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Isolated Handwritten Roman Numerals Recognition Using The Zoning Methods

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Abstract

In this paper, we present two comparisons in isolated handwritten Roman numerals recognition, in fact the first comparison is between zoning methods exploited in features extraction which are the square zones or the triangular zones used in extraction characteristic; in contrast the second comparison is performed in order to deduce what is the most powerful between the type of writing used with a pen or marker. For this purpose we have used for pre-processing each numeral 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 method is that the zoning with 9 square then with 8 triangular. This work has achieved approximately 85% of success rate for Roman numerals database identification.

Keywords: Isolated Handwritten Roman Numerals Recognition, median filter, thresholding, normalization, thinning, centering, skeletonization, zoning method, the support vectors machines.

I. Introduction

The optical character recognition (OCR) is considered as a one of the most successful and powerful applications in the automatic pattern recognition. It's really a very dynamic field of research and development. Several studies have been carried on Latins, Arabic numerals and characters by using the support vectors machines (Jindal et al,2012)(Mota et al,2009)(Sinha et al,2013)(Vapnik,1995)(Adankon et al, 2009).

Moreover, in this work our study is focused in isolated handwritten Roman numerals recognition, we use several efficient techniques in each of the three principal phases forming the system of recognition which are firstly the pre-processing then secondly the features extraction then finally learning-classification. In this framework, our study has been done for recognition of isolated handwritten Roman numerals by using in the features extraction phase the zoning method (Hennig et al,2002)(kessab et al,2014)(kessab et al,2015)(John et al,2012)(Impedovo et al,2014) on the other hand ,in one hand or in the learning-classification phase the support vectors machines (SVM). Hence, concerning this approach, we are interested to isolated handwritten Roman numerals recognition. Therefore, in this sense and in order to achieve this task we have pre-processed each numeral image by the median filter, the thresholding, the normalization, the thinning, the centering and the skeletonization techniques while we extracted the features of each numeral by the zoning method with square or triangular zones, about the recognition of each unknown numeral we have used the support vectors machines. In fact, our targeted purpose is being able to compare between the precision of variation in the size square zones or triangular zones methods of features extraction in one side and between the performances of both type used in writing (pen or marker); in classification we use the support vectors machines on the other side for to isolated handwritten Roman numerals 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 zoning method. In Section 4, the support vectors machines classifier is presented. Section 5 shows the experimental results. Finally, the study is ended by a conclusion.

II. Recognition system

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

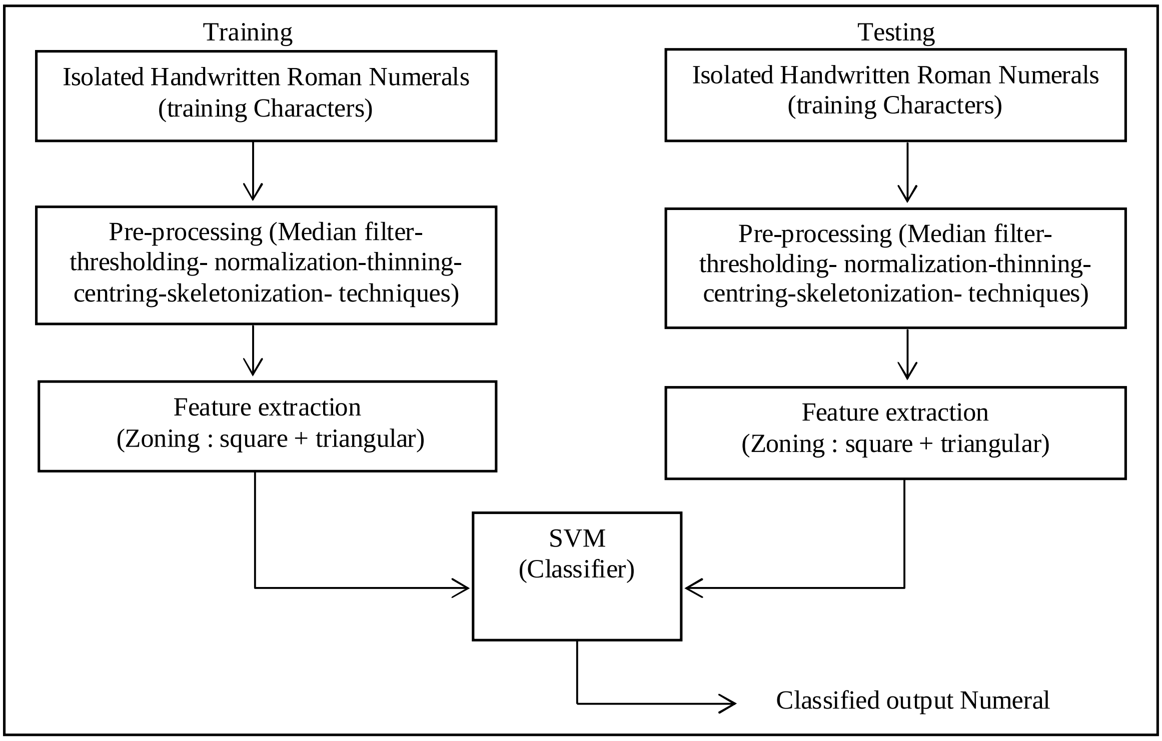

Figure. 1. The proposed system for Isolated Handwritten Roman Numerals.

III. Database

The Roman numerals is the numeric system used in ancient Rome, employs combinations of letters from the Latin alphabet to signify values. The numbers **I** to **X** can be expressed in Roman numerals as follows:

Figure. 2. The Roman numerals

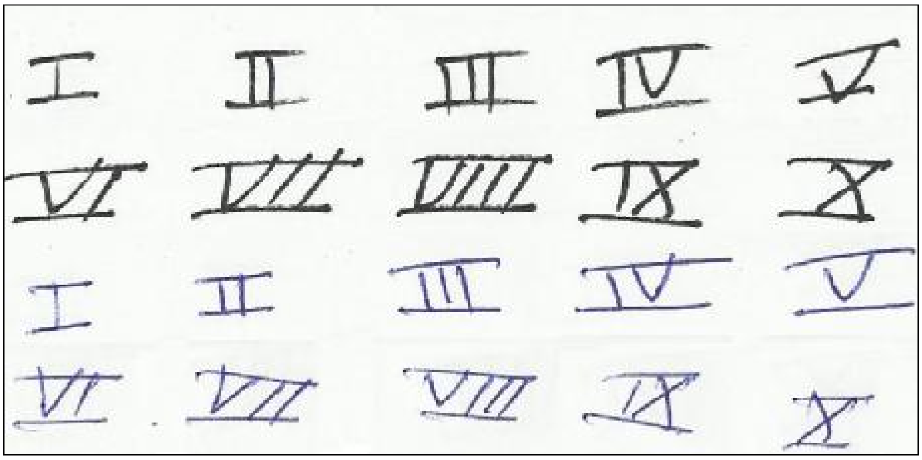

Figure. 3. Example of Roman numerals with marker and pen

IV. PRE-PROCESSING

The first goal of the pre-processing phase 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:

Pretreatment →

Median filter: applied for performing a filtration of image

↓

Normalization: reduce the numerals to be the same size

↓

Thresholding: render each image contains only the black and white

↓

Thinning: make the image of a numerals one easier to process

↓

Centering: exploited for localizing the numeral justly in center of its image

↓

Skeletonization: performed to find the skeleton of numeral

Figure. 3. The pretreatment steps

V. FEATURES EXTRACTION

The role of the features extraction in each OCR system is the great discrimination between characters is truly realized its recognition will be at that time very correct.

In this framework, we have chosen to use the zoning methods which are:
- The zoning method with square zones which are the square number are 4, 6 and 9.
- The zoning method with triangular zones which are the triangular number are 4, 6 and 8.

A. The zoning method

Firstly, given a black image that contains an numeral written in white, the zoning method consists to divide this image to a several zones then calculating in each 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 vector has a number of vector has a number of components equal to that of zones. The vector has a number of components equal to that of zones. In this work we use two types of zones: squares zones and triangular zones.

A.1. SQUARE ZONING

The process of square zoning that we have used is explained as follow:
The zoning technique in the square form is based on the division of image on squares of equal size which are 4 squares, 6 squares and 9 squares (see Figure 4).

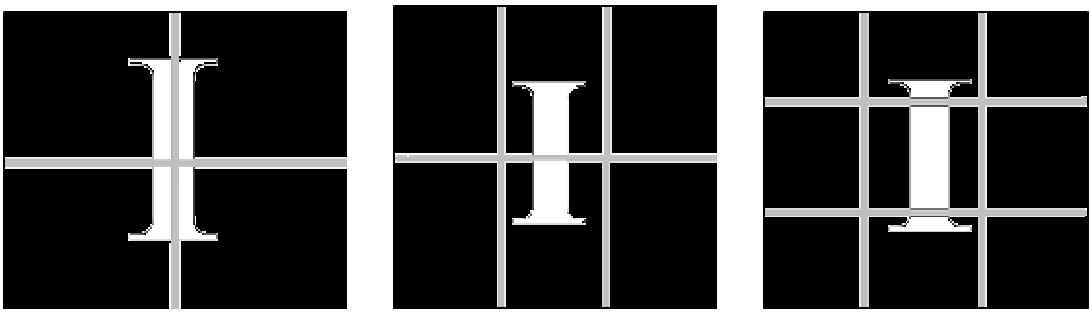

Figure. 4. The process of retinal coding method

A.2. TRIANGULAR ZONING

The process of triangular zoning that we have used is explained as follow:
The zoning technique in the triangular form is based on the division of image on triangles of equal size which are 4 triangles, 6 triangles and 8 triangles (see Figure 5).

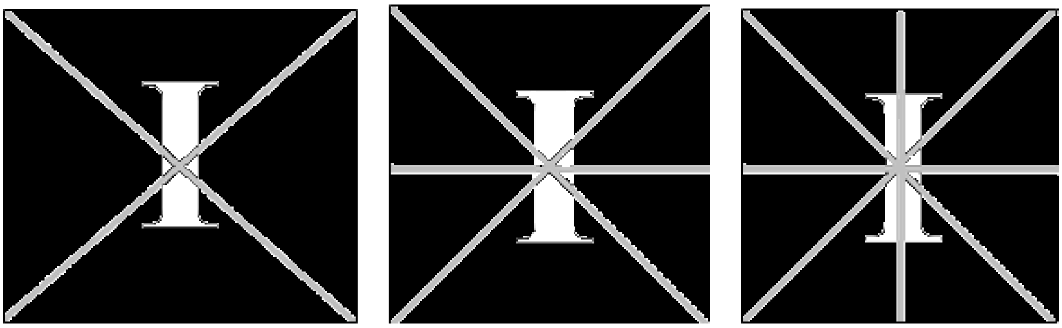

Figure. 5. The process of retinal coding method

VI. RECOGNITION

An SVM(Adankon et al, 2009) (Camastra, 2007) (Drucker et al,1999)(Niu et al, 2012)(LeCun, 1998)(Sinha et al, 2013) is considered as an 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

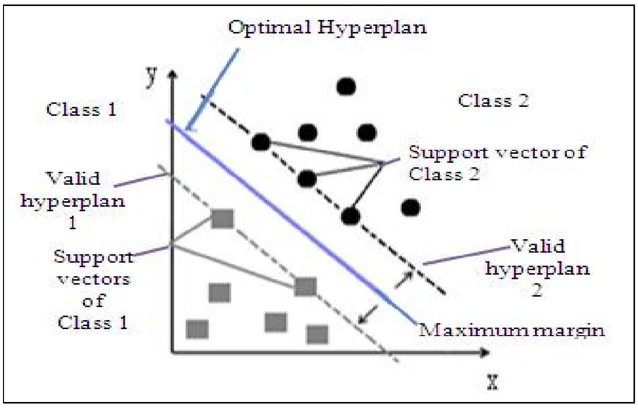

Figure. 6. The determination of optimal hyperplane, vectors supports, maximum Marge and valid hyperplanes.

The linear SVM classifier is then defined as:

$$f(X, w, b) : x \longrightarrow y$$
$$f(X) = wX+b \qquad (1)$$

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 I
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 deviation σ :	$e^{-\frac{\|x-y\|^2}{2\sigma^2}}$

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 (Mota et al, 2009)(Hou et al, 2014) 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.

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

VII. EXPERIMENTS AND RESULTS

In this work we want to compare between the performances of different extraction methods that are. We have chosen the following data:

- Each original numeral image has a size equal to 30x30 pixels.
- The number of the square zones equal to 4, 6 and 9 zones.
- The number of the triangles zones equal to 4, 6 and 8 zones.
- Each numeral is transformed to a vector of 4, 6 and 9 components for square zoning and to a vector of 4, 6 and 8 components of triangular zoning.
- 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 zones to find the best performing.

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

TABLE II
THE OBTAINED RECOGNITION RATE τ_G BY EACH METHOD WITH PEN.

Numerals	**SQUARE ZONING**			**TRIANGULAR ZONING**		
	4	**6**	**9**	**4**	**6**	**8**
I	67,57	68,34	78,00	65,32	71,43	81,00
II	66,40	82,21	85,13	64,21	81,20	82,11
III	62,74	69,28	74,00	65,12	67,70	75,15
IV	58,48	66,41	70,09	55,43	61,32	62,46
V	84,00	85,01	85,21	76,35	73,45	77,21
VI	75,85	82,05	93,25	84,03	85,83	86,00
VII	62,97	67,38	73,18	61,81	62,55	64,33
VIII	87,93	88,73	89,66	82,5I	82,24	89,81
IX	71,71	71,61	74,46	68,49	70,31	72,00
X	79,40	80,10	81,31	76,32	80,11	81,10
τ_g	**71,71**	**76,11**	**80,43**	**68,56**	**73,61**	**77,12**

The graphical representation to recognition rate of each numeral τ_g is :

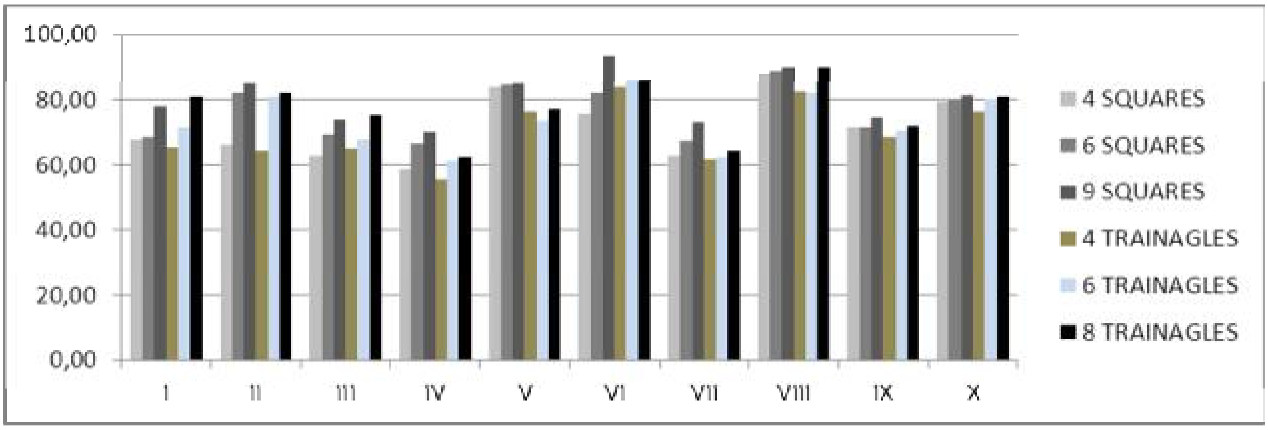

Figure. 7. The graphical representation of recognition rate τ_g of zoning method with Pen

The graphical representation to recognition rate of all numerals τ_g is presented in the following figure:

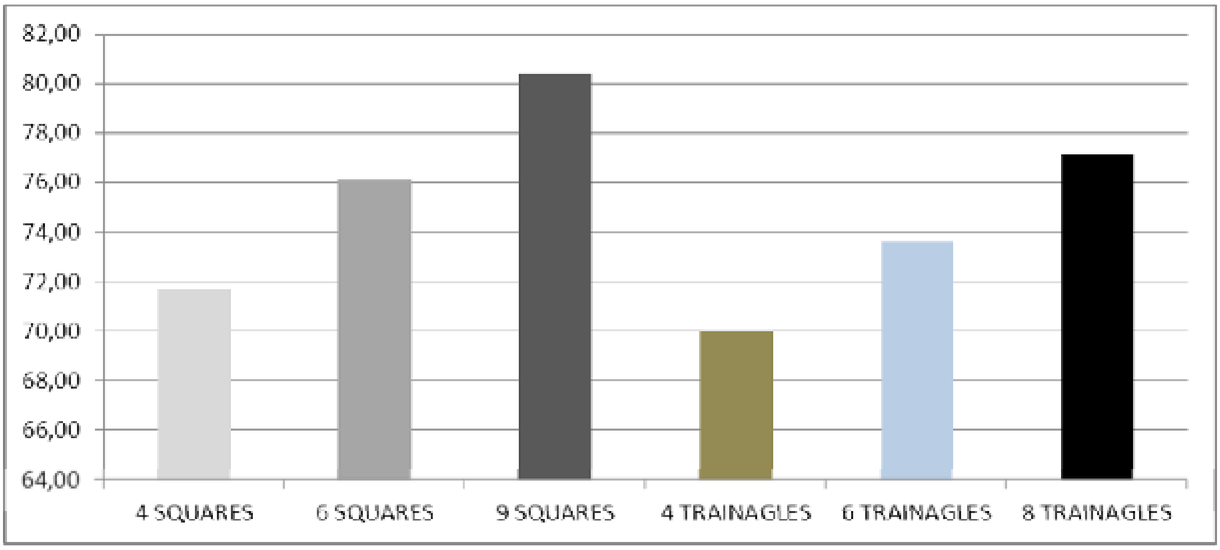

Figure. 8. The graphical representation of global rate recognition τ_g of zoning method

TABLE III
THE OBTAINED RECOGNITION RATE τ_G BY EACH METHOD WITH MARKER.

Numerals	ZONING CARRE			ZONING TRIANGULAIRE		
	4	6	9	4	6	8
I	80,00	90,00	91,10	66,00	88,00	83,49
II	88,00	91,00	93,14	70,00	89,00	90,80
III	83,00	85,00	91,67	62,00	81,67	88,34
IV	76,67	80,00	84,61	74,00	76,67	78,61
V	89,00	90,11	92,33	82,00	85,33	86,78
VI	59,00	61,67	65,00	50,00	55,00	61,68
VII	66,67	68,27	77,39	60,30	68,71	75,21
VIII	71,67	80,00	85,00	70,45	75,00	87,56
IX	53,00	59,16	70,68	55,00	56,67	75,60
X	66,67	73,44	75,34	64,00	70,00	78,96

τ_g	73,37	77,87	82,63	65,38	74,61	80,70

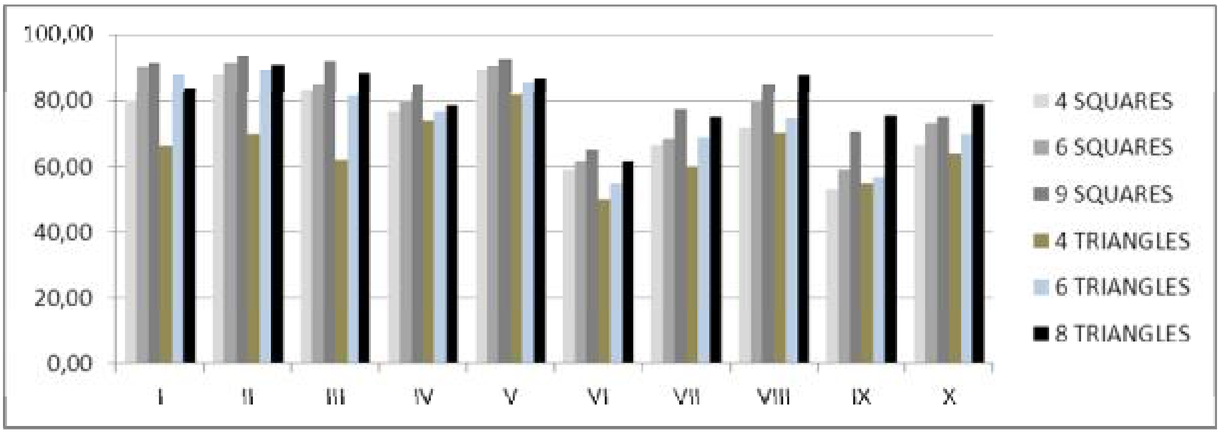

Figure. 9. The graphical representation of recognition rate τ_g of zoning method with Marker

The graphical representation to recognition rate of all numerals $\boldsymbol{\tau_g}$ is presented in the following figure :

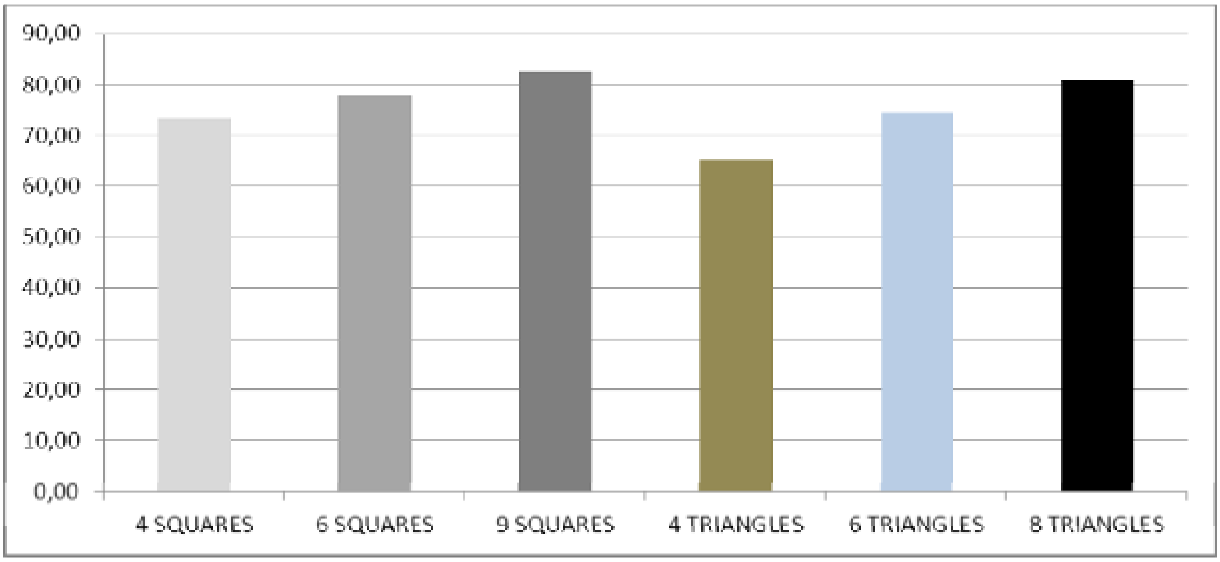

Figure. 10. The graphical representation of global rate recognition τ_g of zoning method

A. Analysis and comment:

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

- The most performant method is the square zoning with 9 zones then the triangular zoning with 8 zones.

- The recognition rates obtained by the data base written with a marker are more than those written with a pen.

VIII. CONCLUSION

In this paper, we have presented a comparison between the performances of two genres of zoning methods which are the square zoning and the triangular zoning for the recognition of isolated handwritten Roman numerals.
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 square zoning method with 9 zones and triangular zoning with 8 zones.

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