

A New System for Recognition of Handwritten Persian Bank Checks

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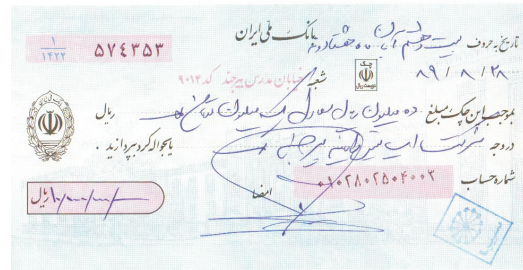
Abstract—In this paper, a novel system for segmentation and recognition of handwritten Persian bank checks is presented. Our focus in this paper is on segmentation and recognition of handwritten courtesy amounts and dates of Persian checks. We present the results of our tests on different levels of check fields including: isolated digits, courtesy amounts, and dates. Courtesy amounts and dates used for experiments in this paper have been taken from a novel database created by the authors. Segmenting and extracting dates and courtesy amounts from this database has been carried out completely automatic. Our newly created database has 500 images of Persian Bank checks which all have been written by 200 men and 200 women participants who have been randomly chosen from a large population to write these checks. Our database has 500 samples of Persian courtesy amounts, 500 samples of Persian dates and 5628 images of isolated Persian handwritten digits which all have been taken from our collected checks. Our experimental results on these samples compare favorably with similar systems for Persian bank check processing. Our new database is also freely available to the research community for Persian handwritten recognition and check processing.

Index Terms—Persian Isolated Digit Recognition, Courtesy Amount Recognition, Date Recognition, Persian Check Processing, Persian Handwritten Recognition, Optical Character Recognition (OCR).

I. INTRODUCTION

Automatic check processing is an important and challenging task in handwritten recognition and pattern recognition community. Check processing is all the processes which are carried out by banks on all incoming checks obtained from the customers which include: accessing and verifying the account numbers, verifying names and signatures, verifying dates, matching the courtesy amount, legal amount and the balance in the accounts [1]. Due to the complex structure of the Persian bank checks, automatic check processing system for Persian bank checks has not been developed yet. The main problems in Persian bank checks are lots of variations in the structure, no standardized designs for the check's structures, and overlapping of different fields due to not limiting regions (areas) of each field on the checks. Figure 1-(a) and (b) shows some examples of these challenges.

Many efforts have been done on automatizing of bank check processing system in the world, which most of them have been carried out on the traditional bank checks. Most of these efforts and researches have been conducted on non-Persian bank



(a)



(b)

Fig. 1. Problems that can be seen in traditional Persian bank checks. (a) overlapping of signature, account number, and the check receiver's name. (b) another check from the same bank. (a) and (b) shows two different structures of the checks from the same bank having variations such as: displacement of the signatures, account numbers, and courtesy amount fields.

checks such as: recognition of digits and courtesy amounts on French checks [2], processing of Chinese checks using SVM [3] and processing of Brazilian bank checks [4]. Few research works such as: approving the legal amount using the courtesy amount on the Persian bank checks [5], recognition of courtesy amounts on Persian bank checks using neural networks [6] have been conducted in Iran on handwritten Persian bank checks. However, still there is no automatic system for processing of Persian bank checks. In this paper, we provide two new contributions for Persian bank check processing: first, we introduce our newly created database for developing and evaluation of Persian bank check processing systems, then we focus on courtesy amounts and dates of Persian checks and we propose our method for recognition of these two important fields of the Persian checks.

The structure of this paper is as follows: in Section II we explain the details of our new database. In Section III we explain the details of our methodology used for recognition of courtesy amounts and dates. In Section IV, the results of our experiments and evaluations are shown. Finally in Section V, we mention the conclusions and our future works.

II. DESCRIPTION OF OUR NEW CHECK DATABASE

To the best of our knowledge and based on our searches, there is no freely available standard database for full Persian bank check processing. The only related databases in this field are [1] for Arabic checks and [7]. Database in [1] cannot be used for Persian check recognition and in [7] only legal amounts words, and courtesy amounts have been presented not the whole image of Persian bank checks. In this, section we explain some details about our newly created Persian check database. So far, we have prepared and included courtesy amounts and dates in our databases. In the future phases other fields such as signatures, legal amounts, name of the payees, also will be added to our check database and the whole database will be made freely available on line for the research community.

In our database, 400 Persian bank checks have been written by 400 different Persian writers which have been chosen randomly from different groups of people in different ages and different regions of Iran. These 400 checks are used for the training set, and another 100 checks also have been written by a subset (100 writers) chosen randomly from our original writers. This set of 100 checks is used for testing set of our database. For the first time among similar databases, in this check database we made an effort in order to balance the number of writers in terms of gender, and writers are equally distributed based on gender (we ask 200 male and 200 female writers to write these checks to make it balance in terms of gender). All of these 500 checks have been scanned with 300 DPI resolution and images are saved in true color in TIFF format files. For each check in our database all the ground truth information are also included in the database such as: true label for legal amounts, true label for courtesy amounts, true dates, and name of the payees, the name (ID) associated with signature (account holder) as well as some useful information including: the approximate age of the writer, education, gender, occupation, residential region of the writer (urban or rural) are provided. This database has been created according to a new design and a proposed structure for Persian checks in order to simplify solving the problems shown in Figure 1. In the phase of separation of different fields of the check (date, courtesy amount, legal amount, signature, account number, name of the payee), our newly designed checks are used which easily helps locating and segmentation of check fields. In our proposed design of Persian checks (which has been supported by some Persian banks), the traditional structure of Persian checks has been modified in such a way that makes locating or segmenting of the items (fields) very easy using some indicators and

separators. For an example of segmented date and courtesy amount see Figure 2.

Currently, in our database there are 500 images of different courtesy amounts and 500 images of different dates which all have been extracted from our Persian checks. Also, the total number of segmented digits (isolated digits) obtained from these courtesy amounts and dates are 5628, which 4096 samples of them (taken from training checks) are selected for training set and 1532 samples of them (taken from testing checks) are selected for testing set. In the next section, we explain the details of our methodology used for the recognition phase of courtesy amounts and dates on our Persian checks.

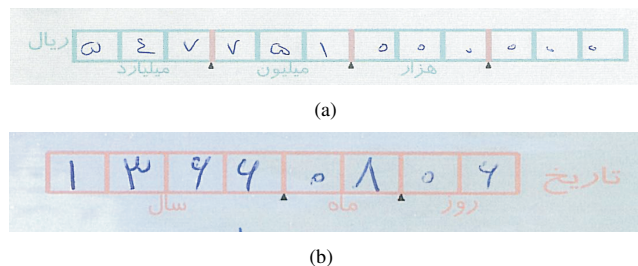


Fig. 2. (a) A sample of extracted courtesy amount on Persian bank checks (the amount is: 547,751,000,000 Rials). (b) A sample of extracted date on Persian bank checks (the date is: 1366/08/06 in Hijri-Shamsi calendar used in Iran). Figure 3, shows the equivalence table between Latin digits and Persian digits seen in Figure 2.

0	1	2	3	4	5	6	7	8	9
۰	۱	۲	۳	۴	۵	۶	۷	۸	۹

Fig. 3. Latin isolated digits and their equivalent Persian digits

III. OUR METHODOLOGY

The overall block diagram of our system is shown in Figure 4. In the following subsections, we describe the details of pre-processing, features extraction, classification, and post-processing steps of our system.

A. Pre-Processing

Preprocessing is one of the most important steps in recognizing handwriting digits particularly in bank checks processing. In this step, we use image processing techniques in order to improve the background images of the checks and make its segmented fields ready for features extraction. The first step in our pre-processing phase is binarization in which by using Otsu algorithm [8] we convert the color (RGB) images into grayscale and then into binary images. An example of this conversion is shown in Figure 5.

After binarization, we segment the digit in each field. Due to considerable space in our new design of Persian checks, it

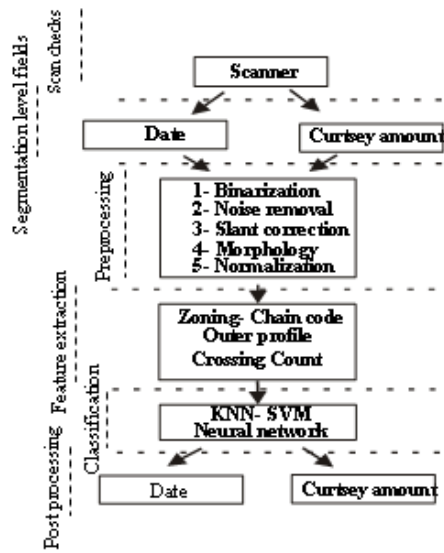


Fig. 4. Block diagram of our recognition system

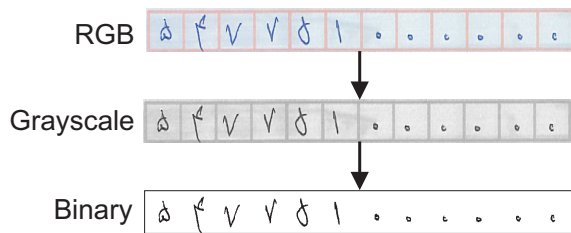


Fig. 5. Transformation of true color courtesy amount images into gray level and then into binary images.

is easily possible to segment the digits in date and courtesy amount fields. For an example of segmentation of courtesy amounts, see Figure 6.

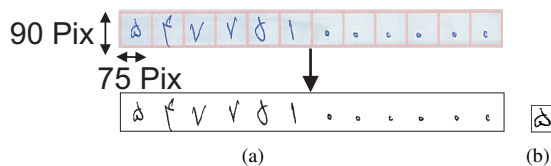


Fig. 6. An example of segmentation of digits in courtesy amounts.

After segmentation, we remove the remaining noises of isolated digits using smoothing and noise removal methods in [9]. Then after noise removal, with the help of an slant correction algorithm [10] the slants of isolated digits are corrected. In Figure 7, an example of slant correction step is shown. After slant correction, for filling the gaps on the

contours of digits we use morphological operations [11]. For an example, refer to Figure 8. In the final phase, the separated digits are normalized by using an aspect ratio adaptation normalization (ARAN) method [9], and they are converted to the size of 81×81 pixels. In the Figure 9 an example of normalizing operation is shown. In the next subsection, we explain our feature extraction methods.

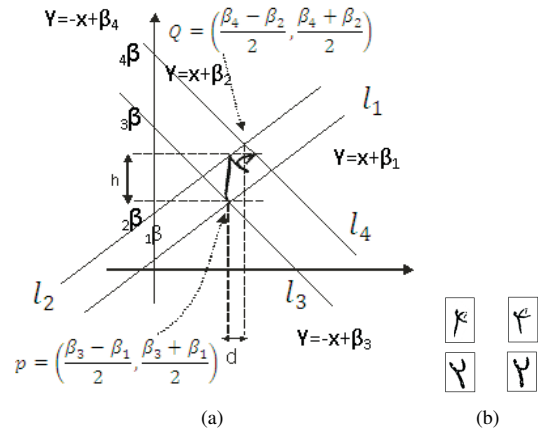


Fig. 7. (a) Using slant correction algorithm, (b) Two examples of slant correction of isolated digits.

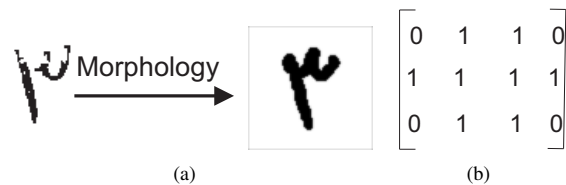


Fig. 8. (a) Filling and smoothing of contours of segmented digits using morphological operations, (b) Structuring element used for our morphological operations.

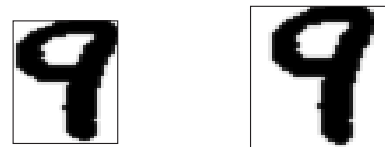


Fig. 9. An example of normalization of isolated digits segmented from courtesy amounts and dates

B. Feature Extraction

We tried several different algorithms for feature extraction and we compared their performance in order to find the best features for classification and recognition of Persian digits. Feature extraction algorithms used in this paper are: Zoning [12], Chain codes [13], Outer profiles [14], and Crossing counts [15].

- For extracting Zoning features, we use windows of size 3×3 and 9×9 simultaneously, and in each window the

number of black pixels are counted. As a result of this method, totally 810 features for each digits are calculated. An example, is shown in Figure 10.

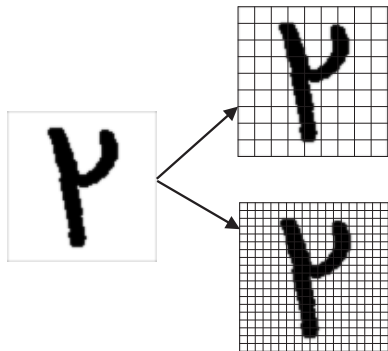


Fig. 10. An example of extracting Zoning features for segmented courtesy amount digits.

- For extracting chain code features, first the outer contour of characters is extracted and then chain codes based on freeman directions are calculated [13]. We count these codes in the frames of $27*27$ in order to equalize the number of features in all digits. The total numbers of frames are 9, therefore the number of chain code features extracted for each digit is $(8*9=)$ 72. An example of extracting chain code feature is shown in Figure 11.

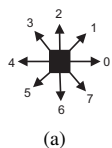
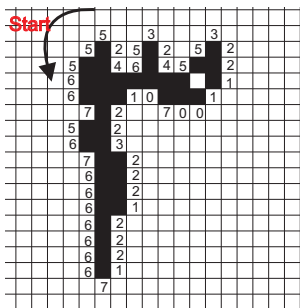


Fig. 11. (a) Freeman directions, (b) An example of extracting chain code features.

- For extracting outer profile features, we use 4 different views (from top, bottom, left, and right), and we count the number of white pixels in each view till we reach to the first black pixels. Then Spline functions [16] are used in order to smooth these profiles (views). As result we can obtain $4*81=324$ features; see Figure 12 for an example.



Fig. 12. An example of extracting outer profile features.

- For extracting crossing count features, the number of horizontal and vertical intersections in crossings are considered. We count the number of changes from black pixel to white pixel during horizontal and vertical scan of digit images. In this procedure, we select 40 horizontal and vertical lines for extracting the horizontal and vertical features. The number of extracted features will be 80. An example for extracting these features is shown in Figure 13.

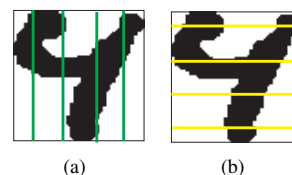


Fig. 13. An example of extracting crossing count features.

Also for improving the discrimination power of the above features, we use their combinations. Selected combinations are crossing counts with outer profiles or chain codes. In the next section, the details of our classification methods are described.

C. Classification

For recognition of courtesy amounts and dates, we tried different classification algorithms in order to obtain the best possible results. We use K-Nearest Neighbour (KNN), Neural Networks, and Support Vector Machine classifiers (SVMs).

- K-Nearest Neighbour (KNN) works based on the nearest neighbor rule. First we measure the distance between all training samples and the test sample based on a distance measure (such as: euclidean distance, city block, hamming, etc). After measuring and sorting these distances, K closet neighbours to the test sample is found. Using majority voting among K neighbours, class label for the test sample is found.
- Neural network is a machine learning procedure, which is created based on connection of some processing units (neurons). This network is formed of several layers of neurons connecting input to the output. In this paper, we use a Multi Layer Perceptron (MLP) network, which has shown very good performance for learning of non-linear problems [17]. These networks also have been used extensively for recognizing handwritten digits in many different scripts such as Latin, Chinese, Arabic, and etc [18]. For training these networks and learning their weights, the backpropagation algorithm is used [18]. We

use an MLP neural network containing of three layers: input, hidden and output layers.

- Support Vector Machines (SVM) [19] have been used for classification of Persian digits such as in [14]. In SVMs first all data points are mapped from the input space to a very high dimensional Hilbert space H (so called feature space) by using a kernel function. Then in the high dimensional feature space H , we try to find an optimal hyper plane by maximizing the margin between the two classes and by bounding the number of training errors (see Figure 14). Here, we use Gaussian (RBF) kernel for implementing of our SVM [20].

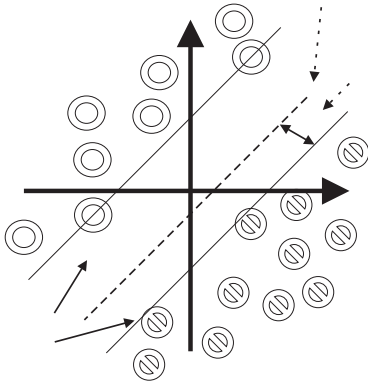


Fig. 14. Maximum margin hyperplane separating the samples in two classes.

D. Post-Processing

Postprocessing of the recognition results on different fields of the checks is very important. After recognition of each isolated digit from date and courtesy amount, digits of each field combined and the results are examined based on the context of each field. We follow the grammatical rules for each field such as: in date fields day's part can be only between 01 to 31. Also in the month's part, the numbers can be only between 01 to 12. In the year's part it should be decided according to each country's banking rules. For example in Iran, each check is valid if its date is not older than the current date – 6 months (the elapsing time of the check after its issuance date must not be more than 6 months). So, based on these rules, some recognition errors on date field can be detected (or corrected). Also due to the high sensitivity of bank checks, the reliability of the recognized digits is very important. The methods used here are based on the score result returned by each classifier for each recognized digit in each field. If the score of each digit/field is less than threshold (T), the system doesn't accept the check and the check will be rejected to be processed manually. The threshold T is set to 0.7 in our experiments.

IV. EXPERIMENTAL RESULTS

The results of our experiments have been calculated in different levels including: isolated digits as well as in two fields of date and courtesy amount and finally in the check

level, but due to lack of space, only a subset of results of features and classifications are presented. We have used the training set of our newly created database for training of all our classifiers and its testing set is used for evaluation and comparison of all our classifiers. All the recognition results on the test set of our Persian bank check database are shown in the following Tables I, II, and III. Here, only the best results for each feature have been shown in these tables. In the case of K-NN we considered $K=3$, and for the case of SVM light package [21] is used for our implementation of SVM, and its parameters are chosen as $\gamma = 0.3$ (RBF kernel parameter), and $C = 10$. For the neural networks, we use 3 layers MLP network in which input layer has the same number of neurons as the dimension of the input feature vector, and the hidden layer neurons have 74 neurons and output layer has 10 neurons each corresponding to one class. Transfer functions used in this network is tangent sigmoid for the hidden layer and logistics sigmoids for the output layers. Based on our current experiments, the best results belongs to neural network classifier using a combination of chain code, and crossing counts features. As seen in Table II, with this classifier we are able to correctly recognize 96.50% of isolated digits, 75.50% of dates, 73.40% of courtesy amounts and in total 60.20% of the checks in our testing dataset. In Figure 15, some correct and incorrect recognized samples are shown.

TABLE I
RESULTS OF K-NEAREST NEIGHBOUR ON DIFFERENT FEATURES AND ON DIFFERENT FIELDS LEVELS.

Classifier	K-Nearest Neighbour (K=3)	
	Chain code	Zoning
Isolated digits	%92.20	%95.00
Dates	%60.29	%71.46
Courtesy amounts	%48.96	%69.42
Check level	%34.71	%55.13

TABLE II
RESULTS OF NEURAL NETWORKS ON DIFFERENT FEATURES AND ON DIFFERENT FIELDS LEVELS.

Classifier	Neural Networks	
	Combination of (Chain code, Crossing counts)	Chain code
Isolated digits	%96.50	%94.70
Dates	%75.50	%62.33
Courtesy amounts	%73.40	%70.42
Check level	%60.20	%46.01



Fig. 15. Some recognition results of our system are shown. The first two examples are misrecognitions as $3 \rightarrow 4$ and $1 \rightarrow 9$, the next two examples are correctly classified as $4 \rightarrow 4$ and $9 \rightarrow 9$.

TABLE III
RESULTS OF SVM CLASSIFIER ON DIFFERNT FEATURES AND ON DIFFERNT
FIELDS LEVELS.

Classifier Features	SVM	
	Combination of (Outer profiles, Crossing counts, Projection histograms)	Chain code
Isolated digits	% 95.60	%95.30
Dates	%62.21	%65.38
Courtesy amounts	%74.42	%68.50
Check level	%49.96	%51.13

V. CONCLUSIONS AND FUTURE WORKS

In this paper, we present a system for segmentation and recognition of handwritten Persian bank checks, also we present a new database for evaluation and designing check recognition systems. We conducted several different experiments with different classifiers and subsets of features. Also, for the first time, we present the results of our experiments on the check level (whole images of Persian bank checks). Our results in this level showed that about 60.20% of the checks in our database can be automatically recognized, which is a good result for bank applications. In the future, we are going to complete our check recognition system such that it can process and recognize all the check fields such as: signatures, legal amounts, and account number and payee's name. Also, we are going to conduct more experiments on our classifiers and on our features in order to improve our current results. Our new database soon will be also freely available to the research community for Persian handwritten recognition and check processing.

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