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A Non-Parametric Approach for Paper Currency Recognition

Anas M. Ali Fattouh

King Abdulaziz University, Faculty of Computing and Information Technology, Department of Computer Science, Jeddah, 21589, Saudi Arabia

afattouh@kau.edu.sa

ABSTRACT

In this paper, a non-parametric approach is proposed for the recognition of paper currency. The proposed approach is based on the development of a non-parametric model for each kind of paper currency. The model is obtained by averaging all available samples of a banknote. In order to get a reliable model, all banknotes should be aligned which is ensured in this work by a new proposed capturing system. A non-known banknote can be recognized by finding the coefficients of determination between the banknote and the non-parametric models and discriminate based on these values. The proposed method is applied to three kinds of Saudi banknotes, and it was able to recognize correctly 100% of tested banknotes.

Keywords: *Paper Currency, Recognition, Non-Parametric model, Averaging, Coefficient of Determination.*

1. INTRODUCTION

Paper currency recognition is an important task in many banking services to count different kinds of banknotes [1]. It is also a useful task for people with some kind of disabilities where a mobile application can be used to help them identify the value of a paper currency [2].

The recognition process usually passes through two phases, a feature extraction phase and a classification phase. In the feature extraction phase, relevant features are extracted from the identified object based on the application. However, in the classification phase, classes are assigned to each group of features [3].

In the context of recognition systems for paper currencies, various feature extraction methods were proposed in the literature to identify banknotes [4]. Among these methods are the Neural Networks [5], the Hidden Markov Models (HMM) [6], Local Binary Patterns (LBP) [7], Adaptive boost (AdaBoost) [8], the Speeded-Up Robust Features (SURF) [9], the pattern matching [10], the Discrete Wavelet Transform (DWT) [11], the Fourier-Mellin Transform [12], the Quaternion Wavelet Transform [13], and recently the Edge Histogram Descriptor method [14]. A comparison of some of these techniques can be found in [15,16].

An efficient recognition system requires robust features of the identified banknote [17]. Robust features means invariant features by transformed or defected banknotes, which required considerable computations and time to obtain these features and, therefore, reduces the applicability of these methods on machines with limited resources such as mobile smartphones.

In this paper, a non-parametric approach is proposed for paper currency recognition. In this approach, an image of the identified banknote is captured using a special application to prevent any kind of transformation. Then the region of interest (ROI) of captured images from the same kind of banknote under different environmental conditions are averaged to eliminate the noise in the images. Note that the averaging technique will remove the noise in the model image as all captured images are aligned by construction using the special capturing application. This averaged image represents a non-parametric model of a given banknote. Once the non-parametric models of all required banknotes are obtained, coefficient of determination can be used to classify an unknown banknote.

The paper is organized as follows: the proposed non-parametric modeling approach is described in Section 2. Sections 3 explains the proposed recognition method. Application to three kinds of Saudi paper currencies is provided in Section 4. A conclusion is given in Section 5.

2. NON-PARAMETRIC MODELING

In order to construct a non-parametric model of a given banknote, a number of captured images of this banknote under different environmental conditions and using different mobile devices is required. To ensure that all these images are free from any kind of transformation, they should be taken using the developed capturing software. The software will only capture an image when the banknote is inside a predefined frame.

The non-parametric model can be obtained by applying the following steps:

1. Capture k images of a banknote under different environmental conditions and using different mobile devices.
2. Extract k regions of interest (ROIs) $I_i, i = 1, \cdots, k$ with same size (n, m).
3. Construct k row images $\overline{I}_i, i = 1, \cdots, k$ using images from previous step with size $(1, n \times m)$. Each image can be constructed by horizontal concatenation of the rows of each image:
$$\overline{I}_i = \left[I_i(1, 1:m) \quad I_i(2, 1:m) \quad \cdots \quad I_i(n, 1:m) \right] \quad (1)$$
4. Calculate the element wise average of all row images result from the previous step:
$$M(1, j) = \frac{1}{k} \sum_{i=1}^{k} \overline{I}_i(1, j), \qquad j = 1, 2, \cdots, n \times m \quad (2)$$

Note that the non-parametric models of all required kinds of banknotes for each country can be constructed and saved in a database. The user can select the country of interest during the installation of the software, and the appropriate database will be downloaded.

3. THE RECOGNITION METHOD

The recognition method used in this paper is based on measuring the correlations between an unknown banknote and the models of all banknotes of the same paper currency.
In order to calculate the correlation between an unknown banknote I_{un} and a model M_i, the coefficient of determination is applied using the following formula [18]:

$$R_i = 100 \times \frac{1 - \sum_{j=1}^{n \times m} \left(I_{un}(1, j) - M_i(1, j) \right)^2}{\sum_{j=1}^{n \times m} \left(I_{un}(1, j) \right)^2} \quad (3)$$

The class of the highest correlation is assigned to the unknown banknote:

$$Class(I_{un}) = Class\left(M_i / R_i = \max_j (R_j) \right) \quad (4)$$

Note that the coefficient of determination calculates the percent variance in unknown banknote that is explained by the model [19]. It was used in many recognition problems (see for example [20,21]).

4. APPLICATION TO SAUDI PAPERS

In order to evaluate the applicability of the proposed method, it is applied to three kinds of Saudi paper currencies 50 SAR, 100 SAR, and 500 SAR.

The first step is to build a database of the three paper currencies. A set of images for each kind of paper currency is captured using the developed Capturing software (see Fig. 1 and Fig. 2).

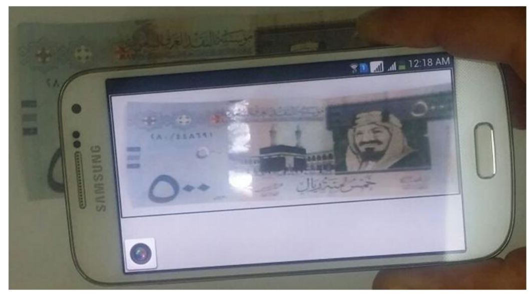

Fig. 1. Capturing Software

Fig. 2. Samples of Captured Images

The region of interest is extracted from each captured image and a row image is constructed as explained in Section 2 (see Fig. 3 and Fig. 4).

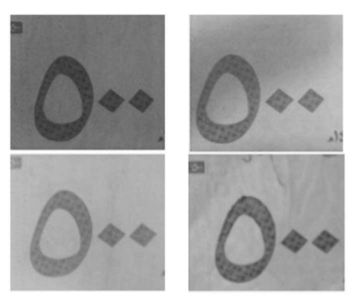

Fig. 3. ROI of Images.

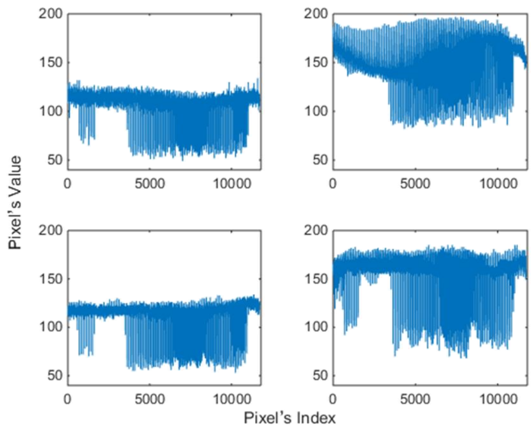

Fig. 4. Pixel Values of Row Images

The row images are averaged and normalized to get the model image. Fig. 5 shows the model images for 50 SAR, 100 SAR, and 500 SAR.

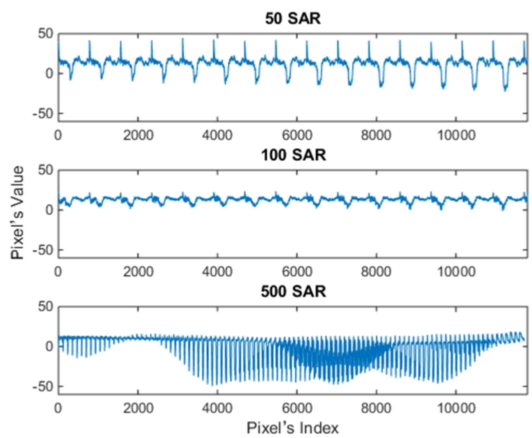

Fig. 5. Pixel Values of Model Images for Three Kinds of Banknotes

Note that the information in Fig 5 should be saved in a database for recognition purposes.
Now, given an unknown banknote, assume 500 SAR, the row image of its ROI is constructed as explained in Section 2. Fig. 6 shows a comparison between the histograms of the three models and the histogram of the unknown banknote. It is clear from Fig. 6 that the histogram of the unknown banknote matches the histogram of 500 SAR model.
Mathematically, matching between the unknown banknote and the models is evaluated using coefficient of determination given in Eq. (3). Calculating the three coefficients of determination gives:

$$R_1 = \text{-}73.1948, R_2 = \text{-}57.8309, R_3 = 34.1612 \qquad (5)$$

From Eq. (5), it is clear that the coefficient of determination of model 3 has the largest value therefore the class of the unknown banknote is the class of model 3 which is 500 SAR.

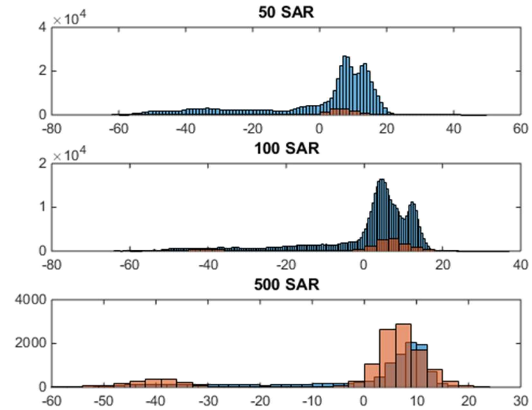

Fig. 6. Comparison between the Histograms of the Three Models (Blue) and the Histogram of the Unknown Banknote (Red).

Statically, more samples are needed to evaluate the proposed method. To this end, 100 samples of each banknote are collected. Nighty samples are selected randomly and used to construct the non-parametric models. The remaining samples are used for evaluation purposes. Table 1 summarizes the obtained results.

Table 1: Classification of unknown banknotes using proposed approach

Unknown Banknote	R1	R2	R3	Assigned Class
50 SAR	9.7	-11.7	-70.4	1 (50 SAR)
50 SAR	-1.3	-10.0	-91.0	1 (50 SAR)
50 SAR	11.5	-8.0	-86.0	1 (50 SAR)
50 SAR	-31.1	-31.0	-49.7	2 (100 SAR)
50 SAR	37.7	-4.4	-147.1	1 (50 SAR)
100 SAR	-12.5	-27.8	-55.2	3 (500 SAR)
100 SAR	-6.4	-3.1	-78.3	2 (100 SAR)
100 SAR	-156.2	-31.5	-1589.7	2 (100 SAR)
100 SAR	-96.8	-31.9	-2471.0	2 (100 SAR)
100 SAR	-285.3	-100.6	-2949.3	2 (100 SAR)
500 SAR	-39.6	-30.3	64.2	3 (500 SAR)
500 SAR	-40.6	-31.2	43.1	3 (500 SAR)
500 SAR	-83.8	-63.9	12.2	3 (500 SAR)
500 SAR	-78.7	-61.4	42.8	3 (500 SAR)
500 SAR	-80.0	-60.7	-16.6	3 (500 SAR)

Three samples out of 30 are classified incorrectly, which means that the error rate is 10%.
Considering the three coefficients of determination as a feature vector for each unknown banknote, a discriminant analysis can be applied. Using a linear classifier, same result was obtained. However, using quadratic classifier, the error rate becomes zero.

5. CONCLUSIONS

In this paper, a recognition system for a paper currency is proposed using non-parametric approach. First, a non-parametric model is obtained by averaging aligned samples of a banknote. Then, the coefficients of determination are calculated between an unknown banknote and all the models. Finally, a discriminant analysis is used to assign a model to the unknown banknote. The proposed method was applied efficiently to recognize three kinds of Saudi banknotes. The efficiency and the simplicity of the proposed method make it appropriate for mobile applications.

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AUTHOR PROFILES

Anas Fattouh received the BSc in Automatic Control and Industrial Electronics from the University of Aleppo, Aleppo, Syria, in 1992 and the Diploma and the Ph.D. degrees in Automatic Control from the Technical Institute of Grenoble, Grenoble, France, in 1997 and 2000 respectively. From 2000 to 2002, he worked as an assistant professor at the University of Aleppo, Aleppo, Syria. In 2002, he did a post-doctorate fellowship at the Automatic Laboratory of Grenoble, Grenoble, France where he worked in a Networked Control Systems project. In 2003 and 2004, he worked as an ATER at the University of Metz, Metz, France. During this period, he participated in the development of an assistive wheelchair for disabled people. From 2005 to 2009, he worked at the department of Automatic Control and Automation in the University of Aleppo, Aleppo, Syria. From 2009 up to now, he has been working as an associate professor at King Abdulaziz

University, Jeddah, Saudi Arabia. His research interests include robotics, brain-computer interfaces, digital image processing, and control systems.