WCCI 2010 IEEE World Congress on Computational Intelligence
July, 18-23, 2010 - CCIB, Barcelona, Spain IJCNN

FBWN: an architecture of Fast Beta Wavelet Networks for Image Classification

Olfa Jemai*, Mourad Zaied†, Chokri Ben Amar‡ and Adel M. Alimi§
REGIM: REsearch Group on Intelligent Machines
University of Sfax, National Engineering School of Sfax (ENIS), BP 1173, Sfax, 3038, Tunisia

Abstract— **Image classification is an important task in computer vision. In this paper, we propose a supervised method for image classification based on a fast beta wavelet networks (FBWN) model. First, the structure of the wavelet network is detailed. Then, to enhance the performance of wavelet networks, a novel learning algorithm based on the Fast Wavelet Transform (FWTLA) is proposed. It has many advantages compared to other algorithms, in which we solve the problem of the previous works, when the weights of the hidden layer to the output layer are determinate by applying the back propagation algorithm or by direct solution which requires to compute matrix inversion, this may be intensive computation when the learning data is too large. However, the new algorithm is realized by the iterative application of FWT to compute connection weights. In the simulation part, the proposed method is employed to classify images. Comparisons with classical wavelet network classifier are presented and discussed. Results of comparison have shown that the FBWN model performs better than the previously established model in the context of training run time and classification rate.**

I. Introduction

In recent years automatic image classification has been increasingly investigated. The goal of a supervised image classification system is to group images into semantic categories giving thus the opportunity of fast and accurate image search. To achieve this goal, these applications should be able to group a wide variety of unlabelled images by using both the information provided by unlabelled query image as well as the learning databases containing different kind of images labelled by human observers.

Neural Networks have been supplied with an access to the frequency analysis with the introduction of wavelets. A wavelet network has more advantages than common networks, e.g., faster convergence, avoiding local minimum, easy decision and adaptation of structure[1].

Zhang and Benveniste[2], Pati and Krishnaprasad[3] were the first to advance the idea of applying the wavelet into neural network to build the corresponding wavelet neural network. Taking advantages of both the time-frequency zooming property of wavelets and the effective learning mechanism of neural networks, wavelet networks are becoming a powerful tool for many applications [4][5][6][7].

With the development of wavelet networks, many works would be devoted to the learning algorithms. The back-propagation error may be the most popular algorithm in the learning of wavelet networks[2]. In the course of training, the error back-propagation is often combined with Orthogonal Least Square-Backward Elimination[8][9][10][11], which is used in the selection of network structures. At the same time, many algorithms are proposed to initialize the weights[12], accelerate the convergence[13] and adjust the structures of wavelet networks when the error back-propagation is applied to the training algorithms[4]. Other algorithms besides the error back-propagation are also proposed to train the wavelet networks, e.g., Kalman filter[14] and genetic algorithms[15][16][17][18]. These above mentioned algorithms mostly stem from the typical neural networks, so they seldom utilize the excellent properties of wavelets, fully in the frequency domain though they have accelerated convergence, avoided local minimum and overcome overfitting to some extent.

During the past decades wavelet analysis has become a powerful tool for multi-resolution analysis. Important applications can be found in various fields, ranging from remote sensing to biomedical imaging and query by content in large image data bases. Intuitively, wavelet analysis is an ideal approach to the classification of images. Much previous works has proposed to solve the image classification problem[19][20].

In this paper, we propose a new algorithm for the learning of wavelet networks constructed from multiresolution analysis (MRA) by application of Fast wavelet transform (FWT).

The remainder of the paper is organized as follows. Section 2 describes an overview of the proposed approach. Section 3 presents the theory of Beta wavelet. This function will be the heart of the new Fast Beta Wavelet Network (FBWN). Wavelet networks and Fast wavelet transform theory are briefly discussed in Section 4. In Section 5 the proposed learning algorithm based on the fast wavelet transform theory is introduced. Section 6 presents the simulation results of the proposed image classification method and Section 7 closes with a conclusion and discussion on possible enhancements.

II. Overview of the proposed approach

We propose in this paper a complete solution of image classification based on wavelet networks. The solution

*This author is with the Higher Institute of Computer Science of Medenine, University of Gabes, Tunisia (phone: +216 75 641 716;email: olfa.jemai@ieee.org)

†This author is with the National Engineering School of Gabes, University of Gabes, Tunisia (phone: +216 75 392 257 ;email: mourad.zaied@ieee.org)

‡,§These authors are with the National Engineering School of Sfax, University of Sfax, Tunisia (phone: +216 74 274 088;emails: ‡Chokri.benamar@ieee.org,§adel.alimi@ieee.org)

which we present proceeds, at first, by the approximation of the Learning benchmark set by a 2D wavelet networks to produce a compact image signature. It is this signature, constituted by wavelets and their coefficients, which will be used to match a test image with all images in the learning benchmark set. In classification stage (on-line), the test image is projected on the wavelet networks of the learning images and new weights (or coefficients) specific to this image are computed. The family of wavelets remains then unchanged (that of the learning images). Finally, we compare the coefficients of the learning images with the coefficients of the test image by computing euclidian distances $(\min(distance(w_{ij}, w))$ where $i = 1..c, j = 1..n$, c is the number of classes and n the number of learning images in each class). The pipeline of all these stages is illustrated in figure 1.

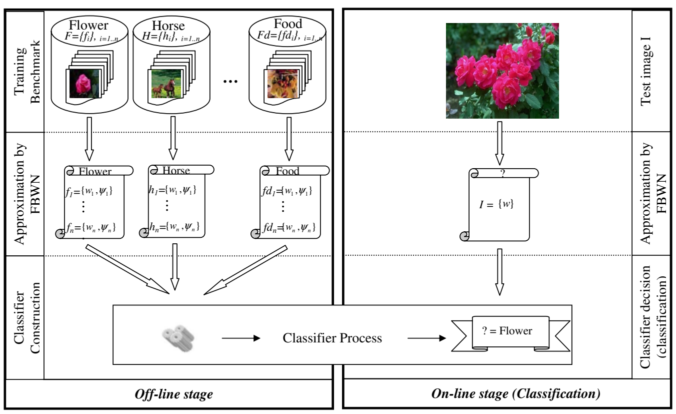

Fig. 1. Complete Framework of image classification by FBWN.

III. The Beta wavelet family

The Beta function is given by Eq.1 [21][22][23][24]:

$$\beta(x,p,q,x_0,x_1) = \begin{cases} (\frac{x-x_0}{x_c-x_0})^p(\frac{x_1-x}{x_1-x_c})^q & \text{if } x \in [x_0,x_1] \\ 0 & \text{otherwise} \end{cases} \tag{1}$$

where $p, q, x_0 < x_1 \in \Re$ and $x_c = \frac{px_1+qx_0}{p+q}$

We have proved in [25][26] that all derivatives of Beta function $\in L^2(\Re)$ and are of class C_∞. The general form of the n^{th} derivative of Beta function is:

$$\begin{aligned} \Psi_n(x) &= \frac{d^n\beta(x)}{dx^n} \\ &= [(-1)^n\frac{n!p}{(x-x_0)^{n+1}} + \frac{n!q}{(x_1-x)^{n+1}}]\beta(x) \\ &+ P_n(x)P_1(x)\beta(x) + \sum_{i=1}^{n} C_n^i[(-1)^n\frac{(n-i)!p}{(x-x_0)^{n+1-i}} \\ &+ \frac{(n-i)!q}{(x_1-x)^{n+1-i}}]P_1(x)\beta(x) \end{aligned} \tag{2}$$

where:

$$\begin{aligned} P_1(x) &= \frac{p}{x-x_0} - \frac{q}{x_1-x} \\ P_n(x) &= (-1)^n\frac{n!p}{(x-x_0)^{n+1}} - \frac{n!q}{(x_1-x)^{n+1}} \end{aligned} \tag{3}$$

If $p = q$, for all $n \in N$ and $0 < n < p$, the functions $\Psi_n(x) = \frac{d^n\beta(x)}{dx^n}$ are wavelets [25][23]. The first, second and third derivatives of Beta wavelet are shown graphically in Fig 2.

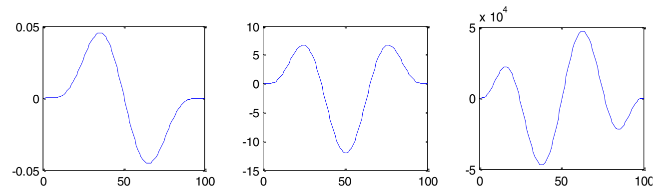

Fig. 2. First, second and third derivatives of Beta function.

IV. Review of wavelet network and wavelet transform

A. The Continuous wavelet transform (CWT)

For a given function $f \in L^2(\Re)$, the continuous wavelet transform is given by:

$$\omega_{a,b} = \frac{1}{\sqrt{|a|}}\int f(t)\psi(\frac{t-b}{a})dt = <\psi_{a,b}, f> \tag{4}$$

The corresponding inverse wavelet transform that rebuilds the function f from its coefficients of wavelets is:

$$f(t) = \frac{1}{C_\psi}\iint \omega_{a,b}\frac{1}{\sqrt{|a|}}\psi(\frac{t-b}{a})\frac{dadb}{a^2} \tag{5}$$

The coefficient C_ψ which is equal to $2\pi\int\frac{\|\tilde{\psi}(\omega)\|^2}{\|\omega\|}d\omega$, known as the admissibility condition must be verified, so that this inverse transform exists:

$$0 < C_\psi < \infty \tag{6}$$

B. The discrete wavelet transform (DWT)

To analyze numerical signals, the CWT seems very redundant, so in this case we must use a set of wavelets generated by considering only a sampled value of a and b parameters. Here, a sampling on a time-frequency grid is adapted in the following manner: $a = a_0^j, b = nb_0a_0^j$ with $a_0 > 1$ and $b_0 > 0$. So for analyzing a signal containing a_0^j points, we use only the family wavelets:

$$\psi(a_0^{-j}t - nb_0) \quad \text{with} \quad j = 1,...m \quad n = 1,...,a_0^{m-j} \tag{7}$$

In the case of DWT, the analyzing wavelets are characterized by two new parameters: the position parameter n and the scale parameter j ($1 \le j \le m$, m represent the number of scales).

$$\omega_{j,n} = \frac{1}{\sqrt{a_0^j}}\sum f(t)\psi(a_0^{-j}t - nb_0) \tag{8}$$

And the inverse wavelet transform is:

$$f(t)=\frac{1}{C_\psi}\sum\sum \omega_{j,n}\frac{1}{\sqrt{a_0^j}}\psi(a_0^{-j}t-nb_0) \quad (9)$$

For the particular case, when $a_0 = 2$, $b_0 = 1$, the sampling is called dyadic.

C. The mutiresolution analysis (MRA)

The multiresolution analysis consists on, firstly, a scaling function $\phi(x) \in L^2(\Re)$ which constitutes an orthonormal basis by varying its position on a given scale j. The functions of every scale generate an approximation of a given signal f to analyze. Secondly, additional functions, i.e. wavelet functions, are then used to encode the difference in information between adjacent approximations[27].

For more details, let's consider $\phi(x)$ a scaling function that engender an orthonormal basis by translation on a space V_j. The approximation of the signal f on V_j is:

$$A_j=\sum_n a_n^j\phi_{j,n} \quad (10)$$

The a_n^j coefficients are computed by applying the scalar products:

$$a_n^j=<f,\phi_{j,n}> \quad (11)$$

An orthogonal complement space W_{j+1} exists and belongs in V_{j+1}, which verifies the following condition:

$$V_{j+1}\subset V_j \Rightarrow V_j=V_{j+1}\oplus W_{j+1} \quad (12)$$

A set of dyadic wavelet functions derived by translations and a same dilations of one mother wavelet exists that engender a basis of W_{j+1}.
The detail of f in W_{j+1} space is given by:

$$D_j=\sum_n d_n^j\psi_{j,n} \quad (13)$$

And the detail coefficients d_n^j are computed by the projection of the signal f on the family wavelets $\psi_{j,n}$:

$$d_n^j=<f,\psi_{j,n}> \quad (14)$$

Since the approximation spaces V_j are nested, the approximation signal A_j can be analyzed several times in a multiresolution scales. At a given scale j, the signal f can be written as:

$$f=\sum_k a_k^j\phi_{j,k}+\sum_i^j\sum_k d_k^i\psi_{i,k} \qquad \text{with} \quad j\le m \quad (15)$$

The analysis can be iterated until the last scales, so f can be written:

$$f=A_n+D_n+\cdots+D_2+D_1 \quad (16)$$

In general, when the $\phi_{j,n}$ constitutes a non orthogonal basis, it is necessary to compute first the duals basis composed by the functions $\tilde{\phi}_{j,n}$ of the scaling functions $\phi_{j,n}$ to be able to calculate the a_n^j coefficients. A dual basis of a set of functions can be computed by [28]:

$$\tilde{\phi}_j=\sum_{i=1}^N(\Phi)_{j,i}^{-1}\phi_i \qquad \text{with } \Phi_{j,i}=<\phi_j,\phi_i> \quad (17)$$

The approximation of f at the scale j and the position n is obtained by:

$$a_n^j=<f,\tilde{\phi}_{j,n}> \quad (18)$$

We can compute the dual family of wavelets and compute the detail coefficients using the same principle:

$$d_n^j=<f,\tilde{\psi}_{j,n}> \quad (19)$$

The following figures represent the decomposition steps of signal f using dual wavelets and scaling functions $(\tilde{\psi}_j,\tilde{\phi}_j)$ and the reconstitution steps with primal wavelets and scaling functions (ψ_j,ϕ_j):

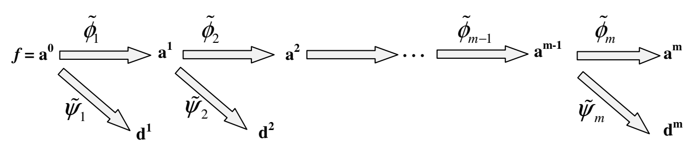

Fig. 3. Multiresolution analysis of a signal f.

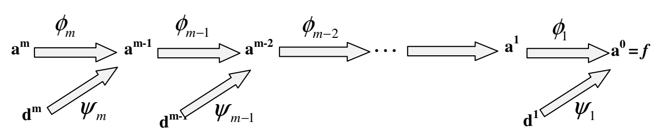

Fig. 4. Reconstitution of the signal f using all the details and the last approximation.

D. Wavelet Network

In 1992, Zhang and Benveniste introduced a new theory called "Wavelet networks" using a combination of artificial neural networks based on radial basis function and wavelet decomposition. In addition, they explained how a Wavelet networks can be generated and showed how they can be used for pattern matching.

Firstly, wavelet network is defined by pondering a set of wavelets dilated and translated from one mother wavelet with weight values to approximate a given signal f.

$$\tilde{f}=\sum_{i=1}^n\omega_i\psi_i \quad (20)$$

The corresponding architecture is:

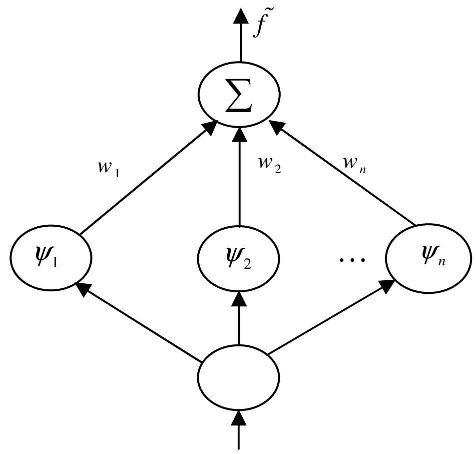

Fig. 5. Wavelet network.

This architecture can be extended by adding some dilated and translated versions of the scaling function of the corresponding used wavelet in the hidden layer of the network. In this case, the approximation of the signal is:

$$\tilde{f} = \sum_{i=1}^{p} \omega_i \psi_i + \sum_{j=1}^{q} \nu_j \phi_j \tag{21}$$

A neural representation of this type of wavelet network is shown in the figure 6:

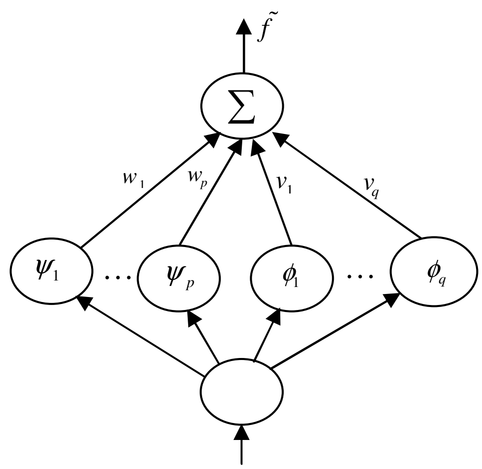

Fig. 6. Wavelet network scaling and wavelet functions based.

In the section 5, we will propose a rapid method to calculate the connection weights of wavelet networks. Our method is based on the Fast Wavelet Transform (FWT), in what follows, we will review some of the relevant FWT theories, and then we will detail our proposed learning algorithm.

E. The Fast Wavelet Transform (FWT)

The FWT aims to give a simple way to handle the multiresolution analysis, in other words with the FWT we want to compute the approximation coefficients a_n^j (Equation 18) and the detail coefficients d_n^j (Equation 19) with other techniques, simpler and easier than those which are based on projection on the dual basis.

Bearing in mind that the approximation spaces V_j are nested, and in particular for V_1 and V_0, we have $V_1 \subset V_0$, for every scaling function ϕ belonging to V_1 we get the following formula:

$$\phi(x) = \sum_n h\,[n]\,\phi_{0,n}(x) \qquad \text{with } \; h\,[n] = <\phi(x), \phi_{0,n}(x)> \tag{22}$$

The projection of f on V_{j+1} can be computed using its projection on V_j with the formula[29]:

$$a_n^{j+1} = \sum_k h\,[k]\,a_k^j \tag{23}$$

With the equation (23) we computed the approximation coefficients of the scale $j+1$ using the approximation coefficients of the scale j and the low-pass filter h.

Also for the corresponding wavelet $\psi \in W_1$ of the scaling function ϕ we have $W_1 \subset V_0$, so we can decompose it on V_0:

$$\psi(x) = \sum_n g[n]\phi_{0,n}(x) \tag{24}$$

We can see that the detail coefficients of the scale $j+1$ can be computed using the approximation coefficients of the scale j.

$$d_n^{j+1} = \sum_k g[k] a_k^j \tag{25}$$

h (Eq. 23) and g (Eq. 25) are known as the scaling function filter and the wavelet filter repectively.

Now we can apply the MRA using only h and g filters and her duals filters for the reconstruction and the decomposition steps respectively.

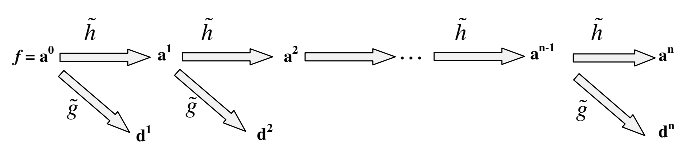

Fig. 7. Multiresolution decomposition of a signal f using dual filter bank.

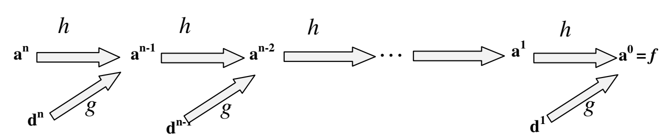

Fig. 8. Reconstitution of the signal f using primal filter bank.

In order to fasten the calculation of the approximation and the detail coefficients, rapid algorithms for decomposition and reconstitution using filter bank are invented. Known by FWT, those algorithms decrease enormously the consumed time of decomposition and reconstitution steps. This figure presents the principle of the FWT.

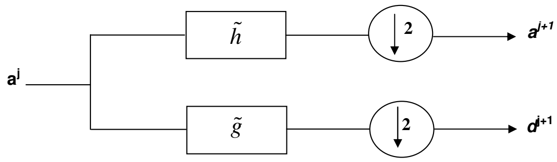

Fig. 9. Rapid decomposition with filter bank.

To get an approximation of the signal f at a scale $j+1$, the approximation a^j at the scale j is convoluted by the dual filter $\tilde{h}$. As such, the obtained signal is decimated by 2 (the coefficients with odd index are eliminated) to get the approximation coefficients a^{j+1}. The same steps are repeated using the dual filter $\tilde{g}$ instead of $\tilde{h}$ to get the details coefficients d^{j+1}.

As we mentioned above, the approximation signal at the scale $j+1$ can also be analyzed, so we can apply the same algorithm to get a^{j+2} and d^{j+2} coefficients. The process can be iterated to analyze the signal at finer scales.

A rapid inverse algorithm to reconstruct the approximation signal at scale j exists, using the coefficients a^{j+1} and d^{j+1}. In this study, we have used the FWT to achieve the decomposition process of a given signal, and the inverse wavelet transform (Eq. 15) to reconstruct it.

V. Learning Wavelet Network using FWT

In this section we will show how we can learn a Wavelet Network using only the FWT technique.

A. Proposed learning algorithm

Step 1:Start the learning by preparing a library of candidate wavelets and scaling functions[30][31]. This step Includes the following items:

1) Choose the mother wavelet covering all the support of the signal to analyze.
2) Build a library that contains wavelets and scaling functions to be used.

Let's nominate those functions g_l with $l = 1 \cdots L$.
Step 2:Set as a stop learning condition, an error E between the signal f and the output of the network.
Step 3:Set a signal s equal to the signal f to be learned and initialize the output network to $\tilde{f} = 0$.
Step 4:Compute the coefficients α_l corresponding to the g_l functions of the library by applying a series of FWT to the signal s using the dual set ($\tilde{h}$,$\tilde{g}$) filters. s can be written :

$$s = \sum_{l=1}^{L} \alpha_l g_l \tag{26}$$

Step 5: Compute the contribution $\alpha_l g_l$ of all the activation functions in the library to reconstruct the signal s.
Step 6:Select from the library a function. This function g_k(k is the number of the selected function) contributes the most to the reconstruction of the signal s.
Step 7:Optimize the dilation and the position parameters of the g_k function to better approximate the signal s and improve the accuracy of the output network.
Step 8:Compute the corresponding weight α'_k(introduced in section E) of the optimized function g'_k of g_k doesn't belong any more to the library.
Step 9:Add the function g'_k to the hidden layer of the network that approximate f and set its corresponding weight to α'_k. The output of the network is $\tilde{f} = \tilde{f} + \alpha'_k g'_k$
Step 10:Compute the residual signal $s = f - \tilde{f}$ and return to the Step 4 if you didn't come to the end of the learning.

B. Creation of the library of wavelets and scaling functions

To construct the library of wavelets and scaling functions candidate to join our wavelet network, a sampling on a dyadic grid of dilation and translation parameters is proceded.

If the length of the signal f is equal to L, this sampling gives in the first scale $L/2$ wavelets. Every time that we climb a scale, the number of wavelets is divided by two. We can stop the sampling at any scale k with $k \leq m$(Eq. 7) but we must complete the library by the corresponding scaling functions of the last scale. The number of functions in this library is equal to L.

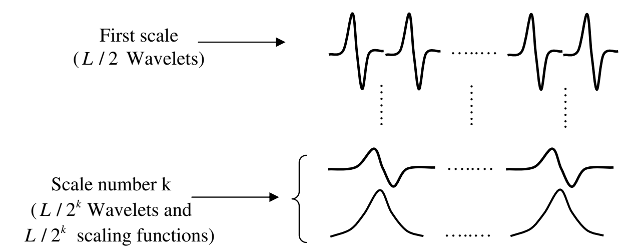

Fig. 10. The library wavelets and scaling functions after k MRA scales.

C. Calculation of the weights

To compute the weights corresponding to the activation functions that belong to the library, we analyze k(k is the number of the scales) times the signal f with the dual filters($\tilde{h}$,$\tilde{g}$) of the scaling function $\tilde{\phi}$ and the wavelet $\tilde{\psi}$. The result is a sum of signals d^i corresponding to the weights of the wavelets of the scales i ($i = 1 \cdots k$) and the weights a^k of the scaling functions of the scale k.

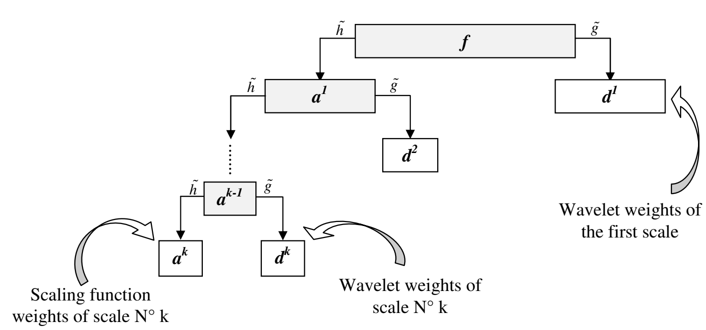

Fig. 11. The calculation process of the weights.

D. Optimization of the function nodes

To increase the efficiency of the network, we optimize the selected function g_k of the step 6 using Levenberg-Marquardt method. Indeed, the parameters of this function are used as initialization of this algorithm. The result is a function g'_k that performs better the output of the network and approximates the best the residual signal s.

At a given iteration k, to get the activation function g'_k, we optimize the dilation parameter a and the position parameter b of the function g_k by minimizing the function:

$$E_k = \min_{a,b}\left(\sqrt{(f - \sum_{i=1}^{k-1} \alpha_i g_i - \alpha_k g_k)^2}\right) \quad (27)$$

E. Computing the corresponding weight of the optimized function

When we select and optimize a function from the library of the wavelet and the scaling functions to use it in the hidden wavelet network layer, we compute its corresponding weight by the flowing way:

1) We have

$$s = \alpha_1 g_1 + \cdots + \alpha_k g_k + \cdots + \alpha_L g_L \quad (28)$$

2) We decompose by FWT the signal g'_k

$$g'_k = \gamma_1 g_1 + \cdots + \gamma_k g_k + \cdots + \gamma_L g_L \quad (29)$$

3) Because $\gamma_k \neq 0$ we can write

$$g_k = \frac{1}{\gamma_k} g'_k - \frac{\gamma_1}{\gamma_k} g_1 - \cdots - \frac{\gamma_L}{\gamma_k} g_L \quad (30)$$

In the equation (28) we replace g_k by the equation (30)

$$\begin{aligned} s &= \alpha_1 g_1 + \cdots + \alpha_k\left(\frac{1}{\gamma_k} g'_k - \frac{\gamma_1}{\gamma_k} g_1 - \cdots - \right. \\ &\quad \left. \frac{\gamma_{k-1}}{\gamma_k} g_{k-1} - \frac{\gamma_{k+1}}{\gamma_k} g_{k+1} - \cdots - \frac{\gamma_L}{\gamma_k} g_L\right) \\ &\quad + \cdots + \alpha_L g_L \\ &= (\alpha_1 - \alpha_k \frac{\gamma_1}{\gamma_k}) g_1 + \cdots + \frac{\alpha_k}{\gamma_k} g'_k + \cdots + \\ &\quad (\alpha_L - \alpha_k \frac{\gamma_L}{\gamma_k}) g_L \end{aligned} \quad (31)$$

We deduce the weight α'_k of the activation function g'_k

$$\alpha'_k = \frac{\alpha_k}{\gamma_k} \quad (32)$$

VI. Experiment and Results

We have performed experiments on different well known datasets. These results are analyzed by evaluating global classification rates. The first database is the Zurich Building Database(ZuBuD)[32] consists of images of 201 buildings captured from five different viewpoints in Zurich city and 115 test images taken from different viewpoints under varying lightening conditions. This database is widely used for classification. To give an impression of the data, some example images are depicted in Fig. 12. The second one is extracted from the SIMPLICITY database[33] and is divided into a learning dataset of 250 images and a test dataset of 250 images. There are five clusters: beaches, buses, dinosaurs, flowers and horses as shown on Fig. 13.

Fig. 12. Images from the ZuBuD database.

Fig. 13. Images from the Simplicity database.

The classification results shown in Table I are conducted by FBWN model using beta wavelets as activation functions and the associate filter banks that are synthesized in [34] [35]. In this paper we use only the first derivative of Beta function to illustrate the proposed design procedure and exhibit its performance.

TABLE I
Classification results for test images collection

Data Set	Classes	Classification rate(%)	Train time(s)	Test time(s)
ZuBuD	201	93.91	0.1585	0.0942
Samples Simplicity	5	84	0.1176	0.0627

The confusion matrix gives the number of images of class X that have been classified in class Y by FBWN when using the samples of Simplicity data set is displayed :

TABLE II
Confusion matrix for the samples of Simplicity data set

Classified as	Beach	Buses	Dinosaurs	Flowers	Horses
Beach	47	0	0	1	2
Buses	22	14	0	2	12
Dinosaurs	0	0	50	0	0
Flowers	0	0	0	50	0
Horses	1	0	0	0	49

To verify the learning capabilities of the proposed method, Table III compare our FBWN model with the classical Beta Wavelet Network (BWN) model[36][37][38][31].

TABLE III
Comparison results for Samples of Simplicity data set

Classification Model	Classification rate(%)	Train time	Test time
BWN	60.2	$20mn$	$2mn$
FBWN(our approach)	84	$0.1176s$	$0.0627s$

Results of comparison have shown that the FBWN model performs better than the classical BWN model in the context of training run time and classification rate.

Comparison of the Proposed Classifier to Popular Methods in the Literature

The performance of the proposed wavelet network trained using Fast Wavelet Transform Learning Algorithm(FWTLA) has been illustrated by comparing with other classifiers reported in the literature. We have carried out experiments on the Zurich Building Database(ZuBuD)[32].

The mother wavelet used in our work is the first derived of the Beta function [39][40][41][42][43]. The optimisation of the parameters of our wavelet network (in step 7 of the learning algorithm) are computed according to the Levenberg-Marquardt method [44]. The following simulations will describe the results of the new wavelet network performance employing Beta mother wavelets. The performance comparison with other learning algorithms reported in Maree[45] is studied.

Information about the maximal reported classification accuracy for this benchmark data set is used to compare with actual measured values using the proposed FWTLA algorithm. One motivation for determining comparative performance across a set of different learning algorithms is to assess whether any particular algorithm demonstrates a significant advantage over the others.

Table IV compare classification rates obtained with different categories of classifier. About five papers have so far reported results on this dataset that vary from a 40,86% classification rate to 100% [45]. The first row give results obtained with decision trees with random subwindows. The second row give results obtained in [46] where invariant regions where used. The next two lines show results where compact DCT based local representations were used [47] and where a combination of four invariant feature histograms with monomial kernel used in [47]. The remaining line report our results.

TABLE IV

COMPARISON OF DIFFERENT CLASSIFIERS

Classification Model	Classification rate(%)
RW+R.Forests[45]	$95,65$
Inv. Reg.[46]	$40,86$
Local DCT repr.[47]	100
$w_m \in \{0,...,10\}$[47]	$89,6$
FBWN(our approach)	$93,91$

Our comparison shows that this general and conceptually simple framework yields good results for image classification.

VII. CONCLUSIONS

This paper proposes a novel wavelet network architecture which can overcome the structural redundancy and bring the scale of calculation into the effective control, so it not only effectively improves the generalization performance of the network but also has the faster learning capacity than the existing wavelet network architecture. This architecture is properly applied to the image classification fields. Based on the experiment results, the proposed approach exhibits high classification rates and small computing times. Although the proposed method, for the second database test has dealt with five-category database, it can be straightforwardly extended to deal with database of higher number of categories.

ACKNOWLEDGMENT

The authors would like to acknowledge the financial support of this work by grants from General Direction of Scientific Research (DGRST), Tunisia, under the ARUB program.

REFERENCES

[1] L. Chunguang, W. Peng, E. Javier, *Complex-valued wavelet network*, J. Comput. System Sci., 67 (3) (2003) 623-632.

[2] Q. Zhang and A. Benveniste, "Wavelet network". *IEEE Trans.Neural Network*, Vol.3,pp.889-898, Nov 1992.

[3] Y. C. Pati and P. S. Krishnaprasad, "Analysis and synthesis of feed-forward neural networks using discrete affine wavelet transformations". *IEEE Trans. Neural Networks*, Vol.4, pp.73-85, Jan.1993.

[4] C. Ben Amar and O. Jemai, *Wavelet Networks Approach-based Image Compression*, ICGST International Journal on Graphics, Vision and Image Processing, Vol. SI1, pp. 37-45, May 2005.

[5] R. K. H. Galvao, Takashi Yoneyama, "A Competitive Wavelet Network for Signal Clustering". *IEEE Trans.Systems,Man,And Cybernetics-Part B:Cybernetics*, vol.34, pp.1282-1288, April 2004

[6] M. Masmoudi, M. Samet and A.M. Alimi, *A bipolar implementation of the Beta neuron*, International Journal of Electronics, Volume 87, Issue 6, June 2000, Pages 675-682

[7] S. Postalcioglu, Y. Becerikli, *Wavelet networks for nonlinear system modeling*. Neural Comput. Applic., vol.16, pp:433-441,2007

[8] W. Bellil, M. Othmani, C. Ben Amar, "Initialization by Selection for multi library wavelet neural network training", *Proceeding of the 3rd international workshop on artificial neural networks and intelligent information processing ANNIIP07, in conjunction with 4th international conference on informatics in control, automation and robotics, ICINCO*, p. 30-37, 2007.

[9] M. Othmani, W. Bellil and C. Ben Amar, "3D Object Modelling using Multi-mother Wavelet Network", *International Conference on Neural Computation*, Madeira Portugal, October 5-7, 2009.

[10] M. Othmani, W. Bellil, C. Ben Amar and A. M. Alimi, *A New Structure and Training Procedure for Multi-Mother Wavelet Networks*, International Journal of Wavelets, Multiresolution and Information Processing, IJWMIP, vol. 8, issue 1, 2010, pp. 149-175.

[11] Q. Zhang, "Using wavelet network in non parameters estimation", *IEEE Trans. Neural Networks*, 8 (1997) 227-236.

[12] Y. Oussar, G. Dreyfus, *Initialization by selection for wavelet network training*, Neurocomputing, 34 (2002) 131-143.

[13] X. Jinhua, W.C. Ho. Daniel, "A constructive algorithm for wavelet neural networks", *First International Conference on Natural Computation*, Changsha, China, 2005, pp. 730-739.

[14] S. Qingmei, G. Yongchao, "A stepwise updating algorithm for multiresolution wavelet neural networks", in *Proceedings of the International Conference on Wavelet Analysis and Its Applications (WAA)*, Chongqing, China, 2003, pp. 633-638.

[15] C. Aouiti, A.M. Alimi, F. Karray and A. Maalej, "A hierarchical genetic algorithm for the design of beta basis function neural network", *Proceedings of the International Joint Conference on Neural Networks*, Volume 2, 2002, Pages 1246-1251.

[16] C. Aouiti, A.M. Alimi, F. Karray and A. Maalej, A genetic-designed beta basis function neural network for multi-variable functions approximation, *Systems Analysis Modelling Simulation*, Volume 42, Issue 7, 1 January 2002, Pages 975-1009.

[17] L. ChangGyoon, K. Kangchui, K. Eungkon, "Modeling for an adaptive wavelet network parameter learning using genetic algorithms," *Proceedings of the Fifteenth IASTED International Conference on Modeling and Simulation*, CA, USA, 2004, pp. 55-59.

[18] I. Kallel, M. Jmaiel and A.M. Alimi, "A multi-agent approach for genetic algorithm implementation", *Proceedings of the IEEE International Conference on Systems, Man and Cybernetics*, Volume 7, 2002, Pages 358-363.

[19] Z. Zhiguo, *Learning algorithm of wavelet network based on sampling theory*, Neurocomputing 71 (2007), 244-269.

[20] Z. Zhiguo, *Iterative algorithm of wavelet network learning from non uniform data*. Neurocomputing 72 (2009) 2979-2999.

[21] A.M. Alimi, *The Bta-Based Neuro-Fuzzy System: Genesis and Main Properties*, TASK Quarterly Journal, Special Issue on Neural Networks edited by W. Duch and D. Rutkowska, vol. 7, no. 1, pp. 23-41, 2003.

[22] M. Kherallah, L. Haddad, A.M. Alimi, A.M. and A. Mitiche, *On-line handwritten digit recognition based on trajectory and velocity modeling*, Pattern Recognition Letters, Volume 29, Issue 5, 1 April 2008, Pages 580-594

[23] M. Zaied, C. Ben Amar and A.M. Alimi, "Award a New Wavelet Based Beta Function", *Second International Conference on SIGNALS, SYSTEMS, DECISION and information technology IEEE, SSD'03*,pages 185-191, Sousse-Tunisia Mars 2003.

[24] M. Zaied, C. Ben Amar and A.M. Alimi, *Beta Wavelet Networks for Face Recognition*, Journal Of Decision Systems JDS, Lavoisier 2005 Edition, Vol. 14, N. 1-2/2005, pages 109-122. 2005.

[25] W. Bellil, C. Ben Amar and A.M. Alimi, "Bta Wavelet Based Image Compression", *International Conference on Signal, System and Design, SSD03*, Tunisia, vol. 1, pp. 77-82, Mars, 2003.

[26] W. Bellil, C. Ben Amar, M. Zaied and A.M. Alimi, "La fonction Bta et ses drives : vers une nouvelle famille d'ondelettes", *First International Conference on Signal, System and Design, SCS'04*, Tunisia, Mars, vol. 1,p. 201-207, 2004.

[27] Y. Meyer, *Ondelettes et oprateurs. I*, Actualits Mathmatiques. [Current Mathematical Topics]. Hermann, Paris, 1990.

[28] Y. Meyer, *Ondelettes et oprateurs. II*, Actualits Mathmatiques. [Current Mathematical Topics]. Hermann, Paris, 1990.

[29] M. Misiti, Y. Misiti, G. Oppenheim and J. Poggi, *Matlab Wavelet ToolBox*, The MathWorks Inc., 2000.

[30] R. Ejbali, Y. Benayed, M. Zaied, A.M. Alimi, "Wavelet Networks for phonemes Recognition", *International Conference on Systems and Information Processing CSPA'09*, May 02-04, 2009 , Guelma-Algeria.

[31] M. Zaied,O. Jemai and C. Ben Amar, Training of the Beta wavelet networks by the frames theory: Application to face recognition, *The international Workshops on Image Processing Theory, Tools and Applications*, Tunisia November 2008.

[32] H. Shao, T. Svoboda, and L. V. Gool, ZuBuD - Zurich Buildings Database for Image Based Recognition, April 2003. [Online]. Available: http://www.vision.ee.ethz.ch/showroom/zubud/

[33] J. Z. Wang , J. Li and G. Wiederhold, SIMPLIcity: Semanticssensitive Integrated Matching for Picture LIbraries, *IEEE Trans. on Pattern Analysis and Machine Intelligence*, vol.23, no. 9, pp. 947-963, 2001.

[34] C. Ben Amar, M. Zaied and M. A. Alimi, *Beta wavelets. Synthesis and application to lossy image compression*, Journal of Advances in Engineering Software, Elsevier Edition, Vol. 36, N7, pages 459 - 474. 2005.

[35] W. Bellil, C. Ben Amar and M.A Alimi, "Synthesis of wavelet filters using wavelet neural networks", *Transactions on Engineering, Computation and Technology*, vol. 13 . ISSN 1305-5313, pp 108-111, 2006.

[36] O. Jemai, M. Zaied, C. Ben Amar and A.M. Alimi, *Pyramidal hybrid approach: wavelet network with OLS algorithm based-image classification*, International Journal of Wavelets, Multiresolution and Information Processing, December 2009.

[37] S. Said, B. Ben Amor, M. Zaied, C. Ben Amar and M. Daoudi, "Vers une Reconnaissance Faciale 3D Robuste aux Expressions utilisant les Rseaux d'Ondelettes", *sixime dition des ateliers de travail sur le traitement et l'analyse de l'information TAIMA'09*, pages 23-28, Mai 2009, Hammamet-Tunisie

[38] S. Said, B. Ben Amor, M. Zaied, C. Ben Amar and M. Daoudi, "Fast and efficient 3D face recognition using wavelet networks", *16th IEEE International Conference on Image Processing*. pp. 4153-4156, 2009.

[39] C. Ben Amar, W. Bellil, M.A. Alimi, "Beta Function and its Derivatives: A New Wavelet Family", *Transactions on Systems, Signals and Devices*, Vol.1, Number 3, p.275-293, 2005-2006.

[40] W. Bellil, C. Ben Amar C. And A.M. Alimi, "Beta wavelets networks for function approximation", *International Conference on Adaptative and Natural Computing Algorithms, ICANNGA05*, Coimbra Portugal, SpringerWien NewYork, p. 18-21, 2005.

[41] W. Bellil, C. Ben Amar and A.M. Alimi, "Comparison between beta Wavelets neural networks, RBF neural networks and polynomial approximation for 1D, 2D functions approximation", *Transactions on Engineering, Computation and Technology*, vol. 13 . ISSN 1305-5313, p. 102-107, 2006.

[42] W. Bellil, C. Ben Amar C. and A.M. Alimi, "Multi Library Wavelet Neural Network for lossless image compression", *International Review on Computers and Software (IRECOS)*, Vol. 2 N. 5, ISSN 1828-6003, p. 520-526, September 2007.

[43] M. Zaied, C. Ben Amar, "Reconnaissances de visages par rseaux d'ondelettes Bta bi-ortogonales", *cinquime dition des ateliers de travail sur le traitement et l'analyse de l'information TAIMA'07*, pages 47-53, 23-27 mai 2007, Hammamet-Tunisie.

[44] Gler and all, *Recurrent neural networks employing Lyapunov exponents for EEG signals classification*, Expert systems with applications, 29: 506-514, 2005.

[45] R. Mare, *Classification automatique d'images par arbres de dcision*, Phd. thesis, Department of Electrical Engineering and Computer Science, University of Lige, February 2005.

[46] H. Shao, T. Svoboda, V. Ferrari, T. Tuyelaars and L. Van Gool, "Fast indexing for image retrieval based on local appearance with re-ranking", *In Proc. IEEE International Conference on Image Processing (ICIP 2003)*, September 2003.

[47] T. Deselaers, D. Keysers and H. Ney, "Features for Image Retrieval: A Quantitative Comparison", *In Proc.26th DAGM symposium on Pattern Recognition (DAGM 2004)*, Vol. LNCS 3175, pages:228-236, August/September 2004.