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An Improved & Hybrid CLAHE-IHS Based Image Fusion Technique

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ABSTRACT

Image fusion is a process which combines the data from two or more source images from the same scene to generate one single image. It contains more precise details of the scene compared to the source images. The image fusion methods like averaging, principle component analysis and various types of Pyramid Transforms, and ANN (Artificial Neural Networking) they are the most common approaches. In this technique we have propose a new fusion scheme for fusing the CLAHE-IHS(Contrast Limited Adaptive Heist Eqn-Intensity Hue Saturation) method used for its efficiency and high spatial resolution to improve the spectral quality of the image. In this process we improve spectral resolution compared to the original image. The adaptive CLAHE-IHS method produces images with higher spectral resolution along the high-quality spatial resolution of the original image. The output image will contain better quality. The performance of the resultant image may calculated by histogram & PSNR (Peak Signal to Noise Ratio).

Keywords: *Artificial Neural Networking**,** Contrast Limited Adaptive Heist Eqn-Intensity Hue Saturation**,** Peak Signal to Noise Ratio.*

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1. INTRODUCTION

Typical examples of multi-band images include hyper spectral (HS) images , multi-spectral (MS)images , integral field spectrographs , magnetic resonance spectroscopy images etc. However, multi-band imaging generally suffers from the limited spatial resolution of the data acquisition devices, mainly due to an unsurpassable trade off between spatial and spectral sensitivities .Generally, the linear degradations applied to the observed images with respect to (W.R.T) the target high-spatial and high-spectral image reduce to spatial and spectral transformations. Thus, the multi-band image fusion problem can be interpreted as restoring a 3D data-cube from two degraded data-cubes. A more precise description of the problem formulation is provided in the following paragraph.

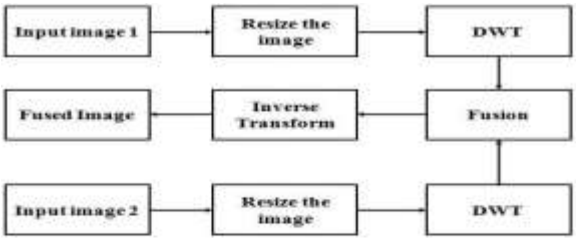


Figure 1.Overall process

In this work, we assume that two complementary images of high-spectral or high-spatial resolutions, respectively, are available to reconstruct the target high-spectral and high spatial resolution target image. These images result from linear spectral and spatial degradations of the full resolution image **X**, according to the well-admitted model .In most practical scenarios, the spectral degradation $\mathbf{L} \in \mathrm{R}\ n\lambda \times m\lambda$ only depends on the spectral response of the sens or, which can be *a priori* known or estimated by cross calibration. The spatial degradation **R** includes warp, translation, blurring, decimation, etc. As the warp and translation can be attributed to the image co-registration problem and mitigated by pre correction, only blurring and decim at ion degradations, denoted **B** and **S** are considered in this work. If the spatial blurring is assumed to be space-invariant, $\mathbf{B} \in \mathrm{R}n\times n$ owns the specific property of being a cyclic convolution operator acting on the bands. The matrix$\mathbf{S} \in \mathrm{R}n\times m$is a $d = dr\times dc$ uniform down sampling operators, which has $m = n/d$ ones on the block diagonal and zeroselsewhere, and such that $\mathbf{S}T\ \mathbf{S} = \mathbf{I}m$. Note that multiplying by $\mathbf{S}T$ represents zero-interpolation to increase the number ofpixels from m to n. Therefore, assuming **R** can be decomposed as $\mathbf{R} = \mathbf{BS} \in \mathrm{R}n\times m$, the fusion model can be rewritten as

$$\mathbf{Y}\mathrm{L} = \mathbf{LX} + \mathbf{N}\mathrm{L} \qquad \text{-----------(1)}$$

$$\mathbf{Y}\mathrm{R} = \mathbf{XBS} + \mathbf{N}\mathrm{R} \qquad \text{---------(2)}$$

Where all matrix dimensions and their respective relations are summarized. Computing the ML or the Bayesian estimators (whatever the form chosen for the prior) is a challenging task, mainly due to the large size of **X** and to the presence of the down sampling operator **S**, which prevents any direct use of the Fourier transform to diagonalize the blurring operator **B**. To overcome this difficulty, several computational strategies have been designed to approximate the estimators.

Based on a Gaussian prior modelling, a Markov chain Monte Carlo (MCMC) algorithm has been implemented in to generate a collection of samples asymptotically distributed according to the posterior distribution of **X**. The Bayesian estimators of **X** can then be approximated using these samples. Despite this formal appeal, MCMC-based methods have the major drawback of being computationally expensive, which prevents their effective use when processing images of large size. Relying on exactly the same prior model, the strategy developed in exploits an alternating direction method of multipliers (ADMM) embedded in a block coordinate descent method (BCD) to compute the maximum a posterior (MAP) estimator of **X**.

2. LITERATURE SURVEY

Li and Dong (2013) [7] has discussed pixel level image fusion. Pixel level image fusion describes the particular processing along with synergistic combination of information collected coming from source images which offers improved perception of a scene.. The demand for significant and spatial correct combination of all available image datasets arises with the development of sensors. Pixel level image fusion technique can be applied in many application areas such as in machine vision, airborne and space borne remote sensing and medical imaging etc.

Sharmila et al. (2013) [4] has shown that multimodality medical image fusion using discrete wavelet transform and entropy concepts provides better quality of information and less noise in the fused image formed. Medical image fusion is the s the technique of deriving very important data simply by incorporating multimodality medical images like computed tomography (CT), Magnetic resonance imaging (MRI), Positron emission tomography (PET) and single photon emission computed tomography (SPECT) into single image. The information thus derived can be used for various purposes such as for diagnosing diseases, detecting tumor, surgery treatment etc. Single modality image cannot provide this useful information. Li et al. has shown that region based multi-focus image fusion using the local spatial frequency in spatial domain performs better in terms of both image quality and objective evaluation as compare to pixel-based image fusion methods. Pixel-based image fusion methods are generally subject to defects connected with source images which influence the quality of fused image. Region based multi-focus image fusion method using local spatial frequency first segments the average image of source images to get the region map and then calculates local spatial frequency for each pixel in source images from a local window. After this, regional spatial frequency is calculated for each region. Then a fused image is constructed from the selected regions according to the RSF calculated. Ganesh et al. has discussed techniques of image fusion to remove noise from digital images. Remote sensing plays a very essential role in satellite communication. Satellite produces images in digital format which are corrupted during acquirement, transmission or due to wrong memory locations in hardware. The density of noise varies depending on various factors such as atmospheric variations and noise communication channels etc. It is important to remove the noise from images for further processing. Images captured by different sensors produce different impulse noise images and for removal of impulse noise, median filters are used. Firstly noisy images are filtered using various types of vector median filters and then these filtered images are combined to form single image by image fusion technique relying on the quality assessment in spatial domain. Then fused image formed is again filtered using absolute derivation vector median which gives more noise free image.

3. **IMAGE FUSION TECHNIQUE**

There are three levels of image fusion which are pixel level, feature level and decision making level. Pixel level image fusion is related to the pixel location which combines the visual information from input images into single image based on the original pixel location. Feature level image fusion use various features like regions or edges and combines source images according to these features to form a fused image. Decision level fusion techniques merge image details directly such as in the form of relational graphs. Pixel level fusion preserves more significant information as compare to feature level and decision level fusion. There are mainly two types of image fusion methods which are

1. Spatial domain fusion.

2. Temporal domain fusion

Spatial domain combination offers mostly with the pixels of origin graphics. It fuses entire graphics utilizing local spatial features including gradient, spatial volume as well as local common deviation. Temporary domain combination consists of your shift of entire graphics straight into frequency domain. In this approach source images tend to be projected on to localized bases which are designed to stand for your sharpness as well as edges associated with an image. Most of these converted coefficients help in extracting pertinent features from input images to form fused image.

3.1 SYSTEM FLOW

In existing high and low spatial spectral resolution images were used to solving a Sylvester equation. Alternating direction method of multipliers based methods of numerical experiments processed the fast fusion method an hierarchical Bayesian inference. The restored noise signal to ratio used and the relative dimensionless global error which synthesized.

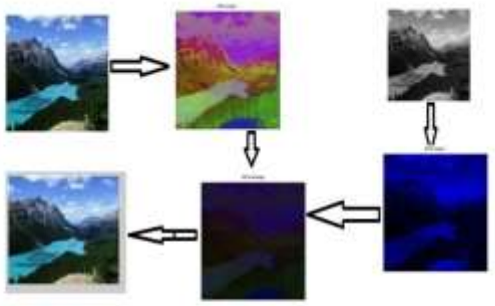


Figure 2.Fusion process

We have propose a new fusion scheme for fusing the CLAHE-IHS(contrast limited adaptive heist eon-intensity hue saturation) method**.** It which is used for its efficiency and high spectral resolution to improve the spectral quality of the image compared to the original image. The performance of the resultant image may calculated by Histogram & PSNR (peak signal to noise ratio).

3.2 CAPTURING IMAGE

Get and select the image from file can take as a input image(rgb). Then input image is converted into gray form. After that both input (rgb) and gray scale images may converted into IHS . Hence the captured image will be displayed as converted IHS image i.e.(Intensity Hue Saturation) refer figure (3).

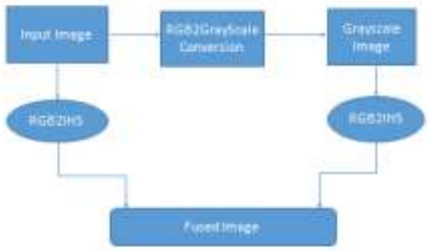


Figure (3)

3.3 IHS CONVERSION

The output of IHS conversion of both images of (rgb) and gray scale images are fused by linear combination technique. After that fused image may converted to original form (i.e. rgb) then value of PSNR will be calculated refer figure (4).

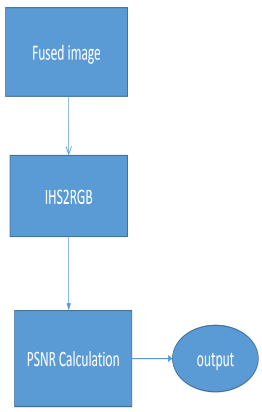


Figure (4)

4. EXPERIMENTAL RESULTS & DISCUSSION

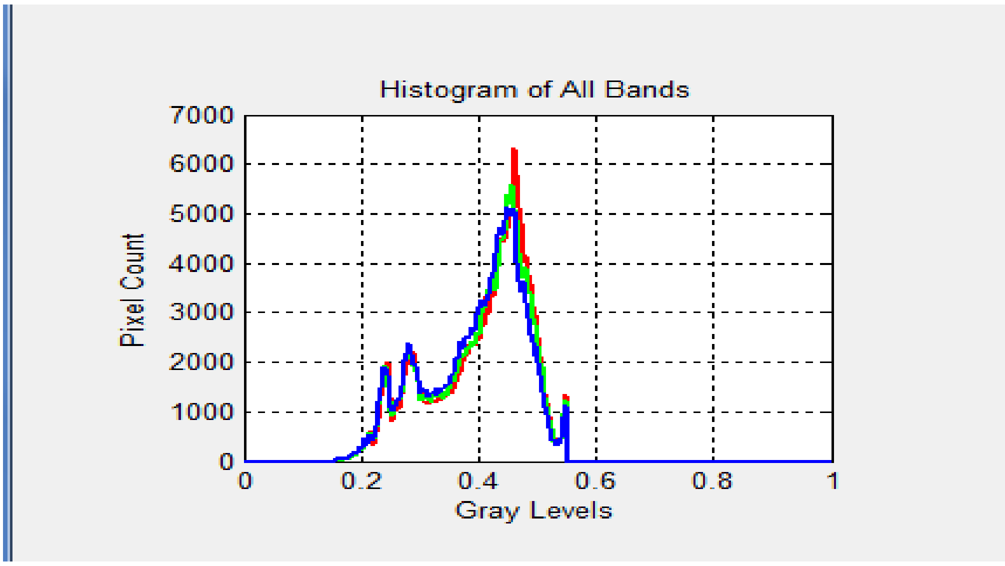
1. The input image should be browsed from the file and read the image to convert the (rgb) image into Intensity Hue Saturation (IHS) image. After converting the image into intensity hue saturation process. The IHS image converted to gray scale image. It which gives the image in added dimension, and it proves the particular result in gray scale converted image. By modifying the image through the range of intensity.

1. Gray Scaled Image

2. The converted gray scale image were processed to intensity hue saturation as second time in the gray scaled image. The dimension of the gray scale image was added and then the dimensioned image is again converted into intensity hue saturation image. Both converted image from rgb to intensity hue saturation and the gray scale image to intensity hue saturation images will be combined.

2. IHS Conversion

3. The converted form of the intensity hue saturation image was initially added its dimensions from gray scale image .Therefore the dimension added image was improved its spectral quality and attaining the clear view towards the respective image. Hence the high spectral quality of the image will be improved . Finally image quality will be improved through its intensity, therefore it gives the high quality of the image provided by its range of pixels. Then the histogram of all bands will be displayed in the graph.



3. Histogram of all bands.

5. CONCLUSION

In this paper, a method of image fusion is proposed. It is based on the use of Stationary Wavelet Transform, Discrete Wavelet Transform and Principal Component Analysis. By surveying all the techniques with its parameters it is concluded that spatial domain techniques have blurring problem and is overcome by transform domain techniques and out of two techniques of transform domain that is Stand DWT concluded that SWT gives less PSNR ratio and high MSE and gives better result compared to DWT. In addition our proposed method is to combine the two techniques SWT and DWT of two same domain that is transform domain and will improve the image quality.

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