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光碟機聚焦光感測器晶片之自動組裝定位法

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行政院國家科學委員會專題研究計畫成果報告

光碟機聚焦光感測器晶片之自動化組裝定位法

Auto-adjusting the Photodetector in an Optical Head System for Optimum Focus

計畫編號： NSC 93-2218-E009-034

執行期間：

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1. Abstract

In the assembly of an optical head system, it is required to mount the photodetector integrated chip (PDIC) in the correct position so that the astigmatism phenomenon can be achieved. The conventional means of adjustment requires an experienced engineer to shift the PDIC in the three dimension (3D) space until the S-word profile is obtained. This paper proposes an automatic method for replacing an experienced engineer, which can be formulated as an optimization problem with parameters trained by a neural network method. During the training process, a convex cost function of the 3D position is established and the minimum of this function indicates the correct position of the PDIC. In the mounting stage, the steepest descent method is then applied to search for the optimum of the trained function, so that the PDIC is automatically mounted at the optimal position.

Keyword: CD-ROM, PDIC, neural network, optimization

中文摘要

在光碟機中,光學頭的組裝是一個非常複雜的流程,它必須將光感測晶片(PDIC)正確的組入光學頭內,使得像散現象(astigmatism phenomenon)得以產生。傳統上，上述的組裝流程是交給一位工程師，憑著經驗在三度空間中移動 PDIC 直到像散現象產生出來;本計畫擬研發出一種自動調整 PDIC 的方法來取代人力，以期未來在產品品質與生產速度上都可以有較好的表現。本計畫中將這樣的組裝問題轉化成一個最佳化問題可藉由類神經的方法加以訓練。我們選取一個純量函數，它含有一些待定係數，我們藉著任意在空間中移動 PDIC，擷取 PDIC 上的光學訊號當成訓練樣本後確定這些未定係數能讓純量函數成為一個位置的嚴格凸函數,且 PDIC 的最佳位置恰好讓此純量函數為最小，則未來就可利用陡降法(the steepest descent method)來尋找 PDIC 的正確位置。

關鍵字： 光碟機，光感測晶片，類神經網路，最佳化

2. Introduction

Optical data storage devices such as compact disk rom (CD-ROM), digital versatile disk rom (DVD-ROM), and digital versatile disk ram (DVD-RAM), have become popular recently. In these devices, a head system is the key component for picking up the data signals from an optical disk. It consists of a objective lens, laser generators, a photodetector integrated chip (PDIC), and actuators. Several studies have dealt with the design and the servo control of a head system. Kouchiyama et al.[1] reported a plasma etched lens in a head system by using a novel selectivity control during the transfer processes. Hashimoto et al.[2] developed a miniature two-axis actuator for the DVD-R format using a miniature objective lens. Takahashi et al. [3] showed that a two-dimensional search for the optimum focus is effective for a high numerical-aperture thin cover-layer disk system. However, there is little information available on the mounting of a PDIC in the head system. Conventionally, the mounting operation of a PDIC in an optical head system relies on an experienced engineer to adjust the mounting position so that the astigmatism phenomenon is achieved. This paper attempts to develop an automatic method for this mounting operation. It is expected to speed up the mounting process and reduce the manual labor required. The proposed method is formulated as an optimization problem with parameters trained by a neural network method. During the off-line neural network training, a convex cost function of the 3D position can be found and the minimum of this function indicates the correct position of the PDIC. The Steepest descent method [4][5] is then applied to the mounting operation to move the PDIC to the global minimum point of the trained function.

An optical head system in a compact disk re-writable (CD-RW) is taken as an example, to verify the proposed method. Experiments show that a convex cost function can be obtained by the proposed neural network method. Only a few of steps are required to achieve the global minimum of the trained cost function by the steepest descent search method.

3. Problem Formulation

Consider the optical head system of a CD-RW driver shown in Fig. 1. Each emitting beam reflected by a beam splitter (BS) is collimated to an optical path, projected onto the objective lens, and then focused on the disk. The reflective beams from the disk pass through the BS and the plano-concave lens so that they are projected on the PDIC. The PDIC is a tool for detecting the focus error of an optical storage system. The signal of the PDIC is used as a feedback signal to control the focus actuator, which moves the objective lens translationally. There are six split photosensors, A, B, C, D, E and F, in the PDIC, as shown in Fig. 2. We define the focus error signal e_{FE} as $(S_A+S_C)-(S_B+S_D)$ and the tracking error signal e_{TE} as S_E-S_F, where S_A, S_B, S_C, S_D, S_E, and S_F are the outputs of photosensors A, B, C, D, E, and F, respectively.

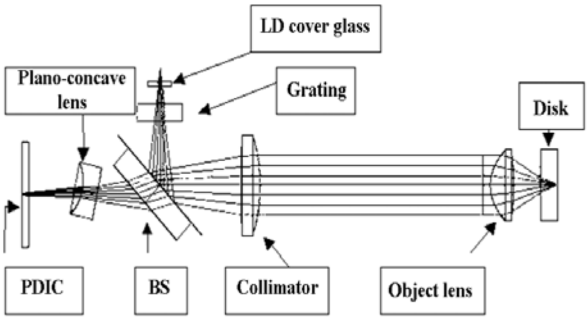

Figure 1: Optical head system in a CD-RW driver.

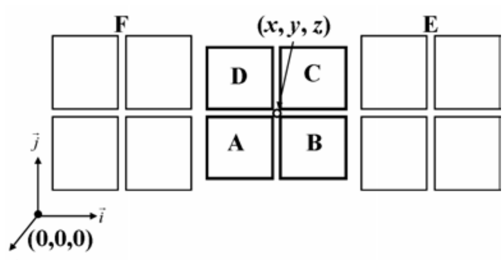

Figure 2: Layout of the PDIC.

In the assembly operation of an optical head system, it is required that the PDIC be mounted in the correct position so that the astigmatism phenomenon can be achieved for the forward and backward movement of the objective lens. The so-called astigmatism phenomenon occurs when the light spot on the four sensors A, B, C, and D of the PDIC forms a circle at the center, as shown in Fig. 3 (b), when the emitting beams are on focus; the light spot on these four sensors of the PDIC forms an ellipse as shown in Fig. 3 (a) and 3 (c), when the emitting beams are off focus. The means of adjusting the mounting position is to place a standard disk on the turntable of a locked spindle motor, and the focus actuator moves forward and backward with the period of $2t_P$. Under such conditions, the astigmatism phenomenon of the PDIC is equivalent to the S-word profile of the e_{FE} signals, as shown in Fig. 4.

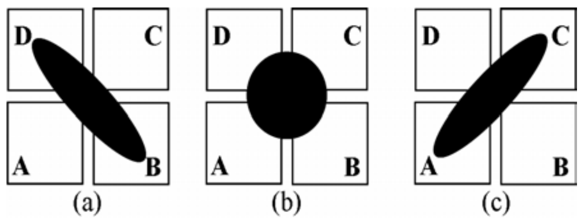

Figure 3: (a) Off focus, e_{FE} <0; (b) on focus, e_{FE} = 0; (c) off focus, e_{FE} >0.

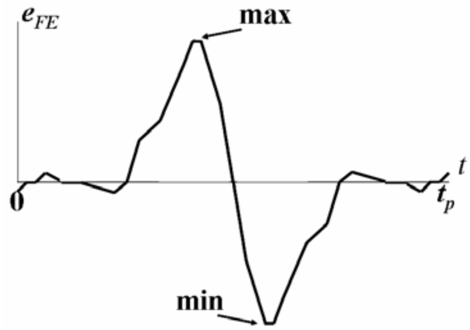

Figure 4: S-word profile of the astigmatism phenomenon.

The conventional means of adjustment requires an experienced engineer to shift the PDIC in the 3D space until the S-word profile is obtained. Instead, this paper proposes an automatic adjustment procedure, which can be formulated as an optimization problem. This means that a convex cost function of the 3D position can be found and the minimum of this function indicates the correct mounting position of the PDIC, for examples, $(x, y, z) = (xf, yf, zf)$ for x, y, z as defined in Fig. 2. It is reasonable to select such a cost function $f(x, y, z)$ as

$$\begin{aligned} f(x,y,z) &= \omega_1 \int_0^{t_p} S_A(x,y,z,t)dt + \omega_2 \int_0^{t_p} S_B(x,y,z,t)dt \\ &+ \omega_3 \int_0^{t_p} S_C(x,y,z,t)dt + \omega_4 \int_0^{t_p} S_D(x,y,z,t)dt \\ &+ \omega_5 \left| \int_0^{t_p} \left(S_E(x,y,z,t) - S_F(x,y,z,t)\right)dt \right| \end{aligned} \tag{1}$$

where S_A, S_B, S_C, S_D, S_E, and S_F are the photosensor outputs and are functions of x, y, z, and time t, while ω_1, ω_2, ω_3, ω_4, and ω_5 are the five weighting factors to be determined. Furthermore, we introduce a constraint of $\|\omega\| = 1$, without loss of generality. Note that the objective lens is still moved forward and backward periodically with the period of $2t_P$.

For the head system with three beams (one main and two side beams), the term $\left|\int_0^{t_p} \left(S_E(x,y,z,t) - S_F(x,y,z,t)\right)dt\right|$ is required to make sure that the astigmatism phenomenon on the sensors of the PDIC is generated by the main beam. The CD-RW specification requires the side beams for the tracking servo, and then specifies that the main beam should be projected onto the sensors A, B, C, D, while the side beams should be projected onto the sensors E and F. The mounting criterion of the PDIC is that the main beam can cause the astigmatism phenomenon on the sensors A, B, C, D and the signals of the sensors E and F generated by the side beams should be equal to each other. Consequently, the cost function $f(x, y, z)$ is selected such that it has a global minimum at which the main beam cause the astigmatism phenomenon and

$$\left|\int_0^{t_p} \left(S_E(x,y,z,t) - S_F(x,y,z,t)\right)dt\right| = 0 .$$

4. Proposed Method

For the present problem, it is assumed that the PDIC has only translational motion, that is, the rotation of the PDIC is negligibly small.

In this paper, a neural network constructed by N nerves is used to determine the five weighting factors in eq. (1). Each nerve has four perceptrons as shown in Fig. 5. A perceptron [4] is a classifier in a neural network, and is used linearly to separate two different clusters by a hyperplane. Each perceptron in Fig. 5 has five inputs, a hyperplane, and an output, that is, a nerve has twenty inputs and four outputs. The perceptron with the inputs $q_{i,1}$, $q_{i,2}$, $q_{i,3}$, $q_{i,4}$, and $q_{i,5}$ classifies the inputs into two clusters, C_1 and C_2, by a hyperplane $vi;1$. If $q_{i,1}$, $q_{i,2}$, $q_{i,3}$, $q_{i,4}$, and $q_{i,5}$ all belong to C_1, then f satisfies the condition of a strictly convex function. Similarly, the perceptrons with the inputs $q_{i,6}$, …,$q_{i,20}$ classify the inputs into two clusters C_3 and C_4 by three hyperplanes, $v_{i,2}$, $v_{i,3}$, and $v_{i,4}$. Also, if $q_{i,6}$, …, $q_{i,20}$ all belong to C_3, then f has a minimum at (xf , yf , zf).

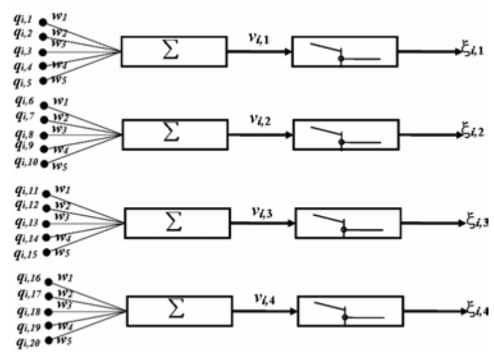

Figure 5: Structure of the i-th nerve in the proposed neural network.

Given any two points $P_{ai} = (x_{ai}, y_{ai}, z_{ai})$, and $P_{bi} = (x_{bi}, y_{bi}, z_{bi})$, we assign $P_{ci} = (x_{ci}, y_{ci}, z_{ci}) = \lambda_i P_{ai} + (1-\lambda_i)P_{bi}$ with $0< \lambda_i <1$. Let $P_o = (x_f, y_f, z_f)$. Furthermore, $S_G(x, y, z, t)$ is defined as $S_E(x, y, z, t)-S_F(x, y, z, t)$, and then, $S_G(P_{ai}, t) = S_E(P_{ai}, t)-S_F(P_{ai}, t)$, $S_G(P_{bi}, t) = S_E(P_{bi}, t)-S_F(P_{bi}, t)$, and $S_G(P_{ci}, t) = S_E(P_{ci}, t)-S_F(P_{ci}, t)$. For a set of $\{P_{ai}, P_{bi}, P_{ci}\}$, we define $q_{i,j}$ and $v_{i,k}$, where $k = 1,…,4$, $j = 1,…,20$, as

$$
\begin{aligned}
v_{i,1} &= \lambda_i f(\mathrm{P_{ai}}) + (1-\lambda_i) f(\mathrm{P_{bi}}) - f(\mathrm{P_{ci}}) \\
&= \begin{bmatrix} \omega_1 \\ \omega_2 \\ \omega_3 \\ \omega_4 \\ \omega_5 \end{bmatrix}^t
\begin{bmatrix}
\lambda_i \int_0^{t_p} S_A(\mathrm{P_{ai}},t)dt + (1-\lambda_i)\int_0^{t_p} S_A(\mathrm{P_{bi}},t)dt - \int_0^{t_p} S_A(\mathrm{P_{ci}},t)dt \\
\lambda_i \int_0^{t_p} S_B(\mathrm{P_{ai}},t)dt + (1-\lambda_i)\int_0^{t_p} S_B(\mathrm{P_{bi}},t)dt - \int_0^{t_p} S_B(\mathrm{P_{ci}},t)dt \\
\lambda_i \int_0^{t_p} S_C(\mathrm{P_{ai}},t)dt + (1-\lambda_i)\int_0^{t_p} S_C(\mathrm{P_{bi}},t)dt - \int_0^{t_p} S_C(\mathrm{P_{ci}},t)dt \\
\lambda_i \int_0^{t_p} S_D(\mathrm{P_{ai}},t)dt + (1-\lambda_i)\int_0^{t_p} S_D(\mathrm{P_{bi}},t)dt - \int_0^{t_p} S_D(\mathrm{P_{ci}},t)dt \\
\lambda_i \left|\int_0^{t_p} S_G(\mathrm{P_{ai}},t)dt\right| + (1-\lambda_i)\left|\int_0^{t_p} S_G(\mathrm{P_{bi}},t)dt\right| - \left|\int_0^{t_p} S_G(\mathrm{P_{ci}},t)dt\right|
\end{bmatrix} \\
&= w^t \begin{bmatrix} q_{i,1} \\ q_{i,2} \\ q_{i,3} \\ q_{i,4} \\ q_{i,5} \end{bmatrix}
\end{aligned}
\tag{2}
$$

$$
\begin{aligned}
v_{i,2} &= f(\mathrm{P_{ai}}) - f(\mathrm{P_o}) \\
&= \begin{bmatrix} \omega_1 \\ \omega_2 \\ \omega_3 \\ \omega_4 \\ \omega_5 \end{bmatrix}^t
\begin{bmatrix}
\int_0^{t_p} S_A(\mathrm{P_{ai}},t)dt - \int_0^{t_p} S_A(\mathrm{P_o},t)dt \\
\int_0^{t_p} S_B(\mathrm{P_{ai}},t)dt - \int_0^{t_p} S_B(\mathrm{P_o},t)dt \\
\int_0^{t_p} S_C(\mathrm{P_{ai}},t)dt - \int_0^{t_p} S_C(\mathrm{P_o},t)dt \\
\int_0^{t_p} S_D(\mathrm{P_{ai}},t)dt - \int_0^{t_p} S_D(\mathrm{P_o},t)dt \\
\left|\int_0^{t_p} S_G(\mathrm{P_{ai}},t)dt\right| - \left|\int_0^{t_p} S_G(\mathrm{P_o},t)dt\right|
\end{bmatrix} \\
&= w^t \begin{bmatrix} q_{i,6} \\ q_{i,7} \\ q_{i,8} \\ q_{i,9} \\ q_{i,10} \end{bmatrix}
\end{aligned}
\tag{3}
$$

$$
\begin{aligned}
v_{i,3} &= f(\mathrm{P_{bi}}) - f(\mathrm{P_o}) \\
&= \begin{bmatrix} \omega_1 \\ \omega_2 \\ \omega_3 \\ \omega_4 \\ \omega_5 \end{bmatrix}^t
\begin{bmatrix}
\int_0^{t_p} S_A(\mathrm{P_{bi}},t)dt - \int_0^{t_p} S_A(\mathrm{P_o},t)dt \\
\int_0^{t_p} S_B(\mathrm{P_{bi}},t)dt - \int_0^{t_p} S_B(\mathrm{P_o},t)dt \\
\int_0^{t_p} S_C(\mathrm{P_{bi}},t)dt - \int_0^{t_p} S_C(\mathrm{P_o},t)dt \\
\int_0^{t_p} S_D(\mathrm{P_{bi}},t)dt - \int_0^{t_p} S_D(\mathrm{P_o},t)dt \\
\left|\int_0^{t_p} S_G(\mathrm{P_{bi}},t)dt\right| - \left|\int_0^{t_p} S_G(\mathrm{P_o},t)dt\right|
\end{bmatrix} \\
&= w^t \begin{bmatrix} q_{i,11} \\ q_{i,12} \\ q_{i,13} \\ q_{i,14} \\ q_{i,15} \end{bmatrix}
\end{aligned}
\tag{4}
$$

$$
\begin{aligned}
v_{i,4} &= f(\mathrm{P_{ci}}) - f(\mathrm{P_o}) \\
&= \begin{bmatrix} \omega_1 \\ \omega_2 \\ \omega_3 \\ \omega_4 \\ \omega_5 \end{bmatrix}^t
\begin{bmatrix}
\int_0^{t_p} S_A(\mathrm{P_{ci}},t)dt - \int_0^{t_p} S_A(\mathrm{P_o},t)dt \\
\int_0^{t_p} S_B(\mathrm{P_{ci}},t)dt - \int_0^{t_p} S_B(\mathrm{P_o},t)dt \\
\int_0^{t_p} S_C(\mathrm{P_{ci}},t)dt - \int_0^{t_p} S_C(\mathrm{P_o},t)dt \\
\int_0^{t_p} S_D(\mathrm{P_{ci}},t)dt - \int_0^{t_p} S_D(\mathrm{P_o},t)dt \\
\left|\int_0^{t_p} S_G(\mathrm{P_{ci}},t)dt\right| - \left|\int_0^{t_p} S_G(\mathrm{P_o},t)dt\right|
\end{bmatrix} \\
&= w^t \begin{bmatrix} q_{i,16} \\ q_{i,17} \\ q_{i,18} \\ q_{i,19} \\ q_{i,20} \end{bmatrix}
\end{aligned}
\tag{5}
$$

Furthermore, an index $\xi_{i,j}$ is introduced as

$$
\xi_{i,j}(w) = \begin{cases} 0 & \text{for } v_{i,j} \geq 0 \\ 1 - v_{i,j} & \text{for } v_{i,j} \leq 0 \end{cases} \tag{6}
$$

where j=1, 2, 3, and 4. It is apparent that if the set $\{\mathrm{P_{ai}}, \mathrm{P_{bi}}, \mathrm{P_{ci}}\} \in C_1$, then $v_{i,1} > 0$, and then $\xi_{i,j} = 0$. Similarly, if f at P_o is less than that at any point in the line segment of P_{ai} to P_{bi}, then $v_{i,2}$, $v_{i,3}$, $v_{i,4} > 0$, and then $\xi_{i,2} = \xi_{i,3} = \xi_{i,4} = 0$. Whenever $\xi_{i,j}$ is not zero, the weighting factors w need to be adjusted. A larger $\xi_{i,j}$ means that the function f with the current weighting factors is further away from the condition of a strictly convex function with the minimum at P_o. A performance index ξ is then defined as

$$
\xi(w) = \sum_{i=1}^{N} \frac{\left(\xi_{i,1} + \xi_{i,2} + \xi_{i,3} + \xi_{i,4}\right)}{4N} \tag{7}
$$

where N is the number of sets, or equivalently, the number of nerves.

The problem of tuning the weighting factors w is found to minimize $\xi(w)$ for all points in the 3D space, and the optimization problem of eq. (7) can be solved by the gradient method. First, find the gradient of $\xi(w)$ as

$$\nabla \xi(w) = \sum_{i=1}^{N} \frac{\left(\nabla \xi_{i,1} + \nabla \xi_{i,2} + \nabla \xi_{i,3} + \nabla \xi_{i,4}\right)}{4N} \tag{8}$$

The update formula for the network is then

$$\hat{w}(k+1) = w(k) - \eta_0 \nabla \xi(w(k)) \tag{9}$$

$$w(k+1) = \frac{\hat{w}(k+1)}{\left\|\hat{w}(k+1)\right\|} \tag{10}$$

where $\eta_0 > 0$, and k is the iteration step. η_0 is the step size of the adjustment, and (10) is used to normalize w. As long as w converges to a constant vector, the training process is then terminated.

5. Implementation

The training process described above is implemented by moving the objective lens periodically with the frequency of 10 Hz, that is, t_p is 50 ms. In this process, a manual adjustment method is still needed to find the correct position of the PDIC and define it as the origin, that is, P_o=(0, 0, 0). This is done only once. After this manual procedure has been completed, a cube in the 3D space is selected as

$$R_{eq1} = \{(x, y, z) \mid x \in [-120\mu m, 120\mu m], y \in [-120\mu m, 120\mu m], z \in [-30\mu m, 30\mu m]\}$$

(11)

The movement of the PDIC is restricted within this cube R_{eq1}. For a collection of approximately 1000 positions randomly distributed within R_{eq1}, the signals of $\int_0^{t_p} S_A dt$, $\int_0^{t_p} S_B dt$, $\int_0^{t_p} S_C dt$, $\int_0^{t_p} S_D dt$ and $\int_0^{t_p} S_G dt$ for each position of the PDIC are measured and calculated.

In this collection of positions, we randomly select 100 pairs of P_{ai} and P_{bi}, and randomly pick out five P_{ci} for each pair of P_{ai} and P_{bi}, that is, we randomly select λ_i for P_{ci}. As a result, there are a total of 500 sets of (P_{ai}, P_{bi}, P_{ci}), i=1,…,500. The signals for these 500 P_{ci} are measured again by moving the PDIC to the assigned positions of P_{ci}. During the training procedure, we let $\eta_0 = 5 \times 10^{-6}$, the initial of w =[1, 0, 0, 0, 0]^t, and the total number of adjustment iterations be 30. It is found that the performance index ξ decays gradually with the increase of the iterations (see Fig. 6). Figure 6 shows that ξ converges to 0.246, which is near zero. Therefore, the training result is reliable. Furthermore, the comparisons of curve levels of the untrained f and trained f are plotted in Fig. 7. The pro_les of the untrained f with w=[1, 0, 0, 0, 0]^t are shown in Figs. 7(a), 7(b), and 7(c) for three di_erent planes with z = 0, y = 0, and x = 0, respectively, while Figs. 7(d), 7(e), and 7(f) show those of the trained f with w=[0.433,−0.526,−0.666,−0.221, 0.206]^t. It can be seen from Fig. 7 that the trained f is a strictly convex function with the global minimum at P_o=(0, 0, 0).

In the automatic assembly operation, the steepest descent method is used to solve the optimization problem (1) with the weighting factors obtained in the training process. The correct position Po of the PDIC for each head system is the minimum point of $f(x, y, z)$ in (1). The search trajectories of the correct position of the PDIC for four initial positions are shown in Figs. 8(a) and 8(b), and the initial positions are marked by circles in these figures.

It is apparent that the correct position is found for these four initial cases and the numbers of search steps are all less than 15. Furthermore, Fig. 8(c) shows that the e_{FE} signal of the PDIC at each of these four initial points is not a S-word profile, that is, it is not the astigmatism phenomenon. On the contrary, the e_{FE} signals all meet the astigmatism phenomenon for the PDIC at the final search points of the steepest descent method (see Fig. 8(d)). This verifies the proposed automatic mounting method.

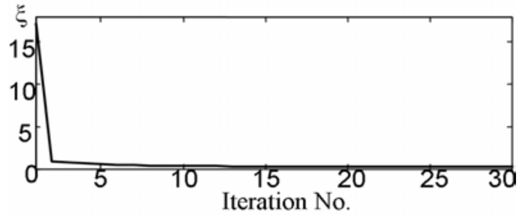

Figure. 6: Plot of ξ and the iteration number.

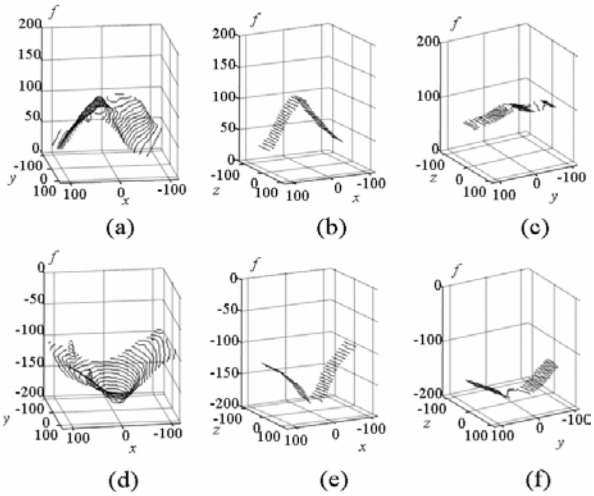

Figure. 7: Curve levels of the untrained f observed in the planes of (a) z = 0, (b) y = 0, (c) x = 0; curve levels of the trained f in (d) z = 0, (e) y = 0, (f) x = 0.

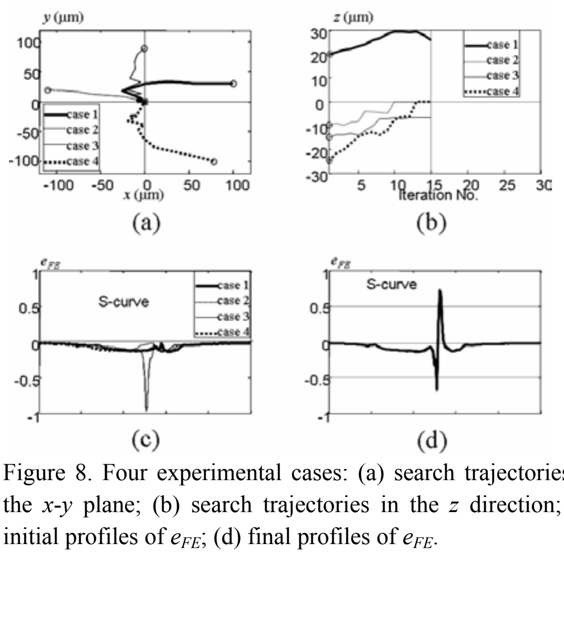

Figure 8. Four experimental cases: (a) search trajectories in the x-y plane; (b) search trajectories in the z direction; (c) initial profiles of e_{FE}; (d) final profiles of e_{FE}.

In the practical implementation, there are a number of correct positions for the PDIC, instead of just one point. These correct points form a connected region, particularly along the z-axis. It is apparent from Fig. 8(b) that the gradients of f along the z-axis are very small and therefore, the convergent rate is also small, particularly in cases 1 and 3. It is therefore not sensible to wait until the steepest descent method converges to the origin set by the manual procedure, since this would require great number of search steps. Alternatively, a program which monitors the profile of the e_{FE} signal is also implemented, and this terminates the steepest descent method when the profile looks like the standard S-word profile. This is the reason why the z-component for cases 1 and 3 in Fig. 8(b) does not converge to the origin.

6. Conclusions

This paper develops an automatic method for mounting the PDIC in the correct position for optimum focus in the assembly of an optical head system. An experienced engineer will take 2 min or more to complete the adjustment of the PDIC. However, the PDIC can be moved to the correct position by the proposed method in less than 30 sec, that is, the automatic method is at least four times faster than the manual method. The experiments demonstrate the implementation of the proposed method and verify its usefulness in industry.

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