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Novel optomechanical alignment method using a numerical optimization methodology

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Abstract. Alignment of optomechanical components is important when designing and manufacturing optical systems. This study used an optical fiber as a case study to develop an alignment method. The core diameter of a single-mode fiber is about 9 μm, and any slight misalignment or deformation of the optical mechanism will cause significant optical losses in connections. Previous studies have shown that the currently used alignment methods are not efficient, and the precise position for the connection is not easy to locate. This study proposes a two-stage method to overcome these problems. In the first stage, the Nelder-Mead simplex method is used to move quickly to the optimum solution. In the second stage, a numerical optimization method is used to improve the accuracy. This study compares different numerical optimization method that can be used to find the ideal connection position. It can be concluded that the most stable method for the search direction is the steepest-descent method, because the light intensity distribution is similar to a Gaussian one, and the most efficient method for the step-size determination is polynomial interpolation. Therefore, the second stage uses the steepest-descent method with polynomial interpolation. [DOI: 10.1117/1.2744345]

Subject terms: optical fiber; active alignment; optimization.

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1 Introduction

Fiber optic communications with low losses and broadband characteristics developed quickly after low-loss fibers were invented in 1970. Because of their high capacity, high transmission rate, and immunity to electromagnetic interference, optical fibers have been steadily replacing copper wire as a means of signal transmission in recent years.

Like other communication media, optical fibers do not have infinite length. Fibers need to be aligned and connected to each other when constructing a network. Both passive and active methods are used to align fibers. The passive methods use optical connectors or mechanisms to align and connect fibers. However, the core diameter of a single-mode fiber is only about 9 μm. Any slight misalignment or deformation of the connecting mechanism will cause significant optical losses across the connection. Therefore, the design of the passive component is extremely important, and high manufacturing precision is necessary for making the components.

On the other hand, an active method will actively search for the optimum position with the least transmission loss, and then connect fibers in this position. It can ensure that a reliable connection of the two connecting fibers is achieved, but the time required to search for the optimum position will increase the time required for component manufacture. It will become impractical if the required search time becomes too great. Therefore, the main objective in the active alignment method is to find the optimum connection position efficiently. These methods mentioned in the literature can be divided into non-gradient-based methods and direction search methods, which are described in the next section.

The distribution of light intensity in an optical fiber is similar to a Gaussian distribution. However, on the fiber end face it is not exactly Gaussian, because of end cutting and polishing. As a result there are many local light intensity maxima on the end face, and avoiding such traps is a requirement on optical fiber alignment methodologies if significant optical losses across connections are to be avoided. For this purpose, CCD cameras are used to do a rough alignment, during which the fibers will be moved quickly to a position near the optimum. Then, accurate alignment methods are used. The CCDs will reduce the search time, but they will increase the cost of the alignment equipment, and the hardware and software are not easy to implement. This additional equipment will also increase the complexity and failure probability of the alignment device.

Therefore, the two major purposes of this study were to avoid the local maximum trap and to increase the search efficiency. A two-stage optimization strategy is proposed to achieve these requirements. The first stage is to use the Nelder-Mead simplex method instead of using expensive CCD cameras or other rough alignment methods. Then, the steepest-descent method with polynomial interpolation is used for accurate searching in the second stage. Compared

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to the traditional optimization methodologies, the two-stage method can reduce the search by about 50%

2 Preliminary Details

The optical fiber alignment problem is a typical optimization problem. It requires adjusting and finding the connection position with the maximum light intensity (the minimum optical power loss). Therefore, the objective function is the light intensity, i.e., the optical power, and the design variables are the coordinates of the connection position. There is no constraint in the optical fiber alignment problem, except for the bound on the coordinate values.

In 2001, Tang et al.[1] used the hill-climbing method to solve the alignment problem. Mizukami et al.[2] simulated the alignment process with the Hamiltonian algorithm equations, and solved the equations to find the position with maximum light intensity. Chen and Chang[3] used a predetermined search direction, and used Swarm's method[4] and the quadratic estimation method[5] to find the step size. In 2002, Siao and Li[6] used the Gaussian function[7] to estimate the light intensity in the search direction. In the following year, Zhang and Shi[8] used Matlab/Simulink to execute the Hamiltonian algorithm to find the optimum connection position. Sung and Huang[9] used the steepest-descent method[10] to calculate the search direction, and used the golden-section search[10] to find the step size. They also used the coordinate search method[11] and the pattern search method[12] to search directly for the optimum connection position in the design space. In 2004, Zhang and Shi[13] used the simplex method to solve the alignment problem, while Sung and Chiu used the genetic algorithm[14] to find the global optimum connection position, and also used the hill-climbing method[1] to improve the solution found with the genetic algorithm.

The coordinate search method, pattern search method, simplex method, and genetic algorithm search directly for the optimum solution in the design space, and are non-gradient-based methods. They do not calculate the search direction, and their efficiency will be poor if the design space is large. If one uses another solution methodology, namely numerical optimization theory, optimization becomes an interactive process. The search direction and the step size along the direction are two key variables during each iteration.[10] The hill-climbing method used in the mentioned literature does not calculate the search direction. The optimum solution is searched for in predetermined directions. Typically, the directions along the X and Y axes will be used repeatedly. The efficiency is limited because these axes need not be the direction of maximum increase in light intensity.

On the other hand, Swann's method, the quadratic estimation method, the Gaussian-function estimation, and the golden-section method described in the literature are used only to calculate the step size without a direction search method, as in the case of the steepest-descent method. Few direction search methods are used for the alignment problem.

In order to avoid local maxima and to reduce costs, various methodologies are used instead of the expensive hardware mentioned to accomplish the rough alignment. These methodologies can be implemented with software programming, and do not need to add to costs. Pham and Castellani[15] simulated the searching process by moving on the light intensity surface to avoid the local maxima, and solved the problem with a gradient-based method. Tseng et al.[16] used a novel simplex method to avoid a local maximum trap, and the two-stage genetic algorithm proposed by Sung and Chiu also has potential for avoiding such traps.

Though non-gradient-based methods may be less efficient than gradient-based methods, they can be used to avoid the local maxima. Therefore, a two-stage method is required to avoid the local maxima and to increase the search efficiency.

3 Two-Stage Method

The standard optimization model is formulated as finding the solution with a minimum objective function value. This formulation can also consider the problem of maximizing the objective function value, on multiplying the objective function by minus one. Therefore, the standard optimization model can be defined as

$$\text{minimize} - f(\mathbf{X}), \tag{1}$$

where $f(\mathbf{X})$ is the measured optical power (dBm), $\mathbf{X}$ is the position vector, and the position coordinates are the design variables. The vector $\mathbf{X}$ can be represented as

$$\mathbf{X} = (x_1, x_2), \tag{2}$$

where x_1 and x_2 are the x and y coordinate values of the connection position on the end face. This study uses planar coordinates as an example; the three-dimensional case can be treated by a similar method. There is no constraint in the alignment problem. The first stage in the two-stage method is the rough alignment. It can move the solution to the optimum point quickly, and it also helps to avoid the local optima. Then, the second stage uses refined searching methods to find the optimum solution accurately. The detailed process is explained in the following.

3.1 *First Stage: Rough Alignment*

The Nelder-Mead simplex method[17] is used as the first stage of the two-stage method. At the beginning, three points, $\mathbf{X}_h$, $\mathbf{X}_g$, and $\mathbf{X}_l$, are selected to form a triangle, and their objective-function values are f_h, f_g, and f_l, where $f_h > f_g > f_l$. The midpoint of the edge $\overline{\mathbf{X}_g\mathbf{X}_l}$ is denoted as $\mathbf{X}_c$. In the search process the new point (solution) is calculated by

$$\mathbf{X}_{n1} = \mathbf{X}_h + (1+\theta)(\mathbf{X}_c - \mathbf{X}_h), \tag{3}$$

where θ is an index. The value $\theta=1$ is used first, and a new point $\mathbf{X}_{n1}$ is obtained. Its function value is f_{n1}. Another new point will be obtained from the following conditions:

1. If $f_l < f_{n1} < f_g$, then $\theta=1$ and $\mathbf{X}_{n2}=\mathbf{X}_h+2(\mathbf{X}_c-\mathbf{X}_h)$.
2. If $f_{n1} < f_l$, then $\theta=2$ and $\mathbf{X}_{n2}=\mathbf{X}_h+3(\mathbf{X}_c-\mathbf{X}_h)$.
3. If $f_{n1} \geq f_h$, then $\theta=-0.5$ and $\mathbf{X}_{n2}=\mathbf{X}_h+0.5(\mathbf{X}_c-\mathbf{X}_h)$.
4. If $f_g < f_{n1} < f_h$, then $\theta=0.5$ and $\mathbf{X}_{n2}=\mathbf{X}_h+1.5(\mathbf{X}_c-\mathbf{X}_h)$.

The objective-function values at $\mathbf{X}_h$, $\mathbf{X}_g$, $\mathbf{X}_l$, $\mathbf{X}_{n1}$, and $\mathbf{X}_{n2}$ are compared, and the smallest three points are selected to form the new triangle. The vertices of the new triangle

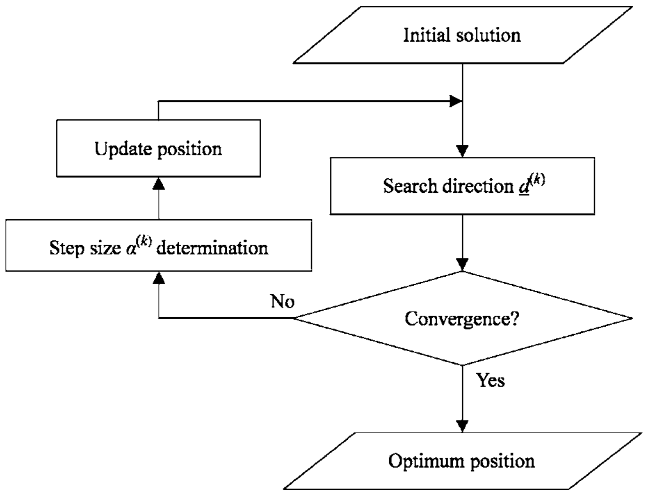


Fig. 1 The solution process for the direct method.

are sorted and update as $\mathbf{X}_h$, $\mathbf{X}_g$, and $\mathbf{X}_l$. New points will continue to be found until the objective-function values satisfy a predetermined criterion, i.e., when the point is close to the maximum light intensity.

3.2 *Second Stage: Accurate Searching Methods*

Many numerical optimization methods can find an accurate solution, but the Nelder-Mead simplex method cannot do so because of the long edges of the triangles. Therefore, a different numerical optimization method is used to improve the accuracy in the second stage.

The optimization methods used to solve unconstrained optimization problems can be divided into indirect and direct methods. Indirect methods are analytic methods. They satisfy the necessary condition first and then check the sufficient condition. The necessary condition of an unconstrained optimization problem requires the gradient vector components of the objective function to be zero, and the sufficient condition requires the Hessian matrix of the objective function to be positive. Indirect methods can find the exact global optimum solution, but these methods require an explicit function relating the objective function and the design variables. Unfortunately, it is difficult to define an explicit function of the light intensity on the fiber end-face, because for that the light intensity has to be detected at every position. Therefore, indirect methods cannot be used to solve the alignment problem, whereas direct methods can.

Direct methods are also called numerical methods, and they solve an optimization problem by *searching*. The search utilizes the search direction as well as the step size, and the process can be described by the following equation:

$$\mathbf{X}^{(k+1)} = \mathbf{X}^{(k)} + \alpha^{(k)}\mathbf{d}^{(k)}, \quad k = 0,1,2, \ldots, \tag{4}$$

where the superscript is the iteration number, α is the step size (scalar), and $\mathbf{d}$ is the search direction in vector form. The whole solution process is shown in Fig. 1. At the beginning, an initial position $\mathbf{X}^{(0)}$ should be selected. There are many methods for determining the search direction $\mathbf{d}^{(k)}$, such as the steepest-descent method, the conjugate-gradient method, the Davidon-Fletcher-Powell (DFP) method, and the Broyden-Fletcher-Goldfarb-Shanno (BFGS) Method.[7]

Before moving along in the search direction, the convergence condition of the process should be checked. The common convergence condition is that the norm value of the search direction is less than a predetermined small value:

$$\|\mathbf{d}^{(k)}\| \le \varepsilon, \tag{5}$$

where ε is a small number, called the convergence condition. It is similar to the necessary condition of indirect methods, but the norm is seldom zero when using numerical methods. Therefore, a predetermined small value is used instead of zero. Another common convergence condition requires checking the difference of the objective function values between two solutions. The solution process will stop if the difference is less than a predetermined small value. This means it is no longer efficient to continue the solution process, because the improvement in the objective function is marginal.

The step size in the search direction has to be calculated if the solution process is to continue. This process is also called a *one-dimensional search* because it searches for the optimum solution along a path in the predetermined search direction $\mathbf{d}^{(k)}$. Hence, the problem becomes a one-dimensional problem for determining the step size, no matter how many dimensions the problem has. There are also many methods for one-dimensional search, as described in the mentioned literature, the most popular being the equal-interval search, the golden-section search, and polynomial interpolation. After determining the search direction and the step size, the position can be updated, and the process can continue to the next iteration.

3.2.1 *Search direction*

Yu et al.[18] used the steepest-descent method to decide on the search direction. It can be calculated as follows:

$$\mathbf{d}^{(k)} = -\mathbf{c}^{(k)} = -\left[\frac{\partial f(\mathbf{X})}{\partial x_1}\frac{\partial f(\mathbf{X})}{\partial x_2}\cdots\frac{\partial f(\mathbf{X})}{\partial x_n}\right]^T, \tag{6}$$

where $\mathbf{c}$ is the gradient vector of the objective function, and this direction will cause the maximum increase on the objective function. The steepest-descent Method uses the simplest approach to decide on the search direction, but it is not efficient in general, because the search directions of two successive iterations are orthogonal to each other. Therefore, many methods have been proposed to modify the search direction of the steepest-descent method, the conjugate-gradient method[10] being one of them. The conjugate-gradient method adds information about the previous direction to the current direction to improve the efficiency. It can be expressed as

$$\mathbf{d}^{(k)} = -\mathbf{c}^{(k)} + \beta^{(k)}\mathbf{d}^{(k-1)}, \quad k = 1,2,3, \ldots, \tag{7}$$

where

$$\beta^{(k)} = \left(\frac{\|\mathbf{c}^{(k)}\|}{\|\mathbf{c}^{(k-1)}\|}\right)^2, \quad k = 1,2,3, \ldots. \tag{8}$$

Other methods use the Hessian matrix to improve the search direction. The Hessian matrix is the first derivative

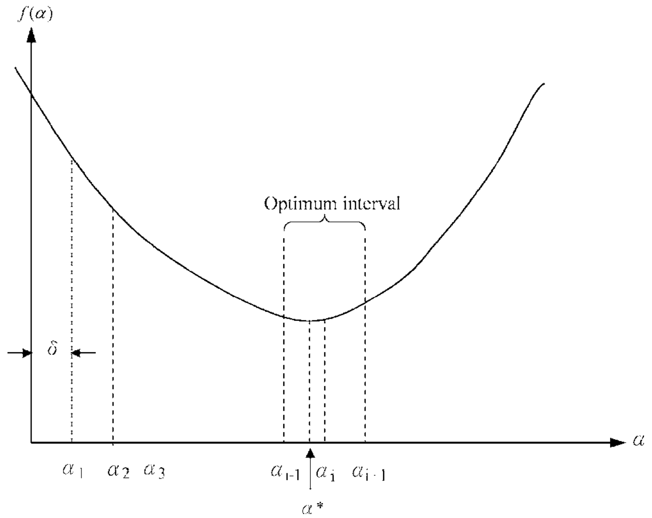


Fig. 2 Step-size determination.

of the gradient vector, i.e., its rate of variation. The search will be more efficient if not only the gradient vector, but also, its the Hessian matrix is used to decide on the search direction. Unfortunately, for some applications, calculating the Hessian matrix may be tedious or even impossible, and sometimes the Hessian matrix will be singular. Therefore, some methods overcome these drawbacks by generating an approximation for the Hessian matrix and its inverse.

The DFP method[10] uses an approximate inverse of the Hessian matrix to determine the search direction. The search direction can be expressed as

$$\mathbf{d}^{(k)} = -\boldsymbol{A}^{(k)}\mathbf{c}^{(k)}, \tag{9}$$

where $\boldsymbol{A}$ is the approximate inverse of the Hessian matrix.[10] The search direction of the BFGS method[10] is given by

$$\mathbf{d}^{(k)} = -(\boldsymbol{H}_A^{(k)})^{-1}\mathbf{c}^{(k)}, \tag{10}$$

where $\boldsymbol{H}_A$ is an approximate Hessian matrix.[10] The matrix A of the DFP method or $\boldsymbol{H}_A$ of the BFGS method is set to the identity matrix in the first iteration, and will be updated during the solution process.

3.2.2 *Step-size determination*

After the search direction has been determined, the step size along the path in that direction has to be found. As mentioned before, the problem becomes a one-dimensional search process to find $\alpha^{(k)}$ after a transformation by Eq. (4). A simplified sketch is shown in Fig. 2. The solid line indicates the function $f(\alpha)$ transformed from $f(\mathbf{X})$ by Eq. (4). The step size can be determined by finding an α^* that minimizes $f(\alpha)$. The methods discussed in this study are the equal-interval search, the golden-section search, and polynomial interpolation.[10] A comparison of these methods is listed in Table 1.

As the name implies, the equal-interval Search evaluates the solutions at the same distance in the search direction until it finds the step size. The interval δ between two adjacent search points determines the accuracy and efficiency of finding the optimum point α^*. The golden-section Search evaluates the solutions with an increased distance until it finds the optimum interval. The increase ratio is 1.618 (the golden ratio), i.e., the distance between the n'th and $n+1$st solutions is 1.618 times the distance between $n-1$st and n'th solutions, as shown in Table 1. The efficiency of the golden-section search will be better than that of the equal-interval search because of the increased distance and the characteristics of the golden ratio.

Table 1 Comparisons.

Method	Formulation
Equal-interval search	$\alpha_i = i\delta,\ i=1,2,3,\ldots$
Golden-section search	$\alpha_i = \sum_{j=0}^{i} \delta(1.618)^j,\ i=1,2,3,\ldots$
Polynomial interpolation	$a_2 = 1/\alpha_{i+1}-\alpha_i\left[f(\alpha_{i+1})-f(\alpha_{i-1})/\alpha_{i+1} - \alpha_{i-1} - f(\alpha_i)-f(\alpha_{i-1})/\alpha_i-\alpha_{i-1}\right]$
	$a_1 = f(\alpha_i)-f(\alpha_{i-1})/\alpha_i-\alpha_{i-1} - a_2(\alpha_i+\alpha_{i-1})$
	$\alpha^* = -1/2a_2a_1$

Polynomial interpolation likewise evaluates the solutions with an increased distance until it finds the optimum interval. The increase ratio is also 1.618, i.e., the same as in the golden-section search. After finding the optimum interval, a quadratic function, as shown in Table 1, is used to approximate the objective function within it.

The experimental results are discussed in the next section.

4 Results and Discussion

Before discussing the results, the experiment setup is introduced as shown in Fig. 3. The six stepping motors are used to achieve the translation along and rotation about the *X*, *Y*, and *Z* axes. The upper fiber is connected to the optical source, and the lower fiber is connected to the optical detector. The piezoelectric stage is used to adjust the *X*, and *Y* positions accurately.

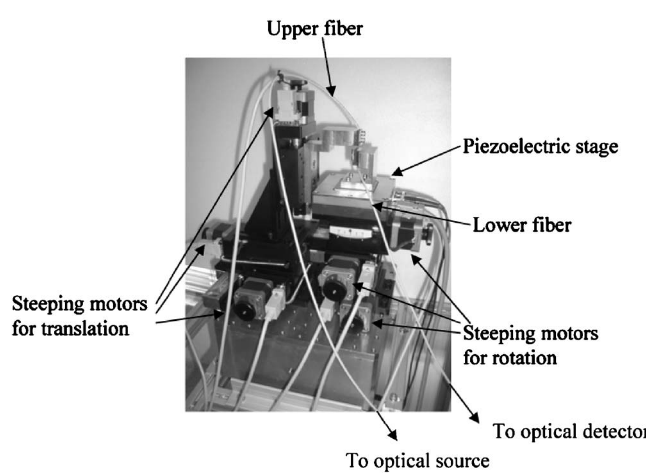
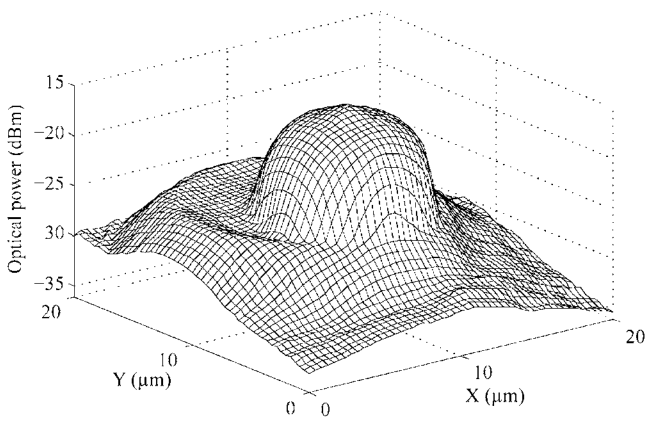
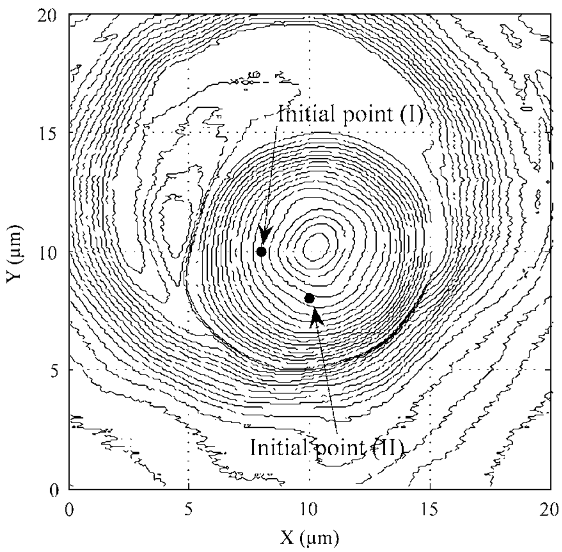


Fig. 3 The experimental setup.



(a)



(b)

Fig. 4 Distribution of light intensity: (a) plot, (b) contours.

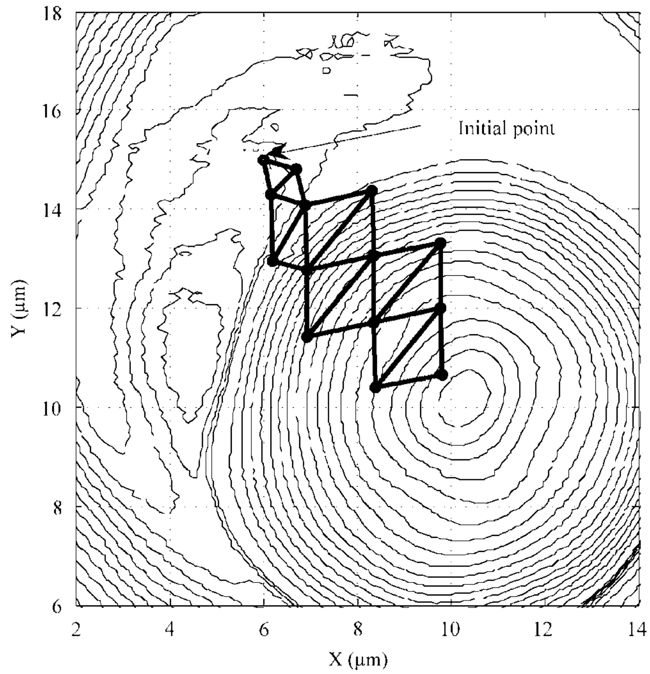


Fig. 5 Search path of the Nelder-Mead simplex method.

The real light intensity detected by the equipment is plotted in Fig. 4(a), while Fig. 4(b) shows the light intensity contours. The central circles represent the light intensity in the fiber with a 9-μm diameter; there are many local optima in the outer region because of interference. The light intensity will be multiplied by minus one later because the standard optimization problem is formulated as finding the minimum objective-function values.

Before starting to search for the optimum connection position, the fibers will first be aligned roughly. The rough alignment may be on any side, at any distance from the optimum connection position. The starting alignment position may be not in the fiber region, i.e., the central circles in Fig. 4(b); sometimes it is outside the fiber region as in Fig. 5. If the initial connection position is far from the optimum, the search process may be easily trapped by a local optimum, and will therefore be inefficient. Therefore, this study uses a two-stage method to align fibers. In the first stage, the Nelder-Mead simplex method is used to avoid a local optimum while moving to the global optimum connection position quickly along the long edge of the triangle. In the second stage, the direction search method and the one-dimensional search method are used to obtain an accurate result. However, there are many methods for either of these searches. This study uses four direction search methods and three one-dimensional search methods to solve the alignment problem, and also compares their efficiencies. The best one will be used in the second stage.

4.1 *Nelder-Mead Simplex Method*

The results of the Nelder-Mead simplex method are shown in Table 2, while the search path is shown in Fig. 5. The optical power is −16.12 dBm, and the search process costs only 74.1 s. The solution moves close to the optimum solution quickly. As shown in Fig. 5, the edge lengths of the triangles are large, and this is why the Nelder-Mead simplex method can move to the optimum solution quickly and avoid the local optima.

4.2 *Search Direction Determination*

Methods to determine the search direction can be classified into the gradient-based (first-order differentiation) and Hessian-based (second-order differentiation) methods.[10] Because these methods are sensitive to different initial conditions, cases with different initial points were used to find a stable method. Within the region shown in Fig. 4(b), case I uses $(X,Y)=(8,10)$ as the starting point, and case II uses $(X,Y)=(10,8)$. The results are shown in Table 3. The "Function calls" column gives the number of objective-function calculations, and these usually cost most of the time involved in the solution process. In this study it means the detector fiber has to move to the determined point, measure the light intensity, and return the value to the program. Thus, the number of function calls and iterations, instead of the total search time, can be used to evaluate the efficiency of the methods.

The iteration number of the conjugate-gradient method is the same as for the steepest-descent method in case II,

Table 2 Results of the Nelder-Mead simplex method.

Iteration	Points (X,Y)	Optical power (dBm)	Time (s)
1	(6, 15) (6.72, 14.81) (6.19, 14.29)	−25.65	74.1
2	(6.72, 14.81) (6.19, 14.29) (6.91, 14.09)	−22.46	
3	(6.19, 14.29) (6.22, 12.95) (6.91, 14.09)	−22.46	
4	(6.22, 12.95) (6.91, 14.09) (6.93, 12.76)	−20.11	
5	(6.91, 14.09) (8.32, 14.38) (6.93, 12.76)	−20.11	
6	(8.32, 14.38) (6.93, 12.76) (8.35, 13.04)	−18.13	
7	(6.93, 12.76) (6.96, 11.43) (8.35, 13.04)	−18.13	
8	(6.96, 11.43) (8.35, 13.04) (8.37, 11.71)	−17.17	
9	(8.35, 13.04) (9.77, 13.33) (8.37, 11.71)	−17.17	
10	(9.77, 13.33) (8.37, 11.71) (9.79, 11.99)	−16.56	
11	(8.37, 11.71) (8.4, 10.38) (9.79, 11.99)	−16.56	
12	(8.4, 10.38) (9.79, 11.99) (9.82, 10.66)	−16.12	

but these numbers are very different in case I. In case I, the search direction of the steepest-descent Method in the first iteration points nearly to the optimum solution, as shown in Fig. 6(a), while the norm value for iteration 1 is larger than for iteration 0, as shown in Table 4. Therefore, $\beta^{(1)}$ [Eq. (8)] is large and the effect of the last search direction is also large when using the conjugate-gradient method. It is obvious that the second search direction of the steepest-descent method is orthogonal to the first directional,[7] and it is close to the optimum solution. However, the second search direction of the conjugate-gradient method will not point to the optimum solution because of the $\beta^{(1)}$ effect, as shown in Fig. 6(a) and 6(c). In case II, the initial point of iteration 1 is close to the optimum solution and the norm value is small, as shown in Table 4. Therefore, $\beta^{(1)}$ is small, and the conjugate-gradient method is similar to the steepest-descent method, as shown in Fig. 6(b) and 6(d).

Although the number of function calls for the DFP and BFGS methods is smaller than for the steepest-descent method, their iteration number is larger in case I. The search directions of the DFP and BFGS methods will be modified far from the optimum point by the approximate inverse Hessian matrix and the approximate Hessian matrix. This is because the light intensity distribution is similar to a Gaussian distribution. If the light intensity distribution is exactly Gaussian, the gradient vector will point to the optimum position. Therefore, any modification of the gradient vector will reduce the search efficiency.

Table 3 Cases of direction-searching methods.

Class	Method	Function calls	Iteration number	Optical power (dBm)
		(a) Data of case I		
Gradient-based	Steepest descent	505	4	−16.10
	Conjugate gradient	1045	1	−16.10
Hessian-based	DFP	504	5	−16.10
	BFGS	398	5	−16.10
		(b) Data of case II		
Gradient-based	Steepest descent	324	3	−16.10
	Conjugate gradient	324	3	−16.10
Hessian-based	DFP	276	3	−16.10
	BFGS	276	3	−16.10

From Table 3, it is obvious that the search process has only a small number of iterations, but its number of function calls is large, meaning that most function calls happen in the one-dimensional search. Thus, enhancing the efficiency of the one-dimensional search will be helpful for enhancing the efficiency of the entire optimization process.

In conclusion, the steepest-descent method needs more function calls during the search process, but it is more stable for the optical fiber alignment, and the Hessian calculations are not required. Therefore, it is used in the following experiments.

4.3 *Step-Size Determination*

After the search direction has been determined, the step size in this direction has to be calculated. The discussion of the one-dimensional search (the step-size determination) in Sec. 3.2.2 leads us to set the initial point at $(X,Y)=(6,15)$. Only one initial point is used, because the effects of different initial points have already been discussed in Sec. 4.2. The steepest-descent method is used as a datum in this section because it is the most stable method. The actual

Table 4 Objective-function norms of conjugate-gradient method.

Case	$\|c^{(0)}\|$	$\|c^{(1)}\|$	$\beta^{(1)}$
I	0.044	0.073	2.705
II	0.076	0.007	0.008

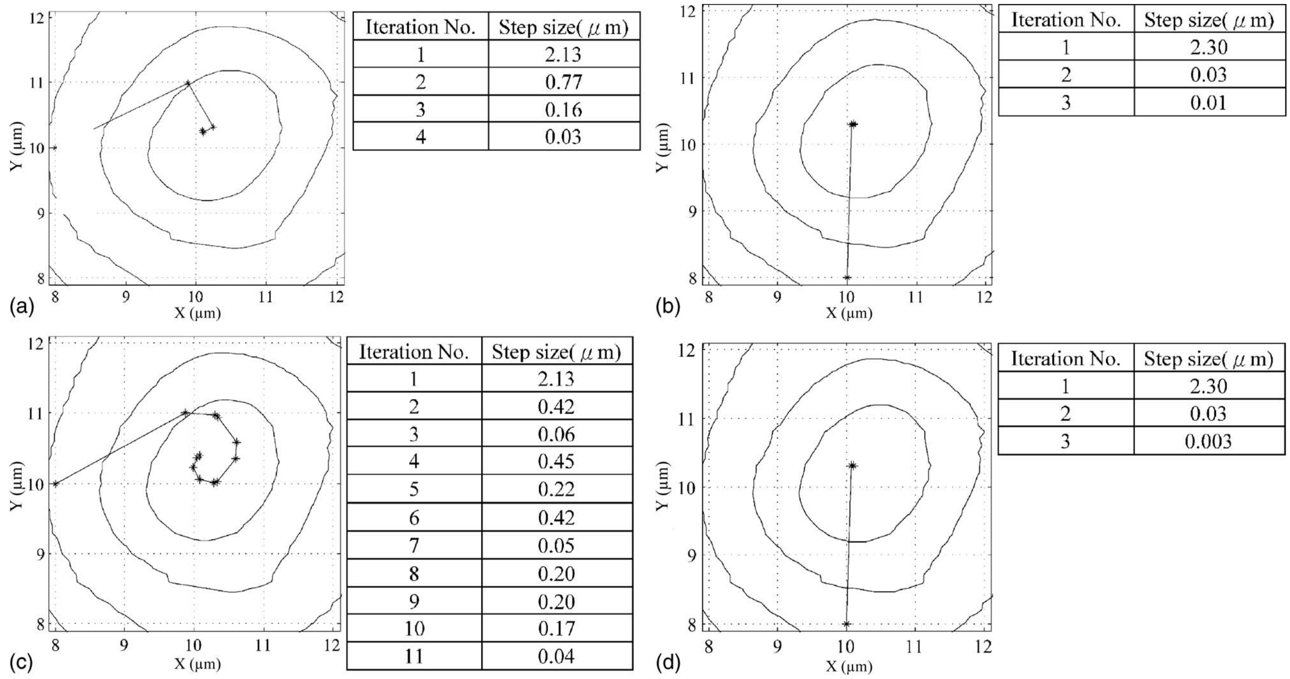


Fig. 6 Search paths of solution methods: (a) steepest-descent method in case I, (b) steepest-descent method in case II, (c) conjugate-gradient method in case I, (d) conjugate-gradient method in case II.

time required for this process is used to evaluate the one-dimensional search methods, because the search time is spent not only on receiving the light signal, but also on moving the fiber to the optimum points. The results of the steepest-descent method with the equal-interval search, the golden-section search, and polynomial interpolation are shown in Table 5. It is obvious that polynomial interpolation is the most efficient method. It saves about half the search time during the process of finding the step size.

4.4 *Full Search Process*

After discussing the characteristics of the individual processes, the selected methods can be combined to perform the full search process. The results of the first stage are shown in Table 6(a) and Fig. 7. There are eight triangles in the first stage. The edge length of the first triangle is 0.74 μm, and it is a realized value. The trajectory is a little different from the previous experiment because of the error

Table 5 Results of steepest-descent method with one-dimensional search methods.

Method	Iteration	Point (X, Y)	Optical power (dBm)	Function calls	Time (s)
Equal-interval search	1	(6, 15)	−26.02	55	180.1
	2	(8.45, 10)	−17.08	31	
	3	(10.21, 11.1)	−16.07	Convergence	
Golden-section search	1	(6, 15)	−26.02	47	156.6
	2	(8.69, 9.96)	−16.17	23	
	3	(10.12, 10.96)	−16.07	Convergence	
Polynomial interpolation	1	(6, 15)	−26.02	23	84.7
	2	(7.57, 10.62)	−17.80	8	
	3	(10.13, 11.44)	−16.07	Convergence	

Table 6 Results of the two-stage strategy.

(a) Results of the first stage

Iteration	Points (*X*, *Y*)	Time (s)
1	(6, 15) (6.72, 14.81) (6.19, 14.29)	30.9
2	(6.72, 14.81) (6.19, 14.29) (6.91, 14.09)	
3	(6.19, 14.29) (6.91, 14.09) (6.22, 12.95)	
4	(6.91, 14.09) (6.22, 12.95) (6.93, 12.76)	
5	(6.22, 12.95) (5.91, 10.38) (6.93, 12.76)	
6	(5.91, 10.38) (6.93, 12.76) (6.63, 10.19)	
7	(6.93, 12.76) (8.52, 13.66) (6.63, 10.19)	
8	(8.52, 13.66) (6.63, 10.19) (8.21, 11.09)	

(b) Results of the second stage

Iteration	Point (*X*, *Y*)	Optical power (dBm)	Time (s)
1	(8.21,11.09)	−16.80	26.4
2	(9.87, 10.23)	−16.07	

inherent in the equipment. The solution is moved very close to the optimum solution. The point with the minimum objective-function value in the first stage is used as the initial point of the second stage, and the results are shown in Table 6(b). There is only one iteration in the second stage, and its step size is 1.87 μm.

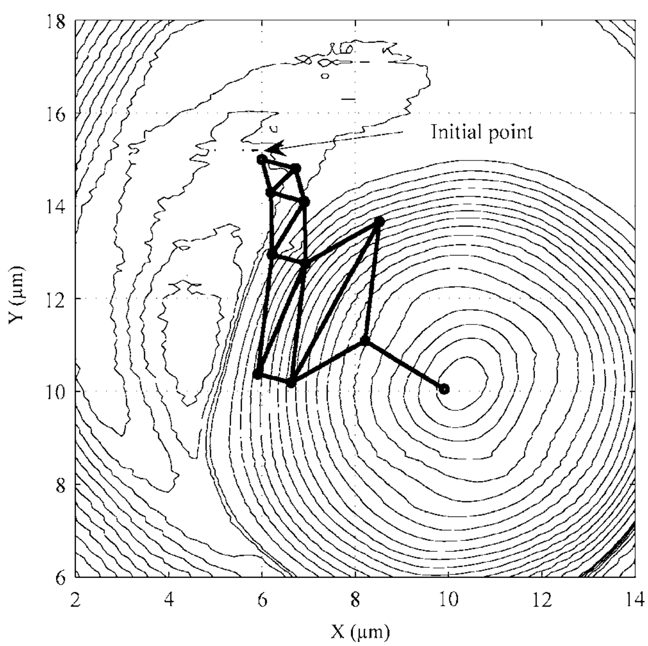


Fig. 7 Search path of the two-stage strategy with $\delta = 0.008$.

The full search process requires approximately 57 s to find the optimum point, and the optimum optical power is −16.07 dBm. Comparing these results with those of the Nelder-Mead simplex method shown in Table 2, we see that the two-stage method can save about 23% of the time, and has a higher accuracy. Compared to the steepest-descent method with polynomial interpolation as shown in Table 5, it can reduce the search time by 32%. Therefore, the proposed two-stage method fully overcomes the previous disadvantages.

5 Conclusions

The optical fiber alignment problem is a typical unconstrained optimization problem. This study uses different optimization methodologies—the steepest-descent method, the conjugate-gradient method, the DFP method, and the BFGS method—for the direction search to find the optimum position, and compares them for efficiency and stability. This study also uses the steepest-descent method with the equal-interval search, the golden-section search, and polynomial interpolation to compare the efficiencies. Based on the experimental results, this study presents a two-stage method to find the optimum position. The first stage uses the Nelder-Mead simplex method, and the second stage uses the steepest-descent method with polynomial interpolation. The following conclusions can be drawn:

1. The number of iterations when using the steepest descent method is small because the light intensity distribution is similar to a Gaussian distribution.
2. The steepest-descent Method is better for the alignment problem because the number of iterations is small and any modification to the search direction will let the search process stray far from the optimum point.
3. A good one-dimensional search method is important during optimization because the number of iterations of the search process is small, and most function calls occur in the one-dimensional search.
4. Polynomial interpolation is better than other methods because it can find the optimum step size more quickly.
5. The Nelder-Mead simplex method used in the two-stage method can get close to the optimum position quickly because it does not calculate the search direction or the step size.
6. The two-stage method is more efficient than using only the steepest-descent method with polynomial interpolation.
7. The method proposed in this study is not only suitable for optical fiber alignment; the manufacture of optical components, such as the transmitter, receiver, and waveguide module, can use this method to minimize the optical loss.

References

1. Z. Tang, R. Zhang, and F. G. Shi, "Effects of angular misalignments on fiber-optic alignment automation," *Opt. Commun.* **196**, 173–180 (2001).

2. M. Mizukami, M. Hirano, and K. Shinjo, "Simultaneous alignment of multiple optical axes in a multistage optical system using Hamiltonian algorithm," *Opt. Eng.* **40**, 448–454 (2001).
3. B. R. Chen and S. H. Chang, "Development of fiber auto-alignment fabrication technology," Master's Dissertation, National Taiwan Univ., Taipei (2001); http://etds.ncl.edu.tw/theabs/english_site/search_simple_eng.jsp.
4. L. Han and J. F. Peters, "Heuristic method in searching for global minima relative to high voltage ac error," in *Proc. 2002 IEEE Canad. Conf. on Electrical & Computer Engineering*, pp. 776–781 (2002).
5. G. V. Reklaitis, A. Ravindran, and K. M. Ragsdell, *Engineering Optimization—Methods and Applications*, John Wiley & Sons, New York (1983).
6. S. J. Siao and M. E. Li, "Nonlinear regression analysis for fiber alignment," Master's Dissertation, National Kaohsiung Normal Univ., Kaohsiung (2002); http://etds.ncl.edu.tw/theabs/english_site/search_simple_eng.jsp.
7. L. A. Reith, J. W. Mann, G. R. Lalk, R. R. Krchnavek, N. C. Andreadakis, and C. E. Zah, "Relaxed-tolerance optoelectronic device packaging," *J. Lightwave Technol.* **9**, 477–484 (1991).
8. R. Zhang and F. G. Shi, "Novel fiber optic alignment strategy using Hamiltonian algorithm and Matlab/Simulink," *Opt. Eng.* **42**, 2240–2245 (2003).
9. M. Y. Sung and S. J. Huang, "Application of piezoelectric-actuating table in optical alignment," Master's Dissertation, National Taiwan Univ. of Science and Technology, Taipei (2003); http://etds.ncl.edu.tw/theabs/english_site/search_simple_eng.jsp.
10. J. S. Arora, *Introduction to Optimum Design*, Elsevier/Academic Press, London (2004).
11. W. C. Davidon, "Variable metric method for minimization," *SIAM J. Optim.* **1**, 1–17 (1991).
12. V. Torczon, "On the convergence of pattern search algorithms," *SIAM J. Optim.* **7**, 1–25 (1997).
13. R. Zhang and F. G. Shi, "A novel algorithm for fiber-optic alignment automation," *IEEE Trans. Adv. Packag.* **27**, 173–178 (2004).
14. M. Murakawa, H. Nosato, and T. Higuchi, "Automatic optical fiber alignment system using genetic algorithms," in *Proc. 6th Int. Conf. on Artificial Evolution*, pp. 223–234 (2003).
15. D. T. Pham and M. Castellani, "Intelligent control of fiber optic components assembly," *Proc. Inst. Mech. Eng., Part B* **215**, 1177–1189 (2001).
16. C. Y. Tseng, C. L. Chang, C. F. Lin, and J. P. Wang, "A fuzzy simplex algorithm for active fiber-laser alignment," *J. Chin. Soc. Mech. Eng.* **26**, 759–764 (2005).
17. J. A. Nelder and R. Mead, "A simplex method for function minimization," *Comput. J.* **7**, 308–313 (1965).
18. M. T. Yu, T. Y. Lin, Y. Y. Li, and P. F. Shu, "A study on the optimization methods for optomechanical alignment," *Proc. SPIE* **6289**, E2890Y (2006).

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