International Journal of Recent Technology and Engineering (IJRTE)
ISSN: 2277-3878, Volume-8 Issue-5, January 2020

Image Fusion Techniques:

Rahul D, Vishnukumar S

Abstract: Image Fusion is a pioneering technique in the area of image processing to generate high quality images. In image fusion, more than one images of a scene with varying conditions are considered and fused together to get an image with more details than the input images. The required features and details will be enhanced in fused image. This technique is used in different areas of application for correcting and enhancing the details that are not visible in sources. This paper provides a clear idea about different Image Fusion approaches. A detailed review on advanced Multi-Exposure Image Fusion methods is also provided. A comparative study on important multi-exposure image fusion methods are done both quantitatively and qualitatively.

Keywords: Multi-Exposure, Image Fusion, Multi-Focus

I. INTRODUCTION

The image fusion is an important method of combining pertinent information from more than one image to provide an image with more information than the input images. The useful details and important features are highlighted in the fused image by avoiding inconsistencies. Optical sensor limitations and imaging conditions may prevent the capturing of entire detail in a single image. In this situation, Image Fusion techniques can be used to incorporate the missing details. Incapability to focus on two items located at different focal lengths and limited depth of field and are major limitations of lenses. Orientation of light source relative to the object of interest and shadows usually lead to loss of information in natural scenes. These problems can be overcome by reconstructing the complete information using fusion of multiple images containing partial information about the scene. Image fusion techniques are mainly used in areas such as astronomy, military, medical imaging and remote sensing. Fusion of images is applied for improving geometric corrections, sharpening the images and enhancing features that are not visible in input images.

Following are the desirable properties of an ideal image fusion technique:

1. It must preserve the useful details of input images.
2. It should not produce artifacts.
3. It must be powerful even with imperfect conditions

Manuscript published on January 30, 2020.
* Correspondence Author
Rahul D*, Department of Computer Science, University of Kerala, Kariavattom, Thiruvananthapuram, Kerala, India. Email: drahul198@gmail.com
Vishnukumar S, Department of Computer Engineering, Govt. Polytechnic College, Nedumkandam, Idukki, Kerala, India. Email: vishnukumars2006@yahoo.co.in

II. CLASSIFICATION OF IMAGE FUSION TECHNIQUES

Image fusion techniques can be mainly classified into two classes such as Spatial Domain Fusion technique and Transform Domain Fusion technique.

A. Spatial Domain Techniques

Spatial domain methods are directly applied on image pixels. The pixel values are manipulated to obtain the intended result. Following are the important steps involved in spatial domain techniques:

1. Production of a quantitative map of the content for each image.
2. Differentiation of content at the pixel level
3. Allocating weights to pixels depends on content, and
4. Weighted combination to generate the fused image.

Averaging, Principal component analysis, Intensity-Hue-Saturation method and Brovey method are examples of spatial domain Fusion methods. The spatial distortion in the resultant image is the major disadvantage of spatial domain methods.

B. Transform Domain Techniques

The image is initially converted into frequency domain (Fourier transform) in Transform domain techniques. The Fusion activities are applied on the fourier transform of the image and the resultant image is obtained by applying Inverse Fourier transform. Discrete wavelet based method, Laplacian transform based method and Curvelet transform based methods are examples of transform domain techniques. Compared to spatial domain fusion methods, transform domain methods provide better performance in spectral quality and spatial quality of the fused image.

Image fusion operations are done at four different phases called signal-level, pixel-level, feature-level, and decision-level.

C. Signal-Level Fusion

Signal-level fusion is performed on signals from different sensors and these input signals are merged to produce a signal with greater signal-to-noise ratio compared to the input signals.

D. Pixel-Level Fusion

Pixel-level fusion is accomplished on the pixels of the images in ordered manner. In pixel-based methods, based on a function of the input images a weighted sum is computed at each pixel location.

E. Feature-Level Fusion

Feature-level fusion needed the extortion of objects identified in input set and salient features depending on edges, textures or pixel intensities. The similar features from input images are fused to obtain the resultant image.

F. Decision-Level Fusion

Decision-level fusion incorporates the results of various methods to generate the resultant image. Input images are considered separately to extract details and the extracted details are merged by applying decision rules, thereby common interpretation is reinforced in the generation of fused image.

G. Single-Sensor Image Fusion

A series of images is captured by single sensors. These sequences of images are fused to obtain the resultant image with optimum information content. Performance of this system is highly depending on the capability of imaging sensor such as dynamic range, resolution and environmental conditions under which it can operate.

H. Multi-Sensor Image Fusion

Multi-sensor image fusion method merges the images from different sensors to form the resultant composite image and thereby overcome the problems in single-sensor image fusion. Here infrared cameras and digital cameras are used to incorporate daylight scenes and poorly illuminated scenes respectively.

I. Multi-Focus Image Fusion

This image fusion method combines more than one images of the same location captured with dissimilar focus positions. A single all-in-focus image with enlarged depth of field will be generated as the result.

J. Multi-Exposure Image Fusion

In a digital photo some areas may be bright (over-exposed) and other portions may be (under-exposed). The presence of low dynamic range (LDR) and high dynamic range (HDR) in a single image leads to the use of fusion techniques for multi-exposure images. Multi-scale exposure fusion can directly produce high quality LDR image by fusing differently exposed LDR images of an HDR scene. But halo-artifacts in the resultant image is a challenge in multi-exposure image fusion.

III. NON-FUSION PROCESSES

The three important non-fusion processes are explained in this section.

A. Image Registration

Image registration process aligns the input images spatially and temporally with each other in order to fuse them properly. With the help of image registration process, lens distortions, resolutions, fields of view, and frame rates of input images are matched and make them to be suitable for fusion process.

B. Image Pre-Processing

Certain pre-processing of the images is desirable before fusion process. Pre-processing removes artifacts and enhances the details required in the resulting image. The noise characteristics, dynamic range and sensitivity of each image are unified in this stage. The use of pre-processing in a wise manner will improve the performance of the fusion process.

C. Image Post-Processing

The post-processing phase is depending on the display type, fusion system and the choice of operator. The basic desirable post-processing is the offset correction and automatic gain that allows manipulations in dynamic range of the resultant image. Suitable display-specific processing is also done during post-processing required.

IV. IMAGE FUSION ALGORITHMS

A. Linear Weighted Average Method

The most simple image fusion method is the application of a linear weighted average of input images as follows:

$$F(x,y) = w_A.A(x,y) + w_B.B(x,y) \qquad (1)$$

Where w_A and w_B are scalars. This method is simple, fast and also suppresses noise in the input images. But it suppresses the salient image features that lead to the production a low contrast fused image.

B. Principal Component Analysis Method

The problem with linear weighted averaging can be overcome by selecting the ‘optimal’ weights. The Principal component analysis (PCA) is a technique to find optimal weights that maximizes the variance of intensity in the required image. The covariance matrix of two images is computed in the first step as follows:

$$\text{C}=\begin{bmatrix} v_A & c_{AB} \\ c_{AB} & v_B \end{bmatrix} \qquad (2)$$

$$v_A = \frac{1}{mn}\sum (A(x,y) - \mu_A)^2 \qquad (3)$$

$$v_B = \frac{1}{mn}\sum (B(x,y) - \mu_B)^2 \qquad (4)$$

$$c_{AB} = \sum (A(x,y) - \mu_A)(B(x,y) - \mu_B \qquad (5)$$

$$\mu_A = \frac{1}{mn}\sum A(x,y) \qquad (6)$$

$$\mu_B = \frac{1}{mn}\sum B(x,y) \qquad (7)$$

By solving the characteristic equation det(C- λI), the eigen values λ_1 and λ_2 of the covariance matrix C are computed. Here I is the identity matrix. w_A, w_B are the optimal weights, the elements of the normalized eigenvector corresponding to the largest eigen value.

One of the input images is selected in PCA method rather than fusing the salient information within in the input images. It uses global variance as a saliency measure and stronger weight is assigned to the input image with higher variance, this property is a disadvantage. This method is also very sensitive to blooming, noise, dead pixels, and other unwanted artifacts.

C. Pyramidal Schemes

A pyramidal scheme is an example for multi-resolution methods. Multi-resolution image fusion schemes overcome the drawbacks of pixel averaging technique. It extracts the salient features such as edges and textures of each input image at various levels of decomposition combine these features to produce the resultant image. This method generally produces high-contrast, sharp images with greater information content and clarity.

The image pyramid concept was introduced in 1980s [1]. The image pyramid is a data structure constructed with sequence of band-pass or low-pass version of image with information pattern in various scale. Gaussian pyramid is an example of pyramid scheme.

D. Wavelet Schemes

The Wavelets were put forwarded in 1980s and it is used for fractal analysis, pattern matching and image coding. The discrete wavelet transform (DWT) represents and analyze data similar to Fourier transform. In wavelet, the basis is a set of functions generated by translating and dilating a function called analysis wavelet. So the wavelet representation is localized spatially and in spectral frequencies level, thereby it is ideal for representing non-uniform data. A signal f(x) is represented as a combination of wavelets by DWT, mathematically it can be represented as follows:

$$f(x) = \sum_{p,q} c_{p,q} \varphi_{p,q}(x) \qquad (8)$$

Where the wavelet functions $\varphi_{p,q}(x)$ are dilated and translated versions of wavelets φ_x .The integer p is the scale index that defines the position and the integer q is the location index that defines position of each wavelet. The two-dimensional DWT is accomplished as sequential applications of the one-dimensional DWT and as a result an image with the wavelet coefficients for different scale is formed.

In 1990 s the first wavelet fusion schemes was reported and it qualitatively and quantitatively outperform the pyramidal techniques in [2][3][4]. With the application of wavelet transform, the input images are decomposed and on application of some rules θ , the different levels are fused together. By using inverse wavelet transform, the resultant image is reconstructed. The process is shown in Figure 1. The DWT is computationally efficient and produces good results. Figure 1 shows the generic wavelet fusion schemes.

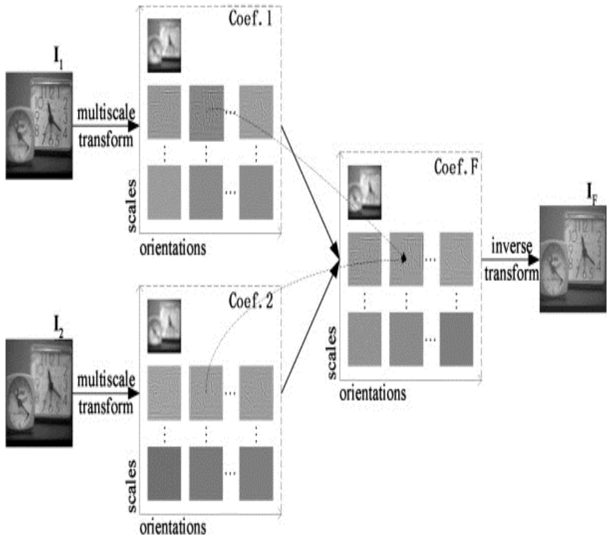

Fig 1: Generic Wavelet Fusion Scheme

E. Advanced Multi-Exposure Image Fusion Methods

This section presents a review and comparative study on different advanced multi-exposure image fusion techniques.

Li et al [5] proposed a fusion method using discrete wavelet frame transform (DWFT) and the support vector machines (SVM). First the features are extracted using DWFT coefficients. The SVM is used to identify the input image with best focus at each pixel location, and with the incorporation of corresponding DWFT coefficients, a composite wavelet representation is generated. Input image details will be preserved by this method. But spatial consistency is not preserved.

Goshtasby et al [6] proposed a multi-exposure images fusion method for static scene copied by a stationary camera. The method divide the image into constant blocks and for these blocks identifies the image with high details within the block. These identified images are merged together by monotonically decreasing blending functions. The main challenge with this method is the selection of the image with high details within block. The local color and contrast will not be changed by this method.

Mertens et al [7] proposed fusion method for an exposure sequence of image, without HDR conversion. Skipping the HDR building stage makes the acquisition pipeline process simple and avoids camera response curve calibration. With the help of quality measures, contrast and saturation, this method blends multiple exposures images. The resulting image quality is comparable with other methods. This method produces artificial color distortions and edges in the resultant image.

Raman et al [8] proposed a fusion method using edge preserving bilateral filter. This method is computationally efficient. The challenge with this method is the merging of multi-exposure images having dark and bright areas within a small dynamic range.

Li et al [9] proposed a multi-exposure image fusion technique based on weighted sum. Image features, color dissimilarity, brightness and local contrast are measured and used for computation of the weight maps and recursive filters are used to refine the same. Finally, the resultant image is generated using weighted sum of input images.

Key merits of this method are the ability to find accurate weight maps with the help of recursive filtering. This method is comparatively fast, but fails in the correct usage of color information as it considers the RGB color channels separately.

Li et al [10] proposed a multi-exposure fusion method using a two-scale decomposition approach. The image is initially divided into a base layer with large-scale intensity variation and a detail layer with small-scale information. Spatial consistency is ensured in both the layers with weighted averaging using guided filter. By subtracting the base layer from the input image, a detail layer is produced. Weight map for input image is generated with guided image filter. High pass image is obtained by applying Laplacian filter. Then saliency map is obtained by local average of the absolute value of high-pass image and the weight map is determined by comparing saliency map. The refined weight map is generated by applying guided image filtering over weight map with the corresponding input image. Then the base layer and detail layers of various input images are merged together by weighted averaging. Finally, by combining merged detail layer and merged base layer, the fused image is obtained.

K. Ma et al [11] proposed a multi-exposure image fusion method that avoids ghosting effect. The image patch is divided into three elements called mean intensity, signal structure, and signal strength. These three elements are fused separately, to construct the required patch and replace back into the resultant image. In this method, post-processing is not required. Here RGB color channels are considered jointly to ensure the correct color appearance. This method effectively removes the ghosting effect.

The performance of three important multi-exposure image fusion methods, [8], [9] and [10] are compared qualitatively and quantitatively. Figure 2 shows the results of methods [8], [9] and [10] applied on the image set Belgium house. It is visible that, the result of method [10] is visually better than the results of other methods. The quantitative evaluation is done with Blur metric [12] and Blind image quality metric [13]. Lower values of these metrics show higher performance. Table 1 shows the comparison with these metrics. From table 1, it is evident that the method [10] provides better performance compared to others.

(a) Result of method in [8]

(b) Result of method in [9]

(c) Result of method in [10]

Fig. 2: Comparison of multi-exposure image fusion methods

Table 1
Comparative Study

Input Images	Metrics	Result by [8]	Result by[9]	Result by [10]
Belgium House	Blur Metric Blind Metric	0.2896 24.154	0.2836 25.907	0.2684 26.630
House	Blur Metric Blind Metric	0.2790 37.118	0.2768 32.293	0.2745 34.979
Venice	Blur Metric Blind Metric	0.2678 31.264	0.2624 23.157	0.2576 19.055
Cadik Lamp	Blur Metric Blind Metric	0.3371 28.116	0.3325 24.459	0.3209 22.449

V. CONCLUSION

Image Fusion algorithm combines information from input images and generating a single merged output image. This paper described various Image Fusion techniques and reviewed different multi-exposure image fusion methods. A comparative study on three important multi-exposure image fusion methods is done quantitatively and qualitatively.

REFERENCES

1. E. Adelson, C.H. Anderson, J.R. Bergen, P.J. Burt and J.M. Ogden, Pyramid methods in image processing, RCA Engineer 29, 33-41, 1984
2. H. Li, B.S. Manjunath and S.K. Mitra, Mulitsensor image fusion using the wavelet transform ,Proc. IEEE International Conference on Image Processing, Austin, Texas, vol. 1, pp. 51-55, 1994.
3. L.J. Chipman, T.M. Orr and L.N. Lewis, Wavelets and image fusion , IEEE Transactions on Image Processing, 3,pp. 248-251, 1995.
4. I. Koren, A. Laine and F. Taylor, Image fusion using steerable dyadic wavelet transforms, Proc. IEEE International Conference on Image Processing, Washinton D.C., pp. 232-235, 1995.

5. S. Li, J. Kwok, I. Tsang, and Y. Wang, Fusing images with different focuses using support vector machines, IEEE Trans. Neural Netw., vol. 15, no. 6, pp. 1555-1561, Nov. 2004
6. A. Goshtasby,Fusion of multi-exposure images ,Image Vision Comput.., vol.23, no.6, pp. 611-618, 2005.
7. T. Mertens, J. Kautz and F. Van Reeth, Exposure fusion, Proc. Pacific Graphics, pp. 382-390, 2007.
8. S. Raman and S. Chaudhuri, Bilateral filter based compositing for variable exposure photography, in Proc. Eurographics, 2009, pp. 14.
9. S. Li and X. Kang, Fast multi-exposure image fusion with median filter and recursive filter, IEEE Trans. Consum. Electron., vol. 58, no. 2, pp. 626632, May 2012.
10. S. Li, X. Kang, and J. Hu, Image fusion with guided filtering, IEEE Trans. Image Process., vol. 22, no. 7, pp. 28642875, Jul. 2013
11. K. Ma, H. Li, H. Yong, Z. Wang, D. Meng, and L. Zhang, Robust MultiExposure Image Fusion: A Structural Patch Decomposition Approach,IEEE Trans. on Image Proc., vol. 26, pp. 2519-2532, May 2017.
12. P. Marziliano, F. Dufaux, S. Winkler, T. Ibrahimi, A no-reference perceptual blur metric, International conference on image processing, vol. 13, pp.57-60, Rochester, NY 2002.
13. A. K. Moorthy and A. C. Bovik, A Two-Step Framework for Constructing Blind Image Quality Indices, IEEE Signal Processing Letter, vol. 17, no.5, pp.513-516, May. 2010.