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Image Fusion Techniques-A Survey

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Abstract: Image fusion is a process of combining two or more images captured from the same scene to produce a single image which contains the high-quality information from the source images. A single image does not contain all the objects that are correctly focused. The purpose of image fusion is to identify the focused regions from the source images and combine them to form a fused image. The fused image contains more detailed information about the source images which is very much useful for human visual perception, feature extraction and other segmentation tasks. The fused image will be more accurate and contains complete information than any of the source images. This paper presents a survey on different image fusion techniques.
Keywords: Image fusion, Focused regions, High-quality.

I. INTRODUCTION

Image fusion is a method that combines the relevant information from two or more source images. The resultant image is a single fused image and it will be more informative than the input images. The quality of the fused image is preserved in the fusion process. Image fusion algorithms can be divided into different types: pixel, feature, and decision level. Pixel level fusion operates directly on the pixel values of the input images. Feature level fusion works on the features extracted from the input images. Decision level image fusion operates on the images individually for feature extraction. Image Fusion can be applied in various fields like medical imaging, microscopic imaging, Satellite imaging, computer vision, robotics, etc.

II. IMAGE FUSION TECHNIQUES

Image fusion can be roughly classified into two types namely, spatial domain and transform domain methods.
The Spatial domain fusion method directly deals with the pixel values of the input images. The pixel values are changed accordingly to obtain the desired result. The fusion methods such as averaging, Bovey transform method, principal component analysis (PCA) and IHS based methods come under the spatial domain methods. In the transform domain methods, the input image is converted into the frequency domain and different operations like low-pass filter is applied to the transformed image. The inverse transform is applied to the image to obtain the fused image. Transform domain methods are classified as, Pyramid based fusion methods and wavelet based fusion methods. The rest of the paper is organized as follows: Section 2 provides the different image fusion techniques. Section 3 provides the review on related work. Section 4 provides the performance evaluation metrics and Section 5 provides the conclusion.

A. Spatial Domain Methods

1) *Averaging Method:* The averaging method is used to obtain a fused image in which all the regions are focused. The sum of pixel values of each image are taken and divided by the total number of input images. The obtained pixel values are assigned to the corresponding pixel value in the output image
2) *Bovey Transform Method:* Pixel level image fusion is done using Bovey transform method. It is also called as color normalization transform because it involves a red-green blue (RGB) color transform method. This method combines the images obtained from the different sensors. It uses arithmetic operations for the fusion of multispectral bands. It is used to increase the visual contrast of the images
3) *Principal Component Analysis:* It is used to reduce the dimension of the input data without loss. The number of correlated variables is converted into number of uncorrelated variables. The pixel information of the image is calculated and subtracted with the mean value. The covariance matrix, Eigen values and Eigen vectors of the covariance matrix are calculated**.** A feature vector is produced by choosing the components from the Eigen vector. A New Dataset of all the input images is calculated and the sum of the pixel values produces the fused image matrix
4) *Intensity Hue Saturation (His) Method:* This method involves the fusion are panchromatic and multispectral satellite images and mainly used in remote sensing applications. The low resolution multispectral images are resized as same as panchromatic image. The RGB bands of the obtained image are converted into HIS color space. The panchromatic image is modified similar

to the multispectral image. The intensity component of the multispectral images is replaced by the panchromatic image. Finally, the inverse transformation is done to obtain the high resolution image.

B. Transform Domain Methods

1) *Pyramid Based Fusion Method:* The pyramid based fusion method consists of three major frameworks known as decomposition, fusion and reconstruction. In decomposition, the pyramid is generated at each stages of the fusion. It consists of low pass filtering, pyramid formation. The images are combined in the fusion process which acts as the input for the reconstruction phase. The pyramids obtained at each stage are reconstructed in the final stage.
2) *Laplacian Pyramid:* The basic step in the Laplacian pyramid is pyramid decomposition. The input image is decomposed into pyramid-based structure which contains the source images obtained from different levels, and the transform domain method is applied to each pyramid to get the high frequency details from the input image. The fused image is obtained by using inverse transform method
3) *Wavelet Based Fusion Method:* Wavelet based method is a linear transformation method which is based on wavelet functions. It can be applicable for variety of applications in image compression, noise reduction, and satellite applications. The fused image is obtained using maximum fusion rule in which highest coefficients are selected from each high pass and low pass bands.
4) *Discrete Wavelet Transform (DWT):* The input images are decomposed into several high pass and low pass bands using DWT. The decomposed (wavelet) coefficients are fused using available fusion algorithm. The fused image is obtained by applying inverse transform on the wavelet coefficients. The signal is decomposed into different bands not like the conventional filters which are mostly based on Fourier transformations. In the reconstruction of irregular shapes, wavelet transform performs better than Fourier transform methods. There will be no loss of information in wavelet based filters.
5) *Stationary Wavelet Transform (SWT):* It is also called as Un-decimated wavelet Transform. Shift invariance is important in many applications such as change detection and denoising. Traditional DWT lacks this property. SWT apply high pass and low pass filters at each level of the data after modifying the filters at each level by padding them with zeros.
6) *Curvelet Transfor:* It is used to represent the images at different scales and different angles. It uses only small number of coefficients and hence can be used to handle the discontinuities. The input image is decomposed into different Curvelet coefficients, the coefficients are fused using appropriate fusion rule. Final fused image is obtained using inverse discrete Curvelet transform.

III. RELATED WORK

J. Lewis et al [1] proposed pixel and region based image fusion using complex wavelets. The individual pixels are combined using fusion rule in pixel-level fusion. In region-based image fusion, several pixel values are grouped to form contiguous regions. A dual tree- complex wavelet transform method (DW-CWT) is used in wavelet transform method. A region map is generated by segmenting the features from the source images. The important pixel information associated with each region is calculated and combined using region-based image fusion. The major advantage of this method over pyramid based method is, it has no blocking artifacts and has better directional sensitivity over the discrete wavelet transform method (DWT).

S. Li et al [2] proposed a multi-focus image fusion using artificial neural networks. The input images are divided into blocks. From the two source images, the neural network is trained to select the clearer block from the source images. Finally, the clearer block is chosen in constructing the fused image. Two neural network models namely, probabilistic neural network (PNN) and Radial basis function network are used (RBFN).This method is better than discrete wavelet transform method, since it helps to identify the object movement and mis-registration problems in source images.

I. De et al [3] proposed a multi-focus image fusion using morphology based focus measure in a quad-tree structure. Early block based methods uses a fixed block size for fusion of images. This method uses a quad-tree based structure in which input images are divided into four quadrants. The corresponding four blocks pairs are obtained at each level of the quad tree. Focus measure is calculated from each pairs, the block with better focus is copied to the final image. Normalized difference in focus measure (NDFM) is used to calculate the focus measure of each block. Energy of morphological gradients (EOMG) is also used to calculate focused regions. This method is robust and performs better compared to the other focus measure schemes.

Zhejiang Zhou et al [4] proposed a multi-scale weighted gradient-based fusion for multi-focus images. Two focus measures were used. A large scale (L1) and a small scale (L2) scheme is used to calculate the gradient weight. The large scale focus measure is used to calculate the focused regions in the source images. The small scale focus measure calculates the weights of the gradient in the focused regions near the boundaries. The regions which are highly focused are set to 1 while the less focused regions are set to 0 in the unknown regions of the image. Due to different focus measure obtained at multiple regions, the errors are reduced in the boundary regions.

Yu Liu et al [5] proposed a multi-focus image using dense SIFT algorithm. A sliding window technique is employed in which the SIFT descriptor is used to measure the activity level of the source images to generate a initial decision map. The indefinite regions in the decision map are refined using feature mapping. The final decision map is generated after applying the fusion rule to the final decision map. The quality of the fused image is improved and the computational efficiency is also reduced than the guided-filtering method.

Mansour Nejati et al [6] proposed a multi-focus image fusion using dictionary based sparse representation. This method consists of two phases: training and testing phase. Focus information is calculated from the source images using k-means singular value decomposition (k-SVD). Features are extracted from the source image patches and sparse representation is computed over this learned dictionary model. Max-pooling is used which produces pooled features that suggests whether the first image or second image is focused. In the testing phase, a score map is generated after the correlation of pooled features. A guided filter is used for the further refinement of the score map and Markov Random Field (MRF) is used to get the the final decision map. This method preserves the focused regions from the source images and produces consistent decision maps.

Zhiping Xu et al [7] proposed Medical image fusion using multi-level local Extrema. The source images are decomposed into course and detail layers and are fused using local energy and contrast fusion rule for selecting coefficients from the decomposed layers. A good fusion result must preserve all the necessary information from the source images with fewer artifacts. The detailed layers generated using multi-level window size conveys all the local properties of the images compared to the existing image representation methods. New fusion rules were employed to fuse those decomposed layers. Finally, the fused image will be suitable for human visual perception and in clinical diagnosis.

Sudeb Das et al [8] proposed a Neuro-Fuzzy Approach for Medical Image Fusion. It deals with Non-Subsampled Contourlet transform and fuzzy-adaptive reduced pulse-coupled neural network (RPCNN). The registered source images are decomposed into low pass and high pass bands and then the coefficients are given to the RPCNN. The fused image is obtained using inverse NSCT. It has less number of parameters and proves better computational efficiency.

P.Ganasala et al [9] proposed Multimodality Medical Image Fusion Based on New Features in NSST Domain. The images are decomposed into anatomical and functional part by using NSST. The source images are transformed into low frequency(LF) and band-pass directional sub-bands or high frequency(HF) sub-bands by using NSST (Non-Subsampled Shearlet transform).Then LF sub-bands are combined by using LF sub-band fusion rule based on novel feature inspired by human visual system. The HF sub-bands are fused by using HF sub-band fusion rule. Finally, the fused image is reconstructed through inverse NSST of fused sub-band.

Yin Fei et al [10] et al proposed medical image fusion based on feature extraction and sparse representation. The decision maps are used in this method namely, structure information map (SM), energy information map (EM), structure and energy map (SEM) to make the fusion results preserve the edge information. The SM contains the local structure feature obtained by the Laplacian of a Gaussian (LOG) and EM contains the energy and energy distribution feature calculated by the mean square deviation. The decision map is added to the sparse representation method to improve the efficiency of the algorithm. This method improves the quality of the fused results by enhancing the contrast by reserving more structure and energy information from the source images.

IV. PERFORMANCE EVALUATION METRICS

The basic metrics which are needed to evaluate the quality of the fused image is discussed below,

A. Peak Signal To Noise Ratio (Psnr) And Mean Squared Error (Mse)

Both metrics are used for performance evaluation of the image quality. The higher the value of the PSNR, the better will be quality of the fused image. It is the ratio between the maximum power of the signal and power of noise that affects the fidelity of the representation. It is the measure of the peak error value. MSE is the cumulative error between the compressed and original image. It is used for estimating the unobserved quantity.

B. Structure Similarity Index (Ssim)

The Structural Similarity Index (SSIM) is a metric that quantifies image quality degradation by loss in data transmission. It is a reference metric that needed two images from the same image capture— a reference image and a processed image.

C. *Entropy*

Entropy is used as a measure of information and in many image processing. It is mainly used to assess the effects of information change in the fused images.

D. *Mutual Information (Mi)*

It is used for image matching. When the images are similar, the corresponding signal also should be the same. It is also defined as a measure of similarity between two signals.

E. *Edge Intensity (Ei)*

Edges define the boundaries between different regions in an image. Edges in an image play an important role in object identification and recognition.

F. *Tone Mapped Image Quality Index (Tmqi)*

It involves tone mapped operators for converting high dynamic range images to low dynamic range on LDR displays. It is used for objective assessment of image by a multi-scale signal fidelity measure based on SSIM. It is used to measure the intensity of the natural images.

V. CONCLUSION

Image fusion is widely used in many applications and has been emerging as a current trend in image processing field by the recent years. It mainly focuses on gathering spectral information in the source images by increasing the resolution for better visual quality assessment. Image fusion can be applied in medical field and remote sensing. In medical field, it helps in diagnosis of tumor and other disease by clearly identifying the damaged region in the organ by the use of different image fusion techniques. A hybrid method can also be used for better image quality.

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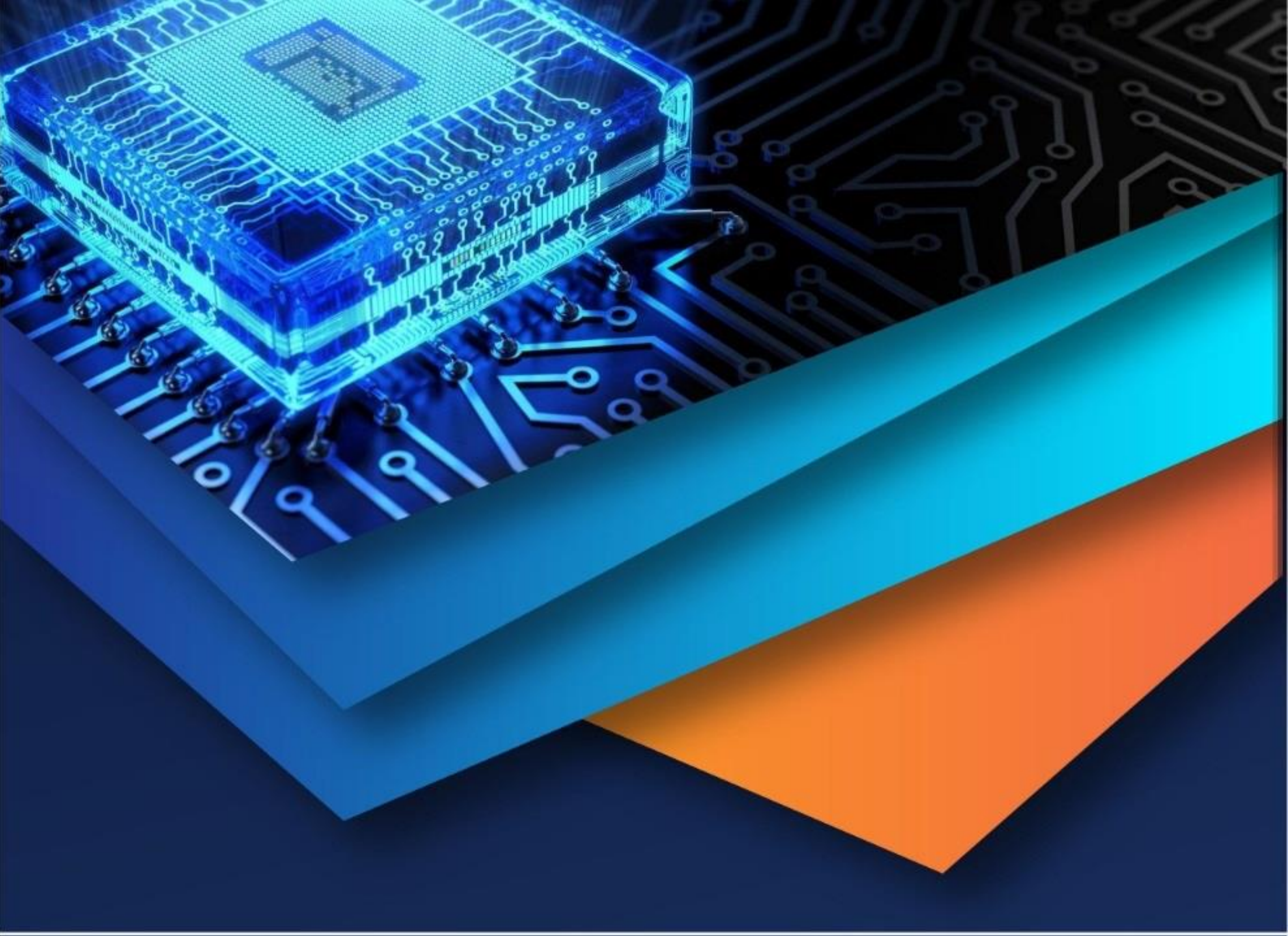

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