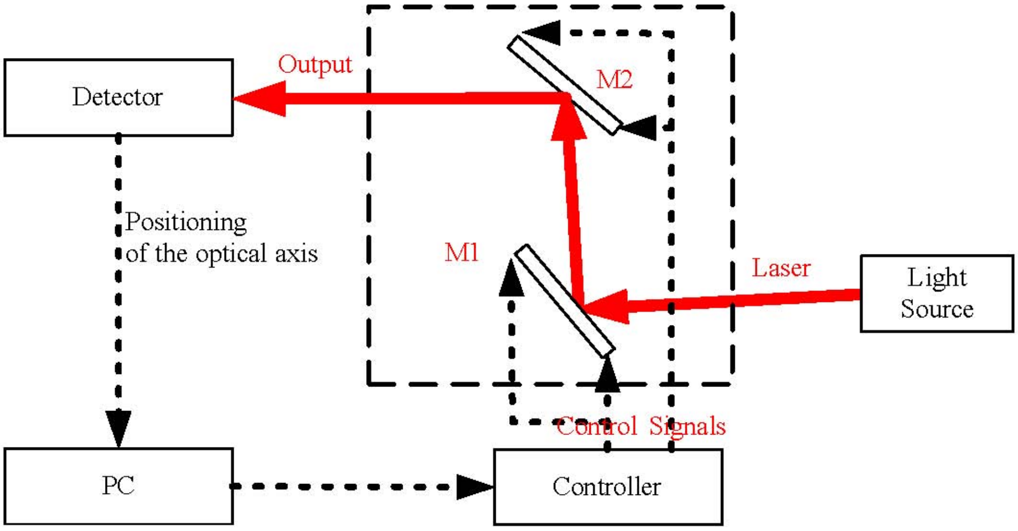

Figure 10: The structure of the experimental system.

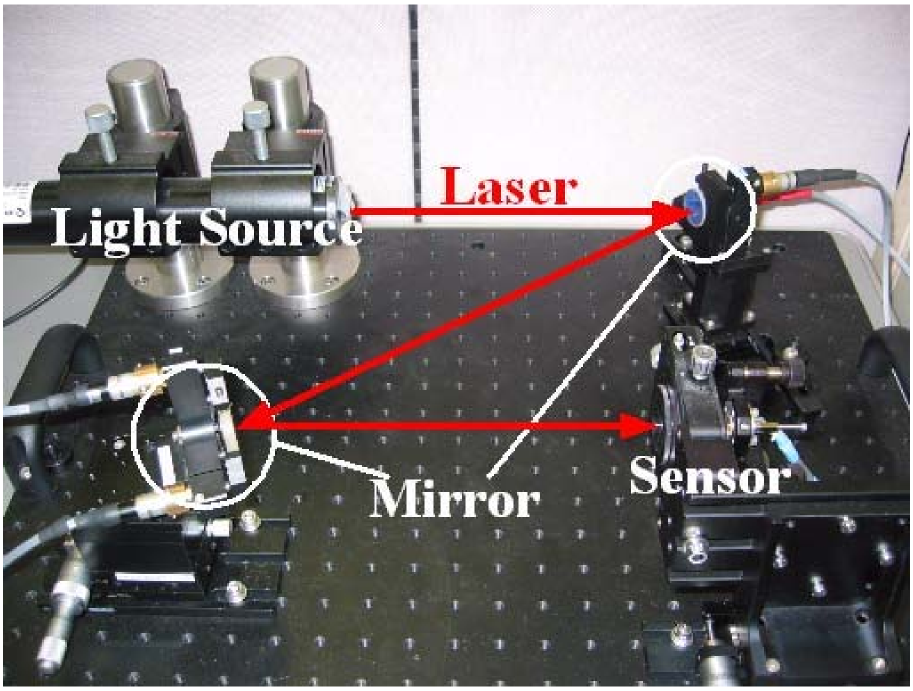

Figure 11: The automatic adjustment system for optical axes with 4-DOF.

2. Evaluation detector

   The detector consists of two-dimensional position sensitive detectors (S2044) and a signal processing circuit (C9069) produced by HAMAMATSU Photonics KK. This detector with a resolution of 1.39µm can detect the X-Y coordinates of the optical axes on the detector front.

3. PC

   The flow, which is explained in Fig. 2, is run on the PC.

4. Light source

   The light source is a He-Ne gas laser (1125P) produced by JDS Uniphase. The beam diameter is 2mm.

The optical axes are adjusted automatically based on the flow shown in Fig. 2. A chromosome in the BSW represents displacement for the four stepping motors, which moves the two mirrors. The displacement of each stepping motor is represented by 8bits. The evaluation value *f(x)* uses a positioning error, which is the Euclidean distance between the positioning of the optical axes and the target position, calculated from the detected X-Y coordinates.

5.2. Noise sources in the adjustment system

In this adjustment system, there are two sources of noise that influence output evaluations. (1) Observational noise from the evaluation detector that evaluates the state of the optical axes. (2) Driving precision noise due to the precision of the stepping motors. While the stepping motors are moved according to constant displacements, actual axial displacements are not constant. Accordingly, the optical axes can deviate from the desired state, even if the motors are moved according to displacement settings in seeking to adjust toward the target state.

Observational results for these noises are presented in Tab. 1, Fig. 12 and Fig. 13. The values in Tab. 1 are root-mean-square (RMS) errors that were observed with the adjustment system. In terms of noise (1), the positioning RMS error was 18.1μm. In terms of noise (2), the positioning RMS error was 129.5μm. Fig. 12 presents the occurrence frequencies for noise due to the evaluation detector, and Fig. 13 presents the occurrence frequencies for noise due to the precision of the stepping motors. These observational frequencies results demonstrate that the noises can be approximated by a normal distribution, as assumed in subsection 3.2.

Table 1: Two kinds of noise sources.

	Positioning error
Error caused by noise (1)	18.1 μm
Error caused by noise (2)	12.9μm

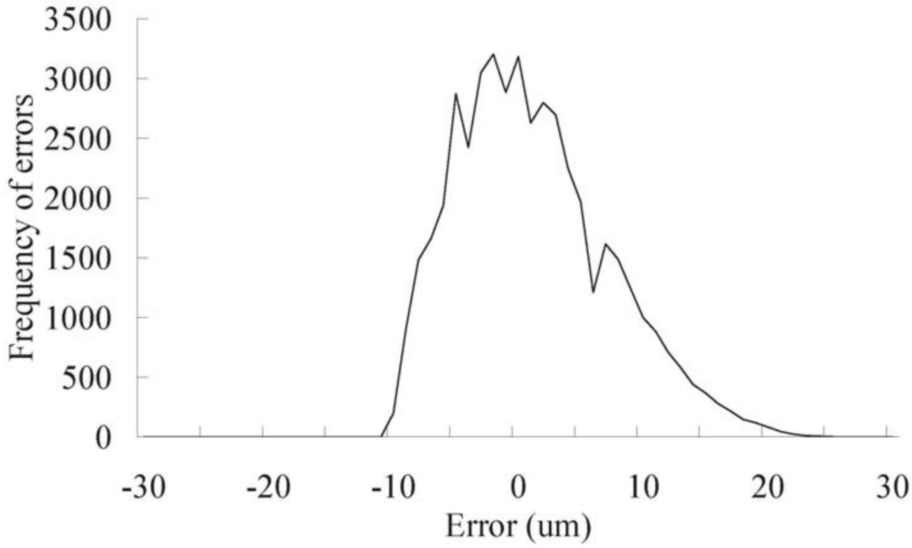

Figure 12: Observational noise from the evaluation detector.

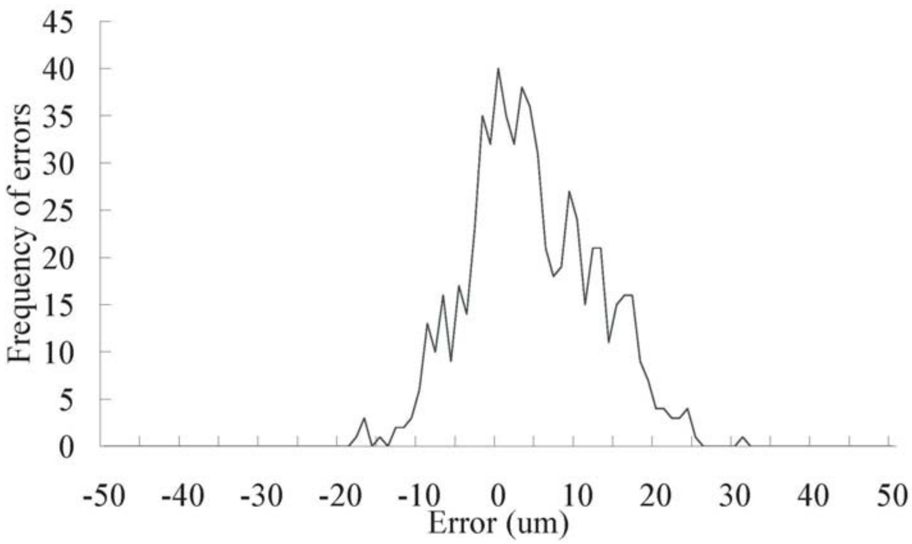

Figure 13: Driving precision noise due to the precision of the stepping motors.

6. Adjustment experiments

6.1. Experimental details

Three experiments were conducted to examine the effectiveness of the proposed method. These were an automatic adjustment experiment using a GA with the MGG model, an automatic adjustment experiment using the BSA and an automatic adjustment experiment using BSW.

The adjustment goal in each case was set to the laser system to its ideal state (i.e., error in terms of the target positioning of the optical axes is 0). The initial conditions were random states where the positioning was altered within a range of ±5mm. Adjustment started from the initial states. Adjustments terminated when the number of fitness evaluations was 500, and were conducted over 10 trials. After adjustment, the optical axes were set to the best state based on the identified elitist individual.

The parameters in these experiments were as following:

· GA: The population size was 20. The probabilities for crossover and mutation were 0.7 and 0.05, respectively.

· BSA: Parameters of *P(t)* were $C = 0.02$, $K = 0.15$, $\sigma = 0.05$ and $N = 500$.

· BSW: Parameters of *P(t)* were the same as BSA and $k = 100$.

6.2. Experimental results

Tab. 2 presents the average results for 10 trials for each adjustment. Each trial result is shown in Tab. 3. In these tables, 'fit' refers to fitness and 'reset' is the evaluation value, i.e. positioning error, when the optical axis is reset to the best state based on the adjustment results. The adjustment results obtained with the GA and the BSA are illustrated in Figs. 14-16. Fig. 14 presents the average of 10 trials. Fig. 15 and Fig. 16 present each trial for both the GA and the BSA. Fig. 17 presents the results for each trial with the BSW which is the method proposed in this paper. In these tables and figures, the fitness values for the GA and the BSA are actual detected values, while the fitness value for the BSW is a calculated weighted average value, which is indicated by * in Tab. 2 and Tab. 3.

Table 2: The results for the three adjustment methods.

	Time	Fit ave.	Fit σ	Reset ave.	Reset σ	Positioning error ave.
GA	26.1 min.	17.7	11.2	31.3	16.8	43.5 μm
BSA	10.6 min.	10.7	16.0	28.9	19.8	40.2 μm
BSW	13.1 min.	22.7*	12.1*	13.5	10.4	18.8 μm

Table 3: Averaged results for each trial in the three adjustment methods.

	GA		BSA		BSW	
	fitness	reset	fitness	reset	fitness	reset
1st trial	14.0	7.6	1.4	10.6	14.0*	4.5
2nd trial	20.0	19.8	7.0	19.0	16.5*	13.0
3rd trial	9.4	40.3	53.6	54.9	13.5*	16.3
4th trial	28.3	51.6	8.5	63.0	11.2*	4.1
5th trial	17.2	22.1	1.0	17.1	46.7*	38.3
6th trial	28.0	24.7	11.4	9.1	23.1*	7.3
7th trial	38.1	49.9	18.0	30.5	21.5*	13.9
8th trial	9.2	56.2	4.1	43.0	26.6*	7.3
9th trial	3.2	23.0	1.0	7.1	40.7*	22.5
10th trial	9.0	17.7	1.4	35.2	13.8*	8.1
Average	17.7	31.3	10.7	28.9	22.7*	13.5
Standard deviation(σ)	11.2	16.8	16.0	28.9	12.1*	10.4

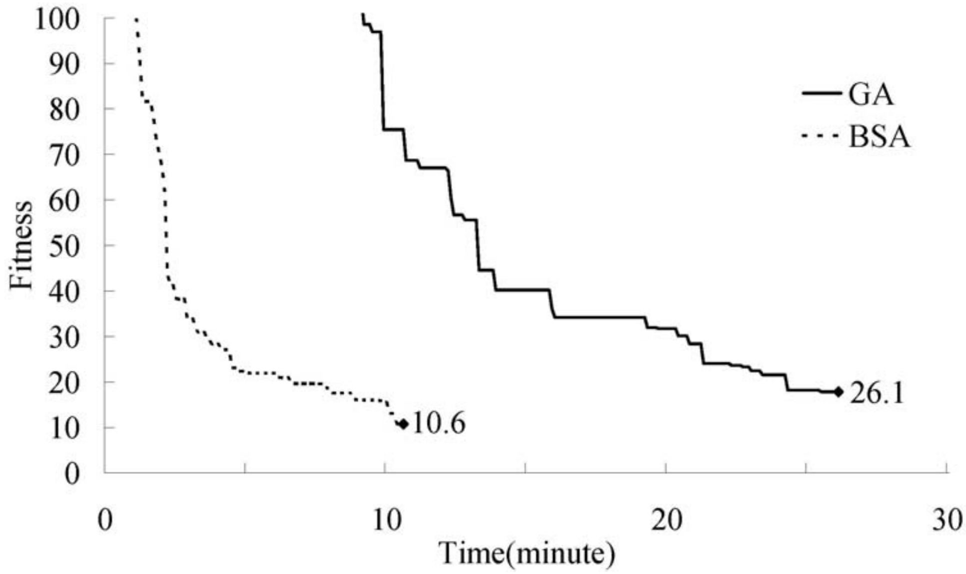

Figure 14: Comparison of BSA and GA.

First, looking at the results for the GA and BSA, clearly both could adjust the optical axes, because the fit-average values were 17.7 (17.7 x 1.39 = 24.6μm) and 10.7 (10.7 x 1.39 = 14.8μm) for the GA and BSA, respectively. Moreover, efficient adjustment was achieved by the BSA, because, in terms of adjustment times, it required 10.6 minutes while the GA took 26.1 minutes, as shown in Fig. 14. The reason for this difference is that BSA does not carry out the exploration step in the final phase. However, the levels of precision with GA and BSA deteriorated after resetting of the optical axes: the precision for the GA dropped to 31.3 (31.3 x 1.39 = 43.5μm) from 17.7 (24.6μm), while the precision for the BSA dropped to 28.9 (28.9 x 1.39 = 40.2μm) from 10.7 (14.8μm). The reason for this is that both the GA and BSA are influenced by observational noise. The large reset-σ values are consistent with this explanation, as shown in Tab. 3. Therefore, both BSA and GA failed to provide robust adjustment.

Second, turning to compare the results for the BSA and BSW, in terms of the average value after the optical axes were reset, the precision with the BSW improves quite remarkably in contrast with that for the BSA, because BSA was 28.9 (40.2μm) while BSW was 13.5 (13.5 x 1.39 = 18.8μm), as shown in Tab. 2. These results indicate that the precision was enhanced by 60% compared to the results for the GA. Moreover, the BSW was able to achieve a robust adjustment, because the reset-σ value for the BSW was 10.4 while the reset-σ value for the BSA was 19.8. The BSW was less influenced by noise than the BSA, because it adopted a weighted average value for the fitness value.

Third, in terms of adjustment times, the BSW could adjust for the optical axes within half time required for the GA, because the BSW required only 13.1 minutes while GA took 26.1 minutes. However, adjustment using BSW took a little more time compared to the BSA, because of the time involved in calculating the weighted average values, although, this can be improved by limiting the extent of search history used.

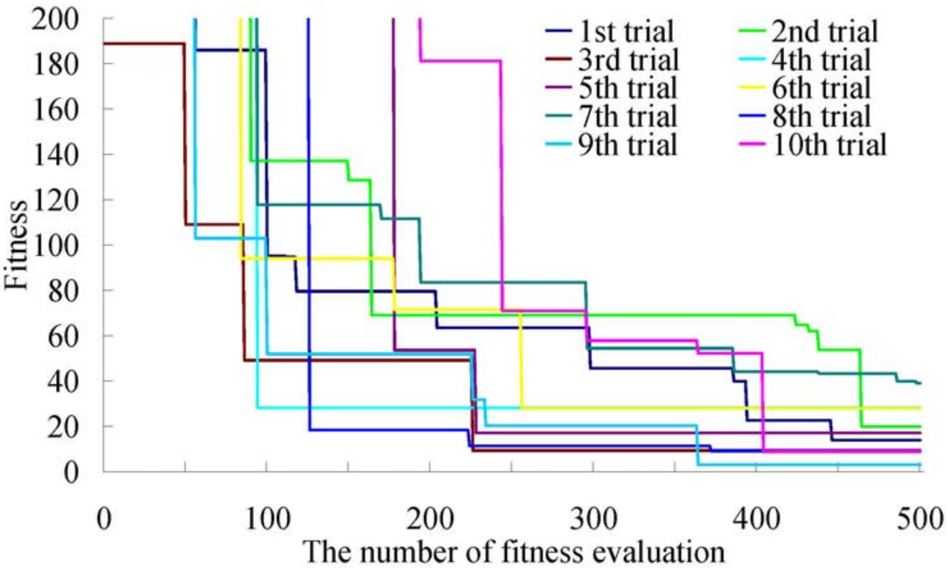

Figure 15: Adjustment results for the GA.

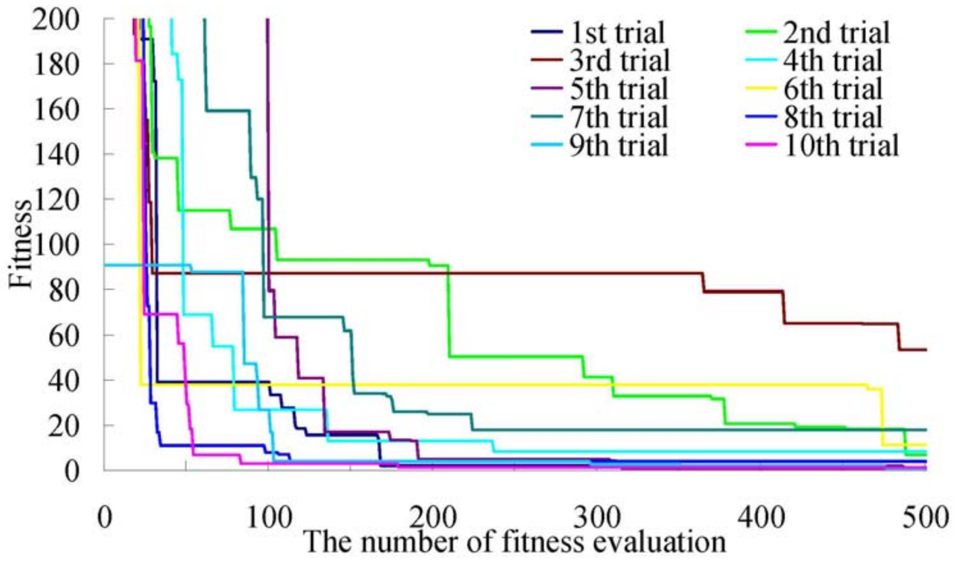

Figure 16: Adjustment results for the BSA.

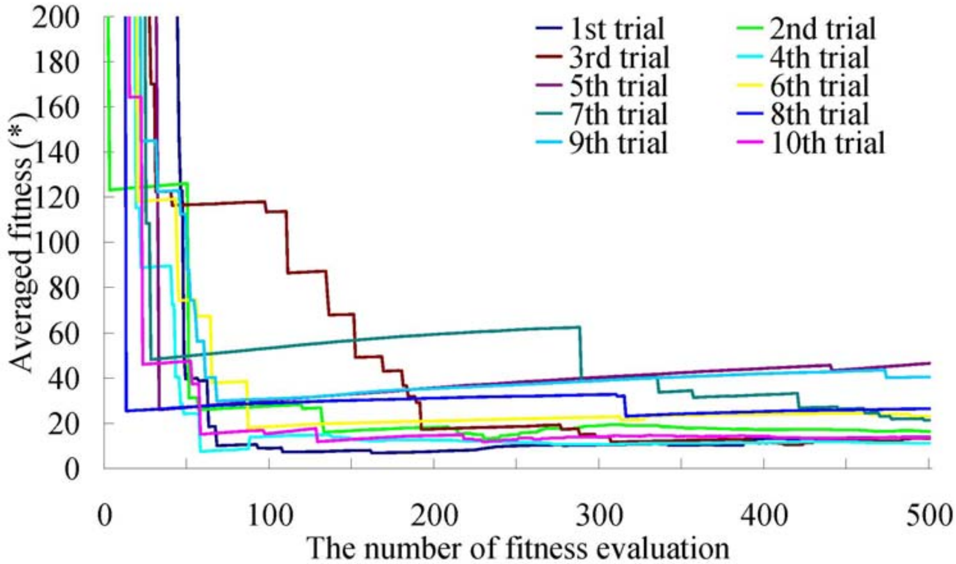

Figure 17: Adjustment results for the BSW.

7. Conclusion

In this paper, we have proposed a method for the robust and efficient automatic adjustment of optical axes using BSW. From the results of adjustments experiments using the proposed method, we have demonstrated that adjustment could be performed in half the time and with a 60% enhancement in precision compared to the conventional method. Our proposed method achieved robust and efficient automatic adjustment of the optical axes.

We have already applied the proposed BSW method to multi-objective adjustment as well as single-objective adjustment [10]. We demonstrated that the proposed method can robustly adjust the positioning and angle of optical axes in about 12 minutes, which represents an adjustment time reduction of 93% compared to the MOGA. Future investigations will be to apply the proposed method to single/multi-objective adjustment of optical systems involving multiple components with several DOF in order to verify its effectiveness for more difficult adjustment tasks.

The proposed method can be employed not only with optical systems but with other kinds of engineering systems. With the proposed method, it is possible to robustly and efficiently execute adjustment with several DOF.

Acknowledgement

The authors would like to thank Dr. Higuchi, AIST, for his consistent encouragement and advice. This work was supported in 2004 by Industrial Technology Research Grant Program of the New Energy and Industrial Technology Development Organization (NEDO) of Japan and Grant-in-Aid for JSPS Fellows in 2005.

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