

Lottery Digit Recognition Based on Multi-features

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Abstract—In this paper, we propose a new method based on multi-features for lottery digit recognition. Since the lottery digits are different from free handwritten ones, we can find a much more simple and reliable scheme to recognize them. Our proposed method is easier implemented than widely used neural network and support vector machine methods. Firstly, pre-processed isolated digit images are input for size normalization. Then image thinning and noise reduction are performed. Finally, the ending point, bifurcation, cross are detected easily. Our recognition system is two-staged. In the first stage, mainly using the number of ending point, the digits are classified into five classes. In the second stage, adopting multi-features such as freeman chain code, orientation information, likeness degree and so on, all the digits are recognized. Each lottery ticket contains 96 digits. The size of each digit image is 48×62 pixels, and the lottery database consists of 4800 digit patterns written by 50 people. The advantages of our method are that it does not require training, which can save a lot of time, and has slightly better recognition rate. Experimental results on this database demonstrate that the obtained recognition rate achieves 95%, which satisfies the lottery digit recognition rate, and multi-features always improve the classifier performance and reliability.

I. INTRODUCTION

HANDWRITTEN digits recognition is still a difficult problem for a machine although it has been a research topic for over three decades. The difficulty is that a large number of variations and styles of digit patterns written by different people. But it is still widely used in a number of fields such as ZIP codes recognition, lottery ticket digit recognition and so on. Lottery ticket digit (Fig. 1) is different from the free handwritten digit for the reason that lottery ticket digit is written according to the patterns supplied by the lottery ticket company, and free handwritten digit has no such constraints. Also lottery ticket digit recognition is seen as very important by the development of lottery ticket business. The primary performance measures of a recognition system are the classification accuracy, recognition speed and system complexity.

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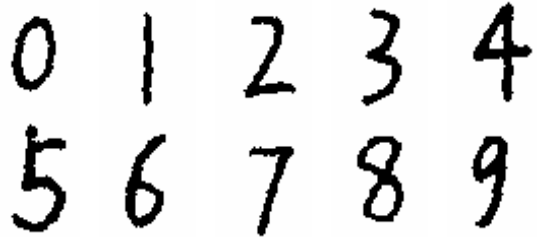


Fig. 1. Sample digit images of lottery ticket

A number of schemes for handwritten digit recognition have been reported in the literature in the past. They include deformable template matching [1], NN(neural network) [2], [3], SVM(support vector machine) [4], [5], hybrid method [6], [7] and so on. Deformable template matching method needs a lot of computational requirements and has to find a better deformation algorithms and better selection of representative prototypes from the train set. NNs have been widely used to solve complex classification problems. However, A single NN often exhibits with the over fitting behavior which results in a weak generalization performance when trained on a limited set of training data. SVMs for digit classification problems are relatively slow and their training on a large data set is still a bottle-neck. Hybrid method combines two or more above or other methods to compensate their individual weakness and to preserve their individual advantages. Hybrid method has been widely used in pattern recognition applications. But it is still a long way to obtain an excellent hybrid method.

In this paper, our research is focused on an accurate and feasible method for lottery ticket digit recognition. Firstly, pre-processed digit images are input for size normalization. Then image thinning and noise reduction are performed. Finally, the ending point, bifurcation, cross are detected easily. Our method includes two stages. In the first stage, mainly using the number of ending point, the digits are classified into five classes. In the second stage, adopting multi-features such as freeman chain code, orientation information, likeness degree and so on, all the digits are recognized. The advantage of method is that it does not require training, which can save a lot of training time. Experimental results on our database will be reported in the paper to support the feasibility of our method.

The remainder of this paper is organized as follows. The system architecture is presented in section 2. The feature extraction is proposed in section 3. The classification is discussed in section 4. Experimental results are shown in section 5 to demonstrate the reliability of our method. Finally

our conclusion is given in section 6.

II. THE SYSTEM ARCHITECTURE

In this section, the system architecture is introduced. The recognition system includes three independent modules: the pre-process module, the feature extraction module and classification module. (Fig. 2)

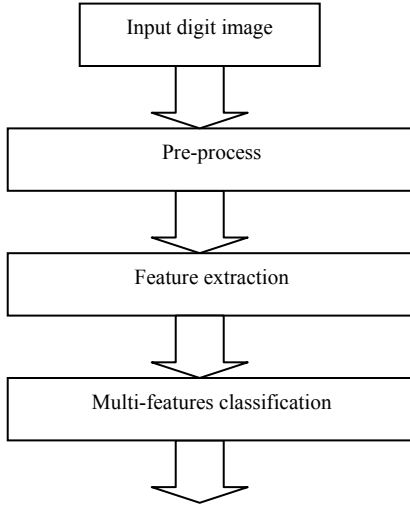


Fig. 2. The system architecture

In our research, each lottery ticket contains 96 digits. So in the pre-process module, Pre-processed isolated lottery digit images are obtained by their fixed location. And size normalization is performed, then image thinning [8] and noise reduction are applied. During the process of image thinning, we introduce Freeman [9] chain code tracking, burr deletion and gap connection. After size normalization, each digit is centered in a square bounding box. On one hand, if the burr is shorter than a fixed threshold, it will be deleted. On the other hand, if the gap between two ending points is not further than a fixed threshold, it will be connected. Also the isolated pixels will be deleted. These three steps can reduce the number of ending point, which will reduce the processing time and lower the complexity of classifier.

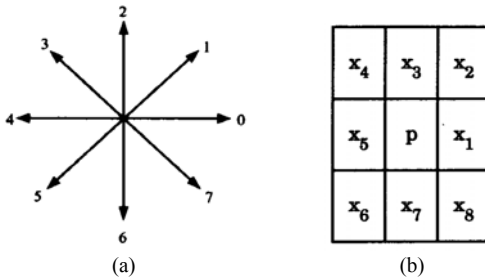


Fig. 3. Freeman chain code and 3×3 template

III. FEATURE EXTRACTION

The complexity of a recognition system is primarily determined by the feature extraction. A fast recognition

system has to consider the processing time. Feature extraction was performed on the thinning image after pre-processed. In the feature extraction module, four feature sets were extracted from each digit image:

1. Numbers of ending point, bifurcation, cross and their location,
2. Number of closed curve,
3. Average Freeman chain code,
4. Absolute Freeman chain code.

The following notations will be adopted in our research. It is understood that a pixel p examined for ending point, bifurcation or cross is a black pixel. And the pixels in its 3×3 template are labeled as shown in Fig. 3 (b). The pixels x_1, x_2, \dots, x_8 are the 8-neighbours of p and are said to be 8-adjacent to p . We will use x_i to denote both the pixel and its value 0 or 1, x_i is called white or black, accordingly. The algorithm for detecting the ending point, bifurcation and cross will be given below.

$$Sum = \sum_{i=1}^8 |x_{i+1} - x_i|, \quad x_9 = x_1 \quad (1)$$

If $sum=2$, pixel p is ending point, if $sum=4$, pixel p is a bifurcation, else if $sum=6$, pixel p is a cross.

Number of closed curve is determined by the following method. The searching begins from an ending point or the top point, if we can go back to the beginning point by a way, this is a closed curve. Here we use the Freeman chain code to search the way back to the beginning point.

Before calculating the average or absolute Freeman chain code, the Freeman chain code has to be encoded at first. The freeman chain is encoded from an ending point. If there is no ending point, it is from the top point of the thinning digit image. The Freeman chain code definition is shown in Fig. 3 (b). $F(i)$ represents the Freeman chain code. The average Freeman chain code is calculated by the following

$$AverageF = \frac{1}{N} \sum_N F(i) \quad (2)$$

The procedure of the calculation of absolute Freeman chain code is shown below. $F(i)$ represents the Freeman chain code of the present pixel i , $F(i-1)$ denotes the Freeman chain code of the before pixel $i-1$. and $R(i)$ is the absolute Freeman chain between pixel i and $i-1$.

$$R(i) = \begin{cases} (F_i - F_{i-1} + 8) \bmod 8 & R(i) \leq 4 \\ (F_i - F_{i-1} + 8) \bmod 8 - 8 & R(i) > 4 \end{cases} \quad (3)$$

The absolute Freeman chain code $R(N)$ from pixel 1 to N is computed below:

$$R(N) = \sum_2^N R(i) \quad (4)$$

IV. CLASSIFICATION

In the classification module, our recognition system is two-staged. In the first stage, mainly using the number of ending point, the digits are classified into five classes. The relation between the number of ending point and digits is

shown in Table I. In the second stage, adopting multi-features such as freeman chain code, orientation information, likeness degree and so on, all the digits are recognized.

TABLE I
THE RELATION BETWEEN NUMBER OF ENDING POINT AND DIGITS

Number of Ending point	0	1	2	3	4	≥ 5
Possible digits	0 8	6 9	1 2 3 4 5 7	2 3 4 5	4	rejected

Here, we give some typical examples to show how to use the freeman chain code, orientation information, likeness degree. After the thinning digit image is encoded by freeman chain code, we can use them to track the way from an ending point, which is discussed above.

To the case of no ending point, this means that is maybe recognized as 0 or 8. Then, the number of closed curve can divide 0 and 8 into two ideal groups.

To the case of only one ending point, two kinds of digits 6 and 9 are obtained. And digits 6 and 9 both have one bifurcation. So we have to separate them into two groups by the relative location of ending point and bifurcation. But to one situation, as shown in Fig. 4, this kind of digit 4 is possible to be recognized as 9. Because we introduce burr deletion, so sometimes a short burr is deleted. For this reason, we introduce the likeness degree. The definition of likeness degree is given below. Firstly, we have to detect the topmost pixel, the lowest pixel, the leftmost pixel and the rightmost pixel. Then, from the information detected above and the ending point, we can describe a template of digit 4 after thinning. Finally, we calculate the distance between the thinning 4 and the template 4. If the distance is less than a threshold, the digit is recognized as digit 4. On the contrary, the digit is considered as digit 9.

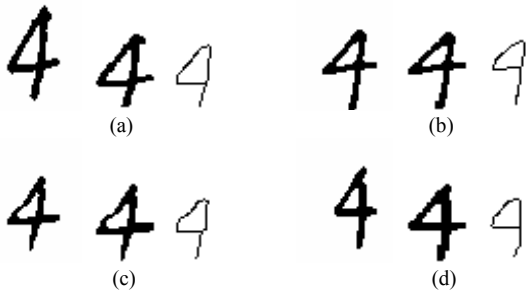


Fig. 4. Some samples of digit 4 misclassified as 9. To each set from the left to the right: The original image 48×62, the size normalized image 30×40, the thinning image 30×40

To the case of two ending points, the possible digits are 1 2 3 4 5 and 7. Firstly, by considering the average Freeman chain code and absolute Freeman chain, digits 1 and 7 are recognized. Then for digit 4, it has two bifurcations or one cross. So it is easily recognized. Finally, by adopting the orientation information of digits 2 3 and 5, they are all

classified.

To the case of three ending points, the possible digits are 2 3 4 and 5. For digit 4, it has two bifurcations or one cross. So it is easily recognized. Then, by the location of their ending points, 2 3 and 5 are all classified. To digit 2, it has one upside ending point and two downside ending points. To digit 3, it has three left side ending points. And to digit 5, it has two upside ending points and one downside ending point. Some samples having three ending points are shown in Fig. 5.

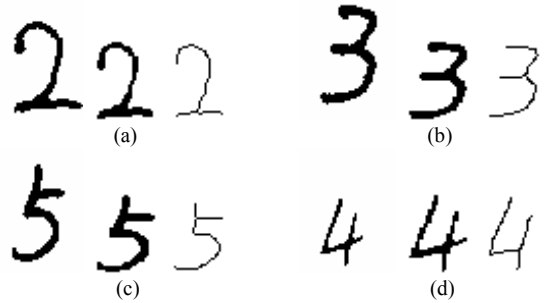


Fig. 5. Some samples having three ending points. To each set from the left to the right: The original image 48×62, the size normalized image 30×40, the thinning image 30×40

To the case of four ending points, only digit 4 is recognized. It has two bifurcations or one cross. To the case of five or more ending points, we do not recognize these kinds of digits. Because in this condition, there are a lot of disconnects, which will lead to the wrong classification results. They are in poor condition. So, these handwritten digit images of poor quality are rejected in our lottery handwritten digit recognition system.

V. EXPERIMENTAL RESULTS

Our experiments were performed on our lottery digits database. Each lottery ticket contains 96 digits. This database consists of 4800 digit patterns written by 50 people. The size of each digit image is 48×62 pixels. And the size of normalized image is 30×40 pixels.

Our experiments were performed using C++ code. The C++ programs were compiled by Microsoft Visual C++ 6.0. All tests were performed on 2.93 GHz P4 processor under Windows XP. The total processing time of each lottery ticket including 96 digits is around 500 ms. That is around 5 ms for each lottery digit.

In Table II, the recognition results (Recognition Rate, Misclassified Rate, Rejection Rate and Reliability) are presented. The Reliability equals Recognition Rate/(100% - Rejection Rate).

From Table II, we can reach the conclusion that the recognition rate of digit 0 is the largest of all the digits. Because the features of digit 0 are the most simple, so it is easily recognized. And the misclassified rate of digit 4 is the biggest of all the digits. The reason is that the written types of digit 4 are the most of all the digits. This characteristic will lead to more misclassification. At the same time, the

TABLE II
THE RECOGNITION RESULTS OF OUR METHOD

Class	Recognition Rate	Misclassified Rate	Rejection Rate	Reliability
0	96.80%	1.22%	1.98%	98.76%
1	94.45%	2.05%	3.50%	97.88%
2	93.53%	2.33%	4.14%	99.47%
3	93.62%	2.50%	3.88%	97.40%
4	92.34%	4.05%	3.61%	95.80%
5	93.33%	2.43%	4.24%	97.47%
6	95.75%	1.36%	2.89%	98.60%
7	93.26%	2.62%	4.12%	97.27%
8	96.64%	1.34%	2.02%	98.63%
9	95.93%	1.35%	2.72%	98.61%

reliability of digit 4 is the lowest of all the digits. The rejection rate of digit 5 is the biggest of all the digits.

VI. CONCLUSIONS

In this paper, the adoption of multi-features for lottery ticket handwritten digits is examined. And a suitable method for lottery ticket digit recognition is proposed. We have to notice the fact that the proposed lottery ticket digits recognition system is fit for lottery digits but not for unconstrained handwritten digits.

The experimental results demonstrate that the obtained recognition rate 95% could satisfy the need of lottery digit recognition, and multi-features always improve the classifier performance and reliability. At same time, it is easy to implement the recognition system. To achieve so high recognition rate, the features set is carefully chosen. Our future work will focus on better selection of multi-features and improve the system performance.

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