Multimodal Medical Image Fusion Techniques: A Survey

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Abstract—**Image fusion has grown increasingly significant in current image processing applications as a result of the large variety of capture devices available. Image fusion is the process of aligning relevant information from several sensors using various mathematical models to create a single compound image. Fusion of images is a technique for combining complementary multi-temporal, multi-view, and multi-sensor data into a single image with improved image quality and important feature integrity retained. It's a crucial stage in a range of applications, including robot vision, aerial, satellite, and medical imaging, as well as robot and vehicle navigation. This study examines a number of state-of-the-art picture fusion approaches at various levels, as well as their benefits and drawbacks, as well as a number of spatial and transform-based methods with quality metrics and their applications in diverse fields. Finally, this study has identified a number of potential future directions for image fusion applications.**

***Index Terms*—**CT and MR image fusion, adaptive structure decomposition (ASD), MI, SSIM, EN.

I. INTRODUCTION

Image fusion (IF) is a new field in which pictures from diverse sensors are combined to form an infrmative image for decision-making [1]. The analytical and visual image quality can be improved by combining several images. By extracting all necessary information from photos and preventing disparities in the final image, effective image fusion can preserve crucial information. After fusion, the fused image is more suitable for machine and human perception. The first step in fusion is image registration, which involves mapping the source image to the reference image. This form of mapping is utilised to match a comparable image for further analysis based on trustworthy features. IF and IR are recognised as crucial aids in the development of important information in a variety of fields [2]. The number of scholarly articles has increased significantly since 2011, according to the literature, reaching a peak of 21,672 in 2019. This fast-growing trend could be attributed to the increased demand for low-cost, high-performance image fusion algorithms. Various methodologies, such as multi-scale decomposition and sparse representation, have recently been published, providing a number of ways to improve the effectiveness of image fusion. An effective fusion strategy is essential because to variances in related images in various applications. For example, a growing number of satellites are being deployed to record aerial images with varying spectral, geographical, and temporal resolutions in the field of remote sensing. The IF is essentially a collection of image data gathered by various imaging features such as aperture settings or dynamic range, spectral response or camera position, or the usage of polarisation filters. The information of interest is retrieved from various photos using correct image fusion methods, which can subsequently be used for traffic management, reconnaissance, automated driving, or quality analysis.

Imaging techniques like computed tomography (CT), magnetic resonance imaging (MRI), positron emission tomography (PET), and single-photon emission computed tomography (SPECT) have provided clinicians with information about the structural characteristics, soft tissue, and other aspects of the human body. Different imaging technologies maintain different features, and different sensors collect different imaging data for the same part. The goal of the fusion is to improve contrast, fusion quality, and overall perception. The fusion result must meet the following criteria: (a) the fused image must maintain all of the information from the source images; (b) the fused image must not produce any synthetic information, such as artefacts; and (c) poor states, such as misregistration and noise, must be avoided [3].

The spatial domain and transform domain are separated in traditional medical picture fusion algorithms. The early study focused on medical picture fusion approaches based on spatial domain. Principal analysis and HIS are two common methodologies. Spatial domain technology, on the other hand, causes spectral and spatial distortion in fused images [4]. Researchers are concentrating their efforts on the transform domain in order to improve fusion effects. It then executes reconstruction procedures after transforming the source image into the frequency domain or other domains to fuse them. The four layers of the fusion process are signal, feature, symbol, and pixel level. Contour transformation, discrete wavelet transform, and pyramid transform are examples of pixel-level transformations that are commonly employed nowadays. The transform domain-based technique offers the benefits of good structure and little distortion, but it also generates noise during fusion processing. As a result, image fusion is similarly hampered by denoising [5]. It is clear from the publications published in the last two years that the proposed fusion algorithm practically never uses the spatial domain alone. However, many novel methods, such as PCA-DWT [6,] integrate spatial domain and transform domain methodologies. In 2017, a medical image fusion method based on deep learning emerged as a result of the deep learning boom. Convolutional neural networks (CNNs), recurrent neural networks (RNNs), U-Net networks, GANs, and other deep learning models have all been utilised in medical picture registration and segmentation in recent years, but only CNNs and U-Net networks have been employed in medical image fusion. A convolutional neural network is a type of image processing neural network that consists of a Convolutional layer, a pooling layer, and a fully connected layer. Caffe, Tensorflow, MatConvNet, and other deep learning frameworks are used for medical picture fusion. Currently, the U-Net network is trained using the Pytorch deep learning framework.

II. FUSION METHODS

The fusion technique relying on spatial domain, the fusion technique based on transform domain, and the fusion approach based on deep learning are all covered in this chapter. As seen in Figure 1.

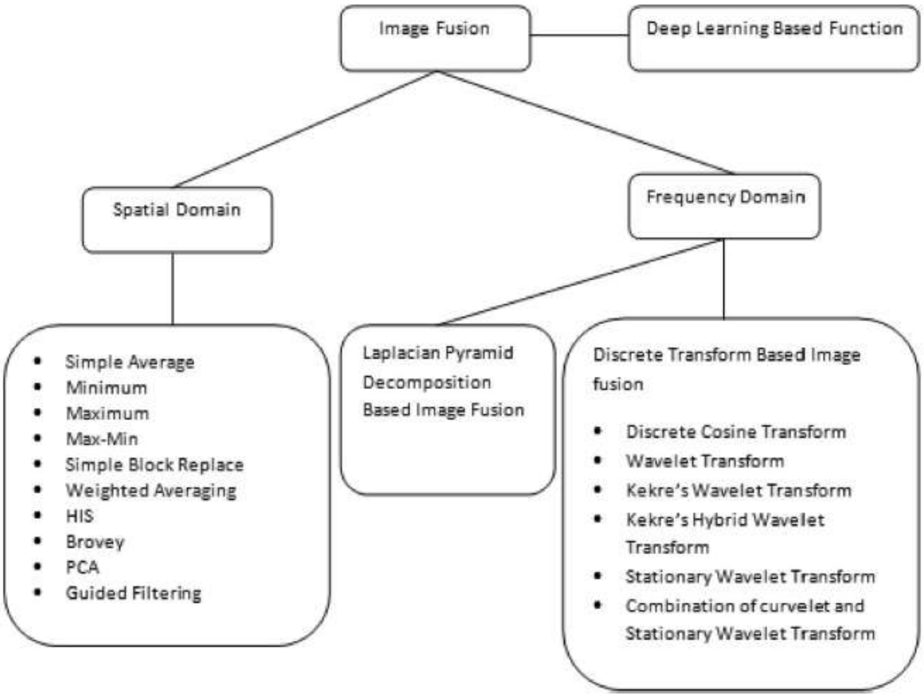

Figure 1: Image Fusion Techniques

Transform Domain

The multiscale transform (MST) theory underpins most medical image fusion approaches in the transform domain, which have been hotspots of study in recent years. Decomposition, fusion, and reconstruction are the three processes of the MST-based fusion approach. To acquire the low-frequency coefficient and high-frequency coefficient, the medical image fusion method based on transform domain transforms the source image from time domain to frequency domain or other domains. The nonsubsampled contourlet transform, nonsubsampled shearlet transform, and discrete wavelet transform are three of the most often utilised transformations in medical image fusion systems [7].

Fusion Based on Nonsubsampled Contourlet Transform (NSCT): Do et al. [8] introduced the contourlet transform, which is multiscale. It offers advantages in smoothness processing and is suited for constructing multiresolution and multidirectional scenarios. However, because it lacks translation invariance and is simple to generate pseudo-Gibbs phenomenon (artefact) near the singular point of the reconstructed picture, causing image distortion, it is not the greatest option for image fusion. Many scholars have done further in-depth studies to this purpose. Cunha et al. [9] suggested a multiscale decomposition approach better to contourlet transform, dubbed nonsubsampled contourlet transform, which is an upgrade of contourlet transform. Translation invariance and the avoidance of spectral aliasing are two features of NSCT. The source image's structural information is kept during decomposition and reconstruction, allowing for greater extraction of direction information. In recent years, nonsubsampled contourlet transform has become one of the most extensively utilised approaches in medical picture fusion of the transform domain. To obtain subband images with diverse scales and directions, the source image is first decomposed by NSCT to obtain the coarse layer and detailed layer, and then the multiscale and multidirection decompositions are computed by NSPFB and NSDFB filters.
Some academics, on the other hand, choose to blend NSCT with other algorithms to create new techniques.
Madanala and Jhansi Rani [10] presented a fusion framework based on DWC +NSCT domain cascade that coupled the advantages of frequency and time localization of wavelet transforms with displacement invariance of nonsubsampled contourlet transforms. In this framework, the detailed coefficient and approximate coefficient were obtained by decomposing the source image using the wavelet transform in the first stage, and the detailed coefficient and approximate coefficient were fused using the principal component analysis method to reduce redundancy. In the first stage, the reconstruction was obtained using the inverse wavelet transform. The high-frequency and low-frequency coefficients are obtained in the second stage by applying NSCT to the products obtained in the first stage. For fusion, the maximum selection rule is employed, and the final fusion image is created using inverse NSCT. The second stage resolves the displacement variance problem that was introduced in the first, resulting in a fused image with high application and effect. Bhateja et al. [11] used a similar method to cascade the stationary wavelet transform and nonsubsampled contour transform domain. This technique improves the contrast of diagnostic markers by reducing duplication in fused images.

Fusion Method Based on Discrete Wavelet Transform (DWT): The discrete wavelet transform can provide a stable output from a variety of input frequency signals and has good placement in the time and frequency domains, which helps to preserve the image's particular information. As a result, in the early development of multimodal medical image fusion algorithms, the discrete wavelet transform (DWT) was the most extensively utilised transform. The discrete wavelet transform is a visual and quantitative fusion technique that overcomes the constraints of principle component analysis. The majority of DWT-based fusion approaches are used for MRI and PET image fusion [12, 13], however they can also be used for other purposes. The intensity component is extracted from the PET image using the IHS transform, which preserves more anatomical information and reduces colour distortion. The source image is preprocessed and improved, and the intensity component is extracted from the PET image through using IHS transform, which conserves more anatomical information and reduces colour distortion. To get high- and low-frequency subbands, the DWT transform is applied to the intensity components of MRI and PET. Different fusion criteria are utilised to fuse the high- and low-frequency subbands, and the fused image is obtained using the inverse DWT transform [14].

The majority of the researchers have done extensive study on fusion rules. Various fusion rules provide various fusion effects. The fusion rule 1: The average approach; rule 2 of the fusion: fuzzy—c denotes clustering. The researchers devised complex wavelet transform to address the drawbacks of discrete wavelet transform, which lacks displacement invariance and phase information (CWT). Singh et al. suggested a multimodal medical image fusion approach based on Daubechies complex wavelet transform (DCxWT), which is superior in the transform domain to the spatial domain fusion method (PCA and linear fusion) and discrete wavelet method. Kingsbury's suggested dual-tree complex wavelet transform (DTCWT) offers directional selectivity and displacement invariance, and can preserve the original image's edge information. It is also an effective image fusion approach; however the elements that are impacted by the direction are relatively big in image decomposition. Researchers have frequently merged DTCWT with other algorithms in recent years to create new techniques.

Image Fusion Based on Deep Learning

Deep learning is a very young subject of medical image fusion study.

Krizhevsky et al. [15] proposed the convolutional neural network (CNN) as a typical deep learning model. Deep learning is commonly utilised in the segmentation and registration of medical images, as opposed to medical image fusion. The activity level measurement (feature extraction) and fusion rules, which require artificial design, are flaws in medical image fusion systems based on spatial domain and transform domain, and the connection between them is exceedingly limited. To address the aforementioned issues, Liu et al. employed CNN to image fusion for the first time in 2017, generating promising results in both the spatial and transform domains. In medical image segmentation, the U-Net network model is commonly utilised. Its research technology has progressed from 2D to 3D [16] and has produced positive results in the field of medical picture segmentation, while medical image fusion is a new subject.

A CNN is a multistage feedforward artificial neural network with supervised learning that can be trained. Convolution is a multidimensional operation. The first parameter in a convolutional network is commonly referred to as an input, the second as a kernel function, and the output as a feature map. Three key architectural concepts in CNN are sparse representations (also known as sparse weights), parameter sharing, and isomorphic representations. Matrix multiplication is used in traditional neural networks to cope with link interactions. Each input unit has an output unit, which necessitates a large amount of storage. However, because of the convolutional network's sparse representation, the neurons are only connected to a few neurons close to the previous stage, and the local convolution operation is used, which minimises storage requirements and increases computing efficiency. The nonuniqueness of weights in classical networks is eliminated with CNN's parameter sharing. The weights in the CNN stage remain constant, which makes it easier to store than other stages. Automatic encoders are fully connected in the traditional sense. While U-Net uses a local connection structure, the vector output and source picture are not always aligned in space. The visual effect of the fusion image is improved since the vector output and source image are aligned in space. The U-Net is a fullconvolution network [17] with contraction and expansion paths. In-depth learning requires a large number of samples for training, however U-Net is based on a full convolutional neural network and can train a minimal number of examples with data improvement. This benefit only addresses the problem of a small sample size of medical picture data.

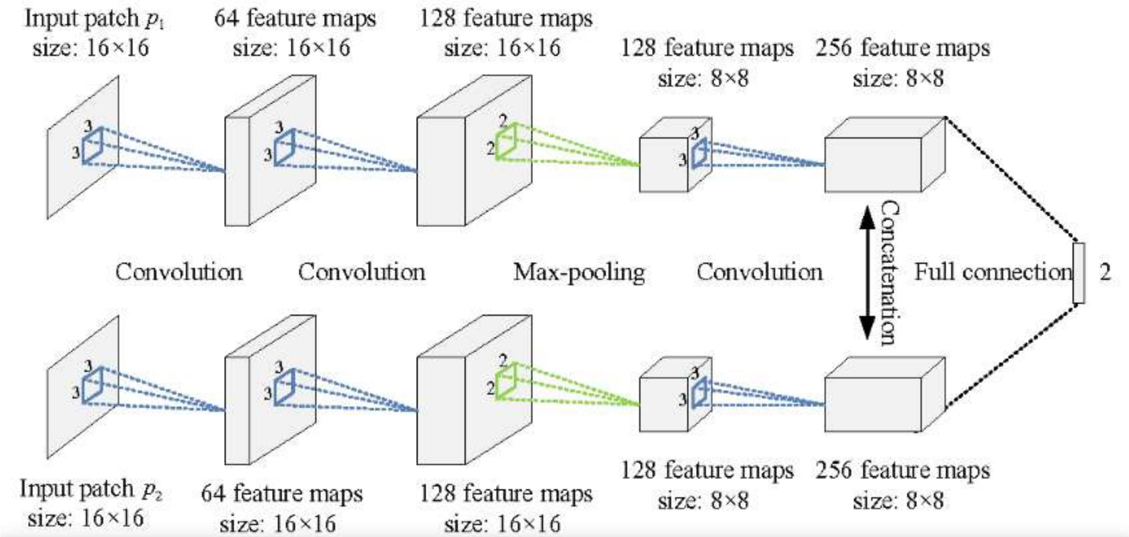

Figure 2: Schematic diagram based on CNN fusion algorithm

Convolutional Neural Network-Based Image Fusion Method (CNN). The fusion approach presented in [18] is not suited for medical picture fusion since medical images differ in intensity at the same location. Yu et al. were the first to propose a CNN-based medical image fusion approach. To build a weight map, this method use the siamese network. In the CNN model, the siamese network is one of three models for comparing patch similarity. Because the source image's two weight branches are identical, the feature extraction and activity level measuring approaches are same. This has several advantages over pseudosiamese and 2-channel models, and the siamese model's simplicity of training is another reason for its popularity in fusion applications. To make the fusion process more in line with human visual perception, the Gaussian pyramid decomposition is employed after acquiring the weight map, and the pyramid transform is used for multiscale decomposition. In addition, the decomposed coefficients are adaptively adjusted using the localised similarity-based fusion technique. To provide a superior fusion approach, the algorithm integrates the standard pyramid-based and similarity-based fusion algorithms with the CNN model. The algorithm is depicted in Figure 2.
The major reasons for this are that (a) a huge amount of annotated training set data is necessary, (b) training takes a long time, and (c) the convergence problem is hard, and overfitting must be addressed periodically. Liang et al. [19] claimed that the MCFNet network approach refers to several forms of medical image histograms and transforms 1.2 million natural photos in ILSVRC 2013 ImageNet into medical images with identical intensity or texture distribution as training data sets. Medical picture data sets are quite similar to reconstructed data sets. 256 256 images are randomly chosen from the modified images and trained with medical images to minimise overfitting. The optimization of this method's loss function is still a study topic for the future.

Spatial Domain

In the early stages of research, medical image fusion technology based on spatial domain is a hot topic. Its fusion method is straightforward, and the fusion rules can be applied directly to the pixels of the source image to produce the merged image. The high-pass filtering method, the principal component analysis method, the saturation method of hue intensity, the average method, the maximum selection method, the minimum selection method, and the Brovey method are all spatial domain fusion methods. The heat of research in the spatial domain of the medical image fusion method has significantly decreased in recent years due to spectral and spatial distortion in the fused image of the spatial domain. To create novel research methodologies, researchers frequently use spatial domain fusion strategies as part of the transformation domain [20].
We will only briefly introduce the IHS method with a high usage value as below.
The IHS model proposed by an American scientist Munsell explains the characteristics of the human visual system. It has two characteristics:
(1) The image's colour information has little to do with the intensity component; (2) the hue and saturation components are directly tied to how individuals perceive colour. As a result, this model is frequently used by researchers to solve the colour problem in image fusion, particularly the fusing of PET/SPECT pictures with colour information. Chen [7] proposed a new approach for fusion of MRI and PET by combining the IHS model with the Log-Gabor transform and decomposing the PET image with IHS to yield the three basic properties of hue (H), saturation (S), and intensity (I) (I). The Log-Gabor transform, which consists of the logarithmic transformation of the Gabor filter to produce the high-frequency subbands and low-frequency subbands, decomposes the intensity components of MRI and PET images to obtain the high-frequency subbands and low-frequency subbands. Fusion of high-frequency subbands uses a novel approach based on two-level fusion of visibility measurement and a weighted average rule; fusion of low-frequency subbands uses a new method based on two-level fusion of visibility measurement and a weighted average rule. To create a fused image, the inverse Log-Gabor transformed component and the original hue and saturation components are inversely HIS. It can efficiently preserve the source image's structures and details while also reducing colour distortion. In terms of visual perception, this method outperforms the previous IHS+FT method. Haddadpour et al. [21] suggested a new fusion approach that incorporates both the IHS and the

two-dimensional Hilbert transform. When integrating high- and low-frequency subbands, the technique [9] introduces the concept of BEMD. Bidirectional empirical mode decomposition (BEMD) is a type of empirical mode decomposition that is extended by empirical mode decomposition. Because of its envelope surface, it is commonly employed in biomedicine. The algorithm is superior to the PCA and wavelet algorithms in terms of contrast and colour intensity, with no visible distortion. The information entropy (EN) is relatively low, which is a drawback. Figure 3 depicts the IHS domain fusion method, which is based on the fusion of MRI and PET scans.

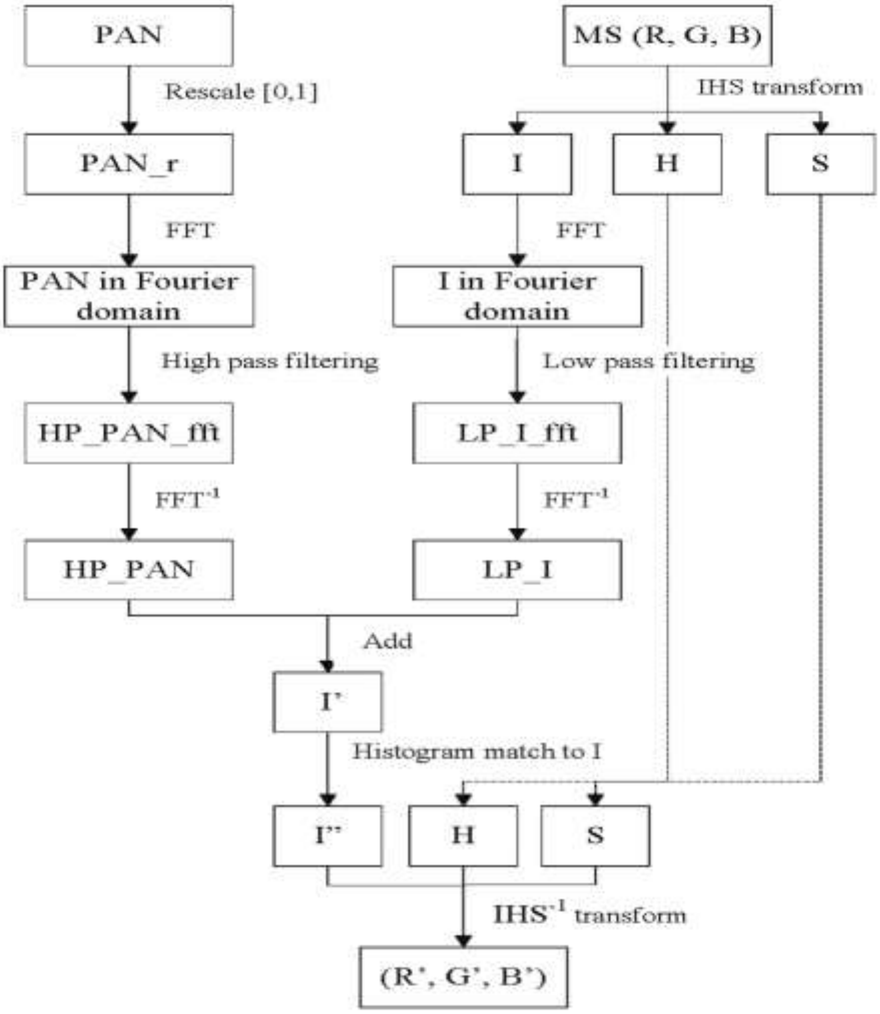

Figure 3: Framework diagram based on the IHS domain fusion method

III. THE MULTIMODAL FUSION APPROACH

Magnetic Resonance Imaging, or MRI, offers information on the soft tissue anatomy of the brain but not on its function. Because protons are abundant in the neurological system, fat, soft tissue, and articular cartilage lesions, the image is exceptionally clear and free of artefacts. It has a high spatial resolution and does not cause radiation damage to the human body, and the advantage of having a lot of information makes it useful in clinical diagnostics. Because the density of protons in the bone is so low, the MRI image of the bone is blurry. Computed Tomography imaging is the name given to the CT image. The human body is scanned using an X-ray. The CT image of bone tissue is exceptionally clear due to the high density absorption rate of bone tissue compared to soft tissue [22]. Because X-rays have a poor permeability in soft tissue and have a low absorption rate, CT images display less cartilage information, which is anatomical information. Single-Photon Emission Computed Tomography, or SPECT, is a functional imaging that shows the metabolism of human tissues and organs, as well as the blood flow through arteries and veins. It offers both benign and malignant tumour information and is commonly employed in the diagnosis of a variety of tumour illnesses. SPECT, on the other hand, has a low resolution and poor positional ability. The PET image is known as Positron Emission Tomography, and it may accurately determine the location of the patient's lesion by revealing the genuine information of blood flow. It works by generating photons when positrons collide with electrons in the tissue. PET's purpose is to detect the number of photons, resulting in a colour image of brain function information suitable for tumour detection; its sensitivity is high, but it is difficult to obtain accurate brain structure position information; soft tissue and bone boundary resolution is lacking, so spatial resolution is very low, and spatial distortion is very likely.

MRI and PET, MRI and CT, MRI and SPECT, CT and PET, CT and SPECT, SPECT and PET, and MRI-T1 and MRI-T2 are only a few examples of imaging method fusions used in medical picture fusion. MRI/PET fusion images are useful for detecting liver metastasis, Alzheimer's disease, and brain tumour diagnosis; MRI/SPECT fusion images are useful for the localization of lesions and vertebral bone metastasis in tinnitus patients; CT/PET fusion image energy improves lung cancer diagnosis; SPECT/PET for abdominal research; and ultrasound/MRI for vascular blood flow diagnosis. The following sections will focus on a few hot fusion methods.

MRI and CT Fusion: The advantages of clear bone information in CT images and clear soft tissue information in MRI images are combined to compensate for the lack of information in a single imaging. Na et al. [23] proposed a guided filtering-based MRI and CT fusion technique (GF). The fused image not only preserves the source image's edge information but also extracts feature information, resolving the edge degree and clarity issue. [24] proposes a Frei-Chen operator fusion technique based on the NSST domain. The contrast and structural resemblance of the fusion products are clearly improved when viewed visually. Quantitative evaluation is also a step forward from current methodologies. Based on the intuitionistic fuzzy inference fusion procedure in [25], selecting the membership degree is tricky. Mishra et al. also proposed the fuzzy-PCNN rule, which uses multiple membership functions to generate fuzzy membership from specific parts of high-frequency coefficients; L2 norm set operation is used to fuse the high-frequency coefficient; and the SF, EN, and SD of the fused image have a higher value. Singh et al. presented a new fusion approach using the ripple transform and NSST transform cascade after fusion of MRI/CT images in the NSST domain, which has a favourable influence on visual quality and quantitative indicators. Contourlet transforms based on non-subsampling, as well as multiscale and multiresolution approaches, are other ways for MRI/CT image fusion [26].

IV. Main Applications in Diverse Domains

IF is now widely employed in a variety of applications, including medical diagnostics, surveillance, photography, and remote sensing. Numerous challenges and difficulties linked to various professions are covered here,

Remote Sensing Applications: In addition to the modalities mentioned above, it has a number of IF techniques that have been useful in IF applications, including Synthetic Aperture Radar, range and light detection, and moderate resolution image spectroradiometer. The area-based IF technique for integrating panchromatic, multispectral, and synthetic aperture radar images was proposed by Byun et al. [27]. By merging Landsat and intermediate resolution imaging spectroradiometer data, a temporal data fusion and high spatial technique is applied to create synthetic Landsat imagery. Furthermore, a combination of spectrum information has recently been investigated for the synthesis of air-bone hyper-spectral and Light Detection and Ranging (LiDAR) data. Earth imaging satellites such as Quickbird, Worldview-2, and IKONOS have contributed several datasets for pansharpening applications.

Medical Domain Applications: A brain image database of registered Computerized Tomography and Magnetic Resonance Imaging has been supplied by Harvard Medical School. Figure 4 illustrates the use of IF in medical diagnosis by combining CT and MRI images. The CT scan captures bone structures with great spatial resolutions, while the MRI scan captures soft tissue structures such as the heart, eyes, and brain [28]. CT and MRI scans can be combined with IF techniques to improve accuracy and medical usefulness. The most difficult task in this field is also completed like follows,

(1) There aren't any IF techniques for medical emergencies.
(2) Estimation of objective image fusion effectiveness
(3) Mis-registration

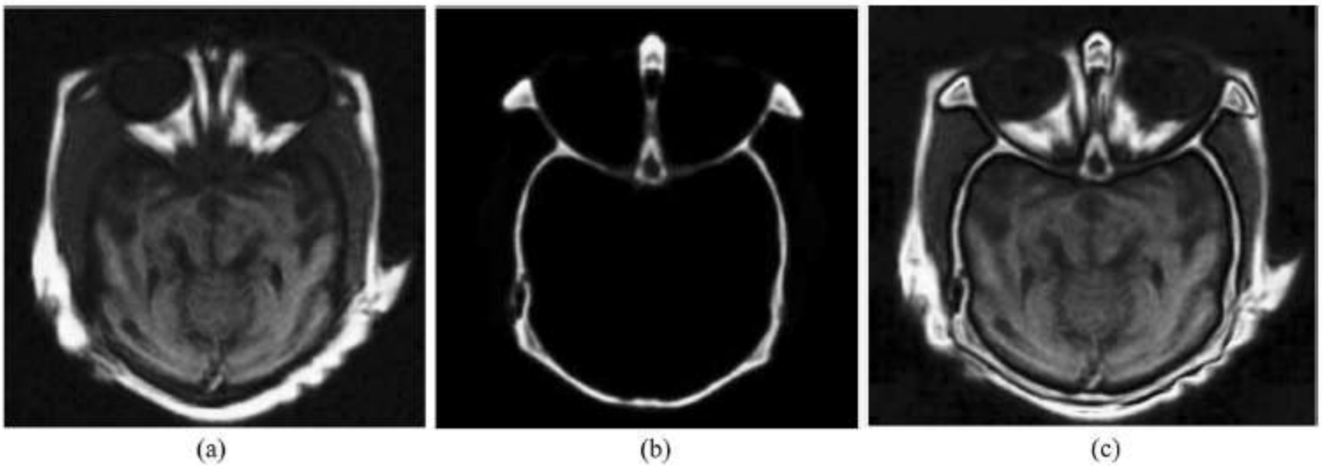

Figure 4: Examples of IF in medical diagnosis domain. **a)** MRI **b)** CT **c)** Fused image

Surveillance Domain Applications: Figure 5 illustrates infrared and visible image fusion as an example of IF in the surveillance sector. Its high temperature allows it to "see in the dark" even when not illuminated because it is sensitive to objects. Infrared images have poor spatial resolution, which can be solved by combining visible and infrared images using a fusion technique. In addition, the fusion of visible and infrared images has been used to solve a difficulty in face identification, image dehazing, and military reconnaissance. The key obstacles in this field are as follows:

(1) Computing efficiency
(2) Imperfect environmental conditions

Figure 5: Examples of IF in surveillance domain. **a)** Visible image **b)** Infrared image **c)** Fused image

Photography Domain Applications: Figure 6 depicts the fusing of multi-focus images as an example of IF in the photography sector. Due to the limited depths of the cameras, it is impossible to focus on all objects at different distances from the camera in a single shot. It is not possible to be all-in-focus within a single image of cameras for all objects with different distances due to the camera's limited depths [29-30]. To solve this, the multi-focus IF approach is used to merge numerous photos of a similar subject with different focus points into a final image that is all in focus. The numerous issues that this domain faces are as follows:

(1) Effect of moving target objects
(2) Relevance in consumer electronics

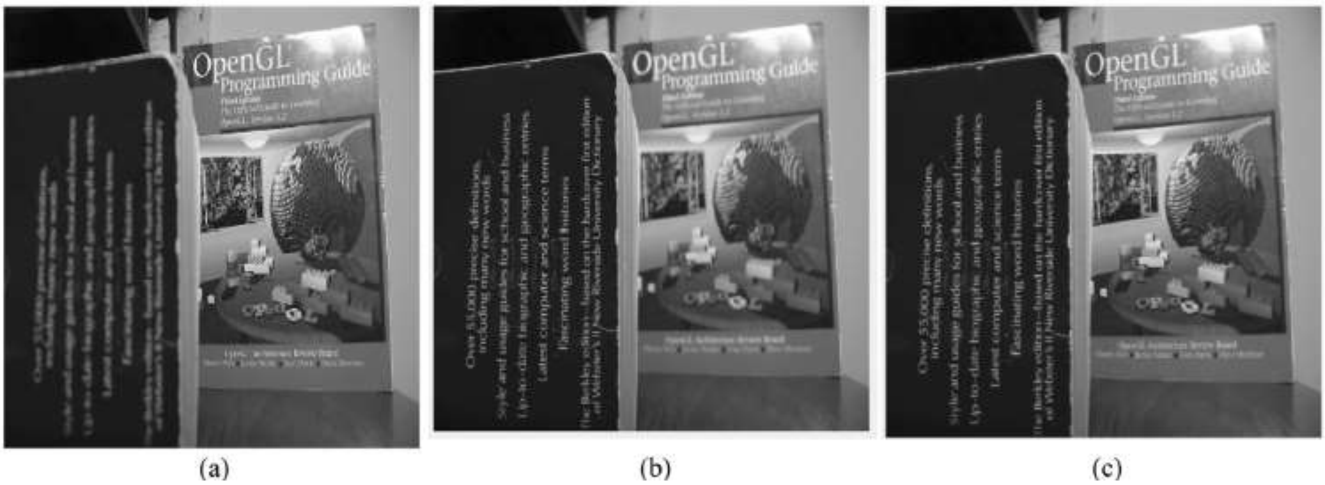

Figure 6: Examples of IF in photography domain. **a)** Back-focus Image **b)** Fore-focus image **c)** Fused image

V. Performance Evaluation Measure

A number of effectiveness evaluation indicators are expected to be used to assess the effectiveness of various IF approaches,

The mean of square error (MSE) determines the inaccuracy as well as the true difference between the ideal and expected results,

$$MSE = \frac{1}{mn}\sum_{i=1}^{m}\sum_{j=1}^{n}\left(A_{ij} - B_{ij}\right)^2$$

The Structural Similarity Index Metric (SSIM) measures how similar two or more images are structurally. It is created by simulating any contrast distortion and radiometric measurements. Between source images and the final image, it is a combination of luminance image distortion and a combination of contrast distortion, loss correlation, and structural distortion,

$$SSIM(x,y) = \frac{(2\mu_x\mu_y + c_1)(2\sigma_{xy} + c_2)}{\left(\mu_x^2 + \mu_y^2 + c_1\right)\left(\sigma_x^2 + \sigma_y^2 + c_2\right)}$$

The peak signal to noise ratio (PSNR) is used to compute the ratio of peak power and noise value power,

$$PSNR = 10log_{10}\left\{\frac{r^2}{MSE}\right\}$$

Mutual Information provides the Information quantity detail of source images, which are merged in the resultant image. The highest Mutual Information represents the effectiveness of the IF technique,

$$MI_{AF} = \sum_{a,f} P_{A,F}(a,f)log\left[\frac{P_{AF}(a,f)}{P_A(a)P_F(f)}\right]$$

Entropy (EN) is used to evaluate the Information content of an image and it produce sensitive noise in the image. Image with large Information content has low cross entropy,

$$EN = -\sum_{l=0}^{L-1} p_l log_2 p_l$$

VI. Conclusion

Medical image fusion has progressed from spatial domain to transform domain to deep learning. Its rapid growth reflects a significant need for computer-assisted clinical diagnostics. Different scholars suggest several fusion procedures, each with its own set of benefits in terms of various evaluation factors. For medical image fusion, however, there are roughly 30 different types of evaluation indexes. To summarise, this article discusses the medical image fusion method and different image fusion methods on medical image fusion research in recent years, combining the proposed fusion method in recent years and the advantages of different methods and fusion effect; for the case different imaging fusion method and the statistics research trend, this paper expounds the research platform and data sets. According to the preceding section, deep learning research in medical image fusion is the future trend.

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