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Image Reconstruction Using Multi-activation Wavelet Network

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Abstract: Wavelet networks (WNs) are introduced recently as a combination of artificial neural networks (RPROP) and wavelet decomposition. These are found very useful for time scale representation and widely used in signal processing and computer vision. In this paper an algorithm is proposed for images reconstruction with lost blocks or uncompleted parts or missing segments. The proposed algorithm of image reconstruction is based on wavelet and resilient back propagation neural network in different segmentation types. It is applied for missing segment of texture images through the combination of the missing parts. The results of reconstruction outperform the existing conventional method.

Key words:

INTRODUCTION

Computer imaging can be defined as the acquisition and processing of visual information by computer. The important of computer imaging is derived from the fact that our primary sense is our visual sense, and the information that can be convened in images has been known throughout the centuries to be extraordinary one picture is worth a thousand words (Starck, 1998).

Fortunately, this is the case because the computer representation of an image requires the equivalent of many thousands of words of data. Without such amount of information, the medium would be prohibitively inefficient. The massive amount of data required for images is a primary reason for the development of many sub areas within the field of computer imaging, such as image compression and segmentation. Another important aspect of computer imaging involves the ultimate "receiver" of visual information –in some cases the human visual system and in others the computer itself. This distinction allows us to separate the field of computer imaging into primary categories, which are:

1. Computer vision
2. Image processing

In computer vision, application the processed (output) images are for use by a computer, whereas in image processing application the output images are for human consumption. The major topic within the field of image processing includes image restoration, image enhancement, and image compression (Umbaugh, 1998; Volker Krüger, 2001).

Rane proposed a method of Wavelet-Domain Reconstruction of Lost Blocks in Wireless Image Transmission and Packet-Switched Networks (Shantanu D. Rane, 2004). A fast scheme for wavelet-domain interpolation of lost image blocks in wireless image transmission is presented in this paper. In the transmission of block-coded images, fading in wireless channels and congestion in packet-switched networks can cause entire blocks to be lost. Instead of using common retransmission query protocols, the lost block was reconstructed in the wavelet-domain using the correlation between the lost block and its neighbors. The algorithm first uses a simple method to determine the presence or absence of edges in the lost block. This is followed by an interpolation scheme, designed to minimize the blackness effect, while preserving the edges or texture in the interior of the block. The interpolation scheme minimizes the square of the error between the border coefficients of the lost block and those of its neighbors, at each transform scale. The performance of the algorithm on standard test images needs low computational overhead at the decoder, however its performance in comparison with other known reconstruction schemes was comparable.

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Al-Zubaidi (Dahi A., 2005) was proposed an algorithm for image reconstruction using multiwavelet transforms in his work on old Iraqi damaged civilization images. He was claimed a better performance than that reported by Rane. However, it needs much more computation complexity and much more time.

A series of experimental tests and evaluation of the results of using the WN in several application of reconstruction were achieved. In addition to the properties of WN in data reduction, representation and optimization, these all highlighted their advantages for image representation. Hence, this paper exploit the efficiency of data reduction of WN and its optimized filter bank principle in the reconstruction of lost blocks during image transmission.

Liu (1999) due to the 'soft-field' nature of electrical capacitance tomography, it is necessary to employ an iterative approach for image reconstruction in order to obtain good-quality images. In an iterative algorithm it is important to determine the gain factor the optimal step length is derived for an iterative algorithm.

Zhang (2007), in this paper the noise suppression with the help of a wavelet transform in synthesis imaging is presented. The method has been used to treat dirty maps observed with the Miyun Synthesis Radio Telescope (MSRT), and the results indicate that the de-noising with the help of the wavelet transform is satisfactory and prospective.

2. Historical Review of Wavelet Network Transform:

Wavelet networks (WNs) were introduced in 1992 as (Volker Krüger, 2001) a combination of artificial neural radial basis function (RBF) networks and wavelet decomposition. Since then, however, WNs have received only little attention. The potential of WNs has been generally underestimated. WNs have the advantage, that the wavelet coefficients are directly related to the image data through the wavelet transform. In addition, the parameters of the wavelets in the WNs are subject to optimization, which results in a direct relation between the represented function and the optimized wavelets, leading to considerable data reduction (thus making subsequent algorithms much more efficient) as well as to wavelets that can be used as an optimized filter bank.

Zhang and Benveniste (Volker Krüger, 2001; Zhang 1992) first mentioned wavelet networks in the context of non-parametric regression of functions in $L^2(R^2)$. In wavelet networks, the radial basis functions of RBF-network are replaced by wavelets. During the training phase, the network weights as well as the degrees of freedom (position, scale, orientation) of the wavelet functions are optimized. Zhang and Benveniste realized that wavelet networks inherit the properties of wavelet decomposition and mention especially their universal approximation property, the availability of convergence rates and the explicit link between the network coefficients and the wavelet transform. However, since their introduction in 1992, wavelet networks (WN) have received little attention in recent publications. Szu *et al* (1996) have used WNs for signal representation and classification. They have explained how a WN template, a *superwavelet,* can be generated and presented original ideas for how they can be used for pattern matching. In addition, they mention the large data compression achieved by such a WN representation. Zhang (1997) showed that WNs are able to handle nonlinear regression of moderately large input dimension with sparse training data. Holmes and Mallick (2000) analyzed WNs in the context of a Bayesian framework. Reyneri (1999) has recently analyzed the relations between artificial neural networks (ANNs), fuzzy systems and WNs have been discussed. It appears that in the cited works, WNs have only been applied to certain problems but that their properties have not been investigated. Starting from a wavelet representation as described by Zhang (2000) we have analyzed the properties such a representation has. Zhang and Benveniste (1992) have mentioned, e.g., that there is an explicit link between the weights (wavelet coefficients) and some appropriate transform. This link is established through wavelet theory. The following properties of wavelet networks are investigated: (Volker Krüger, 2001)

- That the explicit link mentioned above can be exploited to find optimized filter banks.
- That there exists an additional explicit link between the parameters of the optimized wavelet network functions and the represented function, and that the chosen mother wavelet introduces model information for image features that the optimized wavelets in a WN will represent.
- That the optimized wavelets are linearly independent, when the optimization scheme presented here, which is similar to the one propose by Zhang and Benveniste is followed.
- That the wavelets of the network from a low-dimensional subspace in the $L^2(R^2)$ space and that it's dual is a vector over, the wavelet subspace of the vectors of wavelet coefficients.

3. The Proposed Image Reconstruction System (IRWN):

The proposed algorithm achieves image reconstruction using wavelet network for texture image segmentation. It consists of four processes: Wavelet Network Approximation phase (WN), segmentation texture image phase, resilient back propagation neural network (RPROP) and Image Reconstruction phase. It can be applied to gray-scale image (GSI) of size 256 x 256 in any format. The system can control any image size into the desired size. Figure (1) shows the proposed block diagram of WN reconstruction.

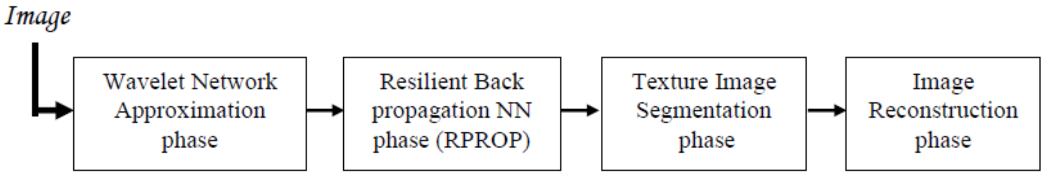

Fig. 1: Block Diagram of Image Reconstruction using Wavelet Network IRWN.

The proposed reconstruction system consists of four phases:

3.1 Images Approximation Phase:

In this phase the WN transform of the given images will be taken in order to approximate their features. This step will also obtain values of the following parameters for each image:

1. Weights.
2. Translations.
3. Dilations.

The wavelet network that is used here is not based on statistical data model unlike for example maximum likelihood classifier. It treats all reconstruction inputs equally, and has often demonstrated robustness in the presence of noise. The proposed wavelet network used for the reconstruction of texture image segmentation type is a feed-forward multi-layer network trained by the stochastic gradient algorithm.

3.2 The Learning Phase:

In order to map classes accurately into image reconstruction it is necessary to carry out a high precision reconstruction. For this reconstruction system it is necessary to use a classifier that could offer the following features:

1. No pre-established parametric data model.
2. Robustness in the presence of noise.
3. Good generalize capability.

A multi-layer feed-forward neural network resilient back propagation training algorithm trained the input (training pattern) to the network.

It obtains the approximation value (weights, translations and dilations) for each image stored in the reference file for all reconstruction types concerned. The application work to make the network learn the characteristics of the set of the reconstruction types. The neural uses five hidden layers with every element of a given layer can be connected to every other element of the next layer. Bias is possible in every layer. The tansigmod function has proven to be suitable for the transfer function hidden layers; it's the most common choice for good convergence of non-linearity. The training algorithm used the resilient back propagation training algorithm, which gives faster convergence and better reconstruction result than the back resilient training algorithm.

There are two important points for the use of such networks:

1. Learning (learning the weights).
2. Application (Re-call phase).

Generally speaking, the learning phase needs an intensive calculation, but for that matter it needs to be run only once. The re-call phase is, on the contrary, free from calculations and can run any number of times.

The resilient back propagation learning phase starts with the initialization of WN parameters (bi, ai, wi). Next the training of the resilient back propagation WN will be started. The task of training resilient back propagation involves estimating parameters in the network by minimizing some cost function, this function a measure of reflecting the approximation quality performed by the network over the parameter space in the network.

The mean squared error (MES) cost function is the most popularly used in estimating the synoptic weights which provides optimal results if the underlying error distribution is Gaussian.

The network continue training with the input patterns from the reference set until the mean square error value between the target (active state) and the approximated value of the input pattern reaches (0.0000 1). At this point the training will stop, and the weights and all trained network variables will be saved in a file to be used in the testing phase. The training parameters are also used to compute the outputs of the Wavelet network which represent the reconstruction types used in this work and the result are stored in a file to be compared with that of the unknown image in the testing phase.

Properly trained networks tend to give reasonable answers when presented with inputs (training pattern) that they have never seen. Typically, a new input leads to an output similar to the correct output for input vectors used in the training that are similar to the new input being presented.

This generalization property makes it possible to train a network on a representative set of input/target pairs and get good results without training the network on all possible input/output pairs.

Save the outputs of the neural network in another data base file to be used in the testing phase for the comparison with the unknown image. Figure (2) shows a block diagram of IRWN learning.

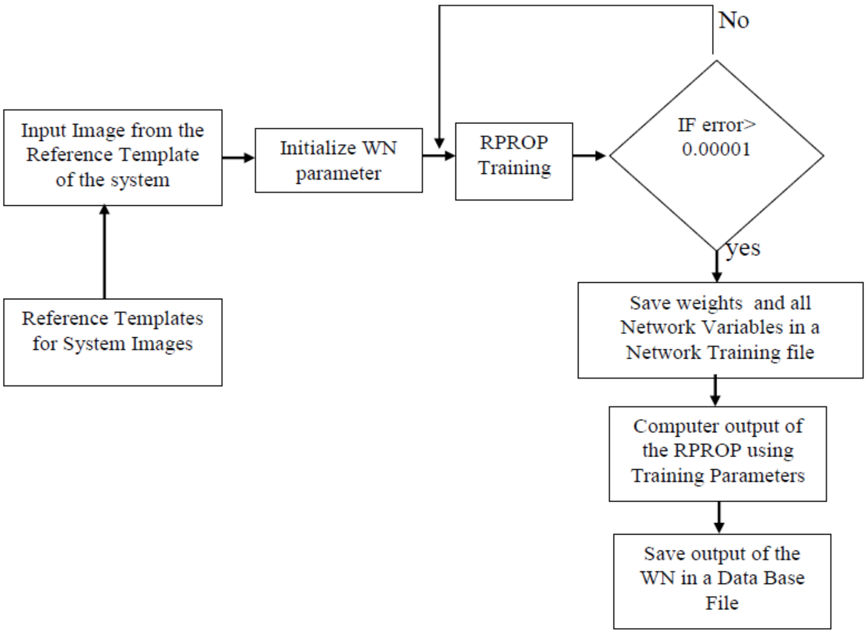

Fig. 2: Block diagram of IRWN learning phase.

3.3 Texture Segmentation Phase:

The segmentation of the image will be done by using shift factor to the approximation of image that obtain from phase one of WN. The translated image result shows that the system can recognize the image even if the translation is in different direction (top, bottom, and left, right). The shifted percentages that are used are 25%, 50%, and 75% as follows:

1. Segmentation of the image is produced by the translation of four parts by a shifting percentage of 25% for each of the four parts of the image:

a For the purpose of evaluation the image will be divided into four equal parts.

b The missing parts will be one of the following cases:

Case a: 25% of the image exactly of the upper left.
Case b: 25% of the image exactly of the upper right.
Case c: 25% of the image exactly of the bottom left.
Case d: 25% of the image exactly of the bottom right.
Case x: 25% of the image in any side.

2. Segmentation of the image is produced by translating two parts by a shifting percentage of 25% in many directions but first starting with segmentation then:

a For the purpose of evaluation, the image will be divided into two equal parts.

b The missing parts will be one of the following cases:

Case a: 75% top plus 25% bottom to the left side of the image which is named D1, and 75% top plus 25% bottom to the right side of the image which is named D2.

Case b: 75% left plus 25% right to the top side of the image which is named D3, and 75% left plus 25% right to the bottom side of the image which is named D4.

Case c: 50% left plus 50% right to the top side of the image which is named D5, and 50% left plus 50% right to the bottom side of the image which is named D6.

3. Segmentation of the image is produced by translating of the four parts. The geometrical rectangle 2-dimention shapes are combined and joined together into a ring shape at the center of image. The translated of these four parts by the following shifting percentage as follow:

a For the purpose of evaluation the image will be divided into four equal parts.

b The missing parts will be one of the following cases:

Case a: 50% of the left plus 50% of the right to the top side of the image which is named S1.

Case b: 50% of the left plus 50% of the right to the bottom side of the image which is named S2.

Case c: 50% of the top plus 50% of the bottom to the left side of the image which is named S3.

Case d: 50% of the top plus 50% of the bottom to the right side of the image which is named S4. All these shifting percentages will be reconstruction when it will be found in the uncorrected place.

3.4 The Reconstruction Phase:

The steps of the reconstruction procedure are given below:

1. The unknown texture segmentation image is entered to the system.
2. Apply wavelet network approximation for the segmentation image by obtaining the translation, dilation and weight parameters.
3. In the test phase, a matching will be performed between the targets unknown segmentation image with the other segmentation parts of the image of other images that had approximation values.
4. From the matching get a vector will be formed that contain the value of the network performance function. The default performance function for feed-forward networks is the mean square error; and the average squared error between the network outputs and the target outputs.
5. The reconstruct of segment part will be depending on the small value of the matching vector.

The resulting will be entered to the trained resilient back propagation, to be simulated using the training parameters resulting from the learning phase. The resulting vector will be compared with the vectors of matching value. The wavelet network is accompanied with an appropriate decision logic that decided upon the particular reconstruction type that the features (symptoms) belong to Figure (3) shows the detail block diagram of the IRWN.

4. The Proposed Algorithm of Reconstruction Using the Texture Segmentation Type:

The proposed structure for texture segmentation and will be given in details in the following sections.

This structure depends on using wavelet network for image approximation, obtaining the value of translation, dilation, and weight. Then reconstruct the approximation image value of the segments in texture image as follow:

Step	General Proposed Method of Image Reconstruction
1.	Input a given image of 256x256 sizes or any size in any format.
2.	Take the Wavelet Network (WN) transform to the given image to approximation their features. This step will also obtain the values of the weight dilation and translation parameters.
3.	This step will be achieved by learning artificial neural network Resilient Back Propagation (RPROP) on the approximation texture image (i.e. learn on its weights, translation and dilation). The ANN-RPROP must have one output node for the pure image that matched with the next test segmented texture image.
4.	For test phase, each image from those generated in next order the segmented algorithm will be compared with all other pure images of the approximation image under processing. If they are alike then it will be reconstructed in active neuron, if not then the result is non-active neuron (0). This means that image segments is not belong to any pure image. Thus such test depends on assign the unknown image to its class in minimum square error.

5. Experimental Results:

Figure (4) shows the property translation invariant of wavelet network. Several experiments are carried on multiple images to examine the reconstruction accuracy. The translated image and the result show that the system can recognize the image even if its translation are in different directions (top, bottom, right, left), and shifted in different percentage that are used (25%, 50% and 75%).

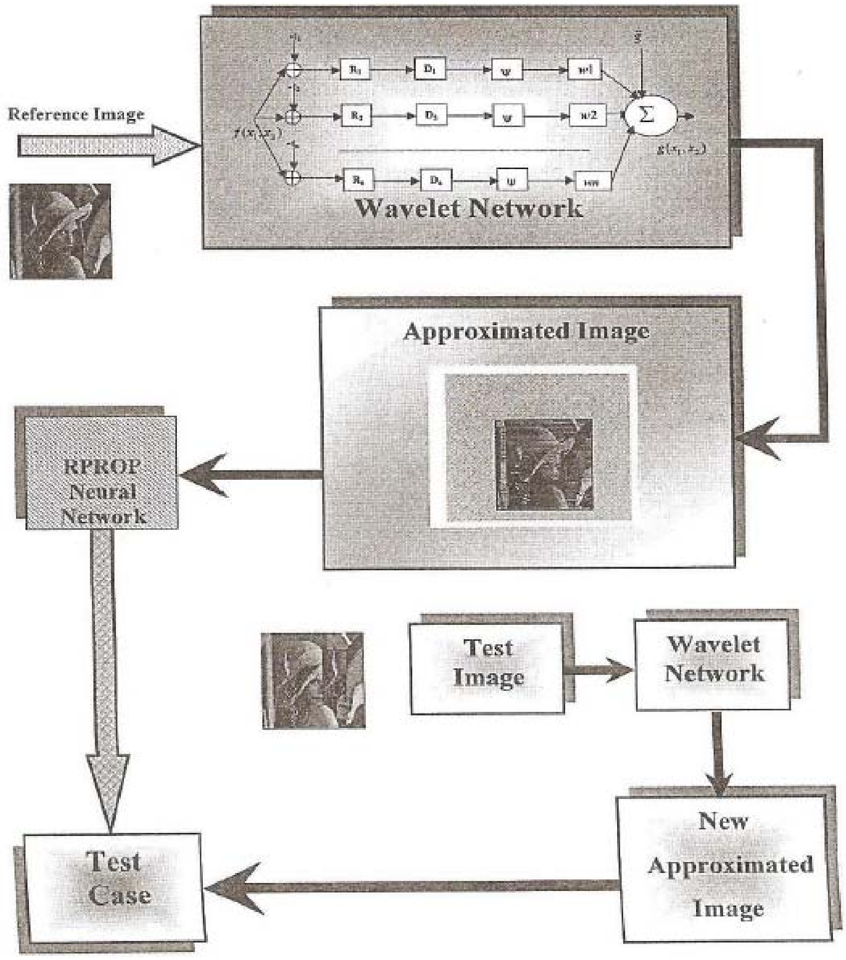

Fig 3: The Detail Block-diagram of the Algorithm of Image Reconstruction using Wavelet Network (IRWN)

In this experiment the images in figure (4) are produced by merging some parts from different segmentation process for each image will do as follows:

1. Input the texture image of missing segments into the system.
2. Take the wavelet network transform to the given image to approximation their feature; this step will also obtain value of the following elements, a) weight, b) Dilation and c) Translation.
3. For reconstruction test phase, input unknown image miss parts, if they were alike then the result is matched, and if not then the result is not matched. Then the result will be reconstruction to those parts that replaced with other parts from the same image parts or the same parts size from other images. The active node specify the image if it's contain the same parts of original parts in the correct place or have unknown parts replaced or exchange with other part. Texture segmentation for the approximation of an image will be achieved using shifting factor. Hence according to the shift type the translated texture image will be divided into 4-equal parts each of 25% percentage, as shows in the figure (4.11, a, b, c and d).

The missing parts will be one of the following cases: Case a: 25% of the image exactly of the upper left. Case b: 25% of the image exactly of the upper right. Case c: 25% of the image exactly of the bottom left. Case d: 25% of the image exactly of the bottom right. Case x: 25% of the other image in any side.

Then will checking the exchanging in some of those parts with the same image parts or same parts size from other images. The reconstruction of these missing parts will be from the same original image or the nearest segment's parameters.

Other part of segmentation is produced three types of translated two-parts, first shift percentage segmentation the image is produced as shown in figure (4, from i-to-n).

The missing parts will be one of the following cases:

Case a: 75% top and 25% bottom to the left side of the image and named D1. 75% top and 25% bottom to the right side and named D2.

Case b: 75% left and 25% right to the top side of the image and named D3. 75% left and 25% right to the bottom side and named D4.

Case c: 50% left and 50% right to the top side of the image and named D5. 50% left and 50% right to the bottom sides and named D6. And the reconstruction will be as mentioned before.

Other part produced by shifting type that translate texture image into 4-different shift percentage of segmentation. This part produced by geometrical rectangle 2-D shape through their combined, joining in rings, cycle in the center of the image. The missing parts will be one of the following cases:

Case a: 50% left and 50% right to the top side of the image and named S1.

Case b: 50% left and 50% right to the bottom side of the image and named S2.

Case c: 50% top and 50% bottom to the left side of the image and named S3.

Case d: 50% top and 50% bottom to the right side of the image and named S4.

The reconstruction miss parts apply to the test phase to be reconstructed again. The miss parts, as in figure (4, o, p, q and r) show that how the miss in the image that test by the system, and the reconstruction on the miss segments.

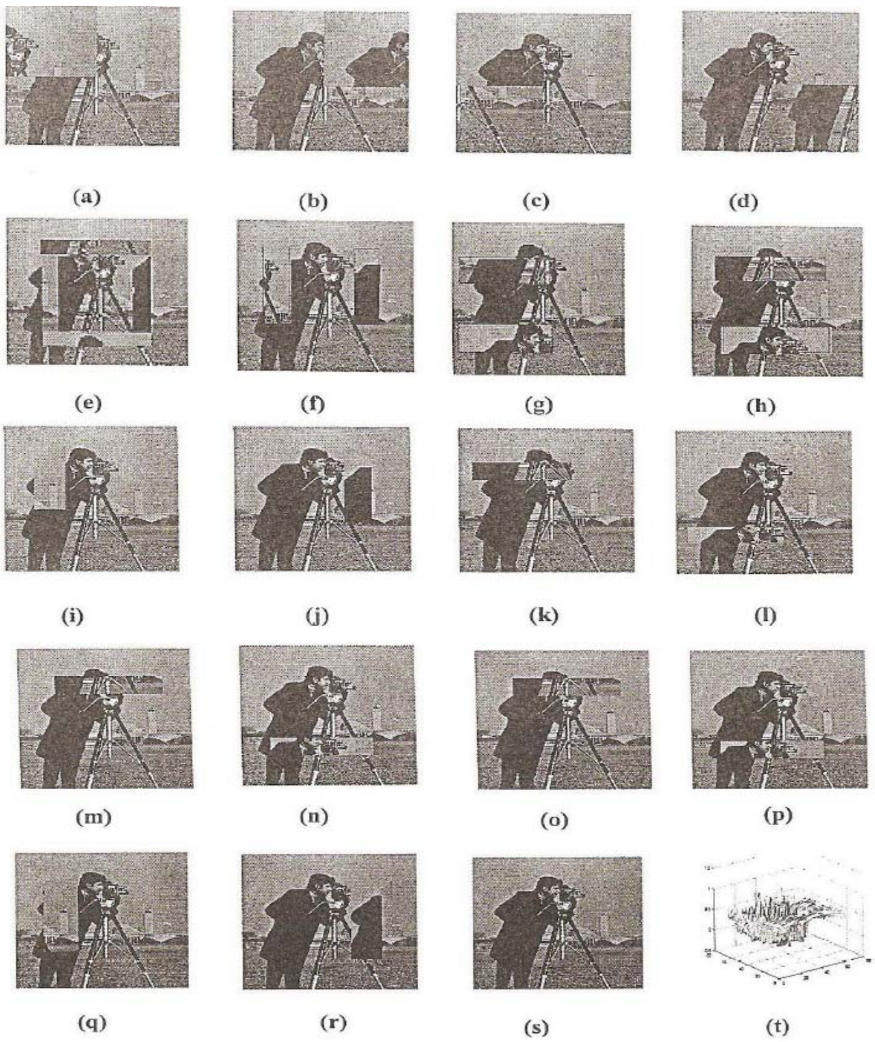

Fig. 4: Experiment: a) missing part 25% upper left, b) missing part 25% upper right, c) missing part 25% bottom left, d) missing part bottom right, e) missing part image, f) missing in part D1 & D2, g) missing in part D3 & D4, h) missing in part D5 & D6, i) D2 instead of D1, j) D1 instead of D2, k) D4 instead of D3, l) D3 instead of D4, m) D6 instead of D5, n) D5 instead of D6, O) S2 instead of S1, p) S1 instead of S2, q) S4 instead of S3, r) S3 instead of S4, s) reconstructed image, (s) mesh of the approximation.

6. Conclusions:

The results of this paper have pointed a number of conclusions which can be drawn, as follows:

1. The experimental results show that three level of wavelet decomposition is fair enough for the reconstruction process.
2. Using wavelet approximation leads to accurate reconstruction even if changes are occurring in the weights, dilations or translations of the approximation image.
3. The system can reconstructs the uncompleted images if the missing part from the original image up to 50% assuming different lost blocks in different positions.
4. A set of systematic tests gave a good discrimination of the system and especially its ability of making concurrent use temporally separated feature.
5. The system needs little memory space size. The proposed algorithm minimizes the image size that applies to the method.
6. The retraining operation gives a powerful reconstruction in the convergence of the training value for the images.
7. The image reconstruction using edges detection method is the most powerful algorithm because it reconstructs the image without any knowledge about the original image depending on the four reconstruction cases in different direction.

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