Sorting and Recognizing Cheques and Financial Documents

Ching Y. Suen, Ke Liu, and Nick W. Strathy*

Centre for Pattern Recognition and Machine Intelligence
Concordia University, Suite GM–606
1455 de Maisonneuve Blvd West, Montreal, QC, H3G 1M8, Canada
suen@cenparmi.concordia.ca

Abstract. In collaboration with financial institutions and utility companies, we have carried out substantial research on document analysis and handwriting recognition. This paper describes our prototype which can differentiate between cheques and remittance slips, between English and French cheques, and recognize their contents. A new technique of sorting handwritten cheques and financial documents will be described. It is based on the detection of the structural properties printed on such documents. Handwritten numeric amounts are recognized by a multiple–expert system. These systems have been applied to read handwritten cheques and numerous financial documents with a great variety of backgrounds, colours, and designs in real–life environments. Their performance will be presented and analyzed.

1 Introduction

Document analysis and recognition technologies play a very important role in information processing. Each day, billions of business and financial documents have to be processed by computer, e.g. bank cheques and utility bills, school and property tax forms, driver license renewals, income tax returns, drawings and maps, credit card payment slips, and a great variety of subscription and remittance forms. According to recent surveys and our visits to several data–processing centres of banks and utility companies, over 55 billion cheques (at a cost of 25 billion dollars) are processed annually in North America where the amounts are mostly keyed in manually. Hence economically there is an urge to fully automate the process of entering handwritten data into the computer. However, it is a great challenge due to immense variations of handwriting, colour, and designs [1]–[6].

Current research on amount recognition has been mainly devoted to bank cheque processing [7]–[8]. Our study reveals that in real–life applications, a bank cheque to be processed is usually accompanied with one or more financial documents from the customer that also contain the amount information, either in machine printed or in handwritten format, or in both, which is relevant to the

* *AMDG*

S.-W. Lee and Y. Nakano (Eds.): DAS'98, LNCS 1655, pp. 173–187, 1999.

Fig. 1. Sample financial document

amount information on the cheque. To read the amounts from a bank cheque and its associated financial documents and verify whether they are consistent or not is an important and necessary process for most banks and utility companies. Therefore, it is very important to have an automatic system which can sort or identify cheques and different documents, and extract and recognize the interested data from them.

In this paper, we first present a novel approach to sort cheques and financial documents and extract data from them. Then, the issues related to amount recognition will be addressed.

2 Sorting Cheques and Financial Documents and Extracting Items

Most existing document processing methods [9]–[10] are based on the analysis of the line features which constitute the layout structures of the documents. Regarding the processing of financial documents, however, some financial documents may be constituted mainly of other kinds of geometrical components such as the regions in different shades, and contain fewer or no lines. Fig. 1 shows a VISA slip used in Canada, in which the rectangle regions and triangle pointer are the geometrical components for the description of the document.

As a result, those methods based only on the analysis of the line features cannot be applied to process financial documents, directly. The financial document processing method should be able to distinguish straight lines and edges of rectangular regions, and to use the geometrical features other than straight lines for the identification of documents. On the other hand, our study indicates that in practice, there are less than one hundred types of financial documents used by a utility company or bank, which means that a *model-driven matching technique* can be employed. Based on the above analysis, a novel approach has been developed for the processing of financial documents, which can be described in four parts, i.e. geometrical feature extraction, model representation, sorting of documents, and item extraction, respectively.

2.1 Extraction of Geometrical Features

The geometrical feature components are extracted from an input document image based on edge analysis since some financial documents such as bank cheques may contain very complicated background pictures. It is reasonable to assume that the skew angle of the scanned input document is within a given range, therefore we can define horizontal lines, vertical lines, and lines in other orientations. Lines other than horizontal or vertical are mainly used for the construction of the triangles and polygons. Hence, the extracted geometrical feature components include horizontal line segments, vertical line segments, triangles, rectangles and polygons.

The extracted geometrical feature components can be represented as set $\mathrm{G} = \{C_i\}_0^{N-1}$ where N is the total number of geometrical feature components, C_i indicates the ith geometrical feature component and is described as follows:

$$C_i = \{GT_i, GP_i, GS_i\} \tag{1}$$

where GT_i takes one of values 0, 1, 2, 3, 4 each of which indicates that the type of component is horizontal line segment, vertical line segment, triangle, rectangle and polygon, respectively. GP_i is the representative point of C_i. When the component is a horizontal line or vertical line segment, GP_i is the mid point between the two end points of the segment. Otherwise, the x and y coordinates of GP_i are taken as the average x and y coordinates of the corner points of the triangle, rectangle, or polygon.

GS_i in formula (1) is a set of points, i.e.

$$GS_i = \{P_0, P_1, ..., P_{n_i-1}\}. \tag{2}$$

When the component is a horizontal or vertical line segment, n_i equals 2 and P_0 and P_1 are the two end points of the segments, respectively. In the other cases, n_i equals 3 for a triangle component, 4 for a rectangle component, and the total number of the corner points for a polygonal component. P_k and $P_{(k+1)\%n_i}$, where $0 \leq k < n_i$, are connected to each other through their common edge, and $P_0, P_1, ..., P_{n_i-1}$ are ordered counter-clockwise.

2.2 Model Representation

Model representation is used for training a new type of financial documents. In our approach, the sample document used for training a financial document can be either a blank sample document or a one filled with a customer's handwriting. From our experience, the extra horizontal or vertical lines may be introduced when people write courtesy or legal amounts. Therefore, if a filled document is used for training the system, an inference may be required to discard those horizontal or vertical line segments. The model for the description of a financial document is mainly based on the above set G of geometrical feature components, and will be used for sorting documents and extracting items, respectively.

Model Description for Sorting Documents In order to apply a model–driven technique to find the match between a model and input document, the *dominant geometrical feature component(s)* is defined and determined from the geometrical feature component set G of a training document. In the stage of sorting documents, when a model is compared with the set of geometrical feature components of an input document, the system first tries to find a match between the dominant geometrical feature component(s) of model and a geometrical feature component(s) of the input document. If it is successful, the system will proceed to further match their corresponding geometrical feature components. The model–driven matching method is described in the next subsection.

Several rules have been developed for the determination of dominant geometrical feature component(s) from set G of a training document. If there is a rectangle in G, of which the long edges are long enough(determined based on the width and height of the training document image), the rectangle can be chosen as the dominant geometrical feature component. If there is a line segment either in horizontal or in vertical, whose length is long enough, it can be chosen as the dominant geometrical feature component. If there is a polygon and the length of its longest edge is exceeds a threshold, the polygon can also be chosen as the dominant geometrical feature component.

When a rectangle is determined as the dominant geometrical feature component, the representative point GP of the rectangle is chosen as the original coordinate point of an image plane coordinate system, called *model-image plane coordinate system*. If the long edges are horizontal, the edge direction from left to right of the long edges is defined as the x-axis direction of the model-image plane coordinate system, otherwise, the direction from up to down of the long edges is chosen as the y-axis direction of the coordinate system.

Similarly, a model-image plane coordinate system can be constituted when the dominant geometrical feature component is a horizontal line segment, vertical line segment or polygon.

If the system is unable to determine a dominant geometrical feature component based on the rules described above, an interactive learning process may be required to ask for the labels of two geometrical feature components, which will be used as the dominant geometrical feature components of the model. The representative point of one geometrical feature component will be chosen as the original coordinate point of the model-image plane coordinate system and the direction from this point to the representative point of another geometrical feature component as the x-axis or y-axis direction of the coordinate system, depending on the angle between this direction and that of the x-axis of the document image.

After the dominant geometrical feature components of the model have been determined and the model– image plane coordinate system is built, the coordinates of the representative point GP and the points of set GS of each geometrical feature component are transformed into the coordinates in the model–image plane coordinate system.

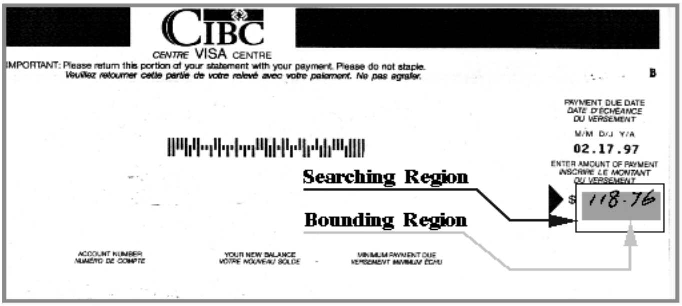

Fig. 2. Searching and bounding regions

Model Description for Item Extraction The second part of model representation is to determine some zones from the training document for the extraction of interested items. As we mentioned before, some financial documents exist neither in table nor in form. Therefore, for these documents, in general, it is impossible to determine the zones for the items automatically, and the knowledge about the positions of interested items is required. Hence, an interactive learning process is needed to incorporate this knowledge.

In our system, after the first part of a model is built, the training system will prompt the original document image, and ask for determining the searching and bounding regions[11], respectively, by selecting four points for each zone using the mouse. The physical meanings of the concepts of searching region and bounding region are: for each item, all its strokes should have their parts inside its corresponding searching region, and the probability of the parts of these strokes going outside of the bounding region of this item should be very low. Fig. 2 shows an example of the determined searching and bounding regions for the numeric amount on the VISA slip.

If more items are to be extracted from the document, their corresponding searching and bounding regions are defined and determined in the same way described above. Besides, the knowledge that whether the handwriting of a item may touch or cross some printed lines or not(for non–table or non-form documents, for example) can also be learned when building model description for the extraction of the item.

The coordinates of the selected points for the searching and bounding regions of each item are also transformed into their corresponding coordinates in the model-image plane coordinate system.

2.3 Sorting Financial Documents

As mentioned before, in practice, extra geometrical feature components such as horizontal or vertical lines may be introduced when people write courtesy or legal amounts on financial documents. Therefore, when the extracted geometrical feature component set G of an input document image I_G is compared with the geometrical feature component set G_m of its corresponding model, G_m may only match a subset of G because the extra geometrical feature components of G, if there are some, should not find any matches from G_m. This is also one of the main reasons the model-driven technique is adopted in our approach.

Suppose

$$C_i = \{GT_i, GP_i, GS_i\} \quad \text{where} \quad GS_i = \{P_0^{(i)}, P_1^{(i)}, ..., P_{n_i-1}^{(i)}\}$$

and

$$C_j = \{GT_j, GP_j, GS_j\} \quad \text{where} \quad GS_j = \{P_0^{(j)}, P_1^{(j)}, ..., P_{n_j-1}^{(j)}\}$$

are two geometrical feature components. Assume that $d(P_1, P_2)$ is the distance between two points on an image plane and, $\alpha(P)$ represents the corner of corner point P of a triangle, rectangle($\alpha(P) = 90^0$ in such case), or polygon. C_i and C_j are said to be *in shape matching* if the followings are true:

1. $GT_i = GT_j$
2. $n_i = n_j$
3. One of the following conditions is true:
   a. $\mid d(P_0^{(i)}, P_1^{(i)}) - d(P_0^{(j)}, P_1^{(j)}) \mid < thd$, if $GT_i = GT_j = 0$ or 1;
   b. $(\mid d(P_{(m+k)\%n_i}^{(i)}, P_{(m+k+1)\%n_i}^{(i)}) - d(P_m^{(j)}, P_{(m+1)\%n_j}^{(j)}) \mid < thd) \wedge$
   $(\mid \alpha(P_{(m+k)\%n_i}^{(i)}) - \alpha(P_m^{(j)}) \mid < th\alpha)$ for $m = 0, 1, ..., n_i - 1$, when $GT_i = GT_j$ = 2, 3, or 4, where k is a specific integer such that $0 \le k < n_i$, *thd* and $th\alpha$ are the given distance and corner thresholds, respectively.

C_i and C_j are said to be *in shape matching under coordinate transformation T* if they are in shape matching and, for the above same integer k, the following two conditions are also true:

4. $d(GP_i, T(GP_j)) < thp$
5. $d(P_{(m+k)\%n_i}^{(i)}, T(P_m^{(j)})) < thp, \quad m = 0, 1, ..., n_i - 1$, where *thp* is a position distance threshold.

Suppose a model has only one dominant geometrical feature component C^*. A geometrical feature component C is a *candidate geometrical feature component* of C^* if they are in shape matching. When a model has two dominant geometrical feature components C_1^* and C_2^*, geometrical feature components C_1 and C_2 are called the *candidate pair of geometrical feature components* of C_1^* and C_2^*, if C_1^* and C_1 are in shape matching and, C_2^* and C_2 are in shape matching, respectively, and the distance between the representative points of C_1^* and C_2^* is almost the same as the distance between the representative points of C_1 and C_2.

Suppose that $G_m = \{C_{m,i}\}_0^{N_m-1}$ where $C_{m,i} = \{GT_{m,i}, GP_{m,i}, GS_{m,i}\}$ is the set of geometrical feature components associated with the m*th* model, where $0 \le m < M$ and $G = \{C_i\}_0^{N-1}$ where $C_i = \{GT_i, GP_i, GS_i\}$ is the set of geometrical feature components extracted from the input document. Assume that $N_m^{(j)}$, $j = 0, \cdots, 4$, indicates the numbers of horizontal line segments, vertical line segments, triangles, rectangles, and polygons contained in G_m, respectively, and $N^{(j)}$, $j = 0, \cdots, 4$, the numbers of the horizontal line segments, vertical line segments, triangles, rectangles, and polygons contained in G, respectively.

Since the extra geometrical feature components, introduced when people write the courtesy or legal amounts on financial documents, can only be horizontal or vertical line segments, therefore, if G_m is the model of G, the following conditions should be true:

a. $N_m^{(0)} \le N^{(0)}$, $N_m^{(1)} \le N^{(1)}$;
b. $N_m^{(2)} = N^{(2)}$, $N_m^{(3)} = N^{(3)}$, $N_m^{(4)} = N^{(4)}$.

The above conditions can greatly reduce the number of models chosen for matching an input document, and can therefore speed up the sorting algorithm.

Based on the above assumptions and descriptions, the algorithm of sorting financial documents can be summarized below.

Sorting Algorithm

Match = -1;
m = 0;
while (m < M) do
if $(N_m^{(0)} \le N^{(0)}) \wedge (N_m^{(1)} \le N^{(1)}) \wedge (N_m^{(2)} = N^{(2)}) \wedge (N_m^{(3)} = N^{(3)}) \wedge (N_m^{(4)} = N^{(4)})$
begin
a. *Find a candidate geometrical feature component of the dominant geometrical feature component of G_m, or a candidate pair of geometrical feature components if G_m has two dominant geometrical feature components;*
b. *If no more dominant geometrical feature component exists(or no candidate pair of geometrical feature components), goto f;*
c. *Constitute a coordinate transformation T_m from the model–image plane of G_m to the document image plane based on the correspondence between the dominant geometrical feature component(s) of G_m and the candidate geometrical feature component(pair);*
d. *For each geometrical feature component of G_m, find its corresponding geometrical feature component such that they are in shape matching under T_m. If it is unsuccessful for a geometrical feature component of G_m, goto f;*
e. *Match = m (successful), break;*
f. *m = m + 1;*
end;
else
m = m + 1;

If the above algorithm assigns m to *Match*, which is positive, the document image is identified as type m.

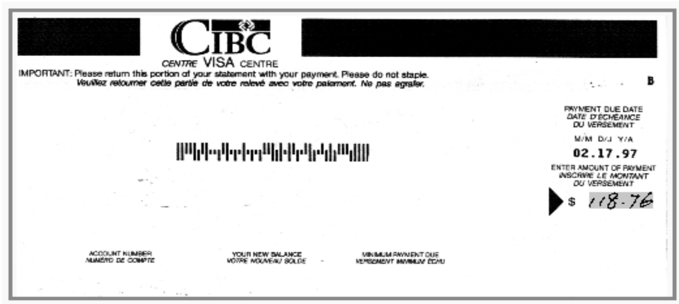
[redacted] CIBC [redacted]
CENTRE VISA CENTRE
IMPORTANT: Please return this portion of your statement with your payment. Please do not staple.
Veuillez retourner cette partie de votre relevé avec votre paiement. Ne pas agrafer.
B
PAYMENT DUE DATE
DATE D'ÉCHÉANCE
DU VERSEMENT
M/M D/J Y/A
02.17.97
ENTER AMOUNT OF PAYMENT
INSCRIRE LE MONTANT
DU VERSEMENT
$ 118.76
ACCOUNT NUMBER
NUMÉRO DE COMPTE
YOUR NEW BALANCE
VOTRE NOUVEAU SOLDE
MINIMUM PAYMENT DUE
VERSEMENT MINIMUM ÉCHU

Fig. 3. Extracted digit amount item

2.4 Model–Driven Item Extraction

Once G_m is identified as the model of the input document image I_G, the points selected for the searching and bounding regions of the model document G_m are transformed into, using transformation T_m, the points on document image I_G, which constitute the searching and bounding regions for extracting item(s) from I_G. Then, the item extraction method presented in [11] is applied to extract an item image, which consists of the following steps:

1. Estimate the grey distributions of handwritten strokes by selecting some pixel points on handwritten strokes from the searching region;
2. Trace the connected components of handwritten strokes within the bounding region based on the estimated grey distributions of handwritten strokes, and by selecting initial tracing points from the searching region.
3. Separate strokes from connected table or form lines if necessary.

Fig. 3 shows the extracted item of numeric amount for the VISA slip shown in Fig. 1

2.5 System of Sorting Financial Documents

Based on the proposed approach, techniques and algorithms, an automatic system has been developed for sorting Canadian bank cheques and more than twenty types of financial documents such as phone bills, MasterCard payment remittance forms, VISA payment remittance forms, Cable TV payment remittance forms, and so on, and extracting of the desired handwriting information from them. Fig. 4 illustrates some sample documents that can be processed by our system. Since Canadian bank cheques are printed in a variety of sizes and styles and, we have also developed an effective method [11] of processing Canadian bank cheques, in which the knowledge about the layout structures of Canadian bank cheques has been incorporated, therefore, in our system, the identification of Canadian bank cheques and the extraction of items from them are still based

Fig. 4. Sample financial document images

on the cheque processing method described in [11]. Our system has been used for the sorting of more than ten thousands of Canadian bank cheques and more than eight hundred other financial documents, and reached over 98.5% correct identification rate with 100% reliability.

3 Courtesy Amount Recognition (CAR)

For handwritten U.S. bank cheques the top courtesy amount recognition (CAR) systems typically achieve 60–75 percent raw recognition i.e., with error–detection capability switched off.

What can be done to improve this 25–40 percent recognition failure?

The most significant improvements today are achieved by combining CAR with legal amount recognition (LAR). The top commercial systems claim raw recognition of 80%. The drawback of these systems is that, instead of the 3 or 4 cheques per second processed by a CAR engine, a CAR–LAR engine has difficulty processing more than one cheque per second. In practice, 10 or more high–priced CAR–LAR engines are needed to keep up with a single high–speed scanner (1000 documents per minute).

Although the cost is high, overall recognition performance appears to be improved by combining CAR and LAR, and it is unreasonable to believe that a CAR system alone can be as reliable as a combined system. Nevertheless, CAR performance needs to be maximized, so let us consider some of the factors limiting that performance.

Scan resolution. A significant limiting factor on CAR performance is the scan resolution. Due to the restricted amount of space provided for the amount on North American personal cheques, the characters are often written quite small, especially the cents portion. Since it is difficult for people to write small characters legibly, it is desirable for the scanner to capture as much detail as possible. Commercial systems typically capture images at a maximum resolution of 200 dots per inch (DPI). Historically this has been done to conserve storage space and processing time, however, it is questionable whether this low resolution can any longer be justified given vastly improved storage costs and hardware speeds.

Image binarization. Traditional CAR systems have been developed to operate on binarized cheque images. Often, important information that makes it easier to distinguish the target ink from the cheque background is lost when the image is binarized. However, today's high–speed scanners can provide a grey–level image as well as a binary image. CAR–LAR systems that make use of grey scans are currently pushing recognition percentages into the low eighties.

Segmentation algorithms. Algorithms for grouping together components of broken characters, and for handling characters that touch other characters are problematic. When combined with LAR, a CAR system typically generates multiple segmentation hypotheses for corroboration with legal amount hypotheses. Since current systems cannot always detect spurious segmentations, it is desirable to avoid generating them. The cents portion of the amount on North American cheques is particularly difficult to segment due to the wide range of formats of varying complexity in which it can be written.

Garbage detection. This property of a recognition system is important for ranking segmentation hypotheses. The bulk of garbage detection is performed by the character classifier. Typical classifiers perform very well on the dialect of data they have been trained to recognize, but when required to detect invalid data, for example mis–segmented characters, they become significantly less reliable. This unreliability leads to 'garbage' being accepted as valid data.

3.1 CENPARMI CAR System

A CAR system developed at CENPARMI has been tested on a blind set of 400 real Canadian personal cheques provided by Bell Quebec with results shown in Table 1. Cheques were scanned at 300 DPI, 8–bit grey level. Location, extraction and recognition are fully automatic. The performances from other sources cannot be compared directly since there is no common test set, however the results may be taken as indicative. Talks with Canadian cheque processing companies using top commercial systems indicate that performances at the 1% error level on Canadian cheques are below 50% and sometimes below 40%. To the best of our knowledge, all error rates quoted are for the entire test set, not just the cheques accepted by the particular system.

The CENPARMI performance indicates strong garbage detection capability since a 1% error rate is achieved at a cost of losing just 10% of the raw recognition rate. This capability will be elaborated on in a later section.

Although the CENPARMI system has the advantages of higher resolution and grey–level image capture, the raw recognition rate is only 72%. Raw recognition on training data is currently over 75%, but the types of recognition failures indicate a need to focus more attention on segmentation, target zone extraction, and background removal in that order. One of the more frequently occurring segmentation challenges not yet solved by the system is 'touching fraction lines,' i.e., cents expressed fractionally where the fraction line touches other characters. This occurs in 5–10 percent of personal cheques. Capture of the cents portion from the legal amount is expected to help here also.

Table 1. Courtesy amount recognition.

System	% Correct	% error	Source/Date
CENPARMI	72	raw	1998
	62	1	
	56	0.5	
	51	0.25	
Lucent	44	1	Advertisement, 1998
ParaScript	47	1	Dzuba et al [12], 1997
Mitek	55	1	Houle et al [17], 1996

3.2 Digit Recognition

The results in Tables 2, 3, and 4 indicate that today's CENPARMI digit recognition system, while far from perfect, has surpassed by a significant margin systems from well known sources on three standard test sets. Performance is reported at two error levels, the 'raw' level where no inputs are rejected, and the 0.1% error level where the system is permitted to reject uncertain decisions. Some systems do not report a raw performance, therefore their highest reported recognition rate is quoted here. Quotes for some systems are perhaps out of date, however newer results from these sources have not appeared in the literature.

The CENPARMI digit recognizer consists of multiple neural networks trained by back propagation on about 450,000 digit images. Training takes about 2 to 3 months on a single processor, but is normally shared between processors to reduce the time to a few weeks. For the record, no data from any of the three test sets has been used in any way to train the system. CENPARMI speeds are based on 300 MHz processor speed.

A point of interest is that the CENPARMI system alone appears to perform as well as the combined digit recognition engines of two industry leaders, AEG and Mitek. In a paper by Houle *et al* [17] the recognition rate at 0.1% error rate for the combined engine was 94–95 percent on a large private test set.

Table 2. Digit recognition. Test set = NIST TD1. Size = 58,646 digit images.

System	0% rej	0.10% err	Date	digits/sec
IBM [14]	96.51	< 50	1992	87
AEG [14]	96.57	< 50	1992	34
AT&T [14]	96.84	68	1992	5
Ha et al [16]	97.10	–	1997	6
Mitek [13]	98.6	90	1993	16
Hewlett Packard [18]	98.60	–	1996	–
CENPARMI	99.07	94.45	1998	56

Table 3. Digit recognition. Test set = CEDAR GOODBS. Size = 2213 digit images.

System	0% rej	0.10% err	Date	digits/sec
Kittler et al [19]	98.19	–	1998	–
CEDAR [20]	98.87	–	1993	–
Ha et al [16]	99.09	–	1997	–
CENPARMI	99.77	99.14	1998	54

Table 4. Digit recognition. Test set = Concordia. Size = 2000 digit images.

System	0% rej	0.10% err	Date	digits/sec
Lee [21]	97.10	–	1996	–
Oh et al [22]	97.4	–	1997	–
AEG [15]	98.30	–	1993	–
AEG-CENPARMI 1 [15]	98.50	–	1993	–
AEG-CENPARMI 2 [15]	–	97.55	1993	–
CENPARMI	98.85	97.65	1998	58

3.3 Garbage Detection

Experiments were done at CENPARMI to study and obtain some measure of garbage detection capability of the digit classifier of the CAR system. Although garbage detection is important for evaluating segmentation, it is rarely mentioned in OCR literature except in passing. It has never to our knowledge been quantified.

Motivated by a desire to have a benchmark for garbage detection in order to measure progress, a 'standard garbage test set' for digit recognizers was constructed from materials in the NIST database SD19. All of the isolated letters from the NIST test set were used, but only from classes not often expected to resemble digits.

The resulting test set (dubbed TD1G for Test Data 1 Garbage) contains 13,561 images from classes in the string 'ACEFKLMNPQRVWXacdefhjkmnprtvwx'. Inevitably, some of these images resemble digits quite closely, but the great majority do not. Ideally, a test set for a digit classifier would consist of data from the domain of mis–segmented digits, yet TD1G comes from a domain not radically different from mis–segmented digits. The great advantages of this test set are that it is part of a readily available NIST database and that it is relatively easy to construct.

The performances of two CENPARMI digit classifiers on the NIST digit test set are compared in Table 5. It will be observed that while the raw recognition rate of the 1998 classifier appears to be significantly higher than that of the 1997 classifier, there is not a corresponding improvement at the 0.1% error level. One might be led to conclude that garbage detection capability has not improved significantly. As we will see, this conclusion is not supported by garbage detection benchmarking tests.

The procedure used to benchmark garbage detection capability of a classifier was to measure its error rate on TD1G at a rejection threshold determined from the classifier's performance on the digit test set (TD1). In this case the threshold that gave 0.1% error on TD1 was used for testing the classifier on TD1G. Table 6 gives the performance for each classifier on TD1G. An error occurs whenever a classifier fails to reject a garbage image and instead classifies it as a digit.

Table 6 [1] can be taken as a positive indication of progress in garbage detection since the TD1G error rate of the new classifier is considerably reduced from the old one.

4 Concluding Remarks

This paper presents a new system developed at CENPARMI for sorting and recognizing a great variety of cheques and financial documents. Both the methodologies and the system configuration have been described, and the performances of the major functions on real–life data have been presented.

[1] The performance reported for the same test in two conference proceedings (DAS98, ICMI99 [23]) was incorrect due to a regrettable error in recording experimental results.

Table 5. Digit recognition. Test set = NIST TD1. Size = 58,646 digit images.

System	0% rej	0.10% err
1997	98.90	94.18
1998	99.07	94.45

Table 6. Garbage detection on TD1G (13,561 images) at 0.1% error on TD1.

System	rej	err
1997	86.90	13.10
1998	90.26	9.74

Acknowledgments

This research was supported by the Natural Sciences and Engineering Research Council of Canada, the National Networks of Centres of Excellence program of Canada, and the FCAR program of the Ministry of Education of the province of Quebec.

References

1. G. Lorette. Handwriting Recognition or Reading? Situation at the Dawn of the 3rd Millenium. In *Int. Workshop Frontiers in Handwriting Rec.*, pages 1–13, Taejon, Aug. 1998. 173
2. J.–H. Chiang and P. D. Gader. Recognition of Handprinted Numerals in VISA Card Application Forms. *Machine Vision and Applications*, 10:144–149, 1997.
3. M. D. Garris, C. L. Wilson, and J. L. Blue. Neural Network-Based Systems for Handprint OCR Applications. *IEEE Trans. Image Processing*, 7:1097–1112, Aug. 1998.
4. I.–S. Oh and C. Y. Suen. Distance Features for Neural Network-Based Recognition of Handwritten Characters. *Int. J. Doc. Analysis and Recognition*, 1:73–88, 1998.
5. S. Bussi and E. Bruzzone. Segmenting Handwritten Character Strings in an ICR System. In*Proc. Int. Workshop on Frontiers in Handwriting Recognition*, pages 189–198, Taejon, Aug. 1998.
6. G. Kaufmann and H. Bunke. Amount Translation and Error Localization in Cheque Processing Using Syntax–Directed Translation. In *Proc. Int. Conf. Pattern Recognition*, pages 1530–1534, Brisbaine, Aug. 1998. 173
7. L. Lam, C. Y. Suen, et al. Automatic Processing of Information on Cheques. In*Proc. IEEE Int. Conf. on Systems, Man, Cybernetics*, pages 2353–2358, Vancouver, Oct. 1995. 173
8. S. Impedovo, P. S. P. Wang and H. Bunke (eds). Automatic Bankcheck Processing. World Scientific Publishing Co. Pte. Ltd., Singapore, 1997. 173

9. L. Y. Tseng and R. C. Chen. recognition and Data Extraction of Form Documents Based on Three Types of Line Segments. *Pattern Recognition*, 31(10):1525–540, 1998. 174
10. Y. Y. Tang, S. W. Lee, and C. Y. Suen. Automatic Document Processing: A Survey. *Pattern Recognition*, 29(12):1931–952, 1996. 174
11. K. Liu, C. Y. Suen, M. Cheriet, J. N. Said, C. Nadal and Y.Y Tang. Automatic Extraction of Baselines and Data from Check Images. In Automatic Bankcheck Processing, S. Impedovo, P. S. P. Wang and H. Bunke (eds), World Scientific Publishing Co. Pte. Ltd., Singapore, pp.213–235, 1997. 177, 180, 181
12. G. Dzuba, A. Filatov, D. Gershuny, I. Kil, and V. Nikitin. Check Amount Recognition Based on the Cross Validation of Courtesy and Legal Amount Fields. *Int. Jour. Patt. Rec. and Art. Intell.*, 11(4):639–655, 1997. 183
13. J. Geist et al. *The Second Census Optical Character Recognition Systems Conference*. U. S. Department of Commerce, National Institute of Standards and Technology, 1993. 184
14. R. Allen Wilkinson et al. *The First Census Optical Character Recognition Systems Conference*. U. S. Department of Commerce, National Institute of Standards and Technology, 1992. 184
15. J. Franke. Experiments with the CENPARMI Data Base Combining Different Approaches. In *Int. Workshop Frontiers in Handwriting Rec.*, pages 305–311, 1993. 184
16. Thien M. Ha and Horst Bunke. Off-line Handwritten Numeral Recognition by Perturbation Method. *IEEE Trans. Patt. Anal. and Mach. Intell.*, 19(5):535–539, May 1997. 184
17. G. F. Houle, D. Bradburn Aragon, and R. W. Smith. A Multi–Layered Corroboration–Based Check Reader. In *IAPR Workshop on Document Analysis Systems*, pages 495–543, 1996. 183
18. Takahiko Kawatani, Hiroyuki Shimizu, and Marc McEachern. Handwriten Numeral Recognition with the Improved LDA Method. In *Int. Conf. on Pattern Recognition*, pages 441–446, 1996. 184
19. J. Kittler, M. Hatef, R. P. W. Duin, and J. Matas. On Combining Classifiers. *IEEE Trans. Patt. Anal. and Mach. Intell.*, 20(3):226–239, May 1998. 184
20. D-S. Lee and S. N. Srihari. Handprinted Digit Recognition: A Comparison of Algorithms. In *Proceedings of the 3rd Int. Workshop on Frontiers in Handwriting Rec.*, pages 153–162, Buffalo, N. Y., U. S. A., May 1993. 184
21. S-W. Lee. Off-line Recognition of Totally Unconstrained Handwritten Numerals Using Multilayer Cluster Neural Network. *IEEE Trans. Patt. Anal. Mach. Intel.*, 18(6):648–652, 1996. 184
22. I-S. Oh, J-S. Lee, K-C. Hong, and S-M. Choi. Class–Expert Approach to Unconstrained Handwritten Numeral Recognition. In *Int. Workshop Frontiers in Handwriting Rec.*, pages 35–40, 1997. 184
23. N. W. Strathy. Handwriting Recognition for Cheque Processing. In *Proc. Int. Conf. Multimodal Interface*, pages 47–50, Hong Kong, Jan 1999. 185