Applied Mechanics and Materials *Online: 2014-01-16*
ISSN: 1662-7482, Vols. 496-500, pp 1801-1807
doi:10.4028/www.scientific.net/AMM.496-500.1801

Identification of tool based on decision fusion of multi features

WANG Jiajing[1,2,a], ZHANG Shusheng[1,b], HE Weiping[1]

[1]The Key Laboratory of Contemporary Design and Integrated Manufacture Ministry of Education, Northwest Polytechnical University, Xi'an Shaanxi, China

[2]The High-Tech Institute of Xi'an, Xi'an Shaanxi, China

[a]shuijing0103@163.com, [b]zzsnet@nwpu.edu.cn

Keywords: feature extraction; decision-making layer; information fusion.

Abstract. In order to solve the problem of bar code failure because of inadequate protection, pollution and other factors in the process of production, presented a new multi-information fusion technology used of residual bar code information, shape, texture and the weight information to identify the tool information in the database and recovery the tool identification. Experimental results show that the proposed scheme has better performance in accuracy, robustness and efficiency, can fully satisfy the actual requirement in production.

Introduction

Direct part identification (DPM) is a kind of marking technologies which can directly mark the text, symbols or images on the surface of metal tools permanently. Data Matrix (DM) code is always selected as the permanent identification of 2D bar code because of the advantages of large capacity, high density and error correction ability [1]. In this paper, the two-dimensional bar code symbol generated by DPM is labeled on the surface of metal parts and machining tools, the reading of 2D bar code image always has the defects of irregular light, low contrast, code points spread, serious pollution and so on, such as shown in Fig. 1. The traditional bar code position methods detect the number and location of peaks and troughs to determine the division with the projection of the transverse and longitudinal gradient, which is suit for the DM code with strong contrast and clear edge [2]. The edge of DM code on the surface of metal parts will have half pixel fuzzy, different sizes and other effects, because of the limitation of image acquisition equipment, the peak and trough of transverse and longitudinal gradient projection will be likely to be 'drowned'. In the extraction of 2D bar code information, all existing algorithms used with threshold to extract data by sampling points. For the loss of information caused by the severe global threshold, some scholars use Bernsen local threshold, but the Bernsen algorithm has the disadvantages of slow speed, sensitive to interference, easy to cause artifacts and so on [3]. Liu used the method of surface fitting with two-dimensional two order polynomial to fit the background of the 2D bar code, which could better solve the image segmentation problem of 2D bar code under the conditions of non-uniform illumination [4]. But this method is more applicable to the images with dark background edge and four corners and bright middle part, incapable for uneven illumination. Wang proposed to extract the bar code information based on the double parameters comparison between the gray and gradient valued of adjacent module, using genetic algorithm and iterative optimal data of DM code [5]. This method has higher robustness to non-uniform illumination, low contrast and noise pollution. However, if the bar code surface is defected due to inadequate protection, pollution and other factors, it will no longer as a unique identification, the traditional

method cannot locate the bar code and extract information, so the accuracy and timeliness of real-time tracking cannot be guaranteed.

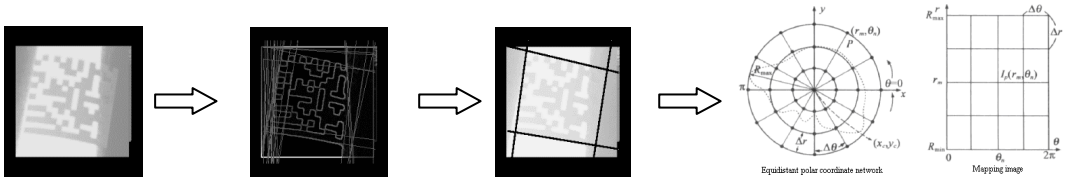
This paper proposed to use with multi information fusion, identify the corresponding tool parts in database with the residual bar code information, shape information, texture information and the weight information, which could make the part identification to restore and remedy.

(a) Non-uniform illumination (b) Noise (c) Scratch (d) High light

Fig. 1: Polluted DM code

Extract the residual information feature of 2D bar code

The 2D bar code on the surface of metal tools could not be as UID to identify the parts if which is failure, but the residual information still has certain value identity. Remove the defective information in the region of bar code with wavelet filtering firstly, then extract target DM code roughly. On the basis of the accurate positioning of the results, divide the bar code region and extract the features. Because the principle of extreme feature is simple and the described regions do not need continuity, the paper selected the extremum characteristic method to describe the structure features of residual code, shown as Fig. 2.



(a) Residual code (b) Candidate edges (c) The best location result (d) Extremum characteristic method

Fig. 2: Extract residual code characteristics

Extract the shape feature

Because the differences of the tool shape may be great, the shape information is an important characteristic that distinguishes the tools. Shape features usually contain certain semantic information, which is the significant core feature. Extraction of the shape feature is the process of converting input image data to shape feature sequence. The image contains a large amount of data, however, it is usually considered to be redundant. Therefore, the input image data should be converted into sequence to represent the simplified features. Using shape feature could distinguish the target effectively, which could improve the precision and efficiency in image retrieval.

Select the shape descriptor. Shape descriptor is a number set used to describe the given shape. The shape of the targe image may not be reconstructed using shape descriptor, but for the different shape, the difference of the shape descriptor should be high enough in order to distinguish different shape effectively. For transformation, rotation, affine and non-rigid transformation, the effective shape descriptors should have good robustness; and also have certain resistance ability for the effects caused by partial occlusion, deformation, noise and so on [6].

In this paper, the tools are in the production process of frequent circulation, which often be damaged or contaminated by the collision, friction, oil and so on. Therefore, extract the shape

features needs to use the profile and regional information of tools to mining the inherent characteristics of the image, and get the shape robust feature with affine transformation, projection transformation, anti noise resistance.

Contour division based on the distribution of local curvature. If the shape of the soiled products is damaged, the shape features extracted will be changed, which is different with the original part ,thus affecting the target recognition results of follow-up [7]. Therefore, this paper described the local feature used of local curvature distribution for the the parts with damaged shape. After getting the feature segments, match all of these with the feature segments in database and find the best approximate one to obtain the accurate information.

The first step: segment the contour of the object product. Select the starting points of the contour as the start of the present contour segment, combine the adjacent points according to the contour direction; When the segment is satisfied to the stop requirement, select the gravure with maximum curvature absolute value as the terminus of the present contour segment from the continuous non-feature points and the next point as the start of the news. Repeat the above process until the end . The stop condition: the number of the continuous non-feature points is more than the given threshold and there will be one gravure in the continuous non-feature points at least.

The second step: after segment the contour, merge the initial contour segment as follow:

(1)initialize T_F *and* w_v, $T_V = w_V \max(V(F)), F \in \mathbf{F}$;

(2)select S, $S = \{F^* : V(F^*) \geq T_V\}$

(3)if $\#(F) \leq T_F$, *end; else*

(4) select $\min_{\substack{F \\ F \in V(F)}}$, *merge;*

(5)select F_L *and* F_R *;*

if $V(F_L) \geq V(F_R)$

then combine F *with* F_L *;*

set $F_{new} = F_L \cup F$ *; else*

combine ***F*** *with* F_R *;*

set $F_{new} = F \cup F_R$ *;*

(6)add F_{new} *to* ***F****, and remove* F *;*

(7)compute $V(F_{new})$ *;*

if $V(F_{new}) \geq T_V$, *set* F_{new} *as features fragment;*

(8)go to step (3).

The segmented threshold T_V is used to judge whether the present contour segment is feature segment which could describe the object feature completely and effectively.

The third step: normalize the feature segments. Sampling the contour segments with points M which represents an ordered set of points $\{p_1, \cdots, p_M\}$. For each point, transform the coordinates according to the following rules [8]: $p_1 \to p_1' = (0,0)$, $p_M \to p_M' = (1,0)$, transform the other contour points $\{p_2, \cdots, p_{M-1}\}$ from the original coordinate to the new one determined by p_1' and p_M'. The feature segments have similar invariance after coordinate transformation.

The forth step: measure similarity. Select shape context distance $D_{SC}(P,Q)$ [9] between feature segments to evaluate the similarity, then find the most similar one from database. $D_{SC}(P,Q)$ represents the shape context distance between the point p_i and q_i at the given contour segment P and Q, the smaller the value is, the greater the similarity between the segment P and Q is.

$$D_{SC}(P,Q)=\frac{1}{n}\sum_{p\in P}\arg\min_{q\in Q}C(p,q)+\frac{1}{n}\sum_{q\in Q}\arg\min_{p\in P}C(q,p) \tag{1}$$

In which， $C_{ij}\triangleq C(p_i,q_j)=\frac{1}{2}\sum_{k=1}^{K}\frac{\left[h_i(k)-h_j(k)\right]^2}{h_i(k)+h_j(k)}$ 。

The fifth step: compute the credibility of the feature segment. Evaluate the credibility of contour segment with the relative length and the value described the feature of the contour segment together. For the target contour $C(t)$ and the feature segment S_i, $\{S_i,i=1,2,\cdots\}$, whose value $\lambda^C(S_i)=\frac{V(S_i)}{V(C_N)}$ measured the significant of feature segment.

The relative length $\lambda^L(S_i)$ of contour reflects the percentage of the features in the feature segment, expressed as formula (2):

$$\lambda^L(S_i)=\frac{l(S_i)}{\max(l(S_i))},\ i=1,2,\cdots \tag{2}$$

The sixth step: target classification. Together the reliability and the similarity of feature segment, and get the best classification of the identified target through the accuracy of object classification. For the defected object S_i^O, select the feature segment S_i^P with the nearest distance from feature database, the similarity is written as $D_{SC}(S_i^P,S_i^O)$. According to the credibility of the feature segment, get the accuracy $D(S_i^O)$ of the feature segment S_i^O corresponding to the target category, which is shown in formula (3):

$$D(S_i^O)=\frac{D_{SC}(S_i^P,S_i^O)}{\lambda^O(i)},\ i=1,2,\cdots \tag{3}$$

In above, $\lambda^O(i)$ represents the credibility of feature segment S_i^O. For the defect product, the important level of the contour segment described is not identical, so it is unnecessary to compute all target categories of the feature segment $\{S_i^O,i=1,2,\cdots\}$. In actual operation, only select the contour segments with greater value to compute the accuracy of the feature segment, which could meet the recognition requirements and reducing the computational complexity of the algorithm.

Extract the texture feature

Texture is an image characteristic reflected the space distribution of the pixel and does not depend on the brightness or color of the image, it also contains the surface structure information and the characteristics surrounding the image[10]. Texture feature is a kind of regional characteristics,

which has matching error caused by local deviation. In addition, it is invariant to rotate, which has good robustness to rotated image. Texture feature as an important visual cues exits in common, the successful extraction will affect the quality of subsequent image processing directly, such as image analysis and retrieval. The common methods to extract the texture feature include statistics, structure and spectral method.

Considering to the objects in the manufacturing workshop, the tools will be polluted , rusted after a long time using which could interfere with the texture discrimination. Therefore, an algorithm to extract the main texture feature of tools and ignore the interference is necessary. This paper used the two-dimensional Discrete Fourier Transform (DFT) to extract the transformed texture feature.

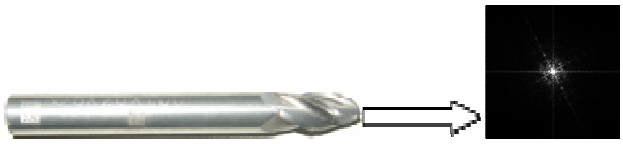
An image of size $m \times n$ is represented by the discrete function $f(x,y)$, whose frequency spectrum function after transformed with DFT is represented by $F(u,v)=\frac{1}{m\times n}\sum_{x=0}^{m-1}\sum_{y=0}^{n-1}f(x,y)e^{j2\pi(ux/m+vy/n)}$ In which, $x\in\{0,1,2,\cdots,m-1\}$, $y\in\{0,1,2,\cdots,n-1\}$, u and v is frequency variable, x and y is spatial variable. $F(u,v)$ is usually a complex, whose another form is represented as the formula (4):

$$F(u,v)=R(u,v)+jI(u,v) \tag{4}$$

In which, $R(u,v)$ is the real part of $F(u,v)$, and $I(u,v)$ is the imaginary part. The image texture feature after DFT transform could be measured by the following parameters:

·Energy: $E=\sum_u\sum_v|F(u,v)|^2$ ·Frequent direction: $D=\left[\sum_u\sum_v\arctan\left(\frac{I(u,v)}{R(u,v)}\right)\right]\Big/E$

Combined the two texture measure parameters into a vector $q=(E,D)$, which is the feature vector of image texture. Fig. 3 describes the texture feature of the part in Fourier domain.



(a) Tool texture (b) Fourier descriptor

Fig. 3: The description of product texture feature in Fourier domain

Multi-information decision fusion

Using only one feature to establish identified model to identify the state and information of tools will not get satisfactory results under the premise of invalid UID. Therefore, this paper established many identified models with different types through extracting the different residual features of the parts, then fusion of multiple recognition decision making to determine the accurate the target.

Structure design of the hierarchical matching. For the failure bar code parts, using multi-modal system with multi-information, include residual bar code information, shape, texture and weight information, is helpful to improve the accuracy and robustness of identification. Rational structure between every modal matching is conducive to improve the efficiency of multi-modal information recognition system. The purpose of the work is to realize the fast search and match in the products

database. The speed is one of the factors that we need to consider. The paper proposed a parts recognition scheme used multi-features during the matching from coarse to fine. Fig. 4 describes the overall architecture of level matching realized with 'and' rules and decision level fusion.

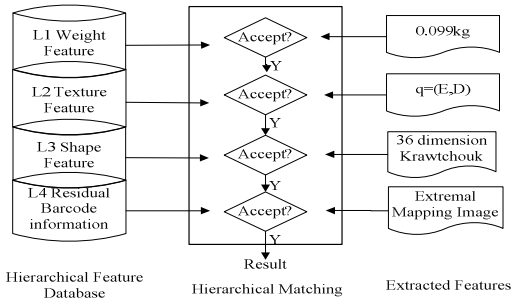


Fig. 4: Architecture of multi-modal level matching

Extract the features from the preprocessed defaced parts, the weight features as the first level characteristics, the texture as the second, the shape as the third, and the residual code as the last. During the matching, compare the input features with the corresponding characteristics obtained from the level database in the form hierarchical modal, then get the result from coarse to fine.

Product identification system based on multi-feature fusion. The method was applied in twenty images whose surfaces were polluted by the irregular illumination, low contrast and other bad conditions. The image size is 200*200 pixels. Fig. 5 is the full flowchart of the parts recognition system which could detect the defaced parts based on two value images automatically after pretreatment. The platforms of hardware to realize the product information recovery based on multi-information fusion is shown as Fig. 6.

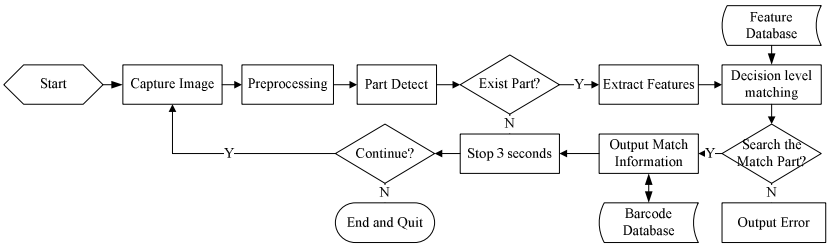
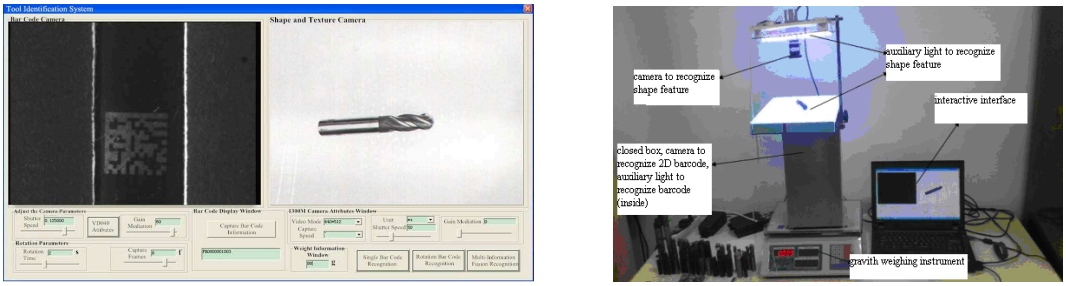


Fig. 5: Flowchart of parts recognition



(a) User interface (b) Hardware equipments

Fig. 6: The Working system to realize the product information recovery based on multi-information fusion

Conclusion and summary

For the products whose unique identifier(DM code) were polluted or damaged seriously during the producing, it is difficult to read the information of the tools or parts through the traditional method, which would affect the following tracking state and extracting information. This paper

presents an implementation scheme of multi modal identification system based on features, which combines the shape and weight features of high efficient with the texture feature of high accurate. At the same time, this scheme chooses the simple 'and' decision rules and information fusion method to identify the products in the form of level matching through the threshold adjustment in each level. Compared with the traditional method with single feature, it improved the recognition precision and the retrieval efficiency. The coarse matching at the front levels could reduce the samples for the further processing, and the top matching could realize the verification exactly. Experimental results show that the proposed scheme has better performance in accuracy, robustness and efficiency, which could fully satisfy the requirements in the actual production.

Acknowledgment

This work was financially supported by the National Nature Foundation (61104169).

References

[1] ISO/IEC 16022. Information Technology-International Symbology Specification-Data Matrix. International Organization for Standardization in Switzerland (2004).

[2] LIU Ning-zhong, YANG Jing-yu: Journal of MINI-MICRO SYSTEMS, Vol. 25(2) (2004), p. 283

[3] D. Chen, F. Zhang and G. M. He: Journal of Computer Engineering, Vol. 29(13) (2003), p.85

[4] LIU Weina, HU Donghong: Journal of Information Technology, Vol. 8(2006), p. 46

[5] WANG Wei, HE Weiping and LEI lei et al: Journal of Computer-Aided Design & Computer Graphics,Vol. 24(5) (2012), p. 612

[6] Yang Mingqiang: Shape-based Feature Extraction and Similarity Matching (Institute National des Sciences Appliqueing, France 2008)

[7] Chai Hua: Journal of Computer and Modernization, Vol. 4(2013), p.197

[8] K. B. Sun , B. J. Super, in: *Proceedings of the 10th IEEE International Conference on Computer Vision and Pattern Recognition*, volume 2 of Progress of Classification of Information, Institute of Electrical and Electronics Engineers Computer Society Publisher (2005), p.727

[9] S. Belongie , J. Malik and J. Puzicha: Journal of IEEE Transaction on Pattern Analysis and Machine Intelligence, Vol. 24(4) (2002), p.509

[10] Liu Li, Kuang Gangyao: Journal of Image and Graphics, Vol. 14(4) (2009), p.622