Ahmad I, Mahmoud SA. Arabic bank check processing: State of the art. JOURNAL OF COMPUTER SCIENCE AND TECHNOLOGY 28(2): 285–299 Mar. 2013. DOI 10.1007/s11390-013-1332-6

Arabic Bank Check Processing: State of the Art

Irfan Ahmad and Sabri A. Mahmoud*, *Senior Member*, *IEEE*

Information and Computer Science Department, King Fahd University of Petroleum & Minerals, Dhahran 31261, Saudi Arabia

E-mail: irfanics@kfupm.edu.sa; smasaad@kfupm.edu.sa

Received December 7, 2011; revised January 9, 2013.

Abstract In this paper, we present a general model for Arabic bank check processing indicating the major phases of a check processing system. We then survey the available databases for Arabic bank check processing research. The state of the art in the different phases of Arabic bank check processing is surveyed (i.e., pre-processing, check analysis and segmentation, features extraction, and legal and courtesy amounts recognition). The open issues for future research are stated and areas that need improvements are presented. To the best of our knowledge, it is the first survey of Arabic bank check processing.

Keywords handwriting analysis, document analysis, text processing, feature evaluation and selection, pattern analysis

1 Introduction

Bank checks are one of the most widespread documents. Nearly one hundred billion checks move all over the world yearly[1]. Most of the checks are still processed manually by human operators. Despite its outward simplicity, a check is a complex document. It integrates images (check layout), pre-printed components (logos, labels of data-entry fields, etc.) as well as handwritten components (legal amount which is also referred to as literal amount, courtesy amount, signature, date, issuing place, and so on). These fields do not have fixed positions and their structure varies according to the countries and institutions[2-3]. Due to its complexity, bank check processing is considered as an important research field both from economic and scientific viewpoint[4].

Arabic bank check processing, apart from not being researched as thoroughly as other checks like Latin and Chinese[1,4-16] has its own challenges[2,17-22] and hence is less advanced compared with check processing systems of other languages. Arabic language is very rich and complex and has different writing styles. Arabic has larger vocabulary for legal amounts than other popular languages like English and French. Large amount of variations are possible in writing similar amount due to complex grammatical rules of Arabic language. Moreover, the same text can be interpreted to be different amounts and hence the context is very important. For more details on these aspects, please refer to [2]. Arabic bank check processing looks easier to address than the general Arabic handwritten text recognition. This may be attributed to the closed vocabulary nature of Arabic bank checks. This enables a limited dictionary to be used with check processing compared with open dictionary for open-vocabulary Arabic handwritten text recognition. In addition, different fields (courtesy and legal amounts) may be used to improve the recognition rates. Moreover, holistic techniques may be used in the case of Arabic check processing, hence segmentation of text may be bypassed. However, bank check processing has its own complexity. The handwritten text on Arabic bank checks may be written over pre-printed text, lines, rectangles, etc. Stamps on checks and text written by other than the writer for check processing require special and complex processing. Reference may be made to the survey of Lorigo and Govindaraju[23] and to a more recent survey of Parvez and Mahmoud[24] on Arabic offline handwritten text recognition.

Bank check processing involves several phases. Fig.1 shows a typical Arabic bank check processing system with major phases. In the following we summarize these phases.

1) Preprocessing is an important task in bank check automation. Preprocessing may involve many steps that can be applied at different levels. For the complete check image, one of the preprocessing steps can be to

Survey

This work is supported by King Fahd University of Petroleum and Minerals (KFUPM) of Saudi Arabia under Grant Nos. RG-1009-1 and RG-1009-2.

*Corresponding Author

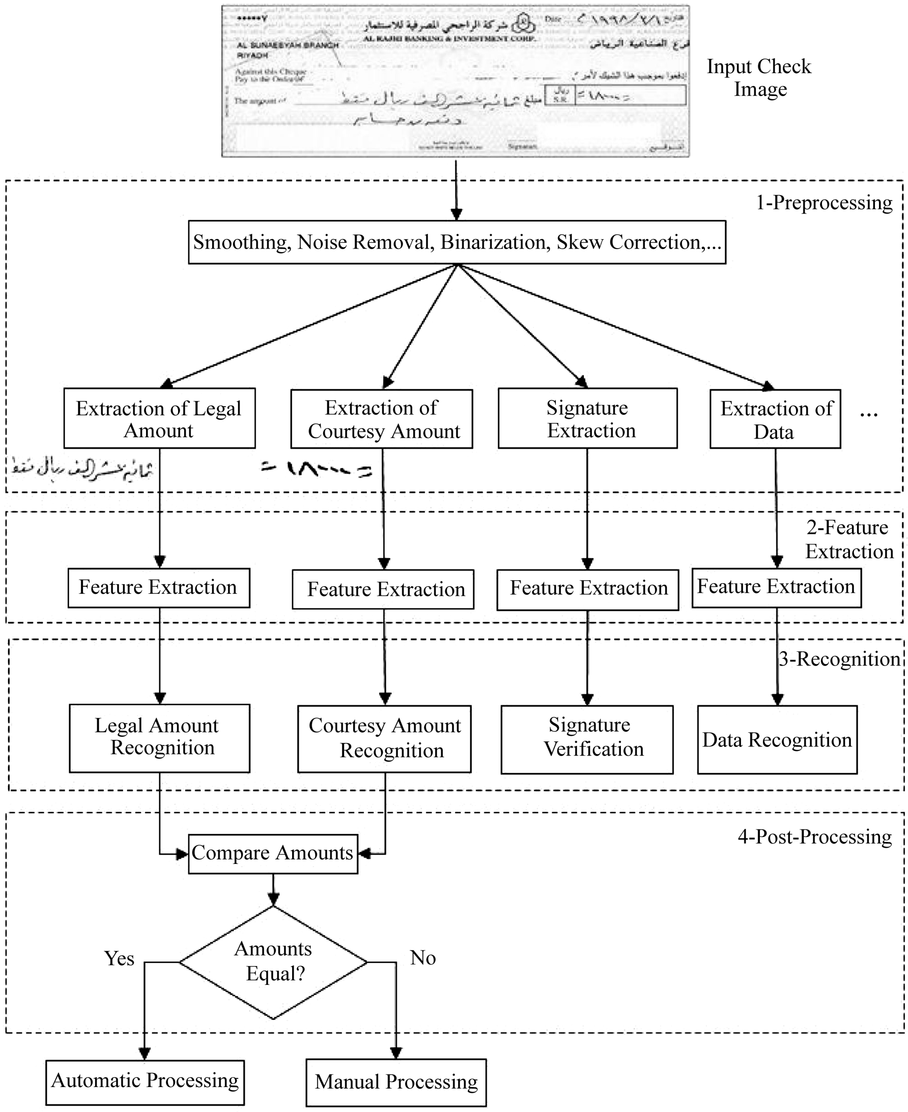


Fig.1. Major phases of automatic check processing.

convert the colored or greyscale check image to binary image. Checks may contain stamps covering part of the legal amount or other areas of interest. Checks may also contain noise due to a number of reasons like digitization process, extraction process, manual handling, and presence of stamps. Therefore, smoothing and noise removal is applied. Skew correction of the check image may be needed due to the introduction of skew as a result of scanning process. Check analysis and zone extraction are applied to extract fields of interest. Different fields may require different techniques for zone extraction. Legal amount (handwritten amount in words) and courtesy amount (amount written in digits) are normally extracted. Date, signature, and payee name fields are sometimes needed. Preprocessing may also be applied to individual regions of interest. Legal amount baseline estimation is needed for feature extraction and recognition. Legal amount may require slant correction before feature extraction and recognition. Baseline and slant detection and correction are necessary to improve recognition rates of legal amount fields. Courtesy amount may require segmentation and addressing of touching digits if classifiers like support vector machine (SVM), neural networks, and nearest neighbor are used. In addition, size and writing line thickness normalization may be needed.

2) Feature extraction phase is applied to the courtesy and legal amount and other fields of interest. Different types of features may be needed for the different types of fields for better recognition rates. In addition, the type of classifier to be used may influence the types of features to be extracted. For example, for using hidden Markov model (HMM), 2-D image features need to be serialized to a 1-D feature vector. The general trend is

to use sliding window that results in 1-D features for the 2-D window.

3) Recognition of the different field types follows the feature extraction phase. The courtesy and legal amount fields are normally addressed separately. The cases with signature verification, payee name, and date field processing, etc. are similar. The courtesy and legal amounts represent the amount of the check. One is based on digit recognition and the other on character or sub-word recognition. Different classifiers are normally used for the different fields to improve the recognition rates. In addition, several classifiers may be used for the same field.

4) Post processing may include validation of courtesy amount with the legal amount. Legal amount is processed to generate its amount equivalent in digits. This amount equivalent is compared with the courtesy amount recognized. If the legal and courtesy amounts are equal, the check is accepted; otherwise the check is passed for manual processing. In addition, textual information with possibly a language model or a dictionary of possible sub-words may be used to improve the legal amount recognition. In addition, contextual information may be useful in the extraction and segmentation of different fields like date, courtesy and legal amounts.

In this paper we survey the state of the art in Arabic bank check processing. Based on the survey the open issues and possible future research directions in this area are presented. Section 2 presents the databases that are available for Arabic bank check processing research. Literature review of the research of Arabic bank check processing is addressed in Section 3. This includes published work on preprocessing, recognition of legal and courtesy amounts and post processing. In Section 4, we present our conclusions.

2 Arabic Check Processing Databases

Having an adequate Arabic database of bank checks is crucial for researchers in the area of Arabic bank check processing. This is not only for research in this area but also to compare and benchmark techniques of different researchers. Moreover, real bank checks' database is preferred than made out checks as it allows the research techniques to be adapted in real-world environments as opposed to laboratory environments[2]. It is clear from our review of the Arabic bank check processing research databases that only one database was extracted from real Arabic bank checks, which is available for a nominal fee[2,19]. The remaining databases are either bank checks that were written by writers to support the research (which is termed as laboratory generated databases), or other databases that use collections of text in the domain of check processing. In the following paragraphs we present these databases. Al-Ohali *et al.*[2,25] of the Center for Pattern Recognition and Machine Intelligence (CENPARMI), developed an Arabic check database in 2003 for research in the recognition of Arabic handwritten bank checks. The database includes 7 000 bank checks of Al-Rajhi Bank, Saudi Arabia. Apart from the original 7 000 gray scale images of the original checks, around 3 000 checks were selected for further tagging. The tagged part contains 2 499 legal amounts, 2 499 courtesy amounts written in Arabic (Indian) digits, 29 498 Arabic sub-words used in legal amounts and 15 175 Arabic (Indian) digits extracted from the courtesy amounts. According to our survey of the databases for Arabic bank check processing, this database has been used by many researchers of Arabic check processing. Although it has limitations, such as uneven distribution of the different classes, the limited size, tagging and segmentation errors, it is based on real bank checks written by the customers of the bank a priori.

Souici-Meslati and Sellami used a database of Arabic words from the vocabulary of Arabic legal amounts[3]. There are a total of 2 788 Arabic words out of which 576 words were written by four writers (48 words were written by each writer, three times each), 532 words were written by three writers (each writer wrote 48 words, three times each), 480 words were written by 10 writers (each wrote 48 words) and 1 200 words were written by 25 writers (each wrote the 48 Arabic words used in legal amounts of check). It seems that the writers were different, however no information was provided regarding this issue. Moreover it is not clear if the database is open for researchers.

Narima *et al.* reported their work on a database of handwritten Arabic words of legal amounts of checks[17]. Altogether 5 000 words consisting of 48 unique words commonly used in Arabic legal amounts were used. Farah *et al.* in [18, 26-28] reported a database of 4 800 words corresponding to 48 common Arabic legal amounts used in bank checks. Each of the legal amounts was written by 100 different writers. As the data was not extracted from real bank checks it lacks the naturalness of real legal amounts. AlMa'adeed *et al.* in [29] used a database of 4 700 handwritten words from Arabic legal amount lexicon written by 100 writers. No further information is available about the database. Further the same group of authors in [30] presented a database of handwritten Arabic text (AHDB). Part of this database consists of handwritten words representing numbers and quantities that were written on checks. Altogether it contains 4 970 words corresponding to 50 legal amounts written by 100 different writers. Maddouri and Amiri in [31] used a laboratory database of 5000 bank checks written by 100 writers. Not much information is available. Ziaratban *et al.* in [32] reported a database of 2 950 digits from 300 courtesy amounts. Not much information on the database was presented.

As we can see from the above discussion, CENPARMI database[2] is the only database that was extracted from real-world bank checks. Table 1 shows a summary of the databases used by researchers on automatic Arabic bank check processing research.

3 Automatic Arabic Bank Check Processing

The research on automatic Arabic bank check processing is surveyed in the following paragraphs. Research work on check preprocessing and analysis, courtesy and legal amounts recognition will be addressed. To our knowledge, the following represents the phases and techniques that were addressed by researchers of Arabic bank check processing.

3.1 Preprocessing and Check Analysis

Researchers of Arabic bank check processing addressed some aspects of the preprocessing and check analysis techniques used for other languages. Check image binarization and smoothing is normally applied using different techniques. Slant detection and correction is applied by researchers to improve recognition rates. In some cases, segmentation of touching digits is needed. In general, zone extraction is addressed in some cases as a computer-aided technique and not fully automated. Mathematical morphology, Hough transforms, horizontal and vertical projection, connected component analysis, and histogram techniques are some of the most commonly used techniques for extracting check fields. Some researchers addressed baseline detection and slant correction of the legal amount. To the best of our knowledge only one research addressed the segmentation of touching digits of the courtesy amount[33]. In the following paragraphs we present the surveyed publications followed by Table 2 which summarizes the addressed publications.

Farah *et al.* performed check baseline detection utilizing the horizontal projections and selecting the densest region as the baseline[18]. It performs binarization using the Otsu technique[34] and smoothing is carried out by looking at proximity pixels (eight direct neighbors of a given pixel).

Samoud *et al.* used mathematical morphology (MM) and Hough transformation (HT) for zone extraction of Arabic checks[35]. To extract the courtesy amount using MM, the authors used a horizontal filter with structuring elements of one-fourth of the image width and a vertical filter with structuring elements of one-tenth of the image height. The combined result was used to extract the bounding box of the courtesy amount. Two additional filters were used to extract the legal amount and date fields using MM. This leads to obtain the connected components in the remaining check image. These connected components were color labeled and the legal

Table 1. Summary of Databases Used for Arabic Bank Check Processing Research

Database	Database Details	Remarks
Al-Ohali *et al.*[2,25]	• 7 000 gray scale images of the original checks out of which 3 000 check images were tagged and the regions of interest (legal amount, courtesy amount and date) were extracted • 2 499 legal amounts • 2 499 courtesy amounts • 29 498 Arabic sub-words used in legal amounts • 15 175 Indian/Arabic digits from courtesy amounts	Original Check Images from Al-Rajhi Bank, Saudi Arabia
Souici-Meslati and Sellami[3]	Arabic words from legal amount vocabulary • 576 words written by four writers • 532 words written by three writers • 480 words were written by 10 writers • 1 200 words written by 25 writers	Each writer wrote 48 words three times Each writer wrote 48 words
Narima *et al.*[17]	5 000 words from 48 different classes of Arabic legal amounts	
Farah *et al.*[18,26-28]	4 800 words corresponding to 48 common Arabic legal words. Each written by 100 different writers	
AlMa'adeed *et al.*[29] AlMa'adeed *et al.*[30]	4 700 handwritten words from Arabic legal amount lexicon written by 100 writers 4 970 words corresponding to 50 legal amounts written by 100 different writers	The database is part of a bigger database on handwritten Arabic text (AHDB)
Maddouri and Amiri[31]	5 000 bank checks written by 100 writers	Each writer wrote 50 checks
Ziaratban *et al.*[32]	2 950 digits from 300 courtesy amounts	

Table 2. Summary of Work Related to Arabic Check Pre-Processing

Reference	Summary of Work	Used Database	Reported Results	Remarks
Alamri *et al.*[33]	Segmentation of touching digits from check courtesy amounts based on bounding boxes	Touching digit database of CENPARMI Arabic check database[2]	Accuracy of segmentation judged by recognition accuracy and not by segmentation itself The segmented touching digits recognition rate of 85.5% and 92.22% after post-processing	Each amount produces 25 different possibilities and the recognition accuracy decides the parameter values
Samoud *et al.*[35]	Zone extraction from Arabic checks using mathematical morphology and Hough transformation	1 775 check images from CENPARMI Arabic check database[2]	Using Mathematical Morphology: • 98% for courtesy amount • 95% for legal amount • 97% for date Using Hough Transformation: • 98% for courtesy amount • 95% for legal amount • 98% for date	
Samoud *et al.*[36]	Zone extraction from Arabic checks using a hybrid technique of mathematical morphology and Hough transformation	1 775 check images from CENPARMI Arabic check database[2]	• 98.27% for courtesy amount • 91.82% for legal amount • 99.63% for date	The evaluation metric used here is different than in [35]
Haboubi and Snoussi Maddouri[37]	Zone extraction from Arabic checks using color histogram and pass band filters	120 Tunisian bank checks	Extraction rate of 95% overall and 97% after performing improvements including dilation	Limited number of checks is used. The approach may be closely tied to the data
Cheriet *et al.*[38]	Preprocessing performed on legal and courtesy amounts. Main steps include binarization, image enhancement, baseline detection and slant correction	CENPARMI Arabic checks database[2]	N/A	Legal and courtesy amounts are statically extracted from the check image
Ahmad and Mahmoud[16]	Zone extraction from Arabic checks using connected component analysis and projection techniques	CENPARMI Arabic checks database[2]	• 99.55% for courtesy amount • 99.94% for legal amount • 99.09% for date	Top-down approach using some prior knowledge of the location of different regions in the bank check image

amount was identified as the component having maximum number of pixels in the same color. The prior knowledge of the position of the legal amount in the checks was utilized. To extract courtesy amount using HT technique, the bounding rectangle was identified and removed. HT was applied on the remaining image to get the longest printed line associated with the legal amount. An estimate of the height of writing script was used to extract the legal amount. The date field was involved using the first horizontal line identified on the top of check image. These two techniques were tested using the CENPARMI database. Extraction rates of 98%, 95% and 97% for courtesy amount, legal amount, and date were reported respectively. Using HT technique, extraction rate of 98%, 95% and 98% for the courtesy amount, legal amounts, and date were reported respectively. A hybrid approach of MM and HT technique is used in [36]. In this work, the broken lines of the HT technique were joined using MM by using a separation threshold of 10 pixels. Using this hybrid technique they reported an extraction rate of 98.27%, 91.82% and 99.63% for courtesy amount, legal amount and date fields respectively. The evaluation metric used by the authors in [36] is different than the one used in [35]. Although the results from both techniques look promising and impressive, it should be pointed out that these two techniques may not work well for real check images, which normally have noise. In addition, lines of check boxes (or parts of the lines) may be missing due to scanning and binarization.

Alamri *et al.* addressed the problem of segmentation of touching digits from check courtesy amounts which cannot be segmented using connected component analysis[33]. They used the concept of bounding boxes for each digit. A number of parameters were introduced to define these bounding boxes. Twenty-five different models were produced for each courtesy amount by varying the parameter values. The model that gives the highest recognition rate was chosen and based on this the final parameters were selected. This technique seems new but the parameter values may be dependent on the used data. To the best of our knowledge this is the only published work that addresses Arabic check touching digits separation. More work is needed to address the touching problems of courtesy amount by the research community.

Haboubi and Maddouri presented a technique for extraction of handwritten regions from a colored check image using a hybrid technique[37]. Initially the check was preprocessed to correct the slant and eliminate the white spaces surrounding the check image. Slant was corrected by using the projection technique. To extract the handwritten regions from the colored check images, an RGB histogram technique was used where pixels of each color was counted. This was done separately for empty and filled checks. The difference between the histograms of these two images was calculated to identify the color of handwriting. A band pass filter was then used to extract the handwritten regions. The extracted handwritten regions were classified as one of the regions of interest (like legal and courtesy amounts) using a priori knowledge. Dilation was performed to join connected components that were close to each other to make sure that all components of a region of interest were included during extraction. This approach is tightly related to the empty check and so all the checks need to have the same structure and even color. This technique is expected to have problems if the handwriting is of the same color as that of the printed regions.

Cheriet *et al.* presented techniques for preprocessing and extraction of regions of interest from bank checks and binarizing them. The legal amount was statically extracted from the check images. Next filling and thinning operations were performed to enhance the image quality. Horizontal projections were used to detect the baseline. Slant correction was performed by computing the density of the baseline at various angles and selecting the angle with highest density. Finally, unwanted noise pixels/components were removed from the legal amount by using some heuristics like, inter-component distances, vertical position of components, size of component, and the slant of a component. Courtesy amounts were statically extracted and underwent binarization, thickening of strokes and smoothing of the image. The amount was normalized based on an algorithm which makes use of the horizontal inertia axis of the amount image. Vertical inclinations were corrected using histogram-based method. Digits were segmented using the run-length of the outer contours.

Ahmad and Mahmoud presented a top-down technique for Arabic check image analysis and zone extraction using connected component analysis and horizontal projections[16]. They initially corrected the skew of the check image. This was done by removing small components (i.e., components smaller than a dynamically calculated threshold) from the image. The remaining components were projected horizontally to identify the printed lines on the image. Next the skew angle was identified by performing regression on the points identified as part of the printed lines. The original check image was then rotated to correct the skew. Once the skew was corrected, the check image was further processed to extract the regions of interest. Vertical and horizontal projections were performed to identify the courtesy amount box. Then the amount itself was extracted from within the box. The legal amount and the date were extracted using the prior knowledge of its approximate location (legal amount is adjacent to the courtesy amount box and the date is located on the top-right region of the check). They used 1 775 check images from CENPARMI database of Arabic check for testing their technique. They reported extraction rates of 99.55%, 99.94%, and 99.09% for courtesy amount, legal amount, and date respectively. The high reported results may be attributed to the use of prior knowledge of the locations of the regions of interest. Table 2 provides summary of work surveyed related to Arabic bank check preprocessing and analysis.

3.2 Courtesy Amount Recognition

Courtesy amount recognition was addressed by several researchers using different techniques. Different types of features were used. Gradient, contour directions, curvature, the derivative of the top-, bottom-, left-, and right-profiles of digits, structural, spatial- and log-Gabor filters, Bernoulli mixtures, etc. were used too. To the best of our knowledge, the researchers applied their techniques to the already segmented digits of the courtesy amount and not to the courtesy amount field. Hence, it is expected that the real recognition rates will be less. One research work[33] addresses the recognition of the touching digits. Support vector machine (SVM), neural networks, k-nearest neighbor (k-NN), nearest mean (NM), hidden Markov models (HMM) classifiers were used for Arabic digits recognition. In the following paragraphs we present these techniques.

Alamri *et al.* used gradient features with SVM classifier for touching numeral pairs recognition[33]. The image was divided into 81 (9×9) blocks. The magnitude and direction were calculated using the Robert's cross operator. The directions were quantized into 32 levels with an interval of $\pi/16$. After extracting the features, the spatial resolution and the directional resolution were scaled down. A transformation $y = 0.4x$ was applied to make the distribution of the features Gaussian-like. Finally the feature vectors were scaled by a constant factor so that the values range from 0 to 1. The radial basis function (RBF) was used as the kernel for SVM. The touching and non-touching digits database of CENPARMI[2] was used for training and testing. For the case of non-touching digits, the best reported recognition rate is 98.48%. The best reported recognition rate for the touching digit database is 85.5% before performing post-processing. A post-processing step was performed which uses the recognition probability produced by the classifiers to decide the final digit. The post processing was based on maximum probability and majority voting schemes. After post processing, best recognition rate of 92.22% was reported on the touching digit database.

Cheriet *et al.* in [38] addressed non-touching digits of the courtesy amount of CENPARMI database[2]. As the first step, digits were extracted from the courtesy amounts. Some heuristics were presented to remove undesired user strokes from the courtesy amount. Thickening of strokes was done to preserve the morphological patterns. This was followed by smoothing. Baseline correction was done by normalization procedure that searches for the horizontal inertia axis of the image. Vertical stroke inclinations were corrected by histogram method where the inclination value that was most frequent in the histogram was selected. Both statistical (freeman directions and curvatures of pixel contour strokes) and structural (morphological like mountain region, valley region and hole region) features were used for recognition as shown in Fig.2. For the structural features, the image was divided into 4 by 4 mesh grids. In each of the 16 resulting zones, the number of pixels pertaining to each of the morphological patterns was counted. For the statistical features, the contour-based chain code was calculated by a run-length scanning of the digit image. The contour was smoothened a priori by averaging the freeman directions with a neighborhood window of 5-pixel length. Five magnitudes for the curvature sampling were used along the eight standard freeman directions resulting in a total of 13 entries for each zone of the mesh grid. Thus a total of 17 structural and statistical features were obtained for each zone. The values were finally normalized by considering the percentage of the total number of pixels of the contour in each zone of the grid. Neural network and SVM were used as classifiers. Multilayer perceptron based neural network was used which has one hidden layer. The weights were randomly initialized regarding a Gaussian distribution and normalized relating to the fan-in of the neurons. For SVM, different values for kernel parameters and the trade-off variable C was tried in order to get the optimum classification. Best recognition rate of 96.69% was reported for neural network classifier and 98.18% for SVM. Given that this result is for non-touching digits, more improvements are needed for practical applications.

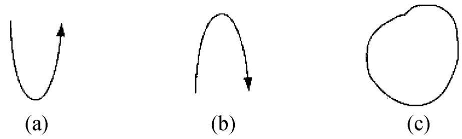


Fig.2. Structural features used in [38]. (a) Valley region. (b) Mountain region. (c) Hole region.

Mahmoud and Al-Khatib in [39] and Mahmoud in [40] presented techniques using Log-Gabor and Spatial-Gabor filters to recognize the isolated digits of check courtesy amounts. Digit images were initially normalized to a height of 64 pixels maintaining the aspect ratio of the original images. Gabor filters with several scales and orientations were used as features. To extract the features, the filtered image was segmented into a number of segments. The mean and variance of each segment were taken as the features of the segment. This process was repeated for all the filtered images at different scales and orientations. Sliding window technique was used for HMM classifier for feature extraction as shown in Fig.3. Four classifiers viz. K-NN, NM, HMM and SVM were used in [39] and 1-NN, K-NN, and NM were used in [40]. The non-touching digit database of CENPARMI[2] was used for training and testing. Recognition rates of 98.95%, 98.75%, 98.62%, 97.21% and 94.43% were achieved with SVM, 1-NN, 3-NN, HMM and NM classifiers, respectively using Log-Gabor filters and 97.99%, 97.37%, and 92.76% were reported using 1-NN, 3-NN, and NM classifiers, respecti-

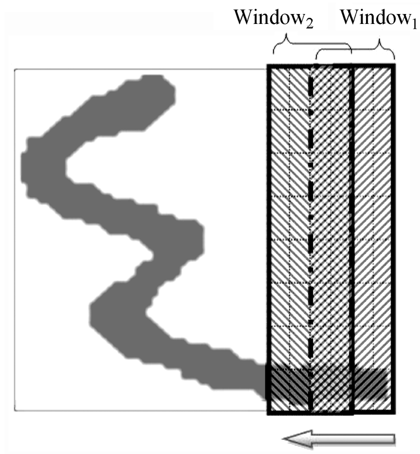


Fig.3. Sliding window technique for feature extraction as used in [39].

vely, using Spatial-Gabor filters. The misclassified digits were evaluated subjectively and results indicate that human subjects misclassified one-third of the misclassified digits.

Juan *et al.* used multivariate Bernoulli mixtures for recognition of isolated digits of check courtesy amounts[41-42]. A total of six expectation maximization (EM) initialization techniques were described. The expectation step (E-step) computes the expected value of the missing data given the incomplete data and the current parameters; whereas the maximization step finds the parameter values which maximize the log likelihood function, on the basis of the missing data which is estimated in the E-step. In [41], three of the six initialization techniques were described namely random, random prototypes, and max-min. In [42] an additional three are presented namely "hypercube center" (where all prototypes are slightly perturbed), "data mean" (where all prototypes are slightly perturbed versions of the data mean), and the "class mean" (where all prototypes of the mixture for class c are perturbed versions of the class c data mean). For each initialization technique and each selected number of clusters, $I\{1;\ 2;\ 5;\ 10;\ 15;\ 20;\ 25\}$, the standard experimental procedure was run 50 times, each of which entailing an I-component Bernoulli mixture classifier trained from a different random seed. They pointed out that max-min initialization was less attractive since it was more computationally demanding and difficult to implement whereas the recognition rate was almost the same as other EM techniques. On the other hand they stated that the "hypercube center" EM technique was the most effective. They used 10 425 non-touching digits from CENPARMI database of Arabic check[2]. The digit images were initially normalized by superimposing them on a white background of a large enough fixed size. Next the images were scaled to a desired size (same for all the images). Fig.4 shows Bernoulli prototypes of digit 2 after different number of iterations. They reported a best recognition rate close to 98%.

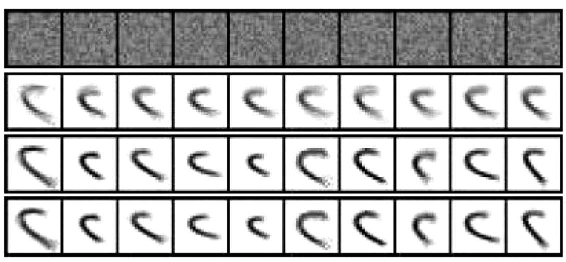


Fig.4. Bernoulli prototypes of digit 2 after different number of iterations[41].

Sadri *et al.* proposed a feature extraction technique for Arabic/Persian isolated digits recognition[43]. A set of 64 features were extracted for each digit. These features were based on calculating the distance of the digit boundary from four different views, i.e., top, bottom, right and left. The number of white pixels was counted from the edge towards the boundary of the digit (the digit initially being normalized to 64 by 64 pixels). These were represented as curves. Each curve was further smoothed and its derivative was computed and sampled. The feature extraction process is depicted in Fig.5. SVM was used as the classifier. Ten SVM classifiers, each of which represents a digit from 0 to 9 were used. For each digit during testing, the classifier that gave the maximum output determined the class of the digit. CENPARMI database of isolated digits[2] was used for training and testing. Best recognition rate of 94.14% was reported.

Ziaratban *et al.* presented an approach for improving the recognition results by using information on legal amount to confirm or correct the courtesy amounts on Farsi bank checks[32]. Initially the digits of the courtesy amount were recognized using two nearest neighbor multi-layer perceptron (NN-MLP) networks. Statistical and structural features were used whose details were not given. As the second step the legal amount sub-words (a total of 40 words), which were heuristically grouped into 12 classes were classified into one of these classes using an MLP-based neural network classifier. Finally each recognized digit was matched to the recognized sub-words representing the digits. The corresponding sub-word was compared with the digit value and if they were same it confirmed the digit recognition otherwise it was rejected. Using this approach, the authors reported an improvement in the average digit recognition rate from 85.33% to 95.67% (a 10.34% improvement) with a rejection of 3.67%.

Table 3 presents summary of research work reported in this paper related to Arabic bank check courtesy amount recognition.

3.3 Legal Amount Recognition

Legal amount recognition is one of the most difficult tasks in automatic check processing. Writing found on checks covers most of the possible and conceivable writing styles. Moreover, these entries are far from being the best writing samples that their authors could produce. For these reasons, researchers try to use all available contextual knowledge and to combine several complementary approaches to achieve reliable results in legal amount recognition[3]. Researchers used statistical and syntactical features in the recognition of the legal amount words/sub-words. Loops, diacritic marks, Fourier descriptors, contour profiles, ascenders, descenders, etc. are normally used. Although HMM is more suited to cursive text recognition, other classifiers are

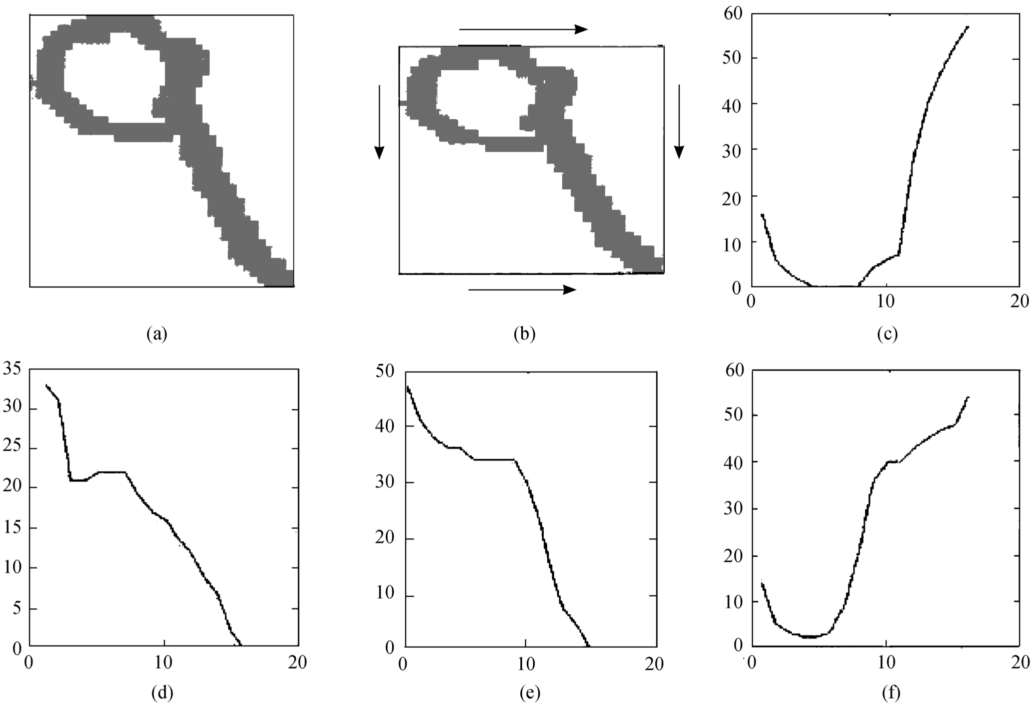


Fig.5. Direction features used in [43]. (a) Original image. (b) Normalized image. (c) Top view. (d) Right view. (e) Bottom view. (f) Left view.

Table 3. Summary of Work Related to Arabic Bank Check Courtesy Amount Recognition

Reference	Features	Database Used	Classifier Used	Reported Results
Alamri *et al.*[33]	Gradient features	CENPARMI database of touching and non-touching digits[2]	SVM with radial basis function (RBF) as the kernel	• 98.48% for non-touching digits • 92.22% for touching digits
Cheriet *et al.*[38]	Statistical and structural features	CENPARMI database of isolated digits[2]	Neural network SVM	• 96.69% for NN • 98.18% for SVM
Mahmoud and Al-Khatib[39]	Log Gabor filters with several scales and orientations	CENPARMI database of isolated digits[2]	K-nearest neighbor (K-NN) HMM SVM	• 98.95% for SVM • 98.75% for 1-NN • 94.43% for NM • 97.21% for HMM
Mahmoud[40]	Spatial Gabor filters with several scales and orientations		1-NN neighbor 3-NN Nearest mean classifier	• 97.99% for 1-NN • 97.37% for 3-NN • 92.76% for NM
Juan and Vidal[41-42]	Multivariate Bernoulli mixtures	CENPARMI database of isolated digits[2]	EM-based learning	Close to 98%
Sadri *et al.*[43]	Features are based on calculating the distance of the digit boundary from four different views	CENPARMI database of isolated digits[2]	SVM	94.14%

also used for legal word recognition like NN, K-NN, fuzzy K-NN, transparent NN to name a few. We are not aware of any system that addresses Arabic bank check legal amount recognition as such. The presented work is addressing the segmented Arabic words or subword used in bank checks. Hence, the real application of the presented technique may result in lower recognition rates of legal amount recognition than reported. In the following paragraphs we present concise details of the surveyed work.

Souici-Meslati and Sellami used a hybrid neuro-symbolic classifier to recognize words of Arabic legal amounts[3]. The word images were initially preprocessed where they were binarized, smoothed, and normalized. The baseline was, then, detected using the projection technique. Contour tracing was performed to extract features such as loops, diacritical dots, number of connected components, ascenders, and descenders as shown in Fig.6. When extracting the diacritical dots, a heuristic-based approach was applied to decide the number of dots based on the X and Y dimensions of the diacritical mark along with the stroke thickness. A knowledge base (symbolic) was constructed describing the words with their features. Later these rules were translated into neural network and finally the neural network model was fine-tuned using back propagation algorithm. They reported a recognition rate of 93% on a database of 1 200 words written by 25 writers by using the hybrid system. The system was trained on 480 words written by 10 writers.

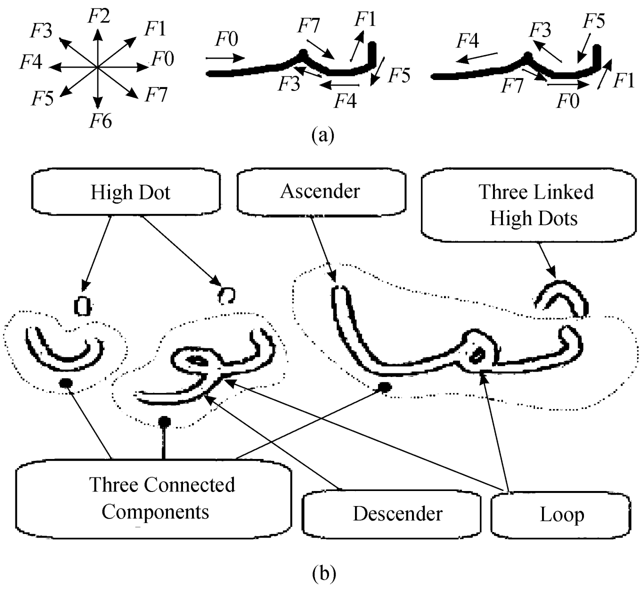


Fig.6. (a) Contour tracing using freeman codes. (b) Contour features used in [3].

Narima *et al.* used a hybrid recognition system for the recognition of handwritten words from the vocabulary of legal amounts in Arabic bank checks[17]. The system uses neural networks and HMM. The word images were transformed into graphemes and further coded into observations using their Fourier descriptors and contour profiles. The graphemes (segments) were grouped into five classes, namely group for points defined as isolated segments with a very small length, group for Hamza defined as a small isolated zigzag, group for segments with loops, group for segments without loops which terminate with connections or intersections, and group for segments without loops which terminate with end point. Three separate neural networks were used, each having two hidden layers and different output units based on the grapheme group it recognizes. A database of 5 000 words using 48 unique words of Arabic legal amounts was used for training and testing. A recognition rate close to 95% at grapheme level was reported using HMM. Recognition at word level was not reported.

Farah *et al.*[18,26-28] used structural (ascenders, descenders, loops, etc.) as well as statistical features (e.g., density of pixels) with neural network classifier to recognize the words from lexicon of Arabic bank check legal amounts. They tested the structural and statistical features individually and in combination. They reported that the best results were achieved using a combination of statistical and structural features (89.17%). Additionally when they used separate NN classifiers to classify the words using structural and statistical features separately and used various combination schemes to make the final decision on classification, they reported an improvement of about four percent. However, the database used in the experiments is not a real-world check database. It is composed of laboratory generated words from check legal amount lexicon written by 100 different writers. Out of the total 4800 words in the database, they used half for training and the other half for testing. The results were reported in [26]. The authors, in [18, 27-28], used three different classifiers (multi-layer neural network, K-NN and fuzzy K-NN) for the recognition of the words of Arabic bank check legal amounts. Holistic structural features (such as ascenders, descenders, loops) as shown in Fig.7 were used. Additionally they performed a syntactic post-classification process to further improve the classification results by combining results from individual classifiers using different statistical combination schemes. Best results of 92.16% were reported using fuzzy K-NN classifier. An improvement to 96% was reported when using syntactic post-classification combination. The result seems to be encouraging. However, the used data is not the legal amount field extracted from real bank checks.

AlMa'adeed *et al.* addressed Arabic legal word recognition using multiple classifiers[29]. The word images

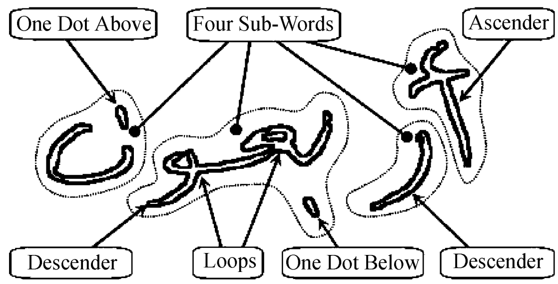
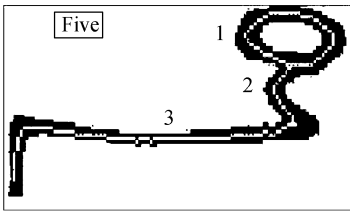


Fig.7. Holistic features used in [28].

were initially preprocessed. The heights of the images were normalized, the stroke width was made one pixel wide, and the slant and slope of the word were corrected. As a next step, the words were classified into eight groups by using a global rule based classifier with three structural features (the number of upper dots, the number of lower dots, and the number of segments). Thus each of the words belongs to one of the eight resulting groups depending on the presence or absence of these three structural features. Finally a separate HMM classifier for each group classified the word using a number of local features. A total of seven structural features (number of loops, ascenders, descenders, dots and their positions, alef and the number of segments) were used. The HMM classifier for each group had different configurations with respect to its number of states, codebook size and the stopping criteria. A database of 4 700 handwritten words, written by 100 writers, from Arabic legal amount lexicon was used for training and testing. Ten percent of the data was excluded because of baseline detection and preprocessing errors. An overall recognition result of 60% was reported. Although the result seems to be too low for practical purposes, recognition rates for words in some groups (out of the eight groups) were high enough. Classifying the groups based on the number of upper dots and the number of segments is problematic as writers may join dots which results in wrong number of dots and the number of segments may change due to the different writing styles of writers and possible segment cuts.

Maddouri and Amiri described an Arabic legal word recognition system based on a transparent neural network (TNN)[31]. The technique proceeds by a global vision of structural descriptors during propagation step and local vision by normalized Fourier descriptors during back-propagation step. They trained and tested their system using word images from 5 000 bank check images written by 100 writers. The best reported recognition rate using both the global structural features and Fourier descriptors, are 95% at sub-word level and 97% at word level. They reported recognition rates of 97.36% at the sub-word level and 100% at the word level using manual global features. A 100% recognition rate needs more elaboration on the experimentation, data, and the manual global features used.

Cheriet *et al.* presented a system for recognition of bank checks[38]. The system has the phases needed for bank check recognition but it seems that the phases are not integrated. Pen trajectory was used as features for the HMM classifier. An example of pen trajectory features used in this work is shown in Fig.8. They proposed a two-step approach, i.e., local level and global levels. At the local level, the words were recognized by combining the sub-words. At the global level it tried to find the correct legal amount from a list of all possible recognized words from the first step. The technique includes the construction of the legal amount from sub-words. HMM models were used for each sub-word and each model was trained only on feature vectors that belong to it. The recognition rates of the sub-words of the legal amount of the combined recognition system is 73.53%, 88.19%, 94.36% for the top 1, top 5, top 10, respectively. This rate is not enough for practical applications given that segmentation errors were not included. Further, their technique assumes the input to be the skeleton of the sub-words. Skeletonization of handwritten text is imperfect and sometimes produces extra lines, circles, etc. Reference may be made to [44] for discussion on the problems of skeletonization of Arabic characters. The technique also suffers from problems in the linear approximation process, noise, and errors due to the selection of wrong starting points, etc. In [45-46], the same authors presented a recognition system based on HMM classifier. Again, pen trajectory estimates were used as features to recognize sub words. Additionally they used dynamic termination states where HMM can terminate in any state and not necessarily in the last state. They reported improvement of the recognition rate as compared to using HMM without dynamic termination states. They conducted experiments for sub-word recognition for check legal amounts. The non-touching sub-word database of [2] was used for training and testing. They reported recognition results of 81.13% for the sub-words and 98.68% of the time the top 10 recognized sub-words were the actual sub-words choices of the system.



Stroke Code	Relative Size	Shape
8.0000	4	○
5.0000	1	↙
6.6000	2	↘
4.0233	6	←
5.8000	2	↓

Fig.8. Pen trajectory features used in [45].

El-Melegy and Abdelbaset proposed a system for recognition of words from the vocabulary of legal bank amounts in Arabic[47]. They tested the holistic structural features on four different classifiers namely K-NN classifier, Bayesian classifier, decision tree classifier and neural network classifier. A total of 39 holistic structural features along with their position information were used. The features were a combination of primary features (viz. the number of primary parts of words, ascenders, descenders, and loop) and secondary features like the number of dots and their position (above or below) and Hamza. They trained and tested their system on 4 970 words from the legal amount lexicon of the database of [30]. The authors reported recognition rates for different techniques, which ranged from 88.8% for the three dots to 100% for the loops. The best overall recognition rate of 86.5% was reported using neural network classifier. The authors attributed 4% of the error rates to bad data; classes with only primary features had the best recognition rate. Worst recognition rate of 50% was obtained for the class "ثلاثمائة" which were attributed to the samples, errors in feature extraction, and errors due to missing loops. Errors due to confusion of some classes and position of the feature with respect to the baseline were also reported.

Table 4 presents the summary of the work reported in this paper related to Arabic bank check legal amount recognition.

4 Conclusions

In this paper, we presented the state of the art of Arabic bank check processing. There are a number of systems that are in use for other languages①,②,③ (English, French, German, Italian, Portuguese and Spanish)[1,4−15,48−51]. To the best of our knowledge there is no fully integrated system for Arabic bank check processing that may be applied to practical problems. On comparing Arabic check processing with other

Table 4. Summary of Work Related to Arabic Bank Check Legal Amount Recognition

Reference	Features	Database Used	Classifier Used	Reported Results	Remarks
Souici-Meslati and Sellami[3]	• Knowledge base describing the words • Holistic structural features	• Trained on 480 words written by 10 writers • Tested on 1 200 words written by 25 writers	Hybrid neuro-symbolic classifier	93%	Word level recognition results reported
Narima et al.[17]	Fourier descriptors and contour profiles	5 000 words from 48 different classes	Hybrid of neural networks and HMM	95% at grapheme level	Recognition rate at word level was not reported
Farah et al.[18,27-28]	Holistic structural features	4 800 words written by 100 different writers	• Neural network • K-NN • Fuzzy K-NN	• 92.16% using fuzzy K-nearest neighbor • 96% using syntactic post-classification combination	Word level recognition results reported
Farah et al.[26]	Structural and statistical features		Neural network classifiers	• 89.17%	
AlMa'adeed et al.[29]	Structural features	4 700 words from Arabic legal amount lexicon written by 100 writers	Global rule based classifier followed by HMM classifier for each group	60%	Word level recognition results reported
Maddouri and Amiri[31]	Structural features along with Fourier descriptors	5 000 bank check images written by 100 scribes	Transparent neural network (TNN)	• 95% at sub-word level • 97% at word level • 97.36% at sub-word level and 100% at word level when manual global features are used	Results reported at sub-word level as well as word level
Cheriet et al.[38] Al-Ohali et al.[45-46]	Pen trajectory estimates are used as features	Non-touching sub-word CENPARMI database[2]	HMM classifier HMM classifier using dynamic termination states	• 73.53% top 1 • 94.36% top 10 • 81.13% top 1 • 98.68% top 10	Recognition results at sub-word level reported. Techniques to combine sub-words to form legal amount was proposed but no results reported
El-Melegy and Abdelbaset[47]	Holistic structural features	4 970 words from the legal amount lexicon from the database presented in [30]	• K-NN • Bayesian classifier • Decision tree • Neural network	Best recognition rate of 86.5% for neural network classifier	Word level recognition results reported

①Parascript® CheckUltra®. http://www.parascript.com/recognition-products, Jan. 2013.

②A2iA. http://www.a2ia.com, Jan. 2013.

③Mitek Systems®. http://www.miteksystems.com/MobileDeposit.asp, Jan. 2013.

languages, we found that the gap is large. In the following we present our observations and conclusions.

Researchers of Arabic bank check processing used a number of datasets as there is no benchmarking dataset for Arabic bank check processing research. Hence, the comparison of the recognition rates of the different techniques using different databases is not justifiable. Most of the available Arabic check databases are not natural check databases. They are databases that were prepared in laboratory settings thereby lacking naturalness and some have repetition of writers. CENPARMI Arabic bank check database is an exception. However, a more comprehensive database is needed. Due to the above there is a need for a real and practical benchmarking database for Arabic bank check processing with enough tagged data for all fields of interest.

In the area of check pre-processing and zone extraction, some studies have been reported. Two of the most commonly used techniques for zone identification and extraction being mathematical morphology and Hough transformation. There is a need to address the automatic check analysis and segmentation including preprocessing at the check level. Hence, all possible fields of interest are to be addressed including date, payee, etc. The emphasis is currently is on legal and courtesy amounts' fields and not on the whole check. Although addressing these fields embeds the whole check, it is done in limited scope. More techniques are needed to address stamp imprints removal from fields of interest, extraction of handwritten text when it over-runs with bounding boxes and pre-printed text. More robust skew detection and correction techniques and better de-noising techniques to handle practical checks are needed. We suggest the use of context to segment the different fields to improve correct segmentation rates. There is a need to address the splitting of digits and characters and the different styles of some writers who may write some characters/digits by splitting some strokes. These models of the characters/digits need to be taken into account or the parts that are split need to be joined before the features extraction and recognition phases. Text normalization and writing line thickness normalization may be needed for some technique. Hence, more work is needed in check analysis and extraction of the fields of interest.

Good amount of work has been done on isolated digit recognition. Researchers have reached high recognition rates for isolated digits of check courtesy amounts using different classifiers like K-NN, SVM, NN, HMM. Better results are achieved using non-HMM classifiers for isolated digits. Hence, to use these classifiers, the courtesy amount needs to be segmented into digits and the touching digits problem needs to be addressed. This problem is nearly untouched for Arabic bank check courtesy amount segmentation. In addition, more techniques and features need to be used to address courtesy amount recognition using HMM and TNN classifiers. HMM does not require the prior segmentation of the courtesy amount. Hence, more research work is needed to address the courtesy amount recognition using HMM.

Comparatively many researches were published on legal amount sub-word and word recognition. However, the recognition rates are not at the level of practical applications. Hence, some more improvements are needed. We are not aware of any research work that addresses the recognition of the legal amount field as a unit. More robust tilt estimation and correction and base line detection techniques are needed to improve the recognition rates of the legal amounts. HMM is suited for the legal amount recognition as pre-segmentation is not needed. We expect that the use of HMM with a dictionary and language models to result in high recognition rates. In addition, additional features and techniques may be needed to address the legal amount field. Other classifiers may be investigated at the word and sub-word levels where the segmentation problem is of less effect, although the issue of touching words/subwords will need to be addressed.

The areas of feature combination and selection and the use of multi-classifier systems need to be explored more. The use of different features and classifiers for different fields is expected to result in practical recognition rates.

Finally there is a need, due to limited resources for Arabic bank check processing, to combine efforts of different researchers and research groups to address the above issues. Sharing of resources can help in developing an automatic Arabic bank check processing system faster. There is a need to develop features and techniques that take advantage of the characteristics of Arabic languages. Hence, researchers of different backgrounds like pattern recognition and natural language processing can, in combination, address the particularities of Arabic language.

References

[1] Palacios R, Gupta A. A system for processing handwritten bank checks automatically. *Image and Vision Computing*, 2008, 26(10): 1297-1313.

[2] Al-Ohali Y, Cheriet M, Suen C. Databases for recognition of handwritten Arabic cheques. *Pattern Recognition*, 2003, 36(1): 111-121.

[3] Souici-Meslati L, Sellami M. A hybrid approach for Arabic literal amounts recognition. *Arabian Journal for Science and Engineering*, 2004, 29(2B): 177-194.

[4] Impedevo S, Wang P S, Bunke H. Automatic Bankcheck Processing. Volume 28, World Scientific, 1997.

[5] Knerr S, Augustin E, Baret O, Price D. Hidden Markov model based word recognition and its application to legal amount reading on French checks. *Computer Vision and Image Understanding*, 1998, 70(3): 404-419.

[6] Knerr S, Anisimov V, Baret O, Gorski N, Price D, Simon J C. The a2ia intercheque system: Courtesy amount and legal amount recognition for French checks. *Journal of Pattern Recognition and Artificial Intelligence*, 1997, 11(4): 43-86.

[7] Gorski N, Anisimov V, Augustin E, Baret O, Price D, Simon J C. A2iA check reader: A family of bank check recognition systems. In *Proc. the 5th International Conference on Document Analysis and Recognition*, Sept. 1999, pp. 523-526.

[8] Guillevic D, Suen C Y. Recognition of legal amounts on bank cheques. *Pattern Analysis & Applications*, 1998, 1(1): 28-41.

[9] Guillevic D, Suen C Y. Cursive script recognition applied to the processing of bank cheques. In *Proc. the 3rd International Conference on Document Analysis and Recognition*, Aug. 1995, pp.11-14.

[10] Kaufmann G, Bunke H. Automated reading of cheque amounts. *Pattern Analysis & Applications*, 2000, 3(2): 132-141.

[11] Lethelier E, Leroux M, Gilloux M. An automatic reading system for handwritten numeral amounts on French checks. In *Proc. the 3rd International Conference on Document Analysis and Recognition*, Aug. 1995, pp.92-97.

[12] Suen C Y, Xu Q, Lam L. Automatic recognition of handwritten data on cheques — Fact or fiction? *Pattern Recognition Letters*, 1999, 20(11/13): 1287-1295.

[13] Leroux M, Lethelier E, Gilloux M, Lemarie B. Automatic reading of handwritten amounts on French checks. *Journal of Pattern Recognition and Artificial Intelligence*, 1997, 11(4): 157-176.

[14] Yu M L, Kwok P C K, Leung C H, Tse K W. Segmentation and recognition of Chinese bank check amounts. *Journal on Document Analysis and Recognition*, 2001, 3(4): 207-217.

[15] Tang H, Augustin E, Suen C Y, Baret O, Cheriet M. Recognition of unconstrained legal amounts handwritten on Chinese bank checks. In *Proc. the 17th International Conference on Pattern Recognition*, Aug. 2004, pp.610-613.

[16] Ahmad I, Mahmoud S A. Arabic bank check analysis and zone extraction. In *Lecture Notes in Computer Science Volume 7324*, Campilho A, Kamel M (eds.), Berlin, Heidelberg: Springer, 2012, pp.141-148.

[17] Narima Z, Messaoud R, Mouldi B. Neuro-Markovian hybrid system for handwritten Arabic word recognition. In *Proc. the 10th IEEE International Conference on Electronics, Circuits and Systems*, Dec. 2003, pp.878-881.

[18] Farah N, Souici-Meslati L, Sellami M. Classifiers combination and syntax analysis for Arabic literal amount recognition. *Engineering Applications of Artificial Intelligence*, 2006, 19(1): 29-39.

[19] Al Ohali Y. Handwritten word recognition: Application to Arabic cheque processing [Ph.D. Thesis]. Concordia University, 2002.

[20] Miled H, Cheriet M, Olivier C. Multi-level Arabic handwritten words recognition. In *Lecture Notes in Computer Science Volume 1451*, Amin A, Dori D, Pudil P, Freeman H (eds.), Berlin, Heidelberg: Springer, 1998, pp.944-951.

[21] Miled H, Olivier C, Cheriet M, Lecoutier Y. Coupling observation/letter for a Markovian modelisation applied to the recognition of Arabic handwriting. In *Proc. the 4th International Conference on Document Analysis and Recognition*, Aug. 1997, pp.580-583.

[22] Jayadevan R, Kolhe S R, Patil P M, Pal U. Automatic processing of handwritten bank cheque images: A survey. *International Journal on Document Analysis and Recognition*, 2011, 15(4): 267-296.

[23] Lorigo L, Govindaraju V. Segmentation and pre-recognition of Arabic handwriting. In *Proc. the 8th International Conference on Document Analysis and Recognition*, Sept. 2005, pp.605-609.

[24] Parvez M T, Mahmoud S A. Off-line Arabic handwritten text recognition: A survey. *ACM Computing Surveys*, 2013 (in press).

[25] Al-Ohali Y, Cheriet M, Suen C Y. Databases for recognition of handwritten Arabic cheques. In *Proc. the 7th International Workshop on Frontiers of Handwriting Recognition*, 2000, pp.601-606.

[26] Farah N, Khadir M T, Sellami M. Artificial neural network fusion: Application to Arabic words recognition. In *Proc. Eur. Symp. Artificial Neural Networks*, Sept. 2005, pp.27-29.

[27] Farah N, Souici-Meslati L, Farah L, Sellami M. Arabic words recognition with classifiers combination: An application to literal amounts. In *Lecture Notes in Computer Science Volume 3192*, Bussler C, Fensel D (eds.), Berlin, Heidelberg: Springer, 2004, pp.420-430.

[28] Farah N, Souici-Meslati L, Sellami M. Arabic word recognition by classifiers and context. *Journal of Computer Science and Technology*, 2005, 20(3): 402-410.

[29] AlMa'adeed S, Higgins C, Elliman D. Off-line recognition of handwritten Arabic words using multiple hidden Markov models. *Knowledge-Based Systems*, 2004, 17(2/4): 757-9.

[30] AlMa'adeed S, Elliman D, Higgins C. A database for Arabic handwritten text recognition research. In *Proc. the 8th International Workshop on Frontiers in Handwriting Recognition*, Aug. 2002, pp.485-489.

[31] Maddouri S S, Amiri H. Combination of local and global vision modelling for Arabic handwritten words recognition. In *Proc. the 8th International Workshop on Frontiers in Handwriting Recognition*, Aug. 2002, pp.128-135.

[32] Ziaratban M, Faez K, Ezoji M. Use of legal amount to confirm or correct the courtesy amount on Farsi bank checks. In *Proc. the 9th International Conference on Document Analysis and Recognition*, Sept. 2007, pp.1123-1127.

[33] Alamri H, He C, Suen C Y. A new approach for segmentation and recognition of Arabic handwritten touching numeral pairs. In *Lecture Notes in Computer Science Volume 5702*, Jiang X, Petkov N (eds.) Berlin, Heidelberg: Springer, 2009, pp.165-172.

[34] Otsu N. A threshold selection method from gray-level histograms. *IEEE Transactions on Systems, Man and Cybernetics*, 1979, 9(1): 62-66.

[35] Samoud F B, Maddouri S S, EL Abed H, Ellouze N. Comparison of two handwritten Arabic zones extraction methods of complex documents. In *Proc. International Arab Conference on Information Technology*, Dec. 2008, pp.1-7.

[36] Samoud F B, Maddouri S S, Ellouze N. On segmentation methods for handwritten Arabic documents. In *Proc. the 5th International Conference: Sciences of Electronic, Technologies of Information and Telecommunications*, March 2009.

[37] Haboubi S, Maddouri S. Extraction of handwritten areas from colored image of bank checks by a hybrid method. In *Proc. the International Conference on Machine Intelligence*, Nov. 2005.

[38] Cheriet M, Al-Ohali Y, Ayat N, Suen C Y. Arabic cheque processing system: Issues and future trends. In *Digital Document Processing*, Chaudhuri B B (ed.), London: Springer, 2007, pp.213-234.

[39] Mahmoud S A, Al-Khatib W G. Recognition of Arabic (Indian) bank check digits using log-Gabor filters. *Applied Intelligence*, 2010, 35(3): 445-456.

[40] Mahmoud S A. Recognition of Arabic (Indian) check digits using spatial Gabor filters. In *Proc. the 5th IEEE GCC Conference & Exhibition*, March 2009, pp.1-5.

[41] Juan A, Vidal E. Bernoulli mixture models for binary images. In *Proc. the 17th International Conference on Pattern Recognition*, Aug. 2004, pp.367-370.

[42] Juan A, García-Hernández J, Vidal E. EM initialisation for Bernoulli mixture learning. In *Lecture Notes in Computer Science Volume 3138*, Fred A, Caelli T, Duin R, Campilho A, de Ridder D (eds.), Berlin, Heidelberg: Springer, 2004, pp.635-643.

[43] Sadri J, Suen C Y, Bui T D. Application of support vector machines for recognition of handwritten Arabic/Persian digits. In *Proc. the 2nd Iranian Conference on Machine Vision and Image Processing & Applications*, Feb. 2003, pp.300-307.

[44] Abuhaiba S, Mahmoud S A, Green R J. Cluster number estimation and skeleton refining algorithms for Arabic characters. *The Arabian Journal for Science and Engineering*, 1991, 16(4B): 519-530.

[45] Al-Ohali Y, Cheriet M, Suen C Y. Dynamic observations and dynamic state termination for off-line handwritten word recognition using HMM. In *Proc. the 8th International Workshop on Frontiers in Handwriting Recognition*, Aug. 2002, pp.314-319.

[46] Al-Ohali Y, Cheriet M, Suen C Y. Introducing termination probabilities to HMM. In *Proc. the 16th International Conference on Pattern Recognition*, Aug. 2002, pp.319-322.

[47] El-Melegy M T, Abdelbaset A A. Global features for offline recognition of handwritten Arabic literal amounts. In *Proc. the 5th International Conference on Information and Communications Technology*, Dec. 2007, pp.125-129.

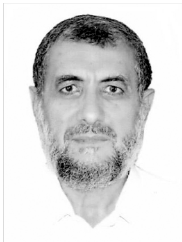
[48] Palacios R, Gupta A, Sinha S. Automatic processing of Brazilian bank checks. *Machine Vision and Applications*, 2002, pp.1-28.

[49] Gorski N, Anisimov V, Augustin E, Baret O, Maximov S. Industrial bank check processing: The A2iA CheckReader$^{\mathrm{TM}}$. *Journal on Document Analysis and Recognition*, 2001, 3(4): 196-206.

[50] Ueda K, Matsuo K. Automatic seal imprint verification system for bank check processing. In *Proc. the 3rd International Conference on Information Technology and Applications*, July 2005, pp.768-771.

[51] Kaufmann G, Bunke H. A system for the automated reading of check amounts-some key ideas. In *Lecture Notes in Computer Science Volume 1655*, Lee S, Nakano Y (eds.), Springer-Verlag, 1999, pp.188-200.

Irfan Ahmad is a lecturer in the Information and Computer Science Department, King Fahd University of Petroleum and Minerals (KFUPM), Saudi Arabia. He got his B.E. degree in computer science and engineering from Visvesvaraya Technological University, India, in 2002 and his M.Sc. degree in computer science from KFUPM in 2008. His research interests include pattern recognition, Arabic document analysis and recognition (including Arabic text recognition), image analysis and software engineering.



Sabri A. Mahmoud is a professor of computer Science in the Information and Computer Science Department, King Fahd University of Petroleum and Minerals. Dr. Mahmoud received his B.S. degree in electrical engineering from Sind University, Pakistan, in 1972, received his M.S. degree in computer sciences from Stevens Institute of Technology, USA, in 1980 and his Ph.D. degree in information systems engineering from the University of Bradford, UK, in 1987. His research interests include pattern recognition, Arabic document analysis and recognition (including Arabic text recognition and writer identification), Arabic natural language processing, image analysis and application of pattern recognition in software engineering, medical imaging, etc. Dr. Mahmoud is a senior member of IEEE. He published over 80 papers in refereed journals and conference proceedings in his research areas of interest.