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A Comprehensive Survey Analysis for Present Solutions of Medical Image Fusion and Future Directions

OSAMA S. FARAGALLAH¹, HEBA EL-HOSEN², WALID EL-SHAFI³,
WAEEL ABD EL-RAHMAN⁴, HALA S. EL-SAYED⁵,
EL-SAYED M. EL-RABAIE³, (Senior Member, IEEE), FATHI E. ABD EL-SAMIE³,
AND GAMAL G. N. GEWEID^{4,6}

¹Department of Information Technology, College of Computers and Information Technology, Taif University, Taif 21944, Saudi Arabia

²Department of Electronics and Electrical Communication Engineering, Al-Obour High Institute for Engineering and Technology, Al-Obour 3036, Egypt

³Department of Electronics and Communication Engineering, Faculty of Electronic Engineering, Menofia University, Menouf 32952, Egypt

⁴Department of Electrical Engineering, Faculty of Engineering, Benha University, Benha 13512, Egypt

⁵Department of Electrical Engineering, Faculty of Engineering, Menoufia University, Shebeen El-Kom 32511, Egypt

⁶Department of Engineering and Technology, Worldwide College of Aeronautics, Embry-Riddle Aeronautical University, Daytona Beach, FL 32114, USA

Corresponding author: Osama S. Faragallah (o.salah@tu.edu.sa)

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ABSTRACT The track of medical imaging has witnessed several advancements in the last years. Several medical imaging modalities have appeared in the last decades including X-ray, Computed Tomography (CT), Magnetic Resonance (MR), Positron Emission Tomography (PET), Single-Photon Emission Computed Tomography (SPECT) and ultrasound imaging. Generally, medical images are used for the diagnosis purpose. Each type of acquired images has some merits and limitations. To maximize medical images utilization for the purpose of diagnosis, medical imaging fusion trend has appeared as a hot research field. Different medical imaging modalities are fused to obtain new images with complementary information. This paper presents a survey study of medical imaging modalities and their characteristics. In addition, different medical image fusion approaches and their appropriate quality metrics are presented. The main aim of this comprehensive survey analysis is to contribute in the advancement of medical image approaches that can help for better diagnosis of different diseases.

INDEX TERMS Medical imaging, fusion process, imaging modalities, dual-tree complex wavelet transform, curvelet transform, discrete wavelet transform, principal component analysis.

I. INTRODUCTION

At the moment, the precipitous advancement in high technology and contemporary instruments result in making the medical imaging the extremely essential diagnostic tool for diseases and treatment [1]–[4]. For the purpose of medical diagnostics, various multimodal medical imaging techniques like MRI, CT, PET, SPECT are employed. Each modality is utilized in a particular application and performs a specific function. The SPECT and PET show the functional and metabolic activity, while the MRI, CT, and Ultrasound provide the anatomical structures of organs. For additional useful images with higher corresponding data and higher image details, medical image fusion is the perfect answer [5]–[9].

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Therefore, medical image fusion multimodalities became a challenging research field, recently.

The image fusion process is defined as combining a group of registered digital images from various times or of various sources into a particular digital image [10]–[15]. Numerous image fusion schemes are developed and designed to sustain a variety of applications such as satellite imaging, medical diagnosis, object recognition and detection, and artificial neural networks. These schemes can be grouped into two major branches: spatial-domain fusion schemes such as PCA, IHS, and Averaging fusion technique [65]–[67]. The transform fusion techniques are divided into two branches: multi-resolution and multi-scale fusion techniques [48], [54], [56], [67], [71], [81]. Many multi-resolution analysis tools are used for image fusion such as DWT and DT-CWT [53], [70], [73], [76], [84]. Multi-scale schemes presented numerous transforms like curvelet, ridgelet, shearlet, and contourlet

transforms [9]–[11], [16], [17], [19], [40], [59]–[62], [77], [81], [83], [87]. Therefore, image decomposition can be considered as a very significant analytical tool that may affect greatly the extraction and the whole fusion quality.

Lately, the optimization process has found concern from scientists to improve the execution of numerous signal processing algorithms. The optimization procedures offer the optimum standards for a scheme to accomplish the greatest feasible accomplishment. Global optimization schemes are a formidable methodology that can deliver better explanations for many challenges.

Various global stochastic optimization schemes have been performed effectively in medical digital image fusion such as GWO (gray wolf optimization) that greatly improves the performance of the fusion technique [74]. The CFO (central force optimization) technique which is depending on the gravity law and it has many benefits like the simplicity of implementation, straightforward mathematics involved, high convergence speed, and short processing time [81]–[84]. The PSO (particle swarm optimization) scheme is depending on swarm intelligence. The main advantages of PSO are very simple calculations, adopting the real number code, no overlapping and mutation calculation, the fast search, and a memory for updating the velocity [40]. The MCFO (modified CFO) algorithm incorporates the great merits of both PSO and CFO optimization techniques to have acceleration time-varying coefficients, a memory capability, and additional velocity into the position probe updated equation.

In fact, the local contrast enhancement techniques have a strong effect for improving the clarity and details information of images. Different techniques are used for medical images contrast enhancement like histogram equalization, intensity adjustment, histogram matching, and adaptive histogram equalization [81], [84].

The main target of such a review study is to give a collective survey of image fusion techniques and their applicability that could be helpful. A number of investigations have addressed the topic of medicinal imaging fusion from various viewpoints. In [55], a medical image fusion algorithm has been presented. This algorithm is based on a multi-wavelet basis and regional variance to prove that fusion procedure based on multi-wavelets with better performance than a single wavelet-based fusion procedure. The fusion process in this case is done through the merge rule, which may or may not depend on the application, and whether or not the sub-band is merged.

In [57], the authors presented a study of a multi-modality medical images fusion algorithm based on DT-CWT that enhances the multi-sensor fusion procedure using DT-CWT instead of DWT implemented with the window-based fusion rule. This achieved much better performance than the pixel-based fusion rule. Also, the authors in [20] have presented an algorithm for fusing multi-focus and multi-modal images using DT-CWT decomposition before segmentation for perfect tumor identification.

In [63] the authors proposed a new scheme for a multi-focus fusion procedure that is based on uniform discrete

curvelet transform. This can manage the problems of conventional multi-scale analysis image fusion of rising data redundancy ratio and poor performance to achieve higher image quality.

Recently, many researchers have been interested in combining PCA fusion algorithm with other transform fusion techniques such as hybrid fusion approach using PCA and wavelet transform [66], PCA and contourlet transform [67], . . . , etc.

In [5], [6], the authors introduced a review study on medicinal imaging fusion approaches used in the health system to provide an overview of the fusion methods utilized in the applications of medical services, like curvature transformation, waveform, contour transformation, standing waveform transformation, and frame transformation.

In [81], the authors presented an optimized medical image fusion system using the Non Sub-Sampled Shearlet Transform (NSST) and MCFO for setting the optimal gain fusion parameter estimations. The MCFO optimization is employed to set the optimum gain parameter scores for the fusion process. The proposed algorithm implements a further enhancement step using adaptive and combined adaptive histogram equalization, and histogram matching to overcome contrast limitations and increase details in the fusion results. Finally, the proposed algorithms are evaluated using different quality metrics. The examined tests demonstrated that the proposed MCFO-based NSST has achieved an improved performance in terms of improving image visualization, enhancing local contrast, and increasing PSNR.

In [82], the authors introduced an optimized Discrete wavelet transform (DWT) fusion system using various wavelet families like Ddb1, Haar, db1, discrete meyer, and Coiflet 1. The proposed fusion system utilizes the MCFO scheme to provide the optimum fusion gain parameter scores. The proposed algorithm performance using various wavelet families is investigated and examined with standard quality measures for proving their superiority and validity with respect to DWT and PCA algorithms. The adaptive histogram equalization has been used for improving the proposed algorithm and providing higher image quality. The histogram matching and the adaptive histogram equalization are the best solution for local contrast enhancement, increasing PSNR, and improving image visualization.

In [83], the authors presented an optimized medical image fusion system that employs the Non Sub-Sampled Contourlet Transform (NSCT) and MCFO for setting the optimal gain fusion parameter estimations. The MCFO optimization is employed to set the optimum gain parameter scores for the fusion process. The proposed algorithm implements a further enhancement step using various local contrast enhancement approaches. Also, the proposed algorithms are evaluated using different quality metrics. The examined results demonstrated that the proposed MCFO-based NSCT has achieved an excellent performance with considerably high scores of edge intensity, average gradient, local contrast enhancement.

This results in improving image visualization, enhancing local contrast, and increasing PSNR.

In [84], the authors presented an optimized medical image fusion approach using the DT-CWT, MCFO, and matched histogram. For achieving an optimum performance of DT-CWT, three approaches have been tested. The proposed optimized (OPT) fusion algorithms with optimum gain parameters improved image quality at a very short processing time and made a good benefit from matched histogram and adaptively histogram equalization for achieving an excellent performance with high image quality, the highest details information, and the best visualization for accurate diagnosis. The Max-OPT fusion technique with matched histogram and adaptive histogram equalization is proposed for extra improvement in quality factor, PSNR, local contrast, and image visualization. The Max-Max fusion technique has the highest quality factor but lower values of the other quality metrics. So, the adaptive histogram equalization is used to improve its performance and provide higher image quality. So, it can be applied in real time applications. The matched histogram and the adaptive histogram equalization are the best solution for local contrast enhancement, increasing PSNR, and improving image visualization.

Recent works for medical imaging fusion using deep-learning techniques have been introduced in [9], [11], [13], [23], [31], [39], [41], [69], [85]–[88].

The importance of studying medical image fusion algorithms lies in the objective analysis of the weaknesses and strengths of the techniques currently used and finding the appropriate solutions that achieve fusion of medical images with high quality and accuracy, which helps specialists in an accurate and precise diagnosis of the disease and then prescribe the appropriate treatment. Besides, clarifying the vital importance of multi-modality fusion process for the same patient in an accurate diagnosis of diseases and develop the medical radiology devices to enable them to fuse multi-modality images that can be used for computer-aided diagnosis applications and increasing the clinical applicability of medical images. Therefore, this research provides a comprehensive study of the latest methods implemented in medical image fusion.

This article is concerned with utilization of medical image fusion to obtain a fused image with as much complementary information, highest clarity, and best visualization as possible helping for accurate diagnosis and optimal therapy. The article objectives can be summed up as follows:

- 1) Review the preliminaries of medical imaging fusion.
- 2) Cover the medical imaging modalities with comparisons and includes the major applications of medical image fusion.
- 3) Introduce medical imaging fusion quality measures.
- 4) Compare the performance of some of the most currently used medical image fusion methods with comparisons.
- 5) Discusses medical image fusion and denoising techniques.

- 6) Explore the recent new trends and directions in medical imaging fusion.

This research work is arranged as follows. Section II includes the preliminaries of medical image fusion. Section III covers the medical imaging modalities with comparisons and includes the major applications of medical image fusion. Section IV discusses image fusion quality measures. Section V explores the performance of some of the most currently used medical image fusion methods with comparisons. Section VI Section VI discusses medical image fusion and denoising techniques. Section VII includes some new trends in the medical image fusion subject. Section VIII gives the conclusions and directions for future works.

II. PRILIMINARIES OF MEDICAL IMAGING FUSION

Image fusion may be considered as a merging tool for relevant knowledge from a series of medical images into one enlightening and comprehensive image. More accurately, fusion is the incorporation of evidence from a set of recorded medical images not including the establishment of misrepresentation [2]–[7].

A. DEFINITION OF FUSION

There are so many applications of image fusion that require high spatial and spectral resolutions within a single image besides achieving higher image quality. This can be provided using a fusion procedure having several advantages [8]–[11]. A comparative study of some main benefits, difficulties, and applications of the fusion process can be observed through this review to describe the importance of the topic of interest and its implementations. Many good features distinguish the fusion process in the medical field such as:

- 1) Accurately provides the image location of lesions and significantly reduce the surgical risk.
- 2) Extraction all the advantageous info from source images into a specific image.
- 3) Fusion of images can improve reliability and capability by complementary information.
- 4) It is convenient for the detection and classification of numerous diseases.
- 5) Fusion process reduces the data storage required and time for transmission.
- 6) It can provide accurate information for a precise localization and size estimation for tumors.

On the contrary, other difficulties may face the fusion process like: Input images must be accurately registered before the fusion process, feature information extraction is required, during the fusion process, noise can affect the fused image, some color artifacts can be produced due to the transformation used in the fusion techniques, the dissimilar illumination problem of the fused image, processing of data is slow when images are fused, and finally, more than a source image is required for the fusion procedure. The main application for implementing medical image fusion process including: Diseases detection, classification, and segmentation,

Computer-aided-diagnosis, Helping the specialists in Diagnosis abnormalities in medical images, clinical application, diagnosis and treatment of diseases.

B. TYPES OF IMAGE FUSION

The image fusion process may be employed in three different manners which can be classified as; at a low level, average, and high-level; or pixel element, feature, and determination levels [12]–[15]. Pixel level fusing the individual pixel values only. Feature level fusing the segmented regions of input images considering their properties. Decision level fusing the segmented regions of input images considering their initial object detection and classification.

Lately, scientists have proved that it is further significant to merge items or areas rather than picture elements. Different advantages can be found in the region-based algorithm over pixel-based algorithm as it is a smaller amount of hypersensitive to the commotion, has brighter differentiate, and a smaller amount of influenced by misregistration, but at the rate of complication. This was proved by John Lewis and Robert Callaghan in their research in 2007 [12].

C. FUSION CATEGORIES

According to the nature of the images to be fused, fusion can be categorized as follows [13]–[22]:

Multi-view fusion: The images to be fused are of the identical sense modality and carried at the equivalent moment in time, but under dissimilar conditions and the main goal of the fusion process in this category is to have all the complementary information under the different conditions in the fused image.

Multi-temporal fusion: The images to be fused are of the same modality too, but they were taken at different times. In this case, the fusion process is performed by subtracting two or more images, and the main purpose of the fusion, in this case, is to detect changes in the scene at different times.

Multi-focus fusion: The images to be fused are divided into regions and the fusion is applied to have a fused image.

Multi-modal fusion: The images to be fused are of different modalities and the main goal in this category is to have a fused image that contains information as much as possible from the different modalities without losses in the overall meaning of the image.

D. MULTI-MODAL FUSION FOR MEDICAL IMAGES

The medical image fusion process, especially the multi-modal medical image fusion process, aims to enhance the imaging quality by reducing the dismissal to improve the medical pertinency of the medical images in medical diagnosis and medical problems evaluation [23].

The fusion algorithms are input dependent. Therefore, building a fusion algorithm depends on three main aspects that must be taken into account the imaging modality used, organs to be imaged, and the algorithm of fusion implemented.

The imaging modalities area focuses on imaging modalities related to medical image fusion, their identification, and improvements.

Fusion algorithms focus on the design and enhancement of different algorithms for the fusion of medical images and their assessment [24].

Organs studies focus on the application of the fusion process in medical images of human organs of concern such as brains, breast, lung . . . , etc. [25].

III. MEDICAL IMAGING MODALITIES

Numerous medical imaging modalities exist with each having distinctive characteristics that provide various sources of information that facilitate the study of organs, diagnosis of diseases, follow-up treatments of patients, and further processing procedures such as the fusion process.

These modalities can be classified into five types: microscopy, 3D reconstruction, visible photography light, radiology, and printed signals (waves). For diagnostics purposes and treatments, radiology imaging modality is the most frequent assistant imaging modality such as CT, MRI PET, SPECT, and ultrasound [26]–[38]. A brief discussion about these modalities is introduced in Table 1 [52]–[70].

A remarkable note from the introduction to these modalities is that medical image quality characteristics have some common limitations of radiological imaging. They are spatial characteristics of the imaged body part that describes its relative size, shape, and position within the body. Also, artifacts, noise, blurring, and contrast sensitivity of the scanned image formed are of concern. These factors can affect scanned images, unequally. For qualitative and informative medical images, hybrid imaging sounds to be a good choice.

In general, the main objective of medicinal imaging fusion is to provide a full description of the anatomical structure of organs and follow up the function, behavior, and interaction of cells inside these organs. Hence, medical imaging can provide images having the required information for diagnosing diseases and can be used for numerous medical applications. Medical image fusion is also applied to several medical fields that require higher resolution images for different parts of the human body such as brain, lung, liver, heart, . . . , etc. [28], [39]–[50]. Table 2 introduces the applications of image fusion between different imaging modalities in the medical field on the human body that mix between mutually functional and anatomical imaging for additional informative and qualitative images [71]–[84].

IV. FUSION QUALITY EVALUATION METRICS

Many features of medical images affect the performance of medical image fusion that can be measured and evaluated based on standard quality metrics. These metrics include average gradient, entropy, edge intensity, standard deviation, local contrast, PSNR, and the Xydeas and Petrovic [35].

TABLE 1. A brief summary of radiological imaging modalities [20], [52]–[70].


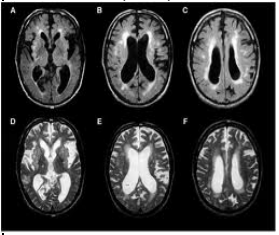
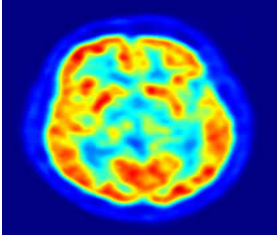
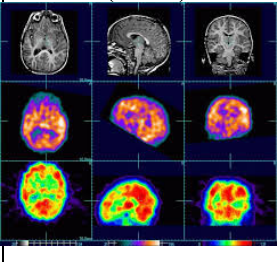

<p>Computerized Tomography (CT)</p> 	<p>Image formation:</p> <ul style="list-style-type: none"> Creates images by using an array of x-ray sensors and a computer to produce a series of cross-sectional based images. 	<p>Body part:</p> <ul style="list-style-type: none"> Bones and hard tissues. <p>EX: bones, the pelvis, abdomen, blood vessels, brain, lungs, and heart.</p>	<p>Applications:</p> <ul style="list-style-type: none"> 3D tumor simulation, brain diagnostic and treatment, tumor detection, deep brain stimulation, and bone tumor surgery.
<p>Magnetic Resonance Imaging (MRI)</p> 	<p>Image formation</p> <ul style="list-style-type: none"> Creates images using radio waves that lie in FM range and a strong magnet that is attached to a computer to produce slices of human body parts (cross-sectional images). 	<p>Body part:</p> <ul style="list-style-type: none"> Soft tissue and non-bony parts. <p>EX: blood vessels, organs in pelvis, breasts, bones and joints chest, abdomen (heart, liver, kidney), and tendon and ligament tears.</p>	<p>Applications:</p> <ul style="list-style-type: none"> Image regeneration, Prostate studies, tissue classification, lung/liver diagnosis, surgical training and planning, cancer diagnosis and assessment, visualization of 3D tumor simulation.
<p>Positron Emission Tomography (PET)</p> 	<p>Image formation:</p> <ul style="list-style-type: none"> Nuclear imaging technique where images are obtained from a scanner connected to a computer and a small number of radiopharmaceuticals is wanted to be injected into a patient's vein that helps in making detailed. 	<p>Body part:</p> <ul style="list-style-type: none"> Provides physicians with information about how tissues and organs are functioning. 	<p>Applications:</p> <ul style="list-style-type: none"> Cancer treatments, gross tumor volume detection, image segmentation and integration, gynecological cancer diagnosis, 3D tumor simulation, inertial electrostatic confinement fusion.
<p>Single Photon Emission Computed Tomography (SPECT)</p> 	<p>Image formation:</p> <ul style="list-style-type: none"> Nuclear imaging scheme where cross-sectional radiotracer images inside the body of the human are regulated. 	<p>Body part:</p> <ul style="list-style-type: none"> Used to study blood circulation to tissues and organs. 	<p>Applications:</p> <ul style="list-style-type: none"> Brain diagnosis and treatment, neck, head, cancer diagnosis, liver diagnosis, lung cancer treatment, a fusion of multi-modality images, tumor detection, and multi-dimensional visualization.
	<p>Functional modality.</p> <ul style="list-style-type: none"> Photons (ionizing). 	<p>Advantages:</p> <ul style="list-style-type: none"> High sensitivity (but lower than PET). Higher penetration depth. Images free of background. Confirm Neurodegenerative diseases (Alzheimer's, Parkinson's). 	<p>Disadvantages:</p> <ul style="list-style-type: none"> Blurring effects. Limited resolution. Radiation. Attenuation reimbursement is not probable because of multiple electron scattering. High cost.

TABLE 1. (Continued.) A brief summary of radiological imaging modalities [20], [52]–[70].

 <p style="text-align: center;">Ultrasound</p>	<p>Image formation</p> <ul style="list-style-type: none"> Uses high-frequency sound waves to construct images within the body by means of transforming the reverting echoes sound into the image. Also, produce audible sounds of blood flow. 	<p>Body part</p> <ul style="list-style-type: none"> Non-bony organs. 	<p>Applications</p> <ul style="list-style-type: none"> Organs in the pelvis and abdomen, pregnancy, breast cancer detection, abnormalities in the heart and blood vessels, esophageal cancer diagnosis, and liver tumor diagnosis.
	<ul style="list-style-type: none"> Anatomical and functional modality. Sound waves (Non-ionizing). 	<p>Advantages:</p> <ul style="list-style-type: none"> Low cost. High spatial resolution. Safety. Widely available. No injections or needles (Noninvasive). No radiation. Easy utilization. 	<p>Disadvantages:</p> <ul style="list-style-type: none"> Operator dependent. Difficult image of lungs & bone. Reflected very passionately on passing from tissue to gas or vice versa. Attenuation can decrease the resolution of images.

A. AVERAGE GRADIENT

It is utilized to express the details or texture variations number within the image. It may be expressed for an image f as:

$$g = \frac{1}{M \times N} \sum_{i=1}^M \sum_{j=1}^N \sqrt{\frac{(\frac{\partial f}{\partial x})^2 + (\frac{\partial f}{\partial y})^2}{2}} \quad (1)$$

where M and N are the image dimensions.

B. LOCAL CONTRAST

It can be utilized as an image quality index and for view clarity. It may be expressed as:

$$C_{local} = \frac{|\mu_{target} - \mu_{background}|}{\mu_{target} + \mu_{background}} \quad (2)$$

where μ_{target} and $\mu_{background}$ define the gray-level average of local region of interest, and the image background average. A high local C value means more image clarity.

C. STANDARD DEVIATION

It can be utilized for determining how much data variation is from the average value. The image is termed as being of better quality when its standard deviation (STD) scores is high. The STD can be expressed using Eq. (3) as:

$$\sigma = \sqrt{\frac{\sum_{i=1}^M \sum_{j=1}^N (f(i,j) - \mu)^2}{M \times N}} \quad (3)$$

D. EDGE INTENSITY (EDGE I)

High image edge intensity indicates a high image quality. The image Edge intensity S can be expressed using the Sobel operator as:

$$S = \sqrt{(S_x^2 + S_y^2)} \quad (4)$$

where

$$S_x = h_x \otimes f, \quad S_y = h_y \otimes f \quad (5)$$

and

$$h_x = \begin{pmatrix} 1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{pmatrix}, \quad h_y = \begin{pmatrix} -1 & -2 & -1 \\ 0 & 0 & 0 \\ 1 & 2 & 1 \end{pmatrix} \quad (6)$$

E. IMAGE ENTROPY

Image entropy measures of the information amount inside in the image. If the image pixel levels probability density is determined, then the image information amount can be expressed using the entropy E as:

$$E = - \sum_{i=0}^{L-1} p(i) \log p(i) \quad (7)$$

where L is the gray levels number of the image.

F. PEAK SIGNAL-TO-NOISE RATIO

The Peak Signal-to-Noise Ratio (PSNR) measure depends on the Root Mean Square Error (RMSE) among the interest image and the reference one. It can be expressed as:

$$PSNR = 10 \times \log \left(\frac{f_{max}^2}{RMSE^2} \right) \quad (8)$$

where f_{max} defines the maximum image pixel score.

G. XYDEAS AND PETROVIC METRIC

The Xydeas and Petrovic (Q^{ab}_f) measures the transferred edge information amount from the original image to the fused image. This metric can be expressed as:

$$Q^{ab}_f = \frac{\sum_{i=1}^M \sum_{j=1}^N (Q^{af}_{(i,j)} W^{af}_{(i,j)} + Q^{bf}_{(i,j)} W^{bf}_{(i,j)})}{\sum_{i=1}^M \sum_{j=1}^N (W^{af}_{(i,j)} + W^{bf}_{(i,j)})} \quad (9)$$

where $Q^{af}_{(i,j)}$, and $Q^{bf}_{(i,j)}$ represent the edge information scores, and $W^{af}_{(i,j)}$, $W^{bf}_{(i,j)}$ represent their respected weights.

TABLE 2. An overview of radiological imaging modalities utilized in medical applications for human body parts and hybrid imaging combinations for better image visualization [71]–[84].

Organ	Existing imaging modalities and their functions		Hybrid imaging modalities
Brain	CT <ul style="list-style-type: none"> Shows the brain structure (bones and hard tissues). Used for brain injuries. 	PET <ul style="list-style-type: none"> Measures brain activity by showing how blood flux and glucose metabolism, and oxygen in the working brain tissues. Used for diagnosing strokes, neuron-damaging, and brain tumor diseases. 	<ul style="list-style-type: none"> MRI/PET. MRI/SPECT. MRI/CT. PET/CT. CT/SPECT.
	MRI <ul style="list-style-type: none"> Shows the brain structure (soft tissues). Measures magnetic activity of the brain. 	SPECT <ul style="list-style-type: none"> measures cerebral blood flow. Used for brain disease processes that produce dementia. 	
	Ultrasound <ul style="list-style-type: none"> Used to detect breast lesions and abnormalities. 	MRI <ul style="list-style-type: none"> Used for precise identification of breast tumours and early detection of breast cancer. 	<ul style="list-style-type: none"> MRI/PET. Are complementary and valuable in monitoring breast cancer treated with chemotherapy.
	PET and SPECT <ul style="list-style-type: none"> predict treatment response in breast cancers. 		
Prostate	Ultrasound <ul style="list-style-type: none"> define the extent and location of cancers in glands. 	MRI <ul style="list-style-type: none"> allows better visualization of prostate zonal anatomy, location, and extent of the tumor within the gland. 	<ul style="list-style-type: none"> MRI/CT. PET/CT.
	CT <ul style="list-style-type: none"> used for pre-treatment evaluation of prostate cancer and identification of abnormally enlarged lymph nodes. 	PET <ul style="list-style-type: none"> Used for the detection of ambiguous metastases in patients with prostate cancer by measuring the metabolic rate of the tissue. 	
Lungs	X-ray <ul style="list-style-type: none"> Used for diagnosis of cancer, pneumonia, and chronic obstructive pulmonary disease. 	MRI <ul style="list-style-type: none"> Used for diagnosis of bronchial carcinoma, cystic fibrosis, pulmonary hypertension, and pulmonary embolism. 	<ul style="list-style-type: none"> PET/CT.
	CT <ul style="list-style-type: none"> Used for detection of acute pulmonary embolism, tumors, pulmonary hypertension, advanced COPD, pulmonary fibrosis, and pneumonia in a high-risk patient. 	PET <ul style="list-style-type: none"> Used for diagnosis of non-small-cell bronchial carcinoma. 	
Liver	Ultrasound <ul style="list-style-type: none"> offers a rapid non-invasive method for monitoring suspected liver metastases. 	MRI <ul style="list-style-type: none"> Provide higher resolution to improve lesion detection. 	<ul style="list-style-type: none"> PET/CT.
	CT <ul style="list-style-type: none"> Used to obtain different phases of tissue for lesion detection of hypervascularity metastases. 	PET <ul style="list-style-type: none"> Provide prematurely abnormal tumor detection metabolism before the anatomic semblance changes, and tumor localization in unsuspected regions. 	
Heart	CT <ul style="list-style-type: none"> Demonstrating excellent visualization of coronary anatomy and assessment of disease. 	MRI <ul style="list-style-type: none"> Used for estimation of global and regional systolic LV function, and myocardial perfusion. 	<ul style="list-style-type: none"> PET/CT. CT/SPECT.
	SPECT <ul style="list-style-type: none"> assessment of perfusion, systolic function, and Coronary artery disease (CAD). 	PET <ul style="list-style-type: none"> Allows appreciation of perfusion and function, at rest and after stress. 	

V. PERFORMANCE EVALUATION OF SOME EXISTING MEDICAL IMAGE FUSION TECHNIQUES

In this section, an investigation of the performance of some existing medical image fusion techniques has been introduced [57], [60]–[62], [70], [71], [81]–[84]. These algorithms applied on several CT and MR image datasets and evaluated using various quality metrics. Samples of the evaluated results are presented in Tables 3 and 4.

VI. MEDICAL IMAGE FUSION AND DENOISING TECHNIQUES

In addition to the fusion process for image enhancement, denoising techniques can also increase image quality by suppressing noise from images. Images could have different

types of noise that affect image visualization like Poisson noise, salt and pepper noise, Gaussian noise, speckle noise, Brownian noise, film grain noise, shot noise, quantization noise, and an-isotropic noise [68]. In medical images, these noise types could affect medical diagnosis badly resulting in an inaccurate diagnosis. This motivates researchers for using denoising techniques for better visualization and higher image quality. Brief classifications of denoising techniques are presented in Fig. 1.

These techniques are used for retrieving the original image from the noisy image and provide enhanced image quality. The type of noise in the image determines the required filter used. Many researchers have discussed denoising problems and some of them are introduced in Table 5.

TABLE 3. Performance comparative analysis between some traditional medical image fusion techniques on dataset 1.

Fused image	PCA based fusion		DWT based fusion		DT-CWT based fusion		Curvelet based fusion		NSCT based fusion		Fuzzy based fusion		AWT based fusion	
Average gradient	0.0382		0.0639		0.0684		0.0902		9.8019		0.0341		0.0683	
Local Contrast	0.6650		0.7443		1.0369		1.1792		0.6711		0.6057		0.7474	
Standard Deviation	0.0010		0.0012		0.0012		0.0013		0.2613		0.0011		0.0012	
STD 2	0.2572		0.2940		0.3167		0.3273		66.6299		0.2827		0.2976	
Edge Intensity	0.3884		0.6325		0.6936		0.9067		99.5667		0.3696		0.6820	
Entropy	7.5646		7.7377		7.4201		7.6022		7.5815		7.7824		7.7436	
SSIM	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.34	0.81	0.99	0.99	0.99	0.99
UIQI	0.27	0.72	0.60	0.45	0.49	0.46	0.35	0.27	0.24	0.74	0.31	0.43	0.62	0.47
FSIM	0.89	0.98	0.93	0.94	0.92	0.95	0.94	0.94	0.59	0.86	0.95	0.94	0.94	0.94
PSNR with Fused	60.3	68.9	60.6	60.6	60.4	63.6	59.3	59.3	12	21.5	61	61.1	60.8	60.8
MI	0.6351		0.8086		0.5348		0.3588		7.4846		0.5614		0.7715	
Q^{abif}	0.2408		0.4746		0.2260		0.1793		0.3975		0.1437		0.4518	
Processing time	2.345 sec		2.558 sec		1.53		333.9 sec		33.1		4.32 sec		1.266	

TABLE 4. Performance comparative analysis between some traditional medical image fusion techniques on dataset 2.

Fused image	PCA based fusion		DWT based fusion		DT-CWT based fusion		Curvelet based fusion		NSCT based fusion		Fuzzy based fusion		AWT based fusion	
Average gradient	0.0330		0.0566		0.0637		0.0833		8.6754		0.0341		0.0611	
Local Contrast	0.6068		0.7060		1.1138		1.1617		0.6233		0.6057		0.7110	
Standard Deviation	0.0011		0.0013		0.0014		0.0014		0.3066		0.0011		0.0013	
STD 2	0.2889		0.3358		0.3475		0.3545		78.1797		0.2827		0.3331	
Edge Intensity	0.3340		0.5467		0.6409		0.8350		88.0744		0.3696		0.6006	
Entropy	7.0595		7.3122		6.8907		7.2201		7.0497		7.7824		7.3740	
SSIM	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.28	0.79	0.99	0.99	0.99	0.99
UIQI	0.30	0.61	0.47	0.46	0.38	0.42	0.22	0.26	0.16	0.74	0.31	0.43	0.53	0.46
FSIM	0.92	0.98	0.92	0.94	0.93	0.95	0.92	0.93	0.64	0.86	0.95	0.94	0.92	0.94
PSNR with Fused	62.1	67.2	60.2	62.7	60.9	63.9	59.1	60.9	12.7	22.2	61.0	61.1	60.5	63.0
MI	0.8409		0.8525		0.5646		0.4770		6.8959		0.5614		0.8317	
Q^{abif}	0.1849		0.3074		0.2372		0.2020		0.3984		0.1437		0.3526	
Processing time	1.24		2.498		1.65		358.35		24.58		2.91		1.24	

VII. MEDICAL IMAGE FUSION NEW TRENDS

Throughout this survey, several basic definitions for medical image fusion have been declared as it presented some existing survey studies in the scope of medical image fusion.

It also presents many kinds of research that are concerned with medical image fusion techniques and their applications in different medical fields, and others that are interested in developing, evolving, and enhancing these techniques. The

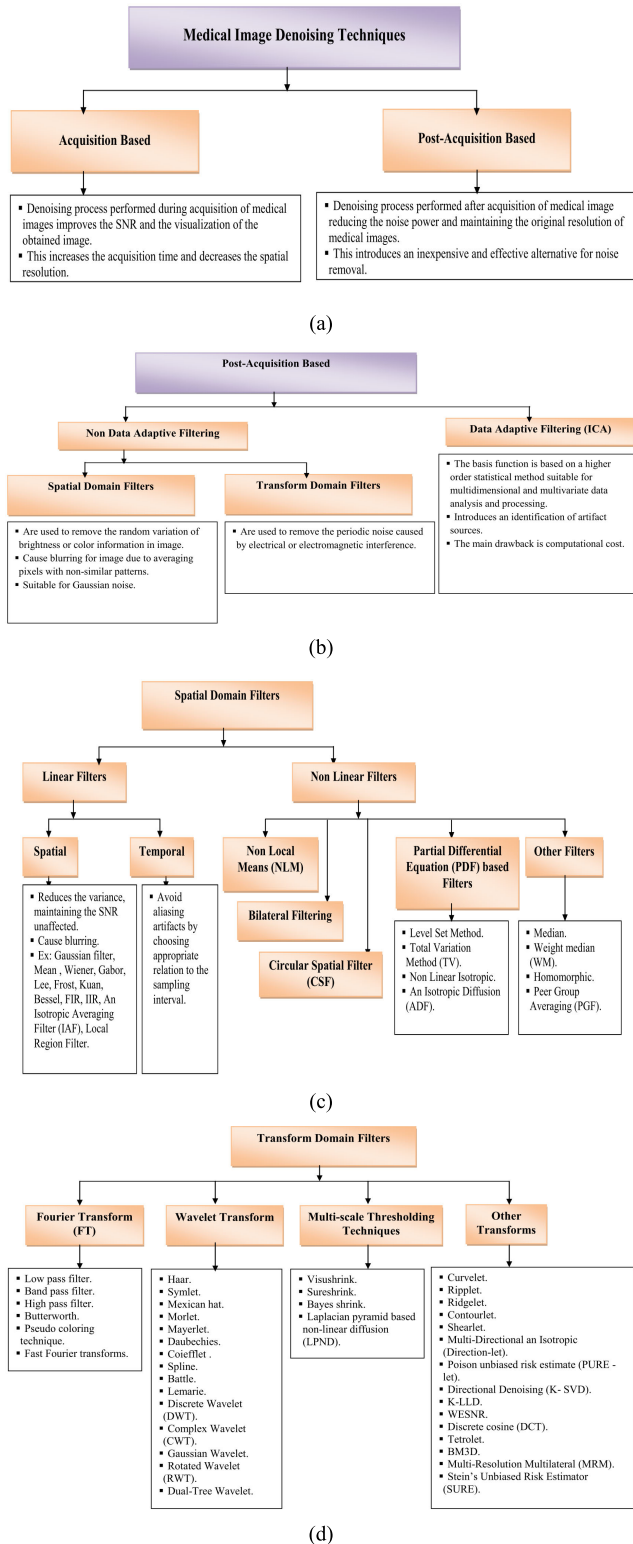


FIGURE 1. a. Medical image denoising techniques. b. Post-acquisition based denoising techniques. c. Spatial domain denoising techniques. d. Transform domain denoising techniques [69].

objective is to handle different problems for better image visualization and higher quality that are required in various medical implementations. Despite that, medical image fusion is a promising research area that is full of benefits for different

applications and investigations that may be explored in the future. Hence, this study has identified some relevant issues and novel trends for the medical image fusion domain that deserve further investigations such as:

- 1) *Hybrid image fusion approaches that combine two transformations before application of fusion rules.*

This makes good use of the characteristics of both transforms for better enhancement of fused image visualization, higher image quality, and suitable processing time. Hybrid Techniques SVM-Shearlet, Wiener filter-Shearlet, Curvelet-Contourlet, DWT-Shearlet can be suggested for better performance. Many works have been introduced for this objective such as a fusion technique for Lungs Tumor images introduced by Naveenadevi R and Nirmala S of a title “Fusion of CT-PET Lungs Tumor images using Dual-Tree Complex Wavelet Transform” [70]. They present a solution for further image processing such as target identification by combining multi-image information in one scene. The proposed fusion technique is based on Dual-Tree Complex Wavelet transforms for image decomposition and the Non-Subsampled Contourlet transform rule is employed for obtaining the high and the low-frequency coefficients of the fused image. Another work was introduced by Sivakumar and Helenprabha entitled “Hybrid medical image fusion using wavelet and curvelet transform with multi-resolution processing” in 2017 [71]. They proposed an algorithm for enhancing the fused image quality by combining wavelet and curvelet transform techniques after the decomposition stage using a sub-band coding algorithm that performs the Multi-Resolution Analysis (MRA). This technique improves PSNR by 5 dB better than curvelet fusion and by 10 dB better than wavelet transform fusion algorithm. Also, the root mean square error has been decreased.

- 2) *Implementation of the optimization techniques where the parameters of the fusion algorithm should have the optimum values to achieve the best performance and perfect image visualization.*

This topic is a future trend and a few kinds of research introduced work in this area. Ebenezer Daniel and J. Anitha introduce the topic of “Optimum spectrum mask based medical image fusion using Gray Wolf Optimization” [72]. This research is interested in providing the best scale value selection for improving the quality of fusion. The proposed OSMF (optimum spectrum mask fusion) is based on a conventional Gray Wolf Optimization (GWO) scheme. This spectrum mask technique provides the swiftest and dynamic scale selection for spatial domain and transform domain fusion algorithm. Another research using Genetic Algorithms (GAs) to obtain the more optimized fused image produced from discrete wavelet transform (DWT) fusion scheme [73].

- 3) *Color artifacts that result from transformation-based algorithms or obtained from imaging mode are an important matter that should take much more concern.*

In B-mode imaging, parallel beamforming is used to increase image quality, but this introduces artifacts in the images. These artifacts are reduced in the research of a title

TABLE 5. Some recent work in medical image Processing techniques.

Presented work	Methodology	Year of publication	Application	Research contribution
[9]	Non-subsampled shearlet transform and pulse-coupled neural network	2020	Medical big data images analysis and diagnosis applications	An efficient medical multimodal image fusion approach is suggested for covering a wide range of medical diagnostic applications. It depends on the utilization of a measured boundary pulse-coupled deep neural network algorithm and attributes energy fusion scheme in a shearlet non-subsampled transform.
[11]	Neural coupled P systems and Non-subsampled shearlet transform	2020	Multi-modality medical images	The utilization of Neural Coupled P Systems and Non-subsampled shearlet Transform to perform the fusion process of medical multi-modality images. The proposed approach depends on two neural coupled P systems with local topology in the NSST domain, where they are utilized to control the fusion process of low-frequency NSST coefficients.
[13]	Sparse deep convolutional representation and Laplacian pyramid algorithms	2020	Multi-modality medical images	The combination of sparse deep convolutional representation and Laplacian pyramid algorithms is suggested for the multi-modality medical image fusion process. The Laplacian pyramid algorithm is employed the pre-registered magnetic resonance images and the computed tomography images to acquire their base layer and detail layers. Subsequently, the sparse deep convolutional representation algorithm is utilized to fuse the features of the base layer with the features of the detail layers to get the fused medical image.
[23]	Deep convolutional neural networks	2019	Multi-modality medical images	An improved intelligent-based diagnosis approach is suggested for rotary medical equipment using data-fusion with multi-sensor based on an enhanced convolutional deep neural model. The proposed approach can efficiently extract the medical image features to improve the fusion efficiency.
[31]	Artificial intelligence and deep convolutional neural networks	2020	CT and MRI images	The exploitation of artificial intelligence and deep learning algorithms for fusing CT and MRI images for the purpose of tumor preoperative margin detection. The suggested fusion approach achieves great efficiency in the diagnosis process for brain tumor recognition.
[39]	Laplacian pyramid, neural convolutional network, and local energy gradient strategy	2020	Multi-modality medical images	Proposal of a deep learning-based medical image fusion approach that depends on the local energy gradient strategy and Laplacian pyramid algorithm. This proposed approach enhances greatly the final medical image edges
[41]	Deep convolutional neural networks	2020	Multi-modality medical images	An improved deep learning-based multimodal medical image fusion algorithm is suggested for the detection of medical image edges to assist the specialists in the diagnosis process.
[49]	Generative adversarial network	2020	Multi-modality medical images	Proposal of an improved end-to-end medical image framework to characterize structural content in multi-modality medical images. The proposed fusion framework depends on a generative conditional adversarial network to avoid the functional data from being weakened in the ultimate medical fused image.
[69]	Contrast pyramid and convolutional neural network	2020	Multi-modality medical images	Proposal of deep convolutional neural network-based medical image fusion approach that utilizes the convolutional Siamese trained network to merge the activity pixel data of the input medical images to implement the weight map generation. The contrast pyramid algorithm is employed to decompose the input medical images.
[76]	Wavelet	2016	MRI image	The paper investigates denoising techniques for MRI images. Three wavelets (db4, bior1.3, sym4) with hard and soft thresholding are implemented. The bior1.3 wavelet with hard thresholding at level 1 achieved higher improvement in PSNR up to 39.856 dB.
[77]	Wavelet, Ridgelet, Curvelet, Contourlet.	2016	Digital images	This paper holding a comparison for different denoising techniques introduces from 2002 to 2015 and their improvement achieved in PSNR. Some novel trends in image denoising are introduced and a new robust parameter performance measure 'P' is introduced.
[78]	2D FIR filter with optimization techniques	2017	Ultrasound images	This paper is implemented metaheuristic algorithms to optimize the 2D FIR filter coefficient matrix by using the PSO, GA, DE, and ABC for optimum image denoising. All parameter adaptation algorithms achieved an improvement in PSNR up to 37 dB especially using ABC and DE.
[79]	Optimal spatial kernel for the bilateral filter	2017	Retinal image	A denoising technique based on the BLF spatial kernel and a specific LSF attained from MF Gaussian-like kernel is suggested. This method improved sensitivity up to 0.998, accuracy up to 0.994, and the dice coefficient up to 0.998 for retinal vessel denoising.
[80]	Compressive Sampling	2016	Medical images	This paper introduced a compressively sampled denoising technique based on two-dimensional discrete Fourier transform and compared to CS-based on optimization methods of orthogonal matching pursuit (OMP) and the stage-wise OMP (ST-OMP). The proposed algorithm improved PSNR up to 27.89 dB and SSIM up to 0.9886.

“Reducing color flow artifacts caused by parallel beamforming” by Hergum *et al.* [74]. The artifact reduction is done by interpolation of the autocorrelation estimates obtained from overlapping receive beams.

- 4) *The problem of uneven illumination of the fused images as the implemented fusion rules could result in darker images or brighter images to enhance image details.*

Hence, solutions for optimum fusion rules that do not disturb the illumination of the fused image should be developed. Hiroshi Tsutsui and S. Yoshikawa proposed an algorithm for reducing halo artifacts [75]. They designed a cost function that is based on illumination characteristics. The parameters of the cost function are adaptively adjusted to reduce these halo artifacts and maintaining image contrast.

- 5) *Noise effect is also a matter of interest that has been neglected in many kinds of research.*

There are so many types of noise that could affect the fused images and denoising procedures are required for clear visualization [76]–[80].

- 6) *Practical implementation of fusion algorithms is still for soft applications only where two input images are applied only to an algorithm after capturing from different sensors or for different times.*

Researchers should pay more attention to developing medical devices that can produce different modalities in the same device which could be inputted to an implemented fusion algorithm to obtain an exclusive fused image of higher quality. These suggestions could be very useful and provide more informative images at a low cost for the patient as more than one image can be taken through the same device and at the same time. The final obtained images could provide excellent visualization for an accurate diagnosis.

- 7) *Evaluation metrics that are used to evaluate the performance of fusion algorithms through complexity, processing time, throughput, PSNR, image entropy, edge intensity, similarity index, mutual information, and other evaluation metrics should be developed to offer a correct approximation of performance of fusion scheme and fused image characteristics that enhance visualization and increase image quality.*

VIII. CONCLUSIONS AND FUTURE WORKS

This paper covered a very hot area of research, which is the integration of different imaging modalities for better diagnosis. Different imaging modalities have been covered in detail by highlighting their advantages and disadvantages. Different approaches have been considered and compared for this objective. The general description and mathematical formulation of these approaches have been presented. In addition, a general discussion has been presented on how to develop new directions for multi-modality medical image fusion. The work in this paper may contribute in the development of automated medical image diagnosis systems. Future Directions of medical imaging fusion may include: 1) Application of the optimization schemes on different factors of fusion algorithms that provides the optimal standards and

realize the greatest accomplishment and ideal image vision; 2) Studying the effect of other optimization techniques on the performance of fusion techniques such as GWO, GAs, and PSO . . . etc. to find the best technique that achieves the best performance; 3) Investigating other multi-scale transforms for medical image fusion such as Ridgelet, K-SVD, Tetrolet, and Ripplet . . . etc.; 4) Applying efficient denoising techniques on images before fusion for higher details information, better clarity and image visualization; and 5) Practical implementation of fusion techniques using Field Programmable Gate Array (FPGA).

REFERENCES

- [1] D.-H. Xia, S. Song, L. Tao, Z. Qin, Z. Wu, Z. Gao, J. Wang, W. Hu, Y. Behnamian, and J.-L. Luo, “Review-material degradation assessed by digital image processing: Fundamentals, progresses, and challenges,” *J. Mater. Sci. Technol.*, vol. 53, pp. 146–162, Sep. 2020.
- [2] P. K. Atrey, M. A. Hossain, A. El Saddik, and M. S. Kankanhalli, “Multimodal fusion for multimedia analysis: A survey,” *Multimedia Syst.*, vol. 16, no. 6, pp. 345–379, Nov. 2010.
- [3] A. P. James and B. V. Dasarathy, “Medical image fusion: A survey of the state of the art,” *Inf. Fusion*, vol. 19, pp. 4–19, Sep. 2014.
- [4] F. E.-Z.-A. El-Gamal, M. Elmogy, and A. Atwan, “Current trends in medical image registration and fusion,” *Egyptian Informat. J.*, vol. 17, no. 1, pp. 99–124, Mar. 2016.
- [5] K. P. Indira and R. R. Hemamalini, “Analysis on image fusion techniques for medical applications,” *Int. J. Adv. Res. Electr., Electron. Instrum. Eng.*, vol. 3, no. 9, pp. 2278–8875, 2014.
- [6] H. Kaur and E. J. Rani, “Analytical comparison of various image fusion techniques,” *Int. J. Adv. Res. Comput. Sci. Softw. Eng.*, vol. 5, no. 5, 2015.
- [7] S. A. Elmasry, W. A. Awad, and S. A. Abd El-hafeez, “Review of different image fusion techniques: Comparative study,” in *Internet of Things Applications and Future*. Singapore: Springer, 2020, pp. 41–51.
- [8] Accessed: Aug. 15, 2019. [Online]. Available: http://www.ece.lehigh.edu/SPCRL/IF/image_fusion.htm#Image_fusion
- [9] W. Tan, P. Tiwari, H. M. Pandey, C. Moreira, and A. K. Jaiswal, “Multimodal medical image fusion algorithm in the era of big data,” *Neural Comput. Appl.*, early access, Jul. 2020, doi: [10.1007/s00521-020-05173-2](https://doi.org/10.1007/s00521-020-05173-2).
- [10] M. Arif and G. Wang, “Fast curvelet transform through genetic algorithm for multimodal medical image fusion,” *Soft Comput.*, vol. 24, no. 3, pp. 1815–1836, Feb. 2020.
- [11] B. Li, H. Peng, X. Luo, J. Wang, X. Song, M. J. Pérez-Jiménez, and A. Riscos-Núñez, “Medical image fusion method based on coupled neural p systems in nonsubsampled shearlet transform domain,” *Int. J. Neural Syst.*, early access, Aug. 2020, doi: [10.1142/S0129065720500501](https://doi.org/10.1142/S0129065720500501).
- [12] J. J. Lewis, R. J. O’Callaghan, S. G. Nikolov, D. R. Bull, and N. Canagarajah, “Pixel- and region-based image fusion with complex wavelets,” *Inf. Fusion*, vol. 8, no. 2, pp. 119–130, Apr. 2007.
- [13] F. Liu, L. Chen, L. Lu, A. Ahmad, G. Jeon, and X. Yang, “Medical image fusion method by using Laplacian pyramid and convolutional sparse representation,” *Concurrency Comput., Pract. Exper.*, vol. 32, no. 17, p. e5632, Sep. 2020.
- [14] T. Akbarpour, M. Shamsi, and S. Daneshvar, “Extraction of brain regions affected by alzheimer disease via fusion of brain multispectral MR images,” in *Proc. 7th Conf. Inf. Knowl. Technol. (IKT)*, May 2015, pp. 1–6.
- [15] S. Budhiraja, “Multimodal medical image fusion using modified fusion rules and guided filter,” in *Proc. Int. Conf. Comput., Commun. Autom.*, May 2015, pp. 1067–1072.
- [16] V. Bhateja, H. Patel, A. Krishn, A. Sahu, and A. Lay-Ekuakille, “Multimodal medical image sensor fusion framework using cascade of wavelet and contourlet transform domains,” *IEEE Sensors J.*, vol. 15, no. 12, pp. 6783–6790, Dec. 2015.
- [17] B. Biswas, S. Ghoshal, P. Chatterjee, A. Chakrabarti, and K. N. Dey, “Medical image fusion by combining SVD and shearlet transform,” in *Proc. 2nd Int. Conf. Signal Process. Integr. Netw. (SPIN)*, Feb. 2015, pp. 148–153.
- [18] H. Wei, M. Viallon, B. M. A. Delattre, K. Moulin, F. Yang, P. Croisille, and Y. Zhu, “Free-breathing diffusion tensor imaging and tractography of the human heart in healthy volunteers using wavelet-based image fusion,” *IEEE Trans. Med. Imag.*, vol. 34, no. 1, pp. 306–316, Jan. 2015.

- [19] B. Biswas, A. Chakrabarti, and K. N. Dey, "Spine medical image fusion using Wiener filter in shearlet domain," in *Proc. IEEE 2nd Int. Conf. Recent Trends Inf. Syst. (ReTIS)*, Jul. 2015, pp. 387–392.
- [20] M. Vani and S. Saravanakumar, "Multi focus and multi modal image fusion using wavelet transform," in *Proc. 3rd Int. Conf. Signal Process., Commun. Netw. (ICSCN)*, Mar. 2015, pp. 1–6.
- [21] R. Pomponio, G. Erus, M. Habes, J. Doshi, D. Srinivasan, E. Mamourian, I. M. Nasrallah, T. D. Satterthwaite, Y. Fan, V. Bashyam, and L. J. Launer, "Harmonization of large MRI datasets for the analysis of brain imaging patterns throughout the lifespan," *NeuroImage*, vol. 208, Mar. 2020, Art. no. 116450.
- [22] K. P. Nguyen, C. C. Fatt, A. Treacher, C. Mellema, M. H. Trivedi, and A. Montillo, "Anatomically-informed data augmentation for functional MRI with applications to deep learning," in *Proc. SPIE, Med. Imag., Image Process., Int. Soc. Opt. Photon.*, vol. 11313, Mar. 2020, Art. no. 113130T.
- [23] H. Wang, S. Li, L. Song, L. Cui, and P. Wang, "An enhanced intelligent diagnosis method based on multi-sensor image fusion via improved deep learning network," *IEEE Trans. Instrum. Meas.*, vol. 69, no. 6, pp. 2648–2657, Jun. 2020.
- [24] S. Huang, Y. Yang, X. Jin, Y. Zhang, Q. Jiang, and S. Yao, "Multi-sensor image fusion using optimized support vector machine and multiscale weighted principal component analysis," *Electronics*, vol. 9, no. 9, p. 1531, Sep. 2020.
- [25] Accessed: Apr. 25, 2019. [Online]. Available: <http://www.medicalimaging.org/about-mita/medical-imaging-primer/>
- [26] P. Ganasala and A. D. Prasad, "Contrast enhanced multi sensor image fusion based on guided image filter and NSST," *IEEE Sensors J.*, vol. 20, no. 2, pp. 939–946, Jan. 2020.
- [27] M. Blendowski, N. Bouteldja, and M. P. Heinrich, "Multimodal 3D medical image registration guided by shape encoder–decoder networks," *Int. J. Comput. Assist. Radiol. Surgery*, vol. 15, no. 2, pp. 269–276, Feb. 2020.
- [28] G. Haskins, U. Kruger, and P. Yan, "Deep learning in medical image registration: A survey," *Mach. Vis. Appl.*, vol. 31, nos. 1–2, p. 8, Feb. 2020.
- [29] L. Li, X. Zhao, W. Lu, and S. Tan, "Deep learning for variational multimodality tumor segmentation in PET/CT," *Neurocomputing*, vol. 392, pp. 277–295, Jun. 2020.
- [30] V. Schwarze, J. Rübenthaler, C. Marschner, M. P. Fabritius, J. Rueckel, N. Fink, D. Pühr-Westerheide, E. Gresser, M. F. Froelich, M. L. Schnitzer, N. Große Hokamp, S. Afat, M. Staehler, T. Geyer, and D.-A. Clevert, "Advanced fusion imaging and contrast-enhanced imaging (CT/MRI–CEUS) in oncology," *Cancers*, vol. 12, no. 10, p. 2821, Sep. 2020.
- [31] X.-H. Du, H. Wei, P. Li, and W.-T. Yao, "Artificial intelligence (AI) assisted CT/MRI image fusion technique in preoperative evaluation of a pelvic bone osteosarcoma," *Frontiers Oncol.*, vol. 10, p. 1209, Aug. 2020.
- [32] Z. Wang, Z. Cui, and Y. Zhu, "Multi-modal medical image fusion by Laplacian pyramid and adaptive sparse representation," *Comput. Biol. Med.*, vol. 123, Aug. 2020, Art. no. 103823.
- [33] A. Millischer, M. Brasseur-Daudruy, H. Mahallati, and L. J. Salomon, "The use of image fusion in prenatal medicine," *Prenatal Diagnosis*, vol. 40, no. 1, pp. 18–27, Jan. 2020.
- [34] S. Maqsood and U. Javed, "Multi-modal medical image fusion based on two-scale image decomposition and sparse representation," *Biomed. Signal Process. Control*, vol. 57, Mar. 2020, Art. no. 101810.
- [35] P. Ganasala and A. D. Prasad, "Medical image fusion based on laws of texture energy measures in stationary wavelet transform domain," *Int. J. Imag. Syst. Technol.*, vol. 30, no. 3, pp. 544–557, Sep. 2020.
- [36] Y. Wang, W. Huang, F. Sun, T. Xu, Y. Rong, and J. Huang, "Deep multi-modal fusion by channel exchanging," in *Proc. Adv. Neural Inf. Process. Syst.*, 2020, p. 33.
- [37] Q. Li, D. Gkoumas, C. Lioma, and M. Melucci, "Quantum-inspired multi-modal fusion for video sentiment analysis," *Inf. Fusion*, vol. 65, pp. 58–71, Jan. 2021.
- [38] S. Polinati and R. Dhuli, "Multimodal medical image fusion using empirical wavelet decomposition and local energy maxima," *Optik*, vol. 205, Mar. 2020, Art. no. 163947.
- [39] J. Fu, W. Li, J. Du, and B. Xiao, "Multimodal medical image fusion via Laplacian pyramid and convolutional neural network reconstruction with local gradient energy strategy," *Comput. Biol. Med.*, vol. 126, Nov. 2020, Art. no. 104048.
- [40] A. Tannaz, S. Mousa, D. Sabalan, and P. Masoud, "Fusion of multimodal medical images using nonsubsampling shearlet transform and particle swarm optimization," *Multidimensional Syst. Signal Process.*, vol. 31, no. 1, pp. 269–287, Jan. 2020.
- [41] S. Liu, H. Liu, V. John, Z. Liu, and E. Blasch, "Enhanced situation awareness through CNN-based deep multimodal image fusion," *Opt. Eng.*, vol. 59, no. 5, 2020, Art. no. 053103.
- [42] Y. Chen, F. He, H. Li, D. Zhang, and Y. Wu, "A full migration BBO algorithm with enhanced population quality bounds for multimodal biomedical image registration," *Appl. Soft Comput.*, vol. 93, Aug. 2020, Art. no. 106335.
- [43] S. P. Yadav and S. Yadav, "Image fusion using hybrid methods in multimodality medical images," *Med. Biol. Eng. Comput.*, vol. 58, pp. 1–19, Jan. 2020.
- [44] D. R. J. Dolly, J. D. Peter, G. J. Bala, and D. J. Jagannath, "Image fusion for stabilized medical video sequence using multimodal parametric registration," *Pattern Recognit. Lett.*, vol. 135, pp. 390–401, Jul. 2020.
- [45] J. Gao, P. Li, Z. Chen, and J. Zhang, "A survey on deep learning for multimodal data fusion," *Neural Comput.*, vol. 32, no. 5, pp. 829–864, May 2020.
- [46] O. Barachini, R. Berni, S. Mirzaei, C. Pirich, K. Hergan, and S. Zandieh, "The impact of 18F-FDOPA-PET/MRI image fusion in detecting liver metastasis in patients with neuroendocrine tumors of the gastrointestinal tract," *BMC Med. Imag.*, vol. 20, no. 1, pp. 1–7, Dec. 2020.
- [47] H. Xu, J. Ma, J. Jiang, X. Guo, and H. Ling, "U2Fusion: A unified unsupervised image fusion network," *IEEE Trans. Pattern Anal. Mach. Intell.*, early access, Jul. 28, 2020, doi: [10.1109/TPAMI.2020.3012548](https://doi.org/10.1109/TPAMI.2020.3012548).
- [48] J. Ma, H. Xu, J. Jiang, X. Mei, and X.-P. Zhang, "DDcGAN: A dual-discriminator conditional generative adversarial network for multi-resolution image fusion," *IEEE Trans. Image Process.*, vol. 29, pp. 4980–4995, 2020.
- [49] Z. Le, J. Huang, F. Fan, X. Tian, and J. Ma, "A generative adversarial network for medical image fusion," in *Proc. IEEE Int. Conf. Image Process. (ICIP)*, Oct. 2020, pp. 370–374.
- [50] T. Uezato, D. Hong, N. Yokoya, and W. He, "Guided deep decoder: Unsupervised image pair fusion," in *Proc. Eur. Conf. Comput. Vis. Cham, Switzerland: Springer*, Aug. 2020, pp. 87–102.
- [51] Y. Liu, L. Wang, J. Cheng, C. Li, and X. Chen, "Multi-focus image fusion: A survey of the state of the art," *Inf. Fusion*, vol. 64, pp. 71–91, Dec. 2020.
- [52] G. Sha, M. Radziński, R. Soman, M. Cao, W. Ostachowicz, and W. Xu, "Multiple damage detection in laminated composite beams by data fusion of Teager energy operator-wavelet transform mode shapes," *Composite Struct.*, vol. 235, Mar. 2020, Art. no. 111798.
- [53] K. Khelil, F. Berzezek, and T. Bouadjila, "GA-based design of optimal discrete wavelet filters for efficient wind speed forecasting," *Neural Comput. Appl.*, early access, Aug. 2020, doi: [10.1007/s00521-020-05251-5](https://doi.org/10.1007/s00521-020-05251-5).
- [54] N. Gessert, M. Nielsen, M. Shaikh, R. Werner, and A. Schlaefer, "Skin lesion classification using ensembles of multi-resolution EfficientNets with meta data," *MethodsX*, vol. 7, Mar. 2020, Art. no. 100864.
- [55] H. Tian, Y.-N. Fu, and P.-G. Wang, "Image fusion algorithm based on regional variance and multi-wavelet bases," in *Proc. 2nd Int. Conf. Future Comput. Commun.*, vol. 2, 2010, p. V2-792.
- [56] Y. Zheng, X. Hou, T. Bian, and Z. Qin, "Effective image fusion rules of multi-scale image decomposition," in *Proc. 5th Int. Symp. Image Signal Process. Anal.*, Sep. 2007, pp. 362–366.
- [57] X. Xiao-Zhu and X. Ya-Wei, "Multi-sensor image fusion scheme based on dual-tree complex wavelet transform," in *Proc. 34th Chin. Control Conf. (CCC)*, Jul. 2015, pp. 4857–4861.
- [58] W. El-Shafai, S. El-Rabaie, M. M. El-Halawany, and F. E. A. El-Samie, "Security of 3D-HEVC transmission based on fusion and watermarking techniques," *Multimedia Tools Appl.*, vol. 78, no. 19, pp. 27211–27244, Oct. 2019.
- [59] H. Zhang, X. Ma, and Y. Tian, "An image fusion method based on curvelet transform and guided filter enhancement," *Math. Problems Eng.*, vol. 2020, pp. 1–8, Jun. 2020.
- [60] J. Jalili, H. Rabbani, A. M. Dehnavi, R. Kafieh, and M. Akhlaghi, "Forming optimal projection images from intra-retinal layers using curvelet-based image fusion method," *J. Med. Signals Sensors*, vol. 10, no. 2, pp. 76–86, 2020.
- [61] U. Mahalaxmi, N. R. Raju, and M. R. Patnaik, "Hybrid fusion approach of medical images using DWT, DCT, Laplacian pyramid and curvelet transform," *J. Crit. Rev.*, vol. 7, no. 14, pp. 601–609, 2020.
- [62] W. Li, Q. Lin, K. Wang, and K. Cai, "Improving medical image fusion method using fuzzy entropy and nonsubsampling contourlet transform," *Int. J. Imag. Syst. Technol.*, early access, Aug. 2020, doi: [10.1002/ima.22476](https://doi.org/10.1002/ima.22476).
- [63] M. Amin-Naji, A. Aghagholzadeh, and M. Ezoji, "Ensemble of CNN for multi-focus image fusion," *Inf. Fusion*, vol. 51, pp. 201–214, Nov. 2019.

- [64] C. Li and A. Zhu, "Application of image fusion in diagnosis and treatment of liver cancer," *Appl. Sci.*, vol. 10, no. 3, p. 1171, Feb. 2020.
- [65] H. Fu, G. Sun, J. Ren, A. Zhang, and X. Jia, "Fusion of PCA and segmented-PCA domain multiscale 2-D-SSA for effective spectral-spatial feature extraction and data classification in hyperspectral imagery," *IEEE Trans. Geosci. Remote Sens.*, early access, Nov. 16, 2020, doi: 10.1109/TGRS.2020.3034656.
- [66] M. J. Fadhil, R. A. Fayadh, and M. K. Wali, "Design and implementation of a prototype system for image fusion by using SWT-PCA algorithm with FPGA technique," *Int. J. Electr. Comput. Eng.*, vol. 10, no. 1, p. 757, Feb. 2020.
- [67] J. A. Bhutto, T. Lianfang, Q. Du, T. A. Soomro, Y. Lubin, and M. F. Tahir, "An enhanced image fusion algorithm by combined histogram equalization and fast gray level grouping using multi-scale decomposition and gray-PCA," *IEEE Access*, vol. 8, pp. 157005–157021, 2020.
- [68] Z. Zhu, M. Zheng, G. Qi, D. Wang, and Y. Xiang, "A phase congruency and local Laplacian energy based multi-modality medical image fusion method in NSCT domain," *IEEE Access*, vol. 7, pp. 20811–20824, 2019.
- [69] K. Wang, M. Zheng, H. Wei, G. Qi, and Y. Li, "Multi-modality medical image fusion using convolutional neural network and contrast pyramid," *Sensors*, vol. 20, no. 8, p. 2169, Apr. 2020.
- [70] R. Naveenadevi, S. Nirmala, and G. T. Babu, "Fusion of CT-PET lungs Tumour images using dual tree complex wavelet transform," *Res. J. Pharmaceutical Biol. Chem. Sci.*, vol. 8, no. 1, pp. 310–316, 2017.
- [71] N. Sivakumar and K. Helenprabha, "Hybrid medical image fusion using wavelet and curvelet transform with multi-resolution processing," *Biomed. Res.*, vol. 28, no. 6, pp. 2758–2762, 2017.
- [72] E. Daniel, J. Anitha, K. K. Kamaleshwaran, and I. Rani, "Optimum spectrum mask based medical image fusion using gray wolf optimization," *Biomed. Signal Process. Control*, vol. 34, pp. 36–43, Apr. 2017.
- [73] C. W. Lacewell, M. Gebril, R. Buaba, and A. Homaifar, "Optimization of image fusion using genetic algorithms and discrete wavelet transform," in *Proc. IEEE Nat. Aeronaut. Electron. Conf.*, Jul. 2010, pp. 116–121.
- [74] T. Hergum, T. G. Bjastad, L. Lvtakken, K. Kristoffersen, and H. Torp, "Reducing color flow artifacts caused by parallel beamforming," *IEEE Trans. Ultrason., Ferroelectr., Freq. Control*, vol. 57, no. 4, pp. 830–838, Apr. 2010.
- [75] H. Tsutsui, S. Yoshikawa, H. Okuhata, and T. Onoye, "Halo artifacts reduction method for variational based realtime retinex image enhancement," in *Proc. Asia Pacific Signal Inf. Process. Assoc. Annu. Summit Conf.*, Dec. 2012, pp. 1–6.
- [76] V. Sowjanya, G. S. Rao, and A. Sarvani, "Investigation of optimal wavelet techniques for de-noising of MRI brain abnormal image," in *Proc. Int. Conf. Comput. Modeling Secur.*, vol. 85, Jan. 2016, pp. 669–675.
- [77] V. M. Kamble, P. Parlewar, A. G. Keskar, and K. M. Bhurchandi, "Performance evaluation of wavelet, ridgelet, curvelet and contourlet transforms based techniques for digital image denoising," *Artif. Intell. Rev.*, vol. 45, no. 4, pp. 509–533, Apr. 2016.
- [78] S. Kockanat and N. Karaboga, "Medical image denoising using metaheuristics," in *Metaheuristics for Medicine and Biology*. Berlin, Germany: Springer, 2017, pp. 155–169.
- [79] Y. He, Y. Zheng, Y. Zhao, Y. Ren, J. Lian, and J. Gee, "Retinal image denoising via bilateral filter with a spatial kernel of optimally oriented line spread function," *Comput. Math. Methods Med.*, vol. 2017, pp. 1–13, Feb. 2017.
- [80] H. Kiragu, G. Kamucha, and E. Mwangi, "An improved reconstruction method for compressively sampled magnetic resonance images using adaptive Gaussian denoising," in *Proc. Int. Conf. Emerg. Trends Elect., Electron. Commun. Eng.*, Cham, Switzerland: Springer, Nov. 2016, pp. 192–200.
- [81] H. M. El-Hoseny, W. A. El-Rahman, W. El-Shafai, G. M. El-Banby, E.-S.-M. El-Rabaie, F. E. Abd El-Samie, O. S. Faragallah, and K. R. Mahmoud, "Efficient multi-scale non-sub-sampled shearlet fusion system based on modified central force optimization and contrast enhancement," *Infr. Phys. Technol.*, vol. 102, Nov. 2019, Art. no. 102975.
- [82] H. M. El-Hoseny, Z. Z. El Kareh, W. A. Mohamed, G. M. El Banby, K. R. Mahmoud, O. S. Faragallah, S. El-Rabaie, E. El-Madbouly, and F. E. Abd El-Samie, "An optimal wavelet-based multi-modality medical image fusion approach based on modified central force optimization and histogram matching," *Multimedia Tools Appl.*, vol. 78, no. 18, pp. 26373–26397, Sep. 2019.
- [83] H. M. El-Hoseny, W. A. El-Rahman, W. El-Shafai, E. M. El-Rabaie, K. R. Mahmoud, F. E. A. El-Samie, and O. S. Faragallah, "Optimal multi-scale geometric fusion based on non-sub-sampled contourlet transform and modified central force optimization," *Int. J. Imag. Syst. Technol.*, vol. 29, no. 1, pp. 4–18, Dec. 2018.
- [84] H. M. El-Hoseny, W. A. El-Rahman, E.-S.-M. El-Rabaie, F. E. A. El-Samie, and O. S. Faragallah, "An efficient DT-CWT medical image fusion system based on modified central force optimization and histogram matching," *Infr. Phys. Technol.*, vol. 94, pp. 223–231, Nov. 2018.
- [85] T. D. Vu, H.-J. Yang, V. Q. Nguyen, A.-R. Oh, and M.-S. Kim, "Multi-modal learning using convolution neural network and sparse autoencoder," in *Proc. IEEE Int. Conf. Big Data Smart Comput. (BigComp)*, Feb. 2017, pp. 309–312.
- [86] R. Hou, D. Zhou, R. Nie, D. Liu, and X. Ruan, "Brain CT and MRI medical image fusion using convolutional neural networks and a dual-channel spiking cortical model," *Med. Biol. Eng. Comput.*, vol. 57, no. 4, pp. 887–900, Apr. 2019.
- [87] S. Singh and R. S. Anand, "Multimodal neurological image fusion based on adaptive biological inspired neural model in nonsubsampled shearlet domain," *Int. J. Imag. Syst. Technol.*, vol. 29, no. 1, pp. 50–64, Mar. 2019.
- [88] X. Han, "MR-based synthetic CT generation using a deep convolutional neural network method," *Med. Phys.*, vol. 44, no. 4, pp. 1408–1419, Apr. 2017.



OSAMA S. FARAGALLAH received the B.Sc. (Hons.), M.Sc., and Ph.D. degrees in computer science and engineering from Menoufia University, Menouf, Egypt, in 1997, 2002, and 2007, respectively. He is currently a Professor with the Department of Computer Science and Engineering, Faculty of Electronic Engineering, Menoufia University, where he was a Demonstrator, from 1997 to 2002, and an Assistant Lecturer, from 2002 to 2007. Since 2007, he has been a Teaching Staff

Member with the Department of Computer Science and Engineering, Faculty of Electronic Engineering, Menoufia University. In 2015, he joined the Department of Information Technology, College of Computers and Information Technology, Taif University, Al-Hawiya, Saudi Arabia. His current research interests include network security, cryptography, the Internet security, multimedia security, image encryption, watermarking, steganography, data hiding, medical image processing, remote sensing, chaos theory, and mobile communications.



HEBA EL-HOSENY received the B.Sc. degree in electronics and electrical communication engineering from the Faculty of Engineering, Tanta University, Tanta, Egypt, in 2009, the M.Sc. degree in electronics and electrical communication engineering from the Faculty of Electronic Engineering, Menoufia University, Menouf, Egypt, in 2014, and the Ph.D. degree in electronics and electrical communication engineering from the Faculty of Engineering, Benha University, Benha,

Egypt, in 2018. She is currently an Assistant Professor with the Department of Electronics and Electrical Communication Engineering, Al-Obour High Institute for Engineering and Technology, Egypt. Her current research interests include medical image fusion, medical image segmentation, cryptography, chaos theory, and image encryption.



WALID EL-SHAFI was born in Alexandria, Egypt, in April 1986. He received the B.Sc. degree in electronics and electrical communication engineering from the Faculty of Electronic Engineering (FEE), Menoufia University, Menouf, Egypt, in 2008, and the M.Sc. degree from the Egypt-Japan University of Science and Technology (E-JUST), in 2012. He is currently working as a Teaching Assistant and a Ph.D. Researcher with the Department of Electronics and Communication Engineering, Faculty of Electronic Engineering, Menoufia University.

His research interests include wireless mobile and multimedia communications systems, image and video signal processing, efficient 2D video/3D multi-view video coding, multi-view video plus depth coding, 3D multi-view video coding and transmission, quality of service and experience, digital communication techniques, 3D video watermarking and encryption, error resilience, and concealment algorithms for H.264/AVC, H.264/MVC, and H.265/HEVC video codecs standards.

WAEEL ABD EL-RAHMAN, photograph and biography not available at the time of publication.



HALA S. EL-SAYED received the B.Sc. (Hons.), M.Sc., and Ph.D. degrees in electrical engineering from Menoufia University, Shebin El-Kom, Egypt, in 2000, 2004, and 2010, respectively. She is currently an Assistant Professor with the Department of Electrical Engineering, Faculty of Engineering, Menoufia University, where she was a Demonstrator, from 2002 to 2004, and an Assistant Lecturer, from 2004 to 2010. Since 2010, she has been a Teaching Staff Member with the Department of Electrical Engineering, Faculty of Engineering, Menoufia University. Her research interests include database security, cybersecurity, network security, data hiding, image encryption, wireless sensor network, secure building automation systems, medical image processing, and biometrics.



EL-SAYED M. EL-RABAIE (Senior Member, IEEE) was born in Sires Elian, Egypt, in 1953. He received the B.Sc. degree (Hons.) in radio communications from Tanta University, Tanta, Egypt, in 1976, the M.Sc. degree in communication systems from Menoufia University, Menouf, Egypt, in 1981, and the Ph.D. degree in microwave device engineering from Queen's University of Belfast, Belfast, U.K., in 1986. In his doctoral research, he constructed a computer-aided design (CAD) package used in nonlinear circuit simulations based on the harmonic balance techniques. Up to February 1989, he was a Postdoctoral Fellow with the Department of Electronic Engineering, Queen's University of Belfast. He was invited as a Research Fellow with the College of Engineering and Technology, Northern Arizona University, Flagstaff, in 1992, and a Visiting Professor with the École Polytechnique de Montreal, Montreal, QC, Canada, in 1994. He has authored or coauthored more than 180 papers and 18 textbooks. He was the Head of the Department of Electronic and Communication Engineering, Faculty of Electronic Engineering, and the Vice Dean of Postgraduate Studies and Research with the Faculty of Electronic Engineering, Menoufia University. His research interests include CAD of nonlinear microwave circuits, nanotechnology, digital communication systems, and digital image processing. He is a member of the National Electronic and Communication Engineering Promotion Committee and a Reviewer of the Quality Assurance and Accreditation of Egyptian Higher Education. He received several awards, including the Salah Amer Award of Electronics in 1993 and The Best Researcher on (CAD) from Menoufia University in 1995. He acts as a reviewer and a member of the editorial board for several scientific journals. He has shared in translating the First Part of the Arabic Encyclopedia.



FATHI E. ABD EL-SAMIE received the B.Sc. (Hons.), M.Sc., and Ph.D. degrees from Menoufia University, Menouf, Egypt, in 1998, 2001, and 2005, respectively. Since 2005, he has been a Teaching Staff Member with the Department of Electronics and Electrical Communications, Faculty of Electronic Engineering, Menoufia University. He is a coauthor of about 200 papers in international conference proceedings and journals, and four textbooks. His current research interests include image enhancement, image restoration, image interpolation, super-resolution reconstruction of images, data hiding, multimedia communications, medical image processing, optical signal processing, and digital communications. He was a recipient of the Most Cited Paper Award from the *Digital Signal Processing* journal in 2008.



GAMAL G. N. GEWEID is currently working with the Department of Engineering and Technology, Worldwide College of Aeronautics, Worldwide Campus, Embry-Riddle Aeronautical University, Daytona Beach, FL, USA. He has a solid background in physics, mathematics, biology, radiology and imaging sciences, and strong programming skills in MATLAB, Python, and C++ programming languages. He has a record of research publications and four patents, all in the field of biomedical engineering. His research work aims in the long term to develop realistic three-dimensional anatomically based electrical models of healthy and diseased neurons based on nanotechnology, in addition to developing novel high-resolution and fast imaging methods for neurological diseases, establishing risk stratification algorithms, and developing new tools for detecting diseases in early stages, optimal diagnostic intervention tools for rehabilitation, and electrophysiology for pathological electrophysiological abnormalities identification. He has experience and interests in using deep-learning, machine learning, image processing, signal processing, radiology and imaging sciences, multimodality medical imaging (ultrasound, PET/CT, and MRI), CT image reconstruction, mechatronics, medical robotics, biomedical instrumentation, computer vision, pattern, recognition, nano-robots in medicine, software reliability and modeling, biosensors, imaging and information technology in biomedicine, excellent analytical, courses development, and problem-solving skills.

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