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A Comparison between the Performances of Several Hybrid Methods of Features Extraction for Isolated Printed Tifinagh Characters Recognition

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Abstract

In this paper, we present two comparisons in isolated printed Tifinagh characters recognition, in fact the first comparison is between four hybrid methods exploited in features extraction which are the retinal coding combined with the Hu then with Legendre then with Zernike invariant moments, finally with these tree moments at the same time; in contrast the second comparison is performed in order to deduce what is the most powerful between both kernel functions used in the support vectors machines classifier. For this purpose we have used for pre-processing each character image the median filter, the thresholding, the normalization, the thinning, the centering and the skeletonization techniques. Furthermore, the experiments results that we have obtained demonstrates really that the most powerful hybrid method is that combines between retinal coding and all tree invariant moments concerning features extraction while the Gaussian kernel is more performant than that polynomial concerning classification.

Keywords: *Isolated printed Tifinagh characters recognition, median filter, thresholding, normalization, thinning, centering, skeletonization, retinal coding method, Hu, Legendre, Zernike invariant moments, the support vectors machines*

1. Introduction

Optical Character Recognition (OCR) is considered recently as a very dynamic field given that its applicability in many different domains such as bank cheque processing, automatic data entry and postal sorting, *etc*. Moreover, the OCR can be applied on both cases printed or handwritten. In fact recognition for handwritten case is more complex than that printed due to varying writing styles from person to another. In this work we use several efficient techniques in each of the three principal phases forming a certain system of recognition which are firstly the pre-processing then secondly the features extraction then finally learning and In this framework, several studies has been done for recognition of isolated printed Tifinagh character or numerals by using in the features extraction phase the retinal coding method or the moments 1-5] in one hand or in the learning-classification phase the support vectors machines (SVM) [16-22] on the other hand. Hence, concerning this approach, we are interested to printed Tifinagh characters recognition. Therefore, in this sense and in order to achieve this task we have pre-processed each character image by the median filter, the thresholding, the normalization, the thinning, the centering and the skeletonization techniques while we extracted the features of each character by the retinal coding method combined in first time with Hu Invariant Moment (HIM) then with Legendre Invariant Moment (LIM) in second time then with Zernike Invariant Moment (ZIM) in third time then with finally the retinal coding is combined with all these moments in fourth time, about the recognition of each unknown character we have used the support vectors machines. In fact, our targeted

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purpose is being able to compare between the precision of these four hybrid methods of features extraction in one side and between the performances of both kernel functions used in the support vectors machines classifier on the other side for to printed Tifinagh characters recognition. Anyway, this paper is organized in the following manner. First, in Section 1 the proposed recognition system is schematized, Section 2 describes techniques for image pre-processing. Section 3 introduces the retinal coding method and the Hu, Legendre and Zernike invariant moments and the hybridization between them. In Section 4, the support vectors machines classifier is presented. Section 5 shows the experimental results. Finally, the study is ended by a conclusion.

2. Recognition System

The recognition system that we have opted in this study is presented in the following Figure:

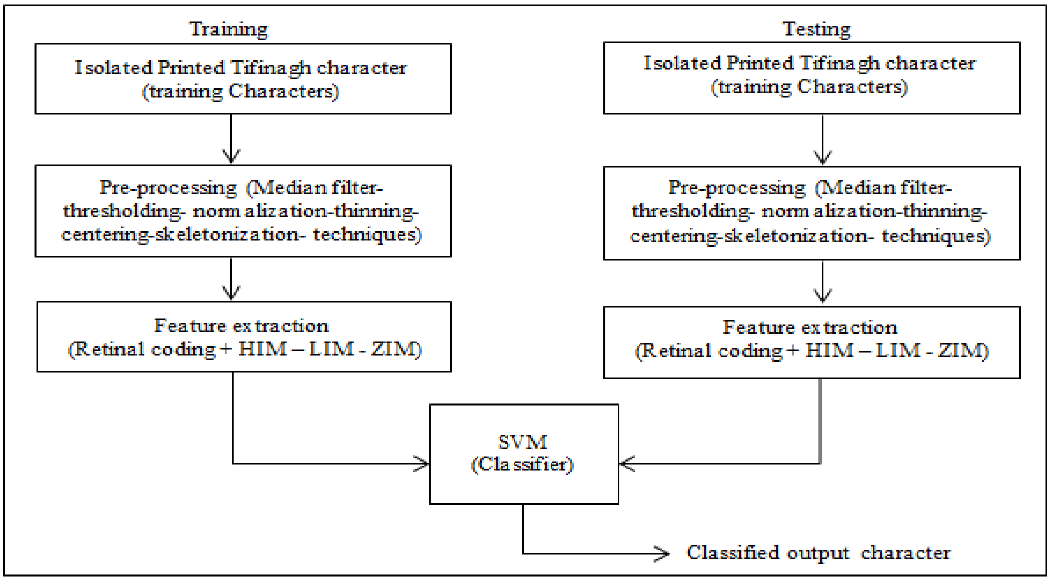


Figure 1. The Proposed System for Isolated Printed Tifinagh Characters Recognition

3. Database

The Tifinagh character is the Amazigh alphabet of North Africa. The number of Tifinagh characters by the Moroccan Royal Institute of Culture Amazigh (IRCAM) is 33 characters: (see Figure 2).

Figure 2. Tifinaghs Characters

Printed Tifinagh character	Printed Latin character	Printed Arabic character
ⴰ	A	أ
ⴱ	B	ب
ⴳ	C	ت
ⴷ	D	ث
ⴹ	E	ج
ⴻ	F	ح
ⴼ	G	خ
ⴽ	H	د
ⵀ	I	ذ
ⵃ	J	ع
ⵄ	K	غ
ⵅ	L	ف
ⵇ	M	ق
ⵉ	N	س
ⵊ	O	ش
ⵍ	P	ص
ⵎ	Q	ض
ⵏ	R	ط
ⵓ	S	ك
ⵔ	T	م
ⵕ	U	ن
ⵖ	V	ل
ⵙ	W	و
ⵚ	X	ى
ⵛ	Y	ر
ⵜ	Z	ز
ⵡ	--	ه
ⵢ	--	ظ
ⵣ	--	--
ⵥ	--	--
ⴽⵯ	--	--
ⴳⵯ	--	--
ⵇⵯ	--	--

Figure 3. Comparison between the Tifinagh, Arabic and French Characters

4. Pre-Processing

The goal of the first phase in each OCR system (pre-processing) is to remove each needless pixel including noise and redundant information in order to render in a best quality the numeral image so that it can be used in an efficient manner in the following phase which is the features extraction. Of this fact, to achieve this task, we have pre-processed in this research the images by the following techniques:

- The median filter applied for performing a filtration of image.
- The thresholding used to render each image contains only the black and white colors according a pre-selected threshold.
- The normalization of a character size to reduce the characters to be the same size.
- The thinning The thinning of a character to make the image one easier to process,
- The centering exploited for localizing the numeral justly in center of its image.
- The skeletonization performed to find the skeleton of character.

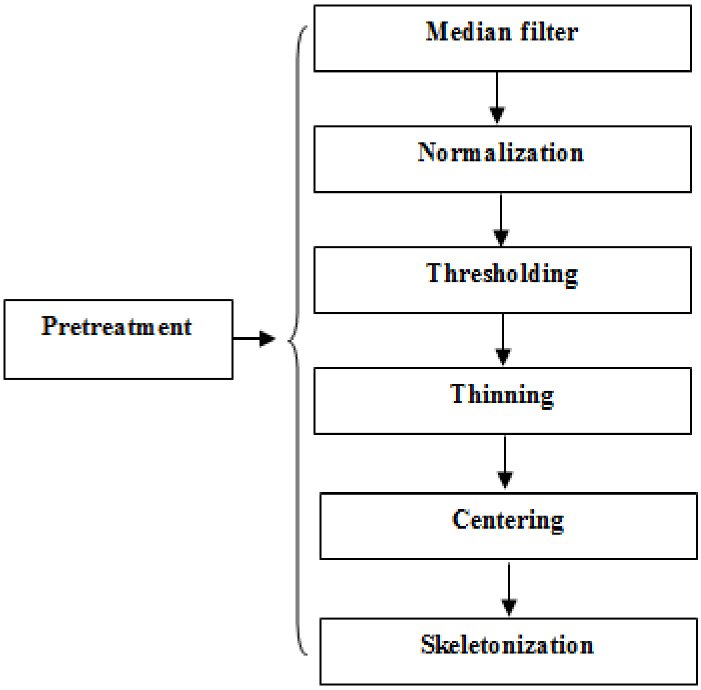


Figure 4. The Pretreatment Steps

5. Features Extraction

The very important role in each OCR system is the features extraction, especially for optical character recognition, in fact the precision of an certain system recognition depends heavily to features extraction operation in reason of if an great discrimination between characters is truly realized its recognition will be at that time very correct. More precisely, feature extraction methods can be divided into two principal categories: structural [7, 15] and statistical [1, 6] features The first category is based on local structure of numeral image while the second is interested to statistical information's localized in character image by way of example within this context there are the moments of images especially those invariants.

In this framework, we have chosen to use these hybrids methods which are:

- Retinal coding method combined with Hu invariant moment.
- Retinal coding method combined with Legendre invariant moment.
- Retinal coding method combined with Zernike invariant moment.
- Retinal coding method combined with these tree invariant moments.

5.1. Retinal Coding

The process of retinal coding that we have used is explained as follow:
Each image is a black containing a character writing in white color and has firstly an size equal to 30x30 pixels. First of all, given a virtual grid or retina having a size equal to 2N/3 x2N/3 pixels while this last of each character image is equal to NxN pixels, therefore in order to applied this method as it should the image must be resized to2Nx2N pixels, afterwards the retina is placed on the first zone of image the on second zone and so on until the ninth zone while at starting from the top located to the left of the image in each putting in zone of the retina the number of white pixels is calculated which will allow thereafter ultimately to convert the image to a vector having nine components.

Moreover, in order to well fix the ideas the schema below illustrates this mechanism (we take N=12):

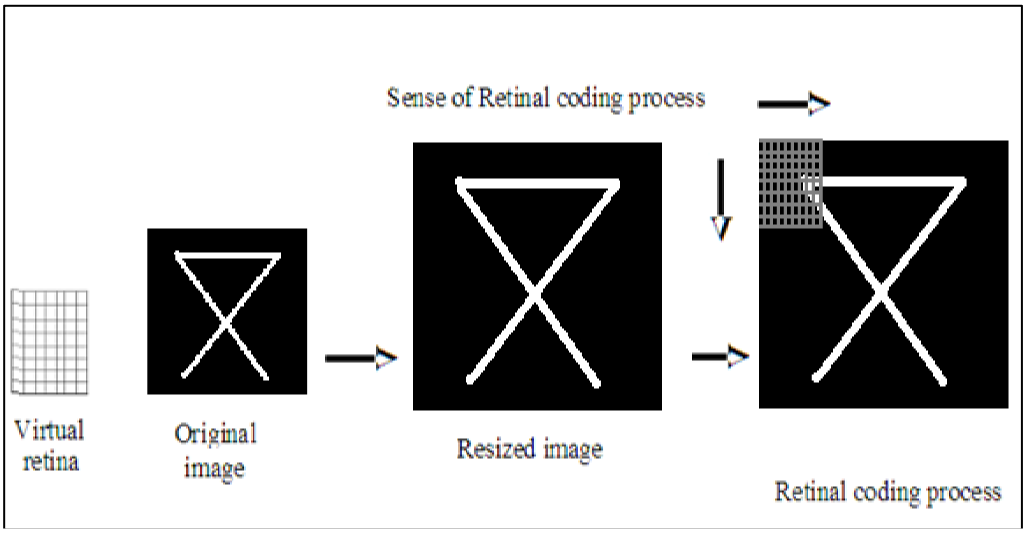


Figure 5. The Process of Retinal Coding Method

5.2. Moments of Images

In the past decades, various moment functions are much successfully exploited in pattern recognition field due to their abilities to extract the features of images in an efficient manner. In this sense we have used tree powerful invariant moments.

5.2.1. Hu invariant moments

The geometric moment of order (*n*+ *m*) of an image function f(x,y) having a size NxM pixels is given by:

$$M_{nm} = \sum_{x=0}^{N-1}\sum_{y=0}^{M-1} x^n y^m f(x,y) \quad (1)$$

These moments are not invariant to geometric transformations: translation, rotation and scaling. For to make it invariant to translation, the central moment of order (*n*+ *m*) is given by:

$$\mu_{nm} = \sum_{x=0}^{N-1}\sum_{y=0}^{M-1} (x-\bar{x})^n (y-\bar{y})^m f(x,y) \quad (2)$$

$(\bar{x},\bar{y})$ are the coordinates of the center of gravity of the image calculated by:

$$\bar{x} = \frac{M_{10}}{M_{00}} \text{and} \bar{y} = \frac{M_{01}}{M_{00}} \quad (3)$$

The centered normalized moment of order **(*n*+ *m*)** which is invariant to translation and scaling is defined by :

$$\eta_{nm} = \frac{\mu_{nm}}{m_{00}^{\gamma}}, \gamma = \frac{n+m}{2}+1, (n+m) \geq 2 \quad (4)$$

Hu was established seven moments following which are invariant to translation, rotation and scaling:

$$\varphi_1 = \eta_{20} + \eta_{02} \quad (5)$$

$$\varphi_2 = (\eta_{20} + \eta_{02})^2 + 4\eta_{11}^2 \quad (6)$$

$$\varphi_3 = (\eta_{30} - 3\eta_{12})^2 + (3\eta_{21} - \eta_{02})^2 \quad (7)$$

$$\varphi_4 = (\eta_{30} - \eta_{12})^2 + (\eta_{21} - \eta_{03})^2 \quad (8)$$

$$\varphi_5 = (3\eta_{30} - \eta_{21})(\eta_{30} + \eta_{12})[(\eta_{30} + \eta_{12})^2 - 3(\eta_{21} + \eta_{03})^2] + (3\eta_{21} - \eta_{03})(\eta_{21} + \eta_{03})[3(\eta_{30} + \eta_{12})^2 - (\eta_{21} + \eta_{03})^2] \quad (9)$$

$$\varphi_6 = (\eta_{20} - \eta_{21})[(\eta_{30} + \eta_{12})^2 - (\eta_{21} + \eta_{03})^2] + 4\eta_{11}(\eta_{30} + \eta_{12})(\eta_{21} + \eta_{03}) \quad (10)$$

$$\Phi_7 = (3\eta_{21} - \eta_{03})(\eta_{30} + \eta_{12})[(\eta_{30} + \eta_{12})^2 - 3(\eta_{21} + \eta_{03})^2] - (\eta_{30} - 3\eta_{12})(\eta_{21} + \eta_{03})[3(\eta_{30} + \eta_{12})^2 - (\eta_{21} + \eta_{03})^2] \quad (11)$$

5.2.2. Legendre Invariant Moments

The standard set of the geometric invariant moments that's independent to rotation, scaling and translation is:

$$V_{nm}=M_{00}^{-y}\sum_{x-1}^{N-1}\sum_{y=0}^{M-1}[(x-\bar{x})\cos\theta+(y-\bar{y})\sin\theta]^{n}[(y-\bar{y})\cos\theta\,(x-\bar{x})\sin\theta]^{m}\,f(x,y) \quad (12)$$

Where:

$$\bar{x}=\frac{M_{10}}{M_{00}} \text{ and } \bar{y}=\frac{M_{01}}{M_{00}},\ \gamma=\frac{n+m}{2}+1,\ \ \theta=\frac{1}{2}\text{arctang}\frac{2\mu_{11}}{\mu_{20}-\mu_{01}} \quad (13)$$

And $\mu_{nm}$is the central moment.

The Legendre moment of order (n+m) of an image f(x,y) can be expressed in terms of geometric moments as shown in equation (13) . The purpose of V_{nm} (given in equation 12) is to provide the Legendre invariant moment against translation, scaling and rotation by replacement M_{nm} by V_{nm}

$$L_{nm}=\frac{(2n+1)(2m+1)}{4}\sum_{i=1}^{n}\sum_{j=1}^{m}a_{n_i}\,a_{m_j}M_{ij} \quad (14)$$

$a_{p_i}$is the Legendre polynomial defined by:

$$a_{p_i}=\ P_n(x)=\sum_{i=1}^{n}(-1)^{\frac{n-1}{2}}\frac{1}{2^n}\frac{(n+i)!x^i}{\left(\frac{n-i}{2}\right)!\left(\frac{n+i}{2}\right)!i!} \quad (15)$$

If n – m is even and $|x|\leq 1$

5.2.3Zernike Invariant Moments

For an image f(x,y) the Zernike moment of order n and repetition m is given by:

$$A_{nm}=\frac{n+1}{\pi}\sum_{x=0}^{N-1}\sum_{y=0}^{M-1}f(x,y)\,V^{*}(x,y) \quad (16)$$

$$V^{*}(x,y)=R_{nm}(x,y)e^{jmarctan(\frac{y}{x})} \quad (17)$$

$$R_{nm}(x,y)=\sum_{s=0}^{(n-|m|)/2}\frac{(-1)^s(x^2+y^2)^{\frac{n}{2}-s}(n-s)!}{s!\left(\frac{n+|s|}{2}-s\right)!\left(\frac{n-|s|}{2}-s\right)!} \quad (18)$$

$$\text{if}: n-|m|\ \textit{is even}\ n\geq|m|, \qquad n\geq 0 \quad j=\sqrt{-1}$$

And x2 + y2 ≤ 1 the symbol * denotes the complex conjugate operator.

The Zernike moment is invariant under rotation but sensitive to translation and scale. So normalization must be done of these moments.

$$f(x,y)=f(x+\frac{x}{a},\bar{y}+\frac{y}{a}) \quad (19)$$

Where $(\bar{x},\bar{y})$is the center of pattern function f (x, y) and $\alpha=(\beta/M_{00})^{1/2}$ and βis a predetermined value for the number of object points in pattern.

6. Recognition

An SVM [20-27] is considered as a statistical and supervised method it is basically defined for two-class problem separation, and it finds an optimal hyperplane which can maximize the margin between the nearest examples of both classes, named support vectors (SVs).

First of all, given a training database of M data: X_i , i=1,2…..M

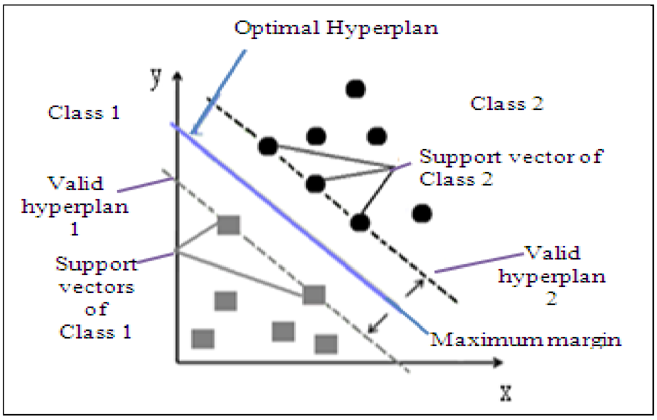


Figure 6. The Determination of Optimal Hyperplane, Vectors Supports, Maximum Marge and Valid Hyperplanes

The linear SVM classifier is then defined as:

$$f(X, w, b) : x \longrightarrow y$$
$$f(X) = wX+b \qquad (20)$$

Where w and b are the parameters of the classifier y is the label.

The linear SVM can be extended to a non-linear classifier by replacing the inner product between the input vectors x and the SVs, through a kernel function K defined as:

Table 1. Examples of Different Kernel Functions used in SVM

Kernel linear	xy
Kernel polynomial of degree n	$(axy + b)^n$
Gaussian radial basis function (GRBF) of a standard deviationσ :	$e^{-\frac{\|x-y\|^2}{2\sigma^2}}$

The method described above is designed for a problem of two classes only, many studies treat a generalization of the SVM to a multi-classification [26, 27] among these studies we cite the two strategies frequently used: the first approach is based to use N decision functions (one against all) allowing to make a discrimination of a class contains a one vector labeled by the value 1 against all other vectors existed in a other class opposite having a label equal to -1. Therefore the decision rule used in this case is usually the maximum such that we will assign an unknown vector X into a class associated with an output of SVM is the largest.

$$\text{Classe (X)} = \arg\max_{i=1,2,\dots,n} f_i(x) \qquad (21)$$

7. Experiments and Results

First of all, we present an example of some isolated printed Tifinagh characters that we have used in our study:

Figure 7. Example of Some Isolated Printed Tifinagh Characters

We have chosen the following data:

- Each original character image has a size equal to 30x30 pixels.
- The size of the virtual retina equal to 20x20 pixels.
- Each original character image is resized to 60x60 pixels.
- Each character is transformed to a vector of 16 components whose 9 of them obtained by the Retinal Coding (RC) and 7 obtained by an invariant moment Hu(H) or Legendre(L) or Zernike(Z).
- The standard deviation of the GRBF kernel function is equal to 0.1.
- The degree of the Polynomial (POL) kernel function is equal to 10 and their parameters a=b=1.
- We realized a variation on the size of the grid to find the best performing.

Now, we group the values of the recognition rate τ_g (given in %) for each character and also those of the global rate recognition, *i.e.*, of all characters (given in %) which we have obtained in the following Table:

Table 2. The Obtained Recognition Rates τ_n and τ_g by Each hybrid Method and Each Kernel Function

Characters	τ_n(RC+H)		τ_n(RC+L)		τ_n(RC+Z)		τ_n(RC+H+L+Z)	
	POL	GRBF	POL	GRBF	POL	GRBF	POL	GRBF
[illegible]	67,57	68,34	70,00	77,32	78,43	81,00	83,49	91,21
[illegible]	86,40	82,21	85,13	86,21	91,20	92,11	91,80	92,00
[illegible]	42,74	49,28	50,00	55,12	57,70	55,15	58,34	86,14
[illegible]	28,48	36,41	40,09	45,43	51,32	52,46	56,61	59,65
[illegible]	84,00	85,01	85,21	86,35	73,45	87,21	86,78	86,92
[illegible]	95,85	92,05	93,25	94,03	93,83	96,00	95,68	95,97
[illegible]	42,97	47,38	50,18	52,81	59,55	64,33	65,00	70,00
[illegible]	87,93	88,73	89,66	92,5I	82,24	89,81	85,56	86,43
[illegible]	41,71	51,61	54,46	55,49	45,31	52,00	55,60	65,16
[illegible]	79,40	80,10	81,31	86,32	85,11	91,10	88,96	89,61
[illegible]	91,43	91,54	93,00	94,85	93,19	93,21	92,73	93,00
[illegible]	64,84	65,00	66,11	66,36	70,44	79,00	82,41	87,24
[illegible]	72,69	77,42	78,67	82,18	84,92	80,00	81,00	84,57
[illegible]	79,29	81,93	83,37	81,65	86,71	87,42	88,44	89,61
[illegible]	66,04	76,14	77,45	76,12	74,15	75,11	77,33	80,00

ⵛ	88,79	90,87	91,79	90,23	88,26	88,55	89,18	93,00
ⵀ	42,30	47,80	48,55	48,48	55,83	59,60	57,54	60,47
ⵅ	79,53	84,35	85,53	85,45	85,74	81,30	84,53	88,86
И	77,59	78,18	79,82	80,62	79,82	83,62	84,20	90,00
ⵇ	57,40	60,50	62,54	68,20	69,30	62,17	65,00	69,00
ⵖ	92,46	93,56	94,66	94,43	95,37	90,85	91,67	92,45
ⴹ	41,21	46,31	47,21	48,33	58,53	66,00	68,33	76,74
ⵏ	74,24	78,54	79,85	83,33	93,13	91,67	92,72	93,21
ⴳ	95,68	94,00	96,12	96,67	80,42	86,67	90,67	89,64
ⵙ	67,52	61,58	64,35	69,77	78,39	80,33	81,00	85,00
ⵥ	87,51	89,11	89,91	90,22	91,61	85,69	88,31	87,65
ⵡ	72,81	74,61	75,08	76,67	72,67	80,00	81,21	83,78
ⵉ	74,20	73,50	74,35	77,67	80,38	81,57	85,16	87,00
ⵔ	91,59	92,19	94,33	93,33	94,67	92,67	93,86	93,00
ⵕ	59,22	61,32	62,42	66,67	65,27	67,45	70,00	69,43
τ_g	**71,11**	**73,32**	**74,81**	**76,22**	**77,23**	**79,14**	**80,44**	**83,89**

The graphical representation to recognition rate of each character τ_n is:

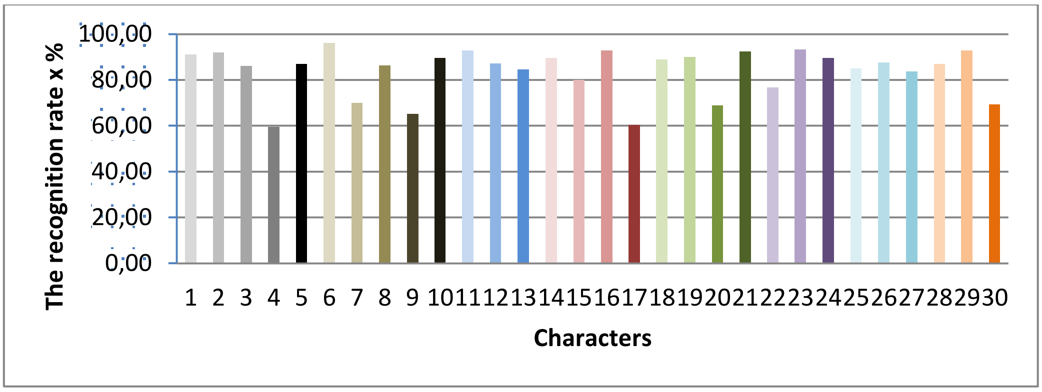


Figure 8. The Graphical Representation of Recognition Rate τ_n of Hybrid Method (RC+H+L+Z) WITH the GRBF Kernel Function

The graphical representation to recognition rate of all characters τ_g is presented in the following Figure:

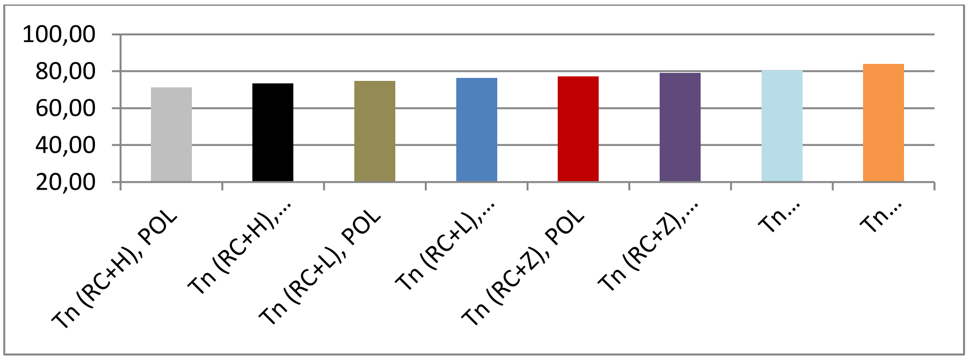
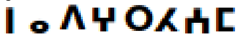


Figure 9. The Graphical Representation of Global Rate Recognition τ_g of Each Hybrid Method and of Each Kernel Function

◈ *Analysis and Comment:*

Taking into account all the results that we obtained, we really can to conclure that:

- The characters the most correctly recognized are : 
- The characters the less correctly recognized are : 

And the most performant hybrid method is the retinal coding combined with all tree moments followed by retinal coding with Zernike moment then retinal coding with Legendre moment then finally retinal coding with Hu moment in one side and the GRBF kernel function is more powerful than the polynomial kernel function on the other side.

8. Conclusion

In this paper, we have presented a comparison between the performances of several genres of hybrid methods which are the structural method retinal coding combined with tree statistical methods which are Hu, then with Legendre, then with Zernike invariant moments, finally combined with all these moments for recognition of isolated printed Tifinagh characters.

In this sense we have verified that the recognition systems used in this approach which contains in the preprocessing phase the median filter , the thresholding, the normalization, the thinning, the centering and the skeletonization and the support vectors machine in the recognition phase really shows that the most powerful recognition system is that contains the hybrid method combined coding with all these tree invariant moments in features extraction phase and the GRBF kernel function used in support vectors machine in the recognition phase.

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