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Automatic Banknote Stain Detection

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Abstract

In this paper, we propose an automatic banknote stain detection method based on brightness ratio analysis. The method uses median filtering, edge detection and connected component analysis. A median filter was used to eliminate small differences such as serial numbers. The brightness difference between a reference banknote and a target banknote was normalized by using the average brightness and the maximum brightness ratio. Sobel edge detection was used to remove differences created by slight mismatches in the edge areas. After applying a thresholding operation to the difference image, connected component analysis was used to remove spurious stain areas.

I. Introduction

It is important for banknotes to be in suitable condition for recirculation [1]. Although banknote recirculation can reduce distribution costs and environmental problems, it is also important to remove stained or soiled banknotes. Therefore, it is necessary for automatic teller machines (ATMs) to measure the soiling level of banknotes. In addition, ATMs should be able to detect fake banknotes. The performance of current soil detectors is not satisfactory because of the low priority of conformity classification [2]. As a result, many banknotes are unnecessarily destroyed due to soiling tests that are too strict. Stain detection can be used to measure the soiling level of banknotes [3]. For example, banknotes with strong stains can be labeled for destruction without further soiling level determination. Therefore, stain detection can help to reduce the processing time in the ATMs. There are various types of stains that can occur in banknotes, such as folding, graffiti, ink, tears, discoloration, and so on. In this paper, a stain detection method is proposed to detect some of these stains.

II. Methodology

A. Median Filtering

Basic stain detection is done by examining the difference between reference banknotes and target banknotes. However, each banknote has a different serial number and the seal may be printed in a slight different position. These differences have nothing to do with stains. Thus, the median filter was used to remove these kinds of differences (Fig. 1).

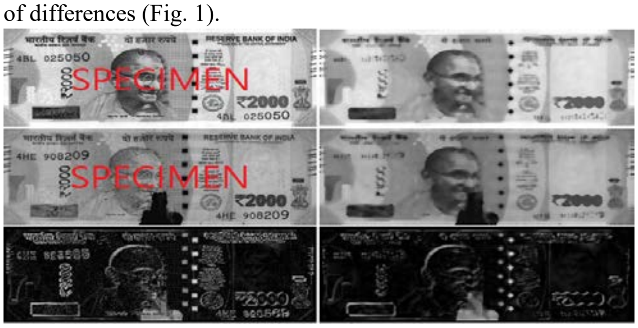

Figure 1. *(a) reference, (b) median filtered reference, (c) target, (d) median filtered target, (e) difference image, (f) median filtered difference image.*

B. Brightness normalization

One of the difficulties of stain detection is the brightness difference between target and reference banknotes. As a banknote circulates in the market, dark areas become brighter and bright areas become darker. Consequently, reference banknote and well-circulated banknote images may show large differences due to this aging process. Therefore, it is important to normalize the brightness to reduce the circulation effect. In this paper, the ratio of the maximum brightness and the ratio of average brightness are used to normalize the brightness levels as follows:

$$BR = \sqrt{\frac{mean(Br_{ref})}{mean(Br_{tar})} \times \frac{\max(Br_{ref})}{\max(Br_{tar})}} \tag{1}$$

$$T'(x,y) = T(x,y) \cdot BR \tag{2}$$

where Br_{ref} denotes the reference image brightness and Br_{tar} denotes the target image brightness. $T'(x,y)$ denotes the brightness of the adjusted target image and BR is the ratio of the brightness between the target image and the reference image.

C. Sobel Edge Detection

The differences created by serial numbers and divergent seal locations can be removed with a median filter. However, if large objects have different locations, their differences can be recognized as stains. Although local registration can solve this problem, it may requires a large amount of operations. In this paper, Sobel edge detection is used to remove such differences. If the edge regions are classified as stains, we excluded these regions from further consideration (Fig. 2). We removed the small differences around the edge areas by using the edge sum image as follows (3):

$$\mathrm{E}_{sum}(x,y) = \begin{cases} \mathrm{E}_{ref}(x,y), & \mathrm{E}_{tar}(x,y) < \mathrm{E}_{ref}(x,y) \\ \mathrm{E}_{tar}(x,y), & otherwise \end{cases} \tag{3}$$

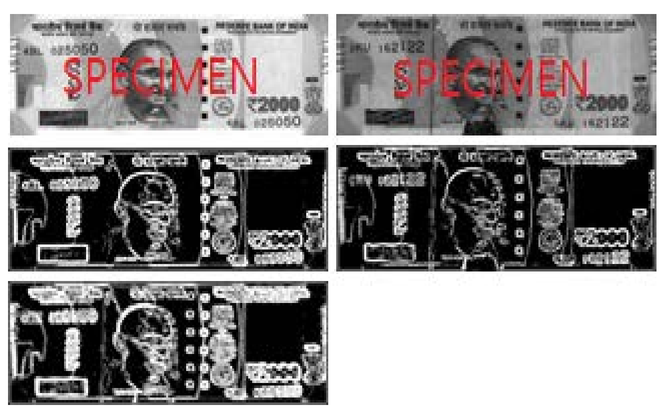

Figure 2. *(a) reference, (b) target, (c) Sobel edges of reference, (d) Sobel edges of target, (e) sum of (c) and (d).*

D. Difference Image Thresholding

Next, we computed the difference images between the normalized target image and the reference images. Then, using the edge sum image of (3), we removed the spurious differences around the edges. Then the difference image was divided by the reference image and a thresholding operation was applied:

$$Diff(x,y) = |R(x,y) - T'(x,y)| \tag{4}$$

$$Diff'(x,y) = \begin{cases} Diff(x,y), & E_{sum}(x,y) = 0 \\ 0, & otherwise \end{cases} \tag{5}$$

$$S(x,y) = \begin{cases} 0, & \dfrac{Diff'(x,y)}{R(x,y)} < Threshold \\ 1, & otherwise \end{cases} \tag{6}$$

where $S(x,y)$ and $R(x,y)$ denote the stain map and reference image, respectively. $Diff'(x,y)$ denotes the difference image where the edge areas were removed. We set the threshold value using the Otsu threshold method [4]. Fig. 3 illustrates this procedure.

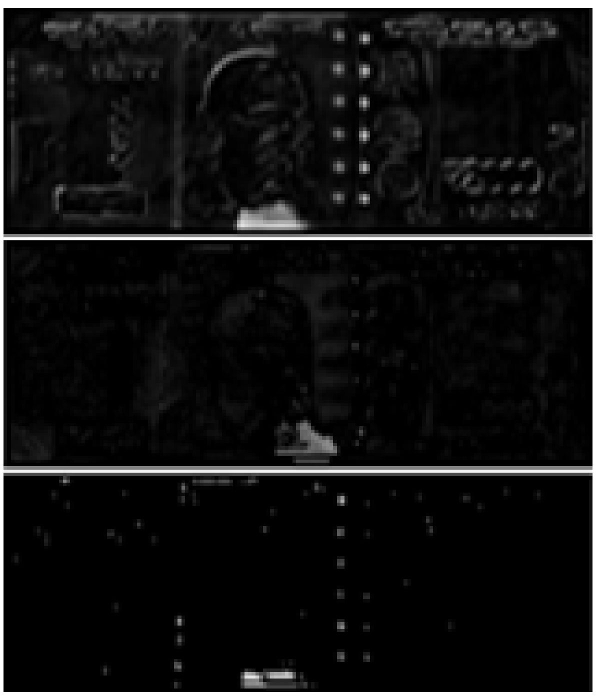

Figure 3. *(a) difference image, (b) subtracting sum of edge image, (c) threshold image.*

E. Connected Component Analysis

Connected component analysis (CCA) was used to detect and label the connected components. The morphology closing operation was performed before applying CCA to improve labelling performance [5]:

$$A \cdot B = (A \oplus B) \ominus B \tag{7}$$

where $\oplus$ and $\ominus$ denote the dilation and erosion. We eliminated small regions that failed to meet the minimum width and height requirements (Fig. 4).

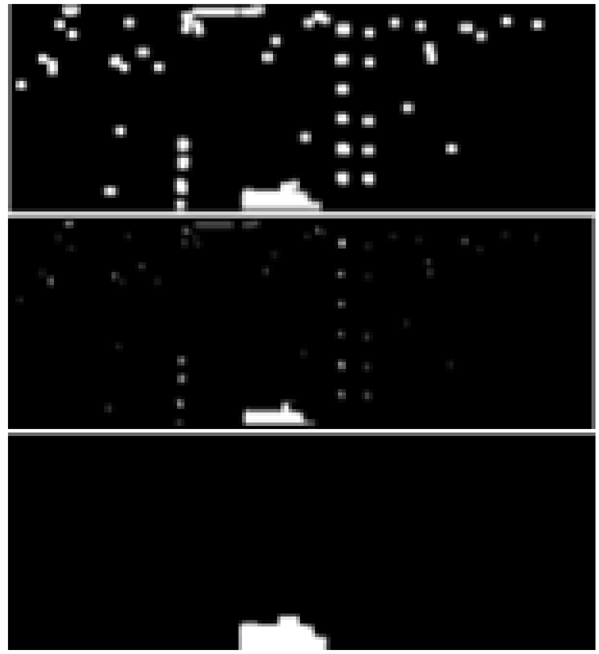

Figure 4. *(a) dilation processed image, (b) erosion processed image, and (c) stain image.*

III. Experiments

A. Database

To evaluate the proposed algorithm, we used Indian Rupees (100 rupees, 500 rupees, and 2,000 rupees). We used the RGB channels of the banknotes (Fig. 5). We used 120 stained banknotes. There were 22 100 rupee notes, 88 500 rupee notes, and 16 2,000 rupee notes. We made ground truth images of the stains and measured the accuracy of banknote stain detection based on the these ground truth images.

Figure 5. *(a), (b) reference of 100 rupees, (c), (d) reference of 500 rupees, (e), (f) reference of 2,000 rupees.*

B. Experimental Results

The input image sizes were 304 x 140, 292 x 125, and 321 x 126 pixels for100 rupees, 500 rupees, and 2000 rupees, respectively. We also halved the input image and then applied the algorithm to reduce the processing time. We used a 5 by 5 median filter for the original images and a 3 by 3 median filter for the reduced images. The proposed algorithm was applied to all the banknotes (Fig. 6, Fig. 7). Tables I and II show the experimental results for the original images and the reduced images. As expected, the original images produced better performance. On the other hand, the processing is critical in ATMs since they have to be able to handle about 10-15 banknotes using a moderate CPU. This makes the use of reduced images a viable option.

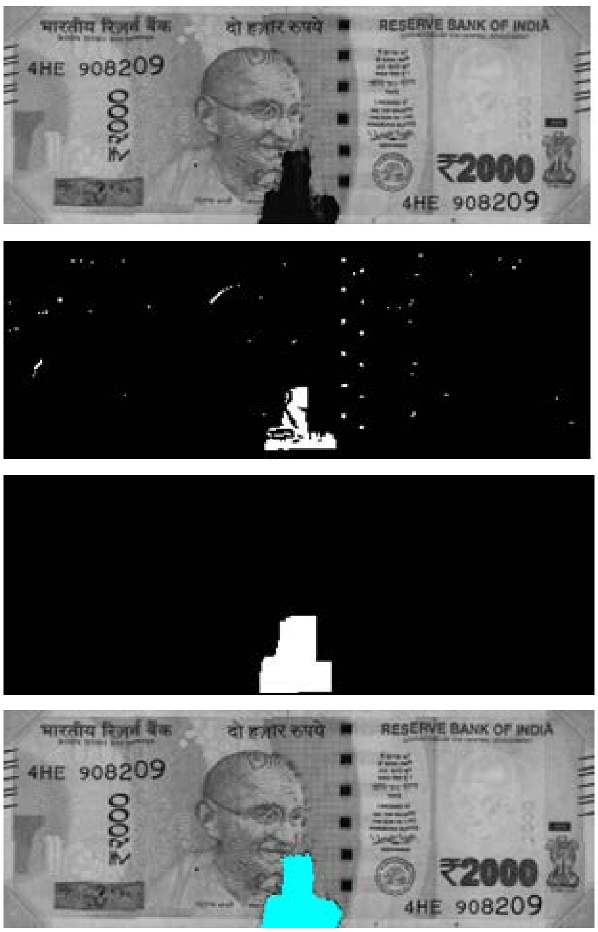

Figure 6. (a) target image, (b) threshold map, (c) decision map, (d) ground truth image of the 2,000 rupees image.

IV. Conclusions

In this paper, we used median filtering, brightness normalization and Sobel edge detection to develop a stain detection algorithm for ATMs. Although stains can be easily recognized, automatic stain detection is rather complicated due to aging and soiling, scanning variations, print variations, etc. These factors can generate spurious differences when a difference image is computed from reference and target images. We proposed several methods to solve these problems. Experimental results with real banknotes with various degrees of stains show that the proposed algorithm can effectively handle banknotes with stains.

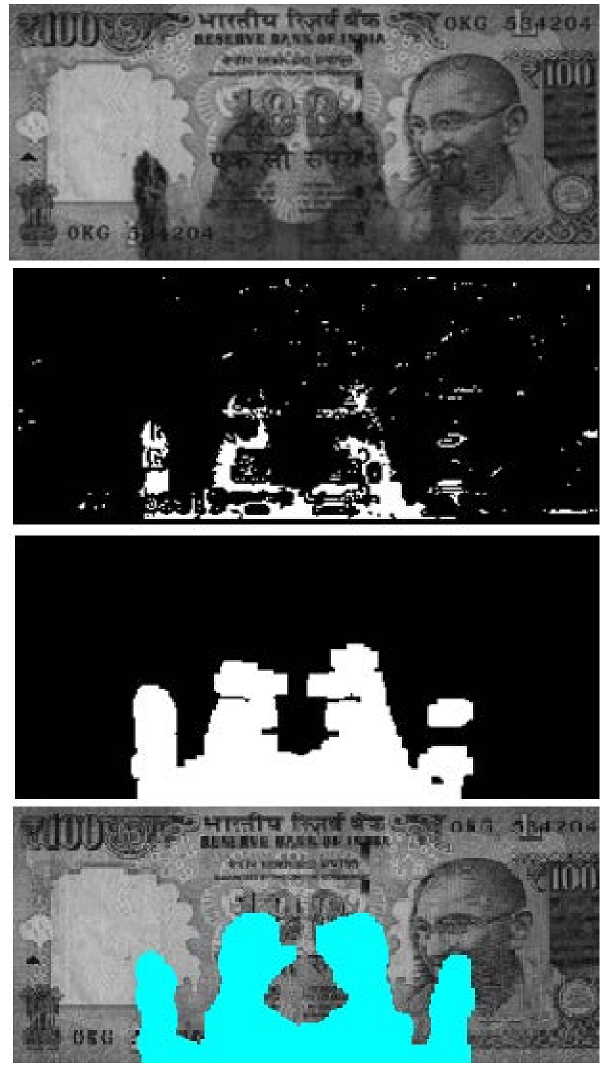

Figure 7. (a) target image, (b) threshold map, (c) decision map, (d) ground truth image of the 100 rupees image.

Table I. Performance analysis (Original size)

Banknote	100	500	2000	Total
Precision	0.417	0.186	0.510	0.408
Recall	0.682	0.673	0.742	0.694
F-Score	0.614	0.301	0.668	0.593
Time	107.611 ms / channel			

Table II. Performance analysis (Half size)

Banknote	100	500	2000	Total
Precision	0.345	0.133	0.372	0.324
Recall	0.740	0.776	0.759	0.747
F-Score	0.593	0.262	0.647	0.567
Time	7.531 ms / channel			

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