Automated Banknote Identification Method for the Visually Impaired

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Abstract. A novel method for automated identification of banknotes' denominations based on image processing is presented. The method is part of a wearable aiding system for the visually impaired, and it uses a standard video camera as the image collecting device. The method first extracts points of interest from the denomination region of a banknote and then performs an analysis of the geometrical patterns so defined, which allows the identification of the banknote denomination. Experiments were performed with a test-subject in order to simulate real-world operating conditions. A high average identification rate was achieved.

Keywords: Segmentation, 2D object detection and recognition.

1 Introduction

According to recent data from the World Health Organization, 285 million people are estimated to be visually impaired worldwide: 39 million are blind and 246 have low vision [1]. Visually impaired people face many challenges in their every-day life, and a number of these could be alleviated to some degree via the use of an aiding device based on artificial vision systems. One particular problem that can be efficiently solved through such systems is determining the denomination of a banknote. This is very useful for a blind person that is on their own because recognizing the denomination of a banknote through the banknotes size or via tactile marks on the paper is quite challenging. Devices explicitly designed to perform this task already exist on the market but the current trend in technological development is to take advantage of cameras found in smartphones, portable computing devices (tablet-like devices), and wearable devices that offer a number of complementing solutions for the user. Mobile applications are being developed and some have already been released into the market. However, improvement to the technology is possible and necessary.

In this paper we present a simple and robust method for the identification of banknotes, which is part of a wearable system for aiding the blind. Our method is based on the identification of the geometrical patterns that characterize the different denominations of banknotes and does not require training (in the machine-learning sense of the word) or the building of a database. We demonstrate the effectiveness of our method through experiments performed on Mexican banknotes, but also speculate that our method can be applied on banknotes of many other countries including Euros, Chinese Yuans (Renminbi) and American Dollars.

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2 State of the Art and Proposed Aiding System

The problem of banknote recognition via an artificial vision system has been tackled recently in the literature through many different approaches including color and texture features [2, 3], the so-called Speeded-Up Robust Features (SURF) [4], wavelet decomposition and Artificial Neural Networks [5] and Principal Components Analysis [6]. Many other systems have been proposed, although the majority of them involve some device that is particularly well-suited for performing the scanning and analysis of banknotes under strictly controlled conditions.

One work that we consider of particular relevance to the present study (because of the similarity in the objectives and system setup) was published by Hasanuzzaman et al. [4]. They proposed a method based on SURF for the recognition of US dollar banknotes and their denomination. Their method is component-based and designed to be used by blind persons in uncontrolled environments. They report that their method is robust to several conditions, including scale variations, rotation, occlusions, wrinkling of the banknote, etc. and reported 100% accuracy when the acquired banknote image is of sufficient quality. However, their method cannot recognize the banknotes in the presence of severe motion blur or whenever only one or none of the characteristic regions of the banknotes can be observed. Also, their method is much more computationally expensive than the one presented in this paper.

Regarding the recognition of Mexican banknotes, we have found only one prior related study published. García-Lamont et al. [2] discuss an artificial vision method based on color and texture features. Their method achieves very good recognition scores. However, a major disadvantage of their methodology is the assumption that there are no illumination variations (i.e. the images of banknotes were always captured under the same illumination conditions). It is well known that without controlled conditions the color information is extremely unreliable, in other words, determining the color of objects under those circumstances is still a challenging and open problem.

In this paper we describe a method for banknote denomination recognition that is a functional module of a wearable system designed for aiding visually impaired people. As such, our method is bound by the requirements of said system. We now briefly describe the design and operation of our aiding system. The components of our aiding system are the following: 1. A wearable frame similar to that of conventional eyeglasses, on which a camera (and other sensing devices not relevant to the present discussion) are mounted. 2. A portable computer which provides a user interface and where the processing of images acquired by the camera is carried on. 3. A set of headphones used by the system to communicate with the user.

The protocol for using the aiding system as a banknote reader is as follows: 1) The user receives a banknote and launches the module for banknote recognition. At this time the system begins scanning for a banknote. 2) The user holds the banknote vertically oriented and shows it to the camera at arms length (distance d as illustrated in Fig.1). 3) The system either identifies the banknote that its being presented and reports the denomination to the user, or continues the scanning until the user has repositioned the banknote and it can be recognized. 4) Once the banknote was recognized, the system exits the banknote recognition module. The user can also terminate the modules activity at any moment or re-launch the module for another reading.

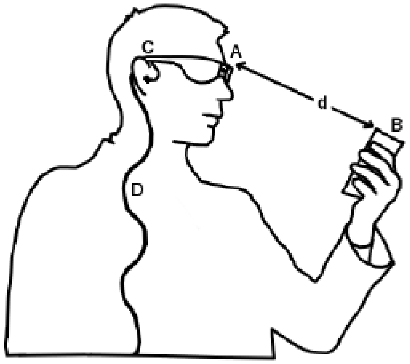

Fig. 1. Aiding system for the blind and its use for banknote-denomination recognition. A.- Camera mounted on a wearable frame. B.- Banknote. C.- Headphone. D.- Cable connecting the wearable system to the processing unit (not shown).

In this paper, our particular interest is the recognition of Mexican banknotes. The appearance of these is shown in Fig. 2. Notice that in every banknote (front and reverse) there is a region showing its denomination in clear large numbers set on a lighter background. This feature is gradually being added onto the banknotes of other nations, see for instance the modern American Dollar banknotes, Euros, etc., and it is the feature to be exploited in the recognition of the banknotes denomination.

3 Geometrical Pattern Extraction

Our initial insight while tackling this problem is related to the fact that only a limited set of numbers is ever used in the denominations of Mexican banknotes and indeed in most of the worlds nations banknotes (see for instance the data reported in [7]). Namely, the banknote denominations only contain the numbers: 1, 2, 5 and these may also be followed by one or more zeros (Fig. 2b). The second crucial observation for the development of our method was that through the detection of the semi-circular regions of the numbers used in banknote denominations it is possible to define intrinsic patterns that unequivocally identify each of the target denominations (Fig. 2c). Combining these observations, we concluded that banknote denominations can be easily identified by first detecting the semicircular regions in each number and then determining the characteristic geometrical patterns or arrangements so produced (Fig. 2d). The rest of this section provides the details of our implementation.

3.1 Detection of Semicircular Regions in Banknotes

The Fast Radial Symmetry (FRS) transform is a gradient based interest operator that was developed by Loy and Zelinsky in 2003, and since has gained popularity in the computer vision research community [8]. The FRS transform takes advantage of the

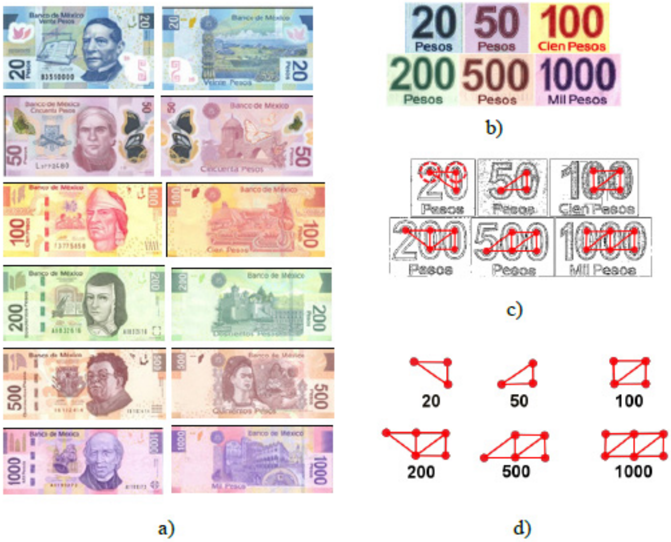

Fig. 2. a) Mexican banknotes in their different denominations (sizes vary slightly between denominations in real life). Characteristic patterns obtained from the detection of semi -circular regions on the printed denomination of the banknotes. b) The different denominations. c) Semi-circular regions detected via the FRS transform (the radius used for detection is overlaid on the 20 pesos denomination). d) Final patterns extracted (all formed by one or more triangles).

inherently ordered orientation of the gradients at points that belong to regions with radial symmetry. Naturally, the gradients at these locations point towards (or away from) the center of the region. If one considers that a location that is being pointed to by a gradient (computed at a discrete point) is somehow being affected, and one quantifies this effect, e.g. by adding to a suitably defined accumulator, then it is easy to show that the center of a region with radial symmetry is a local maximum of the values in the resulting accumulator. The FRS transform is an elegant implementation of this idea that provides the added advantage of a speedy operation. In the present study we have employed the FRS transform for the purpose of detecting the semi-circular elements that form part of the numbers in banknote denominations. The result is presented in Figure 3. The local maxima of the FRS transform accumulator indicate the regions of interest in the image. These have been overlaid on the test image.

As illustrated in Fig. 3, it is possible to retrieve false positives from the application of the FRS transform. In our context, false positives are those maxima in the accumulator of the FRS transform which do not correspond to the banknote denomination region. The removal of false positives is addressed through the following procedure: For each point that is detected via the FRS transform, its Euclidean distance to the rest of the detected points is computed. Any of these points with a minimum distance larger than a certain threshold is considered a false positive and discarded.

a) b)

Fig. 3. Detection of semicircular regions corresponding to the denomination of banknotes via the FRS transform. a) Test image on which the maxima of the FRS transform has been overlaid. Image contrast has been exaggerated for illustrative purposes. b) Accumulator of the FRS transform; local maxima appear as bright spots. Notice that besides the desired maxima corresponding to banknote denomination numbers, some spurious maxima also appear.

An effective distance threshold is easily determined since it is directly related to the parameters used in the detection step. If the FRS transform is set to detect symmetry regions of radius r, any pair of valid points belonging to the banknote denomination region must lie within approximately $2r$ to $2.5r$ of each other (see Fig. 2). A second check is performed on the remaining points after some false-positive points have been removed. The remaining points are organized as triangles for pattern analysis, so that one can examine the geometry of such triangles and decide whether or not it is in accordance with what is expected. Namely, the triangles related to the banknote denomination region are always right triangles, a condition which can be tested by means of the law of cosines. If any triangle found does not comply with these characteristics, it is discarded.

3.2 Identification of Geometrical Patterns

In order to relate each of the geometrical patterns extracted via the FRS transform to their corresponding denomination, it is useful to notice that all of these can be seen as formed by one or more connected triangles which in turn can be characterized by quantities such as: their angles, side lengths and a particularly relevant property dubbed the triangle handedness. The concept of handedness is explained as follows: Let α_{min}, α_{med} and α_{max} be the internal angles of a triangle sorted in ascending order, and let $P1$, $P2$ and $P3$ be the vertices corresponding to each of those angles respectively, where $P_i = (x_i, y_i)$. Define $Z_{jk} = P_j - P_k$; then the triangle handedness is the sign of the cross product of Z_{13} and Z_{21}: $H = sign(Z_{13} \times Z_{21})$. Notice that the triangle handedness is not affected by rotation. The triangle handedness provides decisive information for differentiating between some geometrical patterns. For instance, \$20 and \$50 are represented by a single triangle each, with the same characteristics between them, except for the triangle handedness which is negative for \$20 and positive for \$50. In fact, the handedness is only required for discriminating geometrical patterns with an odd number of triangles; in particular the leftmost triangle in each pattern.

Assuming for a moment that all triangles are extracted correctly (i.e. there are no false positives or missing points), then in order to identify a banknote denomination we only require the number of points N and the handedness of the leftmost triangle H, (in the case of having an odd number of triangles). These properties can be used to define simple rules for determination of the banknote denominations D, as follows:

1. IF $N = 3$ AND $H < 0$ THEN $D = 20$
2. IF $N = 3$ AND $H > 0$ THEN $D = 50$
3. IF $N = 4$ THEN $D = 100$
4. IF $N = 5$ AND $H < 0$ THEN $D = 200$
5. IF $N = 5$ AND $H > 0$ THEN $D = 500$
6. IF $N = 6$ THEN $D = 1000$

These six conditional statements constitute all that is needed for a rule-based banknote classification system using the geometrical patterns described in this section. In order to deal with possible missing points, we perform a verification step that takes advantage of the known geometry of the regions by searching for local maxima (smaller than the detection threshold) at locations where possible missing points could be found. A denomination is reported only when the initial detection and the verification match each other. In the next section we present the experiments performed in order to evaluate the efficacy of our proposed method and its reliability.

4 Experimental Analysis

In this section we describe the experiments that were carried out in order to characterize and evaluate our proposed identification method. In the experiments, a Logitech C920 video camera with HD capability was employed. The images were acquired at a distance of approximately 20 to 30 cm away from the camera (details about the responsiveness distance range are given below). The method was implemented in the C++ language with the help of the OpenCV library (www.opencv.org) and on a tablet computer with a 1.8-GHz CPU. In our aiding system we employ images of VGA resolution, achieving an average processing time of only 0.065 seconds per detection (including initial detection and verification). However, for the sake of comparison we also provide the following datum. The average processing time of our algorithm on images of 1024x768 pixels is 0.30 s. Compare this result with the processing time reported by Hasanuzzaman et al. which is 2.5 s per image on a computer operating at 3 GHz [4]. The banknotes used in experiments were all in good condition. We must point out that $1000 banknotes were very hard to procure and we have excluded these from the experiments.

In order to quantify the stability of the proposed method we have measured the recognition response under different positions of the banknotes. In the first experi-ment, banknotes were presented to the camera ideally oriented (perfectly vertical and facing the camera directly) and only the distance between banknote and camera was gradually changed. The output of the system was recorded as responsive or non-responsive. The parameters of the algorithm were set to detect objects of radius $r = 5$ and 7 pixels with a detection threshold in the FRS transform of 0.7 (relative to the normalized accumulator in [0-1]). This experiment provided us with an operational range. Next, the banknotes were presented to the camera in the ideal position and with a fixed distance between banknotes and camera (distance chosen with base on the range-experiment results, and set to 25 cm). Then the banknotes were rotated in steps of 10 degrees in a clockwise and counterclockwise rotation (from -90 to 90 degrees) with respect to the three standard rotation-axes. The results appear in Table 1.

In order to simulate the real-life operation of the system a blind volunteer was trained in the protocol for using the system. Banknotes of different denominations were handed to him one at a time in a random orientation, so that he had to guess and try to present the banknotes in the correct location and orientation for the system to recognize them. This was repeated 100 times per banknote denomination and the response time and the errors made by the system were recorded. The results appear in Table 2.

Table 1. Responsiveness with Respect to Banknote Rotation

Denomination	Range [10-40] cm	Yaw (deg.)	Pitch (deg.)	Roll (deg.)
$20	17 to 33 cm	-20 to 30	-30 to 40	-90 to 90
$50	20 to 34 cm	-30 to 30	-30 to 30	-90 to 90
$100	20 to 34 cm	-30 to 20	-40 to 30	-90 to 90
$200	17 to 31 cm	-20 to 20	-30 to 30	-60 to 60
$500	16 to 29 cm	-30 to 20	-30 to 20	-50 to 60

Table 2. System Response: Controlled Conditions vs Real-Life

	Controlled conditions		Real-life with positioning time by user		
Denomination	Avg. time (s)	Precision	Avg. time(s)	σ(s)	Precision
$20	0.065	100%	6.16	4.26	98%
$50	0.065	100%	5.02	4.17	100%
$100	0.065	100%	7.76	3.70	99%
$200	0.065	100%	5.58	3.62	97%
$500	0.065	100%	6.13	5.01	97%
Average	0.065	100%	6.13	4.15	98.2%

5 Discussion

The results presented in Section 4 demonstrate that the proposed methodology is robust to the position in which a banknote is presented. This is quite important be-cause it means that the user does not require any particular fixture in order to position the banknote to be scanned. We have found that the system provides approximately 9 cm of tolerance in each direction (i.e. closer to or farther from the camera) to locate the banknote. The system is also tolerant to rotation of the banknote, particularly around the roll axis. The system is less tolerant to rotation around the pitch and yaw axes. We speculate that this is caused by the perspective deformation that the bank-note suffers in these cases. Nevertheless, with an average tolerance of ± 28 degrees around the pitch and yaw axes, it can be concluded that the system is indeed quite robust to the way in which the banknotes are presented. The system can identify a banknote in 2 seconds (considering the processing time of 0.065 s and the minimum time that the user requires to position the banknote) depending on the ability of the user. Regarding the performance experiment, it can be observed that with an average precision of 98.2% the proposed method is very efficient. The errors are attributed to different sources such as bad positioning of the banknote, sharp light variations, and camera failure to adjust focus. These are issues that will be tackled in future work.

6 Conclusion and Future Work

We have presented a novel methodology for recognition of banknote denominations via image processing. The proposed method is fast, efficient and robust with respect to the way in which the banknote is presented to the system. In the future we have planned to design enhancements with the objective of making it even more efficient and robust in the face of illumination variations, poor image-quality, etc.

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