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Medical Diagnosis with Multimodal Image Fusion Techniques

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Abstract: Image Fusion is an effective approach utilized to draw out all the significant information from the source images, which supports experts in evaluation and quick decision making. Multi modal medical image fusion produces a composite fused image utilizing various sources to improve quality and extract complementary information. It is extremely challenging to gather every piece of information needed using just one imaging method. Therefore, images obtained from different modalities are fused Additional clinical information can be gleaned through the fusion of several types of medical image pairings. This study's main aim is to present a thorough review of medical image fusion techniques which also covers steps in fusion process, levels of fusion, various imaging modalities with their pros and cons, and the major scientific difficulties encountered in the area of medical image fusion. This paper also summarizes the quality assessments fusion metrics. The various approaches used by image fusion algorithms that are presently available in the literature are classified into four broad categories i) Spatial fusion methods ii) Multiscale Decomposition based methods iii) Neural Network based methods and iv) Fuzzy Logic based methods. the benefits and pitfalls of the existing literature are explored and Future insights are suggested. Moreover, this study is anticipated to create a solid platform for the development of better fusion techniques in medical applications.

Keywords: Multi modal medical image fusion, Imaging Modalities, Fusion techniques, Quality evaluation metrics.

I. INTRODUCTION

Digital image processing has improved in remote sensing, satellite imaging, under water imaging, medical imaging, and other domains as a result of advances in processors, mathematics, and the practical need for a variety of applications in many fields. Every image obtained by these imaging systems will contain useful information. When it comes to clinical diagnosis, which necessitates a great deal of information, the minimal information offered by single modal medical imaging is insufficient. Hence, Integrating images obtained from various modalities to form a single composite image which will have all complementary information from the source images is indispensible. Image Fusion is an effective approach utilized to draw out all the significant information from the source images and to cut down on the growing number of data, which supports experts in evaluation and quick decision making [1]. Satellite imaging, machine learning, medical imaging , image enhancement, military and astronomy are just a few of the fields where image fusion techniques are extensively used to dramatically increase attributes which were not visible using single image[1]. However, fusion of images should meet certain conditions such as (i) The most significant components in the source images should be identified and incorporated into the fused image without losing any information.(ii) There should be no anomalies or irregularities introduced during the process which may mislead the expert in further processing.(iii)It should be reliable and robust preventing misregistration and noise.[2]. iv) shift invariance should be preserved.

Image fusion is divided into four major groups viz: i) Multi-view Fusion ii) Multi-modal Fusion iii)Multi-temporal Fusion and iv) Multi-Focus fusion. Images from the same modality are collected concurrently in Multi-view Fusion., but from various locations or under various circumstances. In Multimodal fusion, Images are captured using different sensors. In Multi-temporal image fusion, the exact same scene is photographed many times using the same mode of capture, but each time at a different time. Images repeatedly taken at different focal length are fused in Multi focus image fusion.

Multi modal medical image fusion produces a composite fused image utilising sources like X-Rays, Computed Tomography (CT), Magnetic Resonance Imaging (MRI), Ultrasound (US), Positron Emission Tomography (PET), Single Photon Emission Computed Tomography (SPECT),etc to improve quality [3,4] and extract complementary information. Each imaging method uses different sensors, captures different characteristics and provides different imaging information.

Anatomical examinations of the human body are made using X-rays. An X-ray can identify bone anomalies and fractures. The computed tomography (CT) image

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reveals the intricate features of heavy structures like bones., skull and also information on stroke, hemorrhage and any type of brain lesion. However, they don't go into great depth regarding soft tissues [5] MRI scans provide excellent detail regarding abnormalities in soft tissues and in blood vessels. Ultrasound imaging provides both anatomical information and Functional information like movement of tissues and velocity of blood.[6]Imaging techniques used in nuclear medicine such as Positron Emission Tomography (PET) and Single Photon Emission Computed Tomography (SPECT) give both metabolic and functional information. Every imaging technology has its own traits and limitations. [1].Anatomical and functional information can be merged to obtain more information about a disease. Numerous medical disorders affecting the bones, brain, breast, lungs, liver, bone marrow, stomach, mouth, teeth, intestines and soft tissues, can be diagnosed and evaluated using these imaging techniques [1].

The great amount of scholarly articles that have been published in journals and publications since the year 2000 demonstrate the expanding popularity of this research area .Fig 1 compares number of publications in multi-modal image fusion applied in various domains and in medical image processing. From the trend line, we can easily understand that the research papers have increased gradually from 2007 till 2022.This growth is due to technological advancement in medical field and image processing domain, which has led researchers to put forward new fusion algorithms. Many hybrid algorithms were brought out to take advantage of the benefits of already-existing algorithms in order to extract complementary data from the source images.

In order to begin the process of Multi-Modal Image Fusion (MMIF), the researcher must first choose two or more modalities to merge and extract additional information that is necessary for clinical diagnosis. After obtaining the input images, geometric alignment is performed on them by applying image registration techniques to fix any spatial misalignment [7]. The input images are subsequently broken down into number of sub images by employing any one image decomposition techniques, such as the intensity-hue-saturation approach, wavelet-based decomposition, pyramidal decomposition, contourlet-based decomposition, and so on. After the images have been decomposed, features may then be extracted and the fusion technique can be used to combine these features. In the last step, an inverse algorithm is employed to merge the subimages in order to reconstruct the fused image[8].

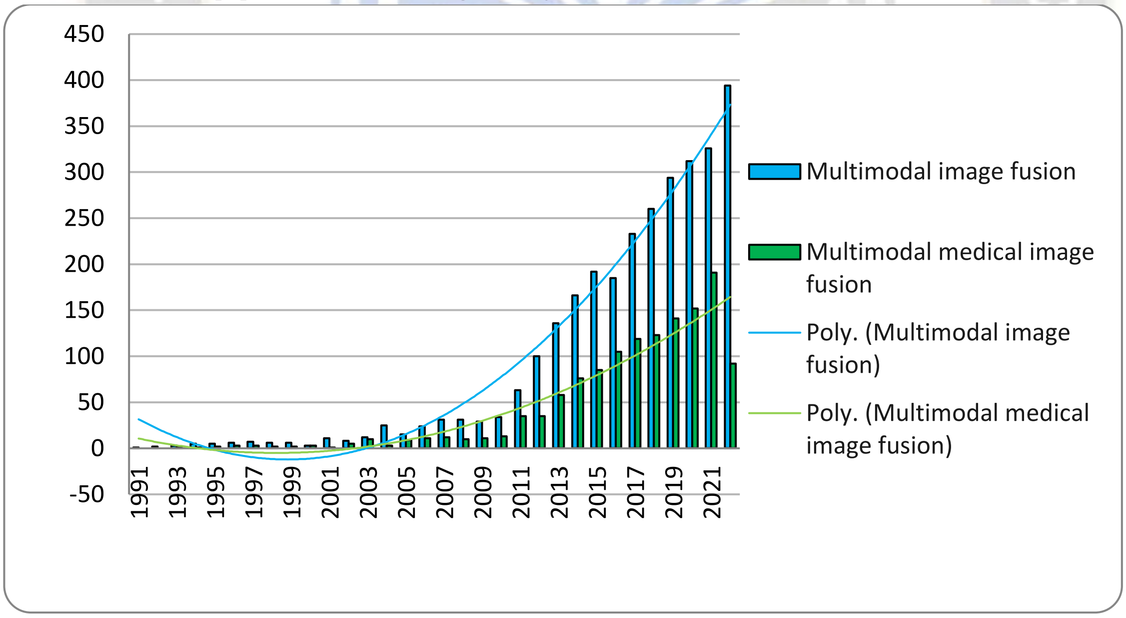

Fig. 1 PubMed publications on multimodal image fusion

Assessing the merged image's overall quality is carried out to evaluate how well the images are fused using evaluation parameters such as standard deviation, entropy, Peak Signal-to-Noise Ratio, Root-Mean-Square Error, Spatial Frequency, Structural Similarity index.Fig.2 depicts the basic steps in image fusion process.

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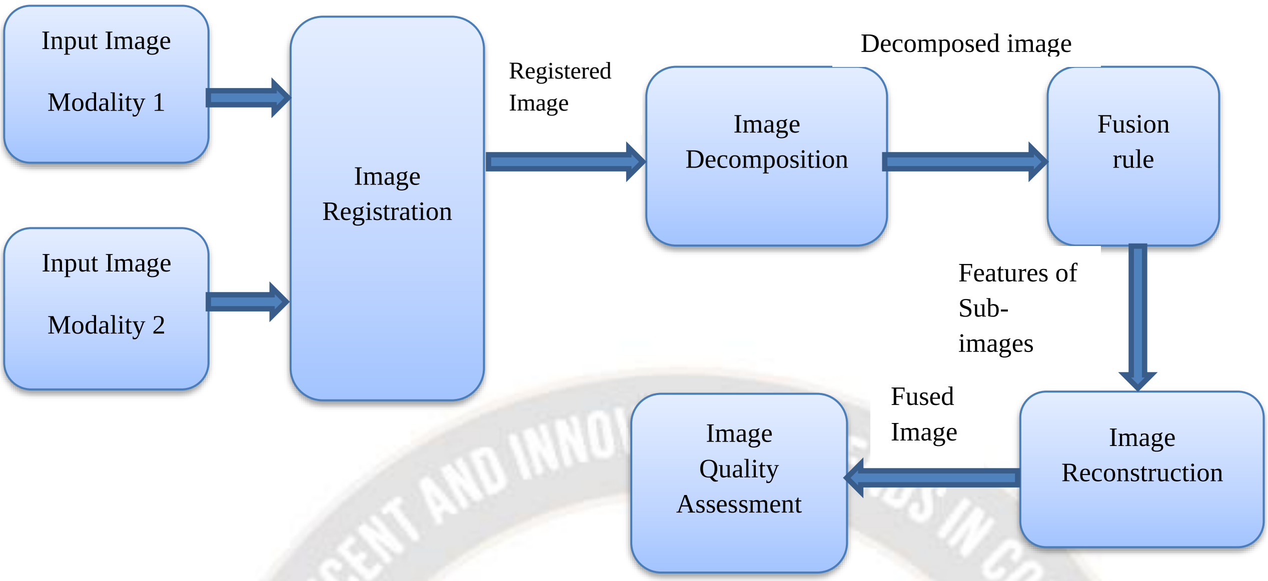

Fig.2 Steps in image fusion process

The overall structure of the article comprises of six parts.. Section 2 presents various medical imaging modalities and their comparison. Section 3 provides different levels of fusion. Section 4 reviews various multimodal medical imaging techniques in literature. Section 5 discusses various quality evaluation measures in multi modal fusion. Section 6 concludes the challenges and future trends in this research.

II. MEDICAL IMAGING MODALITIES

In the realm of medicine, each imaging modality provides information and features that are distinct from the others. A variety of medical imaging techniques like X-ray, CT, MRI, PET, SPECT, US are used to screen and diagnose various disorders affecting mankind. Fig. 3 depicts some of the imaging modalities discussed here. Imagery today reveals every organ and disorder. They show us 3D, colour images of the beating heart, blood flowing through our arteries, destruction of cell due to tumour and antibodies fighting infection[9]. It is nearly impossible to obtain all of the necessary information from a single imaging modality in a manner that would guarantee the clinical accuracy and reliability of the subsequent analysis and diagnosis. Examining images from a variety of imaging modalities is the logical strategy to take in order to make a more trustworthy and precise evaluation. Therefore, images obtained from different modalities are fused Additional clinical information can be gleaned through the fusion of several types of medical image pairings, including MRI-SPECT[10],CT-MRI[11-13],CT-SPECT[14-15],MRI-PET[16],PET-CT[17],Ultrasound-X-rays[18-19][20].

2.1 X-Ray Imaging

X-rays are a part of the electromagnetic spectrum that are comparable to visible light in that they can go through most objects, including the human body. In contrast to light, X-rays have a greater energy level than visible light. and are able to penetrate the majority of materials. X-rays are utilized in the medical field to produce images of the organs, tissues, and other anatomical structures found inside the body. X-rays penetrate through the body, and then hit an x-ray detector on the opposite side of the patient. This produces an image that shows the "shadows" of elements that are positioned inside the body. Bone fractures, specific cancers and other unusual lumps, pneumonia, some forms of traumas, benign growths and dental abnormalities can all be diagnosed with this technique[21,22]. Mammography is a method for determining the existence of breast cancer which relies mainly on X-rays as its imaging source. Multimodal image fusion of X-ray with other modalities include Vibroacoustography images with X-ray mammography [23], X-ray-Ultrasound [24], X-ray-CT[25] and X-ray- MRI [26].

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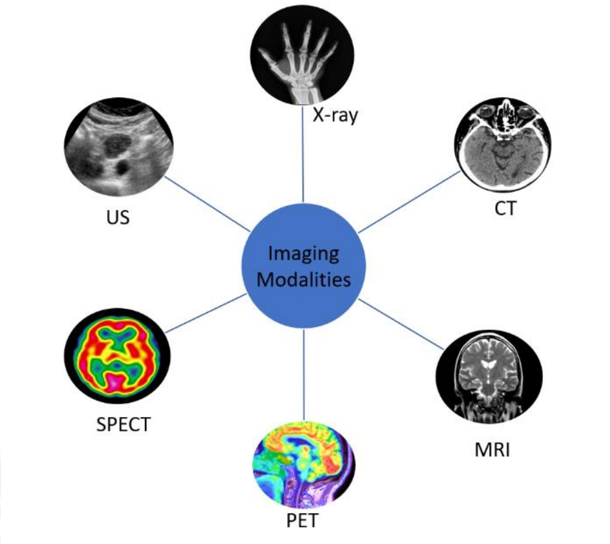

Fig.3 Medical imaging Modalities

2.2 Computed Tomography

Computed tomography, also known as CT, is a computerized imaging method where a constricted beam of x-rays is directed towards the patient as well as the body is also rotated quickly. The above procedure generates signals which are processed and cross sectional images are generated by the machine's computer . The resulting slices are known as tomographic images, which are capable of providing a physician with greater insight than conventional x-rays. After the machine has obtained an appropriate quantity of slices that are in a row, those slices can be "stacked" together via digital means in order to create the patients image in three-dimension . With the help of this image, it is much easier to recognize basic structure inside the patient's body, in addition to tumors and other anomalies.

Because CT is capable of producing more information than a conventional x-ray, it is very beneficial in the diagnosis of bone cancers and severely deteriorated joints. CT is a valuable screening tool for identifying abdominal cancers and lesions, Heart illness or anomalies, can be used to scan the head for injuries, malignancies, stroke clots, and other diseases. Lungs can be scanned to identify malignancies, blood clots, extra fluid and emphysema or pneumonia[27].In multimodal medical image fusion,CT is is one of the main modality which can be fused with other modalities which include CT-MRI[28-32] PET-CT [33-36],SPECT – CT [37-39], Ultrasound – CT [40,41]

2.3 Magnetic Resonance Imaging

Magnetic Resonance Imaging, sometimes known as MRI, is a type of imaging technique that does not require any sort of intrusive procedure to provide comprehensive anatomical images in three dimensions. It is often applied in the fields of disease diagnosis and detection, as well as monitoring of therapy. In this technology, an external magnetic energy stimulates and detects the shift in the proton axis rotation, which is present in all biological tissues. The non-bony sections of the body such as the soft tissues of the body are good choices for imaging using an MRI scanner. In contrast to computed tomography (CT), these methods do not make use of the potentially hazardous ionizing radiation that is produced by x-rays. The muscles and all types of connective tissues, in addition to the brainstem, may be seen more precisely in MRI when compared to normal x-rays and CT; As a result of this, MRIs are often used in the diagnosis process for knee and shoulder issues. However, they take quite a long time to complete scan, taking anything from 35 to 45 minutes on average. Several papers were published by fusing MRI with other modalities. Few to list are MRI-CT [28-32], MRI-PET [42,43], MRI-SPECT[44,45].

2.4 Positron Emission Tomography

Positron emission tomography, sometimes known as PET, is a technique used in nucleology that monitors the metabolic activity of the cells that make up the tissues of the body. In reality, PET is a hybrid field that brings together nuclear medicine and biochemical investigation. PET allows to visualize all biochemical changes including the metabolism of the heart muscle. PET is most commonly used in patients who have conditions related to the brain or heart, as well as cancer. PET identifies metabolism inside body tissues, while other kinds of nuclear medicine investigations detect the quantity of radioactive substance element accumulated in body tissue at a certain place to analyze the function of the tissue. This is where PET

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differentiates from other types in the field of nuclear medicine. It is also possible to employ PET in combination with many other diagnostic procedures, like computerized axial tomography (CAT) or magnetic resonance imaging (MRI), in order to get information that is more conclusive regarding cancerous tumors and other types of abnormalities. The more recent technique known as PET/CT merges PET and CT scanning into a single device. PET/CT has shown promising results in the assessment of brain tumours, seizures, Alzheimer's disease, and coronary artery disease, as well as in the identification and analysis of lung cancer.

2.5 Single Photon Emission Computed Tomography

Single photon emission computed tomography (SPECT) is a medical imaging technique that is based on nuclear medicine imaging and reconstruction of tomographic images from multiple projections. Functional information about patient is represented in the SPECT images. SPECT scans employ radioactive substance known as tracers, which are absorbed by muscles from the blood. SPECT imagers are equipped with gamma camera detectors which can capture the gamma ray emitted from tracers that have already been administered into the patient. These emissions may be used to diagnose a variety of medical conditions. Computers convert tracer information into images. SPECT uses numerous projections of two-dimensional nuclear medicine images to estimate three-dimensional radioactivity distribution. SPECT's radiation source is within the patient, unlike CT's and X-ray.

2.6 Ultrasound Imaging

An ultrasound (also known as a sonogram) is a kind of imaging test that provides an image of the organs, tissues, and other structures that are located within the body by using sound waves . Unlike x-rays, ultrasounds don't emit or produce any radiation. An ultrasound may also reveal moving elements of the body, such as a beating heart or blood travelling through blood channels. This can be very helpful in diagnosing medical conditions. It also helps in directing biopsies, diagnose cardiac issues and evaluate damage after a stroke, search for gall bladder blockages , examine the thyroid gland for any malignant growth, detect abnormalities in the kidneys and abdomen. Since ultrasound is non-intrusive and uses no radiation, administering it carries no risks at all. The most common combinations of fusion techniques are ultrasound with x-ray [24], ultrasound with CT [40,41] or MRI [46], ultrasound with PET[47] or SPECT[48]. A comparison of well-known imaging modalities is provided in Table 1.

Table 1 Comparison of various imaging modalities

Modality	Source of Energy	Invasive/ Non-Invasive	Characteristics	Pros	Cons	Significant Fusion Combination
X-Ray	External X-ray (Ionizing)	Non-Invasive	Produces images of the organs, tissues, and other anatomical structures found inside the body	Detects Fractures and other bone abnormalities	Depth or thickness of the anatomical structure cannot be obtained.	X-ray mammography X-ray-Ultrasound X-ray-CT X-ray- MRI
CT	External X-ray (Ionizing)	Non-Invasive	Using x-rays, cross sectional images of bones, arteries, veins, and other soft tissues are captured and stacked.	Reveals bone structure completely	Doesn't give in depth details on soft tissues	CT-MRI CT-PET CT-SPECT CT-US
MRI	External/ Internal Electric & Magnetic Fields (Non-ionizing)	Non-Invasive	The basic feature of MRI is that it employs magnetic signals to make "slices" that reflect the body organs and gives details about diseased soft tissues.	Gives more details on non-bony structures and no harmful radiation.	Larger scanning time	MRI-CT, MRI-PET, MRI-SPECT
PET	Internal (Ionizing)	Invasive	Helps to visualize metabolic and	Provides functional	High radiation and expensive	PET- CT PET- MRI

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			chemical changes in the body.	information and has high sensitivity		
SPECT	Internal (Ionizing)	Invasive	Provides information on blood flow in the body.	Provides functional information and has high sensitivity	Lower spatial resolution and expensive	SPECT- CT SPECT - MRI
US	External	Non-Invasive	Reveals moving elements of the body and even nerves can be imaged.	Provides both anatomical and functional information	Operator dependent and lower resolution	ultrasound–X-rays ultrasound–CT ultrasound–MRI

III. LEVELS OF FUSION

Multi modal Image fusion can be categorized into three major types based on their level of fusion- pixel level fusion, feature level fusion and decision level fusion.

3.1 Pixel level Fusion

Pixel level fusion acts directly on the pixels and brings together the actual data from the input images.. This is the simplest technique which is performed in the basic level of fusion .It can be categorized into fusion in spatial domain and fusion in frequency domain. Spatial domain approaches apply a basic pixel-level approach, often described as operating on the level of individual image pixels. This technique is computationally efficient and fast, Minimum information loss and maximum signal to noise ratio but this technique produces spectral degradation and blurring effect in the resultant image. In the later approach, Fourier transform is employed to transform the image from spatial domain to frequency domain. After that, the fusion process is applied to the frequency parameters, and then an inverse transformation is performed so that the resultant fused image may be obtained. The transform based approaches avoids distortion but introduces noise during fusion process.

3.2 Feature level fusion

The objective of feature-level fusion is to excerpt complementary features from the input medical images, such as length, edges, regions, shape, segments, and orientations of the image [49] . The features that are taken from the input images are fused to generate more significant features, which results in an image that is more informative.[50**].** Compared to pixel level fusion, image fusion by combining the regions of source images gives more substantial resultant image.

3.3 Decision Level fusion

During the decision level fusion process, every input image is evaluated based on a set of predefined criteria, and the resulting single fused image is created based on the reliability of each decision. The overall structure is broken down into three primary stages. Following the detection and extraction of features from the original image comes the classification of those features through the use of classifiers to provide the expected result. In the last step, decision rules are used to combine them with the goal of reinforcing a consistent understanding and interpretation of the objects.

IV. MULTI MODAL IMAGE FUSION METHODS

Despite the fact that there are various image fusion techniques, let's discuss multi modal fusion methods in four aspects: Spatial fusion methods, Multiscale decomposition based methods, Neural Network based methods and fuzzy logic based methods. Spatial fusion methods are straightforward, where the fusion rules are applied on the source image pixels directly to get the fused image [51].Some of the methods that are widely used in this domain are Principal Component Analysis, Intensity Hue Saturation, Independent Component Analysis, simple average and weighted average, Simple Maximum etc., [52]. However, these techniques have spatial distortion and low signal to noise ratio. One of the most popular fusion procedures is multi-scale decomposition (MSD), which has the ability to extract features across many scales. Here the advantage is minimal loss of information and hence successfully preserves majority of the information from the source images. Multi scale decomposition tools are majorly employed in Pyramidal Transforms and Wavelet Transforms. The concept that biological neural networks have the capacity to learn from inputs in order to analyse information and make overall decisions is the inspiration for

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artificial neural networks (ANN). To determine a set of network parameters known as weights, Artificial Neural Network models require a large input training set. As the characteristics of medical images such as resolution, contrast etc., changes as per the modality, ANN adopts to those changes easily and hence greatly preferred in medical fusion applications. As the number of features extracted from the images increases, the computation time and complexity increases exponentially. Moreover to increase accuracy a huge number of images must be used to train the network. Image processing in the field of medicine has grown enormously in reducing the uncertainity with the implementation of fuzzy logic Some of the medical images have murky areas and may be vague because of inadequate lighting. Fuzzy sets play a vital role in removing such ambiguity or uncertainties in the image. Here, Selecting appropriate membership function which will result in enhanced fused image is little tedious.Fig.4.shows how medical image fusion approaches are categorised.

4.1 Spatial fusion methods

The spatial domain-based medical image fusion technology is a popular area in early studies. As it is a straightforward fusion technique, the merged image can be produced by directly applying the fusion rules to the pixels of the source image. The intended outcome is achieved by manipulating the pixel values. In the statistical technique called Principal Component Analysis (PCA), a collection of uncorrelated variables, which are the principal components, may be constructed from a set of correlated variables. It produces a new set of orthogonal axes [53].The Intensity Hue Saturation (IHS) is a Fusion technique that is frequently used by researchers in remote sensing applications as well as to address the colour issue during the fusion of colour information of PET/SPECT images. The conventional RGB image's spatial information (I) and spectral information (H, S) are effectively separated using this technique. In order to produce the fusion result, these input image components are fused and then converted back to RGB. Independent Component Analysis (ICA) is an extension of standard PCA, which works on higher order statistics when compared with PCA which works on second order statistics. This statistical tool reveals the unknown characteristics that hide behind any arbitrary image. The pixel values of the resultant fused image in the average fusion technique are averages of the equivalent pixel values of the input source images. This approach works well when the input images are well and evenly illuminated and have good contrast [54].The maximum fusion method selects the greatest pixel value of the respective matching pixels in the input images and represents that in the resultant image. In order to create novel research methodologies, researchers frequently employ spatial domain fusion methods in transform domain.

With the aim of developing a unique strategy for the integration of MRI and PET images, Chen [55] merged the IHS model and Log-Gabor transform. The log transformation of the Gabor filter known as the Log-Gabor Transform, breaks down the intensity components of PET and MRI into low and high frequency sub-bands. Maximum selection method is used for the fusion of high frequency components of the input images. Low frequency components of the images are fused by a hybrid approach of two stage fusion. First, visibility of the image is calculated for the low frequency components and then weighted averaging is applied in order to maintain both colour and structure. He conclude that this approach is far superior to already existing combination of HIS and FT . In order to optimize the fusion of MRI and CT image, Krishn et al. [56] proposed a method which combines Principal Component Analysis (PCA) and Ridgelet transform .Here, image is first decomposed using 2D Ridgelet transform and principal component analysis is used as the fusion rule in order to increase the spatial resolution. Higher values of the evaluation metrics such as FF and SSIM are backed by simulation findings that show an improvement in the overall appearance of the merged image. Sindhuja et al.[57] proposed a two level fusion framework for images obtained using CT and MRI,where combination of NSCT and DWT is employed. To reduce duplication, principal component analysis technique is used in the DWT domain as a first step. In the second step, Maximum fusion rule is implemented in the NSCT to improve the contrast of the features of interest. This technique enhanced the effectiveness of the fusion strategy in terms of reducing duplication, improving restoration, and enhancing contrast.

Yan et al.[58] proposed a technique, where, original input images are splited into two components viz. texture components that highlight on edges and textures and approximation components that closely resemble the original image, using a moving frame-based decomposition framework. Additionally, an unique weight map which relies on image characteristics and guide filtering is formed which is used as a final map for fusing approximation components. This method preserves more texture information, maintains the edges and improves the contrast.

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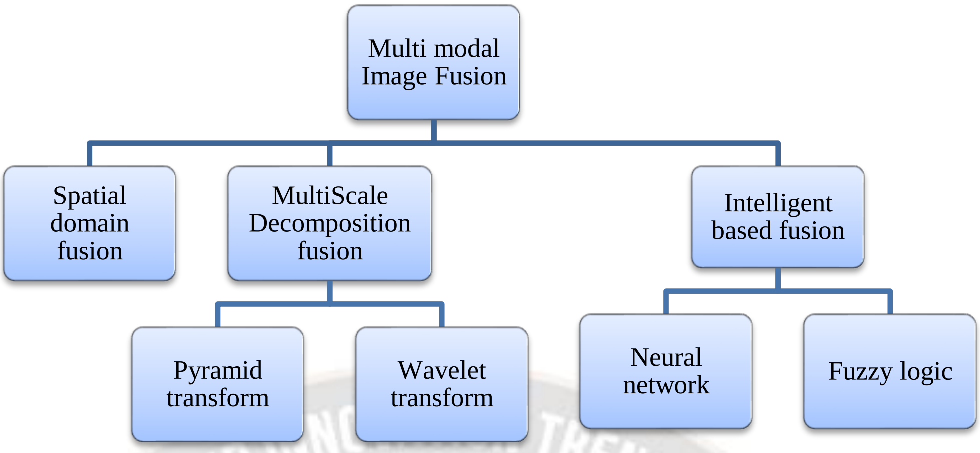

Fig.4 Broad classification of multi modal image fusion methods

4.2 MultiScale Decomposition based methods (MSD)

In MSD based image fusion , a multi-scale transform is utilized to disintegrate and represent the source images as coefficients. These coefficients are then merged using various fusion rules and the transforms inverse is employed to obtain the reconstructed image. Multi scale decomposition tools are majorly employed in Pyramidal Transforms and Wavelet Transforms. The pyramidal transforms were one of the oldest MSD tools used. The source image is decomposed into a sequence of residual images and an approximation of original image, which mimics the pyramid structure, through a sequence of filtering and down-sampling stages. The pyramid is made up of a series of replicas of an original image where the sample-density and resolution are gradually reduced. Some of the pyramidal transforms are Gaussian Pyramid, Laplacian Pyramid, Morphological Pyramid, Steerable Pyramid etc. Wavelets offer better resolution in both the time and frequency domains by disintegrating the input image into scaled and translated copies of the selected mother wavelet. A wavelet is nothing but a tiny wave which rises and decays over a relatively short period of time. Some of the wavelet transforms used in image fusion are Discrete Wavelet Transform(DWT),Stationary Wavelet Transform(SWT), Dual Tree Complex Wavelet Transform (DT-CWT), Discrete Dyadic Wavelet Transform(DDWT), Multiwavelet(MWT), Lifting Wavelet(LWT).In addition to this, more transforms such as Curvelet Transform, Contourlet transform, Shearlet Transform are also used in fusion process.

Qu et al. [59] presented a rule for fusion to determine the wavelet transformation modulus maxima of the source images at multiple bandwidths and decomposition levels. The advantage in this method is it preserves edges and also information on components of the objects in the final merged image. Asokan et al.[60] developed an enhanced method for fusing MRI medical images that combines PCA fusion with a Stationary Wavelet Transform (SWT). Time localization and preservation of features of individual medical images are enhanced by the fusion of complimentary structures in the SWT fused image. Nikolov et al.[61] highlighted that at the cost of computation complexity, the DT-CWT fusion techniques produce improved measurable and qualitative outcomes compared to the DWT. But, this happens at the expense of a higher level of computation. Edge information can be preserved using the DT-CWT approach without substantial ringing distortions. It also retains the texture of the input images. Xianghai Wang *et al* [62] suggested a unique lifting wavelet transform-based image fusion technique where LWT evaluates low frequency coefficients by comparing the covariance of the images and high frequency coefficients by comparing the matching measure of the input images.

4.3 Neural Network based methods

The concept that biological networks have the capacity to learn from inputs so as to analyse information and make overall decisions is the inspiration for artificial neural networks (ANN). The stability of ANN approaches is restricted by the quantity of training samples and the precision of convergence, despite the fact that ANN offers flexibility in applying the training idea. Neural network can be combined with other techniques like neuro–fuzzy, neural-genetic ,neural-pyramid, neural-wavelet in order to increase the quality and accuracy of the training algorithms.Xia et al. [63] developed an innovative method for combining images from different sources. using sparse representation and Pulse coupled neural network. Here, Non sampled Contourlet transform is used to divide the input image into low and high frequency subbands. Then, the K singular value decomposition and orthogonal matching pursuit are used to

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obtain the fused low frequency sub band coefficients while pulse coupled neural network is used to obtain high frequency band coefficients. This method solves the sparsity issue of low frequency sub band and the edge details are highly preserved.Di Gai et al.[64] made a small change in [63] where he applied nonsubsampled Shearlet transform(NSST) to separate high frequency component of input image from the low frequency ones. Low frequency sub band coefficients are fused using improved sparse representation. To preserve edges high frequency coefficients are fused using PCNN.Yu Liu et al. [65] proposed a convolutional neural network based fusion algorithm where the input images are first applied to CNN model with Siamese network for weight generation. Then Laplacian pyramids breakdown the input images while Gaussian pyramids break down the weight map.If similarity level is greater than the set threshold weighted average is used as fusion rule and if the similarity level is lesser than the threshold then selection fusion rule is used for integration.

Ebenezer Daniel [66] presented a novel method where optimum Homomorphic wavelet Image fusion using hybrid genetic based grey wolf optimization is used .This approach has been tried on MR & SPECT, MR&PET, MR T1-T2 and MR&CT. The optimum homomorphic fusion has mapped most of the anatomical and functional features of the source image into a single fused image and also has produced better quality of fusion. Kavitha et al.[67] presented a potential model for multimodal brain image fusion adopting the Modified Dual Channel PCNN algorithm and hybrid edge enhancement technique which combines Canny edge detection and Ant Colony Optimisation The perfectly registered source images are improved and optimized using this hybrid approach ,the output of which is given to modified PCNN to generate the firing maps of source images. After that, in the end, the Maximum Fusion rule is used in order to produce the fused image.

4.4 Fuzzy Logic based methods

Numerous applications have made substantial use of fuzzy logic technique. This can be applied to obtain fused images too. Some of the medical images have foggy areas and may be unclear because of inadequate lighting. To remove such ambiguity or uncertainties in the image, it is required to enhance the image. In spite of applying any enhancement technique, the quality of medical image cannot be improved due to several uncertainties present in the image. For such images, to remove uncertainties, Zadeh first presented an algorithm based on a mathematical tool, Fuzzy set theory.A membership function, which determines how much a component is a part of a set, is used to establish fuzzy logic.

Manchanda et al. [68] suggested an approach based on fuzzy transform which divides N source images into groups of the same size initially. These groups are further subdivided into smaller blocks of various sizes. Maximum entropy fusion rule is applied to these smaller blocks in order to acquire the fused image. Comparatively speaking, the fused image produced employing the suggested method has more feature and detailed information. Y.Yang et al. [69] exhibited a technique that allowed the image to be separated into low and high frequency bands using NSCT and high frequency coefficients were fused using type2 fuzzy entropy whereas based on the features of the image which are calculated locally, low frequency band are fused using local energy. This work show that the suggested algorithm enriches the appearance of the fused image as well as retains a greater amount of information in the merged image. Tirupal et al.[70] introduced a fusion method which finds the ideal value of parameter for membership, non-membership and also hesitation degree after fuzzifying the input images, with the help of exponential intuitionistic fuzzy entropy. Then to enhance the input image, Sugeno's intuitionistic fuzzy system is used. Kaur et al. [71] presented a method where the original input images are first broken down using discrete wavelet transform in parallel with cross bilateral filter. Fuzzy logic is used to fuse the decomposed images. Nagaraja et.al.[72] proposed an unique method in which the initial images are broken up into two different frequency bands viz. low and high as the first step in the process using improved fast discrete wavelet transform. Then, High frequency sub bands are fused using type 2 fuzzy entropy whereas the rule of averaging is used while carrying out the fusion process of low frequency sub band. Further, Adaptive Electric fish optimization is applied to enhance the image.

V. MULTI MODAL IMAGE FUSION QUALITY ASSESSMENT METRICS

Image fusion quality can be evaluated both subjectively and objectively Qualitative method compares the source image with fused image and examines visually based on their colour, geometric pattern size etc,.But the evaluation precision of this subjective method depends on the observer's experience and knowledge. Quantitative analysis is an objective method where the quality indicators are used for evaluation of the fused image. These metrics may be assessed either by comparing them with a standard image or by doing so without using a reference image. [73]. Some of the common evaluation parameters which require a reference image are peak signal to noise ratio (PSNR), root mean square error (RMSE), structural similarity index measure (SSIM), mutual information (MI), correlation coefficient (CC) etc. Assessment metrics like spatial

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frequency (SF), entropy (H), cross-entropy (CE), standard deviation (SD), gradient-based index (QAB/F) etc. are evaluated without any reference image.

Peak signal to noise ratio(PSNR)

It is a quantitative measuring technique calculated by dividing maximum gray value in the source image and the root mean square error between the original image and the fused image. Higher will be the value of PSNR, when the final merged image resembles more like the initial images.

$$PSNR = 20\ log_{10}\left(\frac{I_{max}^2}{RMSE}\right)$$

Root mean square error (RMSE)

RMSE determines the quality of the fused image by computing the deviation in pixel values between the standard and merged images. Its value should be as minimum as possible for an optimal fused image.

$$RMSE = \sqrt{\frac{1}{xy}\sum_{i=0}^{x-1}\sum_{j=0}^{y-1} I_r\,(i,j) - I_f\,(i,j)^2}$$

Structural similarity index measure (SSIM)

SSIM finds the resemblance between the local pattern of fused and reference image. In order to calculate the SSIM value, this quantitative measure takes into account three factors: brightness, contrast, and structural information between the two images. If the value is 1, both the reference picture and the fused image are the same. Here, M_r and M_f represents mean of reference and fused image respectively. S_r and S_f represents standard deviation of reference and fused image respectively.

$$\mathrm{SSIM} = \frac{((2\mathrm{MrMf}\ +\ \mathrm{C1})\ *\ (2\mathrm{Srf}\ +\ \mathrm{C2}))}{((\mathrm{Mr2}\ +\ \mathrm{Mf2}\ +\ \mathrm{C1})\ *\ (\ \mathrm{Sr2}\ +\ \mathrm{Sf2}\ +\ \mathrm{C2}))}$$

Mutual Information(MI)

It is used to quantify how well the reference and fused image intensities match up. Better quality of fused image is signified by a higher MI score.

$$\mathrm{MI} = \sum_{i=1}^{x}\sum_{j=1}^{y} h_{I_r I_f}(i,j)\log_2\left(\frac{h_{I_r I_f}(i,j)}{h_{I_r}(i,j)h_{I_f}(i,j)}\right)$$

Correlation Coefficient(CC)

The correlation coefficient is a measure of how well the spectral features of the reference image and the fused image resemble one another.If the metric value is closer to +1, it implies that the reference image and the fused image are more similar to one another.

$$CC = \frac{2C_{rf}}{C_r C_f}$$

Here C_{rf} denotes the correlation coefficient between the reference and fused image.

Spatial Frequency(SF)

The sequential pattern of light and dark pixels in an image is referred to as spatial frequency. The sharpness of the resulting fused image is determined by spatial frequency employing edge information obtained using row and column frequency. The sharpness of the image is indicated by a greater spatial frequency.

$$SF = \sqrt{F_r^2 + F_c^2}$$

Where Fr and Fc indicates row and column frequency.

Entropy(H)

The average information contained in the fused image is evaluated using the Entropy metric. The value of entropy ranges between 0 and 8. The greater the entropy value, the greater the amount of information that is included in the fused image.

$$H = -\sum_{i=0}^{n-1} p(x_i)log_2 p(x_i)$$

Cross Entropy (CE)

The similarity of the data content between the reference images and the resulting fused images is measured by cross entropy. If the value of this measure is low, it indicates that the information included in the input images and the fused image is same.

$$CE\left(I_{r1}, I_{r2,}, I_f\right) = \frac{CE\left(I_{r1}, I_f\right) + \mathrm{CE}(I_{r2,}I_f)}{2}$$

Standard Deviation (SD)

A statistical tool used to assess the intensity variation in the fused image is called standard deviation. A high standard deviation number reveals that the merged image contains a significant amount of contrast.

$$SD = \sqrt{\frac{1}{XY}\sum_{i=1}^{X}\sum_{j=1}^{Y}[I_f\ (\mathrm{i,j})\ -\ \mu_f]^2}$$

Gradient-based index (QAB/F)

A metric that determines the amount of edge information that was transferred from the reference images used in the input to the image that was fused is known as the edge-based image fusion metric (QAB/F).This metric ranges

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between 0 and 1. Value of 'one' signifies that that all the edges from reference images has been preserved in the fused image.

$$Q_{AB/F} = \frac{\sum_{i=1}^{M}\sum_{j=1}^{N}(Q^{A}\,(i,j)W^{A}(i,j) + \; (Q^{B}(i,j)W^{B}(i,j))}{\sum_{i=1}^{M}\sum_{j=1}^{N}(W^{A}\,(i,j) + W^{B}\,(i,j))}$$

VI. CONCLUSION AND FUTURE TRENDS

Multi modal medical image fusion produces a composite fused image utilizing various sources like X-Rays, CT, MRI , US, PET, SPECT etc to improve quality and extract complementary information. Various imaging modalities were studied, and their features and drawbacks were contrasted while emphasizing various levels of fusion. This article reviewed a comprehensive current research trends in the multimodality medical image fusion arena. The There are several assessment measures that may be used to gauge the fused image's performance..Some of the objective evaluation metrics are discussed in detail. Spatial domain, Multiscale decomposition, neural network, and fuzzy logic based approaches are all part of the advancement in multi modal medical image fusion. Every approach has benefits and drawbacks of its own. Despite the fact that the principal component analysis, intensity hue saturation, and Brovey approaches are computationally more efficient, rapid, and easy, they produce variation in brightness or light intensity . Spatial distortion and a poor signal-to-noise ratio hinder all spatial domain approaches.In order to create novel research methodologies, researchers frequently employ spatial domain fusion methods in transform domain. Transform domain methods overcome these drawbacks and preserve the edges better in the fused image. Neural networks and fuzzy logic techniques incorporating multi-scale decomposition can boost the effectiveness of fusion outcomes. Though Neural networks and fuzzy logic techniques are quite effective , it requires a large data set with time consuming training process and also needs high end hardware configuration for computation. Most of the fusion algorithms are developed from earlier fusion techniques and the challenges in fusion are simply improved rather than totally addressed. Finding an ideal combination of imaging techniques, feature selection and extraction, fusion rule and classification or decision algorithm that specifically addresses a clinical issue is a difficult and time-consuming effort. Despite these difficult circumstances, the fused image give the spectators better viewing and understanding of medical images for various clinical applications.

Though various algorithms in different streams have been discussed in literature, still there are few challenges existing. So more innovative hybrid levels of fusion algorithms need to be explored. Multimodal medical image fusion at decision level which is expected to be the future trend needs more exploration and research. Clinical applications not only require fusion of two images like fusion of functional and structural images, but at times for certain diagnostics require fusion of even three or four modalities ,which is rarely invetigated It is anticipated that in the following years, innovation and useful breakthroughs in multimodal medical image fusion would further increase.

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