Isolated Handwritten Roman Numerals Recognition Using Methods Based on Radon, Hough Transforms and Gabor Filter

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Abstract

This paper presents for isolated handwritten Roman numerals recognition a research interested for carrying out both comparisons between the performances in terms of precision and rapidity, the first comparison is realized between four hybrid methods used to extract the features from numerals that are the zoning combined with Radon transform in first time, then combined with Hough transform in second time, then combined with Gabor filter in third time, finally combined in the same time with all these three descriptors, while the other comparison is performed between three classifiers which the first one is neuronal that is the multi-layer perceptron whereas the second is probabilistic that is hidden Markov model, the third classifier is realized via a combination between these both classifiers. For this purpose we have employed for pre-processing each numeral image the median filter, the thresholding, the centering and the edge detection techniques.

1. Introduction

In recent years the Optical Character Recognition (OCR) became a very dynamic domain in terms of innovation and creativity in wide sense of word due to the increasing use of computers in various fields such as postal code recognition, automatic text entry into computer, language processing, automatic sorting of postal mail, bank cheques recognition, *etc*.

In practice, there is two principal categories in each OCR which the first one is intersted to printed characters while the second is focused to those handwritten, in this context, it is obviously that the last category is more difficult compared to the first taking into account that the intraclass variance is high in reason of the different forms associated to a same character, because there is a particular writing style of each person, furthermore a certain character can be written in many different forms even by a same given person. For this reason, it is necessary to use some efficient techniques in each one of the three principal phases forming a certain recognition system which are the pre-processing used to improve the quality of the character image, and features extraction exploited to convert the image to a vector contains numerical values that not are only of the information characterizing the character. Finally there is the recognition phase employed in order to train all the character images of the learning base and classify those of the test database.

Moreover, we have centered our attention in this study on isolated handwritten Roman numerals recognition, in this sense, for achieving with success this task, we have opted in the first phase the median filter, the thresholding, the centering and the edge detection techniques, concerning the second phase we have exploited four hybrid methods based on a combination between zoning technique and Radon transform firstly then between

zoning with Hough transform secondly then between zoning with Gabor filter, afterwards all these four descriptors are in the same time combined between them, finally in order to recognize each numeral image we have employed three classifiers which are the multi-layer perceptron and hidden Markov model then a hybridization between these both classifiers. In fact, more precisely the main contribution in this work is to compare between the performances of these four hybrid methods of features extraction in one side and between these three classifiers on the other side, in order ultimately to deduct the most performing recognition system in terms of precision and rapidity.

Besides that, there are many studies have been proposed in the literature for recognizing Indian, Latin or Arabic numerals and characters by using the zoning method [1-3] the Radon [4-6] and Hough [7-8] transforms, the Gabor filter [9-10] the multi-layer perceptron [11-15] the hidden Markov model [16-19].

Hence, the remainder of the organization of this paper is as follows. In Section 2, the methodology that we have opted in this study is given. In Section 3, the techniques pre-processing are presented. In Section 4, features extraction methods are described. A Section 5 deal describes the numerals recognition procedures. Experimental methods and results are given in Section 6. Lastly, the conclusion and scope of further work are described in Section 7.

2. Methodology

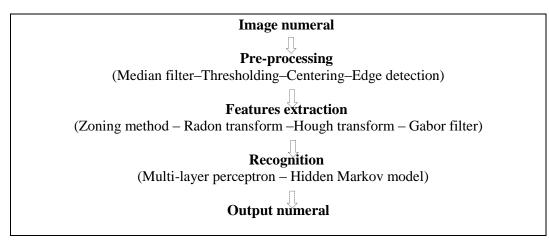The recognition systems which are we have used can be presented as follow:

Image numeral
⇩
Pre-processing
(Median filter–Thresholding–Centering–Edge detection)
⇩
Features extraction
(Zoning method – Radon transform –Hough transform – Gabor filter)
⇩
Recognition
(Multi-layer perceptron – Hidden Markov model)
⇩
Output numeral

Figure 1. The Proposed Recognition Systems

3. Pre-processing

Pre-processing is undoubtedly an important part of each optical character recognition system especially when it comes of handwritten characters, its objective is to render the numeral image in a best quality in terms of removal of noise and of redundant and needless information in character image, for this goal we have employed the median filter used for filtering each numeral image, the thresholding which serves to render the numeral image contains only the black and white colours according a preset threshold, the centering exploited to put the numeral justly in center of image and the edge detection performed to find the edge of numeral.

Figure 2. Different Techniques used for Pre-Processing of Handwritten Roman Numeral IV

4. Feature Extraction

Features extraction is really considered as a one of the major problems of character recognition. In fact the performance of character recognition system is depends enormously on proper features extraction, in fact, a certain method is very effecient if it achieves a great discrimination interclasses and a small discrimination intraclasses of the fact that all of that effectively allows to render the recognition phase will be easier. For this finality, in order to realize all that with success, we have used four hybrid methods which are respectively:

- Zoning method combined with Radon transform.
- Zoning method combined with Hough transform.
- Zoning method combined with Gabor filter.
- Zoning method combined with Radon, Hough transforms and Gabor filter.

4.1. The Zoning Method

Firstly, given a black image that contains a numeral written in white, the zoning method consists to divide this image to a several zones then calculating in each one of them the number of white pixels, all these numbers are stocked in a vector, that is to say image is converted to a vector has a number of components equal to that of zones.
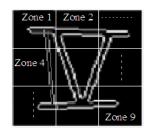
Figure 3. Zoning Method of Handwritten Roman Numeral IV

4.2. Radon Transform

Due to its ability to represent efficiently significant features of an image Radon transform have found wide applications in the fields of image processing and pattern recognition [20-21]. The Radon transform computes the projections of an image $f(x,y)$ along some specified and pre-determined radial directions according a specific set of angles. The Radon transform is defined as follow:

$$T_{R_f}(\rho,\theta) = \iint f(x,y)\delta(x\cos\theta + y\sin\theta - \rho)dxdy \quad (1)$$

Where is the impulse of Dirac given by:

$$\delta(x) = \begin{cases} 1 & if \quad x = 0 \\ 0 & elsewhere \end{cases} \tag{2}$$

Furthermore, the Radon transform needs as input parameters a number of directions denoted n according to which the integrals are calculated generally fixed to 2π and a pitch denoted p which is thus automatically fixed to $\dfrac{2\pi}{n}$ in order to ensure a homogeneous distribution in θ .

4.3. Hough Transform

The Hough Transform (HT) [22] is a technique commonly used in image processing. It is known for its capacity to detect in a given image among other things, straight lines in digital images. In polar coordinates, a straight line can be described via the equation:
In the HT space, a line is represented in its normal form by:

$$\rho = x\cos\theta + y\sin\theta \qquad\qquad 0 \le \theta \le 2\pi \tag{3}$$

The above equation describes a mapping of a point in the Cartesian coordinate plane (x,y) to the sinusoidal curve in the polar coordinats $\rho - \theta$ plane

Each feature point (xi , yi) votes then for a sinusoid of points in the parameter space (accumulator). Where these sinusoids cross, there are higher accumulator values. Localizing maxima in the accumulator is equivalent to finding the existing lines.

The line detection in a binary image using the Hough transform algorithm can be summarized as follows:

1) Define the Hough transform ρ_{min} , ρ_{max} , θ_{min} and θ_{max}

2) Quantify the plane $\rho - \theta$ into cells by forming an accumulator cells array $A(\rho,\theta)$

where ρ is between ρ_{min} and ρ_{max} and θ is between θ_{min} and θ_{max}

3) Initialize each element of an accumulator cells array A to zero.
4) For each pixel of numeral in a binary image, perform the following:

For each value of θ from θ_{min} to θ_{max}, calculate the corresponding ρ using equation:

$$\rho = x\cos\theta + y\sin\theta \tag{4}$$

Round off the ρ value to the nearest interval value.
Increment the accumulator array element $A(\rho,\theta)$
Detect best line candidates as local maxima in the accumulator cell array.

Hence, The following example presents graphically the Radon and Hough transforms for each isolated handwritten Roman numeral knowing that $\theta = \left\{0, \dfrac{\pi}{18}, \dfrac{\pi}{36}.....\pi\right\}$
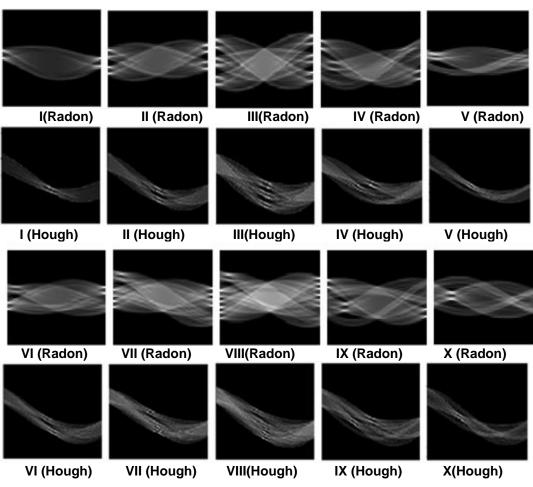
Figure 4. Accumulators of Radon and Of Hough Transforms For Each Handwritten Roman Numeral

4.4 Gabor Filter

Gabor filters is used in many various fields depending on pre-processing image such as image compression, edge detection, texture analysis, object recognition and facial recognition.

Gabor filter is a Gaussian kernel function modulated by a sinusoidal plane wave [23-24] and is defined as follows:

$$G(x, y, \theta, f) = e^{((\frac{-1}{2}(\frac{x'}{o_{x'}})^2 + (\frac{y'}{o_{y'}})^2))} \cos(2\pi f x') \quad (5)$$

With:

$$x' = x\cos\theta + y\sin\theta$$
$$y' = -y\cos\theta - x\sin\theta \quad (6)$$

σ_x, σ_y are the variances of the x and y axes respectively

f is the frequency of the sinisouide function.

θ is the orientation of Gabor filter.

G is the output of Gabor filter for each different values of f and θ

5. Recognition

5.1 Simple Classifiers

5.1.1 Multi-layer Perceptron : The Neural Network presented in this figure is a multi-layer perceptron that we have used in this study.
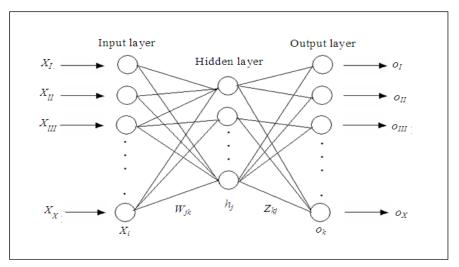

Figure 5. Architecture of Multi Layer Perceptron

The multi-layer perceptron neural networks have been applied successfully to solve some difficult and diverse problems by training them in supervised manner with a highly popular algorithm known as error back-propagation algorithm, Concerning the , the MLP that we have used contains the following elements :

- An input layer of 10 vectors who's each of them represents a handwritten Roman numeral X_i .

- A hidden layer of 7 activations neural h_j

- An output layer of 10 activations neural o_k

- 7×10 connections between input layer and hidden layer, each weighted by W_{jk}

- 10×7 connections between hidden layer and output layers, each weighted by Z_{kj}

The learning of multi-layer perceptron is achieved by the back propagation algorithm in five principal phases which

Phase 1. Initialize the network, with all wight W and Z set to random numbers between -1 and +1.

Phase 2. Present firstly the vectors X_i whose all numerals are converted and obtain the real outputs which are calculated by a sigmoid function :

$$f(x) = \frac{1}{1 + e^{-X_i}}.$$

(7)

Phase 3. Compare between each real output and each desired output which is a10-element vector with a 1 in the position of the numeral it represents, and 0's everywhere else, for example, the numeral "II" is to be represented by a 1 in the second element (because "II" is the second numeral of the Romain numerals), and 0's elsewhere.

Phase 4. Propagate the error backwards:

i) Correct the weight of output layer Z

ii) Correct the input weight W .

Phase 5. Take the average difference between the desired and the output vector to calculate the error.

Phase 6. Repeat from phase 2 until the real output converges to the desired output.

After the learning of MLP, for classifying an test numeral, that is presented as a vector of test X_{test} the value of $f(X_{test}W^*) = h_j$ is calculated then the Euclidean distance between the value of $f(h_j Z^*) = o_k$ (f is the sigmoid function) and each o_k for $j = \{I, II.....X\}$ is calculated.

Therefore, the recognition will be assigned finally to the numeral that is very nearest to test numeral.

5.1.2 The Hidden Markov Model: Hidden Markov model [25] is a probabilistic tool which considered as a one of the most effecient methods in pattern recognition. In fact, it offer many important properties for modeling characters or words. Among these properties is the existence of efficient algorithms allowing to learn automatically the models without any need of labeling of data's. The HMM is based on a doubly stochastic processes whose the first one is hidden while the second is observable. The transition of the process from an actual state to a next is based on this underlying process. The observable outputs or the observations are generated by other stochastic process which is given by probabilities.

The HMM 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 π is the vector probability of initial states.

N : The number of states $s_1, s_2 ......s_N$

T : The number of observations.

q_t The state of the process at the time t

$q_t = \{s_1, s_2,....,s_N\}$

o_t The observation at the time t $o_t = \{v_1, v_2,....,v_M\}$

M The size of observations $v_1, v_2......v_M$

$$A = a_{ij} = P(s_j / s_i) \quad , \quad \sum_{j=1}^{N} a_{ij} = 1 \tag{8}$$

$$\pi = \pi_i = P(s_i) \quad , \quad \sum_{j=1}^{N} \pi_i = 1 \tag{9}$$

$$B = b_j(k) = P(o_t = v_k / q_t = s_i) \tag{10}$$

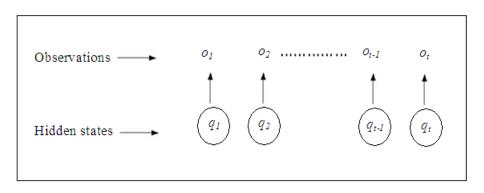$$\sum_{k=1}^{M} b_j(k) = 1 \tag{11}$$

Figure 6. Example of Hidden Markov Model

The hidden Markov model with a continuous observation is defined by $\lambda = (A, B, \sigma i, \mu i)$ where μi and σi are respectively the mean and the standard deviation of the state i of the Gaussian function that used for to generate the probability of observation:

$$b_j(k) = \Pr ob(o_t = v_k / o_t = s_j) = \frac{1}{\sigma_i \sqrt{2\pi}} \; e^{\frac{(o_t - \mu_i)^2}{2\sigma_i^2}} \tag{12}$$

In the context of the learning - classification phase, it carried as follow:

In the learning phase, each numeral image that is converted to a vector in the features extraction phase is used as an observation vector of an initial own HMM of this numeral in order to determine the probability that generated this observation. Then this model is trained for maximizing this probability by using the Baum-Welch algorithm. All these trained models (optimal models) of all numerals are saved for to form a learning base. In the classification phase, an unknown numeral (test numeral) is presented as a vector of observation. Then the probability generated by this observation is calculated by all the optimal models by the forward algorithm. The recognition will be given to the numeral with highest probability.

5.2 Hybrid System MLP+HMM

This hybridization consists to consider each output vector associated to a certain numeral which is produced by the MLP as a vector of observation of a HMM $\lambda_j = (A_j, B_j, \sigma_{i,j}, \mu_{i,j})$ for $j = \{I, II \dots X\}$ that is must be trained by Baum-Welch algorithm for getting an optimal model λ_j^* and a maximum probability(likelihood) $P_j^* = P(O_j / \lambda_j^*)$ generating this observation, then all these optimal parameters (λ_j^*, P_j^*) will be stocked for forming a learning database which contains also the optimal weight matrixes W^* and Z^* of MLP, afterwards concerning the classification phase an unknown handwritten Roman numeral X_{test} is presented then the value of $f(X_{test}W^*) = h_i$ and the value of $f(h_i Z^*) = o_t$ is determined, then the distance $d(P_j^*, P_t) = P_j^* - P_t$ is calculated for each $j = \{I, II \dots X\}$ where $P_t = P(O_t / \lambda_j^*)$ is obtained by Forward algorithm) is calculated.

The evaluation of recognition is ultimately prrsented by :

$$Calss(X_{test}) = \arg_{j=I, II \dots X} (\min(d(P_j^* - P_t))) \tag{13}$$

6. Experiments and Results

Firstly, we present an example of some isolated handwritten Roman numerals.

Figure 7. Example of Some Isolated Handwritten Roman Numerals

The desired aim is to compare between the performances in terms of recognition rate (precision) and recognition time (rapidity) of:
Four hybrid methods of features extraction that are:

- Zoning + Radon (Z+R).
- Zoning + Hough (Z+H).
- Zoning + Gabor (Z+G).
- Zoning + Radon + Hough + Gabor (R+H+G+Z).

In one hand and between the performances of three classifiers which are:

- Multi-Layer Perceptron (MLP).
- Hidden Markov Model (HMM).
- Multi-Layer Perceptron + Hidden Markov Model (MLP+HMM).

On the other hand.
Therefore in order to achieve these comparisons, we have used the following data's:

- Each numeral image has a size equal to 45x45 pixels.
- The number of all images of learning and of test that we have used is equal to 3000 images.
- The number of zones whose each image numeral is divided is equal to 9 zones.

Therefore each numeral image is finally converted to a vector by the following relationship:

$$X = X_{zoning} \bigcup X_{Radon-Hough-Gabor} \qquad (14)$$

Therefore, we grouped the values that we obtained of the recognition rate τ_n of each numeral (given in %) and of the global rate τ_g (given in %) also the global recognition time t_g (given in second), *i.e.,* of all numerals for each hybrid method of features extraction and each classifier in the following Table :

Table 1. The Recognition Rate of Each Numeral and Global Recognition Rate and Global Time of Execution for Each Features Extraction Method and for Each Classifiers

N	τ_n (MLP)				τ_n (HMM)				τ_n (MLP+HMM)			
	Z+R	Z+H	Z+G	Z+R+H+G	Z+H	Z+G	Z+R	Z+R+H+G	Z+G	Z+R	Z+H	Z+R+H+G

I	83.55	82.78	85.64	94.05	81.65	80.55	83.15	93.05	88.15	87.10	90.18	98.95
II	81.34	80.12	83.54	92.34	81.90	80.65	82.10	92.05	86.18	85.25	87.12	98.08
III	82.67	81.85	83.60	93.15	81.45	80.35	82.23	92.30	87.34	86.30	88.15	98.85
IV	82.78	80.14	83.48	92.97	80.48	80.45	81.60	92.18	85.67	84.18	87.62	98.34
V	83.12	81.76	84.55	93.58	81.13	80.76	83.45	92.95	86.85	85.34	87.50	98.05
VI	81.58	80.67	82.37	92.85	80.53	80.55	82.30	92.05	86.55	85.15	87.25	98.15
VII	84.78	83.45	85.34	94.88	82.34	81.43	83.34	93.34	88.87	86.17	89.67	99.30
VIII	85.85	83.75	86.52	96.67	83.67	81.88	84.42	94.85	89.10	87.34	90.40	99.67
IX	84.45	82.65	85.78	96.34	82.44	81.56	83.45	94.75	89.34	86.25	89.75	99.34
X	83.40	81.15	84.70	95.95	81.76	80.25	82.10	94.87	88.34	85.20	89.85	99.15
τ_g	83.35	81.83	84.55	94.28	81.73	80.84	82.81	93.24	87.64	85.82	88.75	98.80
t_g	68.62	73.40	80.25	97.51	41.83	43.14	48.42	68.17	110.64	114.87	119.74	145.61

The associated graphical representation to recognition rate τ_n is:
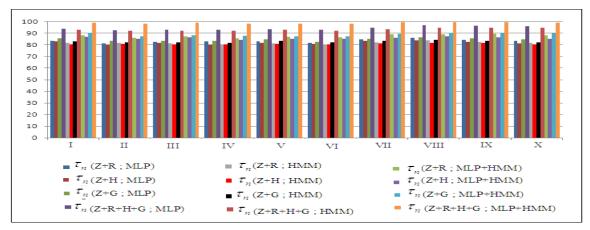

Figure 8. The Recognition Rate of Each Numeral for Each Features Extraction Method and for Each Classifier

◈ *Analysis and comments:*

Considering all the results that we have obtained, we can to conclure that :
- The numerals the most correctly recognized are : *I, II,VIII, IX*.
- The numerals the less correctly recognized are : *IV, X*.
- The most precise hybrid method of features extraction is zoning combined in the same time with Radon, Hough transforms and Gabor filter followed by zoning combined with Gabor filter then zoning combined with Radon transform then zoning combined with Hough transform.
- The most precise classifier is the hybrid system multi-layer perceptron combined with hidden Markov model followed by multi-layer perceptron then hidden Markov model.

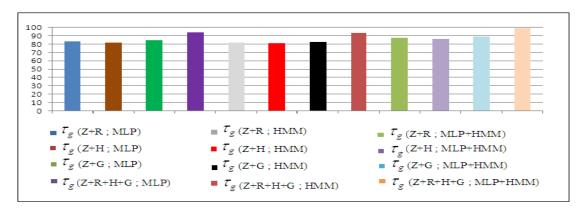The associated graphical representation to recognition rate τ_n is:

Figure 9: The Global Recognition Rate for Each Features Extraction Method and for Each Classifier

❖ *Analysis and comments:*

Taking into account all the results that we obtained, we concluded that the most precise recognition system is that which contains a zoning method combined with Radon, Hough transforms and Gabor filter as a features extraction and the multi-layer perceptron combined with hidden Markov model as a classifier. Moreover the associated graphical representation to time of execution is presented as follow:
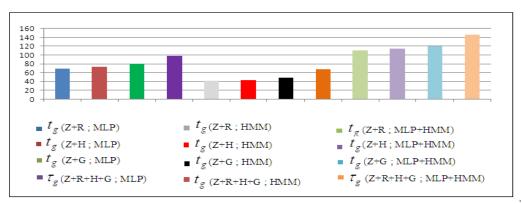

Figure 10. The Global Time of Execution for Each Features Extraction Method and Each Classifier

❖ *Analysis and comments:*

Having regard the results presented in figure 10, we concluded that the most fast hybrid method is the zoning combined with Radon transform then with Hough then with Gabor filter, finally zoning combined in the same time with all these descriptors in one side and the fastest classifier is hidden Markov model followed by multi-layer perceptron followed by multi-layer perceptron combined with hidden Markov model on the other side. For fixing this idea, we note the difference of precision between hm_1, cl_1 and hm_2, cl_2

$$\Delta P = \tau_{g, hm_1, cl_1} - \tau_{g, hm_2, cl_2}$$

(15)

- If $\Delta P > 0$ we have a gain of precision. In this case ΔP is a rate of growth of precision.

- If $\Delta P < 0$ we have a loss of precision. In this case ΔP is a rate of decay of precision.
  In a like manner, we note the difference of rapidity between hm_1, cl_1 and hm_2, cl_2

$$\Delta R = t_{g,hm_1,cl_1} - t_{g,hm_2,cl_2}$$
(16)

- If $\Delta R > 0$ we have an advancement in rapidity. In this case ΔR is a rate of decay of rapidity.

- If $\Delta R < 0$ we have a delay in rapidity. In this case ΔR is a rate of growth of rapidity.
Where hm means to hybrid method and cl to classifier. Hence, the table below presents different values of ΔP (gain of precision) and ΔR (lateness of time of execution).

Table 2. Various Values of Difference of Precision and of Rapidity

$hm_1,cl_1 ; \ hm_2,cl_2$	$\Delta P(\%)$	$\Delta R(second)$
Z + R + H + G , MLP + HMM ; Z + R , MLP+ HMM	11.16	34.97
Z + R + H + G , MLP + HMM ; Z + H , MLP+ HMM	12.98	30.74
Z + R + H + G , MLP + HMM ; Z + G , MLP+ HMM	10.05	25.87
Z + R + H + G , MLP + HMM ; Z + R + H + G, MLP	04.52	48.10
Z + R + H + G , MLP + HMM ; Z + R, MLP	15.45	76.99
Z + R + H + G , MLP + HMM ; Z + H , MLP	16.97	72.21
Z + R + H + G , MLP + HMM ; Z + G, MLP	14.25	65.36
Z + R + H + G , MLP + HMM ; Z + R + H + G, HMM	05.56	77.44
Z + R + H + G , MLP + HMM ; Z + R, HMM	17.07	103.78
Z + R + H + G , MLP + HMM ; Z + H , HMM	17.96	102.47
Z + R + H + G , MLP + HMM ; Z + G, HMM	15.99	97.19

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Therefore, the Table 2 showed that having a gain in precision means to a loss of rapidity

7. Conclusion and Perspectives

The ultimate objective of this study was to carry out both comparisons which the first one is between the performances in terms of precision and rapidity of four hybrid methods of features extraction which are the zoning combined with Radon then with Hough transforms then with Gabor filter, afterwards combined in the same time with all these descriptors. While the second comparison is achieved between three classifiers that are the multi-layer perceptron, hidden Markov model and a hybrid classifier based on a combination between them. For this purpose we have used in order to pre-process each numeral image the median filter, the thresholding, the centering and the edge detection techniques. We have concluded concerning the features extraction phase that the most precise methos is zoning combined with Radon, Hough transforms and Gabor filter but it is the most slow, while in the framework of classifiers the most precise is that realized via a combination between perceptron multi-layer and hidden Markov model but it is the less fast.

Moreover, we will hope later on to introduce more other hybrid methods of features extraction and other hybrid classifiers in order to compare between their performances.

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