

Recognition of Hand written Numerals on bank Cheques using Neural Networks

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ABSTRACT

People have often attempted to create computers that could perform human-like tasks. Man has been very effective in reducing the amount of physical labour required to perform many tasks by developing machines. With the invention of computers, it became possible for computers to minimize the number of workers required for a variety of jobs. However, there is one human skill that computers have yet to master. That is, the ability to recognize a person's handwriting. Of course, advances in machine handwriting recognition have been made, few of us imagine, moreover, that a computer would ever be able to read a human's handwriting or recognize a human's image profile. Even so, approach that focuses that can imitate human recognition abilities, it is not a bad idea. After all, even imperfect handwriting leaves an impression. This paper investigates the problem of reading the numerical amount sector. In the case of cheques, segmenting unconstrained strings into individual digits is problematic due to joined and overlapping digits, disconnected digits, and digits that are physically attached to bits of digits from neighboring digits. There are five steps to the proposed architecture: block of courtesy number locator, segmentation of the string into individual digits, normalization, Gabor filter feature extraction, and neural network classifier recognition of each character.

Keywords

Gabor filter; Neural Networks; Segmentation; Normalization

Introduction

Handwriting recognition is a vast field that can be subdivided into two modes: off-line and on-line recognition. The method of identifying characters as they are written is known as on-line recognition. Off-line acknowledgement recognizes characters after they have been written. Text preparation, mail routing, and cheque verification are all possible applications for off-line recognition systems.

Handwriting recognition efficiency is significantly strengthened by writing constraints, which solves one of the issues of segmentation and encourages world to practice carefully [1]. Banking sector, on the other hand, is unable to modify the shape of cheques to enforce writing restrictions such as guidelines or boxes that indicate where and type of knowledge should be registered. A system that can automatically read checks would be very useful, particularly if it is quick and accurate. Even if misclassification occurs, the error will be identified during the identification process; however, it is preferable if the device refuses a check in the event of doubt, allowing it to be diverted to manual processing from the top.

Document comprehension systems (DUS) are designed to read and label types of identity codes. Only a black pen could be used by the artist, which greatly aided recognition. Checks written in the United States, on the other hand, can be written with any colour ink. Furthermore, for each character, many forms have preprinted boxes. The frequency of connections between adjacent characters is substantially reduced by this restriction. If such boxes could be preprinted on tests, it

would make some preprocessing tasks simpler. It is very difficult to “read” fully unregulated handwritten material on U.S. cheques.

Our approach to "reading" cheques is described in this article, which employs a hybrid architecture that combines conventional and emerging approaches. The new image is dissected into individual characters after the courtesy number area has been found. The implementation of multiple splitting algorithms within the segmentation module is the most difficult part of the procedure. The neural networks in the recognition module were used to identify digits with a high degree of trust and hence the procedure must be computationally efficient.

Block Diagram

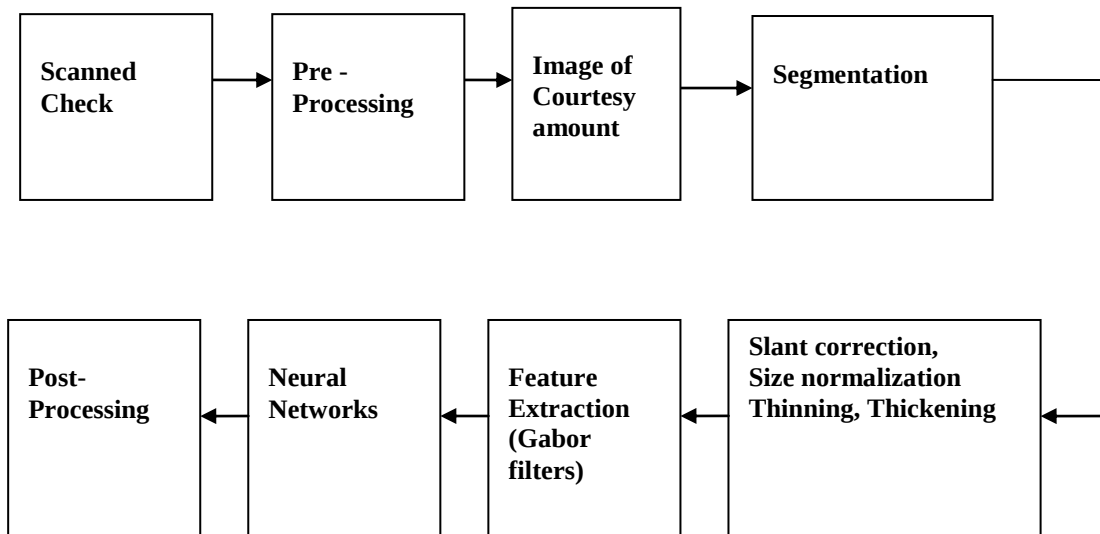


Figure 1: key steps to Read the Courtesy amount

The system is divided into three stages: CAB (courtesy amount block) Location, Segmentation, and Recognition are three steps in the recognition process [2]. The CAB must first be found. This is accomplished by having prior knowledge of the check. After locating the CAB, the next step is segmentation, which involves separating individual digits. The last step is identification, which involves using a neural network classifier to classify each of the digits.

Binarization and CAB location:

A grayscale picture of a scanned check opens the software. The machine stores the digital information provided by the scanners as a matrix, with each value representing the brightness of the corresponding point on the page. The size of the matrix is determined by the size of the check and the scanner's resolution [3]. The latter is expressed in dots per inch (dpi). In the gray scale image the values would be in the range of 0 to 255 where in the range zero represents the darkness of black and the level 255 represents the brightness of white and the different values of the gray levels are represented by median values (The scale for 8 bit depth, also known as colour resolution, is 0 to 255). The majority of the detail in the scanned cheque picture is correlated with the tones of the background drawing and is of little use in reading the check.

As a consequence, distinguishing between white pixels that make up the background and those that make up useful textual elements is the first step in the recognition process [4]. The method here assigns a value of one to the history and zero to handwritten or machine printed text. Figure 1 shows a cheque with a lighter background drawing than the character strings. As a result, by defining a luminance value threshold, the raw inputs can be easily converted into a sequence of zeros and ones. Binarization is the name given to the conversion method since the end result is in binary format.

Figure 2 the histogram of the picture shown in Figure 1[6]. It displays the number of pixels in the image for each brightness level (from 0 to 255). There are a lot of pixels with high values, A small set of pixels has a darker value, which corresponds to the written element, and a larger set of pixels has a lighter value, which corresponds to the context. Divide histogram into background color and text color. The histogram is divided by using optimal thresholding is used for separating the background from the writing [5]. For the optimal thresholding Otsu's method is used which uses the threshold to minimize the intraclass variance of black and white pixels. This procedure is very simple, utilizing only the zeroth and first-order cumulative moments of the gray-level histogram.

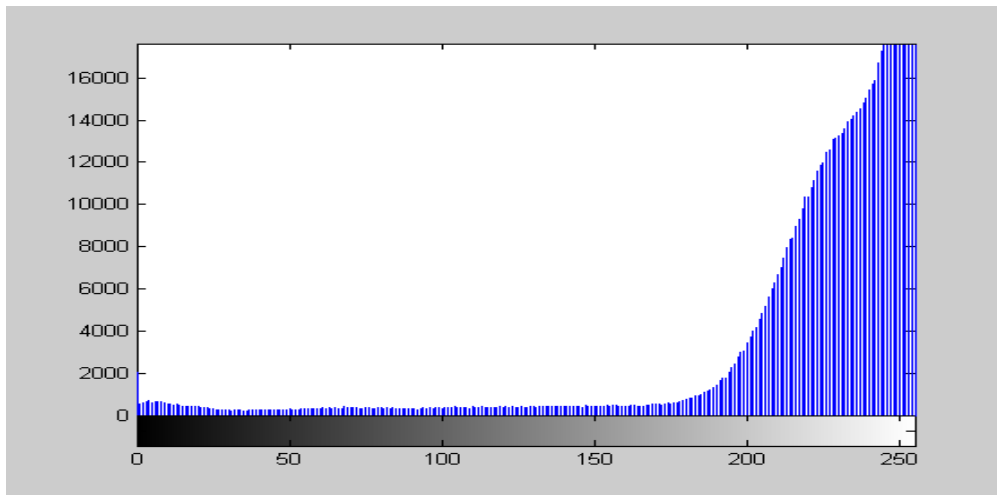


Figure 2 histogram of image of cheque

Implementation

This project is simulated in MATLAB and C explanation given below. The entire process is simulated in *main.m*. In *first.m* we locate and extract the required courtesy amount by the following steps:

This program first asks the reference image and stores dimensions (width & height) of a reference image (unfilled check). Storing the dimensions of reference image is necessary because we know the location of courtesy amount block on the reference image. Next ask to enter the test cheque image name. This image is resized to reference dimensions. Program starts searching for coordinates of amount block by checking two conditions: a set of continuous black pixels horizontally from center of the image towards right side. Whenever it finds such a set of black

pixels of count between 210 and 220, start vertical search downwards from the point where horizontal black pixels' block started for a successive set of black pixels of count 50 to 59. Then the block containing significant figures are extracted by using the edge coordinates obtained in the above step. Therefore the courtesy amount block is located [7]. Next step is to extract the required courtesy amount means user entered amount; removing the unnecessary data like RS does this. This required user entered amount is stored in "courtesy.jpg" and returns this file name.

The program *mynw.m* is trained to the given training numerical image and it returns the network. The required amount block obtained from the *proceed.m* is accessed by the *mbr.m*; this program will use the basic method of segmentation. This *mbr.m* returns the columns at which it finds the unbroken white pixels vertically. Column number obtained from *mbr.m* extracts the individual digits from the courtesy amount. In the main program it calculates the difference between successive column numbers and stores in the variable box. If the minimum difference between the columns is greater than 8 (chosen, because comma, slash and hyphen will occupy this minimum width) then program treats that one digit is segmented from the courtesy amount. But the main program decides whether the segment obtained is containing the single digit or multiple connected digits by the condition that the width of the segment is greater than height or not. If the width is less than height then program decides the segment containing single digit and proceeds for the next process. If it is not happened this segment is passed to the drop fall algorithm that is running on *drop.m*

This *dropfall.m* segment the given array into two tiles. One tile is definitely contains single digit and other tile again send to the previous step. Finally at this level we get single digits. These digits are preprocessed by *slant.m* and *thin.m*. *Slant.m* will use the algorithm with the help of *findwidth.m*. The result obtained at the *slant.m* is passed to the *thin.m*; this program skeletonizes and then rethick to the double mask size. The resultant single digit is resized to 28x28. This standard digit is tested by RBFNN *test.m*. This *test.m* will recognize the digit and returns recognized digit number. Here digit 10 represents -, 11 represents /- and 12 represents comma (.). The programs *dropfall.m*, *slant.m*, *thin.m*, and *test.m* are used iteratively until the end of courtesy amount (by checking the width). Processing time is calculated by taking difference between measured CPU timings at *main.m* starting stage and finishing stage.

Results

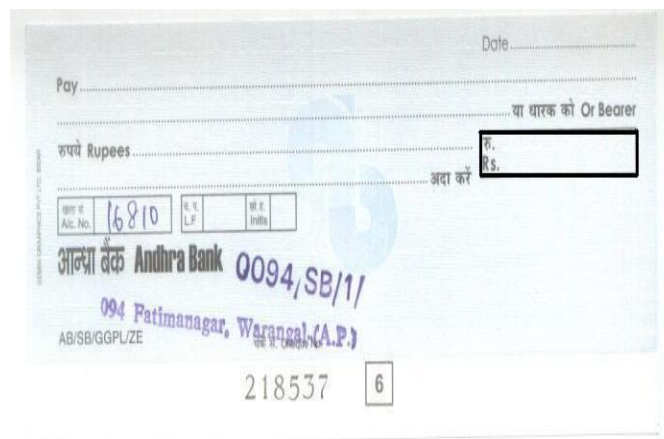


Figure 3 Reference cheque

reference block



Figure 4 Reference block

test block



Figure 5 test block



Figure 6 Required courtesy amount

Training images: -



Test images: -



Figure 7.1 a) skeltanized '8'



b) thickness normalized '8'



Figure 7.2 a) skeltanized '5'



b) thickness normalized '5'



Figure 7.3 a) skeltanized '6'



b) thickness normalized '6'



Figure 7.4 a) skeltanized '0'



b) thickness normalized '0'



Figure 7.5 a) skeltanized '-'



b) thickness normalized '-'



Figure 7.6 a) skeltanized '0'



b) thickness normalized '0'



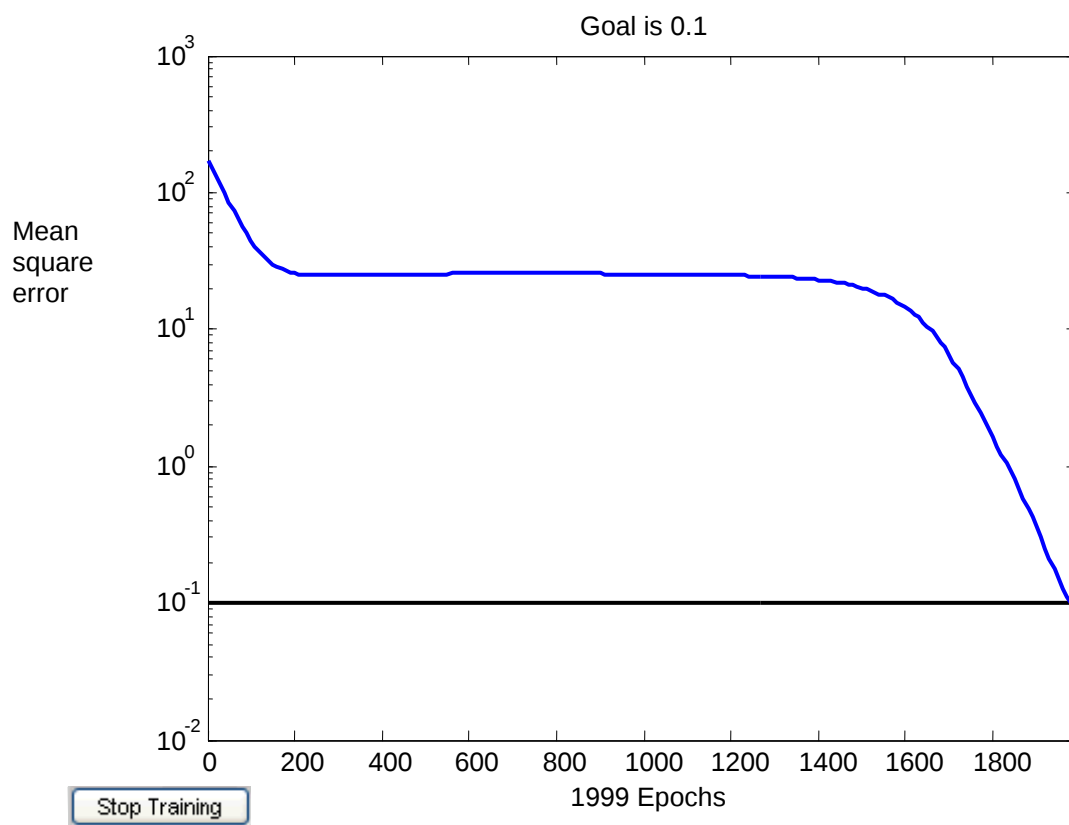
Figure 7.7a) skeltanized '0'



b) thickness normalized '0'

Input Data: 400 Samples collected from different writers

Mean Square Error Versus Epochs:



METHOD1 RESULTS: AMD Processor 1GHz

Number of Hidden Nodes/ Basis Functions	Percentage of Accuracy	Time Taken for Training (In minutes)	Recognition time for one sample(ms)
150	73	2.5	0.05
200	83	3.5	0.085
250	88	6.5	0.12
300	93	7.5	0.143
350	97	15	0.25

METHOD2 RESULTS:

Number of Hidden Nodes/ Basis Functions	Percentage of Accuracy	Time Taken for Training (in minutes)	Recognition time for one sample(ms)
150	75	3.5	0.08
200	84	5.0	0.12
250	90	7.0	0.15
300	94	8.5	0.23
350	98	16	0.42

Conclusion

In this paper we proposed and the courtesy number block at the bottom-right spot is part of an overall approach for cheque acknowledgement that can be seen as the basis for “reading” cheques. The algorithms and techniques used to read bank checks can be used in other situations where automated reading or image processing is beneficial. Image pre-processing involves conversion from gray scale into black and white pixels, courtesy amount block location. The output of the pre-processor serves as the input to the segmentation module. In this paper Features extraction using Gabor filter minimizes the number of inputs to the neural network which reduces

memory requirements and processing time. The neural network architecture employs RBF. The training and total processing times are calculated, and they are in acceptable range. By increasing the number of features extracted by Gabor filter can achieve the more accuracy.

References

- [1] Gonzalez and Woods “*Digital ImageProcessing*” second edition, pearson education.
- [2] Carl G.Looney “*PatternRecognitionUsing Neural Networks*”, new york oxford, oxforduniversity press,1977.
- [3] Rafael Palacios*, Amar Gupta**, and Patrick.S.P. Wang*** “*Handwritten Bank Cheque Recognition Of Courtesy Amounts*”,*Universidad Pontificia Comillas, Madrid, Spain. **Massachusetts Institute of Technology, Cambridge, MA, U.S.A. ***Northeastern University, Boston, MA, U.S.A.
- [4] Rafael Palacios*, Amar Gupta** “ *ASystemForProcessingHanderitten Bank ChequesAutomatically*”, MIT Sloanscholl of management.
- [5] JibuPunnoose “*AnImprovedSegmentation Module ForIdentification Of HandwrittenNumerals*”, MIT sloanscholl of management.
- [6] Tou and Gonzalez“*PatternRecognitionPrinciples*”, McGRAW Hill publisher, 1969.
- [7] Dr. D. Nagajyothi , Rakshith Addagudi , Tejaswini Gunda , Sindhu santhoshi Logitla, “Detection of lung cancer using SVM classifier”, International Journal of Emerging Trends in Engineering Research, May 2020, Vol 8,Issue 5, pp. 2177–2180