Recognizing Handwritten Amounts from Brazilian Checks

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Abstract

This paper discusses automated reading and processing of Brazilian bank checks. It highlights the main characteristics of Brazilian checks and the variety of writing styles that makes recognition more difficult than in countries where handwriting amounts are more uniform. Neural networks are used to recognize isolated digits obtained after segmentation. One set of neural networks was trained with digits from the NIST database and then evaluated using a database of numerical digits from Brazil. Other neural networks were trained with digits from both the NIST database and Brazilian digit samples extracted from real checks. These two approaches were utilized to determine the relative importance of the training set on the final accuracy levels. The same strategy is also applied to deal with other aspects of reading handwritten amounts in Brazilian checks such as delimiters and connected digits.

1 Introduction

During the past 45 years, technology related to optical character recognition has progressed at a significant pace. The principal impetus to the development of automatic recognizers has been fueled by the need to cope with the growing volume of paper generated by an expanding technological society. When the number of bank checks, commercial forms, government records, credit-card imprints, and pieces of mail to be sorted and accounted reach several billion each week, one requires the help of machines to process information on time. Specifically, automatic recognition of amounts on bank checks is an area that has witnessed growing interest. Automatic check processing holds the potential for providing big savings since checks constitute a dominant form of financial transactions. According to the Federal Reserve Bank, checks account for 60% of the non-cash transactions, and nearly 50 billion checks worth \$47.7 trillion were processed in 2001 in the United States alone [1].

There are a number of benefits of using automatic check processing. First, it can reduce check-processing costs. In fact, the social cost of a check transaction was estimated to be between \$2.78 and \$3.09 per check [10]. It is estimated that technology can lower the costs of the payment mechanism to about \$1.50 per check [2]. Secondly, it can reduce the time delays involved with check clearance since converting paper checks into digital format allows automating the clearing process using current Internet Technologies [6]. Finally, it will reduce the costs involved in processing returned checks because the original paper is stored at the bank of deposit and it is not sent and returned in armored cars.

In this paper, the primary emphasis is on the ability to process and effectively recognize Brazilian checks. As described later in this paper, a database from the National Institute of Standards and Technology (NIST) was utilized to train a neural network, and to better understand the differences between handwriting styles in the United States and Brazil.

2 Description of check recognition system

The procedure to read the value of a bank check begins scanning the paper to generate a digital image of the check. This image generally comes in gray level, since color is not relevant for check processing, and should be converted to black and white (binarization) to remove the background from the written text. Then the system must locate the courtesy amount string, which is the number that contains the value of the check. After these initial steps (see Figure 1), the system has to perform the difficult task of converting the image of the amount into the corresponding number.

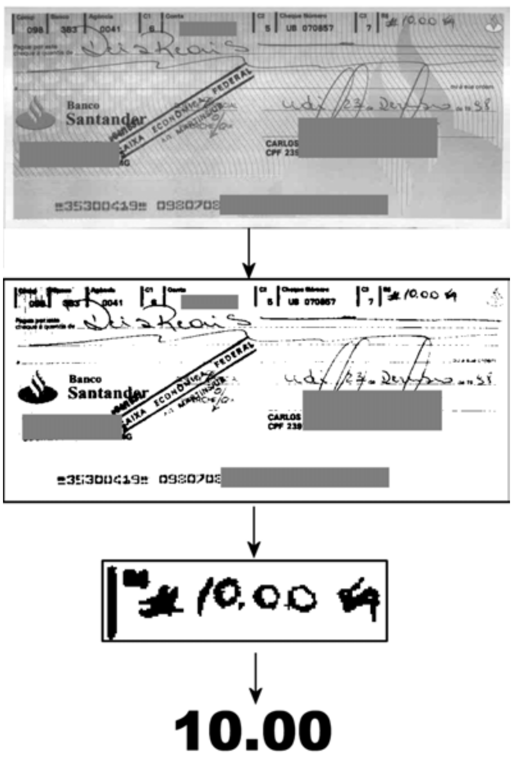

Figure 1: Basic Steps of Check Processing

Our approach for automated check reading is depicted in Figure 2 [8]. This figure describes the key steps, including feedback loop for segmentation. The first step in the process is to detect the courtesy amount within the image of the check. This involves a conversion from the gray scale image into a binary data format.

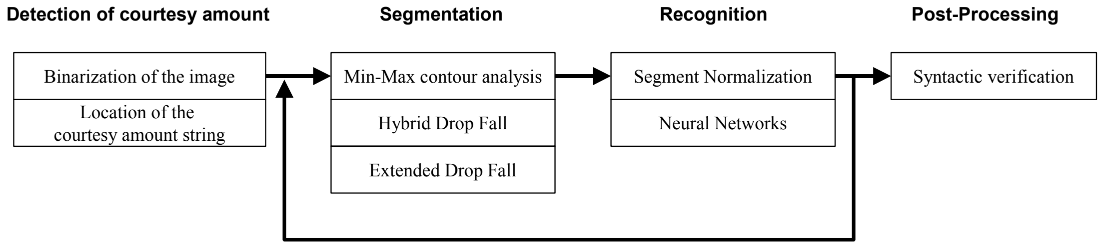

Figure 2: Scheme of Check Recognition Approach

Then, several algorithms are applied to accurately select the area of the image that corresponds to the courtesy amount field, which contains the value of the check (see Figure 3). The most challenging part of the process is segmentation, which involves dissecting the courtesy amount field into individual characters. Individual strokes are separated and grouped accordingly; this can be a very difficult step depending on the numbers involved. For example, Figure 3(a) contains a courtesy amount where number ‘2’ is connected to number ‘9’ and must be separated.

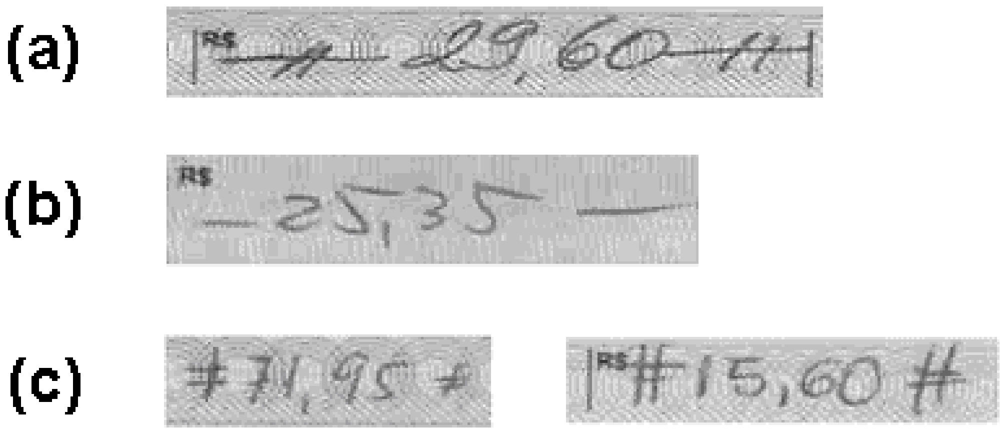

Figure 3: Courtesy amounts from two Brazilian checks

It is difficult to split connected digits because the separation cut must be correct or else an incorrect pair of digits will occur. Several split algorithms are used in this module in order to obtain the correct separation path [8]. On the other hand, digit ‘5’ in Figure 3(b) is broken in two pieces and they must be connected or grouped, otherwise it will be read as two digits (though neither piece can be recognized properly).

Next, the recognition module identifies the number contained in every image produced by the segmentation module. These images must be normalized before calling the classifier; the normalized digits are then fed into a recognition module. Normalization involves slant correction, thickness, and resize [5]. All digits are normalized before being passed into a neural network classifier. There were five phases: slant correction, size normalization, thinning, re-thickening, and final resize; as shown in Figure 4.

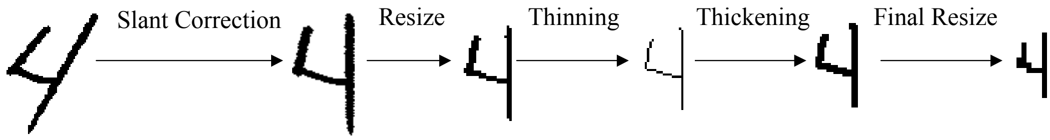

Figure 4: The normalization process

Slant correction is intended to take the tilt away from an image. It is done to improve the accuracy of the recognition system. Size normalization resizes both, small and large, images to a standard size to simplify the recognition process. There were two resizes that take place. The first resize prepares the image to go through the thinning and thickening process. Thinning or skeletonization, removes pixels in uniformity around the image without doing damage to the image. A one pixel in thickness image is produced as well as a cleaner and more simplified image. Thickening produces uniform thickness of about 3 pixels. The result of thickening is a standard image 39x27 pixels, corrected in slant and with uniform stroke thickness. Finally, the image is resized to a 13x9 image, where each pixel maps with one of the inputs to the neural network.

A Multi-Layer Perceptron (MLP) was created, which is one of the most widely used types of networks for character recognition. The basic structure used is a fully connected MLP with 117 inputs, one hidden layer with 50 neurons and 10 outputs [7]. The Backpropagation algorithm was used for training. The classifier is composed of several neural networks, where each neural network independently interprets a digit, thenthe results are combined to obtain the highest confidence level.

The final stage of the system involves post-processing where incorrect digits are removed from the list of possible digits [5, 8]. The post-processing module verifies the syntax of the amount to minimize the instances involving incorrect readings. This module verifies that the amount read makes sense as a valid monetary value, according to the rules that define the format of numbers (the number of decimals, and the number of digits between punctuation).

3 Writing Styles

Handwritten digits vary in style and appearance from one person to another. The slightest differences in the way numbers are written; yield complex difficulties when trying to recognize them using pixel-by-pixel pattern matching techniques. Using more advanced techniques like neural networks, the problem is partially solved. Nevertheless, writing differences can range from loops to straight lines used to denote the same number. Sometimes the same number is written using different number of pen strokes, such as numbers ‘1’, ‘7’ and ‘0’; or it is written using different combinations of straight strokes, closed loops and curved strokes, such as numbers ‘4’ and ‘9’. Figure 5 shows a collection of Brazilian digit samples written in different ways. There are four distinct styles of the number seven (all seven’s shown are of Brazilian origin) according to the number of strokes and its kind. The second “seven” has a loop on the top, whereas the rest do not. The first sample of digit “seven” is missing the horizontal line in the middle, whereas the rest are not. Another example of different writing styles for the same digit is the number “nine”. The first sample has a curved ending to the bottom, the next one has straight vertical stroke, and the last one has an open top loop. All of these slight differences play a huge role in designing strategies for automated character recognition.

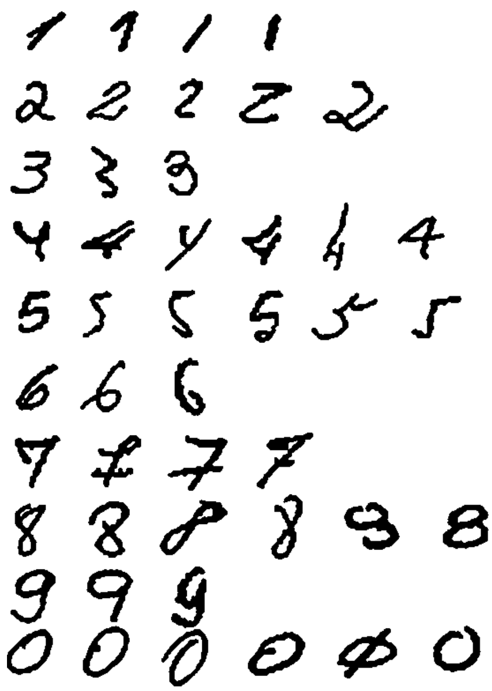

Figure 5: Collection of Brazilian Digit Samples

NIST database of handwriting forms is widely used for training and testing handwriting recognition system. This database contains the full-page binary images of 3699 Handwriting Sample Forms (HSFs) and 814255 segmented handwritten digits from those forms [3]. This NIST database was created using information obtained by Census Bureau employees in Suitland, Maryland. Since the writing style in the U.S. is somewhat different than in Brazil and other countries, Brazilian checks recognition requires a better selection of training sets in order to obtain suitable levels of accuracy. This paper shows that a good recognition system evaluated with digits written by U.S. citizens may attain low recognition rates reading Brazilian digits.

One component that adds to the level of difficulty of processing Brazilian checks is the incidence of delimiters. They are symbols added to avoid alterations of the amount, which are found before and/or immediately after the numerical amount in the courtesy block, as shown in Figure 3 (a, b and c). Delimiters can take various forms such as "#" or different combinations of single or double lines. In some cases they can touch a digit (Figure 3a) making segmentation even more difficult. Therefore delimiters introduce additional complexity for the check processing system. Delimiter are rarely found on U.S. checks, but are very common on Brazilian checks; in a study made with 1500 real checks provided by Brazilian banks, delimiters were found in 36% of the checks. Adding this difficulty to the problem of dealing with a broad variety of digit styles makes automated reading of Brazilian checks a challenging topic of research.

4 Training the neural network with digits

The neural network was first trained using digits from a standard database and then it was tested with Brazilian digits extracted from real checks. The data used for training were the hsf_9 set from Specialized Database19 created by the NIST [3], which is one of the most popular public databases of handwritten characters. Paper forms were scanned at 11.8 dots per millimeter (300 dots per inch); they contain 34 fields: name and date entries, a city/state field, 28 digit fields, one upper-case field, and an unconstrained Constitution text paragraph. The fields of each form were segmented into isolated characters. The resulting images were organized by one of four field types: digits, upper, lower and const, then stored in different directories. For our experiment only the images of digits were necessary, all other images that correspond to letters were not used.

Twenty Thousand NIST digits were used for training the neural network and 10000 digits were used for validation during the training process. It was evaluated with another 10000 NIST digits (different digits than were used for training and validation). These digits were normalized using the procedure described previously.

The neural network obtained performed very well, with 92.2% correct recognition and only 1.8% of wrong reading (see Table I). These results are comparable to those obtained by other authors [9], but with lower incorrect readings than the average at the cost of increasing the level of rejections. It is important to highlight that a low recognition rate is not a problem in check reading applications (in contrast with other applications) as long as the number of incorrect readings remains very low. Any check with a rejected digit will be rejected, meaning that the system is not able to read the check, so a person will process it manually (this is less work that processing all checks manually as it is currently done). However, a wrong reading may trigger an incorrect transfer of money, which may cause important damages and expenses.

Table I - Results of training with NIST

Neural Network Trained with NIST Database

# of NIST Samples	Correct	Rejections	Wrong
10000	9218 (92.2%)	601 (6.0%)	181 (1.8%)

After verifying the results, the next step was to evaluate the neural network with 310 Brazilian digits. These digits were gathered from real handwritten checks provided by several Brazilian banks. The checks were scanned using a flat bed scanner; then individual digits were selected and grouped accordingly. Resolution was not very high, approximately 120 dots per inch, that is enough for recognition and it does not require too much storage capacity. Finally they were normalized using the same functions as for NIST digits.

Table II - Results of training with NIST and testing with Brazilian

Neural Network Trained with NIST Database			
# of Brazilian Samples	Correct	Rejections	Wrong
310	219 (70.6%)	61 (19.7%)	30 (9.7%)

Testing with real Brazilian digits, the percentage of wrong answers is 9.7%, which is five times higher than the first evaluation. This is very unlikely since the number of mistakes may increase a lot, even though some of these mistakes are detected in the post-processing module. The main reason for this increment in the number of wrong answers is the variety of writing styles found in the Brazilian database, in contrast to the uniformity of the database used for training. After reviewing the results, the approach of training the neural network was altered in order to find what level of improvement could be attained. The decision was to create another MLP and train it with both NIST digits and some Brazilian digits. This neural network was trained with 20000 NIST digits and 864 Brazilian digits (as only a limited number of Brazilian checks were available to the research team). During training procedure, validation was done using 10000 NIST digits and 210 Brazilian digits. Finally, the neural network was evaluated separately with NIST digits and Brazilian digits (see Table III). First, a set of 10,000 NIST digits was used to verify there was no significant loss in performance when combining U.S. with Brazilian digits in the training set. Then, the set of 310 Brazilian digits used to test the first neural network was used to verify the improvement in performance.

Table III - Results of neural net trained with both digits and test with both digits

Neural Network Trained with NIST and Brazilian Database				
	# of Samples	Correct	Rejections	Wrong
NIST Samples	10000	9250 (92.5%)	552 (5.5%)	198 (2.0%)

Brazilian Samples	310	235 (75.8%)	55 (17.7%)	20 (6.5%)

There are some positive aspects from the results shown in Table III. One, the incidence of incorrect reads was reduced by 30%, from 30 to 20 wrong digits (see Figure 6). Second, there was an increase in the number of correct answers. Finally, there were no significant changes in the effectiveness at recognizing characters from the NIST database.

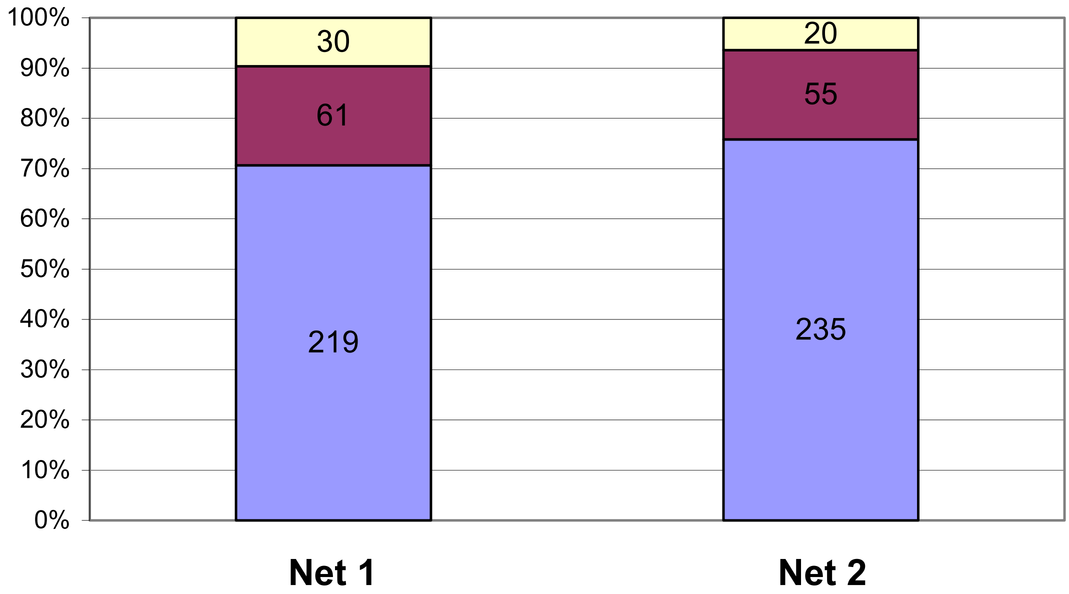

Figure 6: Overall Distribution of Results Reading Brazilian Digits

5 Training the neural network with special sets of characters

The courtesy amount field on checks frequently includes special symbols in front of or behind the value; these symbols are used as delimiters to avoid alterations of the amount. In addition, it is common to find a digit connected to other digit, or a delimiter that is touching a digit. The check recognition system developed by our research group is able to sort out segments consisting of several characters (called multiple segments) at early processing stages and send them to special functions for additional segmentation [8]. But in some cases, multiple segments are sent to the recognition module to try to classify them as digits. At this point, the neural network is supposed to reject these segments since their images do not coincide with any normal digit. However, the neural network is not as effective at rejecting unknown segments as it is at classifying them to the most similar cluster.

It has been found that training the network simultaneously with normal digits and special segments produced the best results. Table IV shows the results obtained by one neural network trained in different ways. In the first case, the network (net10) was trained using

20000 digits from NIST database. Then it was tested with normal digits from NIST database, multiple segments obtained from Brazilian and U.S. checks and delimiters from Brazilian checks. The second network (net11) has 11 outputs and was trained simultaneously with digits and multiple segments. The third network (net12) was trained with digits, multiples and delimiters. The number of samples of multiple segments is 246, and the number of delimiters is 286. Both groups of samples were divided into a training set, a validation set and a testing set. The evaluation of the different neural network was performed with the same testing sets. Other researchers have built larger databases of multiple segments, taken from forms images [11], but no database of delimiters was found in the literature.

Table IV: Results of training with different sets of segments

		samples	Correct	Reject	Wrong
net10	NIST Digits	10000	9256 (92.6%)	520 (5.2%)	224 (2.2%)
	Multiples	64	-----	31 (48.4%)	33 (51.6%)
	Delimiters	72	-----	21 (29.2%)	51 (70.8%)
net11	NIST Digits	10000	9217 (92.2%)	578 (5.8%)	205 (2.0%)
	Multiples	64	36 (56.2%)	23 (35.9%)	5 (7.8%)
	Delimiters	72	-----	36 (50.0%)	36 (50.0%)
net12	NIST Digits	10000	9140 (91.4%)	662 (6.6%)	198 (2.0%)
	Multiples	64	38 (59.4%)	22 (34.4%)	4 (6.2%)
	Delimiters	72	14 (19.4%)	34 (47.2%)	24 (33.3%)

Net10 is able to read the majority of U.S. checks, since this network correctly rejects most of the multiples, and the use of delimiters is rare and negligible in U.S. checks. Nevertheless, net11 does a better job recognizing multiples, even though the number of samples of multiples segments is very low compared to the number of samples of normal digits. By detecting multiple segments, the system is able to apply several splitting algorithms [8] and eventually find the correct solution. On the other hand, if the multiple segments are misread as one digit, an incorrect read occurs. Fortunately, the post-processing module is able to detect this kind of mistakes and reject the check at the final step.

6 Conclusions

This paper has shown that a recognition system, which attained good results with isolated digits from a huge standard database, may perform deficiently if used for Brazilian writing without further tuning. The solution presented in this paper involved the addition of digits extracted from some Brazilian checks to the training set.

Granted there were only a small percentage of Brazilian digits in the training set, the results were promising. In fact, 97% of the digit samples were from NIST and the remaining 3% were from the Brazilian database. If there had been a balanced number of NIST digits and Brazilian digits, than the results would have better.

It is also shown that adding special symbols such as delimiters and multiple segments to the training set can also improve recognition rates. The presence of connected digits is a problem affecting all systems for automatic recognition of unconstrained handwriting, with less impact in automatic recognition of handwritten forms. On the other hand, detection of delimiters is important for check recognition in Brazil, because delimiters are widely used by Brazilians.

Taking into account that the post-processing module is able to detect many mistakes related to alterations in the number of digits that make the amount of the check, two main statements can be concluded:

- Adding samples of Brazilian digits to the training set improves the classifier of isolated digits, therefore reducing the level of wrong readings.
- Expanding the neural network to detect multiple segments and delimiters allows the system to isolate digits properly, therefore increasing the volume of checks processed automatically.

7 References

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