IDENTIFICATION TYPE OF NOISE IN GRAY SCALE IMAGES USING WAVELET-NETWORK (WN)

Dr. W. A. Mahmoud **H. H. Khalil**
College of Engineering – University of Baghdad
Baghdad – Iraq

ABSTRACT

In this paper, Wavelet-Network (WN) model has been recently proposed and applied to image processing, e.g., identification type of noise in Gray-Scale Images (GSI). This paper develops a new technique, which employs a Discrete Wavelet Transform (DWT) and an Artificial Neural Network (ANN). This WN technique uses special mother wavelet $\psi(x1, x2)$ of (DWT) as activation function for (ANN) instead of the traditional activation functions like (Log sigmoid, Tan sigmoid, etc). It is shown here that the benefit of WN circuits which uses WN is a good approximation tool for GSI images. These approximation patterns for images forced ANN to learn on these images which will be used in the test phase after that.

الخلاصة:

يستخدم هذا البحث شبكة المويجة-الخلايا العصبية(W N)، كنموذج اقترح مؤخرا وتم تقديمه كنموذج لمعالجة الصور، وكمثال على ذلك، تصنيف أنواع الضوضاء الذي يصيب الصور الرمادية. وقد تم تطوير واستخدام تقنية جديدة والتي تتضمن كل من تحويل المويجة (D WT) مع الشبكة العصبية (ANN). هذه التقنية تستخدم معادلة المويجة ألام (activation function) بدلا عن الأنواع المستخدمة في (ANN). لقد تبين أن الفائدة من (WN) يكمن في تحديد نوع الضوضاء الموجود في الصور و استخدامها كأداة تقريبية جيدة للصور الرمادية. وقد لوحظ أن هذا العمل يؤدي إلى إجبار (A NN) على التعلم على هذه الصور حيث يؤدي إلى تحسين الأداء في طور الاختبار.

KEY WORDS

Wavelet Networks, Wavelet Transform, Outlier, Function approximation.

INTRODUCTION

The approximation of general continuos functions by nonlinear networks such discussed in [T. Poggio, 1990], [K.. Hornik, 1989] is very useful for system modeling and identification case. Such approximation methods can be used, for example, in black-box identification or noise identification of nonlinear systems. Function approximation involves estimating (approximating) the underlying relationship from a given finite input-output data set has been the fundamental problem for a variety of applications in pattern classification, data mining, signal reconstruction, and system identification. In this paper, we propose a method to identify five types of noise (Gaussian, Salt & Pepper, Speckle, Uniform & Random noise which is mixture of tow or more types of noise). Using WN in this method is just an approximation tool to the noisy images, that's because the values of pixels in any gray scale image of UINT8 (i.e., each pixel contains 8-bit), are large (0-255), or (256-65535) for UINT16 (i.e., each pixel contains 16-bit) so the WN approximate these values and make them adductive small, then this work will force (ANN) which be after WN to learn on these approximated images (i.e., on these types of noise as mentioned above).

NETWORK STRUCTURE

Based on the previous discussion, we propose a network structure of the form:

$$g \sum_{i=1}^{N} \omega i \text{-}(x1,x2) \;\; \psi \;\; [DiRi(x_k - ti)] + \bar{g} \qquad (1)$$

Where

- The additional parameter g^- is introduced in order to make it easier to approximate functions with nonzero average, since the wavelet $\psi(x1,x2)$ is zero mean;
- The dilation matrices Di's is diagonal matrices built from dilation vectors, while Ri's is rotation matrices. This network structure is illustrated in **Fig. (1)**.

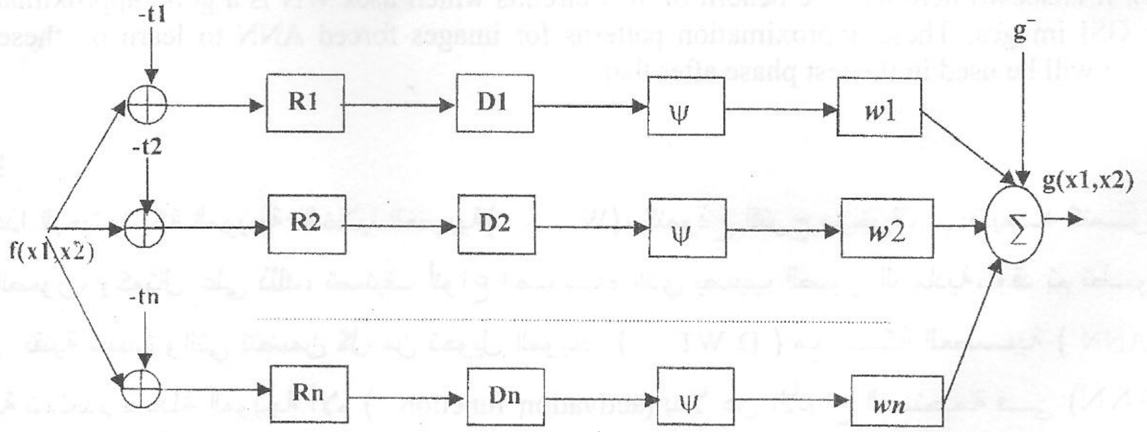

Fig.(1). Wavelet network structure for approximation. The combination of translation, rotation, dilation, and wavelet lying on the same line will be called a wavelon in the sequel.

Where $f(x1,x2)$ is the input image which is (64×64), (128×128) or (256×256). The output image is equivalent to input one but with some threshold value clipping from the output image as a result of approximation, so $f(x1,x2) \cong g(x1,x2)$

Initialization of the Network Parameters

Initializing the wavelet network parameters is an important issue. Similarly to Radial Basis Function networks (and in contrast to neural networks using sigmoidal function), a random initialization of all the parameters to small values (as usually done with neural networks) is not desirable since this may make some wavelets too local (small dilations) and make the components of the gradient of the cost function very small in areas of interest. In general, one wants to take advantage of the input space domains where the wavelets are not zero.

Therefor, we propose an initialization for the mother wavelet $\psi(x1,x2)$ -$\chi_1\,\chi_2$ exp (.5 ($\chi_1^2+\chi_2^2$)) based on the input domains defined by the examples of training sequence.

Procedure of Initialization in (2-D)

Assume that we want to approximate the function $f(x1,x2)$ over the domain D = [a, b] by a network of the form

$$g\sum_{i=1}^{N}\omega i \cdot (x1,x2)\ \psi\quad [DiRi(x_k - ti)] + g^{-}$$

The initialization of this wavelet network consists in the evaluation of the parameter g^{-}, wi ,ti and si for $i = 1,2,\ldots, N$. The wi ' s are simply set to zero. To initialize $t1$ and $s1$,select a point p between a and b; a < p < b. The choice of this point is;

p (a+b)/2 , then $t_1 = p$, $s_1 = \xi$(b-a),

Where $\xi>0$ is properly selected constant (the typical value of ξ is 0.5). The interval [a, b] is divided into two parts by the point p .In each sub-interval, we recursively repeat the same procedure which will initialize t_2, s_2 and t_3, s_3, and so on, until all the wavelets are initialized. This procedure applies in this form when a number of wavelons is used which is a power of 2. When this is not the case, the recursive procedure is applied as long as possible, then the remaining) ti (are initialized at random for the finest remaining scale.

Stopping Conditions for Training

The algorithm is stopped when one of several conditions is satisfied: the Euclidean norm of the gradient, or of the variation of the gradient, or of the variation of the parameters, reaches a lower bound, or the number of iterations reaches a fixed maximum, whichever is satisfied first. The wavelet network model, which satisfied in this paper, depends on whether: (i) the assumptions made about the model are appropriate, (ii) the training set is large enough, (iii) the family contains a function which is an approximation of $f(x1,x2)$ with the desired accuracy in the domain defined by the training set, (iv) an efficient (i.e. second – order) training algorithm is used.

NOISE TYPES

In typical images, the noise can be modeled with a Gaussian "normal", uniform, speckle or salt – and – pepper "impulsive" distribution.

Gaussian Noise

Gaussian noise takes the bell – shaped curve distribution, which can be analytically described in [3]:

$$\text{HISTOGRAM}_{\text{Gaussian}} = \frac{1}{\sqrt{2\pi\sigma^2}}\, e^{-\frac{(gl-m)^2}{2\sigma^2}} \qquad (2)$$

Where:

gl = gray level

m = mean (average)

σ = standard deviation (σ^2 = variance)

About 70% of all the value full with in the range from one standard deviation) σ (below the mean (m) to one above, and about 95% full within two standard deviation. The Gaussian model is most often used to model natural noise in the image acquisition system (i.e. thermal noise). The method of adding this noise to the image is:

J = imnoise (I, 'gaussian', m, v)

Where I = original image, J = noisy image, m = the mean, v = the variance, the default m = 0 and v = 0.01 .

Uniform Noise

With the uniform distribution, the gray level values of the noise are evenly distributed across a specific range, which may be the entire range (0 to 255 for 8 – bit), or a smaller portion of the entire range. This is discussed in [Scott E.1998].

$$\text{HISTOGRAM}_{Uniform} = \begin{cases} \dfrac{1}{(t-y)} & \text{for } y \le gl \le t \\ 0 & elsewhere \end{cases} \qquad (3)$$

Where:

Mean $\dfrac{(s+t)}{2}$ =

Variance $\dfrac{(t-s)^2}{12}$ =

Uniform noise is useful because it can be used to generate any other type of noise distribution and is often used to degrade images for the evaluation of image denoising restoration algorithm because it provides the most unbiased or neutral noise model [Scott E.1998].

Speckle Noise

Speckle noise is completely different from other types of noise, since it is operates on the images in multiplicative manner (i.e. the pixel value of the noise is multiplied by the pixel value of the original image), where the other types of noise mentioned above being additive (the pixel value of the noise is added to the pixel value of the original image). The speckle noise can be modeled by the following equation (4):

$$g(r,c) = x(r,c) + x(r,c) .* z_u(r,c) \qquad (4)$$

Where $\chi(r, c)$, $z_u(r, c)$, and $g(r, c)$, are the original image, uniform noise, and the distorted version image respectively,. * is pixel – by – pixel multiplication. The method of adding this noise to the image is:

J = imnoise(I, 'speckle', v)

Where I = original image, J = noisy image, v = the variance, the default v = 0.04.

IMAGE REPRESENTATION

Binary Images

A binary image is refereed to as a (1-bit/pixel) image because it takes only (1) binary digit to represent each pixel. Binary images are often created from gray scale images via a threshold operation, where every pixel above the threshold value is turned white (1), and those below it are turned black (0).

Gray Scale Images

A gray scale image is refereed to as (8-bit/pixel) image. These images are (one-color) images, they contain brightness information only, no color information. They allows us to have 265(0-255) different brightness levels.

Color Images

Color images can be modeled as three-band image data, where each band of data corresponds to a different color. Typical color images are represented as a model, of Red, Green and Blue, (RGB) images. The corresponding color image would have (24-bit/pixel) – 8 bits for each of the three-color bands.

IDENTIFICATION (CLASSIFICATION) TYPE OF NOISE

As mentioned later this paper proposed the Gray-Scale Images representation. The work-included tests of ten–different image of (GSI), and add a type of noise in each two images, (Gaussian, Salt-and-Pepper, Speckle, Uniform and Random noise which is a mixture of two or more of the previous types of noise), then the noisy images input to the WN to approximate them (WN is 64 – 2 – 64) by taking the error (c = 0.1). The approximated images then input to a neural network to learn the neural network on these images and this network is Backpropagation (64 – 21 – 5) and 10000 epoch, each node for each type of noise. After learning we take the test stage which has in our work (100 – image), 20 – image for each type of noise, and after test these images, the result is 98% successfully. The block diagram of the network is shown in **Fig. (2).**

The Block Diagram

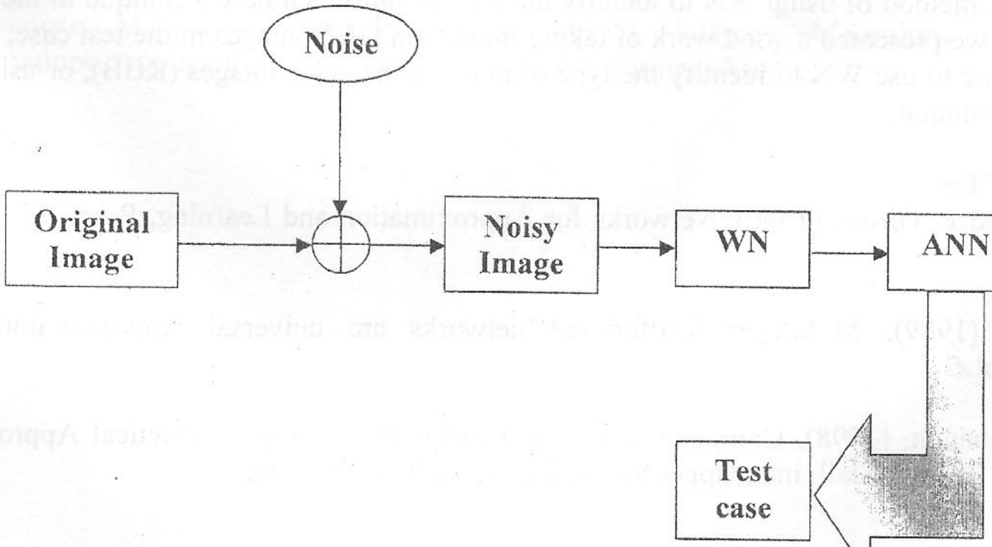

Fig. (2). Block diagram of identification of noise

EXPERMINTS

In this section, we present five experimental results of the proposed method of identification type of noise using WN. First we take one image and add Gaussian noise, then input this image to WN to make the approximation image which will forced the NN to learn, then we take another image and add Salt and pepper noise, and repeat the same previous procedure for Gaussian. Repeat this method for the remaining types of noise until we have five approximated images each of different noise. These approximated images go to ANN for learning. After that the test stage which will test some of different images about the type of noise in these images. This algorithm is shown in figures (3,4,5,6) respectively. We tacked below 6-images, and learned the (ANN) on them after WN for all types of noise, then take random noisy images and test them. Table below shows the results of this example.

Table. Example of some of noise images, and their results.

Images for learning	Types of Noise Added	Noisy Images	Results Gaussian	Results Speckle
S1 & S2	Gaussian	S15	True	False
S3 & S4	Salt & Pepper	S8	False	False
S5 & S6	Speckle	S21	False	True

COCLUSIONS AND SUGGESTIONS

This paper presented a very new and a very important method of classificate the types of noise, which contaminate the images specially the Gray scale images in our work. The other important thing presented by this paper, that using WN to approximate noisy images (i.e. approximate the values of pixels) before input these images to the NN. In this paper we presented pure images and add the noises, which work just for testing, but we can implement any unknown noisy image on this method. Simulation results demonstrate its superiority over the conventional WN in image approximation from outlying data. Experimentation on real-world applications is undergoing. Finally, it is worth noticing that the number of units (i.e., wavelons) is generally smaller in WN than in ANN. Our WN has been used for identification of nonlinear static systems. The method of using WN to identify the type of noise is a new technique in the world, so in this paper we presented a good work of taking more than (100) images in the test case, and in the future we hope to use WN to identify the type of noise in the color images (RGB), or using WN in denoising technique.

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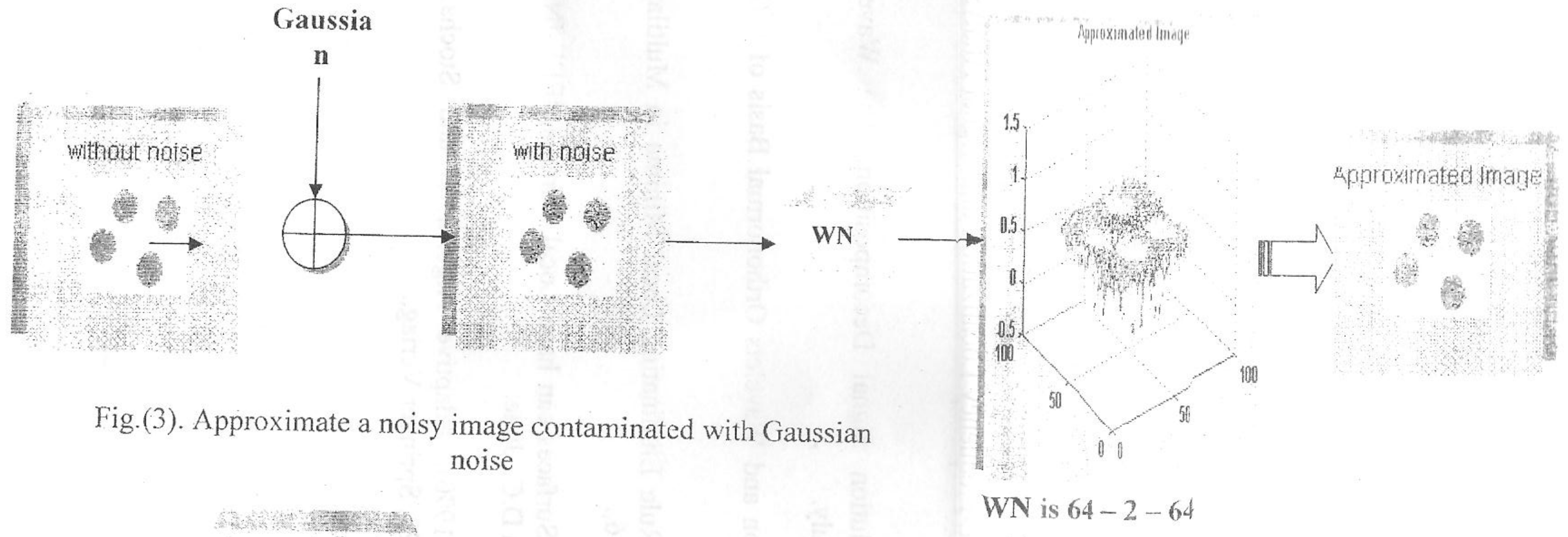

Fig.(3). Approximate a noisy image contaminated with Gaussian noise

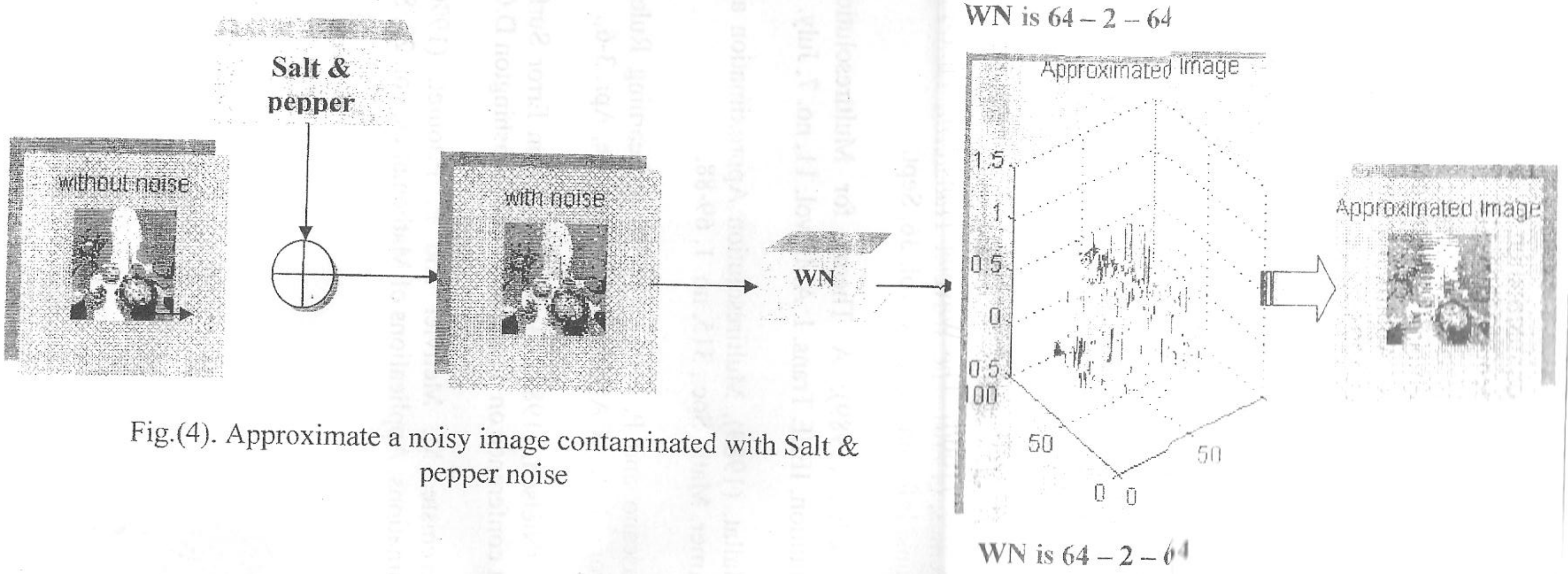

Fig.(4). Approximate a noisy image contaminated with Salt & pepper noise

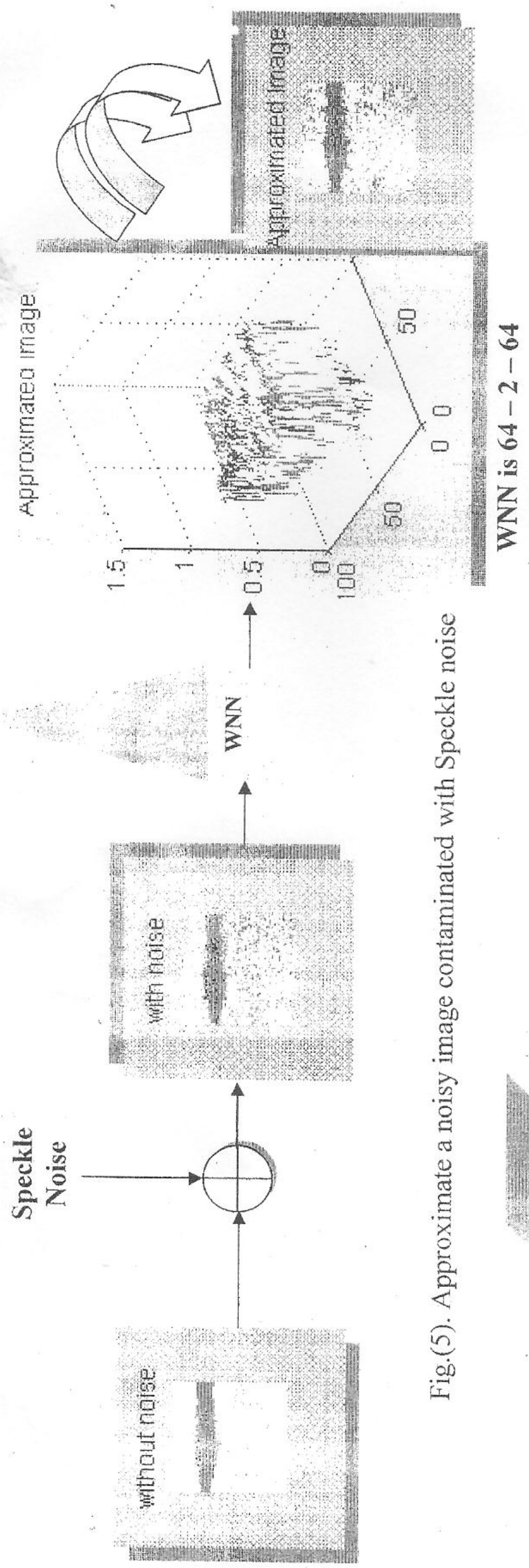

Fig.(5). Approximate a noisy image contaminated with Speckle noise

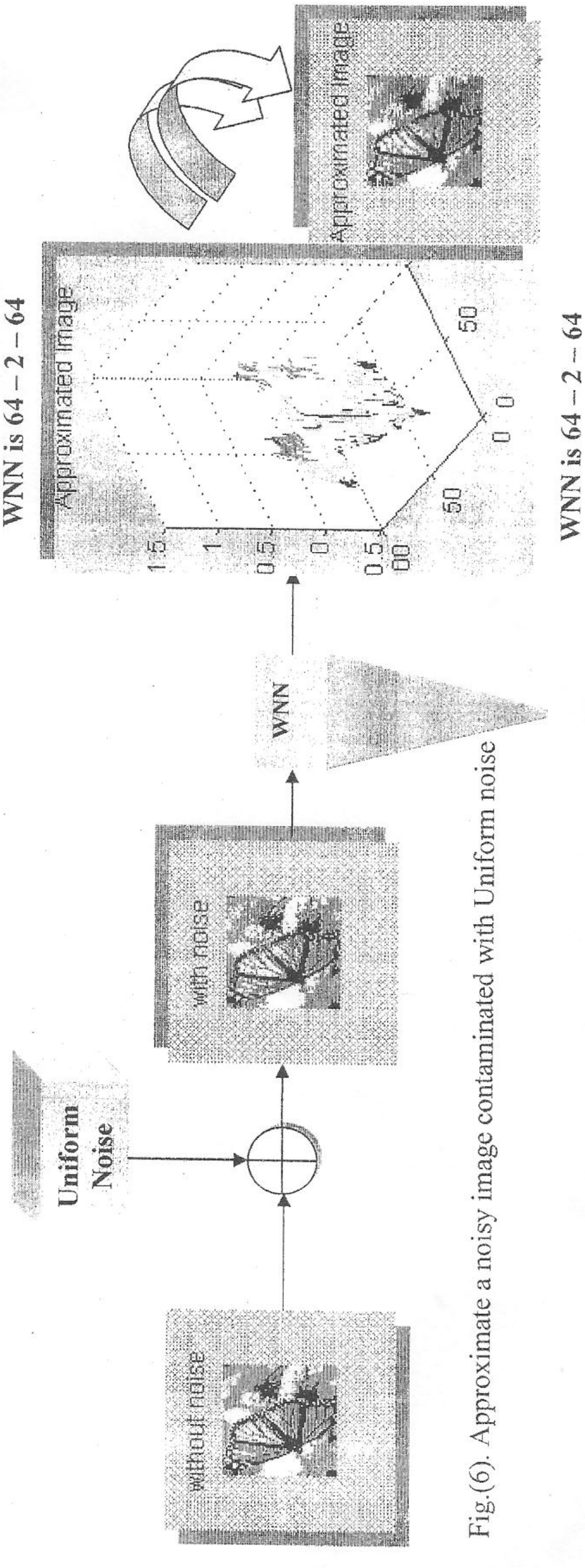

Fig.(6). Approximate a noisy image contaminated with Uniform noise