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A Digit Recognition System for Paper Currency Identification based on Virtual Machines

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Technical Report CS-TR-06/11
May 2006

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Abstract

This paper describes an approach to digit recognition for the serial numbers on the Chinese currency banknotes. The approach consists of a number of components including image preprocessing, image binarisation, morphological filtering, segmentation, feature extraction and digit recognition. The approach is examined and tested on 5000 banknotes with 4000 digits and achieves a single digit recognition rate of more than 99.60%, a serial number recognition rate of 99.50% , and a recognition time of 157ms. The results show that this approach is effective and efficient and can clearly meet the system requirements.

Keywords Digit recognition, banknotes, image processing, computer vision

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1 Introduction

This paper concerns the recognition of the serial numbers of the Chinese paper currency such as 50 and 100 RMB Yuan banknotes. The serial numbers are currency issuance numbers, which are used as the identifiers (IDs) of the banknotes: each sheet has its own serial numbers and the same numbers can not be used more than once. Correctly and fast recognising these numbers is very important due mainly to at least the following three reasons. Firstly, there is a need for proper statistics by the national treasuries and the banks. After the banknotes are produced by some appointed printing factories, they need to be storied into the national treasuries then be sent to different banks for being formally distributed in the markets. Before the national treasuries can accept the banknotes, they need to know the serial numbers of some typical banknotes at the beginning and the end of all units of the banknotes so that the national treasuries can correctly know the total number of each of the different kinds of banknotes such as 50 or 100 RMB Yuan and the total value of the banknotes. So do the different national banks. Secondly, there is a need for reprinting of the destroyed banknotes. When the national treasuries or banks find some banknotes that have been destroyed and can not be used, they need to inform the printing factories to reprint those banknotes with the same serial numbers. Thirdly, there is a need for the diagnosis of the crimes by the public police. It would be very helpful for the public police to find clues of the criminals if the stolen banknotes can be fast and correctly recognised. Accordingly it is very useful to correctly identify some specific banknotes quickly. In this area, the requirement of the recognition is that the recognition rate of more than 98% and the recognition time is less than 500 micro-seconds.

Two sample 100 RMB Yuan banknotes are shown in figure 1. As shown in the figure, the serial numbers appear in the bottom-left corner of the banknotes. The serial numbers consist of two capital letters followed by eight digits. In many cases, the letters and the first few digits are the same, and only the last few digits are different. Accordingly, recognition of these digits is critical to the whole serial number recognition. This paper is focused on the recognition of the digits.

As can be seen from figure 1, the digits on the serial numbers are all printed digits, which in theory should be generally easier to recognise than the handwritten digits. However, the serial numbers on different versions of banknotes have different fonts, making the recognition problem much harder than the trial problem. Some banknotes are quite clean but others are quite dirty after a long time distribution and usage, making the digits on the serial numbers quite "different". In particular, in the new version of the banknotes, the digits on the serial numbers have different sizes, as shown in figure 1 (b), which makes the digit recognition problem on the banknotes even harder.

Since the early 1990s, many digit recognition systems have been developed for a variety of problem domains purposes such as recognition of postal code on the envelopes and recognition of the digits on people's ID cards [1, 3, 4, 13, 6, 10, 11, 8, 12]. The techniques used include as neural networks and nearest neighbour, decision trees. For example, LeCun et al. developed a digit recognition system for USA handwritten zip (postal) code recognition using shared weight neural networks and achieved 93% accuracy [8]. Nakayama et al. developed a system for OCR digit recognition and achieved 95% accuracy [11]. In most existing recognition systems, however the computational cost (particularly the training cost) was quite high, and the recognition rate cannot meet the requirement of the our paper currency recognition.

(a) (b)

Figure 1: Sample 100 RMB Yuan banknotes (Note: colour images!). (a) Old version; (b) New Version.

1.1 Goals

The overall goal of this paper is to investigate a new approach to automatic digit recognition for Chinese Currency serial number identification with a high recognition rate and a low computational cost. To make a short development cycle, we use the newly developed software *Labview*, which is based on the virtual instrument technique. The core is a method that makes use of the software to carry out the functions that can only be implemented by the tradition instruments. Specially, we are interested in investigating:

- how the digit recognition system can be develop,
- whether this system can achieve acceptable accuracy performance, that is, a recognition rate of 98% or over;
- whether the computation cost of this system can meet our special requirement, that is, the recognition time of a digit (or serial number) is less than 500 microsecond.

1.2 Organization

The remainder of the paper is organized as follows. Section 2 briefly overviews the system architecture and what we focus on. Section 3 describes the approach, including image pre-processing, binarisation, morphological filtering, segmentation, feature extraction and digit recognition. Section 4 presents the experiments and results, with an analysis and discussion. Section 5 draws conclusions and gives future work directions.

2 System Architecture

This system consists of a CCD camera with an adjustable light source, an image collection card, a monitor, a printer, a computer, a storage and a target parameter output interface. The banknotes are first passed through the CCD camera with the adjustable light source, and we obtain the continuous analogue signal. The image collection card NI PCI-1411 converts the analogue signal into the AV digital signal and transfers the image to the computer. The computer with our recognition system will process the images and does the digit recognition on the serial numbers of the banknotes. The results are then output to the monitor. The results also must be transfer to the target parameter output interface in order to be used by other computers. The architecture of the entire system is shown in Figure 2.

In this system, the light source is critical for making reasonably "uniform", direct rays without reflection for the use of the CCD camera. We chose the FOSTEC light, an adjustable light source to meet this requirement.

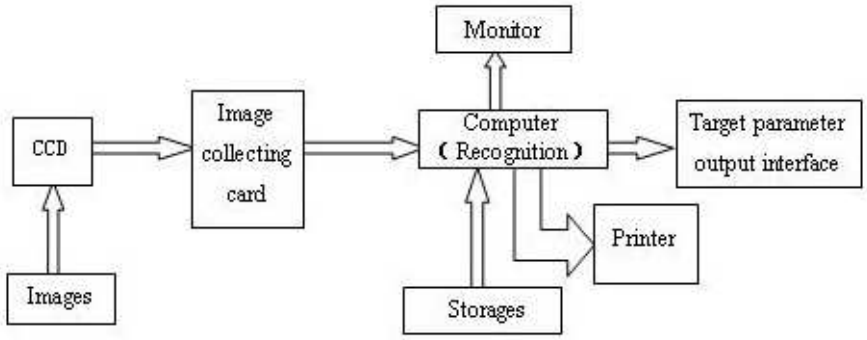


Figure 2: System architecture.

For collecting images, we chose the PCI-1411 image collection card, produced by the American company NI Company. This card has two inputs RS-170/NTCS and CCIR/PAL patterns, can output the homochromatism, RGB, HSL formats of images, and supports a single frame and sequence frames.

In this paper, we focus on the central aspect, the computer with the digit recognition system, which is described in the next section.

3 The Approach

The digit recognition system consists of image preprocessing, image binarisation, image segmentation, morphological filtering, feature extraction, and digit recognition, as shown in figure 3.

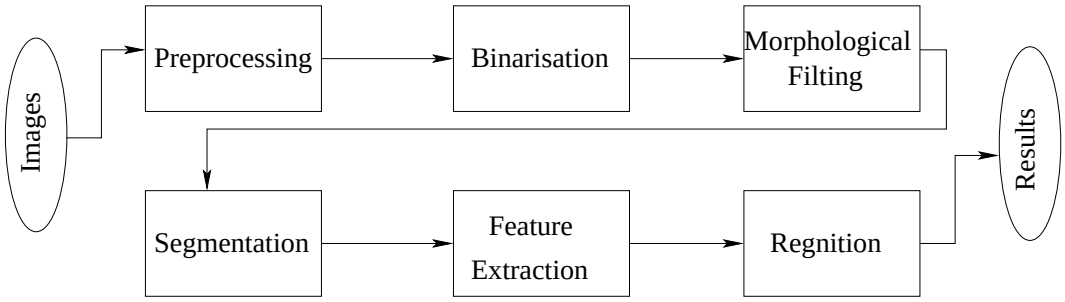


Figure 3: The digit recognition system.

3.1 Image Preprocessing

The collected images are RGB colour images. The image preprocessing module will convert them into grey level, then remove the noise from them by applying the mean filtering.

According to our experiments, the green unit of the RGB space is the most effective one for converting the RGB image into the gray level. Thus, we use the model shown in equation 1 to convert an RGB colour image into grey scale on a pixel-by-pixel basis. A sample grey scale image resulted from the equation together with its original colour format is shown in figure 4.

$$grayscalevalue = 0.299R + 0.687G + 0.114B \tag{1}$$

(a) (b)

Figure 4: A sample banknote for experiments to extract the templates. (a) Original image (note: a colour image); (b) Gray scale image in preprocessing.

As shown in figure 1 (a), many banknotes have a certain level of different kinds of noise as mentioned earlier. In order to make the recognition task easier, we should remove the noise from the images before further processing. Considering the process speed, we chose the mean filtering to smooth the images and hopefully majority of the noise can be removed.

Mean filtering is a simple, intuitive and easy to implement method of smoothing images, i.e. reducing the amount of intensity variation between one pixel and the next. It is often used to reduce noise in images.

The idea of mean filtering is simply to replace each pixel value in an image with the mean ('average') value of its neighbours, including itself. This has the effect of eliminating pixel values which are unrepresentative of their surroundings. Mean filtering is usually thought of as a convolution filter. Like other convolutions, it is based around a kernel, which represents the shape and size of the neighbourhood to be sampled when calculating the mean. In this approach, we use a 3x3 square kernel, as shown in Figure 5. An example image after applying for the mean filter to the image shown in figure 4 (b) is presented in figure 6 (a).

1	1	1
1	0	1
1	1	1

Figure 5: 3x3 square kernel.

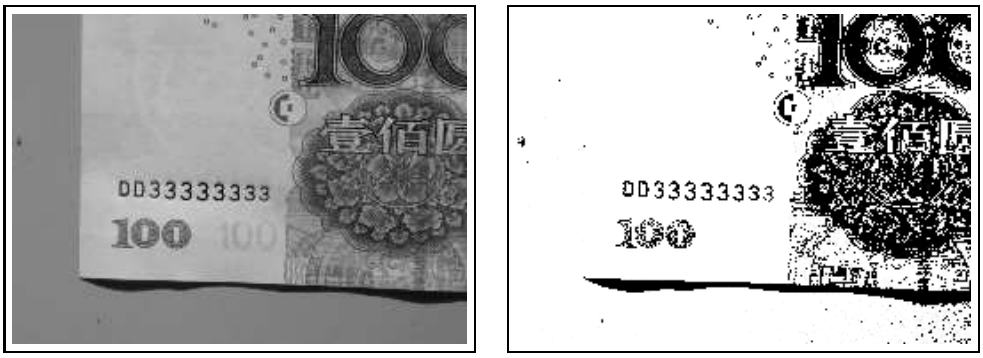
3.2 Binarisation

In this approach, we further convert the preprocessed image into a binary one, in order to achieve the fast recognition. To do this, we need to find a threshold. We use the following method to automatically find the threshold of an image, then use the threshold found to convert a grey level image into binary.

Firstly, we collect the minimum and maximum gray value T_x and T_y, and make the initial threshold T_0.

$$T_0 = \frac{T_x + T_y}{2} \tag{2}$$

Second, supposing that there are a total number of L gray values in the image, we iterate the following equation



(a) (b)

Figure 6: Image processing. (a)Mean Filtering in preprocessing ; (b) Binarisation.

$$T_{i+1} = \frac{1}{2}\left(\frac{\sum_{k=0}^{T_i} h_k \times k}{\sum_{k=0}^{T_i} h_k} + \frac{\sum_{k=T_i-1}^{L-1} h_k \times k}{\sum_{k=T_i+1}^{L-1} h_k}\right) \tag{3}$$

where h_k is the grey intensity of the kth pixel that is less than the intensity T_i, obtained from the previous loop. We run the loop until $|T_{i+1} - T_i| \leq 1$, and the ending T_{i+1} is used as the threshold.

According to the automatically found threshold T_{i+1}, for each pixel in the image, if it less than the threshold, make it black; otherwise, make it white. A sample image after binarisation on the image shown in figure 6 (a) is presented in figure 6 (b).

3.3 Morphology Filtering

After image binarisation, the digits on the serial numbers of the banknotes often have some discontinuous particles, some further noise and some unexpected edges. To make the recognition task easier, we apply four morphological transformations to the binary images.

Morphological transformations extract and alter the structure of particles in an image. We applied four binary processing functions [5] *erosion, dilation, opening*, and *closing*, as described as follows.

- Erosion function: Binary erosion reduces the brightness of pixels that are surrounded by neighbours with a lower intensity. The neighbourhood is defined by a structuring element.

- Dilation function: This faction increases the brightness of each pixel that is surrounded by neighbours with a higher intensity. The neighbourhood is defined by a structuring element. The binary dilation has the opposite effect of the binary erosion because dilating bright regions also erodes dark regions.

- Opening Function: The binary opening function consists of a binary erosion followed by a binary dilation. It removes bright spots isolated in dark regions and smoothes boundaries. The effects of the function are moderated by the configuration of the structuring element. This operation does not significantly alter the area and shape of particles because erosion and dilation are morphological opposites. Bright borders reduced by the erosion are restored by the dilation. However, small bright particles that vanish during the erosion do not reappear after the dilation.

- Closing Function: The binary closing function consists of a binary l dilation followed by a binary erosion. It removes dark spots isolated in bright regions and smoothes boundaries. The effects of the function are moderated by the configuration of the structuring element. This operation does not significantly alter the area and shape of particles because dilation and erosion are morphological opposites. Bright borders expanded by the dilation are reduced by the erosion. However, small dark particles that vanish during the dilation do not reappear after the erosion.

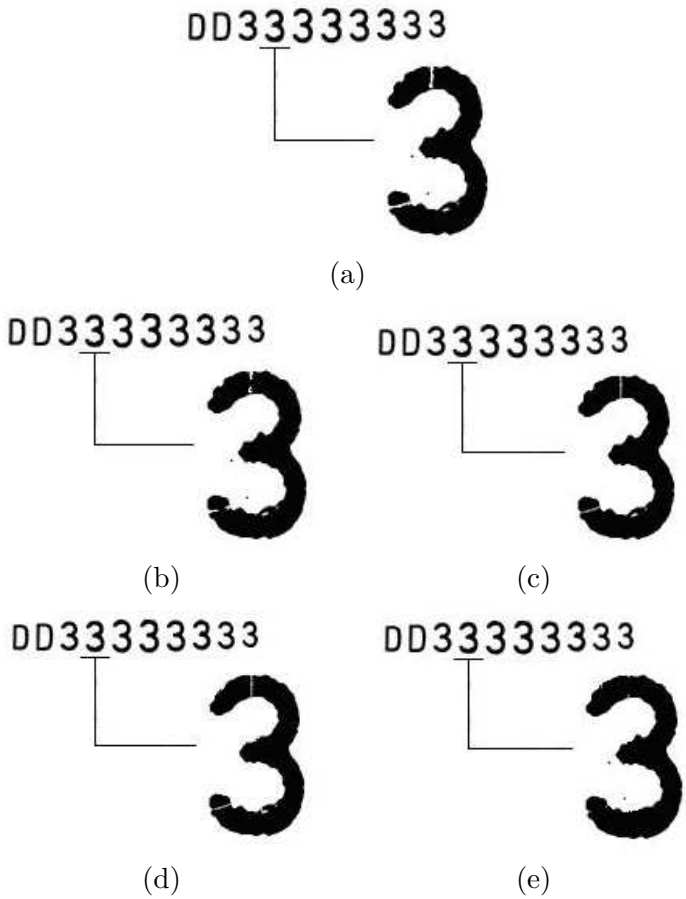


Figure 7: Morphological filtering. (a) Orginial; (b) erosion; (c) dilation; (d) opening; and (e) closing.

Notice that the four operators are applied directly to the binary images. However, to show the effect of them, we now use a single binary digit as an example. Taking a binary digit 3 as example, after applying the four transformation operators, the newly produced images together with the original binary image are shown in figure 7. Experiments show that these operators can satisfy our demand.

3.4 Image Segmentation

Based on the binary images processed by the morphological transformations, we need to segment the small objects, the digits on the serial numbers, from the large banknote images. To implement this, we first used the the Sobel operator to the large binary banknote images in order to distinguish the regions of interest (ROIs) from the background, then extract the

ROIs in order to obtain the small digits (objects for forming the templates of the digits and for recognition.

1	2	1
0	0	0
-1	-2	-1

-1	0	1
-2	0	2
-1	0	1

Table 1: Sobel recognition templates.

Table 1 show the two masks used in the Sobel operator. The Sobel edge detection masks detect both the horizontal and vertical direction and then combine the information into a single metric. Suppose the results from the row and the column masks are s_1 and s_2, then the edge magnitude is

$$\sqrt{s_1^2 + s_2^2}$$

Some sample segmented digits are shown in figure 8, based on which we can extract features and perform digit recognition/classification.

Figure 8: Example segnmented digits.

3.5 Feature Extraction

The segmented images are 87×102 in size, each of which has more than 8700 pixels. While we can directly use the raw pixel values of each digit to match the template digits in the training set, this method would clearly have a very high computational cost, which cannot meet the time requirement of our system.

To reduce the computational cost, we extract 13 features from each unseen digit and each template digit. These include local nine region features and four key point features. We simply take the mean pixel values of the nine regions and the pixel value of the four key points as the feature values. The nine regions and the four key points of a digit image are presented in figure 9. In the figure, the whole square represent a segmented digit example image, the nine labels (1..9) are the nine local regions and the four black points labelled as A, B, C and D are the key points. While these features might not be the best ones, our experiments suggest that they can meet the effectiveness requirement of our system.

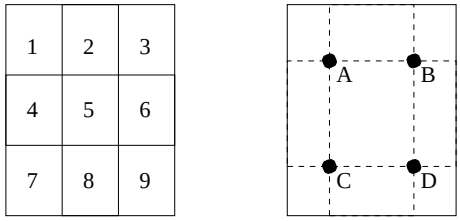


Figure 9: The nine regions and four key points for feature extraction.

The 13 features of each digit image form a feature vector. In order to make the recognition process more consistent and reliable, we normalise all the feature values in all the template digits in the training set and every unseen digit in the test set into the range between zero and one.

3.6 Digit Recognition

In this approach, we use the nearest neighbour method for digit recognition. In this method, we first make a training set consisting of a number of template digits and a test set consisting of a large number of unseen segmented digits with target labels. Based on the 13 features, each digit in the training set and the test is represented as a feature vector containing corresponding 13 values. Each unseen digit feature vector in the test set is compared with all the digit feature vectors in the training set by a distance measure. The class of the template digit image with the smallest distance is considered the class of the unseen input digit image in the test set, that is, the result of the recognition.

In our approach, we use the Euclidean distance. Assuming the two digit feature vectors $\vec{A}$ and $\vec{B}$ are represented as:

$$\vec{A} = (a_1, a_2, ..., a_{13})$$

and

$$\vec{B} = (b_1, b_2, ..., b_{13})$$

then the *Euclidean Distance* is defined as the squared root of the sum squared differences between vector components (features):

$$\begin{aligned} d &= \sqrt{\sum_{i=1}^{13}(a_i - b_i)^2} \\ &= \sqrt{(a_1 - b_1)^2 + (a_2 - b_2)^2 + ... + (a_{13} - b_{13})^2} \end{aligned} \tag{4}$$

4 Results and Discussion

4.1 Data Sets

According to the system requirement, we collect three groups of the segmented digits, a total number of 30 digits, as the template digit images to form the training set. In order to obtain reliable performance, we collect 40000 digit images from 5000 banknotes to form the test set. The 30 template digit images are shown in figure 10. Notice that it is our intention to collect digit images with different fonts (such as 1) and different printing quality and some with a bit noise, so that the training template digit images can include as many different cases as possible.

4.2 Results

In this approach, we use two different evaluation criteria to measure the system performance.

The first measure is the *single digit recognition rate*, which refers to as the number of the correctly recognised single digits by the system as a percentage of the total number of the digit images in the test set. The correct recognition rates for the 10 single digits are presented in table 2.

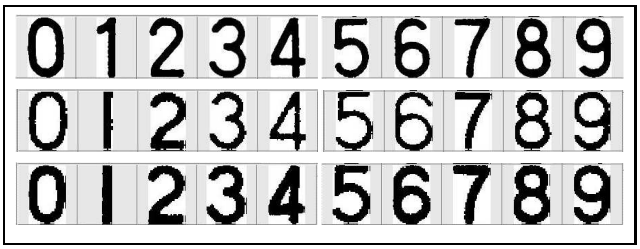


Figure 10: Example templates.

Table 2: Results of single digits recognition.

Digits	0	1	2	3	4
Recognition rate (%)	99.62	99.70	99.82	99.60	99.90
Digits	5	6	7	8	9
Recognition rate (%)	99.72	99.68	99.73	99.61	99.70

As can be seen from the table, the recognition rates for all the 10 digits are more than 99.60%, suggesting that this system is very effective.

The second measure is the *serial number recognition rate*, referring to the number of serial numbers/banknotes that are correctly identified by the system as a percentage of the total number of serial numbers/banknotes in the test set. Note that this rate is much stricter than the single digit recognition rate, as in the rate calculation, if one of the eight digits on a single serial number is incorrectly recognised, then the whole serial number is considered wrong even if other seven digits on the serial number were correctly recognised. In this case, our approach achieved an overall serial number recognition rate of 99.50%, which clearly satisfied the system requirement.

The third measure is the recognition time. Our approach used only 157ms (microseconds) for recognising a serial number, which is much less than 500ms that we required.

4.3 Analysis

The results suggest that our approach is sufficiently effective and efficient, which can clearly meet the system requirement in terms of both effectiveness and efficiency. However the approach still resulted in a small number of errors. We believe this is due mainly to the following three reasons. Firstly, some surfaces of banknotes are quite dirty. The second reason is caused by printing — the banknotes can perhaps loss more or less printing ink or can be polluted by printing ink. The third reason is the different sizes of the digits in the new version of the banknotes. These situations can make the digits on the serial numbers of these banknotes are quite different from those in the templates of the training set. While these situations can be improved by increasing the number of template digit images in the training set, doing so will clearly result in an increase in recognition time. In our case, we still have a bit space to do this as our recognition time is still less than the bottom-line of the requirement. We will investigate this point in the future.

4.4 System Characteristics

This system has some new characteristics, which are summarised as follows.

- We used advanced virtual instrument techniques, such as the LABVIEW, the IMAQ Vision and OCR [2]. These techniques combine the image processing with virtual instruments, and substitute graphic language for traditional code language. Accordingly, this system has many good properties including a low cost, a short development time, a convenient debugging style and a reliable running.

- Compared with similar digit recognition systems, this system is relatively simple but can achieve accurate results, and the running speed of system is very fast.

5 Conclusions

The goal of this paper was to develop an approach to digit recognition for the serial numbers on the Chinese currency banknotes. This goal was successfully achieved by developing a number of modules including image preprocessing, image binarisation, morphological filtering, segmentation, feature extraction and digit recognition using a graphic language LABVIEW. The approach was examined and tested on 5000 banknotes with 4000 digits and the approach achieved s single digit recognition rate of more than 99.60%, a serial number recognition rate of 99.50% , and a recognition time of 157ms. The results show that our approach is effective and efficient and can clearly satisfy the system requirements.

Our experiments also suggest that the current system is still quite sensitive to the noise of the image, but it could be improved by increasing the number of template digits in the training set, which will be further investigated in the future.

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