A Multiresolution Approach for Noised Texture Classification based on the Co-occurrence Matrix and First Order Statistics

M. Ben Othmen, M. Sayadi, and F. Fnaiech

***Abstract*—**Wavelet transform provides several important characteristics which can be used in a texture analysis and classification. In this work, an efficient texture classification method, which combines concepts from wavelet and co-occurrence matrices, is presented. An Euclidian distance classifier is used to evaluate the various methods of classification. A comparative study is essential to determine the ideal method. Using this conjecture, we developed a novel feature set for texture classification and demonstrate its effectiveness.

***Keywords*—**Classification, Wavelet, Co-occurrence, Euclidian Distance, Classifier, Texture.

I. INTRODUCTION

TEXTURE analysis plays an important role in image processing, rangining from remote sensing to medical imaging, robot vision and medical image database. Various methods for texture feature extraction have been proposed in the last decades. [3][7]. Furthermore, texture classification is an important subject in pattern recognition and image processing areas. There are several methods developed for this purpose. The wavelet brought a new breath to the field of the image processing. Indeed, they make it possible to locate and analyze discontinuities in the image on various scales [7]. This feature was used for the classification of textures. This paper presents an improvement of the comparative study of the various techniques of known classification presented in [1]. It also suggests studying the classifying Euclidean distances. Tests were carried out on images with various levels of gray.

M. Ben Othmen (corresponding author) is with the research group SICISI, Ecole Superieure des Sciences et Techniques de Tunis (ESSTT), 5 Av. Taha Hussein, 1008, Tunis, Tunisia (e-mail: moez_ben_othmen@yahoo.fr).

M. Sayadi is with the SICISI, Ecole Superieure des Sciences et Techniques de Tunis (ESSTT), 5 Av. Taha Hussein, 1008, Tunis, Tunisia. He is also associate researchers with LTI Group (EESA), University of Picardie Jules Verne 7, rue du Moulin Neuf - 80000 Amiens - France (e-mail: mounir.sayadi@esstt.rnu.tn).

F. Fnaiech is with the SICISI, Ecole Superieure des Sciences et Techniques de Tunis (ESSTT), 5 Av. Taha Hussein, 1008, Tunis, Tunisia. He is also associate researchers with LTI Group (EESA), University of Picardie Jules Verne 7, rue du Moulin Neuf - 80000 Amiens - France (e-mail: fnaiech @ieee.org).

The first part touches upon the transform in wavelet. The second part is interested in the principle of classifier containing Euclidean distance. The third exposes some methods of classification, as well as the results of these techniques applied to textured images. The fourth presents a comparative study aiming at finding the best method of classification.

II. WAVELET TRANSFORM

The continuous transform in wavelet is defined as a projection of a function X (t) on an analyzing family, obtained by translation and dilation (or contraction) starting from a single prototype oscillating quite localized in time and frequency, called ondelette mother or ondelette analyzing which satisfies the function of following admissibility:

$$\int_{-\infty}^{+\infty} |\Psi(f)|^2 \frac{df}{|f|} = 1 \qquad (1)$$
$$\Psi(0) = 0$$

Where $\Psi(f)$ is the transform of Fourier of the wavelet mother $\Psi(t)$. This condition ensures convergence ad infinitum.

The analyzing family is standardized according to:

$$\Psi ab(t) = \frac{1}{\sqrt{a}} \Psi\left(\frac{t-b}{a}\right), a \in R, b \in R \qquad (2)$$

If $|a| > 1$: the family of functions becomes a contracted version of the ondelette mother.

If $|a| < 1$: the family of functions becomes a dilated version of the wavelet mother.

The families of functions $\Psi_{a,b}$(t) are of which the derivative of the function mother $\Psi(t)$ by translation while varying B and contraction or dilation while varying a.

The wavet transform(WT) is defined by the following representation "time-scale".

$$Xw(a,b) = \frac{1}{\sqrt{a}} \int_{-\infty}^{+\infty} \Psi\left(\frac{t-b}{a}\right) x(t)dt\,. \qquad (3)$$

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The passage to the discrete transformation into ondelette was highlighted by Yves Meyer [3] in 1985. It chose the analyzing function in a more precise way and it discretized the parameters a = 2-j, b = 2-j k, (j, k) $\in$ Z².

There will be the discrete version of the transform in ondelettes following:

$$< x(t)/2^{j/2}\Psi(2^j t-k) > = X_w(j,k) = 2^{j/2}\int_{-\infty}^{+\infty}\Psi(2^j t-k)x(t)dt \quad (4)$$

With:

$$< x(t)/2^{j/2}\Psi(2^j t-k) > = < x(t)/\Psi_{j,k}(t) > : \quad (5)$$

indicate the Hilbertien product of two functions of L ² (R).

The wavelet transform of 2-D signal leads to a decomposition of the image into four parts: one of approximation and three of details, as indicated in Fig. 1. A1 (where L represents the level of decomposition), corresponds to the starting image with a weaker resolution, whereas H1, V1 and D1 contain the horizontal details, vertical and diagonal, lost at the time of the passage of one resolution to the following one [4].

This sub-image (H1, V1 and D1) contains high frequencies and shows fast variations in the image. The noise, corresponding in general to great frequencies, is located thus in these images of details.

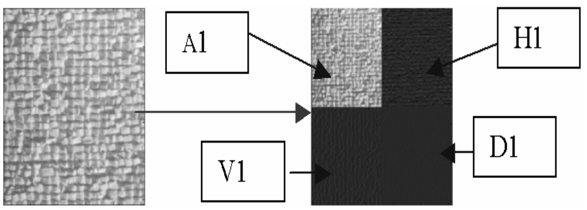

Fig. 1 Wavelet transform: Level 1

III. Textures Features

The analysis of texture gathers a whole of mathematical techniques making it possible to quantify the various levels of gray present in an image in term of intensity and distribution.

A. First-order Statistical Method

Which is well-known and used in several works (moments of ordre1 with 4).

B. First-order Statistical Method

In this part, the matrix of co-occurrence or method of space dependence of the levels of gray is dealt with.

It helps determine the frequency of appearance of a formed "reason" for two pixels separated by a certain distance *D* in a particular direction. In order to limit the number of calculations, 0°, 45°, 90°, 135°, 180° are generally taken as values and 1 for the value of D.

Here in the continuation various attributes containing matrix of co-occurrence are most used:

Inertia

$$V1 = \sum_{K}^{M}\sum_{l}^{N}(k-l)^{\wedge}2\,p(k,l) \quad (6)$$

Total Energie

$$V2 = \sum_{K}^{M}\sum_{l}^{N}p^{\wedge}2(k,l) \quad (7)$$

Entropy

$$V3 = \sum_{K}^{M}\sum_{l}^{N}p(k,l)\log\ p(k,l) \quad (8)$$

Local Homogeneity

$$V4 = \sum_{K}^{M}\sum_{l}^{N}\frac{1}{1+(k-l)^{\wedge}2}p(k,l) \quad (9)$$

Maximum Probability

$$V5 = \max\ p(k,l) \quad (10)$$

Cluster Shade

$$V6 = \sum_{K}^{M}\sum_{l}^{N}(k-Mx+j-My)^{\wedge}3\,p(k,l) \quad (11)$$

Cluster Prominence

$$V7 = \sum_{K}^{M}\sum_{l}^{N}(k-Mx+j-My)^{\wedge}4\,p(k,l) \quad (12)$$

Avec

$$My = \sum_{K}^{M}\sum_{l}^{N}lp(k,l) \quad (13)$$

$$Mx = \sum_{K}^{M}\sum_{l}^{N}kp(k,l) \quad (14)$$

C. Higher Order Method

There are textures which have even statistical order two but differ by their statistics of a higher nature. The choice was to use this concept and to study the matrices length of beaches. It consists in counting the number of beaches a certain length J, of level of gray I, in a given direction (0°, 45°, 90°, 135°, 180° are generally taken as values). One matrix is associated with a direction.

R (θ) matrix associated with a direction with angle:

$$R(\theta) = [q(i,j)/\theta] \quad (15)$$

Where

q (i,j) :a number of beaches of pixels of level of gray i, length j

θ : direction of the beach of level of gray.

A beach of level of gray corresponds to the whole of the pixels of an image having the same value of level of gray. The length of the beach corresponds to the whole of the pixels belonging to the beach; thus it can be said that a fine texture has few pixels in a beach.

The principal parameters from the matrix lengths of beaches are as follows:

The average length: the average length is defined by the following equation:

$$L_{moy} = \frac{1}{T}\sum_{k}\sum_{l}k.q(k,l) \quad (16)$$

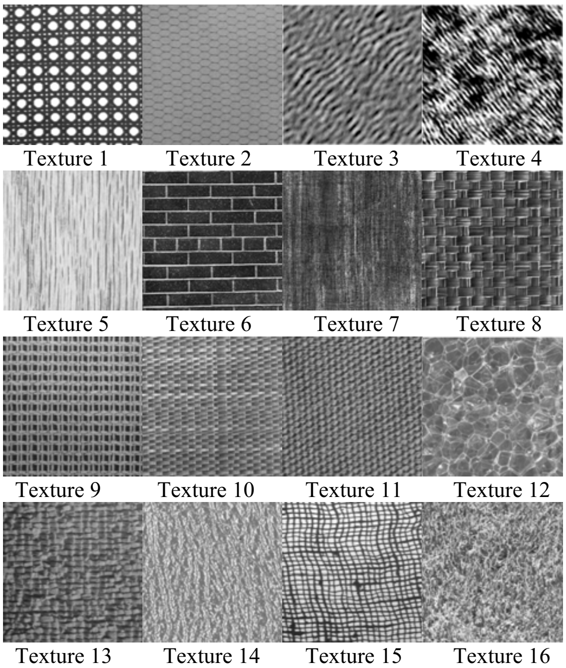

Fig. 2 Textures used in classification experiments

With k*l the dimension of the matrix length of beach represents

$$T = \sum_{k} \sum_{l} q(k,l) \tag{17}$$

Wealth of long beaches:

The wealth of long beaches is the summation of the product of the level of gray by the square of the number of line of each pixel divided by the total sum of the levels of gray. Therefore one can write:

$$R_{pl} = \frac{1}{T} \sum_{k} \sum_{l} k^2 q(k,l) \tag{18}$$

No uniformity of brightness:

No uniformity of brightness is the result of the sum of the square of the sum of the levels of gray located on the same column divided by the total sum of the levels of gray. Thus, it can be written in the following mathematical form:

$$N_{ul} = \frac{1}{T} \sum_{k} \left[\sum_{l} q(k,l) \right]^2 \tag{19}$$

No uniformity length:

No uniformity length is determined by the sum of the square of the sum of the levels of gray located on the same line divided by the total sum of the levels of gray. It is written in the following mathematical form:

$$\mathrm{N}_{\mathrm{uL}} = \frac{1}{T} \sum_{l} \left[\sum_{k} q(k,l) \right]^2 \tag{20}$$

D. Parametric Model

To identify a texture, the need is to find the combination of the parameters which can generate a texture similar to the observation. By modeling an image textured like the realization of a two-dimensional stochastic process (2D), texture can also be characterized by the coefficients 2D obtained by identification of a model AR 2D using an adaptive algorithm [1].

Adaptive algorithm LMS is one of the algorithms most used in the field of linear and nonlinear adaptive filtering thanks to its easy implementation [6]. It was proposed by [6] and was used in many applications in the case of a one-dimensional signal, however, the two-dimensional applications (in image processing), were studied only recently

- To initialize the coefficients $H\,(i,j)$ and the output $y\,(n,r)$ to zero. H is a matrix of order $(p,$ q $)$ which is the order of the filter 2D.
- For $N = 1$ until a number of lines of the image

For $R = 1$ until a number of columns of the image

Calculation of the output of the filter has:

$$y(n,r) = \sum_{i=0}^{p} \sum_{j=0}^{q}{}_{(i,j)\neq(0,0)} H(i,j)y(n\text{-}i,r\text{-}j) \tag{21}$$

Error analysis enters the output of the filter and the desired output: $E\,(n,r) = D\,(n,r) - y\,(n,r)$ (21)

Adaptation of the coefficients of the filter:

For $I = 0$ to p

For $J = 0$ to q

$$H(i,j) = H(i,j) + \mu.e(n,r).y(n\text{-}i,r\text{-}j) \tag{22}$$

d (n, r)is the desired output of the filter [6] and the i term is the step of adaptation. It makes it possible to control the speed of convergence and the stability of the filter.

IV. Classification Algorithm

In this case, the simplest algorithm is proceeded to. For each texture of reference, the distance between the characteristic vector which needs to be classified and each vector characteristic of texture of reference is measured. Then this operation for each texture of reference is repeated. The vector to be classified was assigned with the texture for which this distance is minimal.

Another classifier can be studied in this part: The three weakest distances needed to be born in mind and one vector of it was to be made. This vector is calculated then repeated then for each texture of reference. The vector to be classified was assigned with the texture for which this standard is minimal.

The difference between these two last and the third classifier comes from the definition of "distance". The two first, henceforth called classifying simple Euclidean (ES), classifier Euclidean normal (EN) use simply the Euclidean distance. The third, named classifying (EB) balanced balances this Euclidean distance by the variance of the feature vectors associated with the texture of the reference considered. With this classifier, for a texture of reference K and feature vectors, the distance $d_{k,l}$ between the vector characteristic 1 of the texture of reference K and the vector test is given by:

$$d_{k,l} = \sqrt{\sum_{i=1}^{d} (x_i - y_{i,l})^2} \tag{23}$$

The index i is the component count of the vectors, K is the index of the texture of reference, and 1 = 1..., N the index of the vector characteristic of texture K, if one has N vectors characteristic.

TABLE I
PERCENTAGE OF CLASSIFICATION FOR EACH CLASSIFICATION METHOD

Method	Features number	Euclidean normal	Euclidean simple	Euclidean balanced
Simple energy	1	68.5	72.12	------
Methods of first order based on histogram	3	59	91.37	79
Parametric model of order 3	3	73.87	73.87	75.75
Stamp lengths of beaches	4	71	82.12	72.25
Statistical attributes of first order	4	82	91.25	92.75
Co-occurence	7	89.62	93.37	92.12
Parametric model of order 8	8	85	84.37	87.12
wavelet based on energy	9	87.87	89.25	75.62
wavelets based parametric model of order 8	72	94	94.25	94.87
wavelet based matrix of co-occurrence	**63**	**99.12**	**99.12**	**99.12**

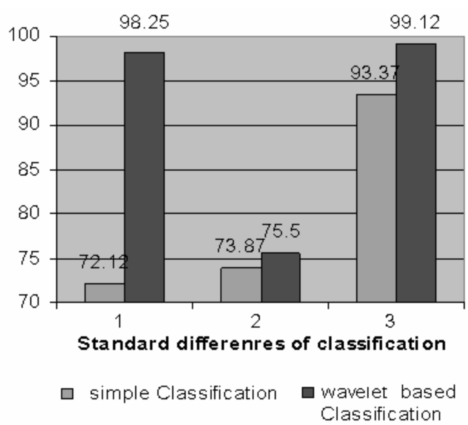

Fig. 3 Variation of percentage of classification according to method of classification simple and containing wavelet

V. EXPERIMENTAL RESULTS

In this section, a whole of 16 textures different of dimension (512*512) extracted starting from the album from Brodatz [2] were considered. To this end, 50 Pixel images (64 * 64) of each class of texture are randomly selected. The various methods of extraction of the attributes of texture for the 800 images are then evaluated, by the classifiers Euclidean. These textures were analyzed with Haar' s wavelet.

The order of decomposition is fixed at three and this choice is explained below. The currency of each texture with sub images wavelet transformation was applied to the order four then for each coefficient of sub images the desired method was applied to extract the characteristic vector.

If the method of wavelet containing matrix of co-occurrence is taken as an example, then there are 9 attributes for each resolution and the total of attributes is 63.

Below is a summary table which highlights the methods used during this work and the percentages of classifications while being based on the various types of classifier?

The combination between the transform in wavelets and co-occurrence matrix gives a better percentage of classification (99.12%) for the various types of classifier containing Euclidean distances.

A. Superiority of the Methods of Classification Containing Wavelet

This figure compares the three methods of classification (simple and at base multiresolution).

1-energy
2-model parametric of order 3
3 matrix of co-occurrence

Classification at base multiresolution has a more significant percentage of classification than that of simple classification.

B. Influence Level of Decomposition

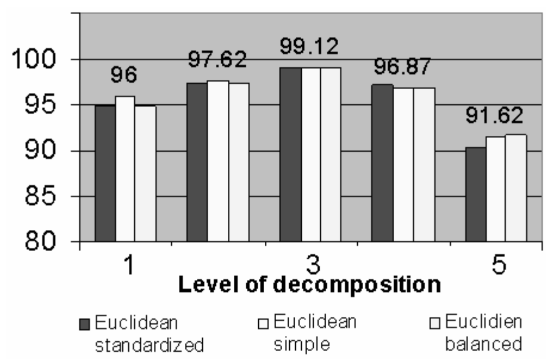

Fig. 4 Variation of percentage of classification of level of decomposition

The preceding histogram informs us that the percentage of classification increases according to increase in level of decomposition (1, 2, and 3). But the question which arises: which level should we stop at? It is worth noting that the rate of classification increases until order 3 then it decreases from this order which is completely logical since the size of the sub image becomes small. It cannot contain the characteristics to classify the textures.

Therefore the problem of level of decomposition is related to the choice of dimension of the initial image. Generally it would not seem possible to go down to the lower part from dimension (16*16) so that classification would not be passive.

C. Influence Angle (Theta) of Co-Occurrence Matrix

The co-occurrence matrix to make it possible to determine the frequency of appearance of a formed "reason" for two pixels separated by a certain distance D in a direction (theta) particular was compared to the horizontal one. This definition enables us to choose the parameters of matrices of co-occurrence which give a better percentage of classifications. In this study, the percentage of classification for each texture for various values of d =1 and (theta) of (0°, 45° 90°, 135°) was determined.

TABLE II
PERCENTAGE OF CLASSIFICATION FOR EACH TEXTURE FOR VARIOUS VALUES OF (θ)

	θ = 0°	θ = 45°	θ = 90°	θ = 135°	Mean of 3 values
Texture 1	100	100	100	32	100
Texture 2	100	68	100	64	34
Texture 3	100	100	94	36	100
Texture 4	100	72	68	100	100
Texture 5	100	100	100	100	100
Texture 6	52	96	78	**12**	**100**
Texture 7	28	52	98	32	100
Texture 8	94	100	100	74	100
Texture 9	48	100	100	100	100
Texture 10	80	90	100	100	100
Texture 11	74	100	96	92	100
Texture 12	90	30	58	100	100
Texture 13	98	98	92	30	100
Texture 14	100	100	100	58	54
Texture 15	100	100	100	100	100
Texture 16	100	100	98	98	98
Mean of all texture	89.62	87.87	92.62	70.5	92.5

The rate of percentage of classification of each texture varies according to the angle. Each texture corresponds to an angle (theta) for which the percentage of classification is maximum.

The angle of orientation (theta) plays a capital role in the phase.

Classification texture 6, for example, has a rate of classification equal to 12% with θ =135° on the other hand this rate amounted to 96% with θ =45°.

For the same texture, there exists more than one angle which gives a good percentage of classification example texture 15 and 5 (100% for all the angles).

Because of this we tried to calculate the average of the vectors of the four angles and the results improved classification for textures 6 and 11. On the contrary, the rate of classification decreased for textures 2 and 14. Then we had to combine different strategies to be able to improve the percentage of classification. The method based on the average of the vectors of the four angles is not always the appropriate choice for classification. On the other hand, one must test the angles and see which the highest rate of classification.

D. Influence of Noise

In Table III, the percentage of classification is given after having to apply an additive noise to textures. This is done to determine the sensitivity of the various methods of classification to the noise. OND.MC1 is calculated way that OND.MC6.

MC1: Method of classification containing matrix of co-occurence for θ=0°. This method is previously detailed (paragraphe.II.1.c). The number of the attributes to be used for classification is equal to 7.

MC5: Method of classification containing the sum of the matrices of co-occurence (θ=0°, θ=45°, θ=90°, θ=135°). For this method, after having extracted the various matrices from co-occurrence, the 7 attributes resulting from the summation of the 4 matrices are calculated.

MC6: Method of classification containing the average and the variance of the attributes of the matrices of co-occurence (θ=0°, θ=45°, θ=90°, θ=135°). The attributes for each matrix are calculated then the average and the variance of each attribute are determined while basing oneself on the 4 values from the various matrices of co-occurence, therefore 14 attributes on the whole.

In addition, one determined the percentage of classification for method MC6 of the decompositions in ondelettes (Ond.MC6).

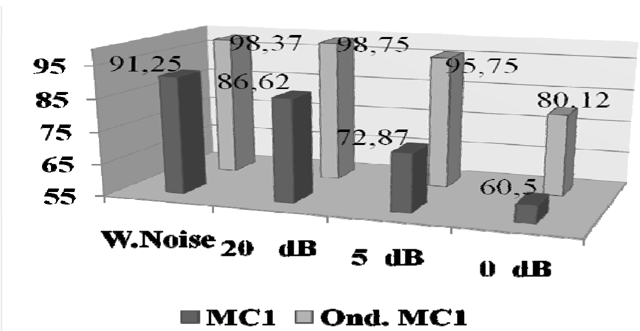

Fig. 5 Variation of percentage of classification of various values of the SNR

It is noted that the rate of classification decreases when the noise level increases. But methods containing ondelettes

(Ond. MC1, Ond.MC6) are less sensitive to the noises than those of (MC1, MC6).

Fig. 5 shows that the rate of classification decreased by 3% for the method ond.MC1 (SNR 5dB). On the other hand, the MC1 percentage decreased almost by 20%.

The methods of classification containing the transform in ondelettes are more robust with the noises than those of the simple methods.

VI. Conclusion

A conclusion section is not required. Although a conclusion may review the main points of the paper, do not replicate the abstract as the conclusion. A conclusion might elaborate on the importance of the work or suggest applications and extensions.

This comparative study between the various methods of classification enabled us to know the most appropriate classification based on multiresolution analysis since it improved the rate of classification. A combination between this transform in wavelet and the statistics of order 2 (matrix of co-occurrence) gave us a better percentage of classification (99.12%) for the various types of classifier containing Euclidean distances. This method containing matrix of co-occurrence must be studied in great details since each texture has parameters so that classification is maximum (99.5%).However, there is no method of universal classification for any types of textures.

A study on the influence of noise showed that the methods containing the coefficients in ondelettes are less sensitive to the noise.

Therefore to make the classification based of textures, the comparative study was essential to find the optimal parameters according to our need. It can be argued that the base of data of texture plays a role in classification, and additional effort must be spread out in order to generalize this work for a great number of images in order to know the limit of this method. Indeed, the application of classification for real applications such as in industry, the military and medical field would certainly benefit from the practical value of the methods.

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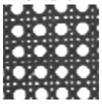
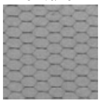
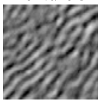
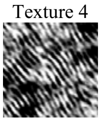
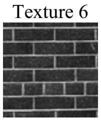
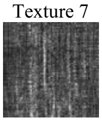
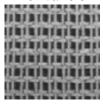
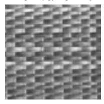
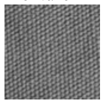
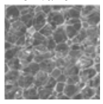
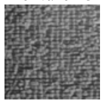
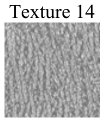
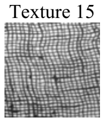
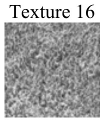
Moez Ben Othmen born in 1979 in Djerba (Tunisia), he received the BSc degree in Electrical Engineering from the High school of sciences and techniques of Tunis, the DEA degree in Automatic and Productique from same school respectively in 2004 and 2006. He is an Assistant at the High Institute of Computer sciences of Mednine. His research interests are focused on signal processing image processing, classification, Texture, and Compression.

Mounir Sayadi born in 1970 in Tunis (Tunisia), he received the BSc degree in Electrical Engineering from the High school of sciences and techniques of Tunis, the DEA degree in Automatic and Signal Processing from same school and the PhD degree in signal processing from the National School of engineers of Tunis, respectively in 1992, 1994 and 1998. He is currently an Assistant Professor at the High school of sciences and techniques of Tunis. Dr Sayadi has published over 40 scholarly research papers in many journals and international conferences. He was the Technical Program Co-Chairman of the IEEE International Conference on Industrial Technology, 2004, Tunisia. His research interests are focused on adaptive signal processing and filtering and image and texture classification and segmentation.

Farhat Fnaiech born in 1955 in la Chebba (Tunisia), he received the BSc degree in Mechanical Engineering in 1978 from Ecole Sup des Sciences et Techniques of Tunis and the master degree in 1980, The PhD degree from the same school in Electrical Engineering in 1983, and the Doctorate Es Science in Physics form Faculte des Sciences of Tunis in 1999.He is currently Professor at the Ecole Superieure des Sciences et Techniques of Tunis. Pr Fnaiech is *Senior Member IEEE* and has published over 150 research papers in many journals and international conferences. He was the general chairman and member of the international Board committee of many International Conferences. His is Associate Editor of *IEEE Transactions Industrial Electronics*. He is serving as *IEEE Chapter committee coordination sub-committee* delegate of Africa Region 8. His main interest research areas are nonlinear adaptive Signal processing, nonlinear control of power electronic devises, Digital signal processing, Image Processing, Intelligent techniques and control.

TABLE III
PERCENTAGE OF CLASSIFICATION FOR EACH TEXTURE FOR VARIOUS VALUES OF ADDITIVE NOISE

Texture	Algorithm	Without noise	SNR 20 dB	SNR 5 dB	SNR 0 dB
Texture 1 	MC1	100%	100%	72%%	54%
	Ond. MC1	100%	96%	100%	80%
	MC5	100%	100%	80%	70%
	MC6	100%	100%	90%	84%
	Ond. MC6	100%	100%	100%	94%
Texture 2 	MC1	100%	100%	100%	98%
	Ond. MC1	100%	100%	98%	84%
	MC5	100%	98%	92%	82%
	MC6	100%	100%	84%	88%
	Ond. MC6	100%	100%	98%	80%
Texture 3 	MC1	86%	90%	84%	52%
	Ond. MC1	98%	98%	100%	96%
	MC5	96%	98%	82%	84%
	MC6	100%	94%	94%	88%
	Ond. MC6	100%	90%	90%	76%
Texture 4 	MC1	84%	62%	18%	4%
	Ond. MC1	100%	100%	94%	78%
	MC5	100%	82%	58%	30%
	MC6	98%	76%	48%	34%
	Ond. MC6	98%	100%	96%	70%
Texture 5 	MC1	100%	98%	100%	98%
	Ond. MC1	98%	100%	92%	66%
	MC5	96%	88%	78%	74%
	MC6	96%	90%	86%	72%
	Ond. MC6	100%	100%	94%	76%
Texture 6 	MC1	98%	98%	82%	88%
	Ond. MC1	100%	100%	100%	96%
	MC5	100%	94%	84%	86%
	MC6	100%	94%	88%	86%
	Ond. MC6	100%	100%	100%	84%
Texture 7 	MC1	100%	100%	100%	94%
	Ond. MC1	98%	98%	96%	74%
	MC5	96%	100%	100%	92%
	MC6	100%	100%	98%	96%
	Ond. MC6	96%	100%	84%	74%
Texture 8 	MC1	90%	86%	72%	72%
	Ond. MC1	100%	100%	100%	96%
	MC5	96%	98%	90%	72%
	MC6	100%	100%	86%	76%
	Ond. MC6	100%	100%	96%	98%
Texture 9 	MC1	100%	94%	100%	78%
	Ond. MC1	100%	100%	100%	92%
	MC5	100%	90%	92%	82%
	MC6	100%	100%	90%	86%
	Ond. MC6	100%	100%	98%	76%
Texture 10 	MC1	84%	88%	62%	58%
	Ond. MC1	100%	100%	100%	98%
	MC5	90%	86%	84%	60%
	MC6	98%	88%	86%	60%
	Ond. MC6	100%	100%	100%	98%
Texture 11 	MC1	84%	80%	64%	38%
	Ond. MC1	100%	100%	100%	98%
	MC5	92%	72%	76%	44%
	MC6	92%	82%	80%	46%
	Ond. MC6	100%	100%	94%	82%
Texture 12 	MC1	80%	70%	56%	24%
	Ond. MC1	100%	100%	100%	88%
	MC5	94%	92%	62%	48%
	MC6	100%	96%	70%	66%
	Ond. MC6	100%	98%	96%	80%
Texture 13 	MC1	66%	46%	42%	22%
	Ond. MC1	100%	100%	98%	58%
	MC5	68%	76%	38%	44%
	MC6	98%	82%	64%	38%
	Ond. MC6	100%	100%	92%	62%
Texture 14 	MC1	96%	96%	88%	84%
	Ond. MC1	88%	96%	74%	54%
	MC5	94%	94%	72%	60%
	MC6	98%	96%	78%	74%
	Ond. MC6	96%	100%	72%	63%
Texture 15 	MC1	94%	82%	42%	38%
	Ond. MC1	100%	100%	100%	80%
	MC5	100%	96%	82%	54%
	MC6	100%	100%	88%	52%
	Ond. MC6	100%	100%	96%	72%
Texture 16 	MC1	98%	96%	84%	66%
	Ond. MC1	92%	92%	80%	44%
	MC5	98%	90%	66%	50%
	MC6	98%	94%	82%	70%
	Ond. MC6	98%	94%	88%	45%