Performance Analysis of Image Fusion Techniques: A Review

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Abstract: Image fusion combines multiple images of the same scene into a single image which is suitable for human perception and practical applications .Image fusion is done to reduce amount of data, retain important information and to create new image that is more suitable for further processing tasks. Input images could be multi sensor, multimodal multi focal and multi temporal. This paper presents a literature review on some of the basic image fusion techniques i.e. wavelet transform image fusion, PCA based image fusion and IHS based image fusion and introduces a hybrid approach which combines PCA, HIS and SWT (Stationary Wavelet Transformation) to get an enhanced fusion image with less possible changes in the pixels and resolution of the images.

Keywords: Image; Image Fusion; Standard fusion methods; Complex fusion methods; PCA; IHS; Wavelet; SWT.

I. INTRODUCTION

An image (from Latin: imago) is an artifact that depicts or records visual perception, for example a two-dimensional picture, that has a similar appearance to some subject – usually a physical object or a person, thus providing a depiction of it. Images may be two-dimensional, such as a photograph, screen display, and as well as a three-dimensional, such as a statue or hologram. They may be captured by optical devices – such as cameras, mirrors, lenses, telescopes, microscopes, etc. and natural objects and phenomena, such as the human eye or water surfaces.

In computer vision, Multi sensor Image fusion is the process of combining relevant information from two or more images into a single image. The resulting image will be more informative than any of the input images. Image fusion is the process that combines information from multiple images of the same scene. These images may be captured from different sensors, acquired at different times, or having different spatial and spectral characteristics. The objective of image fusion is to retain the most desirable characteristics of each image.

In remote sensing applications, the increasing availability of space borne sensors gives a motivation for different image fusion algorithms. Several situations in image processing require high spatial and high spectral resolution in a single image. Most of the available equipment is not capable of providing such data convincingly. The image fusion techniques allow the integration of different information sources. The fused image can have complementary spatial and spectral resolution characteristics. However, the standard image fusion techniques can distort the spectral information of the multispectral data while merging.

Some image fusion methods are:

- IHS transform based image fusion
- PCA based image fusion
- Wavelet transform based image fusion.

IHS transform image fusion: The IHS technique is a standard procedure in image fusion, with the major limitation that only three bands are involved. Originally, it was based on the RGB true color space. It offers the advantage that the separate channels outline certain color properties, namely intensity (I), hue (H), and saturation (S). This specific color space is often chosen because the visual cognitive system of human beings tends to treat these three components as roughly orthogonal perceptual axes.

PCA transform image fusion: The first principal component image contains the information that is common to all the bands used as input to PCA, while the spectral information that is unique to any of the bands is mapped to the other components. Then, similar to the IHS method, the first principal component (PC1) is replaced by the HRPI, which is first stretched to have the same mean and variance as PC1.As a last step, the HRMIs are determined by performing the inverse PCA transform .In data sets with many variables, groups of variables often move together. One reason for this is that more than one variable might be measuring the same driving principle governing the behavior of the system. In many systems there are only a few such driving forces. But an abundance of instrumentation enables you to measure dozens of system variables. When this happens, you can take advantage of this redundancy of information. You can simplify the problem by replacing a group of variables with a single new variable. Principal component analysis is a quantitatively rigorous method for achieving this simplification. The method generates a new set of variables, called principal components. Each principal component is a linear combination of the original variables. All the principal components are orthogonal to each other, so there is no redundant information. The principal components as a whole form an orthogonal basis for the space of the data. There are an infinite number of ways to construct an orthogonal basis for several columns of data.

Wavelet Transform image fusion: A multi-resolution decomposition of an image in a bi-orthogonal basis and results in non-redundant image representation. This basis is called wavelets. First the images are transformed to the wavelet domain with the function wfusimg(), where the number of scales, the wavelet filter and the edge handling are specified .Then, a decision mask is built in the same way as it was explained in the Laplacian fusion implementation. The next step is carried out by constructing the fused transformed image with this decision mask. Finally, the fused image is obtained by applying an inverse wavelet transform. Now let's discuss the particular type of wavelet transformation used in this thesis i.e. the Stationary Wavelet Transformation (SWT). The Stationary wavelet transform (SWT) is a wavelet transform algorithm designed to overcome the lack of translation-invariance of the discrete wavelet transform (DWT). Translation-invariance is achieved by removing the down samplers and up samplers in the DWT and up sampling the filter coefficients by a factor of in the nth level of the algorithm. The SWT is an inherently redundant scheme as the output of each level of SWT contains the same number of samples as the input – so for a decomposition of N levels there is a redundancy of N in the wavelet coefficients. This algorithm is more famously known as "algorithme à trous" in French (word trous means holes in English) which refers to inserting zeros in the filters. It was introduced by Holschneider et al. Stationary Wavelet Transform (SWT), also known as undecimated wavelet transform or Algorithme à trous is a translation-invariance modification of the Discrete Wavelet Transform that does not decimate coefficients at every transformation level

The following block diagram depicts the digital implementation of SWT.

A 3-level SWT Filter Bank.

In the above diagram, filters in each level are up-sampled versions of the previous SWT filters.

II. RELATED WORK

The proposed SPD approach is essentially dynamic range independent. Therefore, it would be interesting to explore its potential use in HDR reconstruction to generate high quality HDR images with little ghosting artifacts. Moreover, the application of SPD is not limited to MEF. As a generic signal processing approach, SPD has been found to be useful in image quality assessment of contrast-changed [66] and stereoscopic images [67]. It is worth considering whether SPD offers any insights that can be transferred to other image processing applications. In addition, although objective quality models for MEF algorithms begin to emerge, the models for objectively comparing MEF algorithms for dynamic scenes are largely lacking. Therefore, it is demanding to switch the focus from developing MEF algorithms for dynamic scenes to developing such objective quality models in order to conduct a fair comparison [1].

The process of image fusion the good information from each of the given images is fused together to form a resultant image whose quality is superior to any of the input images. Image fusion method can be broadly classified into two groups

1. Spatial domain fusion method

2. Transform domain fusion.

In spatial domain techniques, we directly deal with the image pixels. The pixel values are manipulated to achieve desired result. In frequency domain methods the image is first transferred in to frequency domain. It means that the Fourier Transform of the image is computed first. All the Fusion operations are performed on the Fourier transform of the image and then the Inverse Fourier transform is performed to get the resultant image. Image Fusion applied in every field where images are ought to be analyzed. The fusion methods such as averaging, Brovey method, principal component analysis (PCA) and IHS based methods fall under spatial domain approaches. Another important spatial domain fusion method is the high pass filtering based technique. The disadvantage of spatial domain approaches is that they produce spatial distortion in the fused image. Spectral distortion becomes a negative factor while we go for further processing such as classification problem [11].

Spatial distortion can be very well handled by frequency domain approaches on image fusion. The multi resolution analysis has become a very useful tool for analyzing remote sensing images. The discrete wavelet transform has become a very useful tool for fusion. Some other fusion methods are also there such as Laplacian- pyramid based, Curvelet transform based etc. These methods show a better performance in spatial and spectral quality of the fused image compared to other spatial methods of fusion [11].

There are various methods that have been developed to perform image fusion. Some well-known image fusion methods are listed below:-

(1) Intensity-hue-saturation (IHS) transform based fusion

(2) Principal component analysis (PCA) based fusion

(3) Multi scale transform based fusion:-

(a) High-pass Filtering Method

(b) Pyramid Method:-

(i) Gaussian pyramid (ii) Laplacian Pyramid (iii) Gradient pyramid (iv) Morphological pyramid (v) Ratio of low pass pyramid

(c) Wavelet Transforms:-

(i) Discrete wavelet transforms (DWT) (ii) Stationary wavelet transforms (SWT) (iii) Multi-wavelet transforms

(d) Curvelet Transforms

The fused images exhibited spectral accuracy with less spatial distortion and also show high correlation and entropy value compared to other two techniques [12].

The paper for implementation of the techniques [4] is reviewed. In this paper the three techniques are implemented namely HIS, PCA and wavelet. Also the comparison between three techniques based on parameters mean square error, normal cross correlation, peak signal to noise ratio is reviewed in this paper. This review results that spatial domain provide high spatial resolution. But spatial domain have image blurring problem. The Wavelet transforms is the very good technique for the image fusion provide a high quality spectral content. But a good fused image have both quality so the combination of DWT & spatial domain fusion method (like PCA) fusion algorithm improves the performance as compared to use of individual DWT and PCA algorithm. This paper reviewed has a reference of recent paper [5] .Besides this paper one more paper is reviewed about implementation and comparison of these three techniques [6]. Basically, this paper concludes that along this research, some image fusion approaches have been studied. All of them were found reliable fusion methods in multifocal applications, and in this paper has syntax, functions, implemented rules for the fusion techniques conjunction h. As previously mentioned, due to the subjective characteristic of the fusion quality evaluation they gave acceptable results in multisensory fusion schemes, excepting the spatial frequency approacn, it is difficult to conclude which method is the best one for a certain application.

The combination of the techniques of fusion is also done. The techniques HIS + wavelet and PCA + wavelet. Review on the combination the technique is done by referring to the paper [7]. This recent research concludes that PCA combined wavelet transform produce better results spatially, spectrally for the lunar image data compared to other methods. A wavelet combined transform with HIS, PCA to obtain appreciable spatial and spectral resolution. The results shows that the combination of HIS and wavelet produce the fused image with high resolution, clarity and information with less spectral distortion [7].

Morphological processing and Combination of DWT with PCA and Morphological techniques have been popular fusion of image[8][9][10]. These methods are shown to perform much better than simple averaging, maximum, minimum.

Fusion applied in every field where images are ought to be analyzed. For example, medical image analysis, microscopic imaging, analysis of images from satellite, remote sensing Application, computer vision, robotics etc[11].

III. CONCLUSION

In the proposed technique it is seen that the performance parameters are considered more in count for determining the performance of the overall system. Increase in quality determines that the approach used in this thesis is much better than the traditional techniques used for image fusion as stationary wavelets are used so the stability of conversion is more along with the hybridization of IHS and PCA. Results are improved than the traditional approaches.

IV. FUTURE WORK

In this technique it is proposed to that the stationary wavelets are better than the traditional approaches of image fusion for the further research in same are the techniques on bases of division of images for further information extraction will be more suitable and enhancement of fusion can be done by approaching toward the field of pyramidal modals of image fusion.

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