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Comparative Review Of Image Fusion Techniques For Enhanced Quality

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The entirety of data from the source under observation is retrieved using a variety of imaging techniques and acquisition devices. Images can be captured from various perspectives and with different types of imaging equipment, including optical and infrared sensors. They may also involve various diagnostic techniques, including X-ray-based scans and magnetic field-based imaging, or include hyper spectral images like panchromatic and multispectral satellite images, along with multiple exposures and focus levels. For many applications, it is necessary to integrate images obtained using these methods to generate comprehensive data. The technique known as "image fusion" amalgamates information from several images into a cohesive, novel visual representation. In fields including robotic vision, aerial and satellite imaging, medical diagnostics, and navigation systems for robots or vehicles, image fusion is recognized as a critical preliminary step. This article discusses several advanced image fusion techniques at various levels, including their advantages and limitations. It also covers different methods, such as spatial, transform-based, and deep learning techniques, along with their applications in various fields. Additionally, we have examined challenges related to image fusion and provided insights into data sources for fusion studies. Finally, this study investigates a multitude of prospective pathways for various image fusion methodologies.

Keywords: Image Fusion, spatial techniques, frequency-based methods, machine learning, Convolutional Neural Networks (CNNs), Generative Adversarial Networks (GANs).

1. Introduction

The concept of merging images from different sources for enhanced visualization and analysis began to emerge in the early 1960s, particularly in remote sensing and aerial photography. Researchers started investigating methods for integrating images captured by various sensors. Image fusion entails synthesizing crucial components from several distinct images into one unified visual representation. The principal endeavour of image fusion is to produce visuals that offer enhanced significance and clarity for both human discernment and algorithmic evaluation, while simultaneously curtailing the data load [1]. In computer vision, the technique of integrating pertinent Insights from several images into a singular, cohesive image is referred to as multisensory image fusion. The resulting image is typically more informative than any of the individual images used [2]. The field of multi-sensor data fusion has developed into an area that requires more comprehensive formal approaches to address a variety of

practical scenarios. There are several instances in image processing where a single image needs to incorporate a high degree of spectral and spatial information [3] in remote sensing, this is crucial. The instruments are not designed to yield such information, or they are limited in their ability to observe. One method to solve this problem is image fusion.
Image Registration (IR), the initial stage of fusion, consists of aligning the source image with a reference image. This alignment process ensures that corresponding elements are correctly matched for further analysis. In numerous fields, the significance of Image Fusion (IF) and IR is widely acknowledged as pivotal for generating essential information [3].
The growing need for efficient and cost-effective IF techniques has led to a rapid increase in developments in this domain. Various strategies for improving image fusion performance have recently been introduced, including multi-scale analysis and sparse coding. Due to differences between images in diverse applications, an effective fusion technique is required.
The layout of the paper unfolds as follows: Section 2 analyzes various approaches to image fusion techniques. Section 3 outlines various spatial-based fusion methods, while Section 4 covers frequency-based approaches. Section 5 focuses on deep learning image fusion techniques. Data sources for image fusion and associated challenges are reviewed in Section 6. Section 7 explores future research directions, followed by a conclusion summarizing the main concepts.

2. Image Fusion Techniques

The process of deciding how to merge the sensor images is the most crucial aspect of IF. A host of image fusion approaches have crystallized in contemporary times. These techniques are predominantly divided into two realms: spatial domain and frequency domain. The different categories of image fusion are represented in the schematic Figure 1.

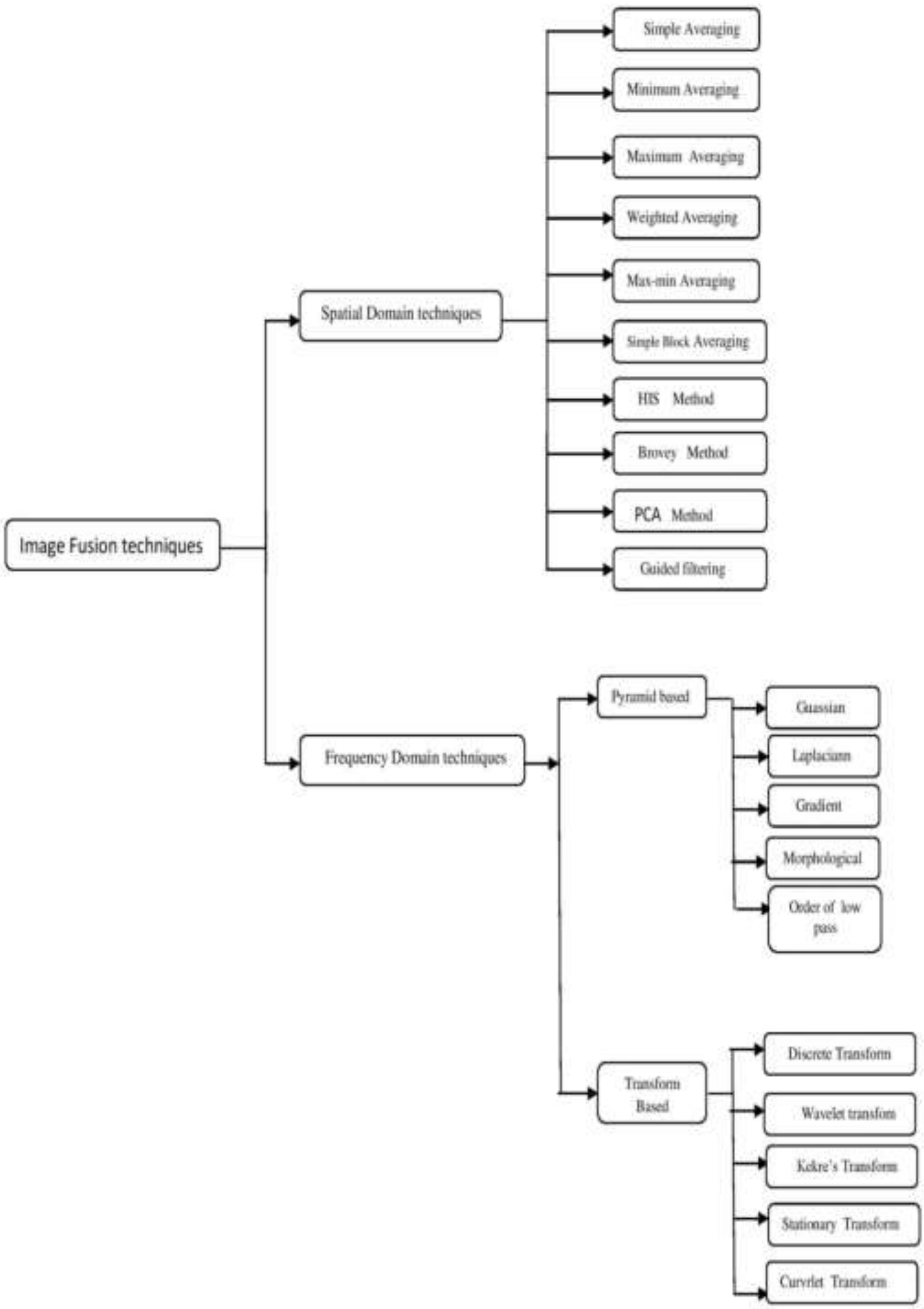
Image Fusion techniques
Spatial Domain techniques
Simple Averaging
Minimum Averaging
Maximum Averaging
Weighted Averaging
Max-min Averaging
Simple Block Averaging
HIS Method
Brovey Method
PCA Method
Guided filtering
Frequency Domain techniques
Pyramid based
Guassian
Laplaciann
Gradient
Morphological
Order of low pass
Transform Based
Discrete Transform
Wavelet transfom
Kekre's Transform
Stationary Transform
Curvrlet Transform

Figure 1: Schema of Image Fusion Techniques

Spatial image fusion methodologies amalgamate the pixel data from multiple images through intricate value integration either linearly or non-linearly. Numerous methods are used in the spatial domain, including weighted average, HIS, Brovey, PCA, and guided filtering. Other methods include simple averaging, maximum, minimum, and max-min averaging, simple block replacement, and simple block averaging [5].
In the frequency domain, the image is first converted into its frequency representation by calculating its Fourier Transform. The fusion procedures are subsequently executed on the Fourier-transformed image, with the resultant image being derived through an Inverse Fourier Transform [6].This approach can be further categorized into two variants: the pyramid method and discrete transform-based image fusion [7].

3. Spatial Domain Techniques:

The spatial domain fusion paradigm entails direct pixel wise processing of the input images [8]. Direct spatial domain amalgamation is conducted on the pristine image datasets. The simplest method in this domain is the weighted average, as it requires no transformation or decomposition [9]. This approach has the advantage of being easy and suitable for instantaneous processing, but this will lower the resultant image's signal-to-noise ratio Table 1 illustrates the array of methodologies accessible within this field.

4. Frequency Domain Techniques

In frequency domain algorithms, the initial phase entails breaking down the input images into multitude scale coefficients. These coefficients are selected or calibrated based on a range of fusion parameters, and the composite image is synthesized via inverse transformations [9].This kind of approach can prevent blocking effects.

4.1 Pyramid Based Techniques

In this process, the source image is segmented into multiple scaled iterations, each characterized by distinct levels of resolution. Pyramid transformation proceeds through three well-distinct stages. The count of hierarchical tiers, 'L,' in the pyramid is contingent upon the image's dimensions and can be established in advance based on these parameters [13]. Table 2 presents a diverse spectrum of approaches employed in this area.

Sl.No	Algorithm	Description	Merits	Demerit
1	Simple Averaging	• Uses pixel averaging to fuse images. • Emphasises on every area of the image, and it works best when the images are captured using the same kind of sensor [10]. • Provides good result if images have strong contrast and brightness levels.	All of these techniques are very easy to comprehend, pertinent and simple to employ[23]	These methods consequence the fused image to become noisier, lowering the ultimate image quality and decreasing contrast. These factors make these methods inappropriate for real-time applications.
2	Minimum Averaging	• It fosters a fused image by choosing the pixels with the minimal intensity value from images [11]. • It is utilized for images with lower brightness levels [12].		
3	Maximum Averaging	• the input image's pixels with the highest intensity are chosen to produce the final fused image [13].		
4	Max-Min averaging	• The fused image is created by averaging the lowest and biggest values of the relevant pixels over all input images [13].		
5	Simple Block Replace	• Every image's adjacent pixels are added, and a block average is computed for each pixel's (x, y) location. • The maximum block average of all the matching pixels in the input images is taken into consideration to determine the pixel (x, y) of the fused image [13].		
6	Weighted average	• the source images that are being used are given varying weights, which means that the respective pixels' grey values are multiplied by a number of different variables and then added together to get the fusion results[14] [15].	The detection reliability is increased by this technique.	The signal to noise ratio (SNR) of the combined image may be high.

7	Brovey Transform Technique	• It aligns with the three multispectral bands that RGB uses to give the image brightness and intensity [18].	The Brovey algorithm enhances image brightness using three multispectral bands for RGB.	It can cause color distortion and struggles with three-band issues.
8	Hue Intensity Saturation (HIS)	• To obtain the fused image, the HIS space is finally converted back to the original RGB space using inverse transformation. This method yields excellent results for remote sensing images, but its major limitation is that it only utilizes three bands.	This yields excellent results for remote sensing images by converting the fused image from HIS back to RGB space.	Its major limitation is that it only utilizes three bands
9	Principal Component Analysis (PCA)	• It transforms a collection of data for a variable that could be correlated into principle components, which are a collection of variables that are linearly uncorrelated. Spectral deterioration and colour distortion are PCA's fundamental flaws [19-21].	This technique is straightforward and highly efficient in calculation, speed, and spatial quality	It leads to spectral deterioration and color distortion
10	Guided filtering	• It smoothes and preserves borders efficiently, operating in linear time with mask size-independent density and a connection to the Laplacian matrix. In graphics and computer vision, it excels in tasks like upsampling, haze removal, detail smoothing, and noise reduction, outperforming PCA and multi-resolution SVD [17][22].	This technique is straightforward and highly efficient in calculation, speed, and spatial quality. [24-26]	It causes spectral deterioration and color distortion[27-28].

Table 1: Overview of Spatial Domain Techniques

Sl.No	Algorithm	Description	Merits	Demerits
1	Gaussian Pyramid	• Here, both source images are decomposed into multi-scale representations using Gaussian pyramids. The corresponding pyramid levels are then combined using a fusion rule, and the fused image is reconstructed by reversing the pyramid decomposition process [29].	Simple to implement	Down sampling in the Gaussian pyramid can cause information loss by discarding high-frequency details, impacting the quality of the fused image.
2	Laplacian pyramid	• The Laplacian pyramid, generated from the Gaussian pyramid through repeated low-pass filtering and down sampling, involves two steps: first, decomposing the Gaussian pyramid and then transitioning to the Laplacian pyramid [30][31].	Excels in preserving fine image details	Increased computational complexity and implementation challenges
3	Gradient Pyramid	• Each Gaussian pyramid level is filtered with four directional filters to create a gradient pyramid [32]. Layering these produces a composite similar to the Laplacian pyramid. Gradient pyramid fusion thus works like Laplacian pyramid fusion, but with the gradient pyramid instead.	This technique ensures enhanced edge preservation.	This is not ideal for tasks that don't depend on gradient and edge details, potentially leading to suboptimal results.
4	Morphological pyramid	• Morphological pyramid fusion is an alternative that replaces contrast or Laplacian pyramids with morphological ones[33].	Preserves image structure	It operates within a binary domain and is not suitable for applications where preserving gray scale or color information is critical.

5	Ratio of Low pass pyramid:	• It entails calculating the ratio between the low-pass pyramid components obtained from the input images. By highlighting the contrasts between the source images' low-frequency components [34].	enhances feature separation which assures improved feature representation in fused image.	it prioritizes magnitude over phase, potentially affecting texture preservation

Table 2: Pyramid Based Techniques

4.2 Discrete Transform Based Image Fusion

In this technique, integrated imagery is utilized. For chromatic images, the Red, Green, and Blue (RGB) spectra are first disentangled. Each spectral channel is then processed through a discrete transformation. The resultant composite is synthesized by aggregating the transformed spectra and executing an inverse transformation [35].

Several algorithms are categorized under discrete transform-based image fusion techniques. These include the Discrete Cosine Transform (DCT) and various wavelet methods such as the Wavelet Transform, Kekre's Wavelet Transform, and the Hybrid Kekre Wavelet Transform. Additionally, approaches like the Stationary Wavelet Transform and Curvelet Wavelet Transform (CWT) are commonly employed. These methods utilize discrete transformations to process images, capturing different frequency components and improving the fusion outcome by enhancing key image features.

In conjunction with these methods, innovative techniques such as the Singular Value Decomposition (SVD) and various advanced multi-scale decompositions have surfaced, offering novel paradigms in image synthesis. These methodologies employ intricate matrix factorizations and elaborate multi-dimensional filtering processes to meticulously deconstruct and reassemble image data. The integration of such sophisticated techniques facilitates the extraction of latent features and augments the fidelity of the final fused imagery, setting a new benchmark in the realm of advanced image fusion. Table 3 delineates range of techniques in this domain.

Sl.No	Algorithm	Description	Merits	Demerits
1	Discrete cosine Transform (DCT)	The image which will be fused is broken down into NxN non-overlapping blocks, and DCT coefficients are obtained for each block. Subsequently fused DCT coefficients are generated by applying fusion rules. The same process is applied for all the blocks [36]	This technique condenses essential information into fewer coefficients, minimizing redundancy.	This is not ideal for tasks where spatial or frequency adaptability is necessary
2	Wavelet Transform	Images are decomposed into various scales and frequency components. The fused image is then created by combining these components from each image at different levels, preserving key features and details [37].	Wavelet Transform provides multiresolution analysis and preserves structure.	Increased computational complexity and implementation challenges
3	Kekre's Wavelet Transform	This involves applying a customizable NxN matrix transformation. Unlike traditional methods, its adaptable matrix size allows tailored fusion for specific applications [38]. Unlike traditional methods, its adaptable matrix size allows tailored fusion for specific applications [38]	It has a very versatile technique, working with an adaptable NxN matrix that enables fusion to be tailored for a great number of specific applications.	The customization and adaptiveness of the matrix increase computational complexity and make its implementation a little challenging.
4	Hybrid kekre wavelet transform	KHWT(Kekre-Hadamard wavelet Transform (KHWT) works by applying Kekre and Hadamard transforms to an image to enhance brightness and detail. The Kekre-DCT method improves this by integrating Kekre wavelets with Discrete Cosine Transform (DCT) to capture and enhance image features more effectively.	KHWT provides better brightness and details by fusing the Kekre and Hadamard transforms, while Kekre-DCT integrates DCT, which enhances the features of an image further.	The combination of a number of transforms might contribute to added computation complexity and, consequently, increased processing time.
5	Stationary wavelet Transform	SWT arose as the conclusion of the DWT technique. It is a new technique of translation invariant	SWT offers multiresolution analysis shift	It comes with complexities in implementation

		better analysis of image facts. This technique is time-consuming, but at the decomposition level 2, better results are achieved[41][42][43].	structural preservation.	demands, and limitations in preserving certain fine details
6	Curvelet Wavelet transform (CWT)	SWT offers better time-frequency characteristics, potentially yielding desirable outcomes. The second-generation Curvelet, a new multi-scale transform, overcomes wavelet limitations in capturing edge orientations in images[44].	Curvelet-based image fusion offers excellent directional sensitivity, multiscale analysis, and sparse representation	It involves implementation complexities, limited adaptability, and sensitivity to artifacts.

Table 3: Discrete Transform Based Techniques

5. Deep Learning based Fusion Techniques

The progress in deep learning has significantly accelerated image fusion processes, thanks to the Vigorous feature delineation and reconstruction prowess of neural networks. Recent advances in deep learning methods have caused an explosion in image fusion. However, there is a dearth of a thorough study and analysis of the most recent deep-learning techniques in various fusion settings. Some recent advances in the sphere of deep learning integration to several scenarios on image fusion, such as multi-modal, sharpening, and picture fusion, are reviewed in this section. The foremost deep learning architectures employed in image fusion entails Convolutional Neural Networks, Convolutional Sparse Representations, and Hierarchical Auto encoders.

5.1.1 Auto Encoders

This is a class of feed-forward neural network models. This model entails—encoding and decoding. These are the same as those in other feed forward neural network models [45].

5.1.2 Convolution Neural Network

This is usually assimilated into the image fusion workflow in two distinct stages. The first aspect is that it addresses feature extraction, feature fusion, and image reconstruction via meticulously crafted loss functions and bespoke network frameworks [46].

5.1.3 Generative Neural network

GAN was first conceptualized for the purpose of unsupervised image refinement with a higher level of realism. Since then, a number of computer vision tasks have been exemplified to have striking performance [47]. This principle is fundamental to GANs, where a min-max game is played between the generator and the discriminator. The discriminator strives to differentiate if a sample emanates from the model or the inherent data distribution, while the generator endeavours to obfuscate this distinction by fabricating diverse instances from continuous noise input [48].

5.2 Applications

5.2.1 In Multi exposure Image fusion

The most prevalent techniques for multi-exposure picture fusion are CNN and GAN. In order to create a fusion map, which is then harnessed to create the final fused image, CNN uses trained networks to elucidate characteristics and pixel positions from source images with the varying exposures [49]. Finding a high performance non-reference metric to assess fused results is the challenging aspect with CNN. To achieve a high-quality multi-exposure fusion, the GAN approach relies on all of the original image's information, including the scene's structure and exposure condition.

5.2.2 Multi Focus Image Fusion

The preeminent neural constructs for amalgamating multi-focus images are Convolutional Neural Networks (CNN) and Generative Adversarial Networks (GAN). In this schema, CNN devises a discernment matrix to differentiate between sharp and defocused pixels. The ultimate fused image is then synthesized by sifting and integrating pixels according to this discernment matrix [50][51]..Commonly, the approach of the decision map-based GAN method is started with the fused result as the output from a generator through a decision map. After that, adversarial learning will be applied to bring the fused result as similar as possible to the reference full-clear image [52]. This GAN method optimizes the reconstructed fused image, guaranteeing richer texture and visual fidelity [53].

5.2 3 Fusion of Infrared and Visible Images

High-contrast, texture-rich infrared and visible image fusion utilizes AE, CNN, and GAN techniques [54]. In AE, the encoder extracts valuable features, while the decoder reconstructs the input image. The improvement of visible and infrared fused images is not possible with AE since the procedures are hand calculated and not learnable [55, 56].

CNN constrains the efficacy of image fusion attributable to the use of pre-trained networks [57]. High-performance fused images are produced using the GAN approach; however, maintaining the correct equanimity between the generator and the discriminator amidst the training process is challenging [54].

5.2.4. In medical Imaging

The CNN and GAN fusion techniques are frequently employed in medical image fusion [58] [59] [60]. In the merging of medical images, GAN guarantees outstanding performance. There's a good chance that function information will cover over texture information. The GAN in medical image fusion must overcome this obstacle [54].

6. Data Sources

In image processing research, the availability of datasets is crucial. Researchers in image fusion benefit from access to publicly accessible datasets, which serve as foundational resources for the evaluation and testing of various image fusion methodologies. Below, we list several publicly accessible datasets that are valuable for researchers delving into image fusion.

Sl. No	**Description**	**Website**
1	NASA offers access to a vast collection of remote sensing satellite imagery and data. You can explore and download datasets related to Earth observation, which are valuable for remote sensing image fusion	https://www.earthdata.nasa.gov/
2	The United States Geological Survey (USGS) provides access to satellite imagery, including Landsat, Sentinel, and other datasets. It's an excellent resource for remote sensing and environmental research	https://earthexplorer.usgs.gov/
3.	For medical image fusion, TCIA offers an extensive repository of medical imaging data, including CT, MRI, and PET scans.	https://imaging.cancer.gov/
4	Kaggle hosts datasets for various data science and computer vision tasks, and you can find a range of image datasets suitable for research, including image fusion.	https://www.kaggle.com/datasets
5	IEEE DataPort is a platform where researchers share datasets related to various domains, including image processing and computer vision.	https://ieee-dataport.org/
6	NOAA offers access to a wide range of environmental datasets, including satellite imagery.	https://coast.noaa.gov/dataviewer/

Table 4: Data sources

7. Challenges

Image fusion has become increasingly prevalent in various applications in recent years including remote sensing, photography, surveillance, and medical diagnosis. Here, several significant challenges pertaining to various fields are explored.

- Finding an authentic and high-quality dataset is a challenging aspect of research the sector of image fusion.

- The predominant deep learning methodologies for image fusion operate under the premise that the images have been pre-synchronized. Digital and multimodal photographs, however, are not registered because the principle sensors differ, the resolution of the source images varies [61].
- Extracting all the data necessary to create an efficient fused image is another challenge [62].
- The fused images frequently serve as useful input for later applications. However, the majority of fusion algorithms don't take the application of the fused image into account when fusing them.
- Real-time picture fusion with high performance is required for several practical applications. Thus, devising a real-time image fusion strategy has become a pressing necessity.

8. Conclusion

The field of image fusion has indeed garnered prominent consideration in recent epochs driven by its wide-ranging applications and the ever-growing demand for enhanced image quality and information extraction. This study has undertaken a comprehensive exploration of various image fusion techniques, spanning from traditional spatial domain methods to the cutting-edge realms of deep learning. Through this investigation, we have delved into the merits and demerits of these techniques, scrutinized their applications across diverse domains, and confronted the notable challenges that confront practitioners in this field.

The survey reveals that image fusion techniques are not one-size-fits-all solutions; instead, they are versatile tools with unique strengths suited for specific applications.. By thoughtfully blending these techniques, researchers can leverage their unique strengths, thereby improving the precision and usefulness of the manifested fused constructs. Consequently, the strategic amalgamation of these techniques opens the door to optimized solutions within the continually evolving realm of image fusion.

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