International Journal of Signal Processing, Image Processing and Pattern Recognition
Vol. 8, No. 2 (2015), pp. 325-336
http://dx.doi.org/10.14257/ijsip.2015.8.2.31

A Comparative Study between the Support Vectors Machines and the K-Nearest Neighbors in the Handwritten Latin Numerals Recognition

B. El Kessab, C. Daoui, B. Bouikhalene and R. Salouan

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

Abstract

In this paper we present a comparison between two methods of learning-classification, the first is the K-Nearest Neighbors (KNN) and the second is the Support Vectors Machines (SVM), these both methods are supervised and used for the recognition of handwritten Latin numerals that are extracted from the MNIST standard database. The recognition process organized as follows: in the pre-processing of numeral images, we exploited the thresholding, the centering and the normalization techniques, in the features extraction we have used the morphology mathematical, the zoning and the zig-zag methods. The classification methods include the K-Nearest Neighbors and the Support Vectors Machines. Our experiments results proved the highest test accuracies 93.13% and 86.50% respectively with SVM and KNN classifiers. The simulation results that we obtained demonstrate the SVM is more performing than the KNN in this recognition.

Keywords: *The handwritten Latin numerals: MNIST Database, The thresholding, the centering and the normalization techniques, the zoning, the zig-zag, the mathematical morphology methods, the K-Nearest Neighbors (KNN), The Support Vectors Machines (SVM)*

1. 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 K-nearest neighbors [8-14] or the support vectors machines [1-7].

However, our study is focused in handwritten Latin numerals recognition. A succession of operations in this recognition system can be divided into three principal phases. The first is a pre-processing which serves to clean the numeral image in order to improve its quality, in our approach we have used in this phase the thresholding, the centering and the normalization techniques. The second phase is the features extraction used to extract several primitives from each image numeral, which must discriminate it in an individual manner and to convert it to a vector which will facilitate its learning and classification, we used in this phase the mathematical morphology, the zoning and the zig-zag methods that are exploited to features extraction. The third phase is the learning-classification. During this last the images of learning base should be trained with a learning process. After, the images of the test database must be classified by the KNN then by the SVM.

ISSN: 2005-4254 IJSIP

In fact, the learning - classification phase takes place as follows:

- By using the KNN:

In the learning phase, each numeral image is transformed to a vector by the zoning, the zig-zag and the mathematical morphology methods, then we will should calculate the Euclidean distance between it and the test vector therefor we chose the K - nearest neighbors from this test vector, and to count the numbers of once these nearest neighbor appears in each class. The recognition will be assigned to the class that is most represented.

- By using the SVM:

In the learning phase, we use the SVM whose the strategy is one against all in order to separate in an optimal manner each image which is included in a class labeled by 1 of the learning base to the rest of all other images that is grouped in another class that bears a label -1. This separation (maximizing the margin between both classes) is therefore creating a decision function which separates these two classes. We have ten numerals, so we obtain then ten decision functions each of them separates a pair of classes (1 and -1) among ten pairs. In the classification phase, we calculate the image of a vector that's models a test numeral by all ten decision functions, the recognition will be assigned to numeral whose its decision function that separates its class to another class that contains the rest of all others numerals that gave the biggest value among all the values calculated of all ten images of the test numeral.

This paper is organized as follows. In section 1 the proposed system is given. In Section 2 pre-processing process is presented. Features extraction phase is described in Section 3. Section 4 deals with the recognition phase. Experimental results are given in Section 5. Finally, this work is ended by a conclusion.

2. Recognition System

Our recognition system is presented as follow:

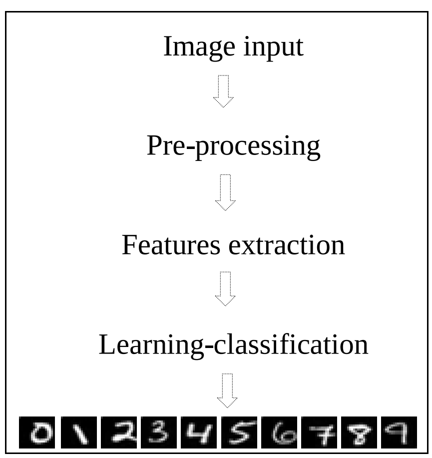

Figure 1. System Recognition for Handwritten Latin Numerals

3. Database

The MNIST database [29] of handwritten Latin numerals contains 70000 digits ranging from 0 to 9. The digits have been size-normalized and centered in a fixed-size image equal to

28x28 pixels. It is free and available on the Web. An example of the MNIST numerals is shown in Figure 2.

Figure 2. Example of Handwritten Latin Numerals MNIST Database

4. Pre-processing

The pre-processing phase is an important process in pattern recognition. It's the first part of a recognition system used to produce a cleaned up version of the original image so that it can be used efficiently in the following phase that's the feature extraction. In this work, we have pre-processed each image numeral by a median filter exploited for removing each noise from image and thresholding used in order to render each image containing only the black and white colors according a preset threshold then we used the centering technique so that the numeral can be positioned just in center of its image, finally we have used the normalization technique in order that to normalize all sizes of numeral image.

5. Features Extraction

5.1. Extraction by Zoning Method

In this phase [20- 25] many methods can be used to extract the features from images. In this recognition system, we use the zoning method that can be explained as follow:

Being given a black image containing a numeral that written in white, The zoning method consists to subdivide this image to several square or rectangular blocks or zones, then to count in each zone the number of white pixels which is finally convert the image to a vector having a number of components which equal to the that of zones (see Figure 3).

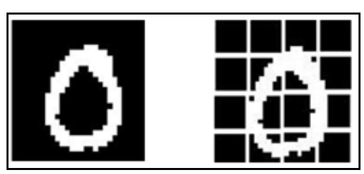

Figure 3. Features Extraction by Zoning Method from Numeral Zero (16 Zones)

5.2. Extraction by Zig-zag Method

This method [26- 28] consists to count the number of all white pixels along each row, each column and each parallel row to diagonal and to anti-diagonal of the numeral image. Then all these numbers must be stocked to a vector.

To better explain this method, the Figure 4 illustrates how its implementation. The result of this method is to have converted the image zig-zagged that has 9x9 pixels to a vector of 16 components.

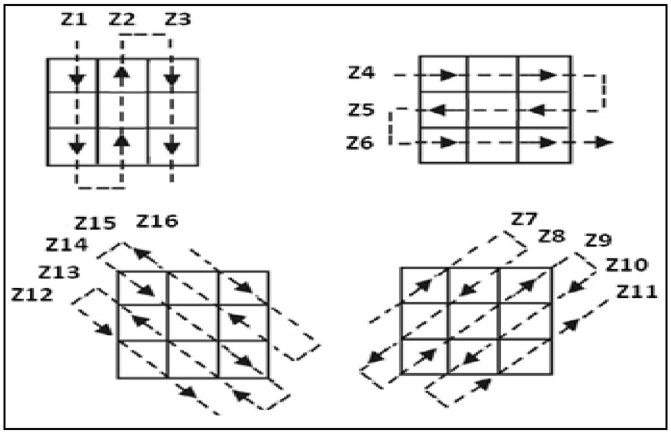

Figure 4. Features Extraction from Image by Zig-zag Method

5.3. Extraction by Mathematical Morphology Method

The feature extraction is based on mathematical morphology [15-19]. The characteristic areas can be detected by the dilatation of the numeral image processed in four directions. The characteristic zones can be detected by the intersections of dilations found to the East, West, North and South.

Each point belongs to the characteristic area if and only if:

- This point does not belong to the limit of the object.
- From this point, moving in a straight line to the South, North, East and West we cross the object.

The result of the extraction is illustrated in the (Figure 5).

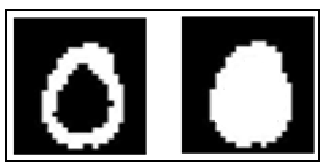

Figure 5. Features Extraction by Mathematical Morphology Method from Numeral Zero

5.4. Extraction by Hybrid Method: Zoning + Mathematical Morphology + Zig-zag

This method consists after the features extraction by mathematical morphology to zoning it, but it is not like to that we carried previously, in fact, it comes this time around to achieve a zoning of the image by a zigzagged manner, in other words the zones in which the image is divided are a horizontal and vertical rectangles and a trapezoids which parallel to diagonal and also anti diagonal of the image. Then we will count the number of all white pixels in each of these zones in order to gather all these numbers in a vector (see Figure 6).

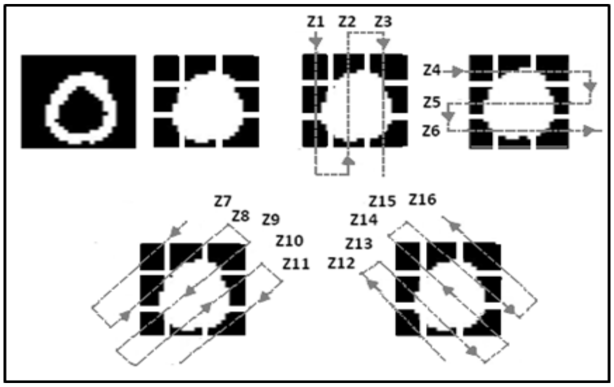

Figure 6. Features Extraction by Hybrid Method used from Image of Numeral Zero

6. Learning-classification Phase

6.1. The K-nearest Neighbors (knn)

Given a training set contains n vectors x_1, x_2 ….. $x_n \in R^p$ and m classes C_1, C_2, ….. C_m. With m<n which each of them includes a part of these vectors. In order to predict the class of a new vector (unknown or test vector) x_{test} the classifier KNN seeks the K-nearest neighbors [8-14] of x_{test} then assigned him to the class that contains the largest number of these K nearest neighbors. This method therefore uses two principal parameters which are a number K and a similarity function for the purpose to compare a new case to cases already studied .In fact, the principle is given by:

- Choosing an integer K (this choice is very important).
- Calculating the following distances (the Euclidean distance is more popular in this case):

$$d(x_{test}, x_j)^2 = \sum_{i=1}^{p}(x_{test,i} - x_{j,i}) \quad , j=1,2……n \tag{1}$$

Keep the K-nearest neighbors of unknown vector which are those that have the minimum distance to this vector. Count the number of once that the K-NN appears in each class assign the test vector to the majority class.

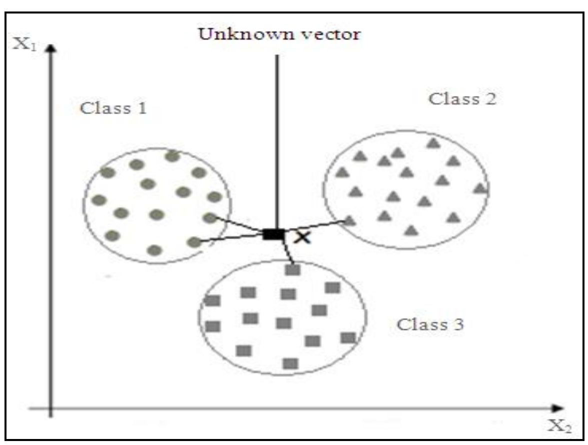

Figure 7. 4-NN of Test Vector X and belongs to Three Different Classes

6.2. The Supports Vectors Machines

6.2.1. Principe of Functioning between Two Classes of the SVM

6.2.1.1. The Linear Case

The SVM[1-7] is a powerful statistic tool used in many scientific fields as data mining applications such as text categorization, handwritten character recognition, image classification and bioinformatics. To have some idea about the principle of learning-classification SVM, we present the following explanations:

For a two-class classification problem, assume that we have a series of input vectors $x_i \in R^n$ (i = 1, 2, ...N) with corresponding labels $y_i \in$ { -1, 1} (i = (1, 2, ... N)). Where +1 and −1 indicate the two classes.

The idea of SVM is to map the input vectors $x_i \in R^d$ into a high dimensional feature space $\Phi(x_i) \in$ H, and it constructs an optimal separating hyperplane H that will maximizes the marginal distance between the hyperplane and the nearest data points of each class in the space H.

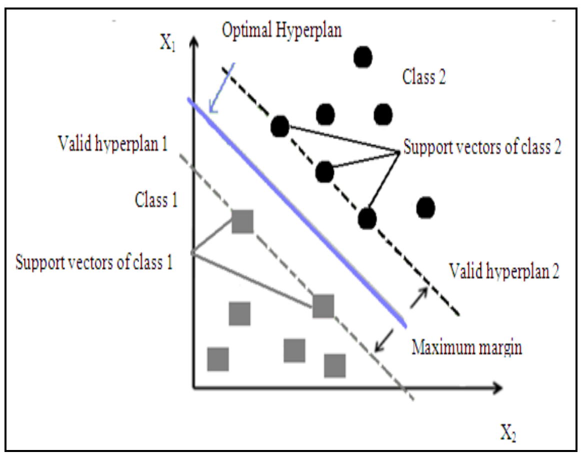

Figure 8. The Determination of Optimal Hyperplane, Vectors Supports, Maximum Marge and Valid Hyperplanes

The nearest points that only are used for the determination of optimal hyperplan are called the support vectors. The classifier is represented by the decision function:

$$f(x) = \sum_{i=1}^{n} \alpha_i^* y_i K(x, x_i) + b \qquad (2)$$

The dual variables α_i intervening in the Lagrangian is called Lagrange multipliers.

To maximize $$D(\alpha) = \sum_{i=1}^{n} \alpha_i - \frac{1}{2} \sum_{i,j}^{n} \alpha_i \alpha_j y_i y_j K(x_i, x_j) + b \quad (3)$$

Subject to $$\sum_{i=1}^{n} \alpha_i y_i = 0, \quad \leq \alpha_i \leq C \; \forall \, i = 1,2,\dots,n$$

The parameter C which appears here is a positive constant fixed in advance; it’s called the constant of penalty. The decision function has the form:

Some example of the kernel functions:

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

6.2.1.2. Principe of Functioning between a Several Classes of the SVM

About a classification between several classes, many studies used for this generalization of the SVM in a multi-classification [30- 31], among these there are two strategies that frequently used: the first is called one against all that bases to use N decision functions f_i (i = 1, 2, ...N) allowing each of them makes a discrimination of a class contains a one vector against all other vectors existed in a other class opposite. 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.

$$i=\arg\max_{i=1,2,\dots,n} f_i(x) \tag{4}$$

The second is called the one against one instead of learning N decision functions; each class is opposed against another. So N(N-1)/2 decision functions are learned and each of them performs a voting for the assignment of a new test (unknown) vector X. its class then becomes the majority class after the vote.

7. Test and Results

7.1. Mnist Numerals(MN) Recognition using SVM

In this work we want to compare between the performances of different extraction methods that are:

- Zoning (Z).
- Mathematical morphology (MM).
- Zig-Zag (ZZ).
- Mathematical morphology + Zig-Zag + Zoning (MM+ZZ+Z).

For this reason we have used in the learning – classification phase the SVM with the Kernel function RBF that has a parameter σ = 0.1 and a one against all strategy and a penalty constant $C=10^4$.

All the results of the recognition rates of each numeral τ_n and the global of all τ_g numerals that we have obtained is regrouped in the following Table:

Table 1. The Obtained Results with SVM

MN	**SVM**			
	Z τ_n **x%**	**MM** τ_n **x%**	**ZZ** τ_n **x%**	**Z+ZZ+MM** τ_n **x%**
	91,67	70.00	75.00	98.00
	97.00	98,33	96,67	99.00
	86,67	92.00	81,67	99.00
	71,67	90.00	56,67	92.00

	91,67	88,33	80.00	95.00
	50.00	70.00	50.00	80.00
	70.00	40.00	70.00	93,33
	70.00	60.00	66,67	90.00
	90.00	50.00	48,33	95.00
	60.00	81,67	60.00	90.00
τ_g **x%**	**77.86**	**74.03**	**68,50**	**93.13**

The graph associated to Table above is:

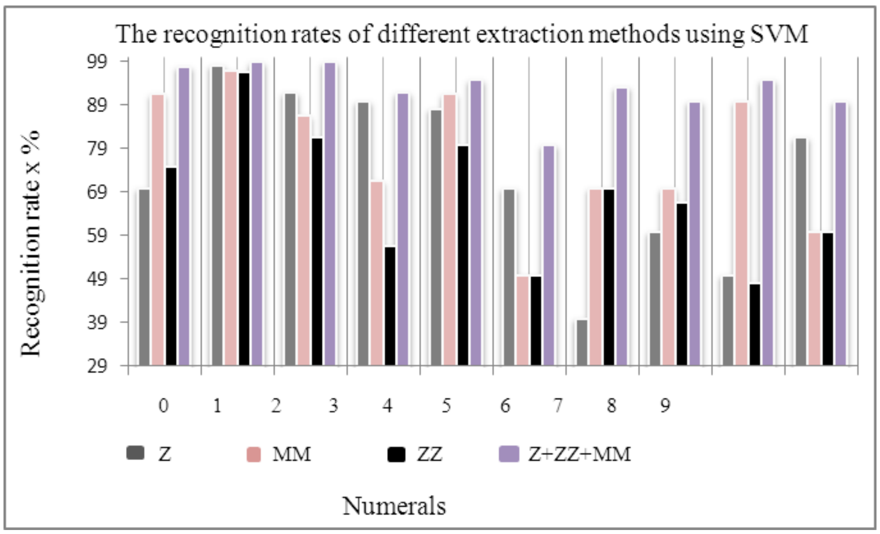

Figure 9. Comparison between the Recognition Rates of Different Extraction Methods using SVM

- *Analysis and comments:*

Having regard the results obtained, we conclude that the most efficient extraction method is that of MM+ZZ+Z then that of zoning, then that of mathematical morphology and finally that of zig-zag.

7.2. Mnist Numerals (MN) Recognition using K-NN

In this once we want to compare between the performances of different extraction methods that are:

- Zoning (Z).
- Mathematical morphology (MM).
- Zig-Zag (ZZ).
- Mathematical morphology + Zig-Zag + Zoning (MM+ZZ+Z).

Concerning the learning – classification phase we have used the K-NN method. For to obtain a precise comparison, we have chosen several different values of number K just for knowing its effect to rate recognition.

All the results of the recognition rates of each numeral τ_n and the global of all τ_g numerals that we obtained is regrouped in the following Table:

Table 2. The Obtained Results with KNN

MN	KNN											
	K = 6				K = 10				K = 15			
	Z τ_n x%	MM τ_n x%	ZZ τ_n x%	Z+MM+ZZ τ_n x%	Z τ_n x%	MM τ_n x%	ZZ τ_n x%	Z+MM+ZZ τ_n x%	Z τ_n x%	MM τ_n x%	ZZ τ_n x%	Z+MM+ZZ τ_n x%
	90.00	63.33	78.33	99.00	90.00	56.67	91.67	99.00	90.00	55.00	93.00	99.00
	98.33	99.00	88.00	99.00	98.33	99.00	90.33	99.00	99.00	99.00	92.00	99.00
	93.33	83.33	66.67	88.33	93.33	85.00	72.67	80.00	91.67	85.00	73.33	76.67
	76.67	90.00	81.33	88.33	80.00	90.00	86.67	91.67	76.67	90.00	91.00	95.00
	99.00	91.67	83.33	96.67	98.33	93.33	89.00	99.00	98.33	96.67	90.00	99.00
	30.00	56.67	49.11	31.67	41.67	71.76	48.33	45.00	55.00	73.33	53.33	48.33
	66.67	95.00	81.31	98.33	66.67	96.67	84.00	99.00	80.00	98.33	92.00	99.00
	71.67	68.33	85.00	95.00	90.00	63.33	95.00	99.00	95.00	46.67	98.33	98.33
	43.33	60.00	60.00	81.67	41.67	56.67	61.67	80.00	56.67	58.33	76.67	76.67
	66.67	66.57	61.67	85.00	65.00	48.33	70.00	73.33	70.00	63.33	75.00	75.00
τ_g x %	**73.50**	**77.39**	**73.47**	**86.30**	**76.50**	**76.07**	**78.93**	**86.50**	**81.10**	**76.56**	**83.46**	**86.60**

The graph associated to Table above is

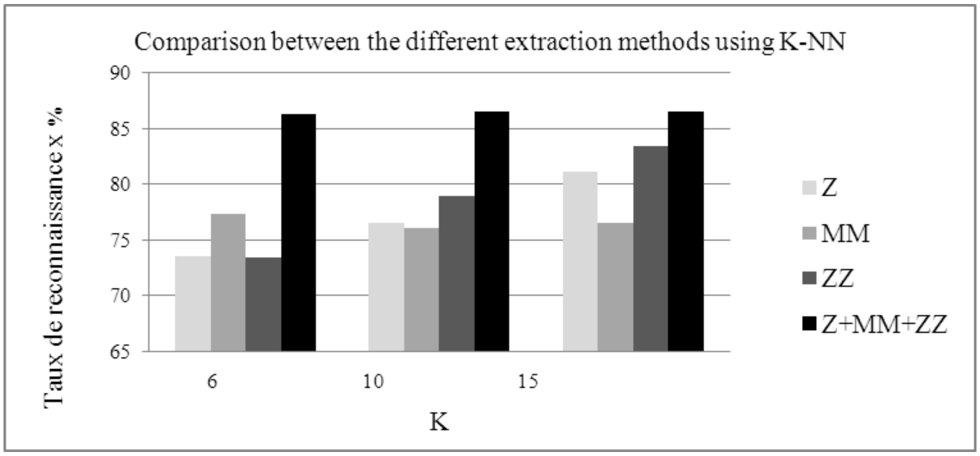

Figure 10. Comparison between the Recognition Rates of Different Extraction Methods using KNN

- *Analysis and comments:*

Taking into account the results obtained, we deduced that the best performing extraction method is that of Zoning+Mathematical Morphology+Zig-Zag then that of Mathematical Morphology, then of Zig-Zag and finally that of zoning in one hand, and the results obtained which are more convincing when we vary K is those produced by K=15 then when K=10, and finally when K=6 on the other hand.

8. Conclusion

In this paper we have used handwritten Latin numerals recognition systems that contain several techniques like the thresholding, normalization, cantering and rotation in the preprocessing phase and the zoning, zig-zag and mathematical morphology methods in the features extraction phase and the K-NN then the SVM in the learning-classification phases. Our goal is to compare between the performances of these learning – classification tool. We really have verified that SVM is performing than the K-NN in this recognition.

Acknowledgements

We Are Grateful To Yan Lecun For The MNIST Database, Which Is A Standard Used By Anyone In The World, Who Wants To Test Its Classifier.

References

[1] V. Vapnik, “Support-vector networks”, Machine Learning, vol. 20, no. 3, **(1995)**, pp. 273.
[2] M. M. Adankon and M. Cheriet Model selection for the LS-SVM”, Application to handwriting. Pattern Recognition, vol. 42, Issue 12, **(2009)** December, pp. 3264-3270.
[3] F. Camastra, “A SVM-based cursive character”, Pattern Recognition, vol. 40, Issue 12, **(2007)** December, pp. 3721-3727.
[4] H. Drucker, D. Wu and V. Vapnik, “Support vector machines for spam categorization”, IEEE transactions on Neural Networks, vol. 10, no. 5, **(1999)**, pp. 1048-1055.
[5] C. Hou, F. Nie, C. Zhang, D. Yi and Y. Wu, ‘Multiple rank multi-linear SVM for matrix data classification”, Pattern Recognition, Volume 47, Issue 1, **(2009)** January, pp. 454-469.
[6] J. John, K. V. Pramod and K. Balakrishnan, “Unconstrained Handwritten Malayam Character Recognition using Wavelet Trandform and Support vector Machine”, Procedia Engineering, vol. 30, **(2012)**, pp. 598-605.
[7] X. Niu and C. Y. Suen, “Anovel hybrid CNN-SVM classifier for recognizing handwritten digits”, Pattern Recognition, vol. 45, Issue 4, **(2012)** April, pp. 1318-1325.

[8] L. Li, L. Zhang and J. SU, "Handwritten character recognition via direction sring and nearest neighbor matching", The Journal of China Universities of Posts and Telecommunications, vol. 19, Supplement 2, **(2012)** October, pp. 160-165,196.
[9] Z. Liu, Q. Pan and J. Dezert, "A new belief-based K-nearest neighbor classification", Pattern Recognition, vol. 46, Issue 3, **(2013)** March, pp. 834-844.
[10] S. H. Rodríguez, J. F. M. Trinidad, J. Ariel and C. Ochoa, "Fast k most similar neighbor classifier for mixed data (tree k-MSN)", Pattern Recognition, vol. 43, Issue 3, **(2010)** March, pp. 873-886.
[11] N. A. Samsudin and A. P. Bradley, "Nearest neighbor group-based classification", Pattern Recognition, vol. 43, Issue 10, **(2010)** October, pp. 3458-3467.
[12] T. Wakahara and Y. Yamashita, "K-NN classification of handwritten characters via accelerated GAT correlation", Pattern Recognition, vol. 47, Issue 3, **(2014)** March, pp. 994-1001.
[13] J. Yang and D. Zhang, "From classifiers to discriminators: A nearest neighbor rule induced discriminant analysis", Pattern Recognition, vol. 44, Issue 7, **(2011)** July, pp. 1387-1402.
[14] J. Yang, L. Zhang, J. Yang and D. Zhang, "From classifiers to discriminators: A nearest neighbor rule induced discriminant analysis", Pattern Recognition, vol. 44, Issue 7, **(2011)** July, pp. 1387-1402.
[15] J. Angulo and J. Serra, "Automatic analysis of DNA microray images using mathematical morphology", Bioinformatics, vol. 19, no 5, **(2003)** March, pp. 553-562.
[16] B. E. kessab, C. Daoui, B. Bouikhalene, M. Fakir and K. Moro, "Extraction Method of Handwritten Digit Recognition Tested on the MNIST Database", International Journal of Advanced Science and Technology, vol. 50, **(2013)** January.
[17] B. E. kessab, C. Daoui, B. Bouikhalene, M. Fakir and K. Moro, "Handwritten Tifinagh Text Recognition using Neural Networks and Hidden Markov Models", International Journal of Computer Applications (0975 – 8887), vol. 75, no. 18, **(2013)** August.
[18] M. Iwanowski and M. Swierez, "Pattern Recognition Using Morphogical Class Distrubition Functions and Classification Trees", Springer, **(2011),** pp. 143-154.
[19] J. Serra, "Image Analysis and Mathematical Morphology", II: Theoretical Advances, Academic Press. London, **(1988)**.
[20] A. Benouareh, A. Ennaji and M. Sallami, "Semi-continuous HMMs with explicit state duration for unconstrained Arabic word modeling and recognition", Pattern Recognition Letters archive, vol. 29, Issue 12, **(2008)** September, pp. 1742-1752.
[21] R. S. Hegadi, "Recognition of Printed Kannada Numerals based on Zoning Method", International Journal of Computer Applications (0975 – 8878) on National Conference of Advanced Computing and Communications - NCACC, **(2012)** April.
[22] A. Hennig and N. Sherkat, "Exploiting zoning based on approximating splines in cursive script recognition", Pattern Recognition, vol. 35, Issue 2, **(2002)** February, pp. 445- 454.
[23] D. Impedovo and G. Pirlo, "Zoning methods for handwritten character recognition", A survey, Pattern Recognition, vol. 47, no. 3, **(2014),** pp. 969–981.
[24] S. Manipal, D. H Manjaiah, R. Bera and H. N. Ashoka, "Based Feature Extraction and Statistical Classification Technique for Kannada Handwritten Numeral Recognition", International Journal of Computer Science & Engineering Technology (IJCSET), **(2010)**.
[25] A. Rahman and B. Verma, "Effect of ensemble classifier composition on offline cursive character", Information Processing & Management, vol. 49, Issue 4, **(2013)** July, pp. 852-864.
[26] M. Kamel and A. Campilho, "An Iris Recognition Method Based On Zigzag Collarette Area and Asymmetrical Support Vector Machines", ICIAR, **(2007),** pp. 854-865.
[27] M. Padmaa and Y. Venkataramani, ZIG-ZAG PVD – A Nontraditional Approach", International Journal of Computer Applications (0975 – 8887), vol. 5, no. 7, **(2010)** August.
[28] K. Roy and P. Bhattacharya, "An Iris Recognition Method Based On Zigzag Collarette Area and Asymmetrical Support Vector Machines", IEEE, **(2006),** pp. 861-865.
[29] Y. LeCun, "THE MNIST handwritten digit database', R. Muralidharan1, C. Chandrasekar: Object Recognition using SVM -KNN based on Geometric Moment Invariant, International Journal of Computer Trends and Technology- ISSN: 2231-2803, Issue 2011, **(1998)** July to August, pp. 215-220.
[30] T. C. Mota and A. Thomé, "One-Against-All-Based Multiclass SVM Strategies Applied to Vehicle Plate Character Recognition", IJCNN, **(2009)**.
[31] G. Sinha and J. kumar, "Arabic numeral Recognition Using SVM Classifier", International Journal of Emerging Research in Management & Technology ISSN: 2278-9359, vol. 2, Issue 5, **(2013)** May.

Authors

B. El KESSAB received his Master's degree in 2009 from Faculty of Sciences and Technology University Sultan Moulay Slimane Beni Mellal Morocco, currently working on his Ph.D. in Information Processing and Decision Aids Laboratory at Sultan Moulay Slimane University. His current research interests include pattern recognition, image analysis, document processing and automatic processing of natural languages using hidden Markov models and neural networks.

C. DAOUI received his Ph.D degree on mathematics in 2002 from Mohamed V University Rabat Morocco. Currently is a professor in Faculty of Sciences and Technology, University Sultan Moulay Slimane Beni Mellal Morocco. His research topics are: the mathematics, operational research and pattern recognition.

B. BOUIKHALENE Received his Ph.D degree on mathematics in 2001 and Master's degree on Science of Computer and Telecommunications in 2007 from the University Ibn Tofel Kenitra. Currently is a professor in the Sultan Moulay Slimane University Beni Mellal Morocco. His research topics are: the pattern recognition, artificial intelligence and mathematics and its applications.

R. SALOUAN received his Master's degree in 2010 from Faculty of Sciences and Technology University Sultan Moulay Slimane Beni Mellal Morocco, currently working on his Ph. D in Sultan Moulay Slimane University. His current research interests include pattern recognition, image analysis, document processing and automatic processing of natural languages using hidden Markov models and neural networks.