

A Novel Approach for Medical Image Fusion Based on Convolution Neural Networks and Wavelet Transformation

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Abstract

The authors provide a novel multimodal medical picture fusion method that is based on deep convolutional neural networks (CNN) and local spatial domain modification. The raw image is first fed into Siamese CNN, which produces the weight map, which is then processed by the Weighted Sum of Eight neighborhood-based Modified Laplacian (WSEML) to produce a new image-based WSEML. Following that, images from CT and MRI are entered into the Weighted Local Energy method (WLE). Finally, the activity level evaluation based on local energy is dedicated to integrating each of the new WLE images and new WSEML images to extract critical information during the reconstruction process. The simulation results suggest that the proposed method acquired more relevant information from source photographs with increased visibility while simultaneously minimizing fused image artefacts.

Key Words: Image Fusion, Convolution neural networks (CNN), Discrete Wavelet Transformation (DWT)

1. INTRODUCTION

The term "fusion" refers to a technique for extracting information from multiple areas. Image fusion attempts to combine information from multiple images of the same scene into a single image while retaining the important and necessary parts of each original image. The primary goal of image fusion is to merge complementary information from many images into a single image. The resulting fused image is more informative and complete than any of the input images, and it is better suited for human and machine perception. Image fusion is the process of merging information from many photos of the same scene. Medical picture fusion is a technique that integrates two mutual images into one by following parameters to produce a clear visual impression. A doctor might quickly determine the location of the illness by seeing a medical fusion image.

CT, X-ray, DSA, MRI, PET, SPECT, and other image information modes are available for clinical diagnosis through medical imaging. Many medical images have unique features that can disclose structural information about different organs. CT (Computed tomography) and MRI (Magnetic resonance imaging) with high spatial resolution, for example, can disclose an atomical structure during organ formation. Based on the wavelet transform^{1,2}, this study proposes a unique approach for fusion of computed tomography (CT) and magnetic resonance imaging (MRI) images. The low and high frequency wavelet coefficients are then subjected to various fusion rules. The study made use of

pictures from registered computer tomography (CT) and magnetic resonance imaging (MRI) of the same people and spatial parts. This project explains the following image fusion techniques.

- Simple Average Method
- Select Maximum Method.
- Select Minimum Method.
- Discrete Wavelet Transform (DWT)method.

1.1. Need of Image Fusion

This technique enables practitioners to investigate human tissue while observing several aspects in the same location. The goal of multi-modal imaging is to provide a comprehensive image of a specific tissue in the human body. The image should allow clinicians to see whatever is there in that particular tissue, including its size, precise location, and metabolic activity. Clinicians should be able to investigate the metabolic activity of neighboring tissues as well. As a result, clinicians can evaluate any abnormalities or changes in tissue function caused by a disease, tumour, or other medical condition.

Scientists may view high-definition images of the virus beginning at the site of infection and progressing through the process in which the virus uses a human body to multiply itself and destroy immune cells using multi-modal imaging techniques. Doctors can be optimistic that multimodal imaging will be able to detect disease in human tissue before it progresses too far. They believe that by investigating a small number of abnormal cells rather than the millions required by traditional methods, they will be able to detect cancer. Doctors may be confident that multimodal imaging will detect disease in human tissue before it spreads too far. They believe that by investigating a small number of abnormal cells rather than the millions required by traditional methods, they will be able to detect cancer.

1.2. Why Image Fusion

Multi sensor data fusion has evolved into a subject that necessitates more comprehensive formal solutions to a variety of application instances. Many image processing circumstances necessitate the inclusion of both high spatial and high spectral information in a single image. This is critical in remote sensing. Unfortunately, either by design or due to observational limits, the equipment is incapable of delivering such information. Data fusion is one such solution.

1.3. Standard Image Fusion Methods

Spatial domain fusion and transform domain fusion are the two basic categories of image fusion algorithms. Spatial domain approaches include fusion methods such as averaging, the Brovey method, principal component analysis (PCA), and HIS-based methods. The high pass filtering-based technique is another key spatial domain fusion method. High frequency features are introduced into an up sampled version of MS pictures in this case. Spatial domain techniques have the problem of causing spatial distortion in the fused image. When we proceed to further processing, such as

a classification problem, spectral distortion becomes a negative factor. Frequency domain techniques to picture fusion can effectively address spatial distortion.

Multiresolution analysis has evolved into an extremely valuable tool for interpreting remote sensing images. The discrete wavelet transform has shown to be an extremely useful fusion tool. Other fusion approaches include Laplacian pyramid-based, curvelet transform-based, and so on. These methods outperform existing spatial fusion methods in terms of spatial and spectral quality of the fused image. Image fusion images should already be registered. Image fusion errors are frequently caused by misregistration. Some well-known picture fusion approaches are as follows:

- High frequency smoothing approach
- HIS convert-based image fusion
- Dimensionality reduction-based image fusion
- Coupled spatial frequency matching

1.4. Picture Enhancing and Filtering

Contrast enhancement, morphological filtering, deblurring, and ROI-based processing are all available. The process of modifying images such that the results are more suited for display or additional image analysis is known as image enhancement. For example, you can eliminate noise from an image, sharpen it, or modify the contrast to make it simpler to identify significant characteristics.

- Image smoothing

Predefined and custom filters, nonlinear filtering, and edge-preserving filters are all available.

- Edge based Alteration

Adjusting the contrast, equalizing the histogram, and lengthening the decorrelation

- Mathematical Morphology Operations

Dilate, erode, rebuild, and carry out other morphological procedures

- Deblurring

Deconvolution for blur reduction

- ROI-Based Processing

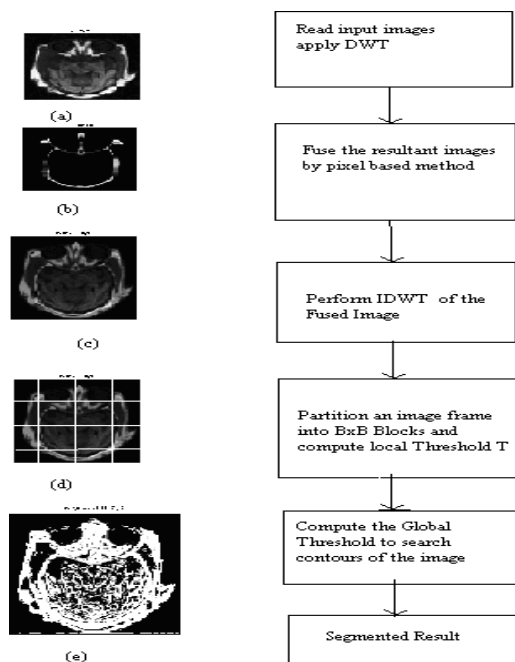
Define and operate on regions of interest (ROI)

- Neighborhood and Block Processing

Define filtering neighborhoods and blocks for I/O operations.

- Image Calculation

Add, subtract, multiply, divide, AND, OR, NOT, XOR and images



Working process of Discrete Wavelet Transformation

1.5. Problem Statement

Medical image fusion is the combination of two images to create a single image. In medical applications, image fusion can commonly contribute to additional clinical information that would not be seen in a separate image. Image fusion was performed to improve the image and clearly visualize the coronary artery blood vessels. Despite the fact that there are numerous signal processing and geometric attacks available, such as mean attack, median attack, noise attack, cropping, scaling, rotation, reflection, shearing, and translation, the existing system is only resistant to translation, shearing, and rotation.

The fused image of decomposed sub bands is created by applying inverse trans forms. In order to boost efficiency effectively, a trans form-based picture fusion technique is used. This approach yields higher PSNR (peak signal to noise ratio) values with lower MSE (mean square error). The image fusion process can be carried out at several levels of picture representation, including feature, pixel, decision, and data. The fused image can be created using the pixel level image fusion technique, in which each pixel selects a collection of pixels from several source images. The advantage of fused images is that they are more informative than the input image and contain original information. When compared to decision level fusion and feature level fusion, pixel level fusion is more efficient and simple to execute.

Inshort:

- How to design a dedicated system that will perform the task of image fusion?
- How to calculate the PSNR of the image?
- How to make the system more reliable under various attacks?

2. LITERATURE SURVEY

DWT is used to decompose source images into low-level sub-band and high-level Sub-bands in the suggested method. Next, low-level sub-images are merged using the type-2 fuzzy fusion rule, while high-level sub-images are fused using the average fusion rule. The next step is to apply inverse DWT to the fused components to obtain the fused image³. Medical image fusion is the only developing approach that has attracted researchers to assist physicians in fusing images and extracting pertinent information from several imaging modalities, such as CT, MRI, FMRI, SPECT, and PET⁴. When scanning sensitive organs such as the brain, both magnetic resonance imaging and computed tomography are favored. CT delivers superior information on denser tissues, whereas MRI provides superior information on soft tissues. These complementarities have led to the notion that combining images obtained with multiple medical devices will produce an image with more information than a single image. Hence, it is anticipated that combining MRI and CT pictures of the same organ would result in a significantly more detailed integrated image⁵.

Image fusion techniques are essential because they enhance the performance of object recognition systems by combining numerous satellite, aerial, and ground-based imaging systems with other related datasets. In addition, it assists in sharpening the images, improving geometric corrections, enhancing some aspects that are not visible in either image, replacing faulty data, and completing the data sets for improved decision making⁶. Picture fusion approaches including Simple Average, Choose Maximum, Select Minimum, Principal Component Analysis, and Discrete Wavelet Transform are described and evaluated using the quality metrics peak signal to noise ratio and root mean square error⁷.

Several assaults on A Real-Time Method for Comparing the peak signal to noise ratio and mean square error Value of Diverse Original Pictures and Noise (Salt and Pepper, Speckle, Gaussian) Uploaded photographs and worked on PSNR, MSE, Real Time, digital image processing, image quality, and noise^{8,9}.

Attack Detection Using PSNR and RGB Intensity in Watermarked Images The article outlined a technique for embedding and detecting chaotic watermarks in huge photographs. Using an adaptive clustering technique, an arbitration representation of the original image is generated¹⁰. A comparison of various transform-based methods for picture fusion. Using a transform-based picture fusion technique allows for the effective enhancement of efficiency. This method yields a peak signal-to-noise ratio measurement with a lower mean square error¹¹.

3. EXISTING SYSTEM

The authors offer a new multimodal medical image fusion method based on deep convolutional neural networks¹² and local spatial domain change. The raw image is first input into Siamese CNN to generate the weight map, which is then processed by the Weighted Sum of Eight neighborhood-based Modified Laplacian to generate a new image-based WSEML. Following that, CT and MRI input pictures are loaded into the Weighted Local Energy algorithm. Lastly, the activity level assessment based on local energy is devoted to merging

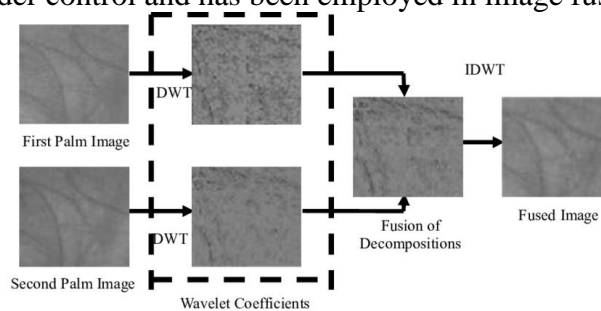
each of the new WLE and WSEML images in order to obtain important information during the reconstruction step.

Limitations of the Existing system

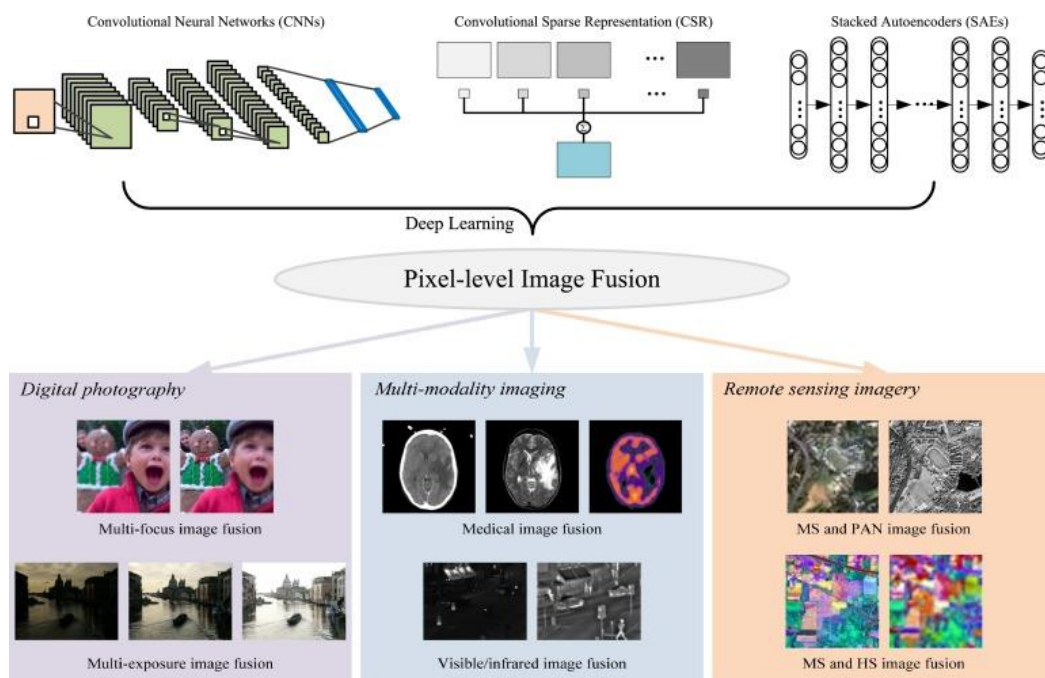
- 1) During there exists the noise
- 2) The spatial domain approach works with the pixels of the input image directly.
- 3) The pixel values are changed to produce the desired result.

4. PROPOSED METHODOLOGY

In this paper we implement the VGG Model with 4 band images and then we reconstruct the image using CNN, CSR, SAE Inverse Wavelet Transform and a new fusion algorithm. The proposed method has two main parameters; (1) First palm image the weighting kernel used in DWT, and (2) Second palm image using DWT both are Decompositions called as IDWT of the fused image with a range. The image of multiple variable s is commonly used, recently known as a variable under control and has been employed in image fusion.



Working process of Discreet Wavelet Transformation



Working process of CNN

Advantages

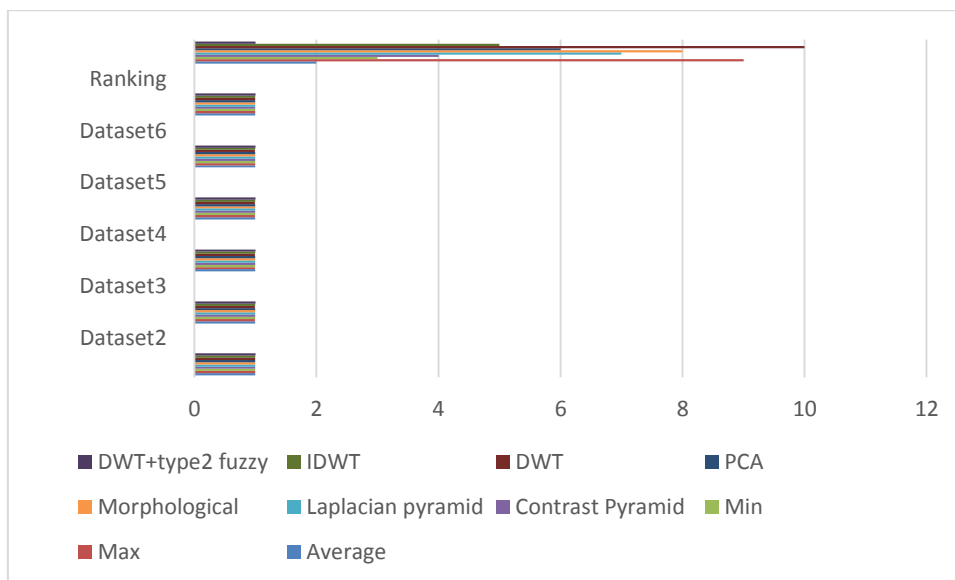
1. The usage of predefined weightages decreases the time complexity.
2. Transform domain methods First, the image is moved into the transform domain.
3. The image's Fourier transform is computed first. All Fusion processes are done on the picture's Fourier Transform, and the resulting image is obtained by performing the Inverse Fourier transform.
4. Averaging, Pick Maximum / Minimum are simple picture fusion methods.

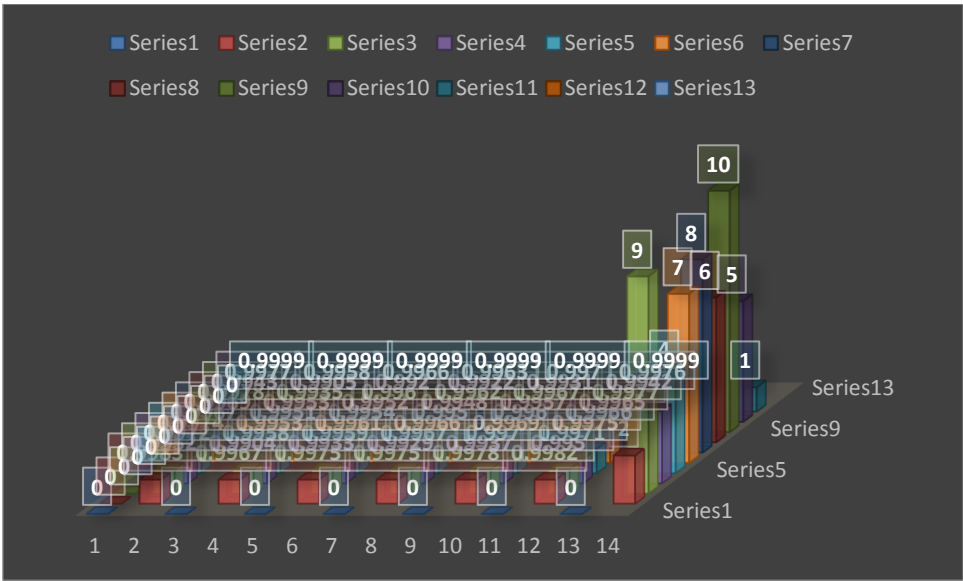
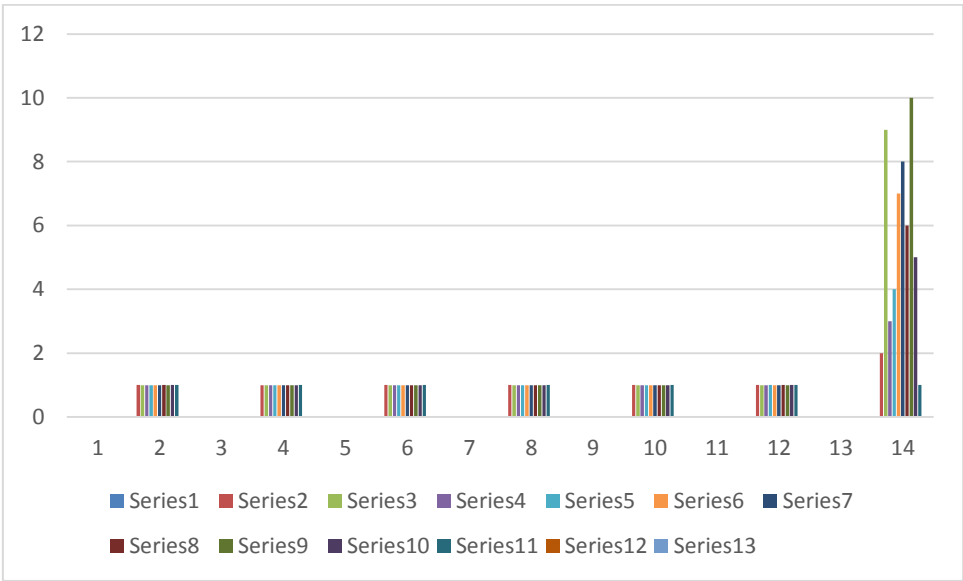
4.1. Analysis of Experimental Findings and Performance

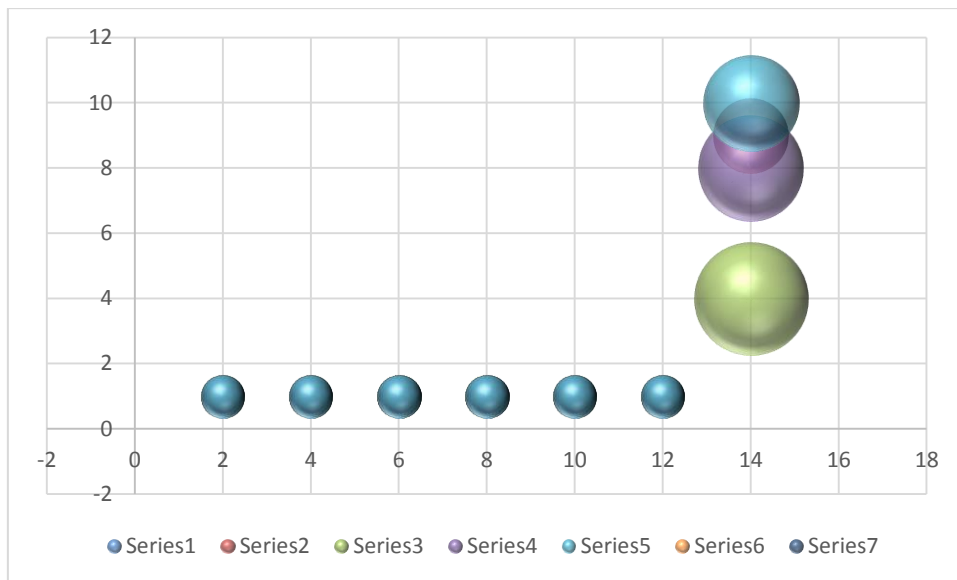
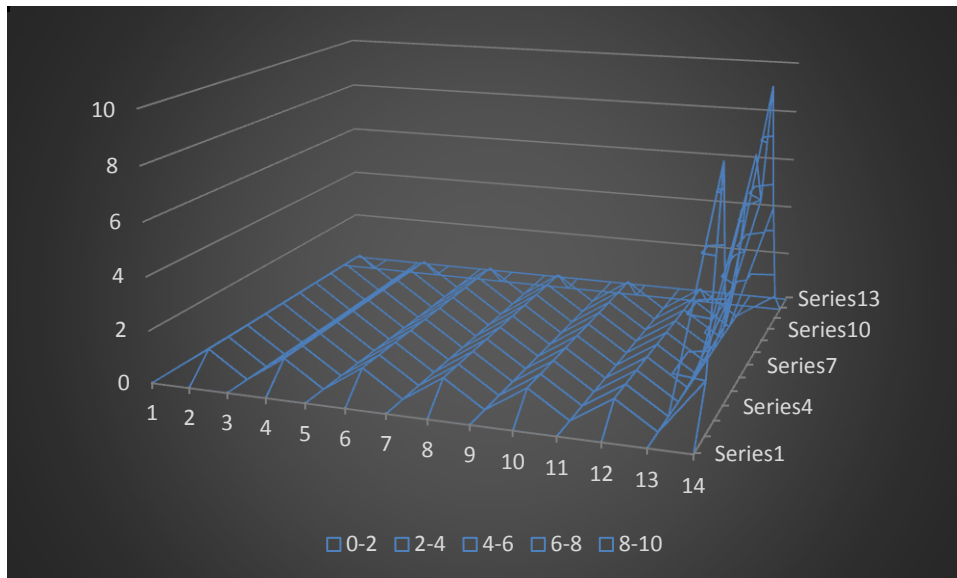
The experimental findings and performance evaluation of the suggested fusion method are presented in this section to demonstrate its efficacy.

	Dataset1	Dataset2	Dataset3	Dataset4	Dataset5	Dataset6	Ranking
Average	0.9983	0.9967	0.9975	0.9975	0.9978	0.9982	2
Max	0.9952	0.9904	0.9933	0.9929	0.9937	0.9950	9
Min	0.9972	0.9958	0.9959	0.9967	0.9970	0.9971	3
Contrast Pyramid	0.9974	0.9953	0.9961	0.9966	0.9969	0.9975	4
Laplacianpyramid	0.9967	0.9951	0.9954	0.9950	0.9960	0.9966	7
Morphological	0.9969	0.9953	0.9952	0.9948	0.9957	0.9965	8
PCA	0.9978	0.9935	0.9960	0.9962	0.9967	0.9977	6
DWT	0.9943	0.9905	0.9920	0.9922	0.9931	0.9942	10
IDWT	0.9977	0.9958	0.9966	0.9963	0.9970	0.9976	5
DWT+type2 fuzzy	0.9999	0.9999	0.9999	0.9999	0.9999	0.9999	1

Comparative Analysis for Different Fusion Methods







Graphical Representation of Comparative Analysis for Different Fusion Methods

Conclusion

The watermark and host pictures were first moved to the discrete wavelet transform domain, and then the host image's HH and LL sub bands were blocked. Following that, LL sub-band blocks of the water mark image were substituted into the singular values of the host image blocks, with a different SF assigned to each block. It can be demonstrated that higher PSNR values and lower MSE values are desirable results. According to the results, image quality assessment is a difficult procedure because the PSNR and MSE values for different test images are not as desirable as desired, and this field still need a lot of hard work to establish acceptable image quality measures.

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