Robust and Effective Component-based Banknote Recognition by SURF Features

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***Abstract*—Camera-based computer vision technology is able to assist visually impaired people to automatically recognize banknotes. A good banknote recognition algorithm for blind or visually impaired people should have the following features: 1) 100% accuracy, and 2) robustness to various conditions in different environments and occlusions. Most existing algorithms of banknote recognition are limited to work for restricted conditions. In this paper we propose a component-based framework for banknote recognition by using Speeded Up Robust Features (SURF). The component-based framework is effective in collecting more class-specific information and robust in dealing with partial occlusion and viewpoint changes. Furthermore, the evaluation of SURF demonstrates its effectiveness in handling background noise, image rotation, scale, and illumination changes. To authenticate the robustness and generalizability of the proposed approach, we have collected a large dataset of banknotes from a variety of conditions including occlusion, cluttered background, rotation, and changes of illumination, scaling, and viewpoints. The proposed algorithm achieves 100% recognition rate on our challenging dataset.**

Keywords - computer vision, component-based, SURF, banknote recognition

I. INTRODUCTION

World Health Organization (WHO) approximates that there were 161 million visually impaired people around the world in 2002, about 2.6% of the total population. Among this statistics, 124 million had low vision and 37 million were blind. Visually impaired people face a number of challenges when interacting with the environments because so much information is encoded visually. One specific difficulty that a blind person would encounter is to know the value of the currency or what bills he/she is holding. Currently, printed denominations of U.S. currency are \$1, \$2, \$5, \$10, \$20, \$50, and \$100. With a few recent exceptions all of the banknotes are identical in size and color and inaccessible to people who are blind or significantly visually impaired. Some redesigned money has been issued with an enlarged color number for visually impaired people. However, it may take years to issue bills with additional blind-friendly changes.

According to the American Foundation for the Blind [1], one way that a blind person can identify paper currency is to fold each denomination in different ways. The recommendation for folding some currency is to fold five-dollar bills lengthwise, ten-dollar bills widthwise, twenty-dollar bills are folded twice and one-dollar bills may remain unfolded and put into a wallet. Although the idea of folding the bills is good, it needs others' help to organize bills. Several systems are available in our society to assist people with banknote recognition. They are very useful devices to make people free from difficulties in counting banknotes, changing money or vending tickets. While sensors and scanning machines can provide visual information and has demonstrated much promise in banknote recognition, their recognitions [4, 9, 11, 14, 19-24] are restricted to specific and standard environment. An automatic system that can assist people with severe vision impairment to independently recognize banknotes is supposed to do the recognition in a wide variety of environments, such as occlusions, cluttered background, changing illumination, and different viewpoints.

The extraction of sufficient, stable, and distinctive monetary features is significant for accuracy and robustness of a banknote recognition algorithm. The development of interest points detector and descriptor [3, 6, 13] enables the sufficient, stable, and distinctive monetary characteristics extraction. Furthermore, the extracted monetary features can be used to match with ground truth banknotes. The matching results will be employed to determine the recognition result. The development of image matching by using a set of interest points can be traced back to the work of Moravec [15] on stereo matching using a corner detector. The detector was improved by Harris and Stephens [6] to make it more repeatable under small image variations and near edges. Harris [7] also showed its value for efficient motion tracking and the Harris corner detector has been used for many other image matching tasks. While these feature detectors are usually called corner detectors, they detect not only corners, but any possible image location that has large gradients in all directions at a predetermined scale. However, the Harris corner detector is very sensitive to changes in image scale, so it does not provide a good basis for matching images with different resolutions. Recent developments in object detection or recognition involve the usage of local informative descriptors such as Haar wavelets, Scale Invariant Feature Transform (SIFT) [13] and SURF [2-3]. Normalization of these descriptors allows them to be invariant to some transformations such as different viewpoints, scales or illumination changes. These properties make it suitable for detecting objects appearing with different scales or orientations in images.

Object detection and recognition systems based on component-based model are becoming increasingly common in the computer vision community. An alternative model to object recognition is referred to as global model, which use the overall object pattern as a whole in the recognition process. The major advantages of a component-based model over the global model are: 1) some components retain more class-specific information, while other components are similar across different classes; 2) some components vary much less than the global pattern under the changes of viewpoint or scaling; and 3) component-based model is insensitive to partial occlusions.

In this paper, we propose a component-based banknote recognition approach by using SURF features to achieve high accuracy and to handle various conditions in different environments and occlusions. The flowchart of our proposed banknotes recognition algorithm is demonstrated in Fig. 1. Monetary features of each query image are first extracted by SURF. These features are then matched with the pre-calculated SURF features of reference regions of the ground truth (reference) image of each class. Both point-level test and region-level test (Section III B2) depend on the feature matching results. If a query image is able to pass the two tests of a ground truth image, it will be recognized as the class of this ground truth image.

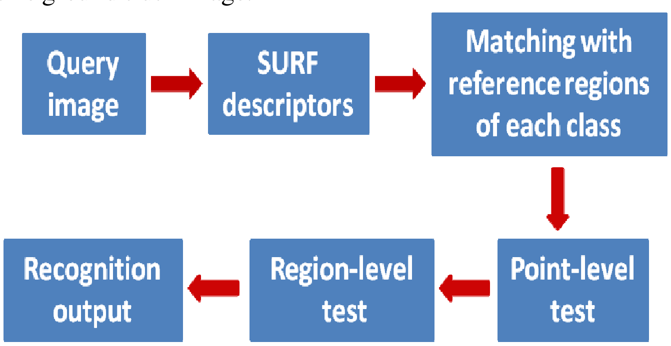

Figure 1: Flow chart of the proposed banknote recognition algorithm.

II. Related Work

Several techniques have been developed to identify banknotes. Lee and Jeon [14] utilized a distinctive point extraction that used a coordinate data extraction method from specific parts of a Euro banknote representing the same color. In order to recognize banknotes, they used two key properties of banknotes: direction (front, rotated front, back, and rotated back) and face value (5 10, 20, 50, 100, 200 and 500). A neural network was trained for banknote classification. The results showed a high recognition rate (about 95%) and a low training period. Forsini and Priami presented a neural network based bill recognition and verification method [5]. Kosaka and Omatu proposed the learning vector quantization (LVQ) method to recognize 8 kinds of Italian Liras [23, 24]. Most banknote recognition methods employed neural network techniques for classification [11, 14, 19-24]. Takeda *et al.* [19-24] first extracted features from the image and then input them to a neural network for training and testing. In the above methods, the whole bill must be visible. A portable bill recognition product in the market is called "Note Teller 2," which is manufactured by BRYTECH of Canada [16]. The bill must be put in a specific position. Based on the evaluation of AFB TECH [10], the "Note Teller 2" is simple and accessible for users, but the overall identification accuracy is only about 80% and has difficulty in identifying worn or wrinkled bills.

Local feature extraction and matching has been applied to object detection and image retrieval. Schmid and Mohr [18] applied a local feature matching process to image recognition problems against a large database of images. By utilizing Harris corners to select interest points, they demonstrated that using multiple feature matches can accomplish general recognition under occlusion and cluttering by identifying consistent clusters of matched features. Scale Invariant Feature Transform (SIFT) features, proposed by Lowe, are commonly used for object recognition [13]. Reiff and Sincak [17] used SIFT detector and descriptors to classify Slovak banknotes in a well-controlled environment.

Symmetrical masks have been used in Vila *et al.* for considering specific signs in a paper currency [25]. In their method, the summation of non-masked pixel values in each banknote is computed and fed to a neural network. This method considers images of both the front and back of the paper currency, but only the front image is used for recognition. In approach of [27], the patterns of an edge on a banknote are used for recognition. In [27], the image of a banknote is vertically divided into a number of equal small parts. Then the number of pixels associated to edges detected in each part are counted and fed to a three layer back propagation neural network for recognition [27]. Hassanpour *et al.* [9] proposed a Hidden Markov Model (HMM) model based method. By employing HMM, the texture characteristics of paper currencies are modeled as random processes and can be extended for distinguishing paper currency from different countries.

III. Proposed Method

A. SURF Detector and Descriptor

SURF [3] is becoming one of the most popular feature detector and descriptor in computer vision field. It is able to generate scale-invariant and rotation-invariant interest points with descriptors. Evaluations show its superior performance in terms of repeatability, distinctiveness, and robustness. The calculation and matching of SURF is also very fast, which is desirable in the real-time applications. SURF is selected as the interest point detector and descriptor based on the following reasons: 1) Banknote image could be taken under the conditions of rotation and scaling change. Interest points with descriptors generated by SURF are invariant to rotation and scaling changes. 2) Computational cost of SURF is small, which enable fast interest point localization and matching. In this section we provide a brief summary of the construction process of SURF.

A1. Interest Point Localization and Description

The SURF detector is based on the Hessian matrix for its good performance in computational cost and accuracy. Given a point (x, y) in an image I, the Hessian matrix $H(X, \sigma)$ at (x, y) with scale σ can be defined as:

$$H(X,\sigma) = \begin{bmatrix} L_{xx}(x,y,\sigma) & L_{xy}(x,y,\sigma) \\ L_{xy}(x,y,\sigma) & L_{yy}(x,y,\sigma) \end{bmatrix}$$

where $L_{xx}(x, y, \sigma)$ is the convolution of the second order derivative of Gaussian with image I at (x, y). This also applies to $L_{xy}(x, y, \sigma)$ and $L_{yy}(x, y, \sigma)$. In [13], it is shown that Gaussians are optimal for scale-space analysis. In real applications, Gaussians have to be discretized and cropped. The SURF approximates the second order Gaussian derivate with box filters (mean or average filter), which is able to be calculated fast through integral images. The localization of interest point is determined by the determinant of Hessian matrix. So, interest points are finally localized in scale space and image space by using non-maximum suppression in their 3×3×3 neighborhood. In the construction of descriptor of an interest point, a circular region around a detected interest point is first constructed. Then, a dominant orientation based on this circular region is calculated and assigned to this region, which enable the descriptor invariance to image rotations. The dominant orientation is calculated by the response of Haar wavelet in x and y directions. This process is also very fast by integral images. After the estimation of the dominant orientation, a square patch around an interest point is extracted to construct the SURF descriptor. The square patch is divided into a 4×4 sub-blocks. The gradients of each sub-block are used to construct the final descriptor vector.

	1	2	5	10	20	50	100
1	1.00	0.18	0.38	0.28	0.29	0.18	0.24
2	0.02	1.00	0.35	0.26	0.27	0.17	0.23
5	0.02	0.18	1.00	0.26	0.26	0.20	0.20
10	0.02	0.15	0.33	1.00	0.30	0.18	0.23
20	0.02	0.20	0.38	0.32	1.00	0.22	0.24
50	0.02	0.18	0.46	0.37	0.36	1.00	0.28
100	0.02	0.14	0.33	0.23	0.26	0.17	1.00

Figure 2: Confusion matrix of interest points matching result by SURF.

A2. SURF Evaluation on Banknotes

In order to validate the effectiveness of SURF in banknote recognition, we evaluate its performance on interest points matching of bills. We collect a testing dataset of 140 banknote images containing 20 images for each class of bill ($1, $2, $5, $10, $20, $50, and $100). The banknote dataset covers a wide variety of conditions, such as occlusion, rotation, changes of scaling, illumination and viewpoints. Then 14 images of seven classes of bills with front and back side are taken as reference images. Several regions contains unique class-specific features of each reference image are cropped as reference regions, which are used to match with images in our banknote dataset by SURF. The matching results are described in the confusion matrix in Fig. 2. Each column in Fig. 2 corresponds to the average matching results for testing images of each class. Element (i, j) corresponds to the average number of matched points between testing images of class j and reference image of class i. Also, each column is normalized by the maximum number of matching points in this column. As we see, the best matching cases occur on the diagonal elements of the confusion matrix. Furthermore, off-diagonal elements are much smaller than 1. Therefore, it can be concluded from this confusion matrix that the SURF is able to represent and match interest points of banknotes accurately even under the conditions of image occlusion, rotation, changes of scaling, illumination, and viewpoints.

B. Component-based Framework

The proposed banknote recognition algorithm is based on a component-based model which has three major advantages. First, class-specific information is not evenly distributed on the banknote. Some regions cover more class-specific features, while other regions are quite similar across different classes. Thus, it will be more effective to use those more class-specific components in terms of classification or recognition of banknote. Second, a component-based model is able to focus on common and stable parts, which vary much less than the pattern of a whole banknote under the changes of viewpoint and scaling. Third, a component-based model is more robust to handle partial occlusions. It is empirically impossible to take account of all conditions which cover the spectrum of possible variations resulted from occlusions. In the component-based model, individual component is detected by its corresponding detectors. Partial occlusions only affect the outputs of a portion of component detectors. As long as a certain amount of components are detected, the whole banknote is still able to be recognized.

Figure 3: Examples of reference regions with class-specific features on the bills of $2, $5, and $10. Each region marked in red box is one reference region.

B1. Components Generation

In our banknote recognition algorithm, we take into account of multiple conditions with variations of illumination, cluttering, scale, and rotation. Furthermore, a component-based method is used to match the testing bills to the reference bills which are taken from the good condition of $1, $2, $5, $10,

$20, $50, and $100 bills. Then, we cropped the vital components out of each reference bill as reference regions. Fig. 3 illustrates examples of three reference bills of $2, $5, and $10 on both front face and back face. As shown in Fig. 3, the marked regions in red are the patches that have been cropped manually. The location and size of these patches are chosen in such a manner that they can provide more class specific information of different kinds of bills. Taking the $5 bill in Fig. 3 as an example, the class specific information in the front face should be the number "5", the letters indicating "five" and the face picture of Lincoln. In the back face, the number "5", the letters of "five" and Lincoln Memorial are the class specific regions. From the $10 bill in Fig. 3, it can be seen that the golden number "10" on the right down corner is not taken into account, because matching of interest points within this region does not perform well. Besides, in the back face of $2 bill in Fig. 3, although the Declaration of Independence supplies the class specific information, it takes much longer time to extract interest points and their descriptors in that region using SURF. Meanwhile, the remaining regions have already well-defined the $2 bill. The same principal applies to all the other bills in both front face and back face.

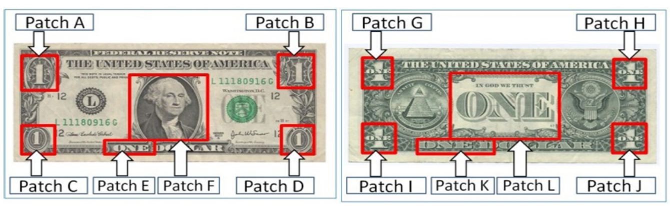

Figure 4: Illustration of the organization of reference regions on the bills of $1.

In addition, we organize the reference regions from *Patch A* to *Patch L* as shown in Fig. 4. The same organization applies to all the other bills in both front face and back face. Table 1 and Table 2 demonstrate the exact sizes of corresponding reference regions on front face and back face for each class of reference bill. The size of the image for a whole reference bill is 835 by 354. The sizes of these regions are chosen by two key ideas: a) if the size is too big, it will incorporate more non-class specific information and increase the chances of false positive detection; b) if the size is too small, it will not provide enough class specific information or increase the chances of false negative detection. We find a balance between the two cases by experimental results. The sizes in Table 1 and Table 2 optimize the recognition accuracy.

Table 1: The patch sizes of reference regions in font face.

	Patch A	Patch B	Patch C	Patch D	Patch E	Patch F
$1	70 × 100	70 × 100	80 × 90	80 × 82	100 × 40	100 × 200
$2	70 × 80	70 × 80	100 × 90	100 × 65	100 × 30	100 × 200
$5	100 × 80	100 × 90	100 × 100	100 × 110	100 × 40	100 × 200
$10	100 × 70	100 × 60	100 × 80	N/A	100 × 50	100 × 200
$20	100 × 70	100 × 60	100 × 60	N/A	200 × 40	100 × 200
$50	100 × 50	100 × 40	100 × 70	N/A	100 × 30	100 × 200
$100	200 × 60	200 × 50	200 × 70	N/A	200 × 40	200 × 200

Table 2: The patch sizes of reference regions in back face.

	Patch G	Patch H	Patch I	Patch J	Patch K	Patch L
$1	80 × 70	80 × 70	80 × 70	70 × 70	170 × 40	270 × 100
$2	80 × 70	80 × 80	80 × 70	80 × 70	30 × 90	30 × 100
$5	90 × 100	90 × 100	100 × 100	160 × 170	140 × 30	360 × 100
$10	100 × 70	100 × 70	100 × 70	130 × 90	150 × 30	400 × 100
$20	100 × 50	100 × 60	200 × 70	150 × 100	200 × 30	500 × 200
$50	100 × 60	100 × 70	100 × 70	140 × 90	200 × 30	400 × 100
$100	100 × 70	100 × 70	100 × 79	150 × 70	200 × 50	400 × 200

B2. Recognition based on Components

For each query image, SURF first locates the interest points and generates corresponding descriptors. Then pre-computed SURF descriptors of each reference region in each reference image are used to match with the detected points of a query image. The point-level test is used to determine whether a certain reference region can be matched with the query image. If the number of matching points of a certain reference region is larger than the threshold of this region, this reference region will pass the point-level test. In the next step, the region-level test is employed to determine the final recognition class of the query image. In order for recognition to occur for a reference image, its reference regions (components) passing the point-level test must be equal or larger than 2, the number of regions it needs in order to pass the region-level test as a bill. The threshold levels are chosen from empirical experiments by balancing the true positive rate and false positive rate. Tables 3 and 4 show the thresholds for reference regions to pass the point-level test of front face and back face, respectively.

Table 3: The thresholds (point-level test) of each reference region in font face.

	Patch A	Patch B	Patch C	Patch D	Patch E	Patch F
$1	5	5	6	4	4	17
$2	6	6	4	3	2	22
$5	11	9	7	8	5	25
$10	7	5	7	N/A	5	20
$20	7	11	10	N/A	7	18
$50	7	6	10	N/A	2	25
$100	9	8	10	N/A	6	25

Table 4: The thresholds (point-level test) of each reference region in back face.

	Patch G	Patch H	Patch I	Patch J	Patch K	Patch L
$1	4	5	7	6	3	16
$2	6	5	5	7	3	3
$5	7	7	11	15	3	35
$10	9	6	9	11	5	35
$20	5	5	7	11	4	20
$50	8	12	15	10	5	30
$100	9	6	11	9	7	30

IV. EXPERIMENTS AND ANALYSIS

To evaluate the performance of the proposed banknote recognition algorithm, a dataset of 140 images containing 20 images for each class of bill ($1, $2, $5, $10, $20, $50, and $100) is created. These images are selected from a wide variety of conditions to approximate the environment of real world application. Experimental results validate the effectiveness and robustness of our component-based recognition algorithm using SURF.

A. Experimental Setup

The dataset collected from a wide variety of environments includes bills taken under the conditions of occlusion, cluttered background, rotation, and changes of illumination, scaling, and viewpoints. Fig. 5 demonstrates four sample images from each condition. The samples from Row 1 to Row 5 correspond to the conditions of occlusion, cluttered background, rotation, scaling change, and illumination change, respectively. The dataset presented in our experiment is more challenging than that from other banknote recognition papers. For example, the dataset in [20] was collected by using a scanner to scan the bills which were taken under restricted or standard conditions. Thus, our dataset generalizing the conditions of taking banknote images is more challenging and more approximates to the real world application environment.

Figure 5: Samples of banknote images taken under different conditions: 1st row (partial occlusion), 2nd row (cluttered background), 3rd row (rotation), 4th row (scaling change), and 5th row (illumination change).

B. Experimental Results

Each class of bills has 20 images covering all of the conditions of partial occlusion, cluttered background, rotation, scaling change and illumination change. Fig. 6 demonstrates the matched points of query images (samples from $20 and $100) and their ground truth reference regions. The dots with different colors are the matched points of different regions with reference regions. We observe that most of matched points distribute within the regions corresponding to the reference regions described in Fig. 3 and Fig. 4. In contrast, background and non-reference-regions generate few matched points. The proposed algorithm achieves 100% recognition accuracy for all seven classes, as shown in Table 5. The experimental results have shown the effectiveness of SURF and our component-based framework for banknote recognition. The scale-invariant and rotation-invariant interest point detector and descriptor provide by SURF is robust to handle the image rotation, scaling change and illumination change. Meanwhile, our component-based framework generates more class-specific information which is more distinctive to distinguish a query image from cluttered background and effective to deal with partial occlusions. However, further experiments show that extreme large scaling change will affect the SURF detection. This is because, although SURF descriptor is invariant to scaling, the system does not receive considerable points in bills with very small resolution. But in real application, it is reasonable to assume a blind person takes the bill in a range without extreme scaling change. The computational cost for recognition include extracting SURF features from testing images and matching them with features of all the reference regions, and displaying the classification output. The average speed of the algorithm on a testing image at the resolution of 1024x768 pixels is 2 seconds on a computer with 3GHz CPU. Although our algorithm is evaluated in a more challenging dataset, our algorithm achieves 100% accuracy and outperforms all of the existing banknote recognition algorithms. For instance, the average recognition rate of the algorithm [17] based on SIFT is 76%. Some neural network based banknote recognition systems achieved recognition rate no large than 95% [19-24].

Table 5: Recognition results for seven classes of banknotes.

Ground Truth	No. of images	False Positive	True Positive
$1	20	**0**	**100%**
$2	20	**0**	**100%**
$5	20	**0**	**100%**
$10	20	**0**	**100%**
$20	20	**0**	**100%**
$50	20	**0**	**100%**
$100	20	**0**	**100%**

V. CONCLUSION AND FUTURE WORK

In this paper, we have proposed a component-based framework for banknote recognition using SURF. Patches with fixed sizes of reference images for each class of banknotes are selected as reference regions for matching with query images. The reference regions contain more class-specific information. Matching based on reference regions that are much smaller than the whole reference image also speeds up the recognition system. The evaluation of SURF on our banknote dataset validates the effectiveness of SURF to match reference regions with query images. Point-level testing and region-level testing with empirically determined thresholds are effective to filter out false positive recognitions, as well as maintaining a good true positive recognition rates. In order to evaluate the performance of the proposed banknote recognition method, we have collected a challenging dataset with a wide variety of conditions under occlusion, cluttered background, rotation, and changes of illumination, scaling, and viewpoints. The proposed algorithm has achieved 100% accuracy on this dataset and is robust to handle partial occlusions as well as worn or wrinkled bills.

Our future work will focus on optimization of the whole system and enlarging the testing dataset by incorporating more banknotes of different countries. The computation speed will be reduced to less than 1 second for each testing image. In addition, we will study the significant human interface issues including auditory output and system configuration.

Figure 6: Matched points of query images of $20 (left column) and $100 (right column) and their corresponding ground truth reference regions. Dots with different colors are the matched points for different regions.

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