



An Efficient Image Preprocessing Technique for Land Use Analysis by Using Remote Sensing Images

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ABSTRACT

The advancement in remote sensing technology expands the choice of selection of images for land use mapping. Mapping, specific land use from remotely sensed images requires significant processing steps begins with image acquisition to classification using related algorithms. Useful properties of remote sensing images inherited with variety of errors requires some set of treatment in the form of preprocessing using various preprocessing techniques before the segmentation and classification of images. These preprocessing steps fine-tune the spatial and spectral feature of the data for future processing of the image. The residual characteristics of the image can be retained by calculating local mean and variance matching (LMVM) image fusion technique to retain the spectral information. The proposed study leverages the use of Just Noticeable Difference (JND) model to detect and map the edges of particular point of interest (POI) with reference to the luminance, contrast and structure of the remotely sensed image.

Key words: Image Preprocessing, Image Fusion, Just Noticeable Difference model for remote sensing images.

1. INTRODUCTION

The advancement in remote sensing imagery is widely adopted in various fields of remote sensing application in the fields of land use analysis like urban planning, natural disaster assessment and agriculture and vegetation mapping etc. The advanced onboard sensors come up with several spectral bands and these bands offers differential spectral frequencies along with the multi-featured information which is useful in the decision making using remote sensing applications. This complete set of image data

further delineate the processing challenges which could be further processed for better information retrieval [1], [2]. The spectral images are generated with a process of electromagnetic radiation on the object acquired from the visible and near-infrared regions [3]. As a result the spectral image consists of different pixel intensity values for the large area. This acquired image usually comprises various noise components like bad lines, intensity variations, atmospheric effects and image coordinate problems etc. There is a need to preprocess these images for future analysis to improve the interpretability of image data [4], [5]. This is the prerequisite for the vegetation area extraction from remotely sensed images. The sensory images accommodate different image bands resulted from a variety of sensors, height of the airborne and also the captured time of the image. To get the single multispectral image an image fusion [6] technique can be used which processes the different image bands into meaningful pixels data. The image improvement for vegetation mapping is proposed using JND model techniques[7].

2. LITERATURE REVIEW

The accuracy of vegetation mapping using remote sensing image[8] should undergo various preprocessing tasks because of the noise component inherent with these images[9]. The author putforth his research finding for a variety of satellites and its use including the sensor types used, and the compatible image preprocessing techniques[10] to be adopted for further processing. The removal of irregular lines or missing line replacement in the image bands is discussed in the article. It also discuss the image quality improvement techniques by ascertaining the band by band analysis. The spectral image covers large coverage, the missing data if any in the cluster

of bands is filled using this process for the better interpretability of the image for future analysis.

The pixel intensity management is carried out using radiometric corrections[11], which helps in improving the reliability of the brightness levels. The spectral signal sometimes will not be sufficiently strong, because of the seasonal phenology, ground conditions, and atmospheric conditions which may affect the temporal spectral responses results in the difference in the original and received image. The radiometric correction algorithms provide a standard template to overcome these differences. Generally, radiometric corrections [9]are classified into two types as absolute correction and relative correction which can be used to measure the target reflectance.

The coordinate calibration of these images carried out using geometric corrections where the geometric correction algorithm restructures the association between the image coordinate system and the geo-coordinate systems. The image calibration can be carried out with map projection and co-registration.

It is also noted that the advancement in the remote sensing imaging in accordance with the remote sensing software provides basic image corrections so the basic image corrections may not be required always. The preprocessing methods discussed further will provide enormous handy techniques to prepare the image for the future segmentation.

The traditional image enhancement technique [1],[12]covers conversion of an image into gray level, histogram analysis, color combination analysis and color conversion techniques like false color generation. These algorithms are frequently used in the image interpretation. The paper Shyu and Leou (1998) discuss the limitations of traditional image enhancement techniques for mapping the vegetation cover with reference to spatial images. The mapping over large area with cloud composition in the images, results in big noise in categorizing the vegetation cover.

Removing the natural noise intrinsic in the hyperspectral image is done using image enhancement. The noise-like, cloud components, shadow, and other irreverent features from the image should be removed for the good visibility of the image for further analysis. The image enhancement procedures cannot be claimed to increase the pixel

information of the image instead will improve some of the characteristics of the images like enhancement of the edges, filtering some of the noises, sharpening the images[4]. Two categories of enhancement techniques are discussed in the article, the first one is using spatial domain which promotes the two methods histogram equalization and local neighborhood operations. The discrete Fourier and wavelet transform are two examples for the transform domain.

In the paper[13], [14], [1] the basic image preprocessing operations were discussed which was a handful to carry out the proposed work. The literature highlights the importance of filtering operations very specifically the histogram equalization. Also the literature review for image preprocessing explores the use of edge detection concepts to identify the boundaries of an object, its size and other features.

3. IMAGE FUSION

The remote sensing sensors capture several bands of images from visual and non-visual region having different spectral frequencies. Always single band image is in monochrome format. The satellite sensors collect several bands of the same scene in different intervals and regions, referred to in the form of a multispectral image. This multispectral image contaminated with different spatial features because of the variations in its acquisition which fails in the quality of spatial resolution which is very important for various analyses. The spatial and spectral resolution of the image can be enhanced and combined into a single image by using various techniques and will greatly help in the application of land use/land cover analysis.

The image fusion of the high resolution images [6] and the low-resolution images has different bands landed with variety of spectral information and the band ranges from one to twelve helpful in segmentation. The thirty meter resolution image with eight bands is known as a panchromatic image. The images with fifteen meter resolution contain more information while thirty-meter resolution images are comparatively coarser resolution images and will give less amount of information. The high resolution and low resolution images can be fused using certain mathematical techniques to get a multi spectral high-resolution image which is experimented in this study by using two variety of tools Matlab and QGIS.

The single band image is hardly used and the kinds of analysis for agriculture applications requires multispectral image because these images are captured in the NIR region and contains good range of bands which are important as far as agricultural applications are concerned [11]. The Landsat 8 images that are used for the proposed work containing of 11 bands. Initially the band combination of 4,3,2 is processed and fused with panchromatic band 8 and resulted into a unrecognized vegetation area as shown in figure 1a and 1b. The band combination of 5,4,3 called near-infrared composite contains the color combination of red indicates 4 and green indicates 3. The band combination 5,4,3 is useful for agriculture analysis as it reflects the chlorophyll content which needs to be processed for better analysis using image fusion as seen in Figure 3a. Similarly, the band combination of 6,5,2 may be specifically used for agriculture monitoring itself. The healthy vegetation appears in dark green and the bareland area is somewhat in magenta hue in this combination. The remote sensing multispectral image data is having enormous resources for the study and a proper band selection is important for our study. Here in our study we used the band combination of 5,4,3 and processed further for analysis is discussed in detail in the result section.

The high-resolution spectral images [15] are frequently used in the remote sensing land use application in the field of agriculture for economical and eco-friendly farming. To assess [16][17][18] the rubber VS arecanut farming area in the Dakshina Kannada district of the Karnataka, India, 11 band Landsat 8 images were used.

The 11 band Landsat images were downloaded using QGIS software. The band number 2,3,4 are fused

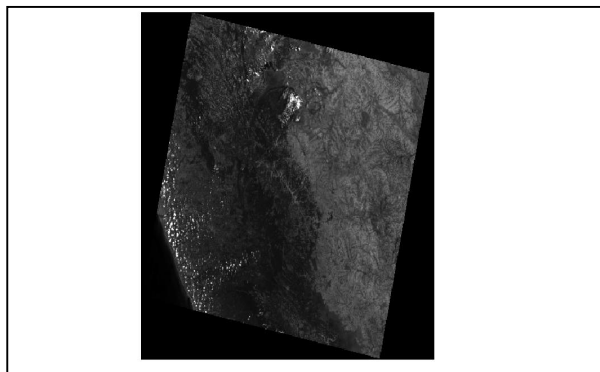


Figure 1a: Image with band combination of (2,3,4)

with aerosol band 8 by using the QGIS software as shown in figure 1a and 1b. The fused image should have the pixel combination of 15: 15 and the expected image should have been in color image format which is not generated because of the weak band combination or because of the other errors inherited with the image. Because of this the expected variations in the land use is not identifiable in the fused version of the image. It is concluded that the cubic convolution method used in the software has less efficient and a more sophisticated method called as LMVM is used for the further study with the band combination of 5,4,3. As per the literature the best results are composed with the Local Mean and Variance Matching algorithm and this algorithm is used in the study. The band combinations to fuse the particular image also very much important. In the process band combination of 2,3,5 are also experimented but the cloud components are visible a lot in the image, which is further cleared in the proposed algorithm.

The algorithm LMVM uses a relative filter along with a normalization function to calculate the local mean and variance $F_{i,j}$ and is calculated and reoffered in (1) of spatial information in the panchromatic band. The improved filter can further eliminate the remaining differences in the resultant image. This image can be correlated between the pan sharpened image and the original image. The abstraction of algorithm is show as below. The results of this algorithm is seen in Figure 3a.

$$F_{i,j} = \frac{(H_{i,j} - \bar{H}_{i,j}) \cdot s^{(L)}_{i,j}(w,h)}{s^{H_{i,j}}(w,h)} E \quad (1)$$

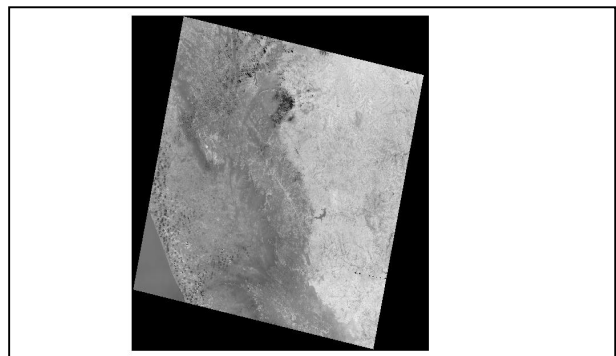


Figure 1b: Fused image with Band 8

4. PROPOSED PRE-PROCESSING METHOD

The fused image by using LMVM algorithm further processed using the JND model which incorporates the edge detection techniques along with luminance adaption with masking are discussed in details in the subsections 4.1 to 4.7. The structural sensitivity of the edge is also sharpened using JND model. Finally the edge reconstruction for the rubber and arecanut plantation are constructed using the proposed model, which further helps in segmentation of the point of objects. Before implantation of this model the grayscale conversion of the image RGB values [19] is carried out using Luminance function along with the weight function of RGB which is represented in (2)

$$GLuminance=0:3R+ 0:59G+0:11B \quad (2)$$

The `rgb2gray` function of MATLAB is used in this study to convert the image into grayscale. The result is shown in Figure 3b. Following are some of the grayscale conversion methods. The efficiency of the algorithms is not discussed here. The algorithms perform better in their way with a variety of input images. The gray scale-conversion techniques like Intensity, Gleam, Luma, Lightness, Value, and Luster are experimented in the initial literature study.

The remote sensing images incorporate enormous pixel resources which are very useful in the remote sensing application. It is required to eliminate the unwanted noisy signals to recognize the pixel change in the images. This proposed method Just Noticeable Difference Model (JND) rectifies the maximum distortion and is used in image preprocessing systems [20], [8], [18]. In this model, the just noticeable difference is calculated using the edge pixel values. The JND model incorporates various sequential steps to fine tune the remote sensing steps.

The steps involved in the model.

1. Edge detection using a canny method
2. Edge map by using the gradient operator
3. Edge map using luminance, contrast, and structure of an image
4. Edge reconstruction technique into a unified JND model to reconstruct the edge profile.

4.1 Edge Detection

The identification of the boundary of the vegetation area in the image is an important preprocessing step

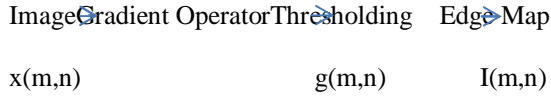
required to be carried out in the land use analysis. The fused image perceives various vegetation crops which are all having almost the same intensity values. The prime objective of the proposed work is to distinguish rubber and areca nut plantation. The intensity values of this POI have almost looks similar to the human eye. To distinguish the canopy of the rubber plantation a histogram analysis is also incorporated in the JND method and the result is seen in Figure 3c. The desired object identification for the analysis can be initialized by identifying the edges of an image using edge detection. In the proposed study the classification algorithm involves the task of identification of the different plantations, which sometimes may fall between similar canopies. It is important to find the boundary of these plantations for the classification. The classification of the said land use also involves various land use categories like coconut plantation and other primary and secondary forest categories and the intense illumination of these categories may fall under the same category. So it is important to detect the edges of these objects and hence the required categories can be classified and other unused objects can be excluded from the analysis.

With the help of available and best-suited operators the edge detection method transforms the regular image into a component of edges, which effectively describe the objects involving in the system and also find the discontinuities in intensity values. The process of edge detection begins with the gray-scale conversion process and then plot the objects with edges with image stretching to equalize varied pixel values referred from the histogram which is shown in Figure 3e. The various techniques like Roberts, Prewitt, Sobel, Laplacian of Gaussian, and Canny detectors are the most popular edge detector used in image preprocessing [21].

In the land-use analysis of rubber and arecanut plantation as the noises are more because of the very small variations in the canopy values, canny edge detector algorithm is used. The experimentation of the RGB converted image is experimented using other edge detection techniques. The canny operator influences a better characterization among others as shown in Figure 3d. The results are also discussed in the result section.

4.2 Edge Map

The edge mapping of the similar objects are done by using gradient operator. Using the gradient operator the pixel colour changing can be calculated for corresponding to the R, G and B values and the edges are detected based on the gradient calculated as shown in Figure 3g.



The edge map for the required POI is constructed and is referred in (3).

$$\begin{cases} 1 & |g(m,n)| > th(3) \\ 0 & otherwise \end{cases}$$

4.3 Edge Modeling

Based on the luminance, contrast and structure values the structure of an image is modeled and is shown in Figure 3f. This process shows the continuous representation of intensity, strength and width of the pixel. The one dimensional representation of the model is calibrated by using the pixel intensities as shown in (4).

$$u(x; b, c, x_0) = cU(x - x_0) + b \tag{4}$$

Where $U(x - x_0)$ represents the unit steps function, b denotes edge basis means luminance and c denotes contrast.

4.4 Luminance adaption

The visibility sensitivity of the image can be calculated by using the luminance adaption and which used the reference of the background luminance. Here the pictorial region and the edge pixels are separated which facilitates the background luminance with a special focus on homogeneous content rather than the textual contents. The process eliminates the edge pixels to measure the background luminance as calculated in (6) and results into a 5X5 mask as shown in Figure 2.

$$T1(P) = \begin{cases} a1. (1 - \frac{\sqrt{I(p)}}{127} + \beta) & \text{if } \overline{I(p)} \leq 127 \\ a2. (\overline{I(p)} - 127 + \beta) & \text{otherwise,} \end{cases} \tag{5}$$

Here

$\overline{I(p)}$ is the average background luminance from 5 x 5 mask.

1	1	1	1	1
1	2	2	2	1
1	2	0	2	1
1	2	2	2	1
1	1	1	1	1

Edge pixel

Figure2: Masking table for average background luminance

4.5 Contrast Masking

The specific pixel quality of the image can be improved by using this technique. A standardized image quality can be obtained by enhancing the image. Contrast is very much deciding characteristics in deciding the quality of an image [22].

Here noticeable edge contrast variations are used to calculate visibility threshold by using divisive normalization which is calculated (6), (7).

$$T_{c+}(P) = \frac{1-f_{th}}{1+f_{th}} . c(p) \tag{6}$$

$$T_{c-}(P) = \frac{1-f_{th}}{1+f_{th}} . c(p) \tag{7}$$

The $T_{c+}(P)$ represents the threshold corresponding to increased contrast and $T_{c-}(P)$ for indicates the decreased contrast.

4.6 Structural Sensitivity

The edge width factor is used to control the edge profile corresponds to a specific shape. The smaller the edge width sharpens the edge profile. But due to the lack of homogeneous content we cannot assign the constant threshold. But the constant threshold can be calculated by calculating the relative change in the edge width as shown in (8).

$$\Delta(\omega) = \omega_t - \omega \tag{8}$$

Where ω_t is the distorted version generated from Gaussian smoothing with the standard deviation value. The result is shown in Figure 3f after sharpening the image.

4.7 Edge reconstruction

The three masking technique is used here to reconstruct the edge profile. At first visibility threshold is identified by using the luminance adaption masking technique by using one dimensional notation of parametric edge model by reconstructing the pixel values as in in the (9).

$$T_{el}(P) = s(p; T_1(p) + b, c, \omega, x_0) - s(p; b, c, \omega, x_0) \tag{9}$$

Similarly to find the visibility threshold on contrast the contrast masking effect is used. This is results in minimum just noticeable value. Further a nonlinear additive masking is performed to overlap these two effects. Sometime some pixels fall in different positions results in variability in structural and non-structural visibility thresholds. The conclusive edge profile is generated by merging and reconstructing the JND profile $T(P)$ as shown in(10) and the result is shown in Figure 3h.

$$T(P) = \begin{cases} T_e(P) & P \in S_E \\ T_l(P) & \text{otherwise} \end{cases} \tag{10}$$

5. RESULTS AND DISCUSSION

The quality of the image fusion is important and the statistical measures correlation coefficient (CC), is a popular measuring criterion to measure the linear matching between the pixels of the images. It identifies the amount of similarity perceived between the images. The CC defines the spectral identity of the individual band, each band of the combined reference and the pan-sharpened image.

Correlation coefficient (CC) for spatial consistency using Laplacian filtering: BAY(Bayesian fusion) is observed in the range of 0.854. The results are shown that the CC between the fused image is 0.854 by using the Laplacian filtering and Bayesian fusion. The range of values falls between -1 to +1 and better close to 1. The experimentation result by using the method Bayesian pan sharpening produced a good performance. Similarly correlation coefficient for Spectral Consistency - (CC) using IMVM method and RCS method prove that the LMVM method produced better results than the RCS method which is 0.969. The results of the study recorded a worst synthesis for Brovey method. There is a significant

improvement in the fused image is recorded by LMVM.

The performance of the canny edge detection algorithm is considerably good in detecting the edges with similar color properties with considerable edge strength and gradients. Further the Hue operator isolates the similar shapes. The edge detected images are isolated with Hough transform by using the different geometric shapes in the image boundary.

The Figure 3b-3h shows the results of the novel model. Initially 11-band landsat-8 image is fused by using LMVM algorithm which has better results over other equivalent algorithms like PCS and other. The next process is to detect the edges in the fused image which is constructed by using canny edge detection. Before the edge detection the image is treated by using luminance gray-scale conversion techniques. The image enhancement is also done by using histogram equalization.

6. CONCLUSIONS

The preprocessing technique for the remote sensing images is very important to stratify the image to the future classification. The extracted image may contain various noise components which is processed with series of predefined steps. The radiometric and geometric corrections are carried out to adjust the image component concerning the sensor values by using the tool. The LMVM image fusion technique is applied to the 11 band Landsat 8 images to get a hypersepctral image with a pixel size of 15: 15 for better vegetation mapping and the expected results were helpful for further analysis compared to other technique. The QGIS tool is also used along with the Matlab and it is observed that the Matlab tool is quite useful to carry out the preprocessing tasks. However the inbuilt mathematical tools available in the QGIS tool for the image fusion helped a lot in the analysis of the band structure of LandSat and LISS3 images.

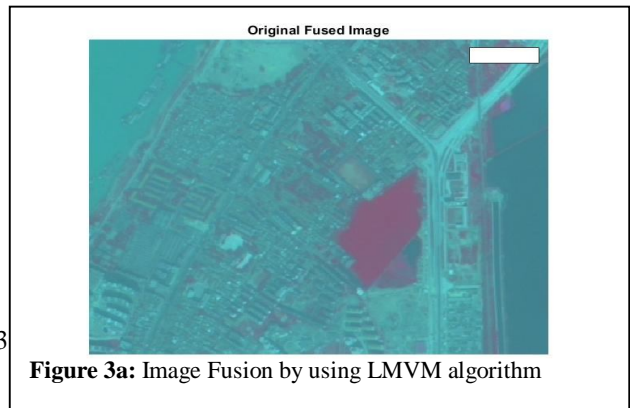
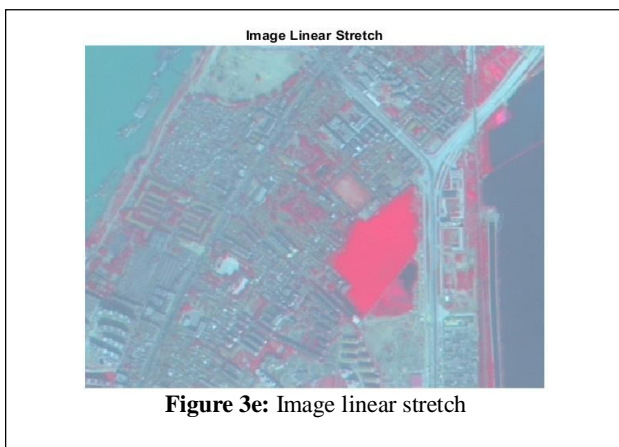
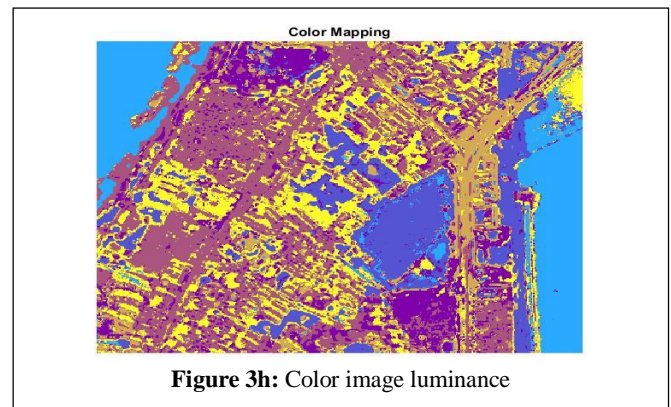
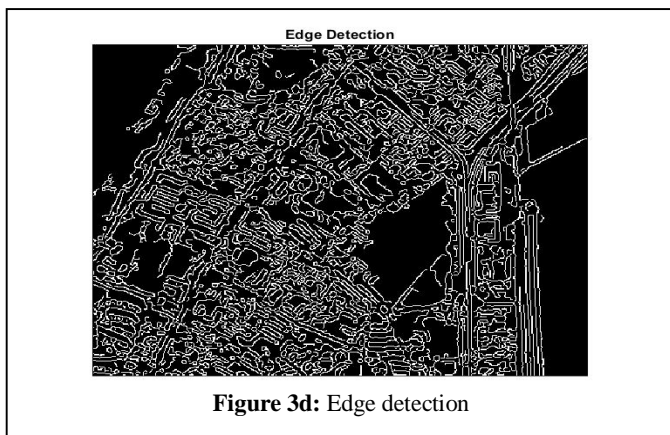
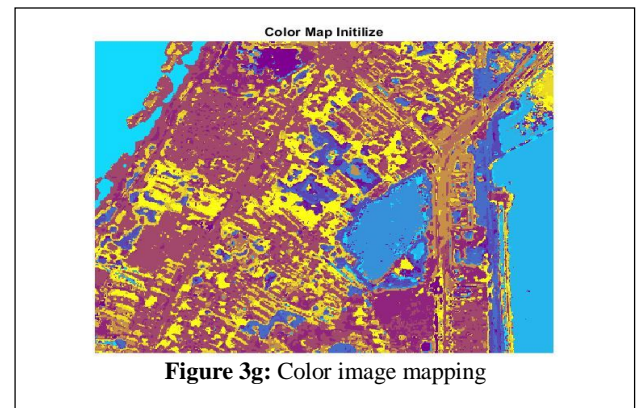
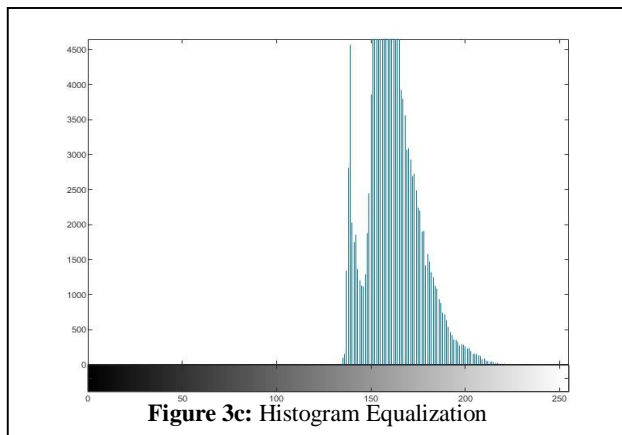
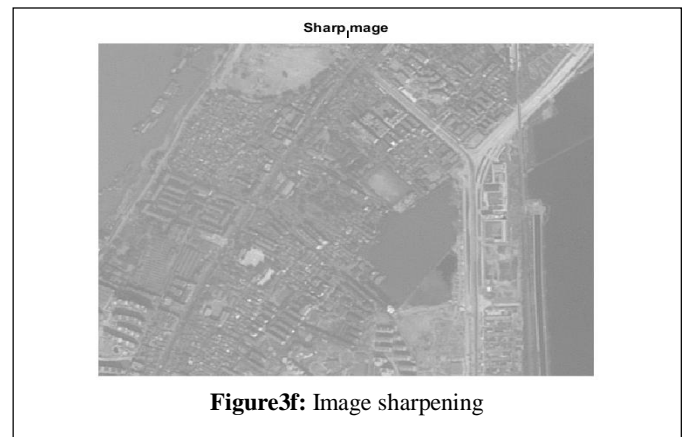
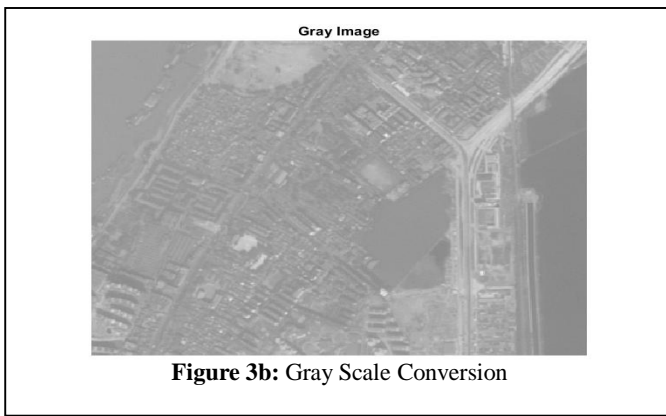


Figure 3a: Image Fusion by using LMVM algorithm



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