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A New off Line System for Handwritten Digits Recognition

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Abstract: In this study, we present an off line method of handwritten isolated digits Recognition. The study is based on the analysis and the evaluation of multi-layers perceptron performances, trained with the gradient back propagation algorithm. It is hoped that the results of the evaluation contribute to the conception of operational systems. The used parameters to form the input vector of the neural network are extracted on the binary images of the digits by two methods: the centred moments of the distribution sequences and the Barr features

Key words: Optical characters recognition, neural networks, barr features, image processing, pattern recognition

INTRODUCTION

Handwriting is one of the most important ways in which civilized people communicate. It is used both for personal (letters, notes, addresses on envelopes, etc.) and business communications (bank checks, tax and business forms, etc.), between person and person and for communications written to ourselves (reminders, lists, diaries, etc.). Our handwriting is the product of brain and hand, mind and body. Thoughts are expressed on paper using physical movements produced by the muscles of the arm and controlled by the brain. A person's handwriting is as unique as his/her fingerprints and facial features. Computers are becoming ubiquitous as more people than ever are forced to contact with computers and our dependence upon them continues to increase, it is essential that they become more friendly to use. As more of the information processing is done electronically, it becomes more important to make the transfer of information between people and machines simple and reliable. In addition to a potential mode of direct communication with computers, handwriting recognition is essential to automate the processing of a great number of handwritten documents already in circulation. From bank checks and letters to tax returns and market research surveys, handwriting recognition has a huge potential to improve efficiency and to obviate tedious transcription. According to the way handwriting data is generated, two deferent approaches can be distinguished: on-line and off -line. In the former, the data are captured during the writing process by a special pen on an electronic surface. In the latter, the data are acquired by a scanner after the writing process is over. In this case, the recognition of off-line handwriting is more complex than the on-line case due to the presence of noise in the image acquisition process and the loss of temporal information such as the writing sequence and the velocity. This information is very helpful in a recognition process. Off-line and on-line recognition systems are also discriminated by the applications they are devoted to. The off-line recognition is dedicated to bank check processing, mail sorting, reading of commercial forms, etc., while the on-line recognition is mainly dedicated to pen computing industry and security domains such as signature verification and author authentication. Optical Characters Recognition (OCR) is one of the successful applications of handwriting recognition; this field has been a topic of intensive research for many years. First only the recognition of isolated handwritten characters was investigated[1-4], but later whole words[5,6] were addressed. Most of the systems reported in the literature until today consider constrained recognition problems based on vocabularies from specific domains, e.g. the recognition of handwritten check amounts[7-11] or postal addresses[12,13]. Free handwriting recognition, without domain specific constraints and large vocabularies, was addressed only recently in a few papers. The recognition rate of such systems is still low and there is a need to improve it. Character and handwriting recognition has a great potential in data and word processing, for instance, automated postal address and ZIP code reading, data acquisition in banks, text-voice conversions, etc. As a

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result of intensive research and development efforts, systems are available for English language[14-16], Chinese language[17], Japanese language [18], Arabic language [19-21] and handwritten numerals[22]. There is still a significant performance gap between the human and the machine in recognizing unconstrained handwriting. This is a difficult research problem caused by huge variation in writing styles and the overlapping and the intersection of neighboring characters.

OPTICAL CHARACTERS RECOGNITION SYSTEMS

Today, the OCR (Optical Characters Recognition) systems are only able to recognition high quality printed or neatly handwritten documents. The current research is now basing on documents that are not well handled and including severely degraded, omnifont machine printed text and unconstrained handwritten text.

A wide variety of techniques are used to perform handwriting recognition. A general model for handwriting recognition is used to highlight the many components of a handwriting recognition system. The model begins with an unknown handwritten character that is presented at the input of the recognition system as an image. Firstly, to convert this image into information understandable by computers, parameterization operation is needed which extracts from the image all of the necessary meaningful information in a compact form, compatible with the computer language. This involves the pre-processing of the image to reduce some undesirable variability that only contributes to complicate the recognition process. Operations like slant correction, smoothing, normalization, etc. are carried out at this stage. The second step is to extract discrimination features from the image to either build up a feature vector or to generate graphs, string of codes or sequence of symbols. However, the characteristics of the features depend on the preceding step. Features extraction method is probably the most important factor in achieving high recognition performance in character recognition systems, extracted features must be invariant to the distortions, translations and rotations. The features vector size is also important in order to avoid a phenomenon called the dimensionality problem. Several methods for features extraction are designed for different representations of the characters, such as binary characters, character contour, skeletons (thinned characters), or even gray levels characters[23]. The features extraction methods are valued in terms of invariance properties and expected distortions and variability of the character. Today, the studies are based not only on how to choose the appropriate features extraction methods, but also on the selection of meaningful and pertinent features from the features vector[24-26].

The final step is the character recognition; most recognizers have adopted classical pattern classification methods. Major approaches are statistical based, structural analysis, template matching and neural network approaches. Significant progress has been made in these classification methods but more work is required to match human performance. Today, some recent research has shown improved performance using a combination of several different algorithms, many examples of such multiple classifier systems can be found in character recognition publications[27,28].

PROPOSITION OF A NEW RECOGNITION SYSTEM FOR HANDWRITTEN ISOLATED DIGITS

In the setting of the handwritten writing recognition, we proposed an off line handwritten digits recognition system, shown in the Fig. 1, this system is divided in three phases:

- Acquisition and preprocessing
- Features extraction
- Recognition

Acquisition and preprocessing

Acquisition: Before analyzing the different processing steps, let's recall that we are especially interested at the off line processing. For our case, the acquisition is done with a numeric scanner of resolution 300 dpi with 8 bits/pixels, the used samples are all possible classes of the handwritten digits (0,1,2,3,4,5,6,7,8,9) with variable sizes and variable thickness and with 100 samples for every class. Let's note that the characters images of our database are formed only by two gray levels: the black for the object and the white for the bottom. The Fig. 2 shows some samples of the used database.

Preprocessing: The preprocessing operations are classical operations in image processing, their objective is to clean and prepare the image for the other steps of the OCR system. The preprocessing attempts to eliminate some variability related to the writing process and that are not very significant under the point of view of the recognition, such as the variability due to the writing environment, writing style, acquisition and digitizing of image. For our case, we used the following preprocessing operations:

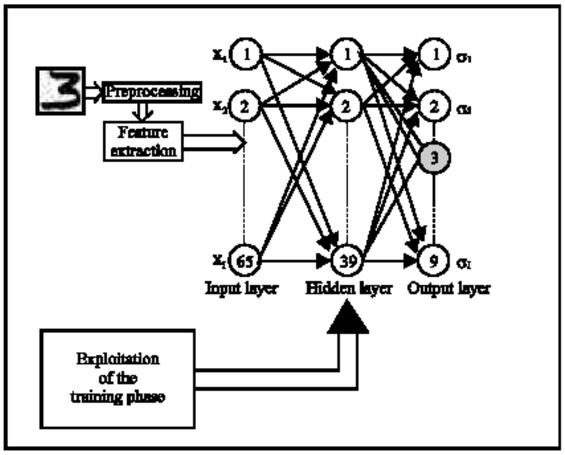

Fig. 1: General Schema of our handwritten isolated digits recognition system

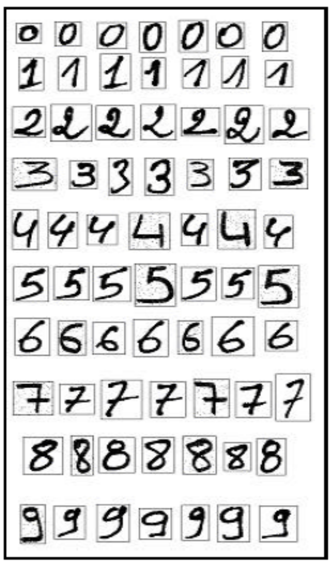

Fig. 2: Some samples of the used database

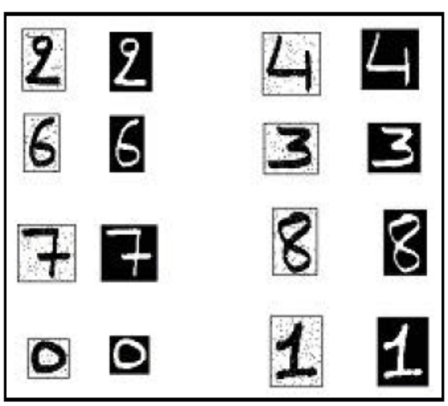

Fig. 3: Filtering and inversion of the gray levels of some handwritten digits

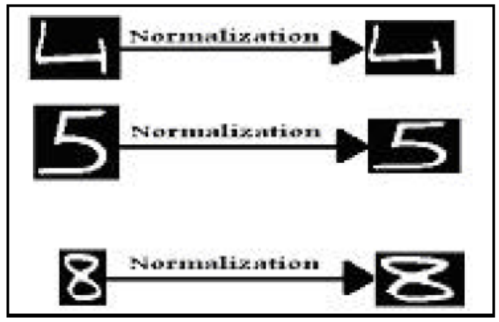

Fig. 4: Normalization of some handwritten digits

Filtering and inversion of the gray levels: This operation consists in eliminating the noises in the binary image due to different reasons (bad Acquisition conditions, bad writing conditions, the writer's mood, etc.), in our case, some digits are marked by the noise of type peppers and salt, the application of the filter median on the digit image permitted us to eliminate easily this type of noise. Let's note that for reasons of calculation we reversed the gray levels of the digit image (black for the bottom and white for the object). The Fig. 3 shows us the filtering and inversion operation of the gray levels of some handwritten digits.

Normalization of the digit image: Knowing that the digits images have variable sizes, this operation consists at normalizing the image size at 64 * 64 pixels (Fig. 4).

Features extraction: Features extraction is an important step in achieving good performance of OCR systems. However, the other steps also need to be optimized to obtain the best possible performance and these steps are not independent. The choice of features extraction method limits or dictates the nature and output of the preprocessing step and the decision to use gray-scale versus binary image, filled representation or contour, thinned skeletons versus full-stroke images depends on the nature of the features to be extracted. Features extraction has been a topic of intensive research and we can find a large number of features extraction methods in the literature, but the real problem for a given application, is not only to find different features extraction methods but which features extraction method is the best?. This question led us to characterize the available features extraction methods, so that the most promising methods could be sorted out. In this study, we are especially interested in the binary image of the digits and the methods used to extract the discrimination features of are the following:

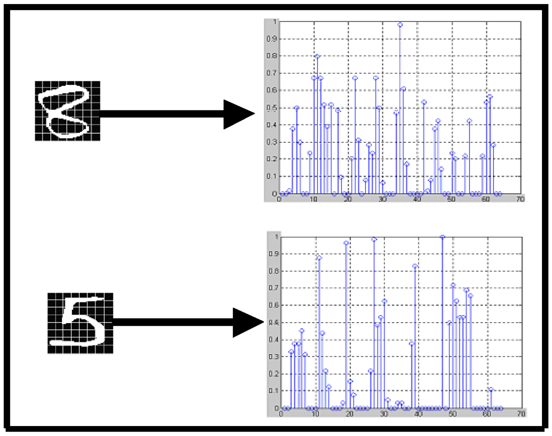

Fig. 5: The numbers eight and five and their distribution sequences

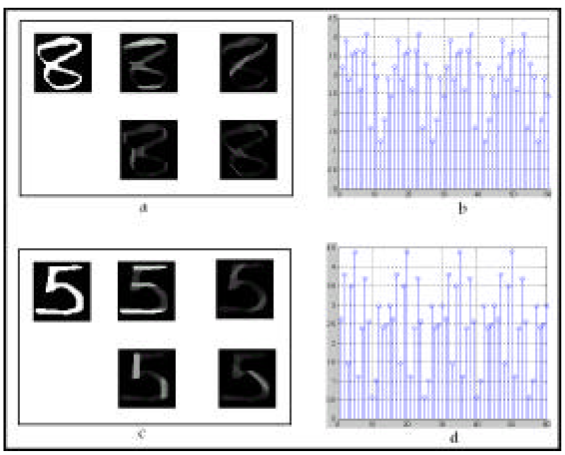

Fig. 6: The images parameters of the digits eight and five (a,c) and their Barr features (b,d)

The centred moments of the distribution sequences: While dividing the digit image at a determined number of zones, the distribution sequence characterizes number of the object pixels in relation to the total pixels number in a given zone. For our application, the digit image is divided in 64 zones (Fig. 5) and the values of the distribution sequence are defined by:

$$x_i = \frac{N_i}{N} \tag{1}$$

With:

- x_I: is the value of i order of the distribution sequence.
- N_i: is a number of the object pixels in the zone i.
- N: is a total pixels number in the zone i.

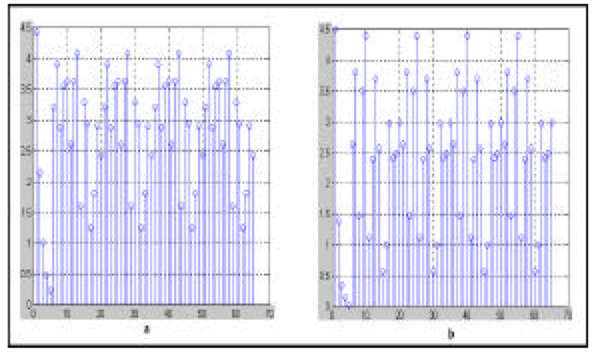

Fig. 7: a) The total features vector of the number eight b) and of the number five

While the centred moments of k order of the distribution sequence are given by:

$$u_k = \sum_{i=1}^{M} (x_i - \bar{x})^k . p(x_i) \tag{2}$$

$$\bar{x} = \sum_{i=1}^{M} x_i p(x_i) \tag{3}$$

- $\bar{x}$: is the mean value of the distribution sequence.
- $p(x_i)$: is the probability of l 'element x_i in the distribution sequence.
- M: is the distribution sequence size.

Barr-features: The Barr features have been used with success in several works[29-31], they are calculated on the binary digits images. Firstly, four images parameters are generated and every image parameter corresponds to one of the following directions: east (e), North (n), Northeast (ne), Northwest (nw). Every image parameter has a whole value representing the Barr length in the direction in question. The features are calculated from the images parameters using zones that overlap to assure a certain degree of smoothing. Fifteen rectangular zones are arranged in five lines with three zones for every line; every zone is of size [(h/3)*(w/2)] where h and w are respectively the height and the width of the image. The high corners on the left of the zones are at the positions {(r0, c0): r0 = 0, h/6, 2h/6, 3h/6, 4h/6 and c0 = 0, w/4, 2w/4}. The values in every zone of the parameters images are added and the sums are normalized and the dimension of the features vector is 15* 4 = 60. If we suppose f_1,f_2,f_3,f_4 are the images parameters associated at a shape in entry and Zi (i = 1,2…. 15) is an rectangular zone of size [(h/3)*(w/2)] with the top corner on the left is (r_0,c_0), the value of the parameter associated to the Zi zone for the image parameter f_k (k = 1,2,3,4) is given like follows:

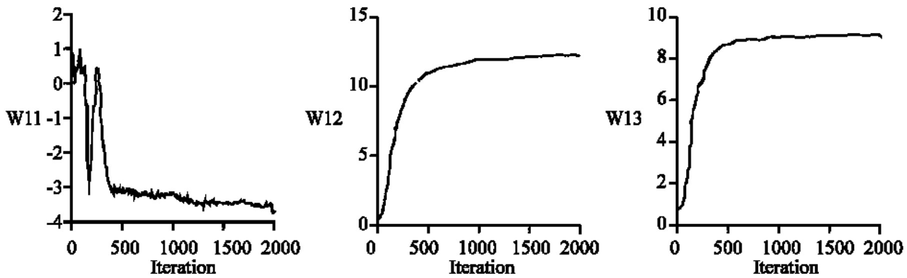

Fig. 8: The variation of the three first values of the connection weights between the hidden layer and the input layer

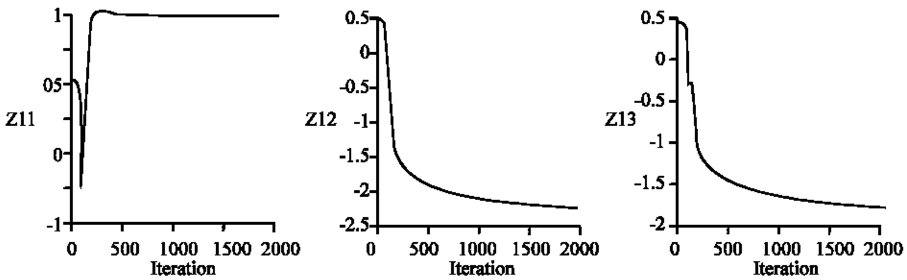

Fig. 9: The variation of the three first values of the connection weights between the hidden layer and the output layer

$$P_{ik} = \frac{1}{N} \sum_{r=r_0}^{r_0+\frac{w}{2}} \sum_{c=c0}^{c0+\frac{h}{3}} f_k(r,c) \tag{4}$$

Figure 6, shows the images parameters of the digits eight and five and their Barr features.

Used features vector: It is the features vector used to characterize the digit image and with which, we will nourish the recognition module. For every digit image, this vector is constituted of the first five moments values of the distribution sequence more the sixty Barr features (Fig. 7).

Digit recognition: The handwritten digits recognition is a problem for which a recognition model must necessarily take in account an important number of variabilities, dice at the time, the recognition techniques based on the neural networks can bring certain suppleness for the construction of such models. For our system, we opted for an MLP (Multi-Layers Perceptron) which is the most widely studied and used neural network classier. Moreover, MLPs are efficient tools for learning large databases. The used MLP in our work is trained with the back propagation with momentum training algorithm. The transfer function employed is the familiar sigmoid function.

The input data: The database consists of 1000 binary images. These images represent all classes possible of the handwritten digits (0,1,2,3,4,5,6,7,8,9) with variable sizes and variable thickness and with 100 samples for every class. This database is divided to two sets, 70? for training the neural network and 30 ? for testing it.

Neural network parameters: The input layer nodes number is equal to the size of the used features vector (N_IL = 65), the output layer nodes number is equal to the classes number to recognize (N_OL = 10), for the hidden layers, we used a single hidden layer with 39 nodes fixed by groping (N_HL = 39). The initial connection weights are in the range [-1,1].

The training process: For training the neural network, back propagation with momentum training method is followed. This method was selected because of its simplicity and because it has been previously used on a number of pattern recognition problems. The method works on the principle of gradient descent and has been described in its basic form in detail by Rumelhart *et al.*[32]. The algorithm uses two parameters which are experimentally set, the learning rate η and momentum μ. These parameters allow the algorithm to converge more easily if they are properly set by the experimenter. For our case, we have opted for the following values: $\eta = 0.35$ and $\mu = 0.9$. During the learning phase the neural network learns by example and the connection weights are updated in an iterative manner (Fig. 8 and 9). The training process for the network is

Table 1: Result and differnet rates.

	R-R (%)	A-R (%)	J-R (%)	NR-R (%)
Training set	97.71	0.71	0.85	0.71
Testing set	88.33	3.66	2.66	5.33

stopped only when the sum of squared error falls below 0.001.

The experimental results: The neural network performances are measured on the entire database (training or learning set and testing set). During this phase, we present the digit image to recognize to the system entry and we collect at the exit its affectation to one of the possible classes.

The results can be:

- Recognized digit: the system arrives to associate one and only one prototype to the digit to recognize.
- Ambiguous digit: the system proposes several prototypes to the digit to recognize.
- Rejected digit: the system doesn't take any decision of classification.
- Non recognized digit: the system arrives to take a decision for the presented digit, but it is not the good decision.

The results and the different rates are regrouped in the Table 1:

With:

- R-R: Recognizer rate.
- A-R: ambiguity rate.
- J-R: Reject rate.
- NR-R: Non recognizer rate.

CONCLUSION

In our work, we presented an off line system for the isolated handwritten digits recognition. The study is based mainly on the evaluation of neural network performances, trained with the gradient back propagation algorithm. The used parameters to form the input vector of the neural network are extracted on the binary images of the digits by two methods: the centred moments of the distribution sequences and the Barr features. The gotten results are very encouraging and promoters; however we foresee the following evolution possibilities:

- To widen the database by taking in account a bigger number of writers and writing instruments.
- To consider other classification methods.
- Use of the algorithms capable to control the ambiguity, reject and non recognizer rates by adjusting the reject and ambiguity rates by use of suitable doorsteps.
- Use of other features extraction methods.
- Use of the post-processing techniques to improve the system performances.

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