Egyptian Journal of Bronchology

Vol. 5, No 2, December, 2011

ORIGINAL ARTICLE

MEDICAL IMAGE FILTERING, FUSION AND CLASSIFICATION TECHNIQUES

Mohamed A. Mohamed,[1] Abdul-Fattah Ibrahim Abdul-Fattah,[1] Aziza S. Asem,[2] Abeer S.El-Bashbishy[2]

[1]Communications Engineering Department, Faculty of Engineering, Mansoura University, [2]Information Systems Department, Faculty of Computers & Information, Mansoura University, Egypt

Correspondence to: Abeer S. El-Bashbishy, Email: smilebird77@hotmail.com

This paper presents a study of different filtering techniques applied to medical image data. The performance of these techniques investigated the problem of image degradation which might occurr during the acquisition of the images, optical effects such as out of focus blurring, camera motion, flat-bed scanner and video images. We touch upon two dimensional images of X-ray, Magnetic Resonance Imaging (MRI) and Computed Tomography (CT) with a set of predefined noise levels. We apply spatial domain and transformed domain filtering techniques. The performance of these techniques was evaluated with respect to two quantitative measures; Signal-to-Noise Ration (SNR), and shape preservation (R). It has been found that filtering using rank order filter provides the best performance among all spatial domain filtering techniques, Wavelet transform with reverse biorthogonal basis functions provide the best performance among all the transformed filtering techniques. We apply Image fusion process which combines the data from two or more source images of the same scene to generate one single image containing more precise details of the scene than any of the source images. Many image fusion methods like averaging, principle component analysis, Discrete cosine transform, Discrete Wavelet Transform special frequency and Artificial Neural Network ANN are the most common approaches. Experimental results are quantitatively evaluated by calculation of Root Mean Square Error RMSE, Entropy, Mean Square Error MSE, Signal to Noise Ratio SNR and Peak Signal to Noise Ratio PSNR measures for fused images and a comparison is accomplished between these methods. We use neuro solution to classify the input image data into normal or up normal image to help in the diagnosis process of the patient in medical care.

Keywords: ***Signal to Noise Ratio (SNR), Shape preservation (R), Active Confusion Matrix (ACM) and Mean Square Error (MSE). Image Fusion, Principal Component Analysis (PCA), Discrete Cosine Transform (DCT) and Discrete Wavelet Transform (DWT).***

INTRODUCTION

Today medical imaging technology provides the clinician with a number of complementary fast, flexible, and precise diagnostic tools such as X-ray, Computed Tomography (CT) and Magnetic Resonance Imaging (MRI) images. MRI, CT scan and X-ray are the most methodologies widely used to visualize human anatomy. Medical images often need preprocessing before being subjected to statistical analysis. A common preprocessing step is filtering. We study spatial domain and transformed domain filtering techniques to solve the noisy problem. The performance of these techniques is compared with respect to (i) the improvement of the SNR and (ii) the shape preservation of images view. Image filtering techniques improve image quality, increase visibility of details, help in the diagnostic and accurate information in medical care.

The purpose of image fusion techniques is to merge multiple images taken from the same scene with different focuses. Fusion techniques include the simplest method of pixel averaging to more complicated methods such as wavelet transform. The objectives of image fusion are extracting all of the useful information from the source images without introducing artifacts or inconsistencies that will distract human observers.[1,2] Such objectives are achieved through creating combined images that are more suitable for human perception and computerized image processing such as segmentation, feature extraction, and object recognition. The fused data should provide more complete information than the separate dataset does, increase reliability and accuracy to imperfection.

We use image classification to classify patient image into normal or up normal through learning and testing process.

II. Overview of Image Noise

We discuss the removal of image degradations which might occurred during the acquisition of the image, such degradations may include noise, optical effects such as out of focus blurring due to camera motion, or the quality of the receiving pixels that vary with time and position [1]. We have three noise types; Salt and pepper noise, Gaussian noise and speckle noise.

1) Salt and Pepper Noise: Salt and Pepper Noise is a randomly scattered white or black (or both) pixels over the image[2] this degradation can be caused by sharp, sudden disturbances in the image.
2) Gaussian Noise: Gaussian Noise is an idealized form of white noise, which is caused by random fluctuations in the added to an image and normally distributed.
3) Speckle Noise: Speckle Noise is modeled by random values multiplied by pixel values.

III. The performance evaluation criteria

The performance of all the filtering techniques was evaluated using two different quantitative measures. These Measures are shortly described below.

(1) Signal to Noise Ratio: It is a neighborhood operation, in which the value of any given pixel in the output image is determined by applying some algorithm to the values of the pixels in the neighborhood of the corresponding input pixel. The noise is characterized by its standard deviation,[3] Sn. The characterization of the information can differ if the data is known to lie between two boundaries α_{min}, and α_{max}; then the SNR is defined as:

$$SNR=(\alpha max- \alpha min)^2/S_2n \qquad (1)$$

Signal to Noise Ratio (SNR_i) of the original image and Filtered image is defined as:

$$\nabla SNR_i = SNR_{\text{Filtered image}} - SNR_{\text{Original image.}} \qquad (2)$$

(B) Shape Preservation: This parameter may be estimated using the correlation coefficient (R) between the original x and output y data of image (i,j).

$$R= \left(\frac{\sum_j \sum_i (X_{ij} - x^{\sim})}{\sqrt{\sum_i \sum_j (X_{ji} - x^{\sim})^2 \sum_j \sum_i (y_{ij} - y^{\sim})^2}} \right) \qquad (3)$$

Two dimensional (2D) filtering techniques can be classified into spatial and transformed techniques. Two spatial filtering techniques are (i) linear, and (ii) nonlinear.

IV. Spatial domain filtering techniques

A traditional way to remove noise from image data is to employ spatial filters. Spatial filters can be further classified into linear and non-linear filters.

A. ***Linear Filters:*** Linear filters tend to blur sharp edges, destroy lines and other fine image details, and perform poorly in the presence of signal dependent noise.[3] Three filters are shortly described below.

   1) ***Mean Filters:*** Mean filtering is a simple, intuitive and easy to implement method of smoothing images, i.e. reducing the amount of intensity variation between one pixel and the next. The idea of mean filtering is simply to replace each pixel value in an image with the mean value of its neighbors, including itself. Mean filtering is usually thought of as a convolution filter. Like other convolutions it is based around a kernel, which represents the shape and size of the neighborhood to be sampled when calculating the mean, the mask has a value of N/1, where N is the mask size.

   2) ***Gaussian Filters:*** The Gaussian smoothing operator is a 2D convolution operator that is used to 'blur' images, remove detail and noise [2]. In this sense it is similar to the mean filter, but it uses a different kernel that represents the shape of a Gaussian. In 2D, the Gaussian distribution follows the equation:

$$\frac{1}{2\pi\sigma^2} exp\left(-\frac{i^2 + j^2}{2\sigma^2} \right) \qquad (4)$$

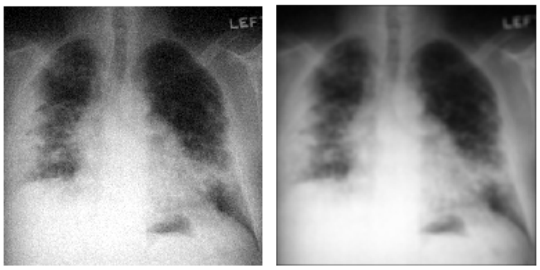
Where σ is the standard deviation. The idea of Gaussian

Smoothing is to use this 2D distribution as a point-spread

Function; achieved by convolution. Once a suitable mask has been calculated, then the Gaussian smoothing can be performed using standard convolution.

There are two Gaussian Filters techniques; (i) average filter and (ii) adaptive filter.

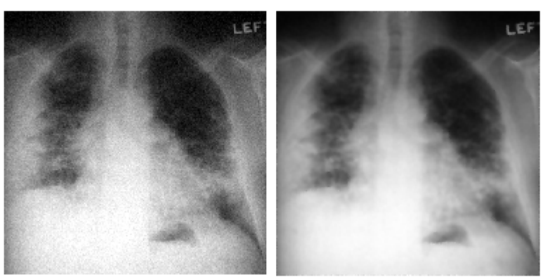
I. Average filter: In such case we take the mean of all the images. If the Gaussian noise has the mean 0, then an average filter would average the noise to 0. The larger the size of the filter masks the closer to zero.



a) Noise image ***b) Average filter***

Fig 1. Average Filter.

II. Adaptive Filter: Which change their characteristics according to the values of the grey scales under the mask; they may act more like average filters, depending on their position within the image [2]. Such a filter can be used to clean Gaussian noise by using local statistical properties of the grey values under the mask.



a) Gaussian noise ***b) Adaptive filter***

Fig 2. Adaptive Filter.

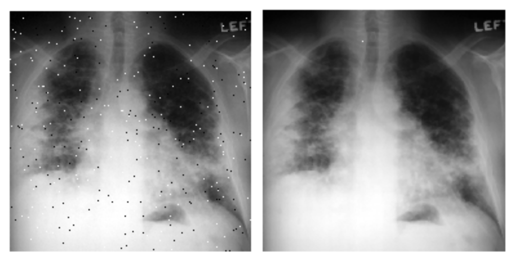
3. Wiener Filter: Wiener filter is commonly used to restore linearly degraded images, and is based on the Minimum Square Error (MSE). Wiener filter is based on the assumption that the power spectra of the ideal image and the noise are known. Since, Wiener filter is the solution of the linear MSE problem of estimating an original image, from a measured one. It can be shown easily that the frequency response of the non-causal Wiener filter is:

$$H(w) = \left(\frac{P_S(w)}{P_S(w) + P_N(w)} \right) \qquad (5)$$

Where $P_S(w)$ and $P_N(w)$ represent the power spectral density of the true signal and the noise, respectively.

B. ***Non-Linear Filters: In nonlinear filters, the noise is*** removed without any attempts to explicitly identify it. In recent years, a variety of nonlinear filters such as weighted median, rank conditioned rank selection, and relaxed median have been developed to improve the drawbacks of standard median filters.

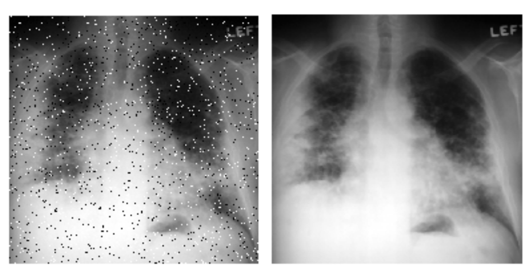
1) ***Median Filters:*** The median filter is normally used to reduce noise in an image, somewhat like the mean filter. However, it often does a better job than the mean filter of preserving useful detail in the image. Median filter considers each pixel in the image in turn and looks at its nearby neighbors to decide whether or not it is representative of its surroundings. Instead of simply replacing the pixel value with the mean of neighboring pixel values; replace it with the median.



a)Noise image ***b) Median filter***

Fig 3. Median Filter.

2) Rank-Order Filter: Median filtering is a special case of a more general process called rank-order filter, rather than take the median of a set, we order the set and take the η-th value, for some predetermined value of η.



a)Noise image ***b) Rank-Order filter***

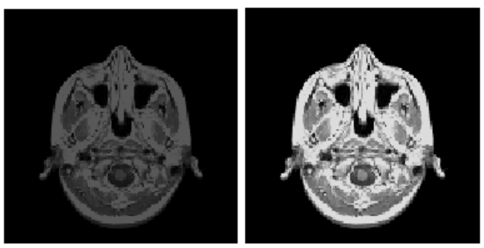
Fig 4. Rank-Order Filter.

IIV. Transformed domain techniques

Transformed filters process an image in any domain other than the spatial domain. The image is transformed, multiplied with the filter function and then re-transformed into the spatial domain. Transformed filter is more appropriate if no straightforward kernel can be found in the spatial domain, and may also be more efficient.

A. Spatial-Frequency Techniques

Spatial-frequency filtering refers to the use of low pass filters using FFT [4]. In frequency smoothing methods the removal of the noise is achieved by designing a frequency domain filter and adapting a cutoff frequency when the noise components are decorrelated from the useful information in the frequency domain. These methods are time consuming; depend on cutoff frequency and the filter function behavior. Furthermore, they may produce artificial frequencies in the processed image. This image was taken from the image processing toolbox in Matlab. (Fig. 5).



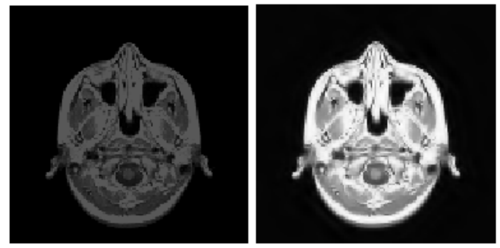
a)Noise image b) Rank-Order filter

Fig 5. Spatial-Frequency Techniques.

B. Wavelet Domain Filters: Wavelet Domain are bases of nested function spaces, which can be used to analyze signals at multiple scales [4]. Wavelet coefficients carry both time and frequency information, as the basis functions varies in position and scale. The wavelet transform efficiently converts a signal to its wavelet representations; in one level a signal x is splitted into an approximate part1 cx and a detail part1 dx. In multilevel, only the approximate part is further decomposed.

1) Thresholding Wavelet Coefficients

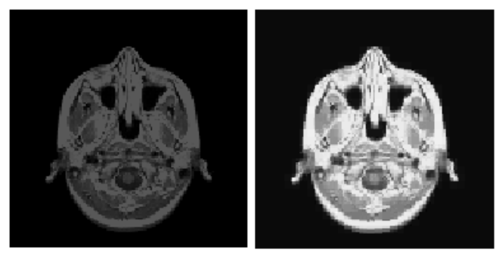
There are two main thresholding techniques of the detail coefficients in the wavelet domain: soft and hard, the selection of any of them is application dependent. This image was taken from the image processing toolbox in Matlab (Fig 6).



a) Noise image b) Filtered image filter

Fig 6. Thresholding Wavelet Coefficients.

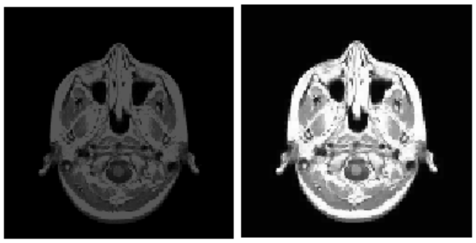
2) Wavelet Packet Transform: Wavelet packets (WP) are waveforms indexed by three naturally interpreted parameters: position, scale, and frequency for a given orthogonal wavelet function [5]. The decomposition parameters of a given dataset are chosen based on an entropy-based criterion. The main difference between wavelet transform and WP is that, in WP both approximate and detail coefficients are decomposed; instead of approximate coefficients in the case of wavelet transform. This image was taken from the image processing toolbox in Matlab. (Fig. 7).



a)Noise image b) Filtered image filter

Fig 7. Wavelet Packet Transform.

3. Smoothing Wavelet Coefficients: The major interests of the noise reduction using wavelet transform are the determination of the wavelet transform and the choice of thresholding parameters, thresholding in wavelet domain is to smooth or to remove some coefficients of wavelet transform of the measured signal [6]. Through the thresholding operation, the noise content of the signal is reduced effectively under the no stationary environment, here; a LPF was used to smooth the wavelet transform coefficients instead of thresholding method. This image was taken from the image processing toolbox in Matlab. (Fig. 8).



a)Noise image ***b) Filtered image filter***

Fig 8. Smoothing Wavelet Coefficients.

IIV. Preprocessing of image fusion

Two images taken in different angle of scene. Most of objects are the same but the shapes change a little. At beginning of fusing images, we have to make sure that each pixel at correlated images has the connection between images in order to fix the problem of distortion; image registration can do this. Two images have same scene can register together using software to connect several control points. After registration, resampling is to adjust each image to fuse to the same dimension. After resampling, each image will be of the same size (Fig. 9). All approaches use pixel-by-pixel fused image. Images with the same size will be easy for fusing process. After the resampling, fusion algorithm is applied. Some time we have to transfer the image into different domain. Inverse transfer is necessary if image has been transferred into another domain [6].

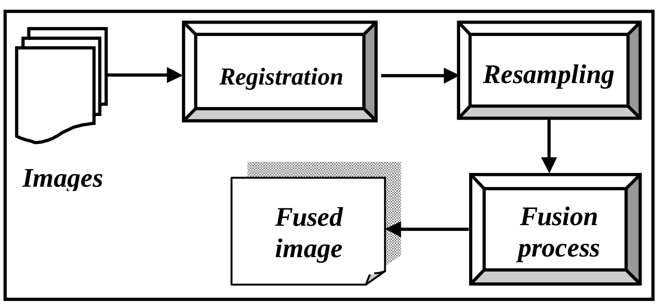


Fig 9. Generic Image Fusion Flow Chart.

V. The performance of image fusion.

Five different measures have been used to evaluate the Performance of fusion process. These are: (1) information Entropy; (2) means-square-error; (3) peak-signal-to-noise Ratio; (4) signal-to-noise ratio, and (5) root-mean-square Error.

1. Entropy: It is one of the most important quantitative measures in digital image processing; which is defined as the quantification of information content of messages. Although used entropy in communication, it can be also employed as a measure and quantify the information content of digital images. A digital image consists of pixels arranged in rows and columns. Each pixel is defined by its position and by its grey scale level. For an image consists of L grey levels, the entropy is defined as:

$$H = -\sum_{i=1}^{L} P(i) Log_2 P(i) \qquad (6)$$

Where P(i) is the probability of each grey scale level.

2. Root-Mean-Square Error (RMSE): The Root-Mean-Square Error RMSE between the reference image; I and the fused image; F, is defined as:

$$RMSE = \sqrt{\frac{1}{MxN} \sum_{i=1}^{M} \sum_{j=1}^{N} [I(i,j) - F(i,j)]^2} \qquad (7)$$

Where i and j denotes the spatial position of pixels, while,

M and N are the dimensions of the images.

3. ***Peak Signal-to-Noise Ratio (PSNR):*** The Peak Signal-to-Noise Ratio PSNR is the ratio between the maximum value of an image and the magnitude of background noise and is commonly used as a measure of quality reconstruction in image fusion. It is defined in terms of the mean-squared error MSE as:

$$PSNR = 10 \log_{10} \left(\frac{(2^n - 1)^2}{MSE} \right) \qquad (8)$$

where n is the number of bits per pixel of the original image I. MSE and PSNR are appealing because they are simple to calculate, have clear physical meanings, and are mathematically convenient in the context of optimization, but they are not well match to perceived visual quality.(7)

On the other hand, SNR between the fused and the original image was calculated using the following equation:

$$SNR = 10 \log_{10} \left(\frac{\sum_{i=1}^{M} \sum_{j=1}^{N} (I(i,j) - F(i,j))^2}{\sum_{i=1}^{M} \sum_{j=1}^{N} I(i,j)} \right) \qquad (9)$$

where I the original image and F is the fused image.

VI. Image Fusion Techniques

The number of proposed concepts for image fusion is growing rapidly, which indicates ongoing research in this area. Technically, image data recorded by different sensors

Have to be merged or composed to generate a new representation. Alternatively, data from one sensor are also Subject of image fusion. Different multispectral channels are to be considered as different sources, as well as images taken at different times by the same sensor. With respect to the conceptual approach, the proposed techniques are averaging; DCT, PCA, DWT, spatial frequency and artificial neural networks .The main characteristics of these techniques are discussed in the mathematical formulation.

VII. Simple Approaches Fusion Techniques

I. Fusion Techniques based on Averaging: The simplest way to fuse two images is to take the mean value of the corresponding pixels. For some applications this may be enough,[8] but there will always be one image with poor lighting and thus the quality of an averaged image will obviously decrease. Like we can see averaging doesn't actually provide very good results.

II. Principal components analysis: Principal component analysis PCA is a general statistical technique that transforms multivariate data with correlated variables into one with uncorrelated variables. These new variables are obtained as linear combination of the original variables.

2.1. Implementation: The implementation process may be summarized as: (i) Images size checking, source images must have the same size; (ii) The input images (images to be fused) are arranged in two column vectors; (iii) The resulting vector has a dimension of n× 2, where n is length of the each image vector; (iv) Compute the eigenvector and eigenvalues for this resulting vector are computed and the eigenvectors corresponding to the larger eigenvalue obtained, and (v) The normalized components are computed from the obtained eigenvector; fused image is:

$$I_f(x,y)=P1I1(x,y)+P2I2(x,y) \qquad (10)$$

where P_1 and P_2 are the normalized components and its equal to: $P1=V(1) / \sum V$ and $P2=V(2) / \sum V$ (11)

where V is eigenvector and P1+P2=1.

III. Discrete Cosine Transform Techniques: To date, different techniques for image fusion have been presented. The simplest method is to take the average of the source images.[9] However, this often leads to undesirable side effects including reduced contrast. Many other techniques including pyramid based image fusion and wavelet transform based image fusion have been introduced to solve this problem. This section studies image fusion in frequency domain based on the DCT transform. We present an image fusion technique based on average measure defined in the DCT domain. An improved version of direct DCT image fusion is obtained from the DCT representation of the fused image by taking the average of all the DCT representations of all the input images. Actually, this image fusion technique is called the DCT + average; modified or "improved" DCT technique. I can be found that, there is a contrast reduction in the fused images obtained by the modified DCT technique.

IV. Discrete Wavelet Transform Techniques: The two-dimensional discrete wavelet transform is becoming one of the standard tools for image fusion. The DWT is computed by successive low pass and high pass filtering of the digital image or images. This is called the Mallat algorithm or Mallat-tree decomposition. Its significance is in the manner it connects the continuous time multi resolution to discrete-time filters. The principle of image fusion using wavelets is to merge the wavelet decompositions.[10,11] of the two original images using fusion methods applied to approximations coefficients and details coefficients. The following two examples examine the process of image fusion to merges two different images leading to a new image: (1) Load two original images Fig. (10.a,b).; (2) Fuse the two images from wavelet decompositions at level 5; (3) Using db2 by taking two different fusion methods; Fusion by taking the mean for both approximations and details Fig. (10.c), and (4) Fusion by taking the maximum for approximations and the minimum for the details Fig. (10.d).

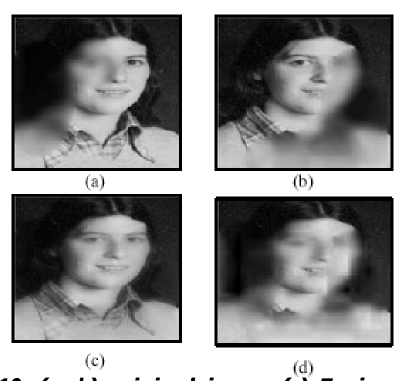
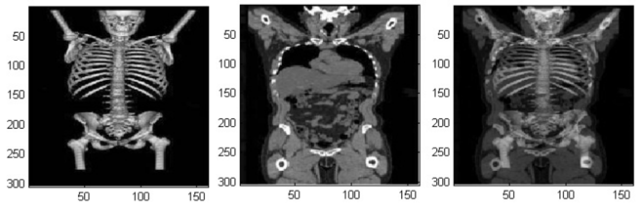


Fig 10. (a, b) original image (c) Fusion by taking the mean for both approximations and details; (d) fusion by taking the maximum for approximations and the minimum for the details.

Take two different images with DWT fusion technique are shown in Fig. 11.



a) b) c)

Fig 11. a) CT-3D Reconstruction Digital Subtraction; b) MRI Coronal Section; c)Decomposed image.

V. Spatial Frequency Techniques (SF):

Spatial frequency is used to measure the overall activity level of an image. For an K×L image F, with the gray value at pixel position denoted by F(x, y), its spatial frequency is defined as:

$$SF= \sqrt{(RF)^2+(CF)}^2 \quad (12)$$

Where RF and CF are the row frequency.

$$RF= \sqrt{\frac{1}{kxL}\sum_{x=1}^{k}\sum_{y=2}^{l}[f(x,y)-f(x,y-1)]^2} \quad (13)$$

And column frequency respectively.

$$CF= \sqrt{\frac{1}{kxL}\sum_{y=1}^{l}\sum_{x=2}^{k}[f(x,y)-f(x-1,y)]^2} \quad (14)$$

The basic algorithm may be written as: (i) Decompose the source images into blocks of size M×N; (ii) Compute the Spatial frequency for each block; (iii) Compare the spatial Frequencies of two corresponding blocks Ai and Bi, and construct the ith block Fi of the fused image as

$$C_{ij} = \begin{cases} SF_i^A & \text{if } SF_i^A > SF_i^B + TH \\ SF_i^B & \text{if } SF_i^A < SF_i^B - TH \\ (A_i+B_i)/2 & \text{Other wise} \end{cases} \quad (15)$$

Where TH is the threshold, and (IV) Verify and correct the fusion result with saliency checking. In this case the aim of this process is to avoid isolated blocks the process is illustrated in flow chart Fig.(12)

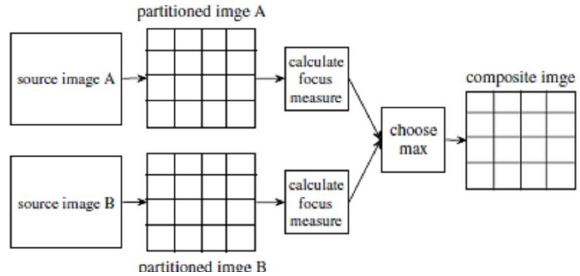


Fig 12. Schematic diagram of the proposed fusion method.

VI. Artificial Neural Networks Techniques:

PCNN is a feedback network and each PCNN neuron consists of three parts: the receptive field, the modulation field, and the pulse generator.(13) PCNN in image fusion is a single layer pulse coupled neural cells with a two dimensional connection as shown in (Fig. 13. In this section, we introduce an image fusion method based on PCNN network. The implementation is computationally simple and can be realized in real-time. (Fig. 14). shows a schematic diagram of the proposed image fusion method.

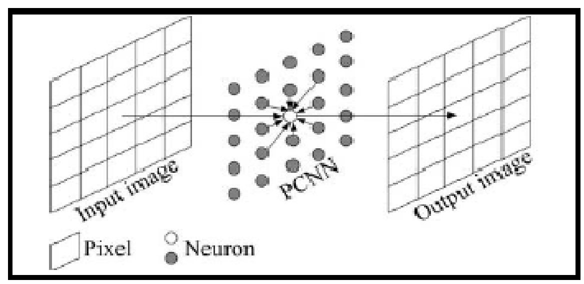


Fig 13. Connection model of PCNN neuron.

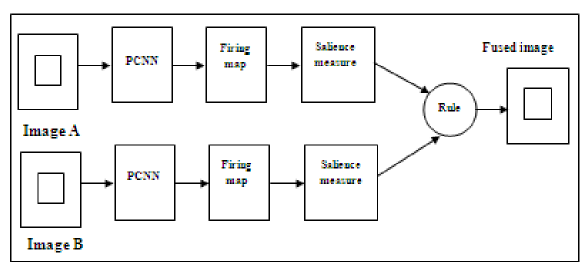


Fig 14. Schematic diagram of PCNN based fusion algorithm.

6.1. Image Fusion Algorithm Based on PCNN:

PCNN in wavelet domain is utilized as follows:

Step-1: source images are decomposed by DWT at the J-th scale, and we obtained sub-images at the J-t scale.

Step-2: each scale DWT coefficients are input to the neurons. There exists a one-to-one correspondence between the coefficients and the network neurons. Each neural cell is connected with neighboring neural cells in linking range, typically within 3×3 (or 5×5) range.

Step-3: the output of each neuron is calculated by formulas (16)-(19), which results in two states, namely firing and non-firing . Then the sum of neuron firing times is counted as formula (20).

$$F_{ij}^{k}(n) = I_{ij}^{k} \qquad (16)$$

$$L_{ij}^{k}(n) = e^{-\alpha L} L_{ij}^{k}(n-1) + V_L \sum_{pq} W_{ij.\,pq} Y_{pq}(n-1) \qquad (17)$$

$$U_{ij}^{k}(n) = F_{ij}^{k}(n) * (1+ \beta L_{ij}^{k}(n)) \qquad (18)$$

$$\theta_{ij}^{k}(n) = e^{-\alpha L} \theta_{ij}^{k}(n-1) + V_\theta Y_{ij}^{k}(n-1) \qquad (19)$$

$$Y_{ij}^{k}(n) = \begin{cases} 1 & \text{if: } U_{ij}^{k}(n) > \theta_{ij}^{k}(n) \\ 0 & \text{Othrwise} \end{cases} \qquad (20)$$

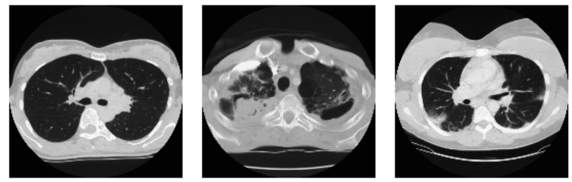
In formulas (13)-(16), the feeding input $F_{ij}^{k}(n)$ is equal to the normalized *DWT* coefficient I_{ij}^{k} corresponding to a pixel in sub-images in wavelet domain and the linking input $I_{ij}^{k}(n)$ is equal to the sum of neurons firing times in linking range$W_{ij,.pq}$ are the synaptic gain strength. a_L is the decay constants. V_L and V_θ are the amplitude gain. β is the linking strength**,** $U_{ij}^{k}(n)$ is total internal activity. $\theta_{ij}^{k}(n)$ is the threshold. k denotes the *k-th* sub-image in wavelet domain. Subscripts i, j denote the location of pixel is (i, j) in sub-image and p, q are the size of linking rang in *PCNN*. If $U_{ij}^{k}(n)$ is larger than $\theta_{ij}^{k}(n)$, then the neuron will generate a pulse $Y_{ij}^{k}(n)$ *in n* iteration is often defined as formula (20) and used to represent image information. Rather than analyze $Y_{ij}^{k}(n)$ one often analyze $T_{ij}^{k}(n)$ instead. $T_{ij}^{k}(n)$, corresponding to one sub-image, consists firing map whose size is equal to the sub-image and value of each pixel in firing map is equal to value of $T_{ij}^{k}(n)$

$$T_{ij}^{k}(n) = T_{ij}^{k}(n-1) + Y_{ij}^{k}(n) \qquad (21)$$

IX. Classification

In classification, the objective is to assign the input patterns to one of several categories or classes.[7] The intent of the classification process is to categorize all pixels in a digital image into one of several medical cover classes, or "themes". This categorized data may then be used to produce the main role of the medical cover present in an image.

1) ***Learning CT Chest Data:*** We work with Specimen of 78 patients in Mansoura University Children Hospital of CT Chest data, using the following data of 11 patients in normal case, 54 patients in bad case and 13 cases in unknown case. (Fig. 15) shows different three cases of patient images.



a) Normal ***b) Bad*** ***b) Unknown***

Fig 15. CT Chest.

2) Active Confusion Matrix (ACM): ACM and MSE using neuro solution network used to classify the input data. as shown in (Fig. 16)

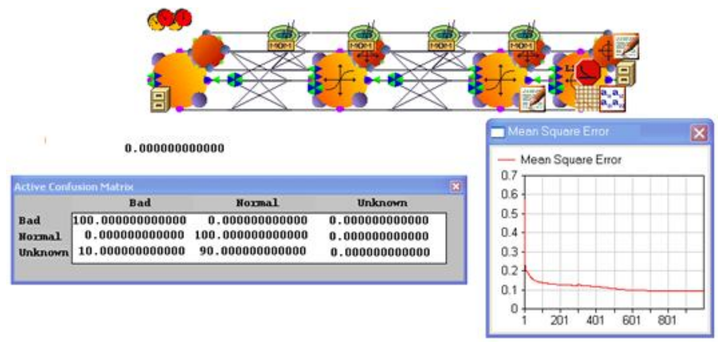


Fig 16. ACM and MSE of CT Chest.

IIX. Results

The following set of tables show the result of applying different filtering techniques in both spatial domain and transformed domain techniques in three levels of SNR were used. Some techniques require certain parameters, which are determined via trial and error approaches. Tables from I to III give the output SNR, while tables from I V to IIIV provide the value of R between noisy input and the filtered images with different noise levels. It has been found that in spatial domain using modified rank order filter gave the best SNR and R as shown in Table I and Table IV. Where as in transformed domain based on wavelet packet of a mother function reversed biorthogonal and soft thresholding of balanced sparcity normal gave the best performance of SNR and R as shown in Table II,

Table III, Table IIV and Table IIIV.

The performance of all discussed image fusion techniques has been examined using sets of images; all taken by digital camera of the “lab” of size 640×480. Objects in images are placed in different distances, thus one object in each image is focused and the other one is blurred. Besides the well-focused image "lab" is used to generate a pair of blurred source images. To perform the blurring process on "Lab" a rotationally symmetric Gaussian low pass filter is used. One object in each image is blurred. Fusion methods are then employed to fuse each pair of the three sets of images. The source images and fusion results for different decomposition levels are illustrated. The performance indices indicate that the image fusion technique based on DWT provides the best results among all discussed techniques. Finally testing ACM of 30% of the CT data to filter the input data into normal or up normal (bad) data.

Table I. the SNR values resulting from using spatial filtered techniques.

Filter type	SNR		
Sharpened Filter	0.04	0.084	0.01
average Filter	4.69	2.33	2.73
Motion Filter	4.81	2.39	2.89
Disk Filter	4.55	2.28	2.68
Rank-order Filter	4.87	2.42	2.95
Median Filter	0.18	3.82	2.95
Wiener Filter	4.87	2.41	2.38

Table II. The SNR values resulting from using DWT techniques.

Wavelet Bases	SNR		
	0.25	0.50	0.75
DB3	2.15	2.68	3.10
Sym3	2.17	2.71	3.13
Meyer	2.20	2.76	3.21
Haar	1.99	2.41	2.74
Bior	2.17	2.69	3.12
R.Bior	2.17	2.72	3.17
Coif.3	2.17	2.71	3.13

Table III. The SNR values resulting from using DWP techniques.

Wavelet Bases	SNR		
	0.25	**0.50**	**0.75**
DB3	2.55	2.82	3.70
Sym3	2.57	2.98	3.62
Meyer	2.71	3.12	3.90
Haar	2.31	2.91	3.65
Bior	2.57	3.03	3.86
R.Bior	2.57	3.12	3.98
Coif.3	2.57	2.98	3.90

Table IV. The Correlation Coefficients resulting from using spatial Filters.

Filter type	R		
	0.97	**0.94**	**0.79**
Sharpened Filter	0.90	0.92	0.90
average Filter	0.92	0.98	0.92
Motion Filter	0.96	0.90	0.91
Disk Filter	0.97	0.97	0.89
Rank-order Filter	0.98	0.99	0.96
Median Filter	0.91	0.98	0.95
Wiener Filter	0.90	0.91	0.94

Table IIV. The Correlation Coefficients resulting from using DWT Filters.

Wavelet Bases	R		
	0.25	**0.50**	**0.75**
DB3	0.69	0.78	0.86
Sym3	0.69	0.78	0.86
Meyer	0.71	0.81	0.85
Haar	0.64	0.74	0.78
Bior	0.71	0.81	0.86
R.Bior	0.73	0.83	0.87
Coif.3	0.71	0.80	0.85

Table IIIV. The Correlation Coefficients resulting from using DWP Filters.

Wavelet Bases	R		
	0.25	**0.50**	**0.75**
DB3	0.69	0.80	0.85
Sym3	0.66	0.77	0.82
Meyer	0.68	0.79	0.84
Haar	0.62	0.73	0.78
Bior	0.67	0.79	0.84
R.Bior	0.69	0.80	0.86
Coif.3	0.68	0.78	0.84

Table V. Measured entropy of fused images by average; PCA, and Modified DCT.

Source Images	Average	PCA	Modified DCT
Lab 1	6.8756	6.8756	6.8756
Lab 2	6.9302	6.9302	6.9302
Fused image	4.8925	6.9658	6.9529

Table VI. Measured RMSE, MSE of fused images by average PCA and Modified DCT.

Source Images	Average	PCA	Modified DCT
RMSE	12.7468	12.3135	12.4987
MSE	162.4801	151.6234	156.2169

Table III. Measured SNR, PSNR of fused images by average PCA and Modified DCT.

Source Images	Average	PCA	Modified DCT
SNR(db)	0.1173	0.2737	0.1162
PSNR(db)	6.0228	26.3231	0.1162

Table IV. Measuring the Entropy, MSE and PSNR of DWT, LPT and SF Technique.

Source Images	Entropy	MSE	PSNR
DWT	7.0223	147.9140	26.4307
SF	6.9576	12.5020	26.1995

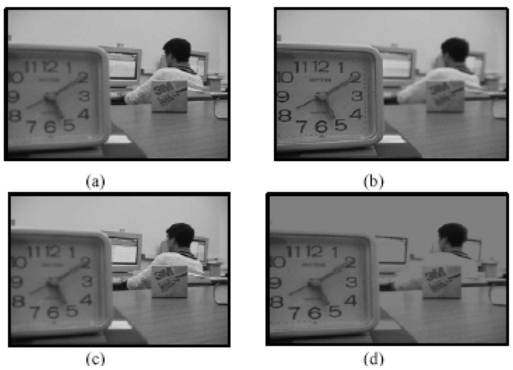


Fig 17. (a) Reference image (everywhere-in-focus) (b) and (c).

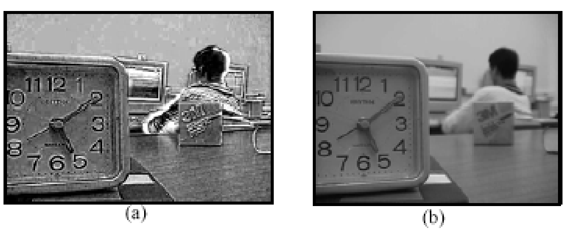


Fig 18. (a) Fused image by PCA (b) Fused image by Modified DC.

Fig 19. Lab images fusion results. (a) Fused image using DWT (b) Fused image using SF.

	Bad	Normal	Unknown
Bad	100.000000000000	0.000000000000	0.000000000000
Normal	0.000000000000	100.000000000000	0.000000000000
Unknown	20.000000000000	80.000000000000	0.000000000000

Fig 20. ACM of tesing CT Chest.

IV. Conclusion

We compared different 2D filtering techniques. Summarizing the results obtained from the study we found that in spatial domain the rank order filter is the best filtering techniques of SNR and correlation coefficient, Where as in transformed domain based on wavelet packet of a mother function reversed biorthogonal and sof t thresholding of balanced sparcity normal gave the best filtering from the point of view of SNR and correlation coeffients. The fusion algorithm based on PCNN in wavelet domain is faster than the wavelet based image fusion technique when the images saved or transmitted in JPEG format. A multi-focus image fusion algorithm using the PCNN is presented in this paper. The energy of image Laplacian is used to measure the clarity of image blocks. The proposed method based on pulse coupled neural network (PCNN) requires no training. We use an iterative method to obtain a proper value. Finally we recommended to use neuro solution to classify the images of different data into normal or up normal cases.

REFERENCES

1. Gonzalez RC, RE Woods, SL Eddins. "Digital Image Processing Using MATLAB: AND" Mathworks, MATLAB Sim SV 07"." 2007.

2. Semmlow JL. Biosignal and Biomedical Image Processing: MATLAB-Based Applications. CRC. 2004.

3. Wink AM, JBTM Roerdink. "Denoising functional MR images: a comparison of wavelet denoising and Gaussian smoothing." Medical Imaging, IEEE Transactions on 23.3. 2004:374-87.

4. Remi K, et al. "An Extensible MRI Simulator for Post-Processing Evaluation," McConnell Brain Imaging Centre, Ne urological Institute, McGill University, Canada.

5. O Rockinger, T Fechner. “Pixel-Level Image Fusion: The Case of Image Sequences”, Procedings SPIE, Vol. 1998;3374:378-88.

6. H Li, BS Manjunath, SK Mitra,’’Multi sensor image fusion using the wavelet transformation‘‘, Graph Models Image Process. 1995;57:235–45.

7. Fausett L. Fundamentals of Neural Networks: Architectures, Algorithms, and Applications. Prentice-Hall Englewood Cliffs, NJ. 1994.