A Teleconsultation System for Medical Image Fusion

Safa Fadl[1], Hossam El-Din Mostafa[2], Hassan H. Soliman[3]

[1, 2, 3] Communication Engineering Dept., Faculty of Engineering, Mansoura University, Al-Gomhoria St., Mansoura, Egypt

Abstract: ***This paper explores different medical image fusion methods and their comparison to find out which fusion method gives better results based on the performance parameters to be a part of medical image teleconsultation system. The teleconsultation in medical diagnosis done by combining images obtained by Computed Tomography (CT) scan and Magnetic Resonance Imaging (MRI) so we get more information and additional data from several different resources to be combined as one fused image. For this, Wavelet Transform, Contourlet Transform and Curvelet transform and its experimental results are employed, evaluated and compared based on its Root Mean Square Error (RMSE), Weighted Peak Signal to Noise Ratio (WPSNR), Mutual Information (MI), Correlation Coefficient (CC) and Entropy (H). Comparison results demonstrate the achievement of better performance of fusion by using Curvelet transform.***

Keywords: about teleconsultation, medical Image Fusion, Wavelet Transform, Curvelet Transform, Contourlet Transform, Web Application, Performance parameters

1. Introduction

With the development of medical imaging equipment, the image diagnosis has made tremendous contributions to the raise of medical standard. A single mode of image cannot provide comprehensive and accurate information, so medical image fusion has become the focus of image research and processing. Medical image fusion refers to the matching and fusion between two or more images of the same lesion area from different medical imaging equipment. It is to obtain complementary information, increase the amount of information, and make the clinical diagnosis and treatment more accurate and perfect [1].

Images are obtained from different imaging systems like CT, MRI, and PET plays an important role in medical diagnosis and other clinical applications by imparting a distinct level of information. Study by vivek [2] et al. showed that accurate size and location of brain tumor can be detected. For example, CT is commonly used for visualizing dense structures and is not suitable for soft tissues. MRI on the other hand provides better visualization of soft tissues and is commonly used for detection of tumor and other tissue abnormalities. Therefore, fusion of images obtained from different modalities is desirable to extract sufficient information for clinical diagnosis and treatment. This information includes the size of tumour and its location, which enable better detection when compared to the source images [3].

The goal of image fusion is to obtain useful complementary information from multimodality images as much a possible number of solutions for image fusion have been introduced in previous literatures [1].

This paper introduces wavelet transform, curvelet transform, and contourlet transform and uses it to fuse images, different kinds of fusion methods are compared at last. The experiments show that the method could extract useful information from source images to fused images so that clear images are obtained.

The performance of the fusion techniques is evaluated based on different quantitative metrics such as WPSNR, MI, CC, RMSE and Entropy.

2. Image Fusion Techniques

The fusion methods such as wavelet transform, curvelet transform and Contourlet transform based methods.

2.1 Wavelet Transform

The most common form of transform type image fusion algorithms is the wavelet fusion algorithm due to its simplicity and its ability to preserve the time and frequency details of the images to be fused. In common with all transform-domain fusion techniques, the transformed images are combined in the wavelet domain using a predefined fusion rule, then transformed back to the spatial domain to give the resulting fused image [4]. Wavelet transform fusion is more formally defined by considering the wavelet transforms w of the two registered input images I_1 (x, y) and I_2 (x, y) together with the fusion rule φ. Then, the inverse wavelet transform w^{-1} is computed, and the fused image I (x, y) is reconstructed:

$$I(x,y) = w^{-1}(\varphi(w(I_1(x,y)), w(I_2(x,y)))) \qquad (1)$$

This process is depicted in figure 1 [5].

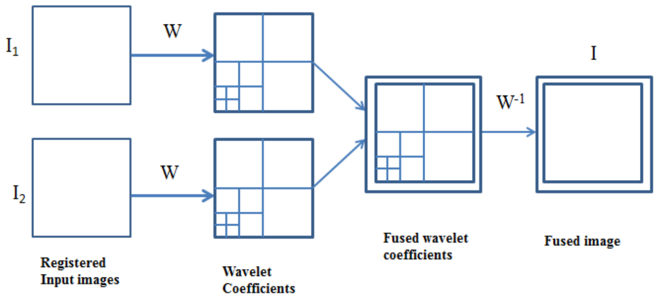


Figure 1: Fusion of the wavelet transforms of two images

2.2 Curvelet Transform

Candes and Donoho (1999) developed a multi-scale transform which they called the curve let transform. Motivated by the needs of image analysis, it was nevertheless first proposed in the context of objects f(x_1, x_2) defined on the continuum plane (X_1> X_2) ϵ R^2. The transform was designed to represent edges and other singularities along curves much more efficiently than traditional transforms, i.e. using many fewer coefficients for a given accuracy of reconstruction. Roughly speaking, to represent an edge to squared error 1/N requires 1/N wavelets and only about $1/\sqrt{N}$ curvelets. According to approximation theory the curvelet transform is more efficient and faster than traditional transforms like Fourier and Wavelet transforms [5].

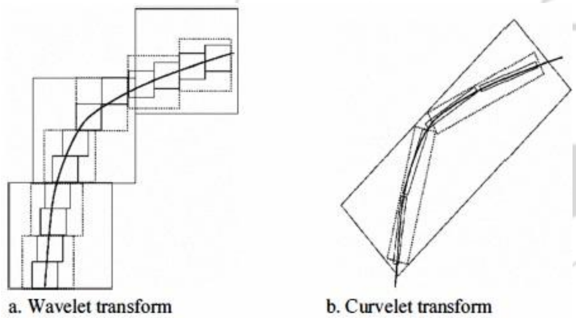


Figure 2: Many wavelet coefficients are needed to account for edges i.e. singularities along lines or curves while curvelet many fewer coefficients.

The curvelet transform is suited for objects which are smooth away from discontinuities across curves. A discontinuity point affects all the Fourier coefficients in the domain. Hence the FT doesn't handle point's discontinuities well. Using wavelets, it affects only a limited number of coefficients. Hence the WT handles point discontinuities well. Discontinuities across a simple curve affect all the wavelets coefficients on the curve. Hence the WT doesn’t handle curves discontinuities well. Curvelets are designed to handle curves using only a small number of coefficients as mentioned before. Hence the curvelet transform handles curve discontinuities well.

Curvelet transform has applications in many fields such as Image processing including image denoising, image fusion and other applications, Seismic exploration, Turbulence analysis in fluid mechanics, and solving of PDEs.

2.2.1Curvelet Transform Analysis

The Curvelet Transform includes four stages:

1. Sub-band decomposition

$$f \to (p_0 f, \Delta_1 f, \Delta_2 f, ...) \qquad (2)$$

The image is divided into resolution layers $P_0, (\Delta_s, s \geq 0)$.

Each layer contains the details of different frequencies:

- P_0 - Low-pass filter
- Δ_1, Δ_2 - Band-pass (high-pass) filters

2. Smooth partitioning

A grid of dyadic squares is defined as:

$$Q_{(s,k_1,k_2)} = \left[\frac{k_1}{2^s}, \frac{k_1+1}{2^s}\right] \times \left[\frac{k_2}{2^s}, \frac{k_2+1}{2^s}\right] \in Q_s \qquad (3)$$

Let w be a smooth windowing function. For each square, w_Q is a displacement of w localized near Q .

Multiplying Δs f with w_Q $(\forall Q \in Q_s)$ produces a smooth dissection of the function into 'squares'.

$$h_Q = w_Q . \Delta_s f \qquad (4)$$

In this stage, this windowing dissection is applied to each of the sub-bands isolated in the previous stage of the algorithm.

$$\Delta_s f \ \to (w_Q . \Delta_s f) \qquad Q \in Q_S \qquad (5)$$

3. Renormalization

For a dyadic square Q, let

$$(T_Q f)(x_1, x_2) = 2^s f(2^s x_1 - k_1, 2^s x_2 - k_2) \qquad (6)$$

Denote the operator which transports and renormalizes f so that the part of the input supported near Q becomes the part of the output supported near the unit square [0, 1] x [0, 1].

In this stage of the procedure, each 'square' resulting in the previous stage is renormalized to unit scale.

$$g_Q = T_Q^{-1} h_Q \qquad (7)$$

4. Ridgelet analysis

In the previous two stages we transform curved lines into small straight lines. That improves the ability of the curvelet transform to handle curved edges. In this stage each normalized square is analyzed in the orthonormal Ridgelet system.

Ridgelet transform:

The Ridgelet transform deals effectively with line singularities in 2-D. The basic idea is to map a line singularity in the two-dimensional (2-D) domain into a point by means of the Radon transform. Then, a one-dimensional (1-D) wavelet is performed to deal with the point singularity in the Radon domain.

2.2.2 The Inverse Curvelet Transform

The procedure of obtaining inverse Curvelet transform can be summarized by simply reversing the previously explained steps as follows:

1. Ridgelet Synthesis
Each 'square' is reconstructed from the orthonormal Ridgelet system.

2. Renormalization
Each 'square' resulting in the previous stage is renormalized to its own proper square.

$$h_Q = T_Q g_Q \tag{8}$$

3. Smooth Integration
The windowing dissection to each of the windows reconstructed in the previous stage of the algorithm is reversed.

$$\Delta_s f = \sum_{Q \in Q_s} w_Q . h_Q \tag{9}$$

4. Sub-band Re-composition
Undo the bank of sub-band filters, using the reproducing formula:

$$f = p_0(p_0 f) + \sum_s \Delta_s(\Delta_s f) \tag{10}$$

2.2.3 The Curvelet Image Fusion Algorithm

The specific operational procedure for the curve let-based image fusion approach is now given. The algorithm is summarized as follows:

1) The two input images are first registered.
2) The curvelet transform steps are performed for both images (each input image is analyzed and a set of curvelet coefficients are generated).
3) The maximum frequency fusion rule or any other rule for image fusion is used for the fusion of the curvelet (or Ridgelet) coefficients.
4) The inverse curvelet transform step is performed (The fused coefficients are subjected to the inverse curvelet transform) to obtain the fused image.

These steps are expected to merge the details in both images into a single image with much more details.

2.3 Contourlet Transform

Contourlet transform brings smoothness in a fused image with any two different modalities of images. This region based transformation is implemented in two stages. In the first stage double filter bank scheme is applied for transformation and in the next stage decomposition is done with fusion rules. Finally, the fused image is retrieved using reconstruction procedure [6].

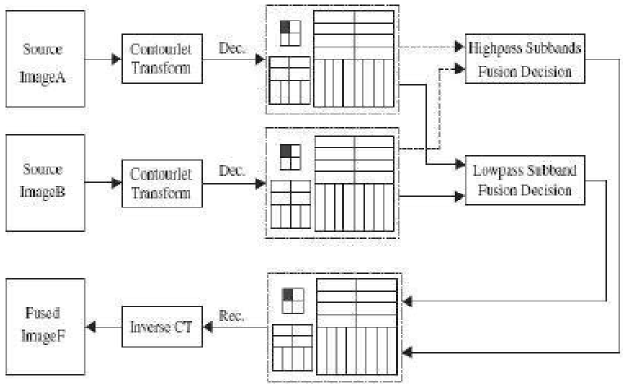


Figure 3: Block diagram of the contourlet based image fusion

The flow graph of the proposed image fusion algorithm is shown in Fig. 3. Here image A and B denotes the input source images CT and MRI respectively. F is the final fused outcome after inverse contourlet transform.

3. Performance Parameters for Determining the Quality of Fused Image

In the present work, we have used four performance measures to evaluate the performance of the wavelet, curvelet and contourlet algorithms.

3.1 Entropy (H)

The Entropy (H) is the measure of information content in an image. The maximum value of entropy can be produced when each gray level of the whole range has the same frequency. If entropy of fused image is higher than parent image, then it indicates that the fused image contains more information [7].

$$H = -\sum_{g=0}^{L-1} p(g) \log_2 p(q) \tag{11}$$

3.2 Root Mean Square Error (RMSE)

A commonly used reference based assessment metric is the RMSE. The RMSE will measure the difference between a reference image, R, and a fused image, F, RMSE is given by the following equation

$$RMSE = \sqrt{\frac{1}{MN} \sum_{m=1}^{M} \sum_{n=1}^{N} (R(m,n) - F(m,n))^2} \tag{12}$$

Where R (m, n) and F (m, n) are the reference (CT or MR) and fused images, respectively, and M and N are image dimensions. Smaller the value of the RMSE, better the performance of the fusion algorithm.

3.3 Correlation Coefficient (CC)

The correlation coefficient is the measure the closeness or similarity in small size structures between the original and the fused images. It can vary between −1 and +1. Values closer to

+1 indicate that the reference and fused images are highly similar while the values closer to −1 indicate that the images are highly dissimilar.

$$CORR = \frac{2c_{rf}}{c_r + c_f} \tag{13}$$

Where

$$Cr = \sum_{i=1}^{M}\sum_{j=1}^{N} I_r(i,j)^2 \tag{14}$$

$$C_f = \sum_{i=1}^{M}\sum_{j=1}^{N} I_f(i,j)^2 \tag{15}$$

$$C_{rf} = \sum_{i=1}^{M}\sum_{j=1}^{N} I_r(i,j) I_f(i,j) \tag{16}$$

3.4 Weighted Peak Signal to Noise Ratio (WPSNR)

The WPSNR is a different quality measurement. The objective evaluations are generally realized by mathematical formulas inspired from treatment of the signal, which make possible to calculate the degradations introduced into the process, by comparing the original image (M x N size) noted f (m,n) and the reconstructed image noted $\hat{f}(m,n)$.The Peak Signal to Noise Ratio (PSNR) between the original and the reconstructed image is a popular metric of image quality used in registration. PSNR is a function of the MSE (Mean Square Error) and is defined as follows:

$$PSNR = 10\log_{10}\left(\frac{MAX^2}{MSE}\right) \tag{17}$$

Where MAX is the maximum possible intensity value in the image and MSE has the form:

$$MSE = \frac{1}{MN}\sum_{m=0}^{M-1}\sum_{n=0}^{N-1}\left| f(m,n) - \hat{f}(m,n) \right|^2 \tag{18}$$

The weighted mean square error (WMSE) is defined as:

$$WMSE = \frac{1}{MN}\sum_{m=0}^{M-1}\sum_{n=0}^{N-1}\left(\frac{(fp - \hat{fp})^2}{1 + Var(m,n)}\right) \tag{19}$$

Where var(m,n) refers to the variance of the image. The WPSNR is defined as follows:

$$WPSNR = 10\log_{10}\left(\frac{MAX^2}{WMSE}\right) \quad (dB) \tag{20}$$

3.5 Mutual Information (MI)

Mutual information is the basic concept of measuring the statistical dependence between two random variables and the amount of information that one variable contains about the others. Mutual information here describes the similarity of the image intensity distributions of the corresponding image pair. Let A and B be two random variables with marginal probability distributions $p_A(a)$ and $p_B(B)$ and joint probability distribution $p_{AB}(a, b)$

$$I_{AB}(a,b) = \sum_{x,y} P_{AB}(a,b)\log\frac{P_{AB}(a,b)}{P_A(a)P_B(b)} \tag{21}$$

Considering two input images A, B and a fused image F we can calculate the amount of information that F contains about A and B according to above equation.

$$I_{FA}(f,a) = \sum_{x,y} P_{FA}(f,a)\log\frac{P_{FA}(f,a)}{P_F(f)P_A(a)} \tag{22}$$

$$I_{FB}(f,b) = \sum_{x,y} P_{FB}(f,b)\log\frac{P_{FB}(f,b)}{P_F(f)P_B(b)} \tag{23}$$

Thus the mutual information is given by

$$M_F^{AB} = I_{FA}(f,a) + I_{FB}(f,b) \tag{24}$$

4. Experimental Results

In this system initially the two different types of modality images CT (anatomical) and MRI (pathological) are given as input. Then the fusion techniques are applied to the registered images to find a more informative fused image. The fused image is validated using quantitative measures. The system design is shown in Fig. 4.

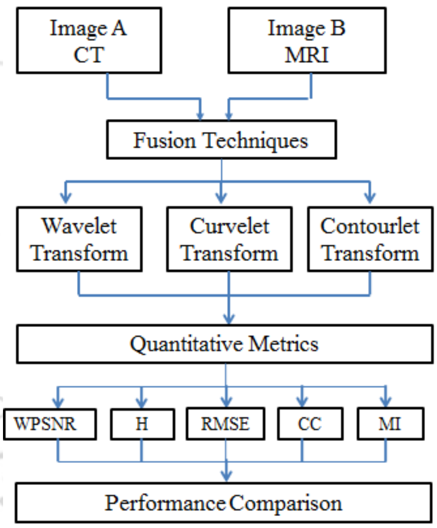
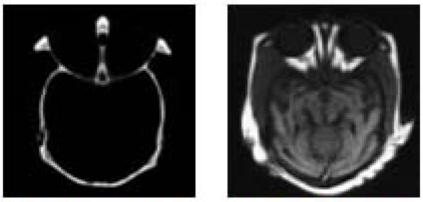


Figure 4: An overall view of system design

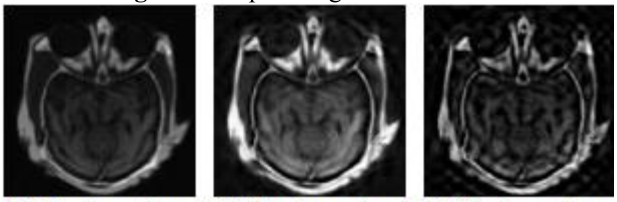
The experiment is performed on two medical images, one CT image and another is MRI image as shown in fig5 (a) and (b). Compared fig.5 (a) with fig.5 (b), it is easy to see that CT image support clear bones information but no soft tissue information, however contrast to CT image object in the two medical image appear distinctly. Hence, in order to support more accurate information for diagnosis and treatment it is necessary to fuse them.

The three methods are then used to fuse the two images, and their corresponding results are displayed in fig.6 (c)-(e) respectively. As can be seen, with all the methods the fused images now preserve the whole information presented in two images. However, the visual inspection it can be seen that fused result of the curvelet method is more clearly and higher contrast then other method.



(a) CT Image (b) MR Image

Figure 5: Input image: CT and MRI



(c) Fusion using wavelet Transform (d) Fusion using Curvelet Transform (e) Fusion using Contourlet Transform

Figure 6: Fusion result of three different techniques

Table 1: Comparison of Fusion Performance

	WPSNR	Entropy	RMSE	MI	CC
Wavelet Transform	20.8034	8.4681	39.9096	3.5124	0.7046
Curvelet Transform	**28.7951**	**10.2456**	**24.4401**	2.3725	0.6566
Contourlet Transform	22.7798	9.8045	39.8261	1.5638	0.6339

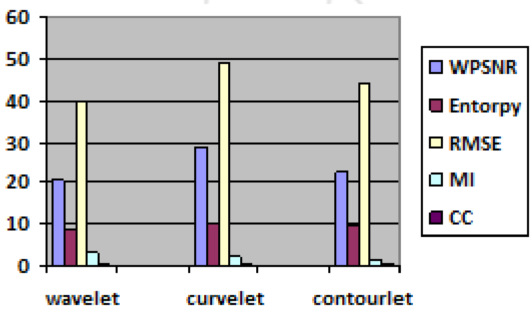


Figure 7: Comparison chart of three algorithms

From the above comparison chart and fusion outputs in fig 7 it is clear that the curvelet fusion result has a better visual quality than the wavelet fusion result and contourlet fusion.

The WPSNR, RMSE, MI, CC and Entropy values of these results are for wavelet fusion, curvelet fusion and contourlet fusion. These values reflect the ability of the Wavelet, curvelet and contourlet transform to capture features from both the MR and the CT images. From these results, it is clear that the curvelet fusion algorithm has succeeded in obtaining better results than the wavelet fusion algorithm and contourlet fusion algorithm from both the visual quality and the RMSE, WPSNR, MI, CC and Entropy points of view.

5. Teleconsultation System

Teleconsultation - remote discussion of the concrete clinical case for the answer to precisely formulated questions for the help in acceptance of the clinical decision.

Traditionally teleconsultation is classified into: off-line; on-line.

Off-line teleconsultation comprises a type of remote consultations not involving real time network communication (video, chat etc.). Consulting and inquiring physicians exchange information via email, FTP-servers, Internet forums. This type of teleconsultation is used for elective medical care.

On-line teleconsultation is a type of remote consultation involving real time network communication systems: video, chat, web applications, etc. This type of teleconsultation is used for emergency (urgent) medical care. It should be pointed out that in routine clinical practice these techniques are usually combined: an off-line teleconsultation may be expanded through real time dialogue between the consulting and inquiring physicians through the web application; a real time image processing may be preceded by the application and its chat channel.

5.1 Real Time Teleconsultation

In Teleconsultation, real-time processing, processing without distortion, and browsing without plug-ins for medical image are these reasons that hinder implementation of medical image teleconsultation system [8]. In this paper, we describe a concept of a web-based system for medical teleconsultation. The system will be applied to combine images obtained by Computed Tomography (CT) scan and Magnetic Resonance Imaging (MRI) so we get more information about patient's in Teleconsultation, real-time processing, processing without distortion, and browsing without plug-ins for medical image are these reasons that hinder implementation of medical image teleconsultation system. In this paper, we describe a concept of a web-based system for medical teleconsultation. The system will be applied to combine images obtained by Computed Tomography (CT) scan and Magnetic Resonance Imaging (MRI) so we get more information about patient's cases. The System Consists of two main steps beginning with Physician report submission and ended with System generated report including the final fused image.

5.2 Physician Report

In this step after the physician logged in to the system will be allowed to fill up the patient details, and then start to upload at least two images as mandatory fields. The physician welcomed to write a short description about the uploaded image as hint for reviewing later Fig. 8.

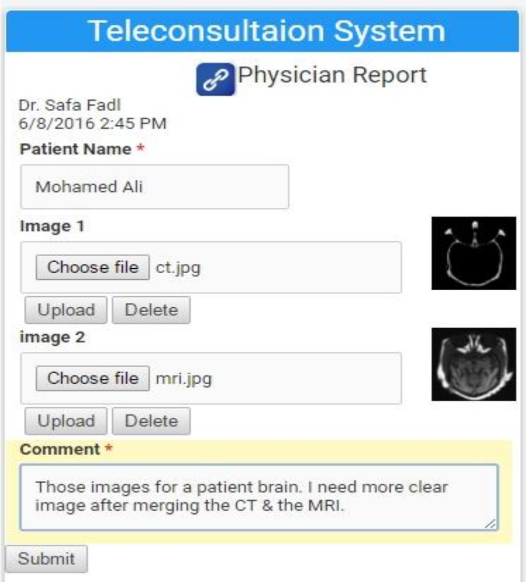


Figure 8: Teleconsultation System-Physician Report

5.3 The System Generated Report

As part of our previously defined techniques we use the uploaded images from the physician to process them throughout our developed teleconsultation system to generate a fused image that obtained complementary information, with high amount of information, and make the clinical diagnosis and treatment more accurate and perfect Fig. 9.

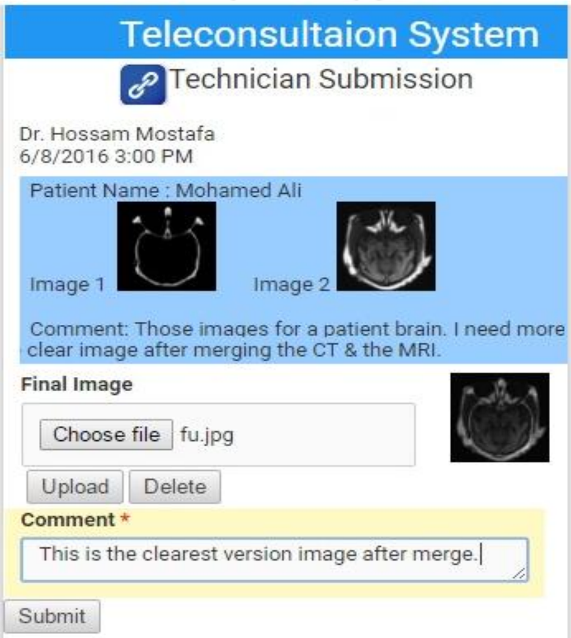


Figure 9: Teleconsultation System –Technician Submission

6. Conclusion

As discussed earlier, performance of different fusion method is evaluated on the basis of WPSNR, RMSE, MI, Entropy and CC. Table 1 shows values of different fusion techniques used in this paper. It can be seen that image fusion using Curvelet has maximum WPSNR, Entropy and minimum RMSE as compared to wavelet transform and Contourlet transform. Lower value of RMSE and higher value of WPSNR and Entropy indicates better fusion performance. Therefore, image fusion using Curvelet provides better fusion results. Future work is to achieve the higher performance by proposed technique.

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Author Profile

Safa I. Fadl received the B.S. degrees in Comm. Engineering from Mansoura University, Egypt in 2007. Safa have 9+ Experience in software development specially that related to medical systems.

Hossam El-Din Moustafa received B.S from Mansoura University Egypt in 2000. Ph.D degree from Mansoura University in 2008. Fields of interest: Digital signal processing, Image processing, Tracking and video Surveillance, Biometrics, Mobile communications. He is an assistant professor at Faculty of Engineering, Mansoura University.

Hassan H. Soliman received the B.S degree from Mansoura University Egypt in 1983. Ph.D degree from Mansoura University in 1993. Fields of interest: Neural Networks, Characters Recognition, Digital signal processing, Image processing. He is a Dean College of Computers and Information Sciences, Mansoura University.