MEDICAL IMAGE FUSION

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Abstract-Image fusion finds numerous applications in remote sensing, satellite imaging, medical imaging etc. In medical science, in order to diagnose a disease, it is required that the image obtained from a particular modality should be highly informative and should have high accuracy and also it should have high spatial as well as high spectral resolution. However, most of the available modalities alone are not capable of doing it convincingly. To solve this problem, a technique called image fusion has been evolved, in which two or more images are fused together to make a new image. In medical image fusion two or more images obtained from different modalities are fused together to give us a desired image. Selection of fusion rule should be such that it must provide us all the relevant information and at the same time does not introduce any undesired features to the resulting image. In this paper we have considered various image fusion techniques to be used as the performance metric evaluators for the research study. We trust that this review would turn into a reference in this consistently developing field of exploration.

Keywords- Image Fusion, Medical Imaging, Medical Image Analysis, Diagnostics

I. INTRODUCTION

Image processing can simply be referred to performing some mathematical operations on image pixels, to get an enhanced image with a better visual quality and to extract some useful information. Image fusion is an efficient way retrieving the information from the multiple sources into one image. The combined information enables the visual perception of more comprehensive image. The complimentary images obtained from multiple sensors; multiple foci or multiple views are fused together to generate a new image which cannot be given by the individual imagery or data set. The concept of image fusion finds its applications in various fields [1,6-8]. For instance, in remote sensing varied type of data is acquired via different sensors to obtain a fused image for instance,

fused image with both higher spatial as well as spectral resolution. Other areas of application of image fusion are surveillance, biometrics, defence applications and medical imaging [44]. Numerous applications of image fusion have been found in the field of medical imaging. The medical images obtained from different sensors are fused together to enhance the diagnostic quality of the image modality. With the advancements in the field of medical science and technology, medical imaging is able to provide various modes of imagery information [26]. Different medical images have some specific characteristics which require simultaneous monitoring for clinical diagnosis. So, in order to know image fusion concept, a survey study is desired. The main target of such review study is to give a collective survey of image fusion techniques applicability that could be helpful in medical applications.

1.1 Basics of Medical Image Fusion

Image fusion may be considered as merging pertinent information from a series of images into one informative and complete image than any input images. More precisely, fusion is the integration of information from a set of registered images without the introduction of distortion [11,17]. There are so many applications of image fusion that requires high spatial spectral resolutions within a single image besides achieving higher image quality can be provided using fusion procedure as it has many advantages [18-21]. A comparable study of some main advantages, drawbacks, and applications of fusion process can be observed through this review and presented in the following table to describe the importance of the interested topicof fusion and areas of implementations.

Table I Comparative study of Image Fusion Methods

Advantages of Image Fusion	**Drawbacks of *Image Fusion***	**Application areas**
• Extracts beneficial information. • Do not introduce artifacts or discrepancies. • Robust to imperfections. • Convenient for identification and recognition. • Reduces the data storage required and time for transmission.	• Some color artifacts can be produced due to transformation. • Noise can affect the fused image. • Processing of data is slow. • More than source image is required for fusion procedure. • Dissimilar illumination problem.	• Object detection andrecognition. • Navigation guidance. • Satellite imaging for remote sensing. • Military and civilian. • Medical diagnosis.

A. Classification of Image Fusion

Image fusion techniques are categorized into different levels: low, middle, and high; or pixel, feature, and decision levels.

- *Pixel level:* Fusion is performed between individual pixel and values.
- *Feature level:* Fusion is performed between segmented regions of input images considering their properties.
- *Decision level:* Fusion is performed between segmented regions of input images considering their initial object detection and classification.

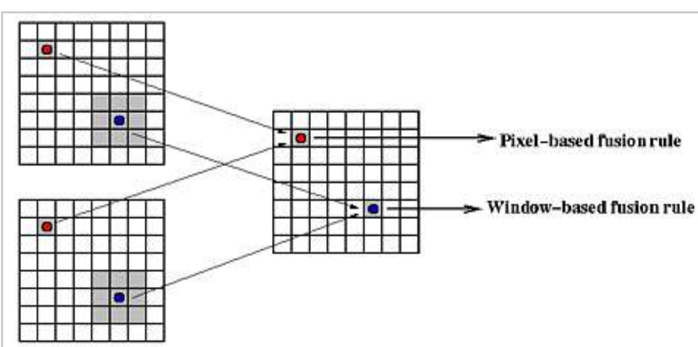
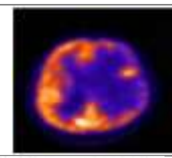
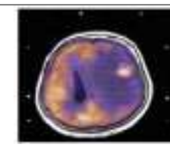
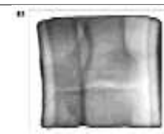
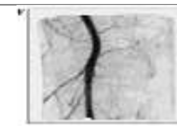


Figure 1: Fusion rules, Pixel based fusion rule and window based fusion rule for both feature and decision level

B. Categories of Fusion

Table II. Fusion categories

Fusion category	Image A	Image B	Fused Image
Multi-modal fusion			
Multi-temporal Fusion			
Multi-focus Fusion			
Multi-view fusion			

a. multi-modal fusion: 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.

b. multi-temporal fusion: The main purpose of the fusion in this case is to detect changes in the scene in different times.

c. multi-focus fusion: The fusion is applied to have a fused image that is everywhere in focus.

d. *multi-view fusion:* The main goal of the fusion process in this category are to have all the complementary information under the different conditions in the fused image.

1.2 Medical Images based multi-modal Fusion procedure

three major focused areas of studies in medical image fusion: (a) identification, improvement, and development of imaging modalities useful for medical image fusion, (b) development of different techniques for medical image fusion, and (c) application of medical image fusion for studying human organs of interest in assessments of medical conditions.

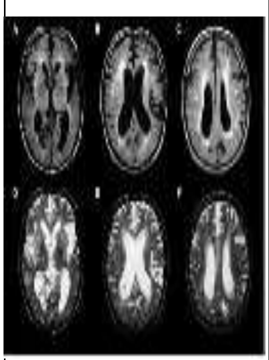
1.3 Medical Imaging: Modalities

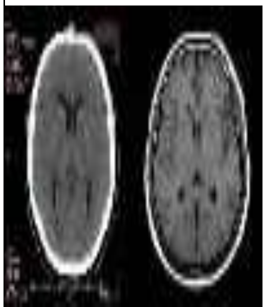
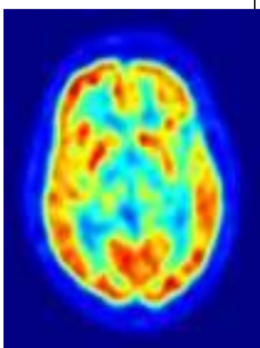
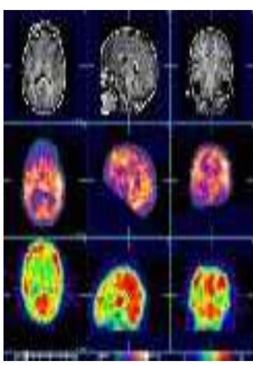
Numerous medical imaging modalities exist with each having distinctive characteristics that provide various sources of information that facilitates study of organs, diagnosis of diseases, follow-up treatments of patients, and for further processing procedures such as fusion process. These modalities can be classified into five types; they are radiology, visible light photography, printed signals (waves), microscopy, and 3D reconstruction. 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 through table IV.

Table III. Significant work done in medical image fusion for diverse applications

Authors & Year	Fusion Technique	Fusion Level	Organ	Modality	Contribution of research
Bhateja, V., et.al (2015)	PCA	Pixelbased	Brain	MRI,CT	Presents a multimodal fusion algorithm that consists of two stages are stationary wavelet transform (SWT) and non-sub-sampled contourlet transform (NSCT) to enhance the shift variance, directionality, and phase information.
Biswas, B., et.al (2015)	Maximum fusion rule	Pixelbased	Spine	MRI, CT	Propose an algorithm that provides both functional and anatomical structure for spine by applying three steps: • Shearlet transform to input images. • Wiener filter and SVD applied to low pass sub bands. • Fusion of low and high pass sub bands is performed
Vani & Saravanakumar (2015)	Dual tree discrete wavelet transforms (DT-DWT)	Pixelbased	Brain	MRI, CT	The paper presents a multi-focus and multimodal image fusion techniques using DT-DWT then applying fuzzy logic clustering for segmentation that helps in tumor identification.
Akbarpour, T., et.al (2015)	Dual tree wavelet transforms. (DTWT)	Pixelbased	Brain	MRI	Presents a new technique for extraction of affected regions by Alzheimer disease from multispectral medical images by means of fusion and segmentation methods.

Table IV. Medical Imaging: Modalities

Modalities	Imaging	Formation/Modality/Body part	Advantages & Disadvantages	Applications
Magnetic Resonance Imaging (MRI)		Image formation: Using radio waves which lie in FM range and a strong magnet hat are attached to a computer to produce slices of human body parts. Modality: Anatomical, functional, and Molecular modality and it also involves Electric & magnetic fields. Body part: soft tissue and non-bony parts i.e., blood vessels, organs in pelvis, breasts, bones and joints chest, abdomen (heart, liver, kidney), and tendon and ligament tears.	Advantages • Safe for babies and pregnant women • No radiation exposure. • Higher accuracy • No short term effects. Disadvantages • Relative sensitivity to the movement of patients and organs that involve movement. • Strong magnetic field disturb. • Cannot be used for patients with metallic devices such as pacemakers. • Low through put. • Time consumer that takes 30-45 minutes. • High cost.	Prostate studies, image regeneration, lung/liver diagnosis, tissue classification, cancer assessment and diagnosis, surgical planning and training, visualization f 3D tumor simulation.

Computerized Tomography (CT)		Image formation: Creates images by using an array of x-ray sensors and a computer to produce a series of cross-sectional based images. Modality: Anatomical and functional modality and also involve x-ray radiation. Body part: Bones and hard tissues	Advantages • High resolution • Wider scan area • Short scan time • Higher penetration depth. Disadvantages • Limited tissue characterization. • Limited sensitivity • Exposure to x-ray radiation • High dose of radiation per examination. • High cost.	3D tumor simulation, brain diagnostic and treatment, tumor detection, deep brain simulation, bone tumor surgery.
Positron Emission Tomography (PET)		Image formation: Images are obtained from a scanner connected to a computer and a small quantity of radiopharmaceuticals is wanted to be injected into a patient's vein that helps in making detailed. Modality: Anatomical, functional, and Molecular modality. Positron (ionizing). Body part: Provides physicians with information about how tissues and organs are functioning.	Advantages • High sensitivity • Provides a functional imaging capability. • Effectively used to distinguish between benign and malignant tumors in single imaging. • Can image biochemical and physiology phenomena. • Higher penetration depth. Disadvantages • Limited resolution • Radiation • High cost • Motion artifacts • Interpretation is very challenging. • Limited number of times for radioactive components used in PET.	Cancer treatments, gross tumor volume detection, image segmentation and integration, gynecological cancer diagnosis, 3D tumor simulation, inertial electrostatic confinement fusion.
Single Photon Emission Computed Tomography (SPECT)		Image formation: nuclear imaging technique where cross sectional images of radiotracer within the human body are structured. Modality: Functional modality and Photons (ionizing). Body part: Used to study blood circulation to tissues andorgans	Advantages • High sensitivity (but lower than PET) • Higher penetration depth • Images free of background Disadvantages • Blurring effects • Limited resolution • Radiation • Attenuation compensation is not possible due to multiple scattering of electrons. • High cost.	Brain diagnosis and treatment, neck, head, cancer diagnosis, liver diagnosis, lung cancer treatment, fusion of multi-modality images, tumor detection, and multi-dimensional visualization.

II. Currently Used Methods Medical Image Fusion

The major medical image fusion methods, the modalities that these methods are applied and the applications in medical imaging studies.

a. **Morphological methods***:* The morphology operators have been explored by image processing community for long, and the concept is used by the medical imaging community to detect spatially relevant information from the medical images. The morphological filtering methods for medical image fusion have been applied, for example, in brain diagnosis [33,47,48]. An example of modalities used in morphology-based fusion can be seen in the fusion of CT and MR images [4,10]. In such applications, the morphology operators depend heavily on the structuring operator that defines the opening and closing operations. These methods are highly sensitive to the inter-image variability resulting from outliers, noise, size and shape of the features.

b. **Wavelet based methods***:* The primary concept used by the wavelet-based image fusion [2,3,5,22,27,28,35] is to extract the detail information from one image and inject it into another. The detail information in images is usually in the high frequency and wavelets would have the ability to select the frequencies in both space and time. The resulting fused image would have the ''good'' characteristics in terms of the features from both images that improve the quality of the imaging.

c. **Knowledge based methods***:* In medical imaging, there are several instances where the medical practitioner's knowledge can be used in designing segmentation, labeling and registration of the images. Generally, the domain-dependent knowledge is needed to set constraints on region-based segmentation and to make explicit the expectation of the appearance of the anatomy under the imaging modality at the stage of grouping the detected regions of interest. There are a range of applications where the domain-dependent knowledge is useful for image fusion such as for segmentation [45], micro-calcification diagnosis [40], tissue classification [39], brain diagnosis [39], classifier fusion [34], breast cancer tumor detection [34] and delineation & recognition of anatomical brain object [45]. The knowledge-based systems can used in combination with other methods such as pixel intensity [40]. These methods place a significant amount of trust in the medical expert in labeling and identifying the domain knowledge relevant to the fusion task. The advantage is the ability to benchmark the images with the known human vision standards, while the drawback is the limitations imposed by human judgment in images that are prone to large pixel intensity variability.

d. **Methods based on fuzzy logic***:* The conjunctive, disjunctive and compromise properties of the fuzzy logic have been widely explored in image processing and have proved to be useful in image fusion. The fuzzy logic is applied both as a feature transform operator or a decision operator for image fusion [12,20,31,39]. There are several applications of fuzzy logic base image fusion such as brain diagnosis [33,41], cancer treatment [46], image segmentation and integration [46], maximization mutual information [38], deep brain stimulation [31], brain tumor segmentation [39], image retrieval [29], spatial weighted entropy [29], feature fusion [29], multimodal image fusion [25], ovarian cancer diagnosis [9], natural computing methods [23] and gene expression [24].

e. Neural network-based methods: The ability of the neural network models to predict, analyse and infer information from a given data without going through a rigorous mathematical solution is often seen as an advantage. This makes the neural network attractive to image fusion as the nature of variability between the images is subjected to change every time a new modality is used. The ability to train the neural network to adopt to these changes enable several applications for medical image fusion such as solving the problems of feature generation [43], classification [43], data fusion [37,43], image fusion [42], micro-calcification diagnosis [40], breast cancer detection [32], cancer diagnosis [36], and natural computing methods [23].

f. **Mexican Hat Wavelet Technique**

It is the technique of continuous wavelet in Gaussian function. It is considered for saving the computation time in image analysis and retrieval for dimensions of two or more. The technique is stable under noise-like processing, yet it is sensitive to some affine transformations. Harris detector Technique It used to detect the similar regions between the images through affine transformation and it belongs to the category of feature extraction. Geometric transformation is basic conversion technique to identify the viewpoint in the image for affinity calculation. Transformation process as follows.

g **RGB Color Space**

The RGB color space is the most widely used color space. RGB stands for Red, Green, and Blue. RGB color space combines the three colors 32 corresponding coefficients have to be transferred to the composite multiscale representation. Failing to do so may result in a degradation of the fusion result due to the possibility of feature cancellation when the inverse transform is applied.

h COMBINATION METHOD

This block is in charge of performing the actual combination of the transform coefficients of the two source images. In the next chapter the influence of different multiscale transforms for the purpose of pixel-level image fusion is investigated (Sarkar&Soundararajan 2000). We start our discussion with a theoretical review of traditional as well as recently developed image decomposition methods. Next, some fusion results obtained by using each transform with varying decomposition levels and filter banks are presented. Finally, by comparing the achieved fusion results, we give the best candidates for the fusion of three different classes of input images.

I **COLOUR SPACE MODELS**

IMAGE REPRESENTATION Color is one of the widely used visual features and is invariant to image size and orientation. To extract the color features from the content of an image, we need to select a color space and use its properties in the extraction. In common, colors are defined in three-dimensional color space. The purpose of the color space is to facilitate the specification of colors in some standard, accepted way. Several color spaces are used to represent images for different purposes. RGB Color Space The RGB color space is the most widely used color space. RGB stands for Red, Green, and Blue. RGB color space combines the three colors 32 corresponding coefficients have to be transferred to the composite multiscale representation. Failing to do so may result in a degradation of the fusion result due to the possibility of feature cancellation when the inverse transform is applied.

J HSV Color Space

It is cylindrical coordinate representation. HSV color space is widely used in color feature extracting. In this space, hue is used to distinguish color, saturation is the percentage of white light added to a pure color and value refers to the perceived light intensity. The advantage of HSV color space is that it is closer to human conceptual understanding of colors. It is well known that color provides powerful information for imageretrieval method, but the human eye cannot perceive a large number of colors at the same time, but it is able to distinguish similar colors well

K Spatial fusion methods

Spatial fusion methods based on the pixels of images, where pixelvalues are manipulated to accomplish the desired results. Spatial domain methods include PCA, IHS, Brovey, High Pass Filtering methods, ICA, Simple maximum, simple average, and weighted average [19]. However, the problem with spatial domain methods is that they generate spatial distortion in the resultant fused image, which is considered a negative factor in the fusion process. Stokking et al. [53] proposed an HSV model for a fusion of anatomical and functional information obtained from MRI and SPECT modalities by using a color encoding pattern

L **Decision level fusion**

Decision Level fusion decides each input image using specific predefine criteria and then merges based on the trustworthiness of each conclusion into global optimum to make the single fused image. These types of techniques produce maximum information using certain rules defined before the fusion process [56].

M Dictionary learning and Bayesian techniques

are the most prevalent methods used in decision fusion. At the decision level, usually, there are three approaches integrated to get fused images, these approaches are the following (information theory, logical reasoning, and statistics approaches); include joint measures, Bayesian fusion techniques, hybrid consensus methods, voting, and fuzzy decision rules. The Bayesian approach is based on probabilities for combining data from various sensors, these techniques rely on the Bayes hypothesis. Nonparametric Bayesian, HWT Bayesian, and DWT Swarm Optimized are examples of Bayesian techniques [57]

N Deep learning fusion methods These methods consist of multiple layers, where each layer takes input from the previous layer. Deep learning contributes to the layered structure and suitability of the complex framework architecture for large data manipulation . The deep learning fusion methods include CCN, Convolution Sparse

Representation (CSR) also known as convolution sparse coding techniques, and Deep Convolution Neural Networks (DCCNs). The CNN model of deep learning, which is more popular among all the other techniques, is trainable and well-tuned to learn features of input data in the multilayered architecture framework. In CNN, every layer consists of several features maps that hold coefficients known as neurons. In the multiple stages, the features maps connect with every stage using different calculations, including spatial pooling, convolution, and non-linear activation. Another popular deep learning fusion technique is Convolutional Sparse Coding (CSC)

P Hybrid fusion methods C

onsidering that the results of the conventional multimodal image fusion methods are not satisfactory, the basic idea behind hybrid methods is to combine two or more fusion techniques, such as spatial or transform fusion and neural network techniques, to improve the fused image quality and performance. The general advantage of the hybrid methods is to improve the visual quality and decrease the artifacts and noise in the fused images. hybrid fusion method based on Retina-Inspired Model (RIM) and HIS fusion methods, which can maintain high spatial features and additional functional data. The performance and visual results showed that this technique was superior to the Brovey, HIS, and DWT methods. In the proposed method, entropy, discrepancy, mutual information, and averaging gradient were used as fusion quality assessment parameters.

Q Sparse representation methods

In the sparse representation (SR) method, an over-complete dictionary is obtained from a sequence of images to achieve a steady and significant representation of the source images . The basic principle of SR representation is based on the treatment of an image signal as a linear combination of less significant atoms from the pre-trained dictionary learning, where the sparse coefficient shows the significant features of the input images. Sparsity refers to the fact that only a minimal number of atoms are necessary to properly reconstruct a signal, resulting in sparse coefficients

1.5 Major Medical Image Fusion Applications

A. Brain

The most commonly used image modalities to study the brain include the following:

CT	Shows the brain structure (bones and hard tissues). Used for brain injuries.
PET	Measures brain activity by showing how blood flux and oxygen, and glucose metabolism in the tissues of the working brain. Used for diagnose strokes, brain tumors, and neuron-damaging diseases which causedementia (such as AD)
MRI	Shows the brain structure (soft tissues) Measures magnetic activity of the brain
SPECT	Measures cerebral blood flow. Used for brain disease processes which produce dementia.
Hybrid imaging modalities	MRI/PET, MRI/SPECT, MRI/CT, PET/CT, and CT/SPECT

B. Prostate

CT	Used for pre-treatment evaluation of prostate cancer and identification of abnormally enlarged lymph nodes.
PET	Used for the detection of ambiguous metastases in patients with prostate cancer by measuring the metabolic rate of the tissue.
Ultrasound	Define the extent and location of cancers in glands.
Hybrid imaging modalities	MRI/CT and PET/CT

C. Breast

MRI	Used for precise identification of breast tumors and early detection for breast cancer.
Ultrasound	Used to detect breast lesions and abnormalities.[60,61,62,63]
Hybrid	MRI/PET are complementary and

imaging modalities	valuable in monitoring breast cancer treated withchemotherapy

D. Lungs

CT	Used for detection of acute pulmonary embolism, tumors, pulmonary hypertension, advanced COPD, pulmonary fibrosis, and pneumonia in a high-risk patient.[49 ,50,51]
X-ray	Used for diagnosis of cancer, pneumonia, and chronicobstructive pulmonary disease.
MRI	Used for diagnosis of bronchial carcinoma, cystic fibrosis, pulmonary hypertension, and pulmonary embolism.[52]
PET	Used for diagnosis of non-small-cell bronchial carcinoma[53,54].
Hybrid imaging modalities	PET/CT

E. Heart

CT	Demonstrating excellent visualization of coronary anatomy and assessment of disease.
SPECT	Assessment of perfusion, systolic function, and coronary artery disease (CAD)[55,56]
MRI	Used for estimation of global and regional systolic LV function, myocardialperfusion.
PET	Allow appreciation of perfusion and function, at rest and after stress[57,58.59]
Hybrid imaging modalities	PET/CT

III. CONCLUSION

This paper presented a review study for the topic of medical image fusion and the basic concepts of it. Fundamentals of medical image fusion were first presented including the fusion main categories and the major areas of the medical image fusion studies with deduced comparisons. Then a discussion for the medical imaging modalities was introduced including a suggestion for possible modality combinations that could be profitable for fusion procedure. The paper also covers in detail the novel trends for future research that provide solutions for many problems in medical image fusion process for achieving perfect image quality.

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