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ISOLATED HANDWRITTEN ARABIC NUMERALS RECOGNITION USING THE K-NEAREST NEIGHBOR AND THE HIDDEN MARKOV MODEL CLASSIFIERS

Badre-eddine EL Kessab, Cherki Daoui, Belaid Bouikhalene and Rachid Salouan

Abstract. This paper deals with a recognition system of handwritten Arabic numerals extracted to the MNIST standard database (Arabic numerals). This system is composed of three main phases: the pre-processing of numerals followed by the extraction of primitives with the zoning method in order to convert each image into a vector number, which is nothing other than a piece of information extracted from this numeral just to differentiate the others. Finally, our recognition system will end with a classification phase using two methods: the K-nearest neighbours (K-NN) and Hidden Markov Model (HMM). This work has achieved a recognition rate of approximately 82 of success.
Keywords: K-Nearest Neighbor, Hidden Markov Model.

1. Introduction

In this paper, we have made a comparison between the performances of the K-nearest neighbour (K-NN) method and those of the Hidden Model Markov (HMM) in the handwritten Arabic numerals recognition. Our recognition system contains the following phases: the pre-processing for which we used the thresholding technique, the feature extraction made by a structural method called the Zoning, and then the learning and classification phase performed by the K-NN and the HMM. The optical character recognition (OCR) is considered one of the most successful and powerful applications of the automatic pattern recognition. It is really a very active field of research and development. Several studies have been carried on Arabic numerals and characters by using the hidden Markov models [1-3] or the K-nearest neighbour [4-8]. However, our study is based on handwritten Arabic numerals recognition. A succession of operations in this recognition system can be divided into three principal phases. The first is pre-processing, which serves

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to clean the numeral image just for the purpose of improving its quality. The second phase is feature extraction from the pattern, the aim of which is avoiding data abundance and reducing their dimension. The third phase is learning-classification. During this phase, the images of the learning base that are converted to vectors in the second phase XXXXXXX should be trained with a learning process XXXXXX. After that, the images of the test database must be classified. In this study, the pre-processing of numerals is carried out using the thresholding technique. In the phase of feature extraction from a numeral image the Zoning method is used to transform each image of the numeral to a vector that will be used as an input vector of HMM and of K-NN. These are used to train the images of the training database and then to classify those in the test database. The learning-classification phase takes place as follows:

*** By using the K-NN:**

In the learning phase, each numeral image is transformed to a vector by the zoning method. Then we calculate the Euclidean distance between the vector and the test vector. We choose the k-nearest neighbors from this test vector and count the numbers of these nearest neighbors in each class. The recognition will be assigned to the class that is most represented.

*** By using the HMMs:**

In the learning phase, each numeral image is converted to a vector by the zoning method; this vector will be an observation vector of the initial HMM of this numeral for determination of probability generated by this observation. Then this model must be re-estimated for the purpose of maximizing this probability using the Baum-Welch algorithm [9-11]. All re-estimated models (optimal models) of all numerals must be saved for the learning base. In the classification phase, we will present an unknown numeral (test numeral), then we calculate the probability generated by this observation by all the optimal models already recorded in the learning base by the Forward algorithm[12]. The recognition will be given to the numeral that the optimal model gave the highest probability. The organization of this paper is represented in the following figure.

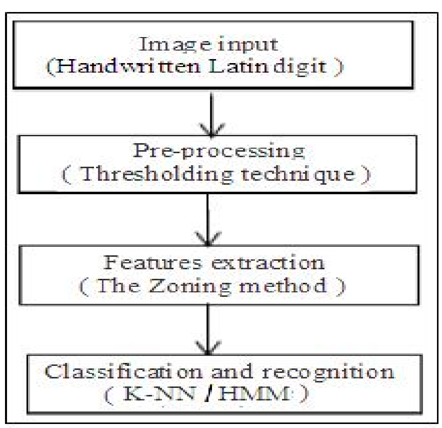

Fig 1 : The proposed recognition system

2. Database

The MNIST database [13] of handwritten numerals contains 70000 numerals ranging from 0 to 9. The numerals have been size-normalized and centered in a fixed-size image with size 28x28. The database is free and available on the Web. Example of the MNIST numeral is shown in Figure 2.

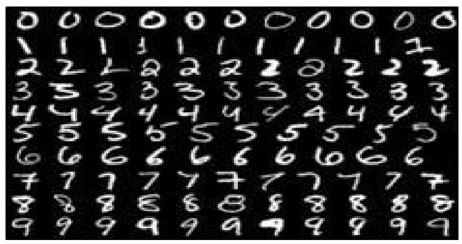

Fig 2 : The Examples of MNIST database

3. Preprocessing

The pre-processing phase is an important process for the recognition of a numeral. It is the first part of the recognition system used to produce a cleaned up version of the original image so that it can be used efficiently in the following phase. i.e. feature extraction. In this work, numeral images are extracted from the standard MNIST database, then the noise is reduced using a median filter after the application of the thresholding technique. Finally, each extracted image is normalized to size 28 x 28 pixels.

4. Features extraction

4.1. Extraction with zoning method

In this phase many methods can be used to extract features from images. In this recognition system, we use the Zoning method that can be explained as follow:

The zoning method consists of subdividing a white image with a numeral written in black to several blocks or zones which are square or rectangular, then counting the number of white pixels in each zone, and finally converting the image to a vector with the number of components equal to the that of zones (see figure 3)

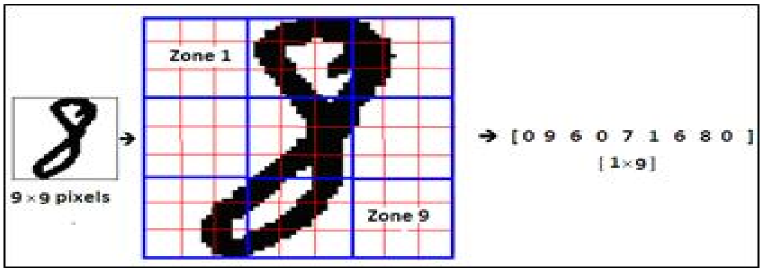

Fig 3 : Features extraction by zoning method from numeral eight (9 zones)

4.2. Features extraction vector

Each image is characterized by a vector of 9 components.

$$V_{extraction} = \begin{pmatrix} SquareNpixelsZ1 & SquareNpixelsZ2 & SquareNpixelsZ3 \\ SquareNpixelsZ4 & SquareNpixelsZ5 & SquareNpixelsZ6 \\ SquareNpixelsZ7 & SquareNpixelsZ8 & SquareNpixelsZ9 \end{pmatrix}$$

$SquareNpixelsZ_i$: the number of pixels equal to value 1 in the square number (zone) i.

5. Learning - Classification phase

5.1. The k nearesat neighbours (knn)

Given a training set of vectors $x_1, x_2, ..x_n$, each of them belongs to classes $C_1, C_2, ..C_n$. To predict the class of a new vector (unknown or test vector), the classifier KNN seeks the K-nearest neighbours of the new xtest and predicts the most common response of these K nearest neighbours. Therefore, this method uses two parameters: the number K and the similarity function to compare the new case to the cases already filed. The principle is given by:

1) Choosing an integer k (this choice is very important)

2) Calculating the distances (the Euclidean distance is more popular)

$$d(x_{test}, x_j)^2 = \sum_{i=1}^{N} (x_{test,i} - x_{j,i}) \tag{5.1}$$

3) Retain k observations for which these distances are smaller (the k nearest neighbors of a reference case, when we talk about a neighbor this implies the notion of distance or dissimilarity)

4) Count the numbers of these observations once they appear in each class, determining the correspondents classes.

5) Choose the class most represented.

These steps are summarized as follows:

For x_{test} we will examine the distance from it to all vectors $x_1, x_2, ..x_n$ which define all classes. Then we select K closest vectors and we assign x_{test} to the majority class among the K vectors:

$$Class(X_{test}) = argmax_k \sum_{x_j \epsilon KNN} d(x_{test}, x_j) \tag{5.2}$$

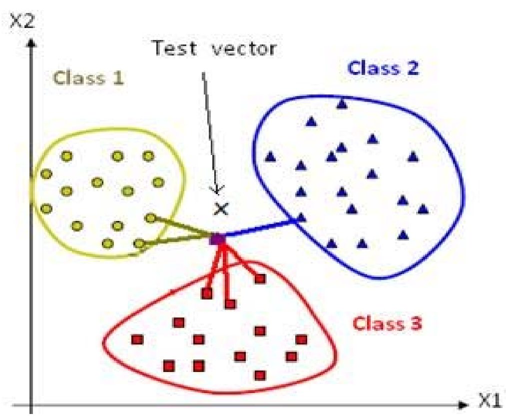

Fig 4 : 6-NN of test vector X and from three different classes

5.2. The Hidden Markov models (HMM)

The Hidden Markov model (HMM) [14-17] is based on doubly stochastic processes, one of them being hidden. The transition of the process from the actual state to the next one is based on this underlying process. The observable outputs or the observations are generated by another stochastic process which is given by probabilities. The hidden Markov model with a discrete observation symbol is defined by $\lambda = (A, B, \Pi)$, where A is the matrix of the probabilities of transitions, B is the matrix of the probabilities of observations, and is the vector probability of initial states N: The number of states S_1, S_2, S_3, S_N.

T: The number of observations.

q_t: The state of the process at the time t.

$$q = (S_1, S_2, S_3, S_N) \tag{5.3}$$

o_t: The observation at the time t

$$o_t = (v_1, v_2, v_3, v_M) \tag{5.4}$$

M: The size of observations v_1, v_2, v_3, v_M

$$A = a_{ij} = Prob(S_j/S_i) \tag{5.5}$$

$$\sum_{i,j=1}^{N} a_{ij} = 1 \tag{5.6}$$

$$\Pi = (\Pi_i = Prob(S_i)) \tag{5.7}$$

$$\sum_{i=1}^{N} \Pi_i = 1 \tag{5.8}$$

$$\mathbf{B} = b_j(k) = Prob(o_t = v_k | o_t = S_i) \tag{5.9}$$

$$\sum_{k=1}^{M} b_j(k) = 1 \tag{5.10}$$

The hidden Markov model with a continuous observation symbol is defined by $\lambda = \Pi, a_{ij}, \mu_i, \sigma_i$ where μ_i and σ_i are respectively the mean and the variance of a state i of the Gaussian function that is used to generate the probability of observation:

$$b_j(k) = P(o_t = v_k | o_t = S_i) = \frac{1}{(2\Pi)^{\frac{1}{2}} \sigma_i} \frac{e^{(O_t - \mu_i)^2}}{2\sigma_i^2} \tag{5.11}$$

In our work we used the HMM with the continuous observation.

6. Experiments and results

All the results that we have obtained are presented in the following table and graphs:

Table 1: The results obtained with K-NN and HMM

Numerals	K=6	K=10	K=15	K=20	HMM
0	90.00	90.00	90.00	91.67	88.00
1	98.33	98.33	99.00	98.33	80.00
2	93.33	93.33	91.67	91.67	62.00
3	76.67	80.00	76.67	86.67	74.00
4	99.00	98.33	98.33	99.00	85.00
5	30.00	41.67	55.00	48.33	50.00
6	66.67	66.67	80.00	80.00	90.00
7	71.67	90.00	95.00	95.00	74.00
8	43.33	41.67	56.67	51.67	65.00
9	66.67	65.00	70.00	70.00	70.00
Global rate	73.50	76.50	81.10	81.30	73.80

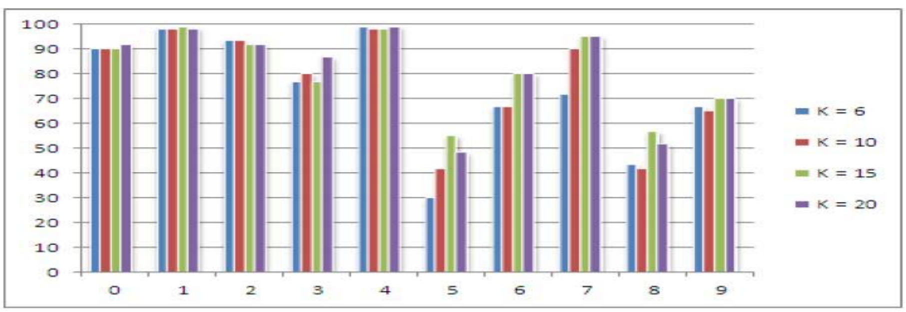

Fig 5 : The recognition rate of each numeral using K-NN

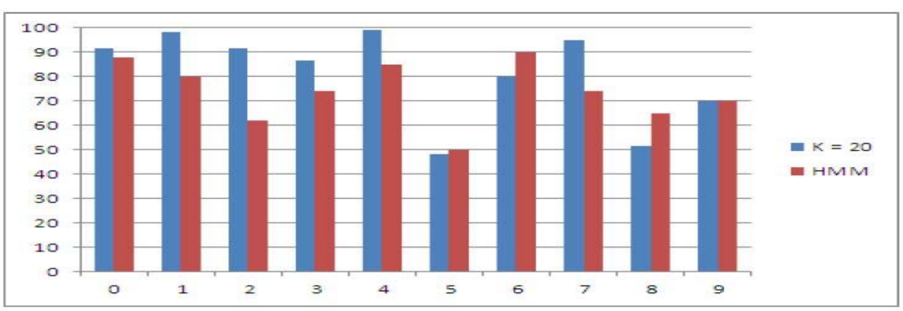

Fig 6 : The recognition rate comparison between K-NN and HMM

7. Conclusion

In this paper we used a handwritten Arabic numerals recognition system that contains the thresholding technique in the preprocessing phase, the Zoning method in the features extraction phase, and the K-NN followed by the HMM in the learning-classification phases. Our goal is to compare the performances of these mathematical tools. The experimental results that we have obtained prove that K-NN is more performing than HMM in this recognition.

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B. EL KESSAB
Faculty of Science and Technology
Laboratory of Information Processing and Decision Support
BP 523, Beni Mellal
Morocco
bade10@hotmail.fr

C. DAOUI
Faculty of Science and Technology
Laboratory of Information Processing and Decision Support
BP 523, Beni Mellal
Morocco
daouic@yahoo.com

B. BOUIKHALENE
Faculty of Science and Technology
Laboratory of Information Processing and Decision Support
BP 523, Beni Mellal
Morocco
bbouikhalene@yahoo.fr

R. SALOUAN
Faculty of Science and Technology
Laboratory of Information Processing and Decision Support
BP 523, Beni Mellal
Morocco
rachidsalouan@gmail.com