Sensors & Transducers, Vol. 182, Issue 11, November 2014, pp. 217-222

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Visual Inspection for Breakage of Micro-milling Cutter

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Received: 23 July 2014 /Accepted: 30 October 2014 /Published: 30 November 2014

Abstract: In order to realize visual inspection for breakage of micro-milling cutter, a developed image acquisition method of the surface of a micro-milling cutter was constructed and a classification method based on multilayer neural network was proposed in this article. While the milling cutter was rotating at a constant speed, a camera was triggered by a rotary encoder to capture a series of images. And the developed image of milling cutter was created by image mosaic algorithms. The moment of regional feature as well as the gray feature of the tooth edge was extracted as the input vector of neural network. The feature vector includes moment of inertia, geometric central moment, three-dimensional invariants moment and the gray value of the projection on two principal axis directions of the tooth region. By designing a proper neural network, breakage defects can be detected 100 %. And the false discovery rate is 0.5 %. *Copyright © 2014 IFSA Publishing, S. L.*

Keywords: Visual inspection, Micro-milling cutter, Breakage defects, Pattern recognition.

1. Introduction

Micro-milling cutter is an important tool for printed circuit board processing, and a milling cutter with breakage has great influence on processing quality. The micro-milling cutter has small size of diameter (0.8-2.4 mm), large number of teeth, as shown in Fig. 1. Manual detection has many disadvantages, such as consumption of time and workforce, large workload and high error detection rate. However, Machine vision is a technique that uses computer or machine instead of human eyes to do measurement and judgment. It includes image acquisition, processing, analyzing and display. And it can greatly satisfy the detection requirement in the production line with its advantages, such as noncontact, high accuracy, fast speed, high automation and high intelligent level [1].

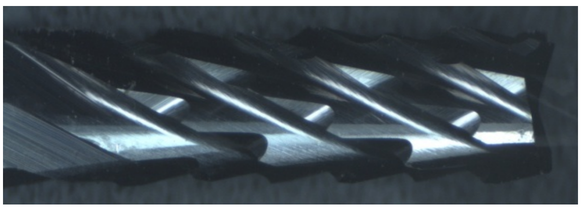


Fig. 1. Physical figure of micro-milling cutter.

As for visual inspection for milling cutter, a detection device for milling cutter was proposed in literature [2]. It integrated the vertical and radial images and combined with a transmission device to achieve automatic operation. This device can measure geometric parameters and recognize the breakage of the milling cutter. However, no specific operating method was given. On the other hand, a diameter measurement method for micro-milling cutter was presented in literature [3]. A well designed setup was proposed, and some basic factors as well as the measurement uncertainty were analyzed in this paper. Furthermore, an online detection approach for RCF type of milling cutter was proposed in literature [4]. It provided a method with simple algorithms and fast speed to detect the breakage of micro-milling cutter. But this method can't meet the requirement on the production site.

In order to detect the breakage of micro-milling cutter, a visual inspection system is proposed in this paper. Firstly, a developed image acquisition method of micro-milling cutter is introduced. Secondly, features of blade tooth such as geometric moment invariants, three-dimensional invariants moment, as well as gray scale of specified region are analyzed to distinguish the breakage. Thirdly, a classification approach based on multilayer neural network for the breakage of micro-milling cutter is designed and trained. Finally, the classification result and data analysis is given.

2. System Design

The inspection system based on machine vision for breakage of micro-milling cutter consists of a camera (UI549xSE-C), a red surface illumination, collets bodies, a precision rotating stage, a rotary encoder (E6B2-CWZ6C) and corresponding measurement software. The red surface illumination and the camera need to be installed at certain angles. The rotating platform is connected to the rotary encoder. The telecentric lens (XF-5MDT0.4*110) has the magnification of 0.4 times and the working distance of 110 mm. Physical map of the detection system is shown in Fig. 2.

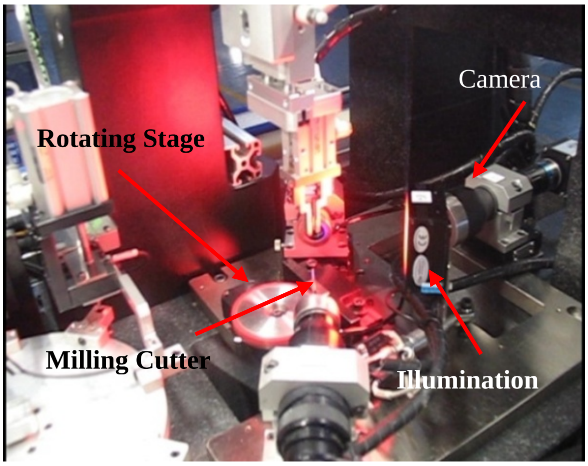


Fig. 2. Physical figure of milling cutter visual inspection system.

The operating process of this system is as follow: 1) The milling cutter to be detected rotates a complete circle. At the same time, the camera is triggered to acquire a series of images. 2) Tiled the images we obtained in step 1 into a whole image, which is the developed surface diagram of the micro-milling cutter, as shown in Fig. 3. 3) Process and analyze the developed image to complete breakage classification of milling cutter [5].

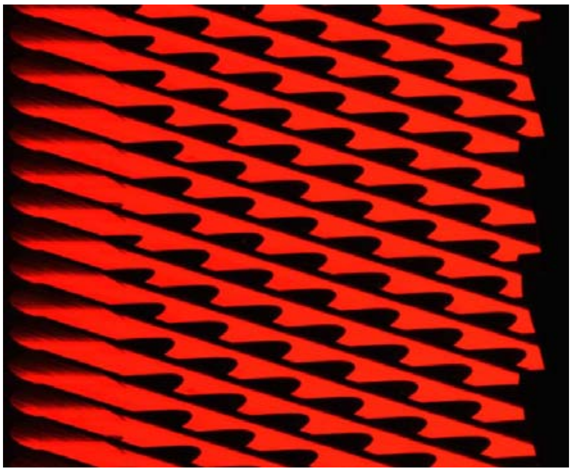


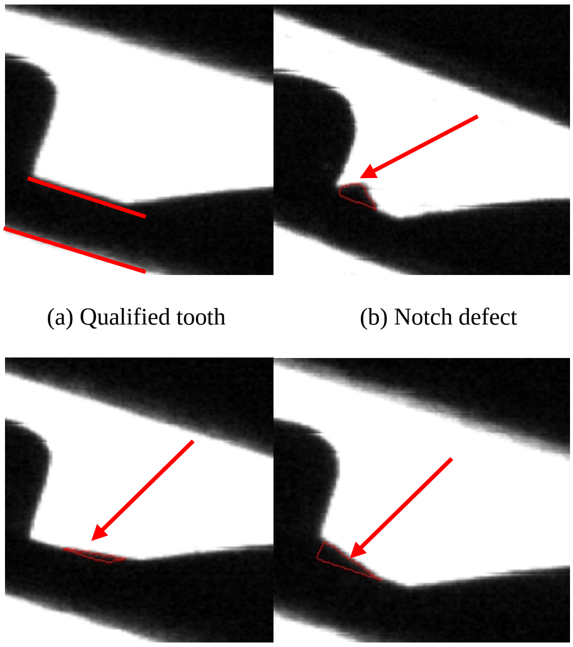
Fig. 3. Developed image after rotating and mosaicing.

3. Image Feature Extracting of Milling Cutter with Breakage

If a milling cutter has breakage defects, it will show some abnormal features at the blade tooth region in the developed image, as shown in Fig. 4. There is one qualified tooth and three typical unqualified teeth with breakages in this figure. The qualified tooth owns a smooth edge, which parallels to the bottom of the next cutting blade, as shown in Fig. 4(a). However, the tooth with breakage will have a notch at the blade, as shown in Fig. 4(b), and other features that show the edge of the tooth is not parallel to the next cutting blade, as shown in Fig. 4(c), Fig. 4(d).

The regular image detection method based on regional algorithms is to match the cutting groove first. Then analyze some region features of the blade tooth to estimate if it is broken. But because of different cutting angles and depths, different radians of back and forth corner, it's easy to cause false and missing detection. That means it is extremely difficult to set a proper threshold to classify the qualified teeth from those unqualified. In addition, the judgment criterion of tooth breakage is very hard to keep consistent with the company standard. Therefore, a neural network approach is introduced to classify the breakage of milling cutter.

The selection and extraction of image features is greatly important to neural network algorithms. And there are many image features of the tooth that is available to chose, such as area, concavity, convexity, total length, circuitry, angle, width and height of minimum enclosing rectangle. However, the wear degree and the cutting angle of the grinding wheel are hard to control. They all can cause a certain deviation, which make the size and the length of each tooth is different. Therefore, single regional feature mentioned above or their simple linear combination can't easily distinguish the qualified teeth from those teeth with breakage.



(a) Qualified tooth (b) Notch defect

(c) Front corner breakage (d) Back corner breakage

Fig. 4. Qualified tooth and typical unqualified teeth.

Features of the tooth chosen in this article are composed of two parts. One part is 10 moments of regional feature of the tooth, including the moment of inertia, geometric moment invariants and three-dimensional invariants moment. The other part is gray values of the projection on two principal axis directions of the blade tooth region, which are 100 and 35 values respectively.

These two dimensional (p+q) moment (m_{pq}) and central moment (u_{pq}) of a digital image f(x, y) are given by:

$$m_{pq} = \sum_x \sum_y x^p y^q f(x, y), \tag{1}$$

$$u_{pq} = \sum_x \sum_y (x - \bar{x})^p (y - \bar{y})^q f(x, y), \tag{2}$$

where f(x, y) is the gray value of image at the point (x, y). And the barycentric coordinates of image are given by [6]:

$$\bar{x} = m_{10} / m_{00}, \tag{3}$$

$$\bar{y} = m_{01} / m_{00}, \tag{4}$$

The moment of inertia can greatly distance the spatial distribution of gray differences. It helps to distinguish the complexity of the gray spatial distribution better. The moments of inertia on two principal axis directions are given by:

$$I_a = h + \sqrt{h^2 - u_{20} * u_{02} + u_{11}^2}, \tag{5}$$

$$I_b = h - \sqrt{h^2 - u_{20} * u_{02} + u_{11}^2}, \tag{6}$$

$$h = (u_{20} + u_{02}) / 2, \tag{7}$$

Geometric moment invariants and three-dimensional invariants moment are mainly used to describe the global feature of the image geometry. They have the invariance of rotation, translation and scaling. It can adjust better to tiny deviation of angles and sizes. Therefore, the moments of regional feature can better reflect the tooth characteristics than common regional features [7].

Four geometric invariants moments are constructed as follow:

$$PSI_1 = I_1 / u_{00}^4, \tag{8}$$

$$PSI_2 = I_2 / u_{00}^{10}, \tag{9}$$

$$PSI_3 = I_3 / u_{00}^7, \tag{10}$$

$$PSI_4 = I_4 / u_{00}^{11}, \tag{11}$$

where

$$I_1 = u_{20}u_{02} - u_{11}^2, \tag{12}$$

$$I_2 = (u_{30}u_{03} - u_{21}u_{12})^2 - 4(u_{30}u_{12} - u_{21}^2)(u_{21}u_{03} - u_{12}^2), \tag{13}$$

$$I_3 = u_{20}(u_{21}u_{03} - u_{12}^2) - u_{11}(u_{30}u_{03} - u_{21}u_{12}) + u_{02}(u_{30}u_{12} - u_{12}^2), \tag{14}$$

$$\begin{aligned} I_4 = {} & u_{30}^2 u_{02}^3 - 6u_{30}u_{21}u_{11}u_{02}^2 + 6u_{30}u_{12}u_{02} \\ & (2u_{11}^2 - u_{20}u_{02}) + u_{30}u_{03}(6u_{20}u_{11}u_{02} - 8u_{11}^3) \\ & + 9u_{21}^2 u_{20}u_{02}^2 - 18u_{21}u_{12}u_{20}u_{11}u_{02} \\ & + 6u_{21}u_{03}u_{20}(2u_{11}^2 - u_{20}u_{02}) + \\ & 9u_{12}\, 2u_{02}^2 u_{02} - 6u_{12}u_{03}u_{11}u_{20}^2 + u_{03}^2\, 2u_{20}^3 \end{aligned}, \tag{15}$$

Another four three-dimensional invariants moments are constructed by:

$$M_{pq} = u_{pq} / u_{00}^3, \tag{15}$$

Therefore, moments of regional feature include ten elements: I_a, I_b, PSI_1, PSI_2, PSI_3, PSI_4, M_{21}, M_{12},

M_{03}, M_{30}. The gray feature of the tooth can be obtained by gray projection algorithms. And the above two parts of features complete a feature vector of the tooth together.

4. Breakage Classification by Neural Network Based on Back Propagation

Artificial neutral network (ANN) is a mathematical model that imitating behavior characteristic of animal neutral network and processing disturbed parallel information [8]. The structure of ANN is shown in Fig. 5.

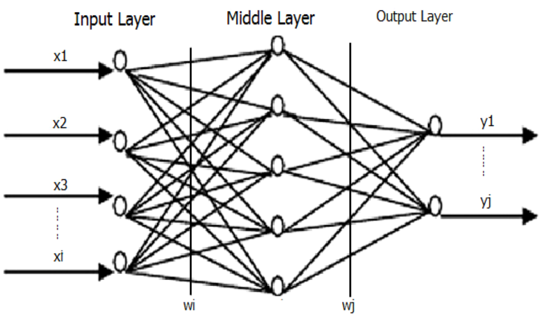


Fig. 5. Neural network structure diagram.

Input signal Xi applies to output node to generate output signal Y_i through hidden layer. Each sample of network training includes input vector X and desired output Y. The difference between input value and desired output value of the neutral network can continuously decrease by adjusting weight W_i between input node and hidden node, as well as weight W_j between hidden node and output node. After repeatedly training until the difference can meet the requirement, this neutral network is convergent [9].

The output of the neural network classification for breakage of milling cutter is either a qualified cutter or a cutter with breakage, so the output layer node is 2. The input layer node is 145, corresponding to 145 values of the feature vector mentioned above. According to empirical formula, the middle layer node is given by:

$$n_1 = \sqrt{n+m} + a \ , \ 1 \le a \le 10 \ , \qquad (1)$$

where n is the input layer node, m is the output layer node. So the middle layer node should be 12 to 22. The neural network used in this paper chose middle layer node as 20. In addition, every element in the feature vector will subtracts mean value of the array, and then divided by standard deviation. Therefore, we obtain a new input feature vector with mean value of 0 and standard deviation of 1. This preprocessing method is called Normalization.

According to parameters selected above, we construct a back propagation neural network with multilayer perceptron structure for a specific type of micro-milling cutter. The training set of this network contains 23 images. Each image includes 32 teeth, a total of 736 teeth, including 708 qualified teeth and 28 teeth with several kinds of breakages. After 300 times of reverse iterations, threshold difference of weights of input values between two iterations is less than 0.1 and mean error of the final training data less than 0.000038. The Output of tooth with breakage classifies 1, and qualified tooth classifies 0. The training process of one image is shown in Fig. 6.

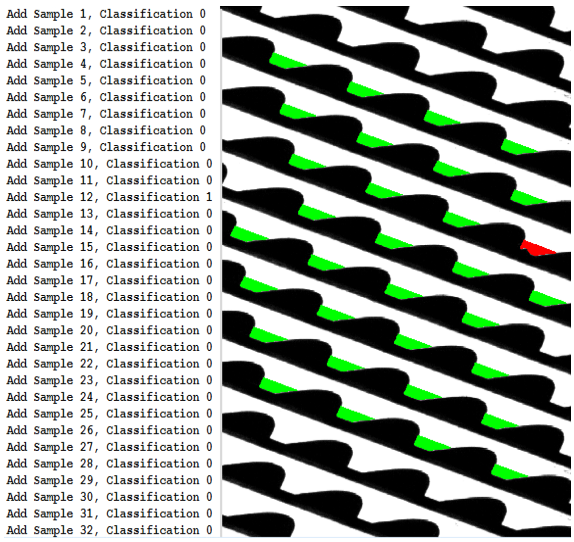


Fig. 6. Training process of neural network.

This training set is just a basic one, including a lot of qualified teeth and some typical teeth with breakages. Moreover, some special images with wrong output results or with teeth that are hard to classify should be added to the basic training set. This training set will gradually consummate by constantly repeat the process above in the subsequent using. As to different type of micro-milling cutter, different training set should be applied to the neural network.

5. Classification Results and Analysis

According to the parameters analyzed above, we construct neural network algorithms to run five groups of tests at the production line of the micro-milling cutters. Corresponding parameters of the milling cutter are as follow: diameter 2.4 mm, valid length 10 mm and type C. Actually there are a total of 29 teeth with breakages among the micro-milling cutters that we tested. And the neutral network method gives a result of 36 teeth with breakages, including all the actual breakages as shown in Table 1. This shows that the inspection system detects almost all the broken blade teeth, and achieves a false discovery rate less than 0.5 %.

Table 1. Test result.

Experiment Times	Total Number	Detection Defects	Real Defects
1	500	2	2
2	500	1	1
3	250	12	10
4	250	21	16
Total	1500	36	29

5.1. Selection of Middle Layer Node

Normally, it is important to decide the node of middle layer of neural network. If node number is too small, it will be hard to reveal the relevance of the sample. And if node number is too much, the sample will be dramatically randomness. Therefore, in order to select the optimal node of middle layer, we tested 100 micro-milling cutters by using different nodes of middle layer of neural network from 14 to 20 according to empirical formula. The statistics in Table 2 demonstrate that the neural network we chose is not very sensitive to the node of middle layer. The total number of detected breakages doesn't change much along with the change of middle layer nodes.

Table 2. Neural network result caused by different MLN (Middle Layer Node).

Test NO.	Actual Bad	MLN 14	MLN 16	MLN 18	MLN 20
1	4	4	4	4	4
2	1	1	1	1	1
3	1	1	1	1	1
4	2	2	2	2	2
5	2	2	3	2	3
<<	<<	<<	<<	<<	<<
100	4	4	4	4	4
Total	58	56	57	56	58

5.2. Selection of Preprocessing Function

The preprocessing function is used to optimize input features of neutral network into a more distinct vector with features. These 100 micro-milling cutters were studied again by neural network with different type of preprocessing functions.

PCA (Principal Component Analysis) is a linear dimensionality reduction technique [10]. It can generalize lower dimensional representation of the original data, in terms of capturing the data direction that has the largest variance. The transformed components are sorted by information content, and hence transformed components with little information content can be omitted. On the other hand, LDA (Linear Discriminant Analysis) can be used to reduce the amount of data without losing a large amount of information, while additionally optimizing the separability of the classes after the data reduction [11]. Different output results by using PCA and LDA were presented in Table 3. As we can see, the result is not as good as preprocessing function of Normalization (N) that we mentioned in paragraph 4.

Table 3. Neural network result caused by different type of preprocessing functions.

Test NO.	Actual Bad	N	PCA	LDA
1	4	4	4	4
2	1	1	1	1
3	1	1	1	1
4	2	2	2	3
5	2	3	2	3
<<	<<	<<	<<	<<
100	4	4	4	4
Total	58	58	53	52

5.3. Comparison between Regular Regional Detection Algorithms and Neutral Network Algorithms

The regular regional detection method mentioned in paragraph 3 was the original plan for this inspection task. However, due to the unpredictable condition of grinding wheel and irregular shape of the tooth, it is hard to accurately extract a perfect edge of the tooth. In that case, the classification result can't be accurate as well. Therefore, in order to avoid too much misjudgment of qualified teeth, the inspection criterion can't be too strict. The statistics in Table 4 show the output result of the comparison between neural network algorithms and regular regional detection method. According to the total number of breakage detection, it is obvious that the proposed neural network approach can achieve better performance than regular regional detection method which missed almost a half of micro-milling cutters with breakage.

Table 4. Results of neural network and regular regional detection algorithms.

Test NO.	Actual Bad	Neural Network	Regional Detection
1	4	4	3
2	1	1	0
3	1	1	0
4	2	2	0
5	2	3	1
<<	<<	<<	<<
100	4	4	4
Total	58	58	28

6. Conclusion

In this paper, we established an inspection system of micro-milling cutter for breakage based on machine vision. By using a special image mosaic method, 3D space parameters of milling cutter are transformed into an image of two-dimensional plane to process. As for the task of image processing, a classification approach of multilayer neutral network was constructed. With superior input features of the tooth and proper parameters of neural network, which have important significance to classification result, this classification method of neural network is very competent for breakage detection of micro-milling cutters. The proposed approach achieves highly performance on the production line with breakage defects detected 100 %. And the false milling cutter discovery rate is 0.5 %. In addition, detection for one milling cutter completes within 3 seconds. The detection accuracy and the time consuming can both meet the testing requirements on the production site.

Acknowledgements

This article is supported by the twelfth five-year support program (2013BAF07B04) of National Ministry of Science and Technology. And the authors wish to express their most sincere appreciation to Xiamen Golden Egret Special Alloy CO., LTD, who supported all the experiments material we used in this article.

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