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A Review on Recent Improved Image Fusion Techniques

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***Abstract*—An image fusion is a process used to increase the visual interpretation of images in various applications. It integrates the necessary features of two or more images into a single image without introducing artifacts. The traditional image fusion methods are generally successful at inserting spatial detail into the multispectral imagery despite the color information in the mechanism is distorted. The significant amount of research has been conducted over the past decade related to the application of wavelet transforms in image fusion. Wavelets have gained a lot of importance due to its energy compaction and multiresolution properties. This paper presents the overview of image fusion technique and the results from a number of wavelet-based image fusion schemes are compared.**

***Index Terms*—Image fusion, multispectral, multiresolution, wavelet transform.**

I. Introduction

Image fusion is one of the most vital techniques in the field of digital image processing. Image fusion is the process of incorporating numerous images from multimodal sources pertaining complementary features of specific images. It enhances the quality of an image for the purpose of human perception. The acquisition of an image that accommodates all significant objects in focus is often impracticable. To overcome this issue image fusion is used, it acquires a sequence of images with different focus orientation and fuses them to attain an extended depth of field in an image. Image fusion is widely used in the area of satellite imaging, medical diagnosis, military, object detection and recognition, robotic vision, surveillance and navigation guidance etc.

Conventional image fusion is categorized into three levels [1], which are signal level, feature level, and decision level fusion. The image fusion algorithms are application dependent. The signal level fusion represents fusing visual information associated with every pixel from the source images into a single image. Feature level image fusion involves fusing feature that has been extracted from independent images. Decision level image fusion represents fusion at a higher level and merges the interpretations of different images obtained by local decision makers. The feature level and decision level image fusion may not result in the accurate transfer of information.

The pixel level image fusion methods are categorized into two types based on the domain of operation which is spatial domain fusion and transforms domain fusion methods. The spatial domain fusion technique directly deals with the manipulation of pixel values of source images such as Intensity Hue Saturation (IHS) [2], [3] and Principal Component Analysis (PCA) [4], [5] are the techniques in the spatial domain. Transform domain fusion comprises of the pyramid based [6], [7] and wavelet based fusion technique [8].

This paper is organized as follows. Section II describes the image fusion techniques which involves spatial domain and frequency domain techniques. In Section III, Image quality analysis is presented. Simulation results are depicted in Section IV. The conclusion is summarized in V.

II. Image Fusion Techniques

An image that has been well fused by an effective fusion technique is a useful tool for increasing the ability of humans to interpret the image and for improving the accuracy. The image fusion techniques are developed based on specific applications. This section provides a brief review about the fusion techniques such as spatial domain and frequency domain.

A. Spatial Domain Technique

The IHS technique is a traditional technique in image fusion [2]. The visual representation of an image is controlled using three properties of a color which are based on Intensity, Hue and Saturation. The human visual system often uses these specific color space because they tend to consider it as roughly orthogonal perceptual axes. In satellite imaging applications, the arbitrary bands are designated to the RGB channel to accomplish false color composites for display purposes.

The IHS method is combined with the variational method in order to fuse the Panchromatic (PAN) and Multi-spectral (MS) images in [3]. The MS band is sharpened quickly by using the IHS model, but it distorts the color in the fusion results. This problem is solved by injecting the geometric structure of the PAN band with the substitute image of the IHS model. The radiometric distortion is reduced by defining the spectral energy term. The weighted parameters are adjusted in this method to obtain the better trade off between the spectral and spatial fusion quality. The better fusion results can be further obtained by using the different parameters.

The multifocal images are fused using PCA based adaptive algorithm in [4]. The information is extracted from the image using PCA in a hierarchical decomposition and the covariance matrix of each pixel is compared with the average covariance matrix. The highest weighted pixel obtained is considered as the useful information and further used in the fusion process. The former uses the optimized fusion method to address the issues such as, misclassification of the boundary

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and redundant calculations. This method features low cost for implementation and obtained image with better visual quality than the traditional methods. The computational complexity is high in this method which can be further reduced.

The multispectral palmprint recognition and spectral band compression method is proposed in [5]. It extracts the coefficients which are optimally weighted relative to the information content and redundancy removal. To obtain the higher accuracy the original multispectral palmprint images are represented using extremely low dimensional data.

The spatial domain technique has a drawback that it introduces spatial distortion in the fused image. However, the transform domain fusion techniques provide better spectral and spatial quality since the fusion is carried out on the transformed coefficients.

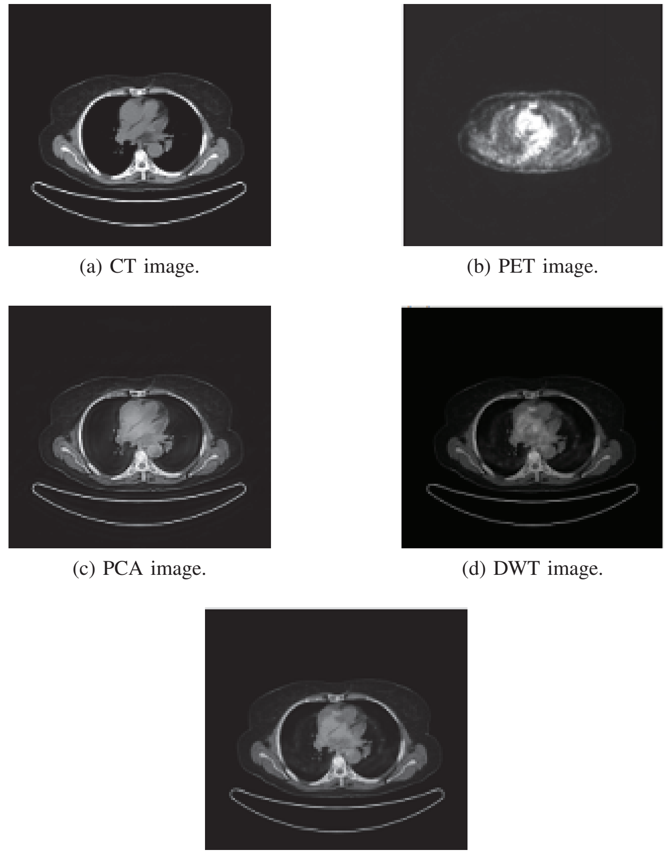
B. Frequency Domain Technique

An image pyramid represents an image at more than one resolution organized into pyramid levels of decreasing resolution. It creates the pyramid representation of the fused image from the pyramid decompositions of the input images. The inverse pyramid transform [6] is applied on the image to obtain fused image. The information about the sharp contrast changes is obtained using pyramid transformation. This method lacks in flexibility.

In [7] an image is analyzed and decomposed into a set of band-pass filtered images and each represents a different band of spatial frequency. To perform fusion the input images obtained from different sensors are first decomposed into their pyramid representations. The composite pyramid is formed by combining the respective pyramids using coefficient selection or averaging. The fused image is obtained from the composite pyramid using the multiresolution reconstruction process. Pyramid transforms are shift variant and fail to introduce any spatial orientation selectivity in the decomposition process, which often cause blocking effects in the fusion results.

The model based image fusion is proposed for Multi and Hyperspectral images in [8], to overcome the complexity and cost issues. The PCA is employed to reduce the dimensionality of the data due to the high spectral redundancy occurred in the hyperspectral images. This method performs the fusion process at lower dimensional principal component subspace. It achieved a very high resistance to noise in the data and the spectral band is estimated for first few principal components only thus the computational complexity is reduced.

The multimodal medical images are fused in [9] which is based on the hybrid algorithm. By applying PCA on image results in the spectral degradation between the fused images and the original low resolution image. The final fused image obtained using DWT have a less spatial resolution. To overcome these issues in the traditional methods the PCA and DWT methods are combined in order to enhance the quality of the image. The source images such as Computed Tomography (CT) and Positron Emission Tomography (PET) images are shown in Fig. 1(a) and (b). The fusion process is performed on these images using PCA, DWT and DWT-PCA



(a) CT image.

(b) PET image.

(c) PCA image.

(d) DWT image.

(e) DWT-PCA image.

Fig. 1. Image fusion using PCA and DWT based technique.

algorithms and the results obtained is shown in Fig. 1(c)–(e). The DWT is applied on the source images to decompose it into different subbands and PCA is applied on the low frequency subbands. Finally the results obtained using DWT-PCA based fusion algorithm is as shown in Fig. 1(d). It is observed that combining PCA and DWT better results can be obtained interms of visual and parametric measures when compared to PCA and DWT algorithms. The spectral resolution can be further increased. The undecimated discrete wavelet transform (UDWT) and contrast visibility are proposed in [10] inorder to overcome the blurring effects which existed in the traditional discrete wavelet transform based image fusion. For real-time systems, the multifocal images are fused more efficiently using UDWT. In this method first, the predefined kernel is convolved with the image which has to be fused followed by the extraction of edge features from the wavelet planes. Then the contrast visibility is computed for each wavelet planes. Finally, the best wavelet plane is selected to obtain the fused image. The maximum information is preserved in this method compared to traditional methods such as PCA and DWT. The fusion artifacts is introduced in the fused image due to the unwanted spreading of coefficients around overlapping image singularities. This reconstruction error can be further reduced by using non orthogonal filter banks.

The wavelet-based Bayesian fusion method is proposed in [11] for both fusions of Multi and Hyperspectral images and pansharpening. This method is based on the observation model in the wavelet domain. The hyperspectral image observed is linked to the high-resolution version which is spatially degraded and corrupted by additive gaussian noise. To avoid the deconvolution problem and to solve it, the hyperspectral images which are observed is interpolated to the same scale as the multispectral image is incorporated in the model. The computational complexity is high in this method.

The DT-CWT and gradient based fusion method is proposed in [12] to overcome the limitations of the DWT such as shift invariance and poor directional selectivity. This method attains six directional subbands which is oriented at $\pm 15°$, $\pm 45°$, $\pm 75°$ at each scale to enhance the directional selectivity. The spatial resolution of the image is increased by retaining the low pass subbands and fusing the detail coefficients using absolute maximum gradient. Finally, the fused image is obtained with limited redundancy, approximate shift invariance and good directional selectivity. The former showed the consistency between the visual content and results of the objective measures.

The multiresolution 2-D images are proposed in [13], which is based on wavelet transform under the combination of gradient and smoothness criterion. The experiments are conducted on various images such as the multifocus, multisensory satellite image. The results of this method are compared qualitatively and quantitatively using various wavelet transform based image fusion methods and it produced the better fused image than traditional methods. The employment of gradient criterion in the fused algorithms assures the edges in the images and the effect of noise is reduced using smoothness criterion.

In [14] the quaternion wavelet transform (QWT) is proposed to fuse multifocal image. It eliminated the blurring problem occurred in images. The QWT is applied to particular color images to obtain the QWT coefficients. Then these coefficients are subjected to different fusion rules to obtain the multiresolution representation. Finally, the inverse QWT is applied to retrieve the fused color image. This method showed better results for multifocal images.

In [15] the hybrid algorithm is proposed. It addressed the combination of image fusion and denoising. The contrast-based fusion of noisy images using discrete wavelet transform has been proposed, which considers contrast of images using local variance of the denoised DWT coefficients of the noisy source images as well as the noise strength. The fused image produces denoised image with better quality. It retains the useful information without introducing artifacts. The former method is used only for gray images which can be further improved for color images.

The image fusion using shearlets is proposed in [16]. The shearlet transform retains the features such as directionality, multi scalability, anisotropy, and localization. Using this transform the image can be decomposed in either scale and direction. The image decomposition in multi-direction is performed using shear matrix. The low and high-frequency coefficients of two source images are averaged and it replaces the fused image. The region based consistency check is performed on the resulting decision map. Performance evaluation is performed and the results showed that this method provided precise information and smaller distortion.

The stationary wavelet transform is proposed in [17] to overcome the need of translation and invariance of the DWT. The downsampling and upsampling of the filter coefficients by a factor of two achieves the translation and invariance. It is an undecimated wavelet transform. This wavelet transform works better in noisy environment.

In [18] a region based contourlet transform is proposed which preserves directionality, localization, and anisotropy on the fused image. The transformation and decomposition are the two stages which are generally implemented followed by fusion rule. The scheme of double filter bank is applied for the first stage of transformation and the decomposition is performed in the next stage considering certain fusion rules. The reconstruction procedure is performed finally to retrieve the fused image. This method increases the computational complexity.

The non subsampled contourlet transform (NSCT) is proposed in [19] inorder to overcome the disadvantages of wavelet based image fusion techniques such as shift invariance, deficiency of phase information and incomplete directionality. The structural information is retained in NSCT while decomposing and reconstructing the images. It contains a structure of filter bank that partitions the two dimensional image into a non subsampled pyramid structure and directional filter bank structure that results in multiscale property and directionality. It uses more memory resources which lead to increase in cost, this issue has to be resolved by the means of GPU-based system.

The improved fusion method is proposed in [20] which is based on NSCT transform and pulse coupled neural network (PCNN). The PCNN contains features such as global coupling and synchronous pulse release which results in the extraction of necessary information from the complex background. The NSCT method is used to acquire the edge and contour information of the images. It decomposes the source images into low and high-frequency components, where the regional variance is used for fusing low-frequency components and high-frequency components are fed to PCNN neurons as external input, it retains the details of the information such as texture and edges. The image quality is improved and it obtained better results both subjectively and objectively. The mutual information contained in the fused image is comparatively small than traditional methods.

The algorithm based on fuzzy clustering model and image change detection is proposed in [21] for remote sensing applications. The wavelet transform is applied on the source images to obtain the extensive differencing map, it reduces the noise and reserves the variation characteristics. The traditional clustering algorithms are modified to increase the final result of the change map. The detection accuracy obtained using this method is higher than previous approaches. The experimental results conducted for the former increased the alarm and false alarm rates at balanced rate. It has to further increase the feasibility for larger ranges.

III. Image Quality Analysis

The image fusion process should preserve all authentic and suitable pattern information from the input images and it should not introduce any artifacts that could hamper with subsequent analysis. To measure the performance of an image with different fusion schemes the parameters used are discussed in this section.

A. Entropy

The quantity of information contained in an image is estimated using Entropy [H]. The higher the entropy value after fusing image, the more will be the information contained in an image and the fusion performance is improved.

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

where p_l is the probability of intensity value l in an image.

B. Standard Deviation

Standard deviation (SD) indicates the contrast size of an image.

$$SD = \sqrt{\frac{\sum_{i-1}^{m}\sum_{j-1}^{n}(f(i,j)-\hat{F})^2}{mn}} \tag{2}$$

where $f(i,j)$ is the intensity of the pixel at (i,j) and m, n are the size of rows and columns of the image. $\hat{F}$ is the average pixel intensity of original image $f(i,j)$.

C. Total Fusion Performance Measure

The total fusion performance parameter $Q^{AB/F}$ is estimated as a weighted sum of source images A and B's edge information. The absolute information conveyed from input images to fused images are obtained.

$$Q^{AB/F} = \frac{\sum_{\Delta n,m} Q^{AF}_{n,m} w^A_{n,m} + Q^{BF}_{n,m} w^B_{n,m}}{\sum_{\Delta n,m} w^A_{n,m} + w^B_{n,m}}. \tag{3}$$

D. Fusion Loss

The total information lacked during the fusion process is measured using

$$L^{AB/F} = \frac{\sum_{\Delta n,m} r_{n,m}[(1-Q^{AF}_{n,m})w^A_{n,m} + (1-Q^{BF}_{n,m})w^B_{n,m}]}{\sum_{\Delta n,m} w^A_{n,m} + w^B_{n,m}} \tag{4}$$

where $r_{n,m}$ [22] is a flag which indicates the value 1 or 0.

E. Fusion Artifacts

Fusion artifacts are estimated as a perceptually weighted integration of the fusion noise estimates over the entire fused image. It represents unwanted information added during the fusion process

$$N^{AB/F} = \frac{\sum_{\Delta n,m} N_{n,m}(w^A_{n,m} + w^B_{n,m})}{\sum_{\Delta n,m} w^A_{n,m} + w^B_{n,m}}. \tag{5}$$

The fusion loss at different locations containing fused gradients that are stronger than input is estimated using $N_{n,m}$ [22].

IV. Simulation Results

The experiment is performed using different wavelets on a multifocus disk image. The analysis of different wavelet transforms is evaluated in terms of visual interpretation and performance criteria. The source images are first decomposed and the subbands are fused using pixel level fusing rule. The fused image are reconstructed using the wavelet coefficient and the performance is measured using parameters Entropy, Standard deviation, Fusion loss, Fusion artifacts. To compare the visual performance the fused image is shown in Fig. 2 respectively. The source images which are focused on different focal length is shown in Fig. 2(a) and (b). The pixel level fusion is applied on these source images using wavelets coiflet5, daubechiesb8, daubechies16, symlet8 and biorthogonal6.8 and the results of the fused image is obtained as shown in Fig. 2(c)–(g) respectively. It is visualized that the quality of integrated images using different wavelets is optically identical. The fused images contain complete information from input images without introducing artifacts. It is impossible to analyze the performance of the fused image visually in this scenario thus in Table I the quantitative measure is tabulated. It is observed that among different wavelets symlet wavelet performs better than other wavelets in terms of $Q^{AB/F}$ and $L^{AB/F}$. Thus it is visualized that fusion using the redundant representation shows better results with regards to preserving the fidelity of finer details and the consistency of dominant features during the fusion of images with different focus points thus reducing the ringing artifacts and increasing the visual interpretation of an image.

V. Conclusion

In this article, the comparative study of different Image fusion approaches and the related work was done till now is presented. The image fusion using various techniques to extract the significant information from the source images and to enhance the visual quality of an image is discussed. It is observed that high spatial resolution is obtained in traditional image fusion techniques which result in image blurring problem. To overcome these issues wavelet based image fusion technique is proposed. Wavelets provide a high quality spectral content with least spectral distortion. In this article different wavelet transform are applied on pixel level based image fusion and the results are compared using different objective based performance measures. The results showed that the

(a) Source image A.

(b) Source image B.

(c) coif8.

(d) db8.

(e) db16.

(f) sym8.

(g) bior6.8.

Fig. 2. Image fusion using wavelet based technique.

TABLE I
PERFORMANCE MEASURES.

Measure	coif5	db8	db16	sym8	bior6.8
H	7.2771	7.2793	7.2785	7.2766	7.2774
SD	45.7241	45.6889	45.5495	45.8451	46.0142
$Q^{AB/F}$	0.8919	0.8899	0.8877	0.8939	0.8936
$L^{AB/F}$	0.1046	0.1064	0.1087	0.1031	0.1038
$N^{AB/F}$	0.0254	0.0256	0.0260	0.0241	0.0182

symlet wavelet performed better in terms of the performance measure. In the future more efficient wavelet transform can be used to obtain the better quality image which produces less artifacts, memory resources and preserves the color.

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