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Multiple classifier for degraded machine printed character recognition

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Abstract : *The general problem of optical character recognition (OCR) remains a fundamental but not entirely solved issue in document analysis. In spite of significant improvements in the area of optical character recognition, the recognition of degraded printed characters, in particular, is still lacking satisfactory solutions. This paper presents an OCR method that combines the Hopfield network with a set of autoassociators for degraded character recognition. In the serial combination, the first classifier must achieve lower errors and be very well suited for rejection, whereas the second classifier must allow only low errors and rejects. A relative distance is used as a quality measurement parameter which makes the Hopfield-based classifier very powerful and very well suited for rejection. We report experimental results for a comparison of three methods: the Hopfield model, the autoassociator-based classifier and the proposed combined architecture. Experimental results show the ability of the model to yield relevant and robust recognition with no errors on poor quality bank check characters even when the patterns are highly degraded.*

Mots-clés : Hopfield model, associative memory, degraded printed characters, autoassociator, OCR, serial combination, character recognition..

1 Introduction

Nowadays, there is much motivation to conceive systems of automatic document processing. Giant stages were made in the last decade [1][2], in technological terms of supports and in software products. The optical character recognition (OCR) contributes to this progress by providing techniques to convert great volumes of documents automatically.

The processing of huge amount of printed documents is a big task to handle economically. In today's world of information, forms, reports, contracts, letters and bank checks are generated everyday. Hence the need to store, retrieve, update, replicate and distribute the printed documents, becomes increasingly important [3][4].

Automatic reading of bank checks is one of the most significant applications in the area of recognition of written data. A local town bank can sort daily thousands of checks. The treatment of these checks is expensive [5][6]. The recognition of degraded documents remains an ongoing challenge in the field of optical character recognition. In spite of significant improvements in the area of optical character recognition, the recognition of degraded printed characters, in particular, is still lacking satisfactory solutions.

Studies on designing recognition systems with high performance for degraded documents are in progress along three different aspects. One is to use a robust classifier, a second is to enhance the degraded documents images for better display quality and accurate recognition, and the third is to use several classifiers [7][8][9].

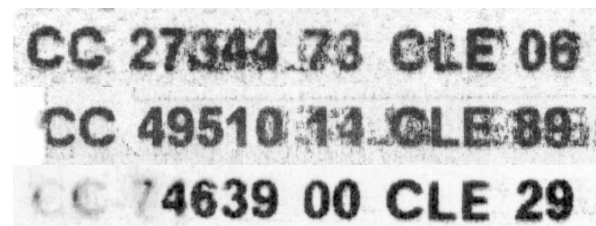


FIG. 1 - Poor quality check account number

M. Sawaki and N. Hagita [7] proposed a robust recognition method based on a complementary similarity measure (CSM) for characters with graphical designs and degraded characters. Their experimental results for newspaper headlines with graphical designs show a recognition rate of 97.7 percent. J. D. Hobby and T. K. Ho [8] proposed a method to enhance such degraded document images for better display quality and recognition accuracy applied to fax images. Outline descriptions of the symbols are then obtained that can be rendered at arbitrary resolution. A. Namane et al. [9] combined sequentially the Hopfield network with the MLP-based classifier for degraded printed character recognition. Their main idea is to enhance or restore

such degraded character images with Hopfield model at different iteration number. The resulted Hopfield network output (if accepted) is then classified during a second stage by the MLP based classifier for recognition accuracy applied to poor quality bank check. They show an achievement of 99.35 % of recognition rate on poor quality bank check characters.

The proposed method is devoted to solve the problem of recognition of poor quality single font gray level character (see Fig.1). The targeted application of our method is third world bank check processing selected as an example, for the following two reasons: Printing and paper are of poor quality, and the important daily use of account numbers for customers balances.

In this paper we present a combined method based on the serial combination of two neural networks, to recognize isolated degraded characters of the account check number with a reliability of 100% (error=0) using appropriate rejection thresholds R_H and R_A . We combine properly the Hopfield network used as a first classifier with a set of autoassociators as a second classifier. A rejection criterion based on the quality measurement of the degraded character is used [10]. The incoming pattern measurement value is compared to a rejection threshold (R_H) in order to accept or reject the character by the Hopfield network used as a first classifier. The proper rejection threshold R_H and the iteration number (T) used in the Hopfield model should be chosen as to keep the error very low. In the second rejection, the autoassociators network output is also compared to R_A [11]. The rejected Hopfield patterns are then classified by the autoassociator-based classifier known by its discrimination capability using an adequate proper rejection threshold (R_A).

The paper is organized as follows: section 2 presents briefly the preprocessing of the printed character. Section 3 describes the proposed combined method, the Hopfield model and the autoassociator-based classifier. Finally, section 4 presents experimental results.

2 Preprocessing

Preprocessing generally consists of a series of image to image transformations to improve the input images quality and to standardize and normalize the input for a given recognition system. Filtering is the first step of any recognition system to improve the image character quality. We propose a Gaussian low pass filtering for noise reduction to be applied to the input image. The binarization of an image has several advantages. One of the most significant is certainly the low memory capacity needed, as well as the simplicity of the operators that are associated to it. The binarization procedure that we propose is carried out with Niblack's method [12], using a local thresholding. Following the thresholding, the resultant image is centred by positioning the image character centroid to the center of a fixed size frame (40x40 pixels).

3 Proposed combined approach

The proposed recognition method is based on the serial combination of the Hopfield and the

autoassociator-based classifier as shown in Fig. 2. Our main motivation comes from the idea of using a relative distance as a quality measurement parameter (QMP) in the first classifier in order to accept or reject the incoming pattern. Thus, this QMP is compared to a rejection threshold R_H . The second classifier is activated only when the QMP of the degraded character is less than R_H . In the present combination architecture (serial combination) decisions are only made either by the first or the second classifier, whereas the rejection is only made by the second classifier (see Fig. 2). A down sampling module [13] is introduced mainly as an additional noise-filtering step and also to speed up the second classification stage rather than feeding the autoassociator with a feature vector of 1600 features (40x40 image size). In down sampling step, the character images were divided into 10×10 zones as shown in Figure 3, where each zone consists of 4×4 pixels. The mean value of the pixels (binarized) in each zone was then used as input data to train the autoassociators network. Therefore, this classifier would have 100 input nodes (one for each zone) and 100 output nodes.

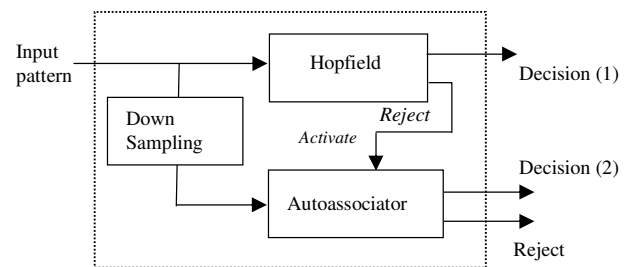


FIG. 2 - Proposed method block diagram

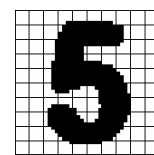


FIG. 3 - Character image divided in 10×10 zones

3.1 Hopfield neural network

The Hopfield model has found applications in the area of image processing [14][15]. A Hopfield network is basically an addressable memory by its contents (associative memory). A memorized form is found by a stabilization of the network, if it were stimulated by an adequate part of this form. It is besides the reason for which this type of network is known as associative [16]. Figure 4 illustrates some examples of addressing a memory by its content at different iteration number T. To improve the error correction, noise tolerance and the storage capacity of the Hopfield model, the Gram-Schmidt orthogonal projection procedure is used that can extract special features of patterns [17].

During the recognition phase, the Hopfield network is fed with the input pattern, and then the output is determined after a fixed iteration number T. Since the

output pattern is binary, then the expected class (C) is determined from a distance δ_m of the output Y and a memorized pattern $S^{(m)}$ as follows:

$$\delta_m = \frac{1}{2} \sum_{j=1}^N (Y_j - S_j^{(m)})^2, \quad m = 1, 2, \dots, M \quad (1)$$

where N is the image character size and M is the number of memorized patterns. The class membership is simply established by:

$$C = \underset{m = 1, 2, \dots, M}{\operatorname{argmin}} \{ \delta_m \} \quad (2)$$

A typical classification criterion which is used consists of rejecting a pattern if the relative distance:

$$\xi_{\alpha\beta} = (\delta_\beta - \delta_\alpha) / \delta_\beta < R_H \quad (3)$$

with

$$\delta_\alpha = \min_{m = 1, 2, \dots, M} \{ \delta_m \} \quad \text{and} \quad \delta_\beta = \min_{m \neq \alpha, m = 1, 2, \dots, M} \{ \delta_m \}$$

This rejection is based on the comparison of the two lowest reproduction errors δ_α and δ_β for an incoming pattern X . R_H is an appropriate threshold which can be chosen depending on the user requirements.

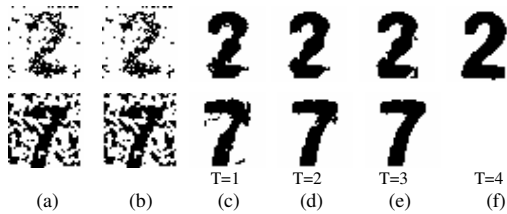


FIG. 4 - Pattern recovering example a) Corrupted input pattern b) Centered pattern c)-f) Memorized pattern restitution ((c)-(e) for the character “7”).

The first iteration can be used to determine the tendency to correct or misclassified recognition of the recovered pattern based on the relative distance used as a measurement in the Hopfield model [10]. The relative distance can be used also as a quality measurement parameter of the printed character for $T=1$ as shown in Fig. 5. A medium and High quality printed characters have their $\xi_{\alpha\beta} \rightarrow 1$ ($\delta_\alpha \rightarrow 0$) for $T=1$, whereas low quality characters have their $\xi_{\alpha\beta} \rightarrow 0$ ($\delta_\beta \rightarrow \delta_\alpha$).

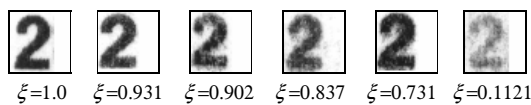


FIG. 5 - Relative distance ξ for quality measurement of printed character for $T=1$

3.2 Autoassociator neural network

The autoassociator neural network is a multi layer

perceptron (MLP) with the principal characteristic is that the output neurons number is equal to input neurons number and the desired outputs are fixed to be equal to the input [11]. Typical autoassociator neural network architecture is shown in Fig. 6. To improve the error correction, noise tolerance and the storage capacity of the Hopfield model, the Gram-Schmidt orthogonal projection procedure is used that can extract special features of patterns [17].

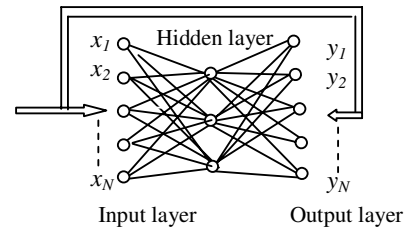


FIG. 6 - Autoassociator neural network architecture

The expected class (C) is determined from a distance δ_m of the output $Y^{(m)}$ of each autoassociator and the input pattern X as follows:

$$\delta_m = \frac{1}{N} \sum_{j=1}^N |y_j^m - x_j|, \quad m = 1, 2, \dots, M \quad (4)$$

where N is the down sampled image character size. The class membership is simply established by:

$$C = \underset{m = 1, 2, \dots, M}{\operatorname{argmin}} \{ \delta_m \} \quad (5)$$

4 Experimental results

4.1 Data extraction and training phase

The character data set represents a single font gray level character that was collected from 490 post checks belonging to the same post. The post checks were scanned at 300 dpi, which avoids the scaling procedure. Hence a frame of 40x40 pixels is sufficient to include each sample of the M pattern classes, where C is equal to 13 (see Fig. 7). The classes considered consist of ten numeral characters and three alphabetic characters of 40-by-40 pixel size.

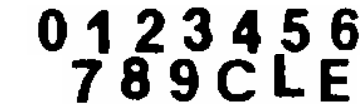


FIG. 7 - Clean character samples

The characters used for learning the autoassociators-based classifier were extracted from 70 post checks, and gave rise to 2800 characters. Before they are fed to autoassociator-based classifier for training phase, the characters are first filtered and binarized, and secondly processed with down sampling procedure. The remaining 420 post checks were used for testing, which consist of 16800 characters. The Hopfield-based

classifier was trained with only thirteen ($M=13$) clean samples from 13 classes and tested with 16800 characters. The autoassociator-based classifier used in the proposed work is a two layer of fully connected neural network module with $\alpha=0.9$ (training speed), $\xi=0.001$ (viscosity coefficient), the number of neurons in the input layer was fixed to $N=100$, the hidden layer was fixed to 80 neurons, the number of outputs is the same as in the input, and the total error to 0.0001. The connection weights v_{ij} and w_{ij} are obtained after convergence and stored for the recognition process. The Hopfield parameters were fixed to: $M=13$ and $N=1600$ (40×40 pixels), where M is the number of memorized patterns.

4.2 Recognition phase

Figure 8 shows the error-reject plots of the Hopfield-based classifier for different iteration number T and R_H ($0.1 \leq R_H \leq 0.9$). The iteration number T is chosen as to give the best performance, and as it can be noticed, the error falls for lower T values and higher R_H , and the best performance in terms of low errors is achieved for $T=1$. Figure 9 shows the error-reject plots of the autoassociator-based classifier for different number of samples per class used in the training set (k) and R_A ($0.0009 \leq R_A \leq 0.5$). As can be noticed, the error rate falls for higher k and higher R_A , and the best performance in terms of low errors is achieved for $k=10$. Figure 10 shows that the error-reject plots of the Hopfield and autoassociator based classifiers exhibit clearly a complementary behaviors on both sides of the reject value of 1%.

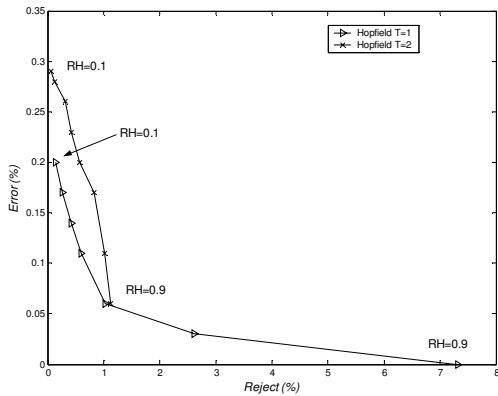


FIG. 8 - Error versus reject plot of the Hopfield-based classifier for different T values

According to Fig. 10, the Hopfield-based classifier outperforms clearly the autoassociator-based classifier for lower reject and vice versa. The curve describing the combination of Hopfield and autoassociator is obtained by choosing $R_A=0.5$, the iteration number $T=1$ and various R_H ($0.1 \leq R_H \leq 0.9$). The error-reject plot of Fig. 10 shows that the proposed modular approach outperforms both the Hopfield and the autoassociator-based classifiers.

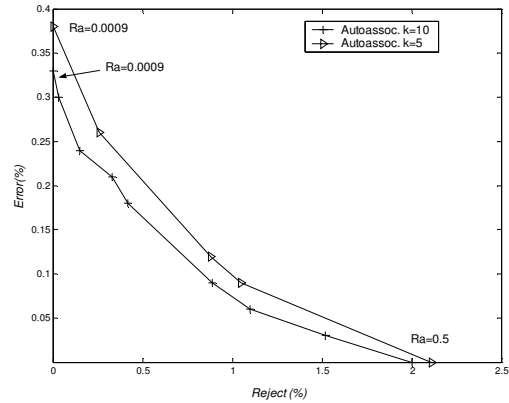


FIG. 9 - Error versus reject plot of the autoassociator-based classifier for different k

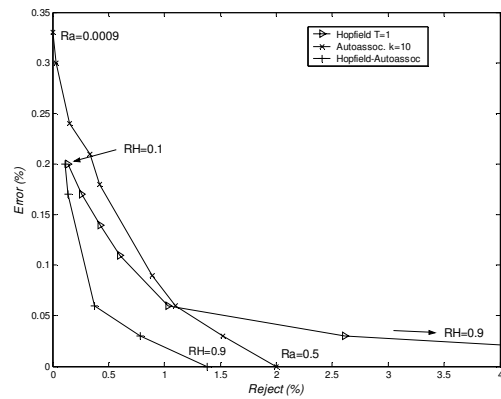


FIG. 10 - Error vs reject plot for the three classifiers using various thresholds values for R_H and R_A

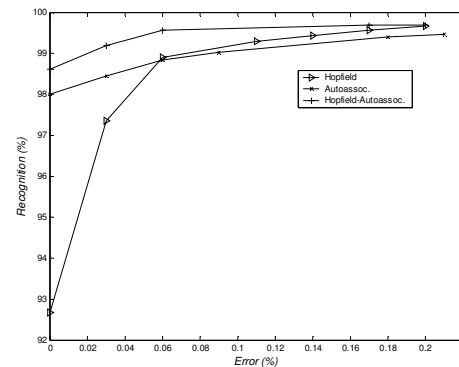
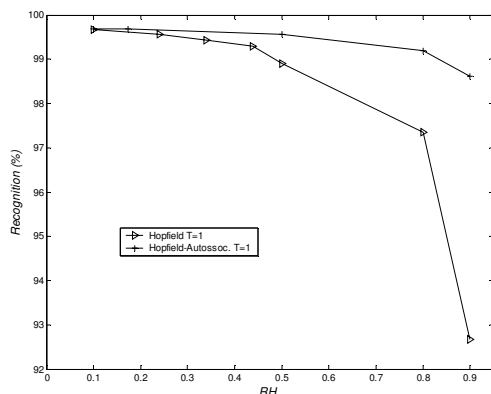


FIG. 11 - Recognition vs error plots for the three classifiers using various thresholds values for R_H and R_A

On one hand, the plot corresponding to the combined approach reaches the plot of the Hopfield-based classifier for very low rejection rates. On the other hand, the proposed approach reaches the plot of the autoassociator-based classifier for high rejection rates. Table 1 summarizes the best performance achieved by the three classifiers, namely, the Hopfield, the autoassociator and the proposed classifier for a reliability of 100 % for $R_H = 0.9$ and $R_A = 0.5$.

Classifiers	REJECT (%)	ERROR (%)	RELIABILITY (%)	RECOGNITION (%)
Hopfield ($R_H=0.8$)	7.32	0	100	92.68
Autoassoc. ($R_A=0.5$)	2.00	0	100	98.00
Hopf-Autassoc ($R_H=0.8, R_A=0.5$)	1.38	0	100	98.62

TAB. 1 – Recognition rate comparison

FIG. 12 - Recognition vs threshold reject R_H plots

This high improvement could be clearly noticed from the plots of the recognition rate versus the error (see Fig. 11). This combination tends in reality to boost the performance of the Hopfield model resulting in a robust multiple classifier for all the threshold reject R_H as shown in Fig. 12. Figure 13 shows samples of degraded characters that were correctly recognized and samples that were rejected by the proposed method.

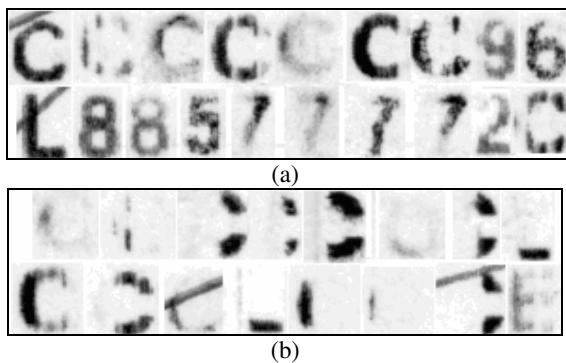


FIG. 13 - Proposed recognition method results (a) Correctly recognized characters (b) Rejected characters.

5 Conclusion

We have presented serial combination architecture of two noise insensitive neural networks, namely, the Hopfield and the autoassociator-based classifiers. Experiments were conducted on collected single font printed characters check of medium and low quality. We report experimental results for a comparison of three neural architectures: the Hopfield network, the MLP-based classifier and the proposed combined method. They show that the combined classifier outperforms both

the individual classifiers. Experimental results show an achievement of 98.62 % of recognition rate with no errors and a rejection rate of 1.38 % on poor quality bank check characters. The proposed method could be also addressed to solve the problem of multi font recognition by increasing the number of the classes.

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