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Automatic processing of handwritten bank cheque images: a survey

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Abstract Bank cheques (checks) are still widely used all over the world for financial transactions. Huge volumes of handwritten bank cheques are processed manually every day in developing countries. In such a manual verification, user written information including date, signature, legal and courtesy amounts present on each cheque has to be visually verified. As many countries use cheque truncation systems (CTS) nowadays, much time, effort and money can be saved if this entire process of recognition, verification and data entry is done automatically using images of cheques. An attempt is made in this paper to present the state of the art in automatic processing of handwritten cheque images. It discusses the important results reported so far in preprocessing, extraction, recognition and verification of handwritten fields on bank cheques and highlights the positive directions of research till date. The paper has a comprehensive bibliography of many references as a support for researchers working in the field of automatic bank cheque processing. The paper also contains some information about the products available in the market for automatic cheque processing. To the best of our knowledge, there is no survey in the area of automatic cheque processing, and there is a need of such a survey to know the state of the art.

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Keywords Bank check processing · Courtesy amount recognition · Legal amount recognition · Date recognition · Signature verification

Abbreviations

ANN	Artificial neural network
BC	Bayesian classifier
BN	Bayesian network
BPNN	Back-propagation neural networks
CM	Co-occurrence matrix
CTS	Cheque truncation system
DBC	Differential box counting
DFA	Deterministic finite automation
DTW	Dynamic time warping
ED	Euclidean distance
EDF	Extended drop fall
EER	Equal error rate
FAR	False acceptance rate
FFNN	Feed-forward neural network
FKNN	Fuzzy K-nearest neighbour
FNN	Fuzzy neural network
FPS	Fixed point-spread
FRR	False rejection rate
GB	Global baseline
GLS	Grey-level space
GRNN	Generalized regression neural network
GSC	Gradient, structural and concavity
HDF	Hybrid drop fall
HDS	Hit and deflect strategy
HMM	Hidden Markov models
HMRF	Hidden Markov random field
HNN	Hopfield neural nets
HNNC	Hierarchical neural network classifier
HT	Hough transform
ICS	Image-based clearing system

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IQA	Image quality assurance
IRD	Image replacement document
KNN	K-nearest neighbour
LBP	Local binary pattern
LGSD	Local granulometric size distributions
LS-SVM	Least squares support vector machines
MBR	Minimum bounding rectangle
MD	Mahalanobis distance
MDC	Minimum distance classifier
ME	Multi expert
MICR	Magnetic ink character recognition
ML	Maximum likelihood
MLP	multi-layer perceptron
MQDF	Modified quadratic discriminant function
MM	Mathematical morphology
MMI	Maximum mutual information
MPR	Most probable region
MRS	Multi resolution shape
MSFC	Multiple structural feature classifier
MSI	Model Sub-Image
MVBC	Majority vote method based on Borda count function
NN	Neural network
NNC	Nearest neighbour classifier
OCR	Optical character recognition
OGMM	Orthogonal Gaussian mixture model
PCAC	Principal component analysis classifier
PCC	Pseudo-cepstral coefficients
PF	Pressure features
PGM	Probabilistic graphical model
PNV	Payee Name Verification
RBF	Radial basis function
RBFNN	Radial basis function neural network
ROC	Receiver operating characteristic
RPBF	Reference pattern based features
RS	Random subspaces
SB	Structural-based
SC	Symbolic classifier
SDT	Syntax directed translation
SF	Slant features
SLFFNN	Simple-layer feed-forward neural network
SOM	Self-organizing map
SSE	Sum-of-squared error
SVM	Support vector machines
TB	Template based
TS	Takagi–Sugeno
TDNN	Time delay neural network
TSI	Target sub image

1 Introduction

Machine simulation of human reading has become a promising area of research after the arrival of digital computers. The main reason for that is not only the challenge in simulating the human reading but also its utility in developing document processing systems capable of transferring data present on documents like bank cheques, commercial forms, government records and envelops into machine readable format. Paper cheques still play a big role in the non-cash transactions in the world even after the arrival of credit cards, debit cards and other electronic means of payment [1]. In many developing countries, the present cheque processing procedure requires a bank employee to read and manually enter the information present on a cheque (or its image) and also verify the entries like signature and date. As a large number of cheques have to be processed every day in a bank, an automatic reading system can save much of the work. Even with the success achieved in character recognition over the last few decades, the recognition of handwritten information and the verification of signatures present on bank cheques still remain a challenging problem in document image analysis [2–4].

To save time and processing costs in clearing the cheques and to offer better customer services, many countries around the world have implemented cheque truncation systems (CTS) [or image-based clearing system (ICS)]. Instead of sending a physical cheque for clearance, the presenting bank captures the image of the paper cheque using suitable hardware and software. The image then will go through various clearing steps, and the transaction will be settled based on the image data. The cheque images can be black and white, grey scale or coloured. Black and white images do not reveal all the subtle features that are there on the cheques. Colour images increase storage and network-bandwidth requirements. So it was decided in countries like India that the electronic images of truncated cheques will be in grey-scale technology [5]. In countries like the United States, after an image of a cheque is transmitted electronically, those banks that cannot process the image electronically can print the image replacement document (IRD), which is then processed similar to a traditional cheque [6]. In countries like India, under the cheque truncation system (CTS), after capturing the image, the paper cheque would be warehoused with the presenting bank. In case the beneficiary or any other connected persons require the instrument, the payee bank could issue a paper copy of the image (IRD), under its authentication. IRD has become a legally recognized replacement of the original cheque for re-presentment [5].

Legal amount, courtesy amount, date, payee details and signature are the fields to be filled by an account holder on a bank cheque as shown in Fig. 1. (In India, the word ‘lac’ or ‘lakh’ is used to write value equivalent to 100,000.) The signature present on the cheque ensures the authenticity of it. Banks have the freedom to customize some parts of the cheques such as the background pattern, which is generally used to personalize the cheques. They can use different colours and imprinted textures. Other variations that may occur

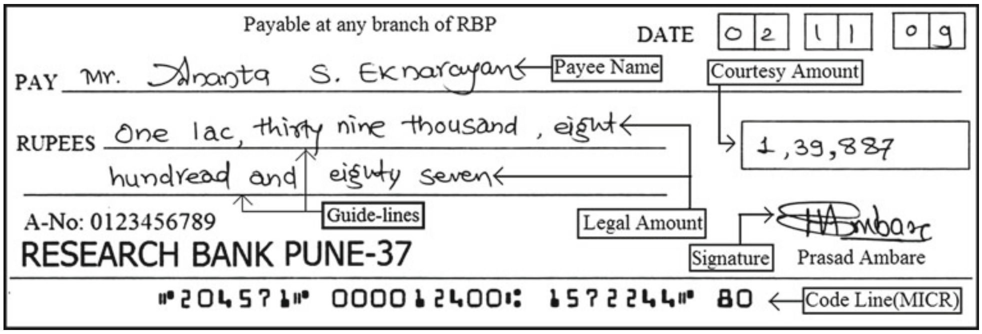

Fig. 1 Image of an Indian cheque written in English language

Fig. 2 Images of handwritten bank cheques from different countries: **a** Brazilian [1], **b** American [203], **c** British [203], **d** Iranian, **e** Chinese [97] and **f** Indian

among the cheques issued by different banks are different fonts, special symbols, logos, lines, etc. Images of cheques from different parts of the world can be seen in Fig. 2. The two fields for writing the value of the cheque named legal and courtesy amounts are intended for redundancy. In case of a disagreement, the legal amount is selected. However, a disagreement between legal and courtesy amount shall be an indicator of amount alteration. The first field (legal) contains the amount written in words, and the second field (courtesy) contains the amount written in numerals. It is considered that the cheque amount recognition has to rely on both courtesy and legal amount recognition. The underlying principle behind this view is that the expressions of a given amount into digits and words are so different that the recognition errors on both sides are likely to be uncorrelated [7]. Automatic recognition of handwritten dates present on bank cheques is also very important in application environments where cheques will not be processed prior to the dates shown. In countries

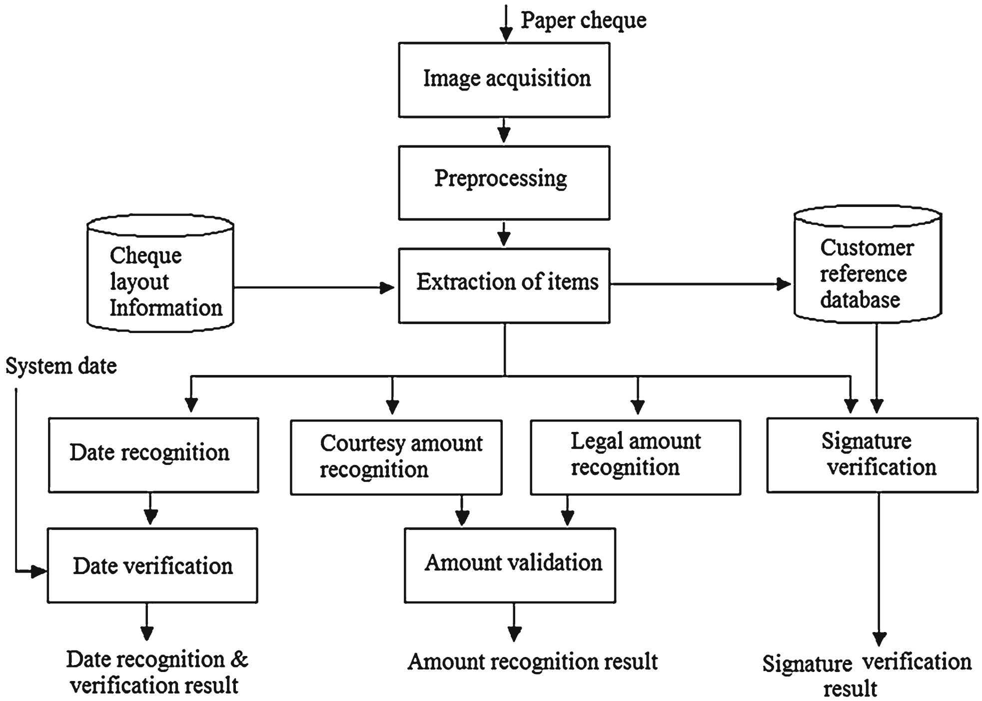

Fig. 3 Main steps involved in automatic bank cheque processing

like India, a cheque cannot be processed after 6 months of the date written on it. Verification of the handprinted signature present on a paper cheque is inevitable as the signature carries the authenticity of the cheque. The main steps involved in automatic processing of a bank cheque are shown in Fig. 3, where the first step is to obtain the image of the paper cheque using a scanner. Preprocessing and segmentation modules follow the image acquisition step. The verification and recognition of different information present in the cheque are done after the extraction phase. Nowadays while processing a cheque, banks are interested to read automatically as much information as possible from the document. This may include the payee-name, payer's address (if present), payer's account number, name of the issuing-bank and code lines [8].

In 1997, a collection of various papers on automatic processing of bank cheques was published in the form of a book edited by Sebastiano Impedovo et al. [9]. Till date, there is no survey paper published in the area of automatic bank cheque processing as per our knowledge. It is obvious that a survey of existing techniques related to the automatic processing of bank cheques will be a great asset to the researchers working in the area. Therefore, in this paper, it is tried to highlight the issues like preprocessing, extraction and recognition of handwritten information and verification of signature.

The paper is organized as follows. Main aspects related to preprocessing like quality assurance, authentication, binarization, skew correction, slant correction and normalization are presented in Sect. 2. The issues related with the extraction of different fields are discussed in Sect. 3. The courtesy amount recognition part is divided into two subsections for discussing touching numeral segmentation and digit recognition, respectively, and they are discussed in Sect. 4. Correspondingly, the legal amount recognition part has three subsections: guideline removal, amount segmentation and word recognition, and they are presented in Sect. 5. The date recognition techniques are discussed in Sect. 6. Cross validation of legal and courtesy amounts is required to achieve higher reliability at the system level for industrial applications. The related works in this area are discussed in Sect. 7. Various signature verification techniques are discussed in Sect. 8. Techniques related to the recognition of payee-name field are discussed in Sect. 9. Nowadays, cheque processing has become an industry, and Sect. 10 of the paper deals with some of the products available in the market for automatic cheque processing. It will help the readers to understand the recent trends in the cheque processing industry. Some observations made during the survey and some challenges in automation are also pointed out in Sect. 11. The survey is finally concluded in the last section.

2 Preprocessing

One of the challenges faced in the adoption of image-based cheque clearing is the 'need' to ensure that high-quality cheque images are transmitted for clearing through the clearing house. If the image is of low quality, then the receiving bank may not be able to process the image for clearing and may result in a cheque return. As the cost of processing 'cheque-returns' is multifold compared to a normal clearing, it is desirable to minimize the incidences of bad cheque-image quality. '3i-Infotech' has developed an image quality assurance (IQA) validation engine, which is a standalone tool that can be used for performing IQA on any cheque image [10]. Another commercial product called 'A2iA check-reader' is capable of locating and reading information from image replacement documents (IRD) or substitute cheques, which are used in Check 21(Cheque Clearing for the 21st Century Act) image exchange in United States [11]. Some of the image quality attributes considered by A2iA check-reader are: 'partial image', 'excessive image skew', 'piggyback image', 'image too light or too dark', 'streaks and/or bands on the image', 'below minimum image size and above maximum image size'. Silver Bullet's 'Ranger-IQA' software is also used for cheque-image quality assurance during the image capturing step. This allows many cheque-image quality problems to be detected at the source before truncation. The quality attributes considered include the following: 'undersize image', 'oversize image', 'below minimum compressed image size', 'above maximum compressed image size', 'excessive document skew', 'image too light', 'image too dark', 'horizontal streaks present in the image', 'folded or torn document corners and edges', 'document framing error', 'excessive spot noise in the image', 'front-rear image dimension mismatch' and 'carbon strip detected' [12]. The following subsections discuss different techniques reported in the literature regarding the preprocessing of bank cheque images.

2.1 Image quality assurance

Quality assurance (QA) plays a crucial role in document digitization projects by making sure that the specified quality standards are reached under cost and time constraints [13]. Many algorithms based on text line distortion models [14–16] are proposed to deal with the nonlinear folding of documents. Sometimes, folding (warping) can be serious that the contents of the document become unreadable. As the actual capturing area is usually larger than the area of interest, junk regions can be present in the forms of black/shaded borders. Fan et al. [17] combined two cropping algorithms, one based on line detection and the other based on text region growing, to achieve robust cropping. Bourgeois et al. [18] proposed an algorithm based on morphological techniques to detect and remove line-frames. Sometimes, poor document quality makes it difficult to capture high-quality images. In large scale document digitization projects, the main challenge is to automatically decide 'when to apply which enhancement'. Image enhancement techniques may adversely affect an image's quality if applied to a wrong image. Boutros in [20] proposed a prototype that can automate the image enhancement process. It is clear that the quality of image acquisition affects the later stages of document image processing. A list of general suggestions for quality control is given in [21]. It is suggested that scanning with 400dpi colour will be sufficient for the next 10 years for applications where scanning is being done just for the purpose of understanding the content.

2.2 Authentication of document

Garain and Halder in [22] presented a technique towards the automatic authentication of bank cheques. Support vector machines (SVMs) and neural networks (NN) were used for the same. The proposed method first computationally extracts the security features from the document images before classifying them into 'genuine' and 'duplicate'. Security features on bank cheques are grouped into three distinct areas namely 'Security design or background artwork', 'Use of color inks' and 'Paper and printing process'. Light fine-line printing or other security patterns that appear on the background of cheques are difficult to reproduce by ordinary printing techniques. Colour ink pigments and special ink types (fugitive inks, thermo chromic inks) also contribute substantially to the security of cheques. Sometimes, paper manufacturers use their own watermarks to provide additional visual protection. The printing process (technique) also provides security to documents like bank cheques. For instance, intaglio printing (used for printing bank cheques) is a special kind of off-set printing that gives the document a very high-quality look that is difficult to reproduce by scanners, colour copiers or colour laser printers. Use of MICR (magnetic ink character recognition) characters at bottom of the bank cheques (for code lines) is also considered as a security means.

Most banks nowadays offer 'positive-pay' services to their corporate customers which have been very successful in identifying counterfeit and altered cheques at the time of presentment [23]. For cheques issued by 'positive-pay' customers, an image-enabled solution namely PNV (Payee Name Verification) enhances the service by detecting the payee line alterations (if any). A tamper-proof encrypted code is printed on the cheque in the form of a bar-code. This encrypted code allows banks to prove authenticity at the point of presentment.

2.3 Binarization

Binarization of the input cheque image is the first step in most of the cheque processing systems reported so far. It is the process by which the foreground and background pixels are represented by '1's and '0's or vice versa [3]. Binarization of a grey-scale cheque image is complicated due to several causes including complex backgrounds, imprinted seal and different intensities of handwritten characters. In general, the binarization techniques can be categorized into two classes: global and local thresholding. Global thresholding algorithms use a single threshold for the whole image, while local thresholding algorithms compute a separate threshold for each pixel based on its neighbourhood [24]. Sahoo et al. [25] compared the performances of more than 20 global thresholding algorithms using uniformity or shape measures. The comparison showed that Otsu's class separability method [26] performed best. Trier and Jain [27] evaluated the performances of 11 established local thresholding algorithms. In that evaluation, algorithms of Niblack [28], Yanowitz and Bruckstein [29], White and Rohrer [30], Trier and Taxt [31] and Parker [32] produced high recognition rates. Some well-established binarization algorithms were compared in the work reported in [24], where binarized outputs were fed into an offline handwritten recognition engine that uses pre-trained neural networks for character classification. A scoring package is then used to automatically examine the recognition results. A survey of various thresholding techniques up to 2004 is discussed in [33].

In [3], a method based on signal matching is proposed to binarize Chinese bank cheque images. The image projection function without noise is the source signal. The projection function of image binarized by an iterative threshold will match the source signal, and the threshold for which the projection function matches best is considered as the optimum threshold. In [24], the binarization of a part of a Canadian cheque image that suffers from noise interference [target sub-image (TSI)] is done using information easily extracted from another noise-free part of the same image [model sub-image (MSI)]. Simple spatial features are extracted from MSI and are used as models for handwriting strokes. This model captures characteristics of the writing strokes and is then used to guide the binarization of the TSI. The binarization algorithm proposed in [34] defines an initial threshold value using percentage of the desired density of black pixels to appear in the final binarized image. After this, a correction is made using receiver operating characteristic (ROC) curves. To improve the efficiency of the algorithm, a cubic function makes a relationship between the initial threshold value and the final one.

In [1], the binarization of the grey-scale image is done with a threshold value calculated dynamically based on the number of connected components in the area of courtesy amount. In [35], initially, the image is smoothed using a mean filter. The background is then eliminated through an iterative thresholding. In [36], gradient and Laplacian values are used to find whether an image pixel belongs to background or foreground. The binarization approach proposed in [37] is based on Tsallis entropy to find the best threshold value. It also uses Histogram specification for preprocessing some images. To eliminate the background from the cheque image in [38], a stored background sample image is subtracted from the skew corrected test image. A binary printed information pattern is generated and is then subtracted from the background free image to generate an image containing only filled information. The background residual noise is eliminated using erosion and dilation operations. To deal with broken lines on cheques, logical smearing is applied with the help of end-point co-ordinates of detected lines in [39]. In [40], the preprinted data present on Chinese bank cheques are eliminated by a subtraction process according to their colour.

2.4 Skew and slant correction

The skew occurred while scanning the cheque can be detected by finding the angle that the guidelines (baselines for writing) make with the horizontal direction (X-axis). This approach would be convenient as almost all the cheques contain guidelines for user inputs. Skew correction is done by simply rotating the image in the opposite direction by an angle equal to the inclination of the guidelines. A comprehensive survey on different skew detection techniques is done in [41]. In [42], the skew of a cheque image is calculated by computing the histograms of pixel densities between $+5$ and -5 degrees with respect to the horizontal axis. Due to the presence of guidelines, the histogram with longest peak corresponds to the skew of the cheque image. To correct the rotation and translation occurred during the image acquisition process, a method based on projection profile [43] has been used in [38].

Slant is the deviation of handwritten strokes from the vertical direction (Y-axis) due to different writing styles. It has to be detected and corrected for successful segmentation and recognition of handwritten user inputs. Different techniques for the same can be found in the surveys carried out in [44] and [45]. In [46], a chain code representation is used for calculating the slant angle of handwritten information. In [47] and [48], the average slant of a word is determined by an algorithm based on the analysis of slanted vertical histograms [49]. The heuristic for finding the average slant is to search for the greatest positive derivative in all the slanted histograms. The slant is then corrected through a shear transformation in the opposite direction. Also in [50] and [51], the slant of handwritten information is computed using the histogram of the directions of the contour pixels.

2.5 Normalization

Image size normalization is a crucial preprocessing stage in the development of robust recognizers [52]. It is also relevant in automatic cheque processing systems as in the United States an image replacement document (IRD) is created with a reduced (70%) image of the cheque. Size-invariance is a key to any robust recognition system. The size normalization step attempts to obscure scale variations of images presented to a recognizer. It is a transformation of an input image of any arbitrary size into an output image of a fixed pre-defined size without compromising the structural details. A method for image size normalization based on multi rate filter theory is proposed in [52]. The proposed method was found better than the ratio-based normalization technique and the simple scaling technique. In the ratio-based normalization technique, the value of each pixel in the output image is calculated as a weighted average of the overlapping pixels in the input image. In the simple scaling normalization, a scaling-factor is first calculated by the ratio of the original image height to the new image height. If the width of the image scaled by the same ratio fits in the specified dimension, then the scaling-factor is selected for further processing. If the normalized width exceeds the specified width, another scaling-factor is applied to reduce the width further.

3 Extraction of handwritten fields

After pre-processing, it is necessary to perform the extraction operation of different handwritten fields prior to their recognition. In [53], for American bank cheques, the extraction of legal amount includes the extraction of 'dollar' and 'cent' portions of the amount. This process is initiated by searching for a long horizontal line, which is usually written after the dollar part. If such a line is not present, the right side of the image is searched to find dashes and slashes to locate the cent portion. In [53], the courtesy amount recognition starts with the localization of handwritten numerical string based on the location of the courtesy amount. The removal of irrelevant objects like lines and box is based on Hough Transform. The dollar and cent portions of the courtesy amount are separated using characteristics such as size, shape, relative position, etc. The algorithm has about twenty simple rules to achieve this. A method based on baselines (guidelines) is used in [19] and [54] to extract the handwritten date, courtesy and legal amounts of Canadian bank cheques. The guideline for legal mount is found by analysing the lengths of the lines extracted trough edge detection. The guidelines for date and courtesy amounts are detected by using the layout information of Canadian cheques. A searching region and a bounding region are decided for each field, and the grey-scale distributions of the handwritten strokes related to each item are extracted by tracing the connected components.

In [55], a blank reference image is used to extract the user-entered components from a handwritten bank cheque. An inter-image morphological subtraction that consists of a GLS (grey-level space) fusion procedure and a logical subtraction procedure (in GLS) is used in the paper to extract the handwritten fields from a cheque. In [42], three features are used to locate the courtesy amount field in French cheques: the horizontal line on which the numerals are written, the letters B.P.F, and the histograms showing the pixel densities in the upper right corner of the image. The box or line in the courtesy amount field is removed by analysing the thickness, direction and curvature of the line components without causing damage to the numerals. The legal amount is located using the presence of two horizontal and parallel guidelines. In [56], Hough transform is used to detect guidelines and boxes on French cheques. The letters B.P.F are used to find the beginning of the courtesy amount. To classify the handwritten and preprinted information in the area of courtesy amount, a classification is performed based on the regularity properties of machine printed text. In [7] also, the guidelines and the letters B.P.F are used to detect the legal and courtesy amounts, respectively. Guidelines are detected using a line following algorithm, and the letters B.P.F are detected by a character recognizer.

For bank cheques written in Bengali language [57], a template describing the locations of user-entered data is used to extract the areas of interest. A stored background pattern is then subtracted from these sub-images to eliminate the background. In [1], the concept of minimum bounding rectangle (MBR) is used for locating the courtesy amount string. For Indian bank cheques in [39], the most probable region (MPR) for finding courtesy amount is determined using configurable rules and semantic analysis. The exact location of courtesy amount is determined by detecting the surrounding bounding box. Generally in India, the courtesy amount is located on the right half of the cheque. A box is detected by identifying the cross-section points where horizontal and vertical lines meet. Another method proposed for extraction in [36] uses fuzzy membership values, entropy, energy and aspect ratio as features, which are fed into a fuzzy neural network (FNN) for the identification of a field. For the extraction of user-entered data from Brazilian bank cheques in [58], a template is used to extract the areas of interest. For each of the resulting sub-images, the background pattern is eliminated by a subtraction operation; the machine printed character strings are eliminated by a subtraction operation between the sub-image and a generated binary image containing the same character string.

A method is discussed in [59] for locating the courtesy amount block on American bank cheques. The connected components in the image are detected first. Then, strings are constructed on the basis of proximity and horizontal alignment of characters. A set of rules and heuristics are applied to these strings to choose the correct one. The selected string is accepted only if it passes a verification test including an attempt to recognize the currency sign. In [60], for Arabic bank cheques, two methods based on mathematical morphology (MM) and Hough transform (HT) for the detection of lines and boxes are compared. It is found that the Hough transform-based method performs better than the mathematical morphology. For the extraction of date, signature, seal imprint and courtesy amount from Japanese bank cheques in [61], the areas of interest are initially located using a template. The filled-in items are then extracted using their colour characteristics. An extraction method based on support vector machines (SVM) is proposed in [62] for Chinese bank cheques. The bank logos are initially recognized using an SVM using layout information and projection profile features. Cheque type characters are then recognized using another SVM with projection profile feature. After knowing the bank and the cheque type, a blank template of the cheque is used to subtract it from the real cheque to get the filled-in items.

In [63], the baselines and background are eliminated by subtracting a blank template from a filled one. For each connected component on the cheque image, its minimal bounding box is found. A box receives the label of an item if it minimizes its specific distance for that item. Reconstruction of the truncated written lines is based on the assumption that a written line does not change its curvature while intersecting with graphic background lines. A method to segment unconstrained handwritings on Iranian bank cheques based on mathematical morphology and connected component analysis is proposed in [64]. A local thresholding technique to separate handwritten strokes from the background is discussed in [65], where baselines are extracted using mathematical morphology and with the layout description obtained by analysing these extracted baselines, the connected components are detected and grouped together to extract the handwritten fields. For the identification of printed and handwritten items in [66], 2-D histogram features, typographical features and morphological features are extracted. The most suitable features are selected using a method based on the separability measure. A Bayesian classifier (BC) then uses the selected features to realize the discrimination.

In order to separate the handwritten dates into day, month and year fields in [67], the segmentation process includes a preprocessing step, a separator detection step and a segmentation and hypothesis step. In the preprocessing step, the image containing high noise is rejected. The machine printed information '19' is used to separate the year field. To differentiate the day and month fields if there is no delimiter between them, the following information has been used: distance-to-digit measure and contextual analysis, confidence value from a connected digit recognizer [68], maximum number of runs and width feature. If delimiters like punctuations are present, some space and shape features [68] are used to recognize them. Same results are shown in [69] also. A knowledge-based segmentation scheme is employed in [70] for the segmentation of date field into day, month and year fields for English and French bank cheques. The possible separator candidates are first detected using shape and spatial features. Some separator candidates are easily confirmed or rejected based on a set of rules formed using the knowledge of writing style.

Almost all cheques have some machine printed information present on them. In [71], a set of shape-related and content-related features are used to discriminate machine printed and handwritten fields. Area and perimeter are useful in searching for regular machine printed patterns. Eccentricity is another measurement, which is the ratio between the lengths of their major and minor axes of the ellipse covering the pattern. An additional way to measure the elongation of a pattern is to determine its rectangularity, which is the ratio between the area of the pattern and the area of its bounding box. The nearer the result to 1, the more rectangular is the pattern. It is noted that machine printed patterns are more consistent in the variability of their grey levels. Range is another useful aspect that shows the consistency of grey levels. Another attribute stroke density is defined as the ratio between mass and volume, where mass is represented by the number of different grey levels in the object and volume is defined as the total number of pixels in the object. Other statistical features can also be used, such as kurtosis, which gives an idea of the degree of distribution of the grey levels in some textual objects. In [72], an algorithm is presented, which is based on the theory of hidden Markov models (HMM) to distinguish between machine printed and handwritten materials. In [73], a method based on projection profile and line merge is proposed to extract handwritten patterns. A sliding window approach is described in [74] to extract signatures from cheque images. Djeziri et al. in [75] tried to tackle the problem of extracting hand-printed signatures by means of an intuitive approach which is very close to human visual perception. They defined a topological criterion specific to handwritten lines that they called filiformity. This approach is inspired by the existence cells in the human eye whose specialized task is the extraction of lines. In [76], the classification of different extracted fields is done using a 'differential box counting' (DBC) method, which calculates the fractional dimensions of the data fields. Table 1 shows the performance details of some of the extraction techniques. The data set shows the number of cheques used for testing the techniques.

4 Courtesy amount recognition

Courtesy amount on bank cheques normally appears as a string of numbers with symbols or characters representing the value of the currency type as shown in Fig. 1. Punctuations like slash ('/'), comma (','), hyphen ('-') and full stop ('.') also appear in the courtesy amount field depending on the writing style of the user. While writing courtesy amount, the digits may touch each other. As a result, the touching numerals have to be successfully segmented before the recognition

Table 1 Performance details of some handwritten field extraction methods

Method	Technique used	Cheque type	Fields	Data set	Success (%)
Agarwal [59]	Rule based	American	Courtesy amount	54	94.4
Madasu [36]	FNN	American	All fields	923	90
Samoud [60]	Hough transform	Arabic	All fields	1,775	96–98
Koerich [58]	Image subtraction	Brazilian	All fields	120	95–99
Santos [71]	Shape and content	Brazilian	All fields	5,035	76
Ye [65]	Morphology	Canadian	All fields	499	100
Liu [19]	Guideline & Layout	Canadian	All fields	196	97–99
Djeziri [63]	Image subtraction	Canadian	All fields	60	96.6
Suen [67]	Rule based	Canadian	Year, month, day	809	83.19
Xu [70]	Knowledge based	Canadian	Year, month, day	3,399	82–90
Xu [66]	BC	Chinese	Date, legal amount	12,158	98–99
Heutte [56]	Hough transform	French	Courtesy amount	3,374	98
Alirezaee [64]	Morphology	Iranian	All fields	500	94.4
Ueda [61]	Colour information	Japanese	Seal imprint	19	94.7

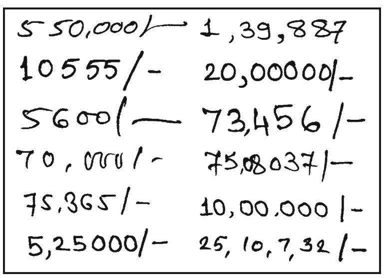

Fig. 4 Some handwritten courtesy amounts

task. Figure 4 shows some handwritten courtesy amounts extracted from different handwritten cheques. Many papers are available on the topic of segmentation and recognition of handwritten numerals. A survey of segmentation techniques used for touching handwritten characters is reported in [77]. A review of various feature extraction techniques is done in [78], and all major character recognition techniques are discussed in [79]. The main steps in the recognition of courtesy amounts are segmentation of touching numerals and the classification of individual digits as discussed in the following subsections.

4.1 Segmentation of touching numerals

Because of different writing styles, some digits in a numeral string (courtesy amount) may touch each other. Such touching digits have to be separated successfully before the recognition step. Some authors claim that there are two types of approaches used for segmentation of touching numerals: local and global. Cutting points between the two touching numerals are extracted in local approaches, and in global approaches, significant splitting points are detected after analysing the numeral string as a whole [80]. A segmentation-based courtesy amount recognition system is presented in [81] where a two-stage segmentation module has been proposed: the global segmentation stage and the local segmentation stage. In the global segmentation stage, the courtesy amount is coarsely segmented into sub-images according to the spatial relationships of the connected components. The recognition module then verifies these sub-images, and the rejected sub-images are divided sequentially using contour analysis in the local segmentation stage. In [7], the segmentation is based on a set of heuristic rules designed by analysing large number of examples. Prospective cut points are situated at the locations determined by minima of the upper contour or maxima of the lower contour. In [82], the segmentation is carried out using monotonic fuzzy valued decision functions computed by feed-forward neural networks.

In [83], the courtesy amount string is segmented into isolated digits using a two-level segmentation approach consisting of local and global approaches. At the first level, each connected component block is given as input to all the recognizers. Recognized blocks are removed from the input image, and the remaining blocks are fed to the second level, where a drop-falling algorithm and a contour-based algorithm are sequentially applied. After each segmentation procedure, the block is divided into two sub-blocks, and they are fed again into the digit recognition system. For segmenting the handwritten courtesy amount strings in [84], a drop-falling method and an upper-lower contour method are applied after identifying the connected components. The isolated components after segmentation are fed into a digit recognizer. If all components are recognized correctly, the segmentation is accepted. A new segmentation hypothesis is taken into account if the recognition is not completed. If the recognition fails for each and every segmentation hypothesis, the cheque will be rejected. In [42], for each connected component, the probability of representing a single character is computed using several geometric features. Large connected components are split along straight lines according to a set of criteria. Again, the probability of representing a single character is computed for each part of the split operation. Positions of the connected components are analysed to detect objects like comma, full stop, etc. In [35], the connected components are found by contour tracing. Connected components with a perimeter length below a specific threshold are rejected. Recognizing the leftmost digit in the connected component carries out the segmentation of touching numerals. If successful, the remainder of the component is recognized recursively.

In [56], the segmentation is based on a pre-recognition task, which controls the digit extraction. Initially, all connected components are detected and small components, which do not respond to size and position, are removed. Connected components containing touching digits must respond to some requirements on location and morphological measurements. A supervisor unit capable of undoing a particular task or preventing the application of it controls the consistency of these operations. In [38], the segmentation process isolates each connected component and detects symbols like commas and dash-lines with their relative low heights to the adjacent numerals. To segment the touching numerals, morphological convolution masks are applied to find the touching part and subsequently separate the touching numerals. For the segmentation of courtesy amount in Chinese bank cheques a combination of dissection, holistic and recognition-based method is used in [40]. In the dissection method, the contour tracing is done first. The broken parts of a digit found in its maximum area are then merged together. The bigger connected components are sent to the segmentation step of recognition-based method as well as holistic method. The recognition-based method then finds the connecting strokes or ligature between digits using features like upper contour, lower contour, vertical width and vertical projection. Holistic method is mainly used for sub-strings containing many zeros. The most distinctive feature considered in the work for connecting zeros is the presence of loops.

In [85], connected components are found by tracing contours. The digit splitter operates by attempting to segment and recognize the leftmost digit from a connected component. If successful, it tries to recursively recognize the remaining part of the string. It attempts up to 5 cuts to separate each digit in the numeral string. The segmentation and recognition processes in [1] are performed using a feedback loop, where different segmentation attempts are evaluated until the goal is achieved. The segmentation is performed by a hybrid drop fall (HDF) algorithm [86,87] and an extended drop fall (EDF) algorithm [88]. In [89], the connected components are extracted using vertical projection and isolated component analysis. Then, the length estimation of connected components is carried out using syntax analysis and waveform analysis. The segmentation of connected numeral strings is finally done using a reverse 'dropfalling' algorithm.

Three techniques used in [90] to segment the touching numerals are connected component extraction, upper and lower contour splitting and the hit and deflect strategy (HDS). After segmentation, an analysis module classifies the symbols into primitive sets, and the syntactic correctness is checked. A legal amount estimator unit decodes the handwritten word representation of the legal amount to find the number of digits in the courtesy amount. The syntactic parser output of the courtesy amount and the legal amount estimator output are decoded by an evaluation unit that determines the validity of the segmentation and re-segments if necessary. In [91], the segmentation is based on the relationship of two complementary sets of structural features called contour profile and skeletal points. The algorithm takes into account an over-segmentation context, and its final objective is to provide the best list of hypotheses of segmentation paths without any a priori knowledge about the context.

4.2 Digit recognition

The accuracy in recognizing constituent digits plays a big role in the recognition accuracy of the handwritten courtesy amount numeral string. After successful segmentation of individual digits from the numeral string, they have to be correctly recognized to get the value of the cheque. From the literature, it is evident that the digit recognition techniques can be grouped into neural network based techniques and other prominent techniques as discussed in the following subsections.

4.2.1 Neural network-based techniques

A neural network consists of an interconnected group of artificial neurons, and it processes information using a connectionist approach. A neural network changes its structure based on external or internal information that flows through the network during the learning (training) phase [92]. The digit recognition module in [7] is based on a combination of a radial basis function (RBF) network using a concavity feature vector and a time delay neural network (TDNN). An RBF is a type of neural network having three layers, and a TDNN is a multiplayer perceptron. Individual digits are recognized in [83] based on a multi-expert approach consisting of pattern matching, crossing line, histogram formation, contour slope, region enhanced loci, structural-based matching and neural network. The A2iA system in [42] uses a number of features and different classification algorithms. Mainly three types of features are considered in the work. The first type of features includes height, aspect ratio, profile and number of intersections with horizontal and vertical lines. The second type of features includes the structural features like loops, ascenders, strokes in different directions, concavities and convexities. Features of the third type depend on the position of the digit relative to the text line. The classifiers used are as follows: Bayes classifier (BC); template-based (TB) classifier and neural network (NN)-based classifier.

The set of features used for digit recognition in [38] is divided into two groups. The first group of features contains holes and their relative locations, number of intersections with the principal and secondary axis and crossing sequences. The second group of feature includes the distribution of foreground pixels and the relative positions of intersecting strokes. The classification procedure in [38] is done in two stages. The first stage is a rule-based classification, and the second stage is a neural classification based on Hopfield neural nets (HNN). In [40], three classifiers are developed for digit recognition. They are hierarchical neural network classifier (HNNC), multiple structural feature classifier (MSFC) and principal component analysis classifier (PCAC). The HNNC uses neural networks to recognize the digits; MSFC uses multiple structural features including stroke features and contour features. The PCAC is based on principal component analysis and employs statistical features. In [46], the courtesy amount recognition is done after the legal amount recognition. The legal amount is converted into corresponding digit string and used as a reference for the courtesy amount recognition. In [85], the digit recognition is done by extracting pixel distance features for classification by a back-propagation neural networks (BPNN).

In [50], the courtesy amount recognizer has four main components. A pre-segmentation module divides the input digit string into independent groups of digits containing one or more digits using projection-based features. Two recognition units then process each group: The digit detection unit recognizes those groups that contain only one isolated digit using features from contour information. The segmentation-free unit recognizes the remaining groups. For both the recognizers, a fully connected feed-forward multi-layer perceptron (MLP) is used for classification. These groups with more than one digit are further processed by searching for possible segmentation points and classifying the segmented parts. A global decision unit finally merges all results to a numeral string. The digits in [35] are recognized by a combination of three back-propagation neural networks (BPNN) using pixel distance features as input.

For the courtesy amount recognition of American bank cheques in [1], each isolated digit image undergoes slant correction, size normalization and thickness normalization. The slant correction algorithm is based on the idea that if the pixels of a numeral are moved horizontally through a series of slanted positions, the digit attains its minimum width when it is least slanted. The classification of digits is performed using structural analysis and multi-layer perceptrons (MLP). The recognition module has an array of three to four neural networks working in parallel. Their results are analysed by a function which can select or reject the results. In a post-processing stage, the resulting numeral string is analysed using deterministic finite automation (DFA) to verify whether the recognized value is a valid amount or not. Two MLP classifiers are combined into a single module for the purpose of recognition in [81]. In [93] and [94], it is proved that by combining MLPs, one could improve the accuracy of courtesy amount recognition. In [95], it is shown that the results can be improved further by combining one MLP with a generalized regression neural network (GRNN) and Elman back-propagation MLP (ELM). In countries like Brazil, the use of delimiters is very common in the courtesy amount field. On an average, 36% of the Brazilian cheques contain delimiters. In [4], the problem of recognizing delimiters in courtesy amount fields is investigated, and a new approach is proposed which combines different MLP classifiers to perform the recognition of delimiters and digits.

4.2.2 Other prominent techniques

The courtesy amount recognition module in [56] is based on a combination of two classifiers based on cluster hyper planes. The first one is based on concavity features, and the second one is based on statistical and structural features. The output of the recognition module is the ordered list of classes with decreasing confidence level. The digit string recognition in [53] is based on matching the input sub graph with graphs of symbol prototypes as described in [96]. The symbol prototype consists of the symbol graph and description of its elements in terms of geometrical characteristics of edges, mutual position of edges and nodes, etc. First, a graph of the input string is created. Then, the digit string is segmented into separate symbols. After selecting the sub graphs of the input string, each sub graph is compared with the prototype. Some transformations are applied to the sub graph during the matching process. A match is found if there is an isomorphism between the transformed sub graph and a part of the prototype.

Before courtesy amount recognition in [39], a number of symbols including currency symbol, delimiters, terminals and noise are removed. Recognition of numeral string is based on concurrent concatenation and recognition using dynamic programming optimization. A modular system to recognize numerical amounts on Brazilian bank cheques is presented in [91]. The system uses a segmentation-based recognition approach, and the recognition function is based on a recognition and verification strategy. This approach consists of combining the outputs from different levels like segmentation, recognition and post-processing in a probabilistic model. A new feature set is fed to the verifier module to identify the segmentation effects such us over-segmentation and under-segmentation. In [97], the handwritten numeral classifier is based on a combination of self-organizing map (SOM) and a fault tolerant (FT) technique based on a dynamic cipher code. In [98] and [99], for the recognition of courtesy amount on UK, US and French bank cheques, the segmentation process produces several options, each option is then processed and interpreted separately. Four complementary optical character recognition (OCR) systems recognize potential characters producing a list of class candidates with associated probability estimates. A log-linear integrator [100] combines the OCR results and outputs the final class probability estimates. Table 2 shows the performance details of some courtesy amount recognition systems with highest level of confidence. The performance is given at digit level and full amount level. From the table, it can be seen that the amount level accuracies are lower than the digit level accuracies.

5 Legal amount recognition

The legal amount is the value of a cheque written in words. As it is difficult to modify the legal amount, higher priority is always given to legal amount than the corresponding courtesy amount. The recognition of legal amount present on a bank cheque is a big challenge because of the structural complexity of characters and variability of writing styles. There are mainly two types of approaches used for handwritten legal amount word recognition: analytical and global (holistic). In analytical approaches, each handwritten word of the legal amount is recognized by recognizing its constituent characters. For the same, a word is segmented into components like characters or graphemes (part of a character) first. Analytical approaches can still be divided into full character recognition methods and sub-characters recognition method. In global approaches, the entire word is considered as a single unit (pattern), and recognition is done without any sort of character-level segmentation. As the legal amount words written in English language can be case sensitive as shown in Fig. 5, the size of the lexicon for word-level recognition can go up significantly [101]. Various techniques for the recognition of handwritten words can be found in the surveys carried out in [44,45] and [102]. A survey of character level segmentation of handwritten words is done in [103]. Papers directly related to the processing of legal amounts and bank cheques are only considered here in the coming sub-sections. The important steps in legal amount recognition are guideline removal, segmentation of the amount into words and the classification process as described in the following subsections.

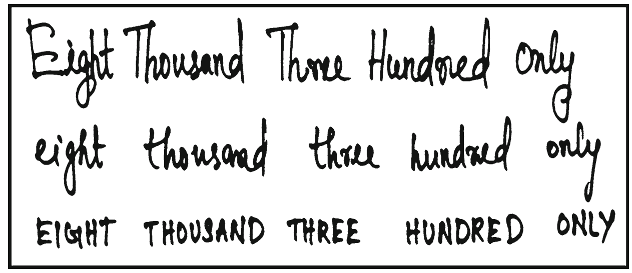

Fig. 5 Different ways of writing the same legal amount

5.1 Guideline removal

Guidelines (base lines) are present on cheques for the user to write legal amount as shown in Fig. 1. They can be of different widths and lengths. When these guidelines are eliminated for the recognition of handwritten data, some parts of the strokes get eliminated where they touch the guideline. It is needed to reconstruct the eliminated parts of the strokes as they play a big role in the successful recognition of the legal amount. For guideline removal in [104], smooth strokes are detected after a thinning process, and a procedure based on stroke length is carried out. For the removal of guidelines from handwritten text, Dimauro et al. in [105] proposed a technique based on mathematical morphology with a dynamic selection of structuring element. In [83], two independent approaches are used for baseline removal. The first one is based on a controlled deletion strategy consisting of line detection, controlled thinning and baseline deletion. The second one is based on mathematical morphology and the use of a dynamic procedure. Guidelines on the cheque image in [46] are removed by the analysis of connected components using run length coding.

In [43] and [19], Sobel operator is initially used to calculate the gradient images. A local thresholding technique is then applied to select the candidate edge points of the guidelines. The least square fitting and Hough transform are the two important techniques used for the detection of baselines. The baseline is first eliminated, and then both morphological and topological processing restore the lost information corresponding to the strokes. In [42], the guidelines are removed by analysing the thickness, direction and curvature of the line components without causing damage to the handwritten information. To restore the handwritten strokes intersecting with baseline in [35], a morphologic closing operation is applied with a suitable structuring element. But when the intensity of the baseline is very close to the intensity of the handwritten data, morphologic operations may not preserve the handwritten data completely. So topologic operations based on edge detection and orientation information are used to detect and fill the gaps created during the line elimination process. In [7], the overlapping between the handwritten

Table 2 Performance details of some courtesy amount recognition systems (with highest level of confidence)

Method	Technique	Cheque Type	Data set	Level	Correct (%)	Reject (%)
Palacios [95]	MLP, GRNN, ELM	American	50,000	Digit	93.1	5.7
Dzuba [53]	Graph based	American	5,000	Amount	75	0
Lee [38]	Rule based & HNN	Brazilian	606	Digit	92.4	0
Oliveira [91]	Probabilistic	Brazilian	2,000	Amount	77.49	0
Zanchettin [4]	MLP	Brazilian	10,871	Amount	67.54	19.44
Palacios [1]	MLP	Brazilian	1,500	Amount	47	45
Suen [35]	BPNN	Canadian	2,711	Digit	97.31	0
Zhang [81]	MLP	Canadian	400	Amount	66.5	33.5
Su [40]	HNCC, MSFC & PCAC	Chinese	10,000	Digit	88.7	11.3
Song [97]	SOM and FT	Chinese	1,000	Amount	85	15
Knerr [42]	BC, TB & NN	French	10,000	Digit	97.8	2.1
Heutte [56]	Hyper planes	French	5,000	Digit	86.81	13.13
Gorski [98]	Log-linear integrator	French	35,000	Amount	75–80	0
Leroux [7]	RBF & TDNN	French	10,000	Amount	74	0.1
Knerr [42]	BC, TB & NN	French	32,000	Amount	70.6	3.7
Heutte [56]	Hyper planes	French	3,374	Amount	52.94	5.5
Chandra [39]	Dynamic programming	Indian	4,777	Amount	89.7	–
Dimauro [83]	Multi expert	Italian	1,500	Digit	99.9	0
Kaufmann [50]	MLP	Swiss	1,500	Amount	79.3	0

strokes and guidelines is treated locally through a heuristic rule that extracts pixel runs in the guideline when the pixels are far enough from the closest stroke of the legal amount. A threshold equal to the normal thickness of the guideline is set in [106]. The thickness of the guideline is calculated by counting the black pixel run along the vertical direction. If the count exceeds the threshold, a crossing stoke is probably present and the line pixels are preserved. The baselines of Canadian bank cheques are detected and eliminated by using grey-level mathematical morphology in [65]. The information lost during baseline elimination is restored by mathematical morphology with dynamic kernels [107].

5.2 Segmentation into words

A handwritten legal amount has to be segmented into its constituent words for the recognition purpose. Many times, a word is further segmented into its constituent characters or pseudo characters for effective recognition. In [7], the words are separated using the empty space between them and then segmented into pseudo letters by cutting only the low concavity strokes. The recognition module handles the ambiguities between intra letter spaces and intra word spaces. In [42], the legal amount is segmented into parts called graphemes (parts of characters), which may result in over segmentation. The graphemes are then grouped into words from left to right based on word segmentation probabilities.

In [46], the legal amount is segmented into words by considering the variation of spacing between the characters as a function. The concavities, the centre of mass information of the characters and bounding boxes were used for the same. For handwritten Italian legal amounts in [83], the mean length and standard deviation in terms of the number of local minima in the vertical direction are used to carry out the segmentation process. The system proposed by Dimauro et al. [108] for the recognition of legal amounts on Italian bank cheques uses contextual knowledge (derived from courtesy amount) for the segmentation of legal amount into words. For segmenting American legal amount into words in [90], projection profile is used to measure the linear density. Points are chosen based on the regions with zero linear density. The connected components are then extracted using an 8-connectivity grid. The average spacing between connected components acts as a threshold for word boundaries. The final segmentation is performed using average word length.

In [106], the segmentation of Chinese legal amount into characters is carried out by finding the gaps in the vertical projection profile of the amount. The segmentation process is an optimization process that minimizes the variance of the widths of the segments as the Chinese characters occupy similar widths. The segmentation of French legal amount sentences into words is done in [47] using a combination of explicit and implicit segmentation. In explicit segmentation, the words are separated easily by computing the horizontal distance between handwritten connected components. In the implicit approach, the recognition takes place as the amount is scanned from the beginning till the end of the sentence (legal amount) is reached.

5.3 Word recognition process

The accuracy in recognizing constituent words and characters plays a big role in the recognition accuracy of the legal amount string. After successful separation of words from the legal amount string, they have to be correctly recognized to understand the value of the cheque. From the literature, it is evident that the word recognition techniques can be grouped into HMM-based techniques and other techniques as discussed in the following subsections.

5.3.1 HMM-based methods

A hidden Markov model (HMM) is a statistical Markov model in which the system being modelled is assumed to be a Markov process with unobserved (hidden) states. Even though the states are not visible in an HMM, the output that is dependent on a state is visible. Each state has a probability distribution over its possible output tokens. Therefore, the sequence of tokens generated by an HMM gives some information about the sequence of states [109]. The word recognition in [7] is based on extraction of features from pseudo letters. The main features considered are closed loops, upper and lower extensions. The system performs two types of extraction. The first is based on a pseudo-character and the second is based on a full character. In both cases, the features are combined into word recognition scores trough HMMs of the words. The word recognition in [42] for French cheques is done using two complementary recognition chains each computing a list of word candidates along with probabilities. The first is an analytical approach based on HMM, and the second is a holistic approach based on structural features and Bayes classifier (BC). For the automated reading of German bank and postal cheques, in [50], each word of the legal amount is normalized by scaling in both the directions. An estimation of word length in terms of horizontal line crossings is used as a scale factor in x direction. The scale factor along the y direction depends on the distance between upper and lower baselines. A sliding window is used to scan the word from left to right using a sliding window to compute the feature vector. Each sliding window is further divided into small sub-windows, and for each sub-window, the number of black pixels is counted. The legal amount models are integrated in a hierarchical network of HMMs where each path represents a valid amount.

In [110], each English word is scanned from left to right by a sliding window for feature extraction, where the features are based on the word contours. The feature vectors are represented by a set of observation symbols (code words) called a codebook. Each word is then represented with a left-right HMM model with the number of states being a function of the average length of the observation sequences for that class. The training procedures used are maximum likelihood (ML) and maximum mutual information (MMI). The legal amount recognition unit in [47] for French cheques is a combination of two approaches. The first is based on global features like the relative position of the ascenders, descenders and loops within a handwritten word with a (K-nearest neighbour) KNN classification engine. The second is based on a HMM that uses feature set based on the orientation of contour points along with their distance to the baselines. A hidden Markov model (HMM)-based word recognition algorithm for the recognition of legal amounts from French bank cheques is presented in [111]. Initially, the words are segmented into graphemes. Then, geometric features are extracted from the graphemes, and the feature vectors are quantized in a sequence of symbols for each word. An HMM-NN hybrid model computes the likelihood of all the word classes.

There are two complementary word recognizers in [98,99] for UK, US and French cheques. The first one is based on holistic features and the second one uses hidden Markov models [112]. Word recognition results are combined and presented as a list of word class candidates with associated probabilities. In [113], a system is developed for the recognition of the handwritten legal amount on Brazilian bank cheques. The recognizer, based on HMM, does a global word analysis; therefore, it does not carry out an explicit segmentation of words into characters or pseudo characters. This set of features is based on the representation of concavities and convexities. A methodology of legal amount recognition based on word segmentation hypotheses is introduced in [114]. The word-level segmentation hypotheses are derived as per the grapheme-level segmentation results of legal amount. Hybrid schemes of HMM-MLP classifiers are also introduced in the same paper for producing the ordered legal word recognition results with reliable decision values. These values can be employed for getting an optimal word segmentation path of over-segmentation hypotheses as well as a rejection criterion of word recognition result.

5.3.2 Other prominent techniques

The result of courtesy amount recognition module is used as a priori information for legal amount recognition written in Italian language in [83]. Three different recognition methods for word recognition are combined in the system: analytical, global and mixed. The fully analytical approach is based on the assumption that each character consists of a sequence of basic strokes: cusps, circles, humps, oriented lines, semi circles, etc. The global approach is based on a graph description of handwritten words. The mixed approach combines an analytical method for the analysis of singularities and global method for the analysis of regular patterns in a word. The results obtained by legal and courtesy amount recognition modules are evaluated by an amount validation module, which accepts the most probable amount, if the level of confidence is higher than a specific threshold. In [53], the dollar part of the American legal amount field is recognized using a holistic approach based on feature sets having information about vertical and horizontal extremums (point located farthest from the middle). Feature transitions based on the similarity between different types of features are employed to measure the similarity between an input and a prototype. Probable points of segmentation into words and letters are also taken into account for best matching. Dynamic programming based on Levenshtein distance is also used to match the input phrase representation with all the lexicon entry representations. In [46], the word recognition module is based on dynamic programming. The algorithm compares the feature vector of a word (combination of segments) with the reference feature vectors and finds the best match. The recognition results at word level are arranged in a lattice, and it is traversed to generate meaningful amounts.

In [115] and [116], the classification system consists of a symbolic classifier (SC) and a neural network (NN) classifier. The symbolic classifier has to detect the ascenders, descenders and notable letters. A letter is called 'notable' if it has an ascender and it occurs at the leftmost part of the word. When the symbolic classifier is unable to classify a word, the neural classifier is then used to classify the word. In [2], the system uses a set of geometrical and topological features like loop, endpoints, branch-points, crossing-points, convex-points and concave-points. The proposed scheme maps each word into two strings of finite symbols based on the spatial distribution of these features. An indexing (hashing) scheme is used on these strings to organize a lexicon. For an unknown word, the system uses the same indexing scheme to find a set of three words having highest similarity. A verification process is then carried out to find the best match based on seven invariant moments and a nearest neighbour classifier (NNC). For the recognition of English legal amounts in [48] seven types of global features like ascenders, descenders, loops, an estimate of the word length, as well as vertical, horizontal and diagonal strokes. A KNN classifier is employed to classify the feature vectors. In [117], the failure of NN-HMM hybrid recognizer on Chinese bank cheque legal amount recognition is discussed, the main reason for the failure is the inability of the NN-HMM hybrid recognizer to handle the complexity in the training Chinese words. A spiral recognition methodology is proposed as a substitute in the same paper.

Global features like ascenders, descenders, loops, word length, vertical, horizontal and diagonal strokes are used to create the feature vector for word recognition in [35] and [85]. The feature vector for each word consists of 11 components, based on the relative positions of ascenders, descenders, loops, strokes as well as the number of ascenders, descenders and loops and the word length. The words are then classified using a nearest neighbour classifier (NNC). To recognize Chinese legal amounts in [106], best five sets of segmentation points (got from the segmentation unit) are passed to the recognition stage, where an integrated segmentation-recognition approach is employed. The character recognizer used is a combination of a statistical and a structural recognizer. The structural recognizer uses an elastic matching approach, and the statistical recognizer employs a threshold-based approach for the recognition of characters. The matching scores are entered into a segmentation lattice, which is used for subsequent parsing. A Chinese language grammar checker is used to evaluate the probable legal amounts. It employs a static transition table and a dynamic transition method for grammar checking. In [107], Chinese character set associated with the currency units is used to locate the legal amount on bank cheques. The system initially tries to identify the smallest currency units in the image. Then, it tries to locate the strings associated with each currency unit. A rule-based approach is then adopted to recognize the strings.

For the recognition of handwritten Arabic amount words in [118] holistic structural features like the numbers of descenders, ascenders, loops, one dot above, two dots above, three dots above, one dot below, two dots below and sub-words are considered. These features are then presented to three classifiers: a multi-layer neural network (NN), a K-nearest neighbour (KNN) and a fuzzy K-nearest neighbour (FKNN) classifier. Each classifier gives a list of three candidate words together with their confidence value. Combining the results consists of merging the three lists of candidates from the three classifiers to produce a new list by confidence values by taking the sum of confidence values, if a word is present in the list of two or more classifiers. For the recognition of French amount words in [119], two structural representations of a word based on strokes (8 different strokes) and graphemes (42 representations) are used. Each of them is analysed using a Markov model. These models are individually optimized by a rigorous choice of the order to fit the structural properties of the observed data.

For American bank cheques in [120] and [121], the legal amount recognition is based on spotting words from the legal word lexicon by using confusion matrices. The recognized words are then parsed to obtain a correct syntax. The words are segmented using a disjoint box approach where the number of segments is greater than the actual number of constituent characters. Segments are merged into characters using a dynamic programming approach with a modified quadratic discriminant function (MQDF). In [122], hidden Markov random field (HMRF) is used for the recognition of legal amount

Table 3 Performance details of some legal amount recognition systems (with highest level of confidence)

Method	Technique	Cheque type	Data set	Level	Correct (%)	Reject (%)
Han [2]	Indexing and NNC	American	141	Word	71	26.7
Shridhar [120]	MQDF	American	10,000	Amount	70.5	–
Dzuba [53]	Dynamic Prog.	American	5,000	Amount	59	0
Farah [118]	NN, KNN and FKNN	Arabic	4,800	Word	94	–
Freitas [113]	HMM	Brazilian	11,736	Word	67.3	–
Kim [114]	HMM and MLP	Canadian	750	Word	84.53	–
Suen [35]	KNN	Canadian	2,208	Word	79	–
Dodel [116]	SC and NN	Canadian	1,150	Word	70	30
Yu [106]	Lattice based	Chinese	212	Amount	74	15.6
Tang [117]	Spiral methodology	Chinese	59,800	Amount	60	39
Knerr [111]	HMM-NN	French	50,000	Word	89	–
Knerr [42]	BC and HMM	French	10,000	Word	87.1	12.8
Guillevic [47]	KNN and HMM	French	1,861	Word	86.7	–
Leroux [7]	HMM	French	4,815	Word	83	–
Guillevic [110]	HMM	French	4,500	Word	76.9	–
Olivier [119]	MM	French	6,000	Word	72	–
Guillevic [48]	KNN	French	1,496	Word	71.8	–
Knerr [42]	BC and HMM	French	32,000	Amount	78	13.4
Leroux [7]	HMM	French	4,815	Amount	70	–
Gorski [98]	BC and HMM	French	35,000	Amount	60–65	34
Dimauro [83]	Multi expert	Italian	400	Word	83.2	13.7
Lecce [123]	Graph based	Italian	1,083	Amount	44	13
Kaufmann [50]	HMM	Swiss	1,500	Amount	71.9	0

fields of Amharic (Ethiopia) bank cheques. The features are based on the surrounding information of each pixel and projection profiles. Contextual information based on the syntactical structure of Amharic cheques is also used to enhance the results. In [123], a hybrid approach for legal amount recognition on Italian bank cheques is presented. It makes use of the consideration that a legal amount can be treated as a series of 'core' groups of words separated by appropriate 'separator' words. An analytical approach is used to achieve amount segmentation into 'core' groups of words, which are then recognized according to a global graph based approach. Lexical and syntactical a-priori knowledge of the domain of application is used for both amount segmentation and recognition. The recognition of legal amount words in [108] is accomplished using a simple matching procedure. This is based on the consideration that a word consists of a periodical signal that forms the regular part of the word and non-periodical signals that are robust in discriminating the word. Table 3 shows the performance details of some legal amount recognition systems with highest level of confidence. In the table, the results are summarized based on full amount recognition score as well word wise recognition score.

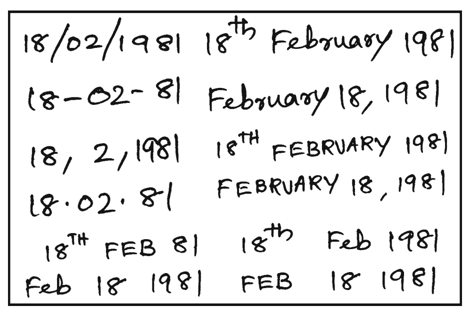

Fig. 6 Some popular styles of writing date information in English language

6 Date recognition

Automatic recognition of handwritten dates present on bank cheques is also very important in application environments, where cheques cannot be processed prior to the dates shown. In countries like India, a cheque cannot be processed after 6 months of the date written on it. A date field can contain only numerals or a mixture of alphabetic letters (for Month) and numerals (for Day and Year). Punctuations and suffixes are also present in the date field as shown in Fig. 6. Month can

Table 4 Performance details of some date recognition systems

Method	Level	Techniques	Cheque type	Data set	Correct (%)	Reject (%)
Morita [126]	Month	HMM	Brazilian	2,000	84–91	0
Morita [125]	Month	HMM	Brazilian	2,000	83.66	0
Kapp [130]	Month	MLP	Brazilian	6,000	81.75	–
Morita [131]	Entire date field	HMM, MLP	Brazilian	2,000	62–65	32–36
Xu [128]	Month	HMM, MLP	Canadian	2,063	85.36	0
Suen [35]	Entire date field	NN and KNN	Canadian	1,261	75.8	6.4
Xu [70]	Entire date field	HMM, MLP	Canadian	3,399	57–62	1–4

be written either before or after Day. Punctuations like slash ('/'), comma (',') and hyphen ('-') can be used to identify the end of one field. Some users write suffixes such as 'th', 'st', 'nd' and 'rd' (specific to English language) after 'Day'. In [124], date processing of bank cheques is considered as the most difficult target in cheque processing because of the worst segmentation and recognition performance.

For date recognition in [85] and [35], the information is segmented into different fields, and appropriate recognition system(s) is applied to each field. The year field being always numeric is processed first. The technique used for courtesy amount is repeated for year recognition. The day and month fields are located using the space (gap) information between the connected components and by recognizing the special symbols like punctuations. The width of each field is used to determine whether they are numeric or alphabetic. The numeric fields are passed to the digit recognizer based on a NN classifier, which is used for the courtesy amount. Alphabetic fields are processed by the word recognizer based on K-nearest neighbour classifier (used for the legal amount processing), which has been trained with lexicon of month words and their abbreviations.

In [125], the recognition of month name in a Brazilian cheque is based on a combination of holistic and analytical approaches with a single explicit segmentation technique to provide a grapheme sequence for the Hidden Markov Models of each recognizer. To improve the results in [125], a feature set based on concavity analysis is used. For the recognition of handwritten month words, features based on concavity analysis and global features were used to improve the discrimination among several writing styles in [126]. A word image is represented by two feature vectors of equal length to feed the HMMs. Another system mentioned in [127] deals with English month word recognition by combining a Multi-Layer Perceptron (MLP) classifier and an HMM classifier. Some improvements and modifications are reported to recognize both French and English month words in [128]. An effective conditional combination topology is presented to combine two MLP classifiers and one HMM classifier, and a new modified product fusion rule is also proposed in the same. In [70], a complete date recognition system is developed in which the month name recognizer of [128] is used. For the year and day fields, the digit recognizer of [129] (for processing the courtesy amount) is used.

In [130], for the classification of hand written month words on Brazilian bank cheques, two architectures of artificial neural networks (ANN) are evaluated. The performances of conventional and class-modular MLP architectures are compared. Using global features (holistic approach) like perceptual features and characteristics based on concavities/convexities, it has been found that the class-modular architecture is superior to the conventional MLP architecture. The system described in [131] first segments a date image into sub-fields through the recognition process based on an HMM-based approach. Then, the three date sub-fields are processed by the system (day, month and year). A neural approach has been adopted to work with strings of digits, and a Markovian strategy is employed to recognize and verify words. A concept of meta-classes of digits is also introduced, to reduce the lexicon size of the day and year and to improve the precision of their segmentation and recognition. Table 4 shows the performance details of some date recognition systems.

7 Validation of legal and courtesy amounts

In a complete cheque value recognition system, the consistency between the results provided by the courtesy and legal amount recognition units has to be verified. It is a common practice to reject a bank cheque for which the courtesy amount recognition unit and the legal amount recognition unit indicate different quantities [132]. In some cases, both the recognition units may supply a list of 'n' candidates having high level of confidence. In [83], the ranked lists of candidates supplied by the courtesy and legal amount recognition units are combined using a majority vote method based on Borda count function (MVBC). In [42], two methods are proposed for taking the final decision. The first method is based on a set of rejection rules, and the second is based on

Table 5 Performance of some systems after the cross validation of legal and courtesy amounts

Method	Technique	Cheque type	Data set	Correct (%)	Reject (%)
Dzuba [53]	Confidence level function	American	5,000	67	32
Kim [46]	Number of digits	American	235	47.2	51
Knerr [42]	Rejection Rules and NN	French	32,000	65	34.9
Leroux [7]	Weighted sum	French	5,000	65	–
Kaufmann [50]	Syntax directed translation	Swiss	628	65.2	36.4

a neural network (NN). In [7], the final decision is taken by computing the weighted sum of the scores provided by the courtesy and legal amount recognition modules. In [53], the confidence levels of the probable answers are corrected using mutual properties of courtesy and legal amount recognizers. In [46], the number of digits in the probable legal amounts is calculated with the help of flags saved during the parsing of legal amount. This in combination with the confidence values of the first two choices of the courtesy amount recognizer is used to take the final decision.

In [133] and [50], a new technique for error correction on Swiss postal cheques is proposed in which the legal amount is converted into a digit string using syntax directed translation (SDT). Once the result of the legal amount recognizer has been translated into the corresponding digit string, it can be easily compared to the result of the courtesy amount recognizer. Thus, discrepancies between the legal and the courtesy amount can be detected and correctly located at the level of individual words in the legal amount and digits in the courtesy amount. Table 5 shows the performance details of some systems capable of cross-validating the outputs of legal and courtesy amount recognizers.

Fig. 7 Genuine signatures of an individual and the corresponding skilled forgeries from the GPDS database [165]

8 Signature verification

Verification of hand-printed signature present on a paper cheque is inevitable as it carries the authenticity of the cheque. Automatic verification of signatures is essential because of the difficulty in distinguishing genuine signatures from skilled forgeries on the basis of visual evaluation. Such techniques can also be applied to verify the authentication of contracts, identity cards, formal agreements, administrative forms, acknowledgements, etc [134]. Hence, static (off-line) signature verification has become a field that attracts more and more researchers [135]. So many techniques have been proposed in the recent past towards the offline verification of signatures. Impedovo and Pirlo in [134] and [136] did a detailed survey on the techniques available up to 2007 for the same. Some discussions on the prominent techniques as well as the latest advancements (after 2007) related to the detection skilled forgeries are included in the following sub-sections. Skilled forgeries are produced with close imitations. It is very hard to visually differentiate a genuine signature and its skilled forgery as shown in Fig. 7. The Table 6 shows the performance details in terms of false acceptance rate (FAR), false rejection rate (FRR) and equal error rate (EER) of some of the techniques discussed in this paper. As many of the researchers have used their own databases, it is not fare to compare the methods based on their performance alone. The following sub-sections discuss some of the prominent techniques reported in the literature for the verification of offline signatures.

8.1 Neural network based techniques

Bajaj and Chaudhury [137] used different types of global features like envelop and projection profiles for offline signature verification. The classification was done by feed-forward neural network (FFNN) classifiers, and the decisions were combined using a simple-layer feed-forward neural network (SLFFNN). Cordella et al. [138] proposed a hybrid multi-expert (ME) scheme based on cascaded two-stage classifiers

Table 6 Performance details of some offline signature verification schemes

Method	Features	Approach	Data set	Performance (%)
Sansone [144]	Pressure region	MLP	1,960	FAR (19.8), FRR (2)
Bajaj [137]	Global	FFNN	250	FAR (3), FRR (1)
Quek [161]	RPBF, GB, PF, SF	FNN	535	EER (22.4)
Cordella [138]	Contour, grey	MLP	1,960	FAR (19.8), FRR (2)
Huang [140]	Geometric	MLP	3,528	FAR (11.8), FRR (11.1)
Huang [141]	Geometric, gradient	MLP, SM	8,904	FAR (8.2), FRR (6.3)
Dimauro [139]	Fourier	ED, SB, ANN	765	FAR (22), FRR (2)
Santos [142]	Graphometric	MLP	900	FAR (15.6), FRR (10.3)
Xiao [143]	Directional, grid	MLP	738	FAR (17), FRR (9.2)
Armand [146]	Structural	RBFNN	2,106	Verification Rate (91.1)
Baltzakis [145]	Global, grid, texture	RBFNN	57,500	FAR (9.81), FRR (3)
Deng [148]	Zero crossings	DTW	3,500	FAR (5.6), FRR (9.2)
Shanker [150]	Vertical projection	DTW	1,431	EER (2)
Fang [149]	Projection	DTW	2,640	FAR (23.5), FRR (22.1)
Jayadevan [151]	Radon transform	DTW	2,106	EER (22)
Batista [156]	Static, pseudodynamic	HMM	7,920	FAR (20.5), FRR (12.8)
Batista [167]	Similarity measure	HMM, SVM	7,920	FAR (15.5), FRR (8.3)
Justino [153]	Pseudodynamic	HMM	5,200	FAR (22.6), FRR (2.8)
Coetzer [154]	Radon transform	HMM	4,800	EER (12. 2)
Madasu [159]	Grid based	Fuzzy logic	510	FAR (3.5), FRR (0)
Ismail [160]	Global, local	Fuzzy	330	FRR (2)
Hanmandlu [162]	Angle	TS model	1,200	FAR (21), FRR (0)
Vargas [165]	Texture	SVM	5,400	EER (11.04)
Hairong [164]	Static, dynamic	SVM	1,100	EER (5)
Justino [153]	Static, dynamic	SVM	3,000	EER (4)
Bertolini [166]	Graphometric	SVM	3,000	FAR (4.6), FRR (17.6)
Nguyen [171]	Gradient	SVM	8,640	EER (15.11)
Vargas [168]	PCC	LS-SVM	5,400	FAR (7.3), FRR (5)
Ruiz-del-Solar [174]	Local descriptors	Bayesian	2,106	FAR (14.2), FRR (16.4)
Kalera [175]	GSC	Bayesian	2,640	FAR (23.1), FRR (20.6)
Xiao [173]	Profile	Bayesian	160	FAR (14), FRR (20)
Fang [176]	Peripheral	Mahalanobis	2,640	EER (11.4)
Mizukami [177]	Position	Euclidean	400	EER (24.9)
Ramesh [178]	Moment, wavelet	Hybrid	645	FAR (2), FRR (10)
Ueda [179]	Pattern	Matching	2,000	EER (9.1)
Hairong [180]	Landmark points	PGM	16,000	EER (5.4)
Chen [181]	MRS	Graph matching	2,640	FAR (8.2), FRR (6.7)

for offline signature verification. The scheme used contour-based features and grey-level features in the first and second stages, respectively. The classification was performed using MLP in each stage. Dimauro et al. [139] used Fourier transform for extracting projection-based, slant-based and geometric-based features and Granlund descriptors for offline signature verification. The proposed ME system combined a holistic approach based on a Euclidean distance (ED) classifier, a structural-based (SB) classifier and an ANN-based classifier. A voting strategy then combines the results from the three classifiers to reach the final decision.

Huang and Yan [140] proposed a scheme based on geometric features with different scales for offline signature verification. Combining the decisions taken at each scale using an MLP classifier gives the similarity measure. Huang and Yan [141] also proposed another scheme where geometric and directional features were considered along with MLP and structural matching (SM) algorithms for signature verification. Santos et al. [142] used graphometric features and MLP to verify offline signatures. Xiao and Leedham [143] used an MLP classifier along with direction-based grid features. High-pressure region is the feature used to detect skilled signature forgeries in the work of Sansone and Vento [144] where MLP is used for the purpose of verification. Baltzakis and Papamarkos [145] proposed a system based on global, grid and texture features for offline signature verification. For each one of these feature sets, a special two level Perceptron classification structure (one-class-one-network) has been implemented. The results of the first-level classifier are fed into a second-level radial base function neural network (RBFNN) structure capable of taking a decision. Armand et al. [146] proposed a scheme based on radial basis function neural network (RBFNN) for signature verification using structural features.

8.2 DTW-based techniques

Dynamic time warping (DTW) is dynamic programming method by which an optimal match between two given sequences (vectors) can be found under certain restrictions. The sequences (vectors) are 'warped' nonlinearly to determine a measure of their similarity [147]. The zero crossings of the curvature data obtained using wavelet transform are employed as features for matching signatures in the scheme proposed by Deng et al. [148]. The matching is performed using dynamic time warping (DTW). Fang et al. [149] used vertical projection profiles as features and DTW for matching signatures. Shanker and Rajagopalan [150] proposed a modified DTW algorithm that incorporates a stability factor for better verification of handprinted signatures. Vertical projection profile of the signature is used as the feature vector for the same. Jayadevan et al. [151] considered the area formed by the matching path around the diagonal of the DTW-grid also for calculating the difference between the feature vectors of the test and stored samples. The features were extracted using discrete Radon transform in the same work.

8.3 HMM-based techniques

For the verification, purpose Nel et al. in [152] extracted dynamic information like pen trajectory from the images of signatures. They assumed that a dynamic version of the static image is already available (obtained during an earlier registration process). A hidden Markov model (HMM) is derived from the static image and is then matched with the dynamic version of the image. A Viterbi algorithm matches a dynamic exemplar to the HMM and determines the most likely state sequence that can be translated into the most likely pen trajectory. In the scheme of Justino et al. [153], simple, static and pseudodynamic features and multiple codebooks in an HMM framework were used for offline signature verification. An HMM with a ring topology along with Radon transform-based features was used by Coetzer et al. in [154] and [155] for offline signature verification. A ring structured HMM is helpful in achieving rotational invariance in the verification process. Static features (related to the signature shape) and pseudo-dynamic features (related to the dynamics of the writing) were extracted locally from the signature images in the approach of Batista et al. [156]. A multiple-hypothesis principle is employed to select the most suitable solution for a given input sample from a set of different HMMs (left to right topology).

8.4 Fuzzy logic-based techniques

Fuzzy logic is a form of many-valued logic derived from fuzzy set theory to deal with reasoning that is approximate rather than exact [157]. Velez at al. [158] introduced a fuzzy snake approach for offline signature verification problem by using only one training signature per person. The signature verification is performed in two stages. In the first stage, a created snake model is adjusted over the test signature image using a fuzzy approach. In the second stage, degree of similarity between the test signature and the snake model is measured using a Takagi–Sugeno (TS) model. Madasu et al. [159] proposed a fuzzy-modelling approach for signature verification, where a well-defined fuzzification function with structural parameters was employed. The signature image was partitioned into a number of segments by a grid-based approach. For each segment, a normalized vector angle was considered as a feature. In the work of Ismail and Gad [160], handwritten Arabic signatures are recognized and verified using a grade of membership in the set of genuine samples. Fuzzy concepts are applied in the verification phase in making decisions. A set of global and local features is used for the same. Quek and Zhou [161] proposed a scheme based on fuzzy neural network (FNN) for offline signature verification. Reference pattern-based features (RPBF), global baseline (GB), pressure features (PF) and slant features (SF) were considered as the features for the same. Hanmandlu et al. [162] proposed an approach based on fuzzy modelling that employs the Takagi–Sugeno (TS) model with multiple rules for offline signature verification. Angle features extracted using a box approach were fuzzified by an exponential membership function of the TS model.

8.5 SVM-based techniques

A support vector machine (SVM) constructs a hyper-plane or set of hyper planes in a high or infinite dimensional space, which can be used for classification. A good separation is achieved by the hyper-plane which has the longest distance to the nearest training data points of any class [163]. Hairong et al. [164] proposed an SVM-based method for offline signature verification. Static (moments, directions) and dynamic (stroke width distribution and grey distribution) features for extracted for the same. A comparison between HMM and SVM for offline signature verification was done by Justino et al. [153] in terms of learning and verification tasks. SVM showed better results for both the conditions. Static and pseudo-dynamic features were used as the features for the same. The scheme proposed by Vargas et al. [165] measures the variations in the grey level of the signature image using statistical texture features. The co-occurrence matrix (CM) and local binary pattern (LBP) are analysed and employed as features in the same paper. A support vector machine (SVM)-based model has been used for the purpose of verification. Graphometric features considering the curvature of stroke segments are used in the work of Bertolini et al. [166]. An ensemble of SVM classifiers was built using a genetic algorithm, and different fitness functions were evaluated to drive the search. A dissimilarity representation is used in the approach proposed by Batista et al. [167]. The signature verification is done in two stages where left to right HMMs are used in the first stage and SVMs along with random subspaces (RS) are used. In [168], pseudo-cepstral coefficients (PCC) are calculated to get information about the pressure distribution on a signature image. Least squares support vector machines (LS-SVM) are used for the verification purpose. The research of Nguyen et al. [169] compared the performance of neural networks, and SVM classifiers using structural features and found that the performance of SVM was better than neural networks. Global features based on the boundary of a signature and its projections are used for enhancing the performance of SVM-based signature verification in [170]. In [171], gradient features are used along with SVM for offline signature verification.

8.6 Bayes classifier

A Bayes classifier is a simple probabilistic classifier based on Bayes' theorem (from Bayesian statistics) with strong assumptions. A naive Bayes classifier assumes that the presence (or absence) of a particular feature of a class is unrelated to the presence (or absence) of any other feature [172]. Xiao and Leedham [173] proposed a Bayesian network (BN) representation for offline handprinted signature verification. The proposed network is capable of capturing topological relations among the components associated with the nodes. In the approach of Ruiz-del-Solar et al. [174], local interest points of the signature image are detected, then local descriptors are computed in the neighbourhood of these points. These descriptors are then compared using local and global matching procedures. Bayes classifier is used to carry out the final verification. Kalera et al. [175] proposed a scheme based on gradient, structural and concavity (GSC) features where the verification is done using Bayes classifier.

8.7 Other techniques

A set of peripheral features and a Mahalanobis distance-based (MD) classifier were considered by Fang and Tang [176] for offline signature verification. Mizukami et al. [177] proposed a Euclidean-distance-based scheme for offline signature verification. The test image has to be compared with a genuine one for measuring the similarity. For offline signature verification, Ramesh and Murty [178] used geometric, moment-based, envelope and wavelet features. Genetic Algorithms were used to weigh the pattern characterization capability of the individual feature components. A hybrid classification scheme is employed to reach the final decision on authenticity. Ueda [179] investigated pattern matching for offline signature verification. Signature strokes were thinned first for this purpose and then blurred by a fixed point-spread (FPS) function. Hairong et al. [180] proposed a probabilistic graphical model (PGM) capable of capturing the dependence and variations of signature landmark points. Chen and Srihari [181] proposed a graph matching approach for signature verification using multi resolution shape (MRS) features. An approach based on visual perception is proposed by Sabourin et al. in [182] and [183] for offline signature verification. Local granulometric size distributions (LGSD) along with nearest neighbour classifier (NNC) and a minimum distance classifier (MDC) were used for the same. A component-oriented approach for signature verification is proposed by Dimauro et al. in [132]. Each connected component of a signature is classified using a set of topological and spectral features. The verification step is carried out using a nearest neighbour approach in which if the number of true components in a signature is greater than a specific threshold, the signature is judged as a genuine specimen; otherwise, it is judged to be a forgery. For off-line signature verification in [184], Sabourin et al. investigated the use of shape matrices as a global shape factor, where the position of local measurements is taken into account. Zimmer and Ling in [185] and [186] proposed a hybrid verification system, where an online reference signature serves as a basis for extracting features from the off-line signature. A set of global and local features along with Euclidean distance (ED) classifiers were used for the verification process.

9 Recognition of payee name

The payee-name field on a cheque is used to write the name of the person to whom the money is paid through that cheque. In almost all the countries, payee name (details) field is located above the legal amount field as shown in Fig. 1. As the legal amount is very near to payee name field, it will be difficult to segment the two into separate fields in case of overlapping handwritten segments. The technique used for payee name recognition (word matching) in [124] is the same as that of [187] and [51]. If the payee name is machine printed, then a graph of the spotted words will be created and traversed to display a list of ranked payee names from the lexicon. It is claimed in [124] that a metadata analysis of the bank database identifies the stop-words, abbreviations and the misspelled words. To ensure accurate payee name matching, metadata tools should be provided to the banks to analyse their data on an ongoing basis.

In [8], the payee name field is located using the key phrase 'pay to the order of' that always precedes the actual payee name. Then, the recognition of handwritten payee name is done using hidden Markov Models (HMMs). The extracted handwritten text is segmented into graphemes which can be smaller than characters. The graphemes after classification by a neural network (NN) form a class probability vector. The sequence of vectors is then matched with HMM models of dictionary words (phrases). The best-matching word models generate the list of possible answers.

One of the difficulties in payee name recognition is the presence of aliases [8]. Aliases are different forms of a word (in particular, a name), which have identical semantic meaning. Some possible aliases are as follows: 'reduced or abbreviated form(s) of the prototype name', 'prototype name with suffix or prefix words', 'misspelled name' and 'permutated words in the name'. The presence of aliases reduces the recognition rate and increases rejection rare. Two instruments named 'alias detector' and 'alias generator' are proposed in [8] to detect the presence of possible aliases in the name field and to overcome the difficulty. The 'alias detector' evaluates the probability of input name being an alias. It is based on a neural network trained to distinguish aliases from non-aliases. The task of the 'alias generator' is to produce the list of probable aliases of a given name. A name thesaurus is being used for the same.

The system described by Gorski in [8] has a name detection process, besides the ordinary payee name recognition. Name detection is a search process, in which the system is supplied with a 'black list' of wanted people (e.g. terrorists, criminals, etc.). Then, every name recognized is matched with names from the black list and upon successful matching, the cheque goes to a special basket of items to be manually inspected.

10 Cheque processing industry

During the last decade, automatic cheque processing has become an industrial problem. Some of the prominent vendors in the area of automatic bank cheque processing are 'A2iA', 'Mitek', 'Parascript' and 'SoftPro'. The following subsections discuss the products and services offered by these vendors.

10.1 A2iA

A2iA 'CheckReader' is capable of reading all types of writing on cheques including printed, cursive or handwritten capital letters. For recognizing the 'payee-name' field, user-defined vocabularies up to thousands of entries are used. This will ensure optimal results on any types of cheques [188]. A2iA 'CheckReader' performs courtesy amount recognition and legal amount recognition independently. A2iA's artificial intelligence and neural networks combine these results and decide on the returned values and confidence levels. A2iA 'CheckReader' is available in 6 languages (English, French, German, Italian, Portuguese and Spanish) and in 23 versions for countries like France, UK, Ireland, Italy, USA, Canada, Mexico, Brazil, Thailand, Hong Kong, Sweden, Netherlands, Portugal, New Caledonia, Australia, Germany, Chile, Belgium, Malaysia, Singapore, India and South Africa. A2iA 'CheckReader' yields 99% recognition accuracy for machine printed text and 96% for 'constrained' handwritten text [189].

A2iA 'CheckReader' has the facility to spot money laundering and terrorism financing. The software recognizes the name of the cheque's drawer and payee and can spot fraudulent and money-laundering operations by validating cheques against various blacklists. A2iA 'CheckReader' recognizes cheques deposited at ATMs and completes the mandatory consistency controls. The software facilitates the address block printed on the cheque to be validated against the data supplied by the bank-card (Debit card) in order to verify the customer's identity and provides entire cheque recognition, including cheque stock analysis, counterfeit cheque detection and real-time acceptance at the ATM [189]. A2iA 'CheckReader' is also capable of recognizing the code line present at the bottom of the cheque. In order to comply with the U.S. Check 21 initiative, A2iA 'CheckReader' helps to determine the image quality, usability and validity. The presence of signatures can also be detected by an A2iA 'CheckReader'.

10.2 Mitek

The 'ImageNet-Payments' system of Mitek is capable of reading and processing personal (handwritten) and business (machine printed) cheques [190]. The system can automatically locate and read the date information, legal amount and courtesy amount. It is also capable of extracting names and addresses as needed. It validates the cheque image by automatically processing the code line present. It can assess document-image quality against the specified standards and is 'Check 21' compliant. It works with image replacement documents (IRDs) as well. The recognition rate available is 85% for handwritten cheques and 95% for printed cheques. The vendor claims that the product reduces the manual data entry costs by 90%.

Mitek's mobile-banking application 'Mobile Deposit' allows consumers and business people to deposit cheques using their camera-equipped smart-phones [191]. Using their smart-phones as scanning devices, users can deposit cheques from anywhere at any time. Also, it supports the 'Check 21' industry standards for image quality. The application automatically corrects many different types of problems, such as photos of cheques that may be wrinkled, skewed, distorted or taken under poor lighting conditions. The other features are similar to 'ImageNet-Payments'.

10.3 Parascript

The three main products of Parascript related to automatic bank cheque processing are 'CheckPlus', 'CheckUltra' and 'CheckUsability'. Parascript 'CheckPlus' automates the recognition of courtesy and legal amounts [192]. 'CheckPlus' also reads the payee line, code line and cheque number on personal cheques; recognizes dates; detects signature presence; executes signature verification; and locates payer blocks on personal and business cheques. Currently, different versions of the product are available for Argentinean, Australian, Brazilian, Canadian, Chilean, French, Indian, Italian, Malaysian and Portuguese personal and business cheques. Parascript 'CheckUltra' not only reads courtesy amount, legal amount and code line on financial documents, but also analyses image integrity and detects defects in images of personal cheques, business cheques and image replacement documents (IRDs) [193]. 'CheckUsability' solves the challenges of 'Check 21' by analysing personal and business cheques for scanning distortions and field entry mistakes and provides an automatic analysis of field readability [194].

10.4 SoftPro

According to the '2003 Check Fraud Survey' of the American Bankers Association (ABA), 'Forged Maker Signature' and "Counterfeit Items" continue to be a favourite target of fraudsters [195]. Together, these two categories make up over 40% of cheque fraud attempts annually. The 'Softpro' group developed the 'FraudOne' cheque fraud solution together with its technology partners. Its initial aim is to mine the digital artifacts on cheque images to uncover the fraud [195]. In co-operation with six of the US banking industry's leading institutions, 'Softpro' defined cheque fraud prevention best-practice requirements in 2001 as part of the 'FraudOne' initiative. In many institutions, the product 'FraudOne' is successful in reducing the losses by 60% due to counterfeit and forged maker signature cheques.

11 Some observations

A cheque amount processing system becomes commercially efficient only when the error rate is very low. So a cheque reader must be able to refuse to give an answer when the probability to make mistake is high. Human eyes can read a 'rejected' cheque afterwards or other more advanced automated approaches can be used. However, a cheque 'read' incorrectly is very difficult to deal with, in terms of costs and time involved to correct the mistake.

Ideally, automated recognition process should replace manual typing of information. In reality, this is true only to a certain extent. The reading ability of automatic reading systems is still much lower than the reading abilities of human beings. However, it is definitely possible to reduce a part of manual work (typing) by automatic processing. As reported by Gorski in [8], the three main characteristics of a recognition system are: 'read rate'(number of automatically read items / total number of items), 'substitution rate'(number of incorrectly read items / number of read items) and 'recognition rate'(number of correctly read items / total number of items). Commercial people prefer to speak about the 'read rate' (as it is connected with labour saving), while the scientific community often uses 'recognition rate', as it shows recognition ability of the system.

Sometimes, detection processes are required to find the absence of any mandatory cheque fields [8]. One of the traditional detection tasks is to find cheques without payer's signature. Such cheques are not valid and require human inspection. In general, a detection process should select a set of suspicious items for human inspection. The efficiency of a detection process can be characterized by two complementary terms: 'detection rate' (number of detected target items / total number of target items) and 'suspect rate' (number of suspicious items / total number of items). Lower the suspect rate, lower will be the cost of the detection process. Higher the detection rate, higher will be the revenue from the process implementation.

From the literature, it is clear that almost all the authors have used their own databases for the purposes of testing and performance evaluation. An attempt has been made in [196] to create a database of 3000 Arabic bank cheques with data tagging. The paper also describes a validation procedure including grammars and algorithms to verify the correctness of the tagging process. Impedovo et al. in [197] presented a database that contains more than 146,000 images of isolated digits, characters, words and signatures. This database can serve as a basis for research on automatic processing of bank cheques from the countries belonging to European Union.

There is no fixed format for cheques even in a country itself. Each bank has its own standard; so the cheques of different banks differ not only in background, but also in type and position of the machine printed and handwritten information. The area of interest should be located first in those systems, which do not depend on specific cheque formats. Location searching is difficult for cheques with poor scan quality. Failure in location searching will present false samples to different recognition modules. A hybrid model based on a combination of an orthogonal Gaussian mixture model (OGMM) and a multi-layer perceptron (MLP) is proposed in [198] for locating and recognizing machine printed numeral recognition.

There are some language-specific challenges in recognizing handwritten amounts and dates present on bank cheques. Recognizing Italian legal amount is tough as the entire legal amount is written as a single word without using any delimiters [83]. Although the lexicon size of legal amount words is limited in countries like Brazil, common sub-strings present in such words can affect the performance of the recognizer [199]. Even though the vocabulary is limited in Chinese bank cheques, the grammar is very rigid [106]. Also, the number of numerals may differ in the presence or absence of a horizontal stroke (line). A problem may arise when the stroke appears as a short line. It is difficult to decide whether it is the presence of line or noise.

Magnetic ink character recognition (MICR) technology based on magnetic approach has widely been used for recognizing the code lines (cheque number and bank branch code) present on cheques. An OCR approach is used in [200] as MICR character set uses a special type font readable by human being. Exterior character profile is used as the feature for each symbol, and sum-of-squared error (SSE) is used to measure the distance between two feature vectors for classification.

There are some published works on the extraction and recognition of seal and logo information from images of bank cheques. Seal imprints are extracted from images of Japanese bank cheques using histogram-based colour information in [201]. Local and global features including coordinates of outermost points of imprint strokes, line width of strokes, mean radius of an outer frame figure from its centroid, average line width of a seal imprint are extracted. In the verification stage, an algorithm based on local and global features of seal imprint is used first. Another algorithm uses a special correlation based on a global approach. The two algorithms are then combined in the multi-expert system by a voting strategy. The approach presented in [202] employs mathematical morphology to automatically locate and extract logos from the image of Brazilian bank cheques. Subtracting the bank cheque grey-scale image from the image resulting from the Fillhole morphological operator does the removal of artistic background from the logo information.

Contextual analysis is also critical in controlling the error rate of the entire system [120]. The contextual information for each field can be expressed as a set of specific rules. For example, by comparing the recognized legal and courtesy amount, the error rate can be further reduced. For the date field, contextual information can be the current month and year. Sometimes, the handwritten information contains broken characters and symbols, which need to be repaired. Occasionally, the handwritten text regions may overlap each other, and it will be difficult to segment and recognize them. The processing of skewed handwritten text regions is also difficult if the image is not skew free.

In case of the recognition of courtesy amount in a handwritten personal cheque, the extraction and recognition of the fractional part is difficult as some writers often include fractional parts on cheques [120]. Many times, the connected components make recognition almost impossible. Another difficult aspect is the way the double zero '00' is written. It is often recognized as '50' or '60' because of the connecting link at the top. The date segmentation and recognition task is the most difficult one as there are many formats to write a date. A density factor and a regularity measure must be computed to detect the presence of signature on a cheque image. Stamped directives present on a cheque should also be reliably detected and processed.

The common approaches employed for the extraction of user-entered information are based on the detection of base lines, which point to locations where handwritten information can be found. In other cases, the use of special symbols including currency indicators that point to the area on the image where the courtesy amount is written. One problem of eliminating the base lines is the loss of information where text and line intersect each other. Even though the lines can be successfully eliminated, it is necessary to reconstruct the handwritten information at the points where they overlap. It would be very difficult to recognize the modified (damaged) handwritten information if the reconstruction is not done properly.

One of the main difficulties in developing an effective cheque reading system is the high degree of variability and uncertainty in the handwritten date information. People usually write the date zones in free styles that little a priori knowledge and few reliable rules can only be applied to identify the layout of a date pattern [70]. As there are many banks in this world and each one of them uses a specific background pattern. Another difficulty is to develop an automatic binarization algorithm capable of calculating threshold value suitable for different background patterns.

In [98] and [99], it is shown that a character recognizer trained on data from a particular country can be weak in processing data from another country, even if they are culturally close and use same language. Structural complexity of characters and variability of writing styles are the biggest challenges in recognizing legal amounts present on a bank cheque. Sometimes, the courtesy amounts cannot be recognized in advance, the recognition of legal amounts needs to be conducted even without any reference values.

The advances in computer and information technology allow banks to develop automatic recognition and verification systems [37]. In the research and development of such a system, a big cheque-image database, which contains hundreds of cheque images, is usually used for training or testing. Although the colour image of a cheque contains richer information than that of its grey-scale image, it will consume more memory to process a colour cheque and more space to store it. Therefore, the main trend of the current research on automatic processing of bank cheques is based on the grey scale or binarized cheque images [19].

12 Conclusions

Automatic cheque processing is an interesting field of research from both scientific and commercial points of view. The variability of the size, structure and background of bank cheques, together with the complexity of the character recognition, makes the development of universal algorithms and strategies extremely challenging for automatic bank cheque processing. The survey presented in this paper will give the reader the state of the art information in cheque processing. The performance details shown in the tables of the paper are clear indications of awareness and interest that many institutions at national and international levels give to automatic bank cheque processing. It is also apparent that issue like the recognition of payee details is still to be explored further. The time required for the entire process of recognition by different methods also needs to be studied further, and it should be lesser than the time required for visual recognition, typing and verification. In real conditions of a cheque reader application, the price of a recognition error is greater than the savings from a correctly recognized cheque. Thus, a cheque processing system becomes commercially efficient only when the error rate is very low. A cheque reader must be able to refuse to give an answer (or reject) when the probability to make mistakes is high. The reliability [recognition rate/ (100%—rejection rate)] of a cheque processing system can be used to test its efficiency. As cheques are written in all major languages, almost all the major cheque processing systems reported so far have used their own databases for experimentation, so their performances cannot be compared effectively. But from the industrial point of view, the A2iA 'CheckReader' outperforms the others in accuracy. Majority of the researchers used a combination of two or more classifiers for the recognition purpose and many of them are based on hidden Markov models and neural networks. As the technology advanced, outstation cheque clearances even in developing countries can be made faster by just sending the image of the cheque to the payer's bank through cheque truncation systems. The interoperability of such cheque processing systems with the existing banking software is also an area of great significance.

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References

1. Palacios, R., Gupta, A.: A system for processing handwritten bank checks automatically. Image Vis. Comput. **26**(10), 1297–1313 (2008)
2. Han, K., Sethi, I.K.: An off-line cursive handwritten word recognition system and its application to legal amount interpretation. Int. J. Pattern Recognit. Artif. Intell. **11**(5), 757–770 (1997)
3. Zhang, H.G., Chen, G., Liu, G., Guo, J.: Bank check image binarization based on signal matching. In: Proceedings of the Fifth International Conference on Information, Communications and Signal Processing, pp. 1430–1433 (2005)
4. Zanchettin, C., Cavalcanti, G.D.C., Doria, R.C., Silva, E.F.A., Rabelo, J.C.B., Bezerra, B.L.D.: A neural architecture to identify courtesy amount delimiters. In: Proceedings of the International Joint Conference on Neural Networks, pp. 3210–3217 (2006)
5. http://www.banknetindia.com/banking/chqtruncationb.htm
6. http://www.rosettatechnologies.com/image-replacement-document.asp
7. Leroux, M., Lethelier, E., Gilloux, M., Lemarie, B.: Automatic reading of handwritten amounts on French checks. Int. J. Pattern Recognit. Artif. Intell. **11**(4), 619–638 (1997)
8. Gorski, N.: Bank cheque data mining: integrated cheque recognition technologies. In: Chaudhuri, B.B. (ed.) Digital Document Processing, pp. 437–458. Springer, Berlin (2007)
9. Impedovo, S., Wang, P., Bunke, H. (eds.): Automatic Bank Check Processing. World Scientific, Singapore (1997)
10. http://www.3i-infotech.com/content/payment_solutions/image_quality_assurance.aspx
11. www.a2ia.com/Addon_Site/Upload/Autres/checkreader_3.4.pdf
12. http://www.sbullet.com/products_IQA_benefits.html
13. Lin, X.,: Quality assurance in high volume document digitization: a survey. In: Proceedings of 2nd International Conference on Document Image Analysis for Libraries, pp. 312–319 (2006)
14. Ulges, A., Lampert, C.H., Breuel, T.M.: Document image dewarping using robust estimation of curled text lines. In: Proceedings of 8th International Conference on Document Analysis and Recognition, pp. 1001–1005 (2005)
15. Zhang, L., Tan, C.L.: Warped image restoration with applications to digital libraries. In: Proceedings of 8th International Conference on Document Analysis and Recognition, pp. 192–196 (2005)
16. Cao, H., Ding, X., Liu, C.: Rectifying the bound document image captured by the camera: a model based approach. In: Proceedings 7th International Conference on Document Analysis and Recognition, pp. 71–75 (2003)
17. Fan, J., Lin, X., Simske, S.: A comprehensive image processing suite for book re-mastering. In: Proceedings of 8th International Conference on Document Analysis and Recognition, pp. 447–451 (2005)
18. Le Bourgeois, F., Trinh, E. et al.: Document image analysis solutions for digital libraries. In: Proceedings International Workshop on Document Image Analysis for Libraries, pp. 2–24 (2004)
19. Liu, K., Suen, C.Y., Cheriet, M., Said, J.N., Nadal, C., Tang, Y.Y.: Automatic extraction of baselines and data from check images. Int. J. Pattern Recognit. Artif. Intell. **11**(4), 675–697 (1997)

20. Boutros, G.: Automating Degraded Image Enhancement Processing (DIEP), Symposium on Document Image Understanding Technology, College Park, Maryland (2005)
21. Smith, E.H.B., Baird, H., Barrett, W., Bourgeois, F.L., Lin, X., Nagy, G., Simske, S.: DIAL 2004 working group report on acquisition quality control. In: Proceedings of the Second International Conference on Document Image Analysis for Libraries, pp. 373–376 (2006)
22. Garain, U., Halder, B.: Machine authentication of security documents. In: Proceedings of 10th International Conference on Document Analysis and Recognition, pp. 718–722 (2009)
23. http://www.carreker.fiserv.com/main/solutions/payments/CO/pnv.htm
24. Dawoud, A., Kamel, M.: Iterative model-based binarization algorithm for cheque images. Int. J. Document Anal. Recognit. **5**, 28–38 (2002)
25. Sahoo, P.K., Soltani, S., Wong, A.K.C., Chen, Y.C.: A survey of thresholding techniques. Comput. Vis. Graph. Image Process. **41**(2), 233–260 (1988)
26. Otsu, N.: A threshold selection method from gray-scale histogram. IEEE Trans. Syst. Man Cybern. **8**, 62–66 (1978)
27. Trier, O.D., Jain, A.K.: Goal-directed evaluation of binarization methods. IEEE Trans. Pattern Anal. Mach. Intell. **17**(12), 1191–1201 (1995)
28. Niblack, W.: An Introduction to Digital Image Processing. Prentice-Hall, Englewood Cliffs (1986)
29. Yanowitz, S.D., Bruckstein, A.M.: A new method for image segmentation. Comput. Vis. Graph. Image Process. **46**, 82–95 (1989)
30. White, J.M., Rohrer, G.D.: Image thresholding for optical character recognition and other applications requiring character image extraction. IBM J. Res. Dev. **27**(4), 400–411 (1983)
31. Trier, O.D., Taxt, T.: Improvement of integrated function algorithm for binarization of document images. Pattern Recognit. Lett. **16**, 277–283 (1995)
32. Parker, J.R.: Gray level thresholding in badly illuminated images. IEEE Trans. Pattern Anal. Mach. Intell. **13**, 813–819 (1991)
33. Sezgin, M., Sankur, B.: Survey over image thresholding techniques and quantitative performance evaluation. J. Electron. Imaging **13**(1), 317–327 (2004)
34. Mello, C.A.B., Bezerra, B.L.D., Zanchettin, C., Macario, V.: An efficient thresholding algorithm for Brazilian bank checks. In: Proceedings of 9th ICDAR, pp. 193–197 (2007)
35. Suen, C.Y., Lam, L., Guillevic, D., Strathy, N.W., Cheriet, M., Said, J.N., Fan, R.: Bank check processing system. Int. J. Imaging Syst. Technol. **7**, 392–403 (1996)
36. Madasu, V.K., Lovell, B.C.: Automatic segmentation and recognition of bank cheque fields. In: Proceedings of the Digital Imaging Computing: Techniques and Applications, pp. 33–38 (2005)
37. Neves, R.F.P., Mello, C.A.B., Silva, M.S., Bezerra, B.L.D. A new algorithm to threshold the courtesy amount of Brazilian bank checks. In: Proceedings of IEEE International Conference on Systems Man and Cybernetics, pp. 1226–1230 (2008)
38. Lee, L.L., Lizarraga, M.G., Gomes, N.R., Koerich, A.L.: A prototype for Brazilian bank check recognition. Int. J. Pattern Recognit. Artif. Intell. **11**(4), 549–570 (1997)
39. Chandra, L., Gupta, R., Kumar, P., Ganotra, D.: Automatic courtesy amount recognition for Indian bank checks. In: Proceedings of IEEE Region 10 Conference, 2008, pp. 1–5 (2008)
40. Su, H., Zhao, B., Ma, F., Wang, S., Xia, S.: A fault tolerant Chinese check recognition system. Int. J. Pattern Recognit. Artif. Intell. **11**(4), 571–594 (1997)
41. Hull, J.J.: Document image skew detection: survey and annotated bibliography. In: Hull, J.J., Taylor, S.L. (eds.) Document Analysis Systems II, pp. 40–64. World Scientific, Singapore (1998)
42. 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. Int. J. Pattern Recognit. Artif. Intell. **11**(4), 505–548 (1997)
43. Akiyama, A., Hagita, N.: Automated entry system for printed documents. Pattern Recognit. **23**, 1141–1154 (1990)
44. Vinciarelli, A.: A survey on off-line cursive word recognition. Pattern Recognit. **35**(7), 1433–1446 (2002)
45. Steinherz, T., Rivlin, E., Intrator, N.: Offline cursive script word recognition—a survey. Int. J. Document Anal. Recognit. **2**(2), 90–110 (1999)
46. Kim, G., Govindaraju, V.: Bank check recognition using cross validation between legal and courtesy amounts. Int. J. Pattern Recognit. Artif. Intell. **11**(4), 657–674 (1997)
47. Guillevic, D., Suen, C.Y.: Recognition of legal amounts on bank cheques. Pattern Anal. Appl. **1**(1), 28–41 (1998)
48. Guillevic, D., Suen, C.Y.: Cursive script recognition applied to the processing of bank cheques. In: Proceedings of 3rd ICDAR, pp. 11–14 (1995)
49. Guillevic, D.: Unconstrained Handwriting Recognition Applied to the Recognition of Bank Cheques. PhD thesis, Concordia University (1995)
50. Kaufmann, G., Bunke, H.: Automated reading of cheque amounts. Pattern Anal. Appl. **3**, 132–141 (2000)
51. Kimura, F., Tsuruoka, S., Miyake, Y., Shridhar, M.: A lexicon directed algorithm for recognition of unconstrained handwritten words. IEICE Trans. Inf. Syst **E77-D**(7), 785–793 (1994)
52. Srikantan, G., Lee, D.S., Favata, J.T.: Comparison of normalization methods for character recognition. In: Proceedings of 3rd ICDAR, pp.719–722 (1995)
53. Dzuba, G., Filatov, A., Gershuny, D., Kil, I., Nikitin, V.: Check amount recognition based on the cross validation of courtesy and legal amount fields. Int. J. Pattern Recognit. Artif. Intell. **11**(4), 639–655 (1997)
54. Liu, K., Suen, C.Y., Nadal, C.: Automatic extraction of items from cheque images for payment recognition. In: Proceedings of 13th ICPR, pp. 798–802 (1996)
55. Okada, M., Shridhar, M.: Extraction of user entered components from a personal bank check using morphological subtraction. Int. J. Pattern Recognit. Artif. Intell. **11**(5), 699–715 (1997)
56. Heutte, L., Pereira, P.B., Bougeois, O., Moreau, J.V., Plesis, B., Courtellemont, P., Lecourtier, Y.: Multi-bank check recognition system: consideration on the numeral amount recognition module. Int. J. Pattern Recognit. Artif. Intell. **11**(4), 595–618 (1997)
57. Khan, M.R.H., Hossain, G.: Bengali handwritten bank check recognition using automatic extraction of the User–Entered Data. In: Proceedings of 8th ICCIT, pp. 650–654 (2005)
58. Koerich, A.L., Lee, L.L.: A novel approach for automatic extraction of the user entered data from bankchecks. In: Proceedings of International Workshop on Document Analysis Systems, pp. 141–144 (1998)
59. Agarwal, A., Granowetter, L., Hussein, K., Gupta, A., Wang, P.S.P.: Detection of courtesy amount block on bank checks. In: Proceedings of 3rd ICDAR, pp. 748–751 (1995)
60. Samoud, F.B., Maddouri, S.S., Abed, H.E., Ellouze, N.: Comparison of two handwritten Arabic zones extraction methods of complex documents. In: Proceedings of International Arab Conference on Information Technology, pp. 1–7 (2008)
61. Ueda, K., Maegawa, H., Matsuo, K.: Automatic extraction of filled-in items from bank-check images. In: Proceedings of International Workshop on Document Analysis Systems, pp. 225–228 (2004)
62. Huang, L., Li, S., Li, L.: Extraction of filled-in items from Chinese bank check using support vector machines. In: Proceedings of 4th International Symposium on Neural Networks, pp. 407–415 (2007)

63. Djeziri, S., Nouboud, F., Plamondon, R.: Extraction of items from checks. In: Proceedings of 4th ICDAR, pp. 749–752 (1997)
64. Alirezaee, S., Ahmadi, M., Alijamat, A., Alahiari, M.A.: Segmentation of Iranian bank checks. In: Proceedings of the 12th IEEE International Multitopic Conference, pp. 460–462 (2008)
65. Ye, X., Cheriet, M., Suen, C.Y., Liu, K.: Extraction of bank check items by mathematical morphology. Int. J. Document Anal. Recognit. **2**, 53–66 (1999)
66. Xu, W., Zhang, H., Guo, J., Chen, G.: Discrimination between printed and handwritten characters for cheque OCR system. In: Proceedings of International Conference on Machine Learning and Cybernetics, pp. 1048–1053 (2002)
67. Suen, C.Y., Xu, Q., Lam, L.: Automatic recognition of handwritten data on cheques—fact or fiction?. Pattern Recognit. Lett. **20**, 1287–1295 (1999)
68. Fan, R., Lam, L., Suen, C.Y.: Processing of date information on cheques. In: Proceedings of the Fifth International Workshop on Frontiers in Handwriting Recognition, pp. 207–212 (1996)
69. Lam, L., Fan, R., Xu, Q., Suen, C.Y.: Segmentation of date field on bank cheques. In: Proceedings of the Joint IAPR International Workshops on Advances in Pattern Recognition, pp. 163–172 (2000)
70. Xu, Q., Lam, L., Suen, C.Y.: Automatic segmentation and recognition system for handwritten dates on Canadian bank cheques. In: Proceedings of the Seventh International Conference on Document Analysis and Recognition, pp. 704–708 (2003)
71. Santos, J.E.B.D., Dubuisson, B., Bortolozzi, F.: Characterizing and distinguishing text in bank cheque images. In: Proceedings of the 15th Brazilian Symposium on Computer Graphics and Image Processing, pp. 203–209 (2002)
72. Guo, J.K., Ma, M.Y.: Separating handwritten material from machine printed text using hidden Markov models. In: Proceedings of the Sixth International Conference on Document Analysis and Recognition, pp. 439–443 (2001)
73. Ma, M., Guo, K.: Detecting and Utilizing Add-on Information from a Scanned Document Image. Technical Report PINTL-IM-142-099. Panasonic Information and Networking Technologies Laboratory (2000)
74. Madasu, V.K., Yusof, M.H.M., Hanmandlu, M., Kubik, K.: Automatic extraction of signatures from bank cheques and other documents. In: Proceedings of DICTA, pp. 591–600 (2003)
75. Djeziri, S., Nouboud, F., Plamondon, R.: Extraction of signatures from check background based on a filiformity criterion. IEEE Trans. Image Process. **7**(10), 1425–1438 (1998)
76. Chaudhuri, B.B., Sarkar, N.: Texture segmentation using fractal dimension. IEEE Trans. Pattern Anal. Mach. Intell. **17**(1), 72–77 (1995)
77. Casey, R.G., Lecolinet, E.: A survey of methods and strategies in character segmentation. IEEE Trans. Pattern Anal. Mach. Intell. **18**((7), 690–706 (1996)
78. Trier, D., Jain, A.K., Taxt, T.: Feature extraction methods for character recognition—a survey. Pattern Recognit. **29**(4), 641–662 (1996)
79. Govindan, V.K., Shivaprasad, A.P.: Character recognition: a review. Pattern Recognit. **23**(7), 671–683 (1990)
80. Fenrich, R.: Segmenting of automatically located handwritten numeral strings. In: Impedovo, S., Simon, J.C. (eds.) From Pixels to Features III-Frontiers in Handwriting Recognition, pp. 47–60. Elsevier, Amsterdam (1992)
81. Zhang, L.Q., Suen, C.Y.: Recognition of courtesy amounts on bank checks based on a segmentation approach. In: Proceedings of the Eighth International Workshop on Frontiers in Handwriting Recognition, pp. 298–302 (2002)
82. Westall, J.M., Narasimhsa, M.S.: An evolutionary approach to the use of neural networks in the segmentation of handwritten numerals. Int. J. Pattern Recognit. Artif. Intell. **11**(5), 717–735 (1997)
83. Dimauro, G., Impedovo, S., Salzo, A.: Automatic bankcheck processing: a new engineered system. Int. J. Pattern Recognit. Artif. Intell. **11**(4), 467–504 (1997)
84. Dimauro, G., Impedovo, S., Pirlo, G., Salzo, A.: Bankchecks recognition systems: reengineering the design process. In: Downton, A.C., Impedovo, S. (eds.) Progress in handwriting recognition, pp. 419–425. World Scientific Publishing (1997)
85. Lam, L., Suen, C.Y., Guillevic, D., Strathy, N.W., Cheriett, M., Liu, K., Said, J.N.: Automatic processing of information on cheques. In: Proceedings of ICSMC, pp. 2353–2358 (1995)
86. Dey, S.: Adding Feedback to Improve Segmentation and Recognition of Handwritten Numerals. Master Thesis, Massachusetts Institute of Technology (1999)
87. Khan, S.: Character Segmentation Heuristics of Check Amount Verification. Master Thesis, Massachusetts Institute of Technology (1998)
88. Punnoose, J.: An Improved Segmentation Module for Identification of Handwritten Numerals. Master Thesis, Massachusetts Institute of Technology (1999)
89. Chuang, Z., Zhiqing, L., Bo, X., Jun, G.: The segmentation algorithm for handwritten numeral strings in bank-check recognition. Front. Electr. Electron. Eng. China **2**(1), 39–44 (2007)
90. Hussein, K., Agarwal, A., Gupta, A., Wang, P.: A knowledge based segmentation algorithm for enhanced recognition of handwritten courtesy amounts. Pattern Recognit. **32**(2), 305–316 (1999)
91. Oliveira, L.S., Sabourin, R., Bortolozzi, F., Suen, C.Y.: Automatic recognition of handwritten numerical strings: a recognition and verification strategy. IEEE Trans. Pattern Anal. Mach. Intell. **24**(11), 1438–1454 (2002)
92. http://en.wikipedia.org/wiki/Artificial_neural_network
93. Palacios, R., Gupta, A., Wang, P.S.P.: Feedback-based architecture for reading courtesy amounts on checks. J. Electron. Imaging **12**(1), 194–202 (2003)
94. Palacios, R., Gupta, A.: Training neural networks for reading handwritten amounts on checks. In: Proceedings of IEEE International Workshop on Neural Networks for Signal Processing, pp. 607–616 (2003)
95. Palacios, R., Gupta, A., Wang, P.S.P.: Handwritten bank check recognition of courtesy amounts. Int. J. Image Graph. **4**(2), 1–20 (2004)
96. Filatov, A., Gitis, A., Kil, I.: Graph based handwritten digit string recognition. In: Proceedings of ICDAR, pp. 845–848 (1995)
97. Song, W., Feng, M., Shaowei, X., Hui, S.: A fault tolerant Chinese bank check recognition system based on SOM neural networks. In: Proceedings of International Conference on Neural Networks, pp. 2560–2565 (1997)
98. Gorski, N., Anisimov, V., Augustin, E., Baret, O., Maximov, S.: Industrial bank check processing: the A2iA check-reader. Int. J. Document Anal. Recognit. **3**, 196–206 (2001)
99. Gorski, N., Anisimov, V., Augustin, E., Baret, O., Price, D., Simon, J.C.: A2iA Check Reader: a family of bank check recognition systems. In: Proceedings of 5th ICDAR, pp. 523–526 (1999)
100. Gorski, N. : Practical combination of multiple classifiers. In: Downton, A., Impedovo, S. (eds.) Progress in Handwriting Recognition, World Scientific, Singapore (1997)
101. Jayadevan, R., Pal, U., Kimura, F., Recognition of Words from legal amounts of Indian bank cheques. In: Proceedings of 12th ICFHR, pp. 166–171 (2010)
102. Madhvanath, S., Govindaraju, V.: The role of holistic paradigms in handwritten word recognition. IEEE Trans. Pattern Anal. Mach. Intell. **23**(2), 149–164 (2001)
103. Lu, Y., Shridhar, M.: Character segmentation in handwritten words—an overview. Pattern Recognit. **29**(1), 77–96 (1996)
104. Govindaraju, V., Srihari, S.H. : Separating handwritten text from interfering strokes. In: Impedovo, S., Simon, J.C. (eds.) From

Pixels to Features III-Frontiers in Handwriting Recognition, pp. 17–28. Elsevier, Amsterdam (1992)
105. Dimauro, G., Impedovo, S., Pirlo, G., Salzo, A.: Removing underlines from handwritten text: an experimental investigation. In: Downton, A.C., Impedovo, S. (eds.) Progress in Handwriting Recognition, pp. 497–501. World Scientific Publishing (1997)
106. Yu, M.L., Kwok, P.C.K., Leung, C.H., Tse, K.W.: Segmentation and recognition of Chinese bank check amounts. Int. J. Document Anal. Recognit. **3**, 207–217 (2001)
107. Yu, C.L., Suen, C.Y., Tang, Y.Y. Location and recognition of legal amounts on Chinese bank cheques. In: Proceedings of 4th ICDAR, pp. 588–591 (1997)
108. Dimauro, G., Impedovo, S., Pirlo, G.: Automatic recognition of cursive amounts on Italian bank-checks. In: Impedovo, S. (ed.) Progress in Image Analysis and Processing III, pp. 323–330. World Scientific (1994)
109. http://en.wikipedia.org/wiki/Hidden_Markov_model
110. Guillevic, D., Suen, C.Y.: HMM word recognition engine. In: Proceedings of the 4th International Conference on Document Analysis and Recognition, pp. 544–547 (1997)
111. Knerr, S., Augustin, E., Baret, O., Price, D.: Hidden Markov model based word recognition and its application to legal amount reading on French checks. Comput. Vis. Image Underst. **70**(3), 404–419 (1998)
112. Augustin, E., Baret, O., Price, D., Knerr, S.: Legal amount recognition on French bank checks using a neural network-HMM hybrid. In: Proceedings of IWFHR, pp. 45–56 (1998)
113. Freitas, C.O.A., Yacoubi, A.E., Bortolozzi, F., Sabourin, R.: Brazilian bank check handwritten legal amount recognition. In: Proceedings of the 13th Brazilian Symposium on Computer Graphics and Image Processing, pp. 97–104 (2000)
114. Kim, K.K., Kim, J., Chung, Y.K., Suen, C.Y.: Legal amount recognition based on the segmentation hypotheses for bank check processing. In: Proceedings of ICDAR, pp. 964–967 (2001)
115. Dodel, J.P., Shinghal, R. : Recognition of worded amounts. In: Impedovo, S., Wang, P.S.P., Bunke, H. (eds.) Automatic Bankcheck Processing, pp. 309–326. World Scientific Publishing Company, Singapore (1997)
116. Dodel, J.P., Shinghal, R.: Symbolic/neural recognition of cursive amounts on bank cheques. In: Proceedings of 3rd ICDAR, pp. 15–18 (1995)
117. Tang, H., Augustin, E., Suen, C.Y., Baret, O., Cheriet, M.: Spiral recognition methodology and its application for recognition of Chinese bank checks. In: Proceedings of the 9th International Workshop on Frontiers in Handwriting Recognition, pp. 263–268 (2004)
118. Farah, N., Souici, L., Sellami, M.: Classifiers combination and syntax analysis for Arabic literal amount recognition. Eng. Appl. Artif. Intell. **19**, 29–39 (2006)
119. Olivier, C., Paquet, T., Avila, M., Lecourtier, Y.: Recognition of handwritten words using stochastic models. In: Proceedings of 3rd ICDAR, pp. 19–23 (1995)
120. Shridhar, M., Houle, G.F., Kimura, F.: Comprehensive check image reader. In: Proceedings of the International Conference on Computing: Theory and Applications, pp. 407–416 (2007)
121. Shridhar, M., Houle, G.F., Kimura, F.: Document recognition strategies for bank cheques. In: Proceedings of IEEE International Conference on Electro/Information Technology, pp. 170–173 (2009)
122. Alemu, W., Fuchs, S.: Handwritten Amharic bank check recognition using hidden Markov random field. In: Proceedings of the Conference on Computer Vision and Pattern Recognition Workshop, pp. 28–35 (2003)
123. Lecce, V.D., Dimauro, G., Guerriero, A., Impedovo, S., Pirlo, G., Salzo, A.: New hybrid approach for legal amount recognition. In: Proceedings of the Seventh International Workshop on Frontiers in Handwriting Recognition, pp. 199–208 (2000)
124. Houle, G.F., Aragon, D.B., Smith, R.W., Shridhar, M., Kimura, F.: A multi-layered corroboration-based check reader. In: Proceedings of the Workshop on Document Analysis Systems, pp. 495–546 (1996)
125. Morita, M.E., Lethelier, E., Yacoubi, A.E., Bortolozzi, F., Sabourin, R.: Recognition of handwritten dates on bankchecks using an HMM approach. In: Proceedings of XIII Brazilian Symposium on Computer Graphics and Image Processing, pp. 113–120 (2000)
126. Morita, M., Yacoubi, A.E., Sabourin, R., Bortolozzi, F., Suen, C.Y.: Handwritten month word recognition on Brazilian bank cheques. In: Proceedings of 6th ICDAR, pp. 972–976 (2001)
127. Kim, J., Kim, K., Nadal, C.P., Suen, C.Y.: A methodology of combining HMM and MLP classifiers for cursive word recognition. In: Proceedings of 15th ICPR, pp. 319–322 (2000)
128. Xu, Q., Kimy, J.H., Lam, L., Sue, C.Y.: Recognition of handwritten month words on bank cheques. In: Proceedings of the Eighth International Workshop on Frontiers in Handwriting Recognition, pp. 111–116 (2002)
129. Strathy, N.W.: Handwriting recognition for cheque processing. In: Proceedings of the 2nd International Conference on Multimodal Interface, pp. 47–50 (1999)
130. Kapp, M.N., Freitas, C.O.A., Sabourin, R.: Methodology for the design of NN-based month-word recognizers written on Brazilian bank checks. Image Vis. Comput. **25**, 40–49 (2007)
131. Morita, M., Sabourin, R., Bortolozzi, F., Suen, C.Y.: Segmentation and recognition of handwritten dates: an HMM-MLP hybrid approach. Int. J. Document Anal. Recognit. **6**, 248–262 (2004)
132. Dimauro, G., Grattagliano, M.R., Impedovo, S., Pirlo, G.: A system for bankcheck processing. In: Proceedings of 2nd ICDAR, pp. 454–459 (1993)
133. Kaufmann, G., Bunke, H.: Detection and correction of recognition errors in check reading. Int. J. Document Anal. Recognit. **2**, 211–221 (2000)
134. Impedovo, D., Pirlo, G.: Automatic signature verification: the state of the art. IEEE Trans. Syst. Man Cybern. Part C Appl. Rev. **38**(5), 609–635 (2008)
135. Yoshimura, M., Yoshimura, I.: Investigation of a verification system for Japanese countersignatures on traveler's checks. Trans. IEICE **80**(7), 1764–1773 (1997)
136. Impedovo, S., Pirlo, G.: Verification of handwritten signatures: an overview In: Proceedings of 14th International Conference on Image Analysis and Processing, pp. 191–196 (2007)
137. Bajaj, R., Chaudhury, S.: Signature verification using multiple neural classifiers. Pattern Recognit. **30**(1), 1–7 (1997)
138. Cordella, L.P., Foggia, P., Sansone, C., Tortorella, F., Vento, M.: In: Kittler, J., Roli, F. (eds.) A Cascaded Multiple Expert System for Verification, LNCS, vol. 1857, pp. 330–339. Springer (2000)
139. Dimauro, G., Impedovo, S., Pirlo, G., Salzo, A.: A multi-expert signature verification system for bank check processing. IJPRAI **11**(5), 827–844 (1997)
140. Huang, K., Yan, H.: Offline signature verification based on geometric feature extraction and neural network classification. Pattern Recognit. **30**(1), 9–17 (1997)
141. Huang, K., Yan, H.: Offline signature verification using structural feature correspondence. Pattern Recognit. **35**(11), 2467–2477 (2002)
142. Santos, C., Justino, E.J.R., Bortolozzi, F., Sabourin, R.: An offline signature verification method based on the questioned document expert's approach and a neural network classifier. In: Proceedings of 9th IWFHR, pp. 498–502 (2004)
143. Xiao, X.H., Leedham, G.: Signature verification by neural networks with selective attention. Appl. Intell. **11**, 213–223 (1999)

144. Sansone, C., Vento, M.: Signature verification: increasing performance by a multi-stage system. Pattern Anal. Appl. **3**, 169–181 (2000)
145. Baltzakis, H., Papamarkos, N.: A new signature verification technique based on a two-stage neural network classifier. Eng. Appl. Artif. Intell. **14**, 95–103 (2001)
146. Armand, S., Blumenstein, M., Muthukkumarasamy, V.: Off-line signature verification based on the modified direction feature. In: Proceedings of 18th ICPR, pp. 509–512 (2006)
147. http://en.wikipedia.org/wiki/Dynamic_time_warping
148. Deng, P.S., Liao, H.M., Ho, C.W., Tyan, H.R.: Wavelet-based off-line handwritten signature verification. Comput. Vis. Image Underst. **76**(3), 173–190 (1999)
149. Fang, B., Leung, C.H., Tang, Y.Y., Tse, K.W., Kwok, P.C.K., Wong, Y.K.: Offline signature verification by the tracking of feature and stroke positions. Pattern Recognit. **36**(1), 91–101 (2003)
150. Shanker, A.P., Rajagopalan, A.N.: Off-line signature verification using DTW. Pattern Recognit. Lett. **28**(12), 1407–1414 (2007)
151. Jayadevan, R., Kolhe, S.R., Patil, P.M.: Dynamic time warping based static hand printed signature verification. J. Pattern Recognit. Res. **4**(1), 52–65 (2009)
152. Nel, E.M., Preez, J.A., Herbst, B.M.: Estimating the pen trajectories of static signatures using hidden Markov models. IEEE Trans. Pattern Anal. Mach. Intell. **27**(11), 1733–1746 (2007)
153. Justino, E.J.R., Bortolozzi, F., Sabourin, R.: Off-line signature verification using HMM for random, simple and skilled forgeries. In: Proceedings of 6th ICDAR, pp. 1031–1034 (2001)
154. Coetzer, J., Herbst, B.M., du Preez, J.A.: Offline signature verification using the discrete radon transform and a hidden Markov model EURASIP. J. Appl. Signal Process. **4**, 559–571 (2004)
155. Coetzer, J., Herbst, B.M., du Preez, J.A.: Off-line signature verification: a comparison between human and machine performance. In: Proceedings of 10th IWFHR (2006)
156. Batista, L., Granger, E., Sabourin, R.: Improving performance of HMM-based off-line signature verification systems through a multi-hypothesis approach. IJDAR **13**, 33–47 (2010)
157. http://en.wikipedia.org/wiki/Fuzzy_logic
158. Velez, J., Sanchez, A., Moreno, B., Esteban, J.L.: Fuzzy shape-memory snakes for the automatic off-line signature verification problem. Fuzzy Sets Syst. **160**, 182–197 (2009)
159. Madasu, V.K., Hafizuddin, M., Yusof, M., Hanmandlu, M., Kubik, K.: In: Gedeon, T.D., Fung, L.C.C. (eds.) Offline Signature Verification and Forgery Detection System Based on Fuzzy Modeling, LNAI 2903, pp. 1003–1013. Springer (2003)
160. Ismail, M.A., Gad, S.: Off-line Arabic signature recognition and verification. Pattern Recognit. **33**, 1727–1740 (2000)
161. Quek, C., Zhou, R.W.: Antiforgery: a novel pseudo-outer product based fuzzy neural network driven signature verification system. Pattern Recognit. Lett. **23**, 1795–1816 (2002)
162. Hanmandlu, M., Yusof, M.H.M., Madasu, V.K.: Off-line signature verification and forgery detection using fuzzy modeling. Pattern Recognit. **38**, 341–356 (2005)
163. http://en.wikipedia.org/wiki/Support_vector_machine
164. Hairong, L., Wang, W., Wang, C., Zhuo, Q.: Off-line Chinese signature verification based on support vector machines. Pattern Recognit. Lett. **26**, 2390–2399 (2005)
165. Vargas, J.F., Ferrer, M.A., Travieso, C.M., Alonso, J.B.: Off-line signature verification based on grey level information using texture features. Pattern Recognit. **44**, 375–385 (2011)
166. Bertolini, D., Oliveira, L.S., Justino, E., Sabourin, R.: Reducing forgeries in writer-independent off-line signature verification through ensemble of classifiers. Pattern Recognit. **43**, 387–396 (2010)
167. Batista, L., Granger, E., Sabourin, R.: Applying dissimilarity representation to off-line signature verification. In: Proceedings of ICPR, pp. 1293–1297 (2010)
168. Vargas, J.F., Ferrer, M.A., Travieso, C.M., Alonso, J.B.: Offline signature verification based on pseudo-cepstral coefficients. In: Proceedings of 10th ICDAR, pp. 126–130 (2009)
169. Nguyen, V., Blumenstein, M., Muthukkumarasamy, V., Leedham, G.: Off-line signature verification using enhanced modified direction features in conjunction with neural classifiers and support vector machines. In: Proceedings of ICDAR-2007, pp. 734–738
170. Nguyen, V., Blumenstein, M., Leedham, G.: Global features for the off-line signature verification problem. In: Proceedings of ICDAR-2009, pp. 1300–1304
171. Nguyen, V., Kawazoe, Y., Wakabayashi, T., Pal, U., Blumenstein, M.: Performance analysis of the gradient feature and the modified direction feature for off-line signature verification. In: Proceedings of 12th ICFHR, pp. 303–307 (2010)
172. http://en.wikipedia.org/wiki/Naive_Bayes_classifier
173. Xiao, X., Leedham, G.: Signature verification using a modified Bayesian network. Pattern Recognit. **35**, 983–995 (2002)
174. Ruiz-del-Solar, J., Devia, C., Loncomilla, P., Concha, F.: Off-line signature verification using local interest points and descriptors. In: Ruiz-Shulcloper, J., Kropatsch, W.G. (eds.) LNCS 5197, pp. 22–29 (2008)
175. Kalera, M.K., Srihari, S., Xu, A.: Offline signature verification and identification using distance statistics. IJPRAI **18**(7), 1339–1360 (2004)
176. Fang, B., Tang, Y.Y.: In: Zhang, D., Jain, A.K. (eds.) Reduction of Feature Statistics Estimation Error for Small Training Sample Size in Offline Signature Verification, LNCS 3072, pp. 526–532. Springer (2004)
177. Mizukami, Y., Yoshimura, M., Miike, H., Yoshimura, I.: An off-line signature verification system using an extracted displacement function. In: Proceedings of 5th ICDAR, pp. 757–760 (1999)
178. Ramesh, V.E., Murty, M.N.: Offline signature verification using genetically optimized weighted features. Pattern Recognit. **32**(2), 217–233 (1999)
179. Ueda, K.: Investigation of offline Japanese signature verification using a pattern matching. In: Proceedings of 7th ICDAR, pp. 951–955 (2003)
180. Hairong, L., Bai, X., Yin, W., Dong, J.: Off-line signature verification using graphical model. In: Proceedings of 20th ICPR, pp. 3784–3788 (2010)
181. Chen, S., Srihari, S.: A new off-line signature verification method based on graph matching. In: Proceedings of 18th ICPR, pp. 869–872 (2006)
182. Sabourin, R., Genest, G., Preteux, F.: Pattern spectrum as a local shape factor for off-line signature verification. In: Proceedings of International Conference on Pattern Recognition, pp. 43–48 (1996)
183. Sabourin, R., Genest, G., Preteux, F.: Off-line signature verification by local granulometric size distributions. IEEE Trans. Pattern Anal. Mach. Intell. **19**(9), 976–988 (1997)
184. Sabourin, R., Drouhard, J.P., Wah, E.S.: Shape Matrices as a Mixed Shape Factor for Off-line Signature Verification. 4th ICDAR, pp. 661–665 (1997)
185. Zimmer, A., Ling, L.L.: A Hybrid On/Off Line Handwritten Signature Verification System. 7th ICDAR-7, pp. 424–428 (2003)
186. Zimmer, A., Ling, L.L.: A Window-based hybrid signature verification system. In: Zhang, D., Jain, A.K. (eds.) ICBA 2004, LNCS 3072, pp. 562–568. Springer, Berlin (2004)
187. Kimura, F., Shridhar, M., Chen, Z.: Improvements of a lexicon directed algorithm for recognition of unconstrained handwritten words. In: Proceedings of 2nd ICDAR, pp. 18–22 (1993)
188. http://www.a2ia.com
189. www.techinfocenter.com
190. http://www.miteksystems.com/ImageNet_Payments_details.asp
191. http://www.miteksystems.com/MobileDeposit.asp

192. http://www.parascript.com/products2/CheckPlus.cfm
193. http://www.parascript.com/products2/CheckUltra.cfm
194. http://www.parascript.com/products2/CheckUsability.cfm
195. http://www.signplus.com/en/solutions/fraudone.php
196. Ohalia, Y.A., Cheriet, M., Suen, C.Y.: Databases for recognition of handwritten Arabic cheques. Pattern Recognit. **36**, 111–121 (2003)
197. Impedovo, S., Dimauro, G., Modugno, R., Pirlo, G.: A new database for research on bank-check processing. In: Proceedings of 8th IWFHR, pp. 524–528 (2002)
198. Zhu, H., Tang, X.L., Liu, P.: An MLP-orthogonal Gaussian mixture model hybrid model for Chinese bank check printed numeral recognition. Int. J. Document Anal. **8**(1), 27–34 (2006)
199. Morita, M., Sabourin, R., Bortolozzi, F., Suen, C.Y.: A recognition and verification strategy for handwritten word recognition. In: Proceedings of 7th ICDAR, pp. 482–486 (2003)
200. Chin, F., Wu, F.: A microprocessor based optical character recognition check reader. In: Proceedings of 3rd ICDAR, pp. 982–985 (1995)
201. Ueda, K., Matsuo, K.: Automatic seal imprint verification system for bankcheck processing. In: Proceedings of the 3rd International Conference on Information Technology and Applications, pp. 768–771 (2005)
202. Jesus, A., Facon, J.: Segmentation of Brazilian bank check logos without a priori knowledge. In: Proceedings of the International Conference on Information Technology: Coding and Computing, pp. 259–263 (2000)
203. http://www.smartmoneydaily.com/personalfinance/15-historical-interesting-bank-checks.aspx