Testing of Rounded Corner for Micro-Drill on Hybrid of BP Neural Network and Adaptive Particle Swarm Optimization

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***Abstract*—A new approach based on hybrid of linear BP neural network and particle swarm optimization algorithm for fitting of micro-drill's margin projection is proposed. The network is structured according to fitting equation, where sampled point coordinates of micro-drill and their recombination are taken as 6 inputs, and one output is obtained. The square of difference between the output and constant 0 is taken as performance index. The weights between input neurons and output neuron are tuned in the light of gradient descent method. In order to obtain global optimal solution, improved particle swarm optimization algorithm is integrated into the fitting program, where inertia weigh ω is modifying adaptively and mutation operator is carried on to increase the variety of particle dynamically. While the iteration is finish and the desired performance index of BP neural network is reached, thus stable weight values are obtained, according to which expression coefficients of ellipse can be solved. The rounded corner and diameter of the micro-drill can be tested easily. The presented approach provides a new solving method for ellipse fitting with advantages of programming easily and high precision.**

***Index Terms*—BP neural network; particle swarm optimization; micro-drill; margin projection; rounded corner**

I. Introduction

Micro-drill is applied in printed circuit board manufacturing industry widely, and its defects often take place in edge of cutting facet; if defects such as eccentric, rounded corner, main lips' straightness errors (that is chips) are out-of-tolerance, they would result in vibration, excursion and break at super high speed processing, and decrease processing precision of PCB's hole, such as hole wall surface roughness. The micro-drill's defects should are smaller than 0.5 μm as for micro-drill's diameter among 0.1-0.3 mm [1-3]. There are many means such as least squares method for ellipse or straightness fitting in the data processing [4]. By hybriding BP neural network and particle swarm optimization algorithm, we put forward a novel data processing method to achieve the fitting of micro-drill's margin projection and testing of its rounded corner and so on.

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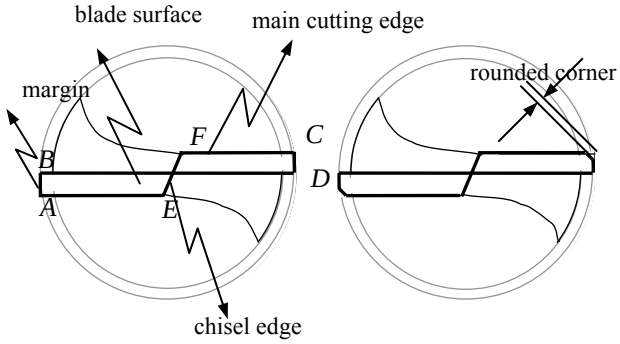
II. Collection of Training Samples

The projection of micro-drill blade surface is shown in Figure 1. Because the rounded corners locate at outermost of main lips, their linear speed are the highest, where the serious wear-out take place usually, and breaking and breach are inclined to resulting because of stress concentration. The rounded corner has large effect for the quality of micro-drill. While the rounded corners are measured, the steps are adopted as follows: measurement positions are the intersection points A and C that margin projection cuts across main cutting edges AE and FC.



1.a Projection of micro-drill 1.b Rounded corner

Figure 1. Blade surface of micro-drill

Distances from A and C to actual edge of micro-drill are taken as rounded corner. Thus the key technique is to fit ellipse equation for the margin projection, and then the intersection points' coordinates for A and C are acquired.

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Let the fitted equation of a micro-drill's margin projection be as follows

$$ax^2 + bxy + cy^2 + dx + ey + f = 0; \quad (1)$$

where $\sqrt{a^2 + b^2 + c^2 + d^2 + e^2 + f^2} = 1$.

III. Fitting of Micro-Drill's Margin Projection

A. Linear BP Neural Network Structure

A BP neural network is designed to fit a micro-drill margin projection according to Eq. (1), whose structure is shown in Figure 2. The network's input layer has 6 neurons, whose input signals are composed of sampled point coordinates, whose output lay has 1 neuron, its desired value is constant 0. The weights between input layer and output layer constitute a vector $[a, b, c, d, e, f]^T$, whose elements are corresponding with the ellipse's fitting coefficients in Eq.(1).

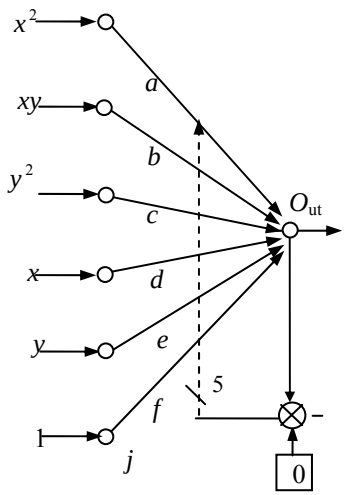


Figure 2. Structure of BP neural network

The input of the output neuron is

$$net = \sum_j \boldsymbol{W}^T \boldsymbol{I}_j, \quad j = 1,2,\cdots,6. \quad (2)$$

where weight vector $\boldsymbol{W} = [a, b, c, d, e, f]^T$, and input vector $\boldsymbol{I} = [x^2, xy, y^2, x, y, 1]^T$.

The activation function $f(x)$ is a linear function in the network, that is

$$f(x) = x + \theta. \quad (3)$$

where θ is threshold, which is 0 in this experiment.

The neuron's output is shown as follows,

$$O = f(net). \quad (4)$$

During the learning, the square of difference between network's actual outputs and desired value constant 0 is taken as performance index, which is shown as follows

$$E = \frac{1}{2}(-O)^2. \quad (5)$$

And the performance index is taken as objective functions for particle swarm optimization.

While the neural network is trained, the 6 weights a, b, c, d, e, f are tuned via errors back propagating in light of gradient descent rule. Thus the weights are tuned as follows [5-6]

$$\Delta w_j(n+1) = -\alpha O I_j + \beta(w_j(n) - w_j(n-1)), \quad (6)$$

where $\alpha > 0$ is learning rate; $\beta > 0$ is momentum factor. $j = 1,2,\cdots,5$, the weights are iterated as follows

$$w_j(n+1) = w_j(n) + \Delta w_j(n) \quad j = 1,2,\cdots,5. \quad (7)$$

On the other hand, the 6th element is tuned as follows

$$f = \begin{cases} \pm\sqrt{1 - a^2 - b^2 - c^2 - d^2 - e^2} & \\ \qquad a^2 + b^2 + c^2 + d^2 + e^2 < 1. & \\ ran(.) & else \end{cases} \quad (8)$$

where $ran(.) \in (-1,1)$ is random variable, while $a^2 + b^2 + c^2 + d^2 + e^2 < 1$, positive or negative is selected for f in the light of its corresponding performance index being smaller.

B. Integration with Particle Swarm Optimization Algorithm

While the ellipse equation of micro-drill's margin projection is fitted with BP neural network, its solution trajectory frequently trapped in local minima. In case the local minima, we integrate particle swarm optimization (PSO) algorithm to get out these minimum valleys, which is a stochastic optimization algorithm. In experiment swarm consists of 40 particles moving around in a 6 dimensional search space at a variant velocity according to individual experience and swarm experience adjusting their velocity dynamically, and the search space is $(-1,1)$, each particle is taken as a potential solution to a problem. Assume the position of the ith particle is represented as $\boldsymbol{x}_i = (x_{i1}, x_{i2}, \cdots, x_{i6})$; the best previously encountered position of the ith particle is denoted its individual best position $\boldsymbol{p}_i = (p_{i1}, p_{i2}, \cdots, p_{i6})$, a value called p_{besti}; the best value of all individual p_{besti} values is denoted the global best position $\boldsymbol{g}_i = (g_{i1}, g_{i2}, \cdots, g_{i6})$ and called g_{best}; a velocity along each dimension is represented as $\boldsymbol{v}_i = (v_{i1}, v_{i2}, \cdots, v_{i6})$, the objective function is the performance index of BP neural network, which is shown in Eq.(5). The updating equations are formulated as follows:

$$\boldsymbol{v}_i(t+1) = \omega \boldsymbol{v}_i(t) + c_1 r_1 (\boldsymbol{p}_i - \boldsymbol{x}_i(t) + c_2 r_2 (\boldsymbol{p}_g(t) - \boldsymbol{x}_i(t)) \quad (9)$$

$$\boldsymbol{x}_i(t+1) = \boldsymbol{x}_i(t) + \boldsymbol{v}_i(t+1) . \quad (10)$$

where the velocity vector has three components, the first is the inertia which keeps the particle move next position, which plays the role of balancing the global and local searches, and coefficient ω has a bigger chance to find the global optimum within a reasonable number of iterations, a large inertia weight facilitates a global search while a small inertia weight favor high ability for local search; the second is the cognitive component, which is its own thoughts and experience; the third is the social component, which represents the messages shared all particle swarms and guide to the global best. c_1 and c_2 are the two acceleration coefficients, they are all set to values of 2.0 in the experiment; r_1 and r_2 are uniformly distributed in the range of [0, 1] [7-8].

C. Evolution speed factor and Square deviation of fitness

1. Evolution speed factor

The anti-evolution speed factor measures the performance of the particle evolution process of the PSO by far, it is expressed as follows,

$$e = \frac{F(g_{best}(t)) + \varepsilon_1}{F(g_{best}(t-1)) + \varepsilon_1} . \quad (11)$$

where $F(g_{best}(t))$ is fitness value of current global optimum value; ε_1 is constant nearly approximately zero taken as offset bias value, in case $F(g_{best}(t))$ nearly equal to zero, and $0 \le e < 1$. The larger the e is, the slower the evolution speed is; while $e = 1$, the algorithm stagnate or the optimal solving is achieved [9].

2. Square deviation of fitness

The square deviation of fitness describe the particles' distribution, it is give by the following equation:

$$\sigma = \left[\frac{1}{40} \sum_{i=1}^{40} \left(\frac{F(\boldsymbol{x}_i(t)) - F_T}{\max\{F_g(t) - F_T + \varepsilon_2, F_T - F_b(t) + \varepsilon_2\}} \right)^2 \right]^{1/2} . \quad (12)$$

where 40 is the number of population, $F(\boldsymbol{x}_i(t))$ denote the fitness of ith particle vector in t^{th} iteration. $F_b(t)$ is the smallest fitness of particles, $F_g(t)$ is the largest fitness of particles, ε_2 is offset bias value which is constant nearly approximately zero in case $F_g(t) - F_T(t) = 0$ or $F_T(t) - F_b(t) = 0$. $F_T(t)$ is the mean value of current all particles' fitness value in t^{th} iteration, that is $F_T = \frac{1}{40} \sum_{i=1}^{40} F(\boldsymbol{x}_i(t))$.

It is obvious that $0 \le \sigma < 1$, and the bigger the σ is, the more diversity of particle is.

D. Self-adaptive algorithm of inertia weight

If the evolution speed of particle is fast, the algorithm can search optimization solving at large scope, if its evolution speed is slow, we can search at small space. On the other hand, if the square deviation of fitness of particle is small, the particle swarm will trap into local optimization, so we should improve dynamically the search space to improve the global optimization ability of particle. Thus according to the characteristic of the inertia weight ω [10-11], which should increase along with the increasing of gathering of particle, and decrease with decreasing of particle evolution speed accordingly, the dynamically modifying of inertia weight was proposed as follows,

$$\omega = \omega_{ini} - \omega_e \times e - \omega_\sigma \times \sigma . \quad (13)$$

where ω_{ini} is the initial inertia weight, ω_e and ω_σ are the coefficient of evolution speed factor and the square deviation of fitness; the range for them are defined as $0 < \omega_e < 1$, $0 < \omega_\sigma < 1$.

E. Mutation mechanics of algorithm

On the other hand, a mutation operator is used by the view of genetic algorithm, which is the random-perturbation is adopted, the mutation coefficient is obtained as follows

$$p_m = \begin{cases} k, & \sigma < \sigma_d \, and F(gBest > f_d \\ 0, & other \end{cases} . \quad (14)$$

where k is the any value between 0.1 and 0.2, $\sigma_d = 0.08$, $f_d = 0.06$.

The velocity mutation and position mutation are dealed with as follows

$$v_{ij}(t+1) = v_{ij}(t)(1 + r_1) , \quad (15)$$

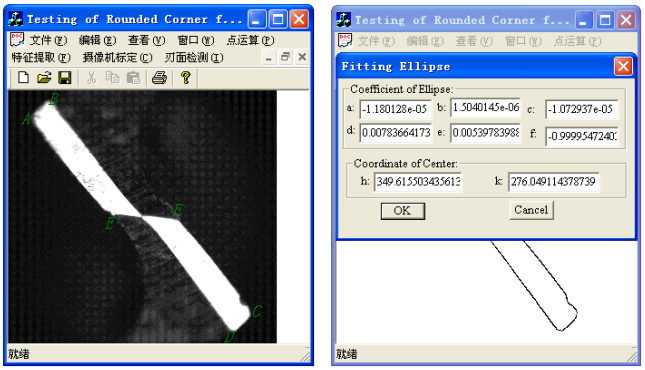
$$x_{ik}(t+1) = \begin{cases} x_{ik}(t) + r_2 (x_{ik\max}(t) - x_{ik}(t)) \\ \qquad 0 \le r_2 < 0.5 \\ x_{ik}(t) - r_2 (x_{ik}(t) - x_{ik\min}(t)) \\ \qquad 0.5 \le r_2 \le 1 \end{cases} . \quad (16)$$

where v_{ij} is the jth element of speed vector $\boldsymbol{v}_i$ of ith particle selected according to p_m, and x_{ik} is the kth element of position vector $\boldsymbol{x}_i$ of ith particle selected according to p_m, $x_{ik\max}$ and $x_{ik\min}$ are the boundaries of position mutation element, that are -1 and 1; r_1 and r_2 are random between (0, 1).

IV. Fitting Experiment

The experiment is carried out in PCB Micro-drill high precision automatic test system, composed of illuminator, optical imagery (zoom lens, CCD and image data acquisition card), mechanical motion system (XY axes work platform, Z axis motion parts) and so on, and the camera of system is calibrated before test. A Φ0.3mm

micro-drill is used to test in the experiment. Firstly its projection image is collected by CCD. While the projection of micro-drill margin is fitted, the sampled point's coordinates should be obtained first. Then the corresponding 2D coordinates in image plane are estimated in the light of improved Canny operator and come to sub-pixel accuracy [12]. The projection of micro-drill's blade surface and running interface of program are shown in Figure 3.



3.a Blade surface of micro-drill 3.b Running interface of program

Figure 3. Main interface of program

In the program, let learning rate $\alpha = 1\times10^{-4}$, and momentum factor $\beta = 1\times10^{-5}$, while the iteration is proceeded, and the iterations of BP neural network is 10 each generation interior; iterations of PSW is 280 generations; initial value of the network is generated at random, $\omega_{ini} = 1.1$, $\omega_e = 0.5$, $\omega_\sigma = 0.04$, $k = 0.1$, the offset value $\varepsilon_1 = 1\times10^{-8}$, $\varepsilon_2 = 1\times10^{-8}$, As the training is completed, that is the system comes to the global optimal point, thus the fitting equation of micro-drill margin projection was achieved according to the stable weights of BP neural network, which is shown follows,

$$1.1801\times10^{-5}x^2 - 1.5040\times10^{-6}xy + 1.0729\times10^{-5}y^2 - 7.8366\times10^{-3}x - 5.3978\times10^{-3}y + 0.99995 = 0. \quad (17)$$

On the other hand, the equations of main cutting edge are obtained according to the proposed method as follows:

$$-1.74904\times10-2\ x + 1.39356\times10-2\ y + 0.99975 = 0, \quad (18)$$

$$-4.65656\times10^{-3}x + 3.60398\times10^{-3}y + 0.99998 = 1. \quad (19)$$

The centre of fitting ellipse $O(h,k)$ can be solved according to Eq.(20),

$$h = \frac{be - 2cd}{4ac - b^2}, \quad k = \frac{bd - 2ae}{4ac - b^2}. \quad (20)$$

Thus the centre (h, k) of ellipse is (349.6155, 276.0491) (measured in pixel). positions of measured that is the intersection points A and C are obtained respectively. Rounded corners are the distances from A and C to actual edge of micro-drill. That is the minimum distances between intersection points A/C and sampled point are the rounded corner of micro-drill, which are 7.7664 (pixel) and 8.3052 (pixel) locating at (106.1424, 61.4774) and (593.7925, 489.7503) respectively; and the micro-drill's diameter is 652.2397 (pixel). In the light of calibration data of camera, the object is 52 mm in length and the scale factor is 0.4569 ($\mu m / pixel$) while system is working. Thus the micro-drill's radiuses of rounded corners are 3.5485 μm and 3.7947 μm separately; and the diameter of micro-drill is 0.2980mm.

If the least square method is adopted, its fitting equation can be obtained as follows

$$-1.2082\times10^{-5}x^2 + 2.0963\times10^{-6}xy - 1.0990\times10^{-5}y^2 + 7.8738\times10^{-3}x + 5.3303\times10^{-3}y = 1. \quad (21)$$

And the fitting equations of main cutting edge are obtained according to the least square method as follow

$$1.72582\times10^{-2}x - 1.36138\times10^{-2}y = 1, \quad (22)$$

$$4.66039\times10^{-3}x - 3.60904\times10^{-3}y = 1. \quad (23)$$

If Hopfield NN is adopted, its solution trajectory always moves toward energy-lost direction, but frequently trapped in local minima, according to method which is partially similar in report [13], the fitting equation of micro-drill margin projection is shown as follows

$$-1.5269\times10^{-5}x^2 - 8.6961\times10^{-6}xy - 1.3775\times10^{-5}y^2 + 8.3000\times10^{-3}x + 4.5431\times10^{-3}y = 1. \quad (24)$$

And the fitting equations of main cutting edge are obtained in the light of Hopfield NN as follow

$$1.72582\times10-2\ x - 1.36138\times10-2\ y = 1, \quad (25)$$

$$4.66039\times10-3\ x - 3.60904\times10-3\ y = 1. \quad (26)$$

On the other hand, if the particle swarm optimization isn't introduced, micro-drill's margin projection is fitted only by BP neural network; its solution trajectory frequently is trapped in local minima. According to the method in research reports [14-15], a fitted equation of hyperbolic curve is obtained as follow:

$$1.1463\times10^{-4}x^2 - 2.5626\times10^{-4}xy + 9.6251\times10^{-5}y^2 - 9.0123\times10^{-3}x + 3.6054\times10^{-2}y = 1. \quad (27)$$

Thus the ellipse center, rounded corner and diameter obtained according to above fitting equations are obtained in Table 1.

The original data and all fitting curves of the micro-drill according to Eq. (17), Eq. (21), Eq. (24) and Eq. (27) are shown in Figure 4.

TABLE I. ELLIPSE CENTER AND TECHNOLOGY INDEXES OF MICRO-DRILL

	Centre of ellipse (/pixel)	Rounded corners /pixel (/μm)	Diameter /pixel (/mm)
BPNN & PSW	(349.6155, 276.0491)	7.7664 (3.5485), 8.3052 (3.7947)	652.2397 (0.2980)
LSM	(349.7765, 275.8774)	7.5379 (3.4441),8.2385 (3.7642)	652.2314(0.2980)
Hopfield NN	350.2201, 275.4423	6.7906 (3.1026), 7.4456 (3.4019)	652. 2298 (0.2980)

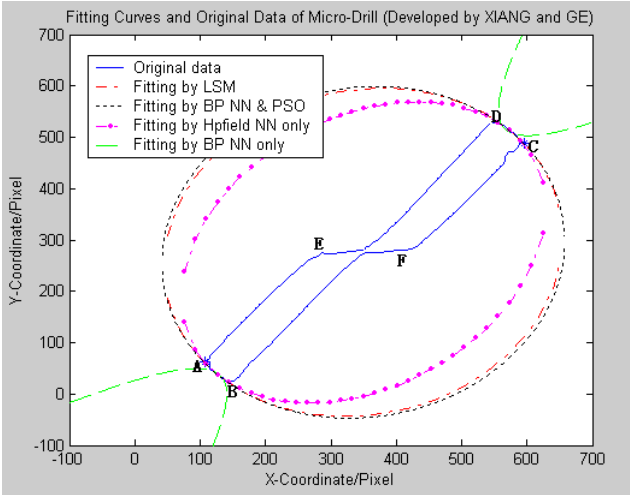


Figure 4. Original data & fitted curves

V. CONCLUSION

The proposed approach has the following key features as opposed to other techniques: The coefficients of margin projection's ellipse equation are obtained from the stable weight vector between the input layer and output layer of the BP neural network in the experiment. In order to obtain the global optimal solution, particle swarm optimization is integrated to fitting program, thus the coefficients of margin projection's ellipse can be achieved. On the other hand, the characteristics of BP NN and Hopfield NN frequently trapped in local extremum is demonstrated in paper, too.

The proposed operator in this experiment possesses merits of programming easily and high accuracy, and makes the test system meet the precision requirement for intelligent test in many scenes, and has value of reference for data processing in machine vision and geometrical errors test of work-pieces.

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