A new schema of Image Compression using wavelet networks

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Abstract

For many years, we have witnessed an increasing growth in the need of numeric pictures (whether stationary or animate) in numerous fields such as telecommunications, multimedia diffusion, medical diagnosis, telesurveillance, meteorology, robotics, etc. However, this type of data represents a huge mass of information that is difficult to transmit and to stock with the current means. Thus, it was necessary to have new techniques that rely on the efficiency of images compression. Recent researches on images compression have shown an increasing interest toward exploiting the power of wavelet transforms and neural networks to improve the compression efficiency.

In this paper, we have chosen to implement a new approach combining both wavelets and neural networks (and called wavelet networks). The results are compared to some classical MLP neural networks techniques and to other schemes of networks depending on the wavelets used in the hidden layer, the number of these wavelets and the number of iterations.

The obtained results perfectly matches the results from the experiments mentioned in the paper, which prove that wavelet networks outperform neural networks in term of both compression ratio and quality of the reconstructed images.

Keywords: *Images compression, Wavelets, Neural networks, Wavelet networks.*

1. Introduction

The fast development of computer applications came with an enormous growth of the use of numeric pictures, notably in the domain of multimedia, games, satellite transmissions or medical imagery.

The representation of the information under numeric shapes fiabilises the transmissions and facilitates their manipulation. However, the transmission and the storage of images or video sequences cause some problems: the digitalization requires that the devices of storage and the widths of the transmission line strips are sufficiently important; the quantities of information to transmit constantly increase. These constraints imply the research of more and more effective algorithms of compression.

The basis idea of images compression is to reduce the middle number of bits by pixel (bpp) necessary to their representation. The images compression techniques can be structured in two methods: lossless and lossy.

Different compression techniques have been studied in the literature, as the techniques by transformation. The compression by transformation consists in decomposing the picture on a basis of orthogonal functions, then to quantify the spectral coefficients with scalar quantization for example. The quantification of the coefficients misleads a loss of information and returns thus the irreversible compression. A binary coding will be applied thereafter to convert information under binary shape. This coding step of quantized data is important because it permits to increase the rate of compression.

The wavelet networks were mentioned for the first time by Zhang [1] and Benveniste [2] in the context of the non parametric regression functions of L2(IR2). In the wavelet networks, the basis radial functions in some RBF-networks are replaced by wavelets.

However, since their introduction in 1992, the wavelet networks (WN) caused little attention in recent publications [15] which used the WNs for signals representation and classification. They explained how a set of WN, "a superwavelet", can be produced and the original ideas presented for the way of which they can be used for the assortment of model. Besides, they mention the big compression of data achieved by such a representation of WN. Zhang [1] proved that the WNs can manipulate the non-linear regression of the moderately big dimension of entry with the data of training.

The remainder of the paper is organized as follows: Section 2 focuses on the presentation of theoretical concepts of wavelet networks. Section 3 emphasizes on the approach of images compression using neural networks (MLP). In section 4, we present another approach of images compression based on neural network using wavelet coefficient decomposition. Section 5 gives an overview of the approach of images compression using wavelet networks. In the last section, we present some results and tables related to the performances of neural and wavelet network approaches.

2. Theoretical concepts of wavelet networks

2.1 Wavelet

To analyze a signal from its graph is far from permitting to reach all information that it contains. It is often necessary to transform it that is to say to give another representation that appears more clearly such or such of its features. The baron Jean Baptiste Joseph Fourier suggested that all functions must be able to express themselves in a simple way like sum of sinus. In "the analytic theory of the heat", Fourier gets the equations to the partial derivatives describing the transfers of heat, and the resolute while developing them in short infinite of trigonometric functions.

The Fourier analysis decomposes the functions as sums of elementary functions. In this case, it is about periodic functions, as functions sinus and cosine. Being given a function f(t), supposed periodic to simplify, that means as f(t+T) = f(t), we have [3]:

$$f(t) = \frac{1}{2} a_0 + a_1 \cos\frac{2\pi t}{T} + b_1 \sin\frac{2\pi t}{T} + a_2 \cos\frac{4\pi t}{T} + b_2 \sin\frac{4\pi t}{T} + \dots \quad (1)$$

However this technique present some limits, in fat [4]:
- The Fourier analysis makes disappear all the information of the temporal domain: the beginning and the end of the signal are not more localizable;
- The frequency associated to a signal is inversely proportional to its period. Therefore, if one wants to get some information on a low-frequency signal, the interval on which one must observe must be big. Inversely, a high frequency signal can be observed on one short time interval. It would be consequently interesting to have a method of analysis that can take in account the frequency of the signal to analyze.

It would be consequently interesting to have a method of analysis leaning on a time-frequency representation: it is the wavelet analysis. This one leans on an approximation of a signal by a superposition of functions.

The wavelet decomposition of function consists in writing it like a pondered sum of functions gotten from simple operations done on a main function named "mother wavelet". These operations consist in translations and dilations. The mother wavelet or the wavelet analyzing presents the following properties [5]:

a) Admissibility

Either a function ψ belonging in L2(R) and TF (ψ) its Fourier transformed satisfying the condition of admissibility if:

$$\int_{-\infty}^{+\infty} \frac{|TF(\psi(\omega))|^2}{|\omega|} d\omega < +\infty \quad (2)$$

b) Localization

Wavelet is a function that must have fast decrease on the two sides of its domain of definition or better it must have a compact support (hopeless outside of finished one interval).

c) Oscillation

(Moment of order 0, or the average is hopeless)

$$\int \psi(t)\, dt = 0 \quad (3)$$

ψ(t) must have an ondulatory character, it changes sign at least once.

d) The Translation and dilatation

The wavelet mother must satisfy the properties of translation and dilatation for what can generate other wavelets.

2.2 Neural Networks

Since some years, the formal neural networks benefit from a large attention on behalf of the scientific community, and the number of study about their case doesn't stop growing.

The first modelling of a neuron dates to the forties. It has been achieved by MacCulloch and Pitt. Being inspired by their works on the biologic neurons, they proposed this model:

A formal neuron receives a number of inputs (x_1, x_2,…, x_n), to each of these inputs is associated a weight w representative of the strength of the connection. The neuron does the pondered sum of its inputs and calculates its outputs by a non linear transformation of this sum [6].

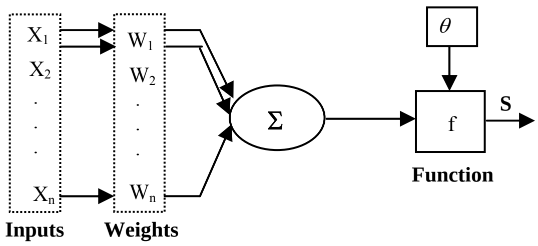

Figure 1. *McCulloch and Pitts Model*

A neural network is a set of connected neurons forming an oriented graph and permitting the exchange of information through connections.

There are different types of neural networks, among which we can mention two categories:
- The model of the Multi - Layers perceptron or known as supervised network because it requires desired output (target) to learn. The input data is presented repeatedly to the neural network, to every presentation the output of the network is compared to the target and an error is calculated. This error is then used to adjust the weights so that the error decreases with every iteration and that the model becomes closer and closer to the reproduction of the target [7].

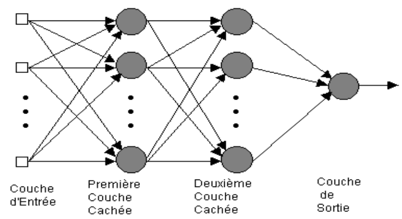

Figure 2. *MLP Model*

- The radial basis function networks possess three layers, which they form a particular class of the Multi - Layers networks. Every neuron of the hidden layer uses a core function (kernel function) as the Gaussian, as function of activation. This function is centred to the specified point by the weight vector associated to the neuron. The position and the "width" of these curves are learned from the bosses. There is, in general, a lot less core functions in a RBF network that of inputs. Every neuron of outputs implements a linear combination of these functions; the idea is to approximate a function by a set of functions. From that point of view, the hidden neurons provide a set of functions that form a basis representing the inputs in the "covered space " by the hidden neurons [7].

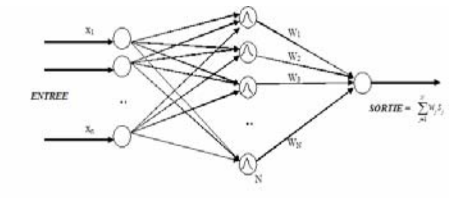

Figure 3. *RBF Neural Network*

2.3 Wavelet Networks

The wavelet networks result from the idea to combine the two approaches wavelets and neural networks. Let's do start with seeing continuous wavelet transformed of the function f that is defined as the scalar product of f and the mother wavelet ψ.

$$W \quad (a,b) = \frac{1}{\sqrt{a}} \int f(x) \quad \psi\left(\frac{x-b}{a}\right) \quad dx \qquad (4)$$

The reconstruction of the function f from its transformed is given by this expression:

$$f(x) = \frac{1}{c_\psi} \int_R \int_{R_+} W(a,b) \quad \frac{1}{\sqrt{a}} \quad \psi\left(\frac{x-b}{a}\right) \quad da \quad db \qquad (5)$$

This relation gives the expression of a function with additional squares under the shape of an integral on all dilatations and all translations of the mother wavelet. Let's do suppose that one only has a finished number Nw of wavelets ψ_{ab} gotten from the mother wavelet ψ. We can consider the relation (6) as an approximation of an inverse transformed.

$$f(x) \approx \sum_{j=1}^{N_w} c_j \ \psi_j(x) \qquad (6)$$

It can also be seen as the decomposition of a function in a pondered sum of wavelets, where each weight cj is proportional with W(aj,bj). It is in this perspective that the idea of wavelet networks has been proposed [10].

This network can be considered like constituted of three layers. A first layer with Ni inputs, a hidden layer constituted by Nw wavelets and an additional (or linear neuron) of output receiving the pondered outputs of wavelets. Both of input layer and output layer are fully connected to hidden layer. The propagation of the values makes itself in the sense feed-forward that means from inputs neurons toward outputs neurons [9].

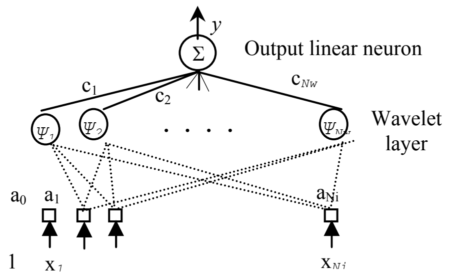

Figure 4. *G*raphic representation of wavelet network

As we saw it, the wavelet networks present certain proximity of architecture with the neural networks, the main resemblance between these two networks resides to the fact that the two networks calculate a linear combination, to adjust parameters, of non linear functions whose shape depends on adjustable parameters (dilatations and translations). But the essential difference between them holds to the nature of the transfer functions used by the hidden cells. Here we will mention these differences:

- Contrary to the functions used in the neural networks, wavelets are functions that decrease quickly, and stretch toward zero in all directions of the space. They are therefore local if has small.

- Contrary to the functions used in the neural networks, the shape of every mono-dimensional wavelet is determined by two adjustable parameters (translation and dilatation) that are wavelet structural parameters.

-Every mono-dimensional wavelet possesses two structural parameters, of where for every multi-dimensional wavelet, the number of adjustable parameters is the double of the number of variables.

3. Images compression using MLP neural networks

As we have already mentioned, the wavelet networks present certain proximity of architecture with the MLPS networks to only one hidden layer. But the essential difference between these two networks holds to the nature of the transfer functions used by the hidden neurons.

We proposed, in a first time to develop a neural network of MLP type, to three layers: input layer, hidden layer and output layer, and that uses the back propagation training algorithm that is permitting to reduce the error committed by the network on the examples of the training basis, while correcting the weights of connection. The steps of our purpose are mentioned [10][11][12]:

1. Divide the original image into m pixel blocks (m=lxl where l is the number of lines or columns of the block) and reshape each one into column vector.
2. Arrange all column vectors (correspondent to every block) in a matrix.
3. Let the target matrix equal to the matrix in step 2.
4. Choose a suitable learning algorithm and define the learning parameters: the number of iterations, the number of hidden neurons as well as the margin of error to start training.
5. Simulate the network by taking the two matrices of inputs and targets.
6. Rebuild the compressed picture.

4. Images compressing using MLP neural networks with wavelets coefficients

We have faced the problem of block effect in the reconstructed picture, especially when we increased the compression rate; it gave us the idea to exploit the interesting results of wavelet transformation in the imagery field. Of this fact, we took for the inputs of our neural network, not the grey levels of the pixels of the picture but their wavelet coefficients decomposition.

We used the same approach described before with the neural networks except that we first applied the wavelet transformed decomposition on the original picture, then, the wavelet coefficients generated following this transformation constituted the input values of our network. Finally, following the training step, we applied inverse wavelet transformed to generate the reconstructed compression picture. An improvement has been observed on the quality of the reconstructed picture.

We applied these two approaches on the Barbara picture (256x256), we got these figures for a compression rate of 75%:

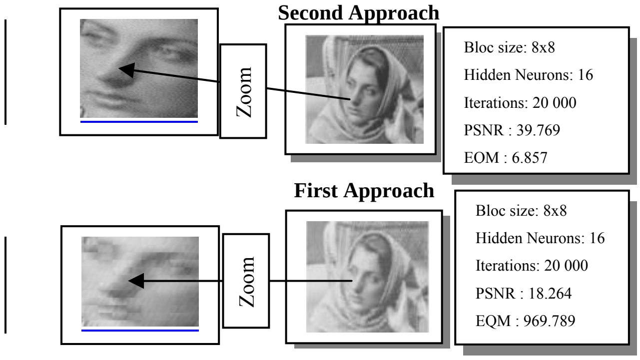

Figure 5. *Reconstructured images with the two approches*

5. Images compression using Wavelet networks

We will want to construct a system taking in input any picture represented in the spatial domain and providing in output the reconstructed picture after its compression by that system.

Our purpose is to use an artificial neural network and more especially a wavelet network. We move to describe the architecture of the network adapted to the problem of pictures compression. The architecture that we propose includes a layer of input neurons, a hidden neuron layer, and a layer of output neurons. Both of input layer and output layer are fully connected to hidden layer. The propagation of the values makes itself in the sense feed-forward that means from inputs toward outputs neurons.

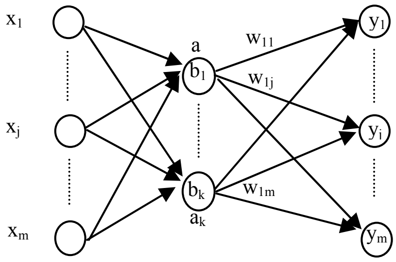

Figure 6. *Wavelet network architecture*

5.1 Principle of the method

Having the picture compression picture, first, it's necessary to segment it while cutting it in a set of blocks of stationary size m which m=lxl (l represents the number of lines or columns of the block). These blocks are used like inputs of our wavelet network. For our purpose three layers feed forward neural network had been used. Input layer with m neurons, these are the m pixels of any block, output layer with m neurons and hidden layer with a number of neurons strictly lower to m implementing used wavelets family. Our network is training in order to reproduce in output the information received in input. We design by X=(x1,….. xm) the input block and by Y=(y1,…..., ym) the output of the network. At the end of the training, we want to have Y=X, for every block presented in the network.

5.2 Training of the network

5.2.1 Training algorithm

We chose to use wavelet networks constructed through a phase of training pairs input/output. During training, the weights, dilatations and translations parameters are iteratively adjusted to minimize the network performance function which is the mean square error for the feed forward networks. We used a quadratic cost function to measure this error. Training aims then to minimize the empiric cost, given by:

$$E = \frac{1}{2}\sum_{t=1}^{T}\left(y_d(t) - y(t)\right)^2 \qquad (7)$$

Where y(t) is the output gotten by the network and yd(t) the desired output.

The expression of the network output is :

$$y(t) = \sum_{k=1}^{K} w_k \cdot \psi_k\left(\frac{t - b_k}{a_k}\right) \qquad (8)$$

In the basic back propagation training algorithm, the weights are moved in the direction of the negative gradient, which is the direction in witch the performance function decreases most rapidly. Iteration of this algorithm can be written as [9]:

$$V_{t+1} = V_t - \varepsilon(t)\frac{\partial E}{\partial V} \qquad (9)$$

where Vt is a vector of current weights, dilatations and translations, e(t) is the step of the pressure gradient to the iteration t.

While putting e(t) = yd(t)–y(t), we will have these formulas of derivation [13]:

$$\frac{\partial E}{\partial \omega_{ij}} = \sum_{t=1}^{T} e(t)\,\psi(\tau) \qquad (10)$$

$$\frac{\partial E}{\partial a_i} = \sum_{t=1}^{T} e(t)\,\omega_{ij}\,\frac{\partial \psi(\tau)}{\partial a_i} \qquad \tau = \frac{t - b_i}{a_i} \qquad (11)$$

$$\frac{\partial E}{\partial b_i} = \sum_{t=1}^{T} e(t)\,\omega_{ij}\,\frac{\partial \psi(\tau)}{\partial b_i} \qquad (12)$$

These formulas permit to use the descent gradient algorithm. For many results presented in this work, the parameters of the wavelet network have being initialized randomly. Finally, the different parameters are updated in accordance with these rules [13][14]:

$$\omega(t+1) = \omega(t) + \mu_\omega \Delta\omega \qquad \Delta\omega = -\frac{\partial E}{\partial \omega} \qquad (13)$$

$$a(t+1) = a(t) + \mu_a \Delta a \qquad \Delta a = -\frac{\partial E}{\partial a} \qquad (14)$$

$$b(t+1) = b(t) + \mu_b \Delta b \qquad \Delta b = -\frac{\partial E}{\partial b} \qquad (15)$$

where μ_w, μ_a, μ_b are the training rates of the three parameters of the network.

5.2.2 Application of the algorithm

The technique of compression enhancement in the setting of this memory is based on the wavelet networks. Back propagation algorithms had been employed for the training processes. The compression starts with the segmentation of the picture in blocks of stationary size (whose value is to choose by the user). The effect of this operation is shown in figure 7. The training of our network makes itself while applying the algorithm of back propagation already seen in the previous paragraph. To do the training input prototypes and target values are necessary to be introduced to the network so that the suitable behaviour of the network could be learned. Our training basis contains the vectors that each one represents a block of the picture. The input values of the network represent the values of intensities of the pixels in the same block; the target values must be equal to those of the inputs.

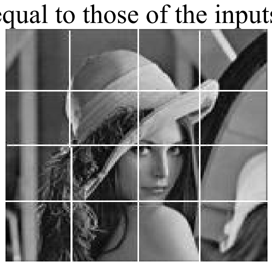

Figure 7. *Segmentation effect*

We will start with initializing randomly the parameters of the network. Thereafter we will start the training process; it requires a set of prototypes and targets to learn the proper network behaviour. During training, the parameters of the network are iteratively adjusted. We can schematize the stages of training by this figure:

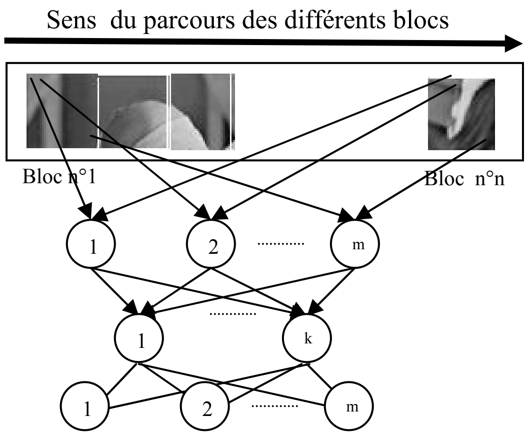

Figure 8. *Representation of training phase*

We will repeat the course of the training basis until the verification of stop criteria that we chose, a maximal number of iterations (iteration is a course of the basis), and this number is also fixed by the programmer.

6. Implementation and results

The presence of distortion in the reconstructed image will be unavailable, in view of that a process was carried through, that it causes loss of constituent elements of the original image. As it is the case in any process of compression. Two general classrooms of criterion are used to evaluate this distortion: the mean square error (EQM) and the peak signal to noise rate (PSNR).

6.1 Comparison between neural and wavelet networks

These first results concern the comparison between the MLP model and the wavelet one. The criteria of comparison are the EQM and the PSNR according to the compression rate. These results are gathered in the table below:

Compression rate	Neural network		MLP & Wavelet coeff.		Wavelet network (Mexican hat)	
	PSNR	*EQM*	*PSNR*	*EQM*	*PSNR*	*EQM*
25%	19.023	814.121	40.568	5.704	42.500	3.656
50%	18.809	855.235	40.402	5.926	40.454	5.855
75%	18.264	969.789	39.769	6.857	38.382	9.437
87.5%	17.659	1114.714	37.917	10.502	23.01	325.101
93.75%	17.095	1269.08	23.117	317.179	18.022	1025.359

Table 1. *Performances MLP/Wavelet Network*

These performances are gotten by the application of the three models of network on the Barbara picture, the conditions of training being identical. We can note according to this picture that the results are in favour of the wavelet model, the performances of the MLP model using wavelet coefficients are near, intermediate between the one of the wavelet model and those of the MLP model. These results show a good behaviour of the models, MLP using the wavelet coefficients and the one of the wavelet network therefore. The following curves present the evolution of the performances in terms of PSNR and EQM according to the compression rate of these three models.

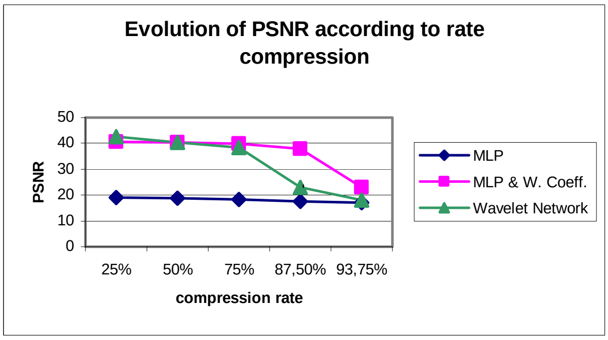

Figure 9. *Evolution of the PSNR according to the compression rate for the three models of networks*

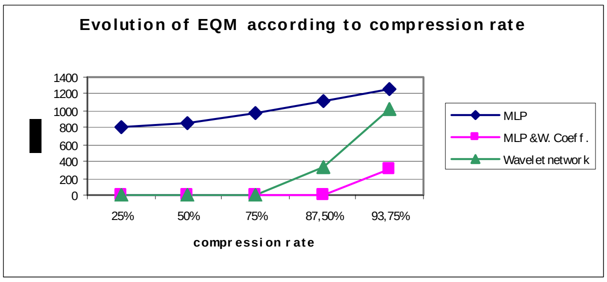

Figure 10. *Evolution of the EQM according to the compression rate for the three models of networks.*

The different gotten results showed that the wavelet networks are more effective when the compression rate is lower to 75%, but less effective when this rate passes this limit. At this moment, the results become in favour of the approach of the MLPS networks using the wavelet coefficients.

Of where, we can noticed the superiority of the models using the wavelet analysis, the model of the wavelet network and the one MLP using the wavelet coefficients.

6.2 Results and discussion

The tests are made on three pictures of the library of Matlab: Barbara, Lena and Belmont1.

The performances of pictures compression are essentially based on these criteria:

-The compression rate

-The quality of the reconstructed picture

These performances depend on several criteria: the wavelet used in the hidden layer; the number of these wavelets ; the number of iterations

In the following part, we try to modify the values of these different parameters, and we observe their effects on the quality of the reconstructed picture. The different obtained results are presented below.

6.2.1 Performances according to the number of wavelets

The following table presents the results of the tests achieved on the Barbara picture for a number of iterations equal to 20.

Wavelet	PSNR	EQM	compression rate
Morlet	40.117	6.329	46.777%
	37.135	12.576	73.388%
	33.706	27.697	86.694%
	32.324	38.075	90.020%
	21.586	451.235	93.347%
Mexican Hat	40.454	5.855	46.777%
	38.382	9.437	73.388%
	23.01	325.101	86.694%
	19.089	801.911	90.020%
	18.022	1025.359	93.347%
Slog1	30.596	56.684	46.777%
	26.951	131.213	73.388%
	21.102	504.432	86.694%
	17.554	1141.862	90.020%
	16.474	1464.341	93.347%
Rasp3	44 .325	2.401	46.777%
	43.206	3.107	73.388%
	30.019	64.734	86.694%
	18.916	834.46	90.020%
	6.257	15393.7	93.347%

Table 2.*Variation of the number of wavelets and effects on the Barbara picture*

The evolution of the PSNR and the EQM according to the number of wavelet of the Barbara picture is presented in these figures:

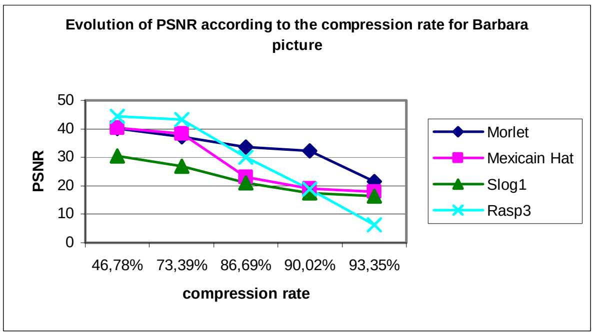

Figure 11.*Evolution of the PSNR according to the compression rate for Barbara picture.*

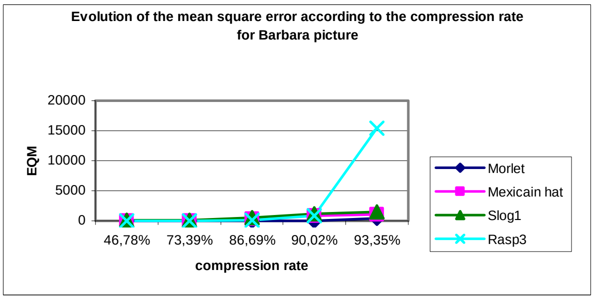

Figure 12.*Evolution of the EQM according to the compression rate for Barbara picture.*

6.2.2 Performances according to the number of iterations

We are going to give here the behaviour of our wavelet network opposite the variation of the number of iterations.

The following performances are gotten on the Barbara picture while setting a compression rate equal to 73.388%

Wavelet	PSNR	EQM	Number of iterations
Morlet	25.537	181.679	3
	27.161	124.993	5
	33.141	31.546	10
	35.269	19.324	15
	37.135	12.576	20
Mexican Hat	14.486	2314.257	3
	17.752	1091.081	5
	19.894	666.262	10
	21.255	487.019	15
	38.382	9.437	20
Slog1	19.459	736,453	3
	20.976	599.644	5
	21.912	418.654	10
	23.787	271.869	15
	43.361	2.672	20
Rasp3	27.095	126.926	3
	31.925	41.738	5
	38.856	8.460	10
	41.774	4.321	15
	43.206	3.107	20

Table 3.*Variation of the number of iterations and effects on the Barbara picture*

The evolution of the PSNR and the EQM according to the number of iterations of the Barbara picture is presented in these figures:

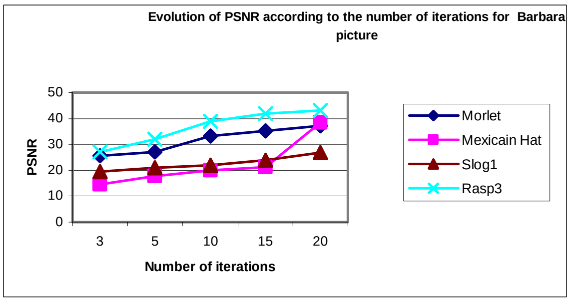

Figure 13.*Evolution of the PSNR according to the number of iterations for Barbara picture.*

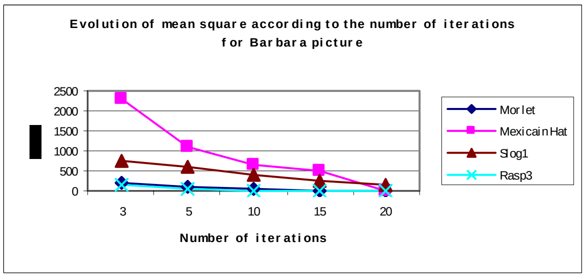

Figure 14.*Evolution of the EQM according to the number of iterations for Barbara picture.*

7. Conclusion

In this paper, we have presented a new schema of images compression based on wavelet networks. Many combinations are made depending on the type and the number of wavelets used. To test the robustness of our approach, we implement and compare the results with some other techniques based neural networks (MLP). These results showed that the wavelet networks performances are satisfactory and competitive. It permits us to situate the wavelet network model, in terms of performances in compression, in relation to previous works, especially for lower rates of compression to 75%.

8. References

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