Improving Illumination Normalization in Multiple remote sensing images using Laplacian and Gaussian Pyramids

Swapnil Ambade, Hemant Kumar Soni, Geetesh Wagadre

M. Tech scholar, EC Deptt., PIES, Bhopal, swapnil.ambade29@gmail.com

Asst. Prof., EC Deptt., PCST, Bhopal, hemantsoni04@gmail.com

HOD, EC Deptt., PCST, Bhopal, wagadregeetesh@gmail.com

Abstract— The Modulation Transfer Function (MTF) is a fundamental imaging system design specification and system quality metric often used in remote sensing. The MTF defines how the sensor optics and electronics modulate the original signal (image). In a two-image comparison method to find the MTF, with three groups of images picked up on altered dates. The approach prerequisites all images at same illumination conditions. Thus, it is essential to do illumination normalization. In this paper we introduce a method which is a combination of Laplacian and Guassian pyramids; it achieved a good result of illumination normalization. In this method the illumination regularity is assessed by a parameter named p(rho).

Keywords— Modulation Transfer Function, Remote Sensing Images, Illumination Normalization, Image Pyramids, Laplacian and Gaussian enhancement, Quality measures.

INTRODUCTION

Illumination is an important element for image quality. Changes of the source of light cannot only affect the brightness of the image, but also tends to details lost and distortion. The variation of illumination on the satellite images in mountain areas, including Landsat, have as dominant source the shadow due to the mountainside slope. Consequently, there emerge topographic effects that create an ambiguity between the scene elements and cause confusion in the accurate establishment of surface categories. In practice, control of illumination conditions is challenging, and not always possible. Comparison of high and low resolution images based method [8] estimates the MTF of low resolution image by computing the MTF of high resolution image on the condition that the two images to be compared have a same state of illumination. However, it is hard to meet the requirements. Therefore, illumination normalization is needed for these kinds of remote-sensing images, especially in rough terrain, important for improving analysis of remote sensing data (e. g. image classification).

Although numbers of illumination correction methods have been proposed in the past, none of them has been found to be universally applicable, and therefore illumination normalization is still a pre-processing issue rarely used. However, previous traditional methods can only normalize illumination in a single image and cannot make illumination consistent among multiple images. Thus, we propose a method to post-process captured remote sensing images to normalize the illumination. We employ Laplacian enhancement to improve course illumination of image. This process can bring their brightness to the same level and eliminate uneven illumination in each image. Then the contrast is adjusted by Gaussian functions by improving detail or fine illumination of image. The illumination consistency assess by a parameter named p. So we can evaluate the performance of the method visually and quantitatively. Finally, the illumination of the output images will look consistent.

LITTERETURE SURVEY

Histogram equalization [10], gamma correction [10] and Retinex [29] are traditional methods, which are popular but cannot maintain average brightness level and may result in either under or over saturation in processed images. Majumder's [11] and Fattal's [11] gradient domain method have a good performance on contrast enhancement. Simultaneously they can achieve the effect of correcting uneven illumination. However, these methods can only normalize illumination in a single image and cannot make illumination consistent among multiple images. To solve the problem there are two ways. One is histogram specification [10], which is simple and practical, but may cause problems as traditional methods mentioned before. The other way is to extract characteristics that are not sensitive to illumination, such as Scale-Invariant Feature Transform (SIFT) [16]. SIFT has been proven to be the most robust local invariant feature descriptor. However, this way just avoids the problem and does not solve it.

Demirel et al. [4] proposed an improved method (DWT-SVD) combined discrete wavelet transform and singular value decomposition, which has a better effect on contrast enhancement. But when the images have a big difference in contrast and brightness, the result may not turn out satisfactory. Pedro et al. [12] proposed the affine illumination model can be applied to compensation of illumination variations in a series of multispectral images of a static scene. However, it does not meet our requirement. The satellite images to be normalized are random. The senses of the images may be different and the number of the images is arbitrary. It is also observed that there is only a small work was done on this remote sensing image enhancement. The main problem of these earlier proposed approaches is that some methods are not able to achieve normalization of illumination in images with simplest algorithm or the method which achieved the goal satisfactorily were complex, hence in this thesis such an algorithm is proposed which meets the above mention features.

PROPOSED APPROACH

The proposed methodology includes combination of two methods Spatial domain method and frequency domain method, Laplacian of Gaussian pyramid. First, laplacian enhancement applied for improve course illumination of image and detail or fine enhancement is done using Gaussian enhancement. Finally both laplacian enhanced and Gaussian enhanced images are added together to achieve illumination normalised image. Then quantitative assessment of illumination consistency is done by comparing parameter *'p'*.

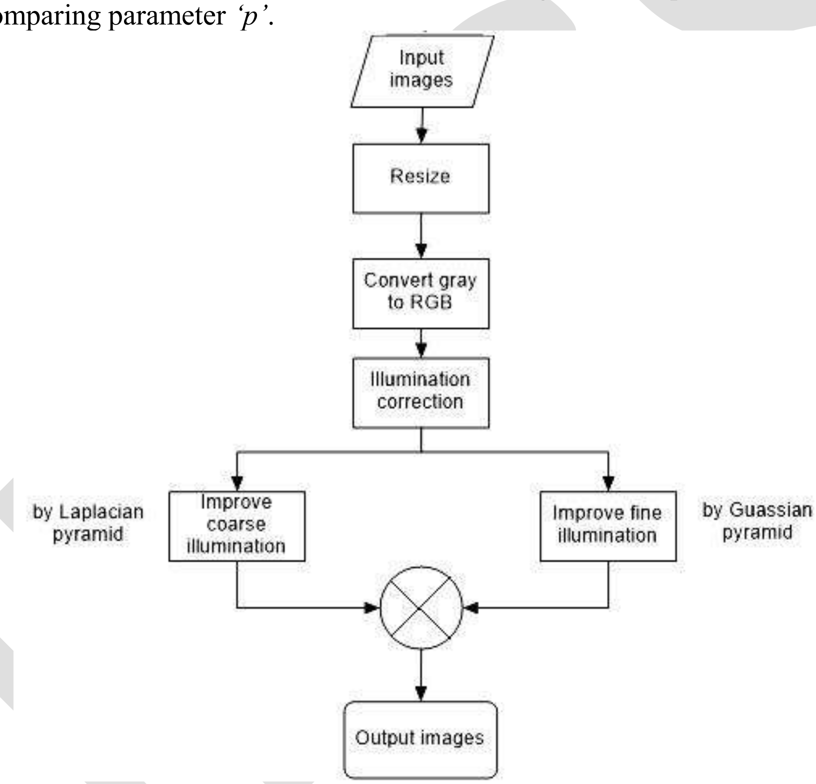

Fig. 1. Flow chart of proposed method

Input images are satellite images obtained from Satellite-based scanner imagery. The images used square measure within the bmp or jpg gray or colour format. The sizes of pictures square measure 250*250 pixels. The presence of any degradation within the image is reduced. Then we convert Gray image to RGB image, RGB image is an image in which each pixel is specified by three values one each for the red, blue, and green components of the pixel scalar[3] . Then we apply Illumination correction function by using Laplacian of Gaussian pyramid method.

IMAGE PYRAMID

A pyramid is a common data structure used for representing one input image I at different sizes. The original image is the base layer of the pyramid. Images of reduced sizes are considered to be subsequent layers in the pyramid. If scaling down by factor 2, then all additional levels of the pyramid require less than one third of the space of the original image, according to the geometric series

$$1 + \frac{1}{2.2} + \frac{1}{2^2.2^2} + \frac{1}{2^3.2^3} + \cdots < \frac{4}{3} \quad (1)$$

When reducing the size from one layer to the next layer of the pyramid, bottom up, the mean was calculated for 2 × 2 pixels for generating the corresponding single pixel at the next layer.

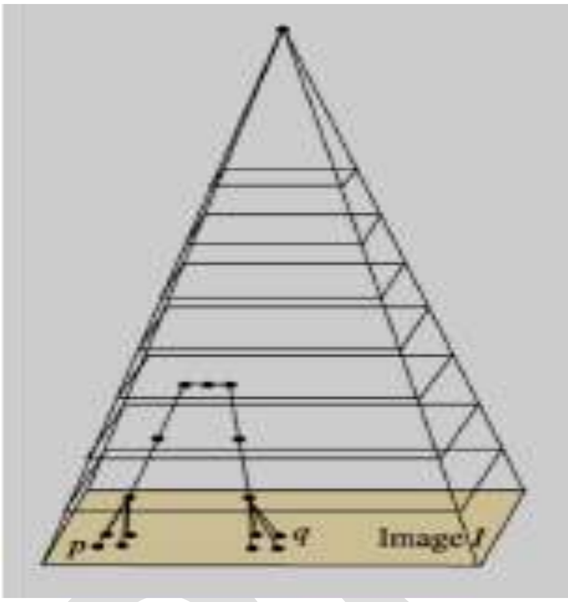

Fig. 2. A regular pyramid is the assumed model behind subsequent size reductions

In our proposed method first we generate Laplacian pyramid. It has three pyramid level 1,2,3 Pyramid level 1 contains the detail component, Pyramid 2 contains the brightness component, Pyramid 3 contains the contrast component.

LAPLACIAN PYRAMID

Laplacian pyramid is used for separating the brightness and contrast components of an image. The brightness component is characterized by slow spatial variations and contrast components tend to vary abruptly. Therefore, the brightness component has low frequency while the contrast component tends to have a relatively high frequency. Each band of Laplacian pyramid [2] is the difference between two adjacent low-pass images of the Gaussian pyramid [I_0, I_1, …, I_N].

For the given input image as RGB, we will separate images according to its components as R image, G image and B image. We need to perform contrast as well as detail enhancement on each of these images. When the individual images are enhanced in contrast and detail manner, we combine them together and get the enhanced output image. So apply laplacian enhancement to the image this will improve the course illumination of image.

We consider in some detail the use of two-dimensional, second order derivatives for image enhancement. The approach basically consists of defining a discrete formulation of the second-order derivative and then constructing a filter mask based on that formulation. We are interested in isotropic filters, whose response is independent of the direction of the discontinuities in the image to which the filter is applied. In other words, isotropic filters are rotation invariant, in the sense that rotating the image and then applying the filter gives the same result as applying the filter to the image first and then rotating the result [10].

It can be shown (Rosenfeld and Kak [1982]) that the simplest isotropic derivative operator is the Laplacian, which, for a function (image) f(x, y) of two variables, is defined as

$$\nabla^2 f = \frac{\partial^2 f}{\partial x^2} + \frac{\partial^2 f}{\partial y^2} \quad (2)$$

Contrast enhancement [2] improves the perceptibility of objects in the scene of enhancing the brightness difference between the objects and their backgrounds. Here we are using laplacian method for improving contrast of an image.

Generate the histogram The histogram with luminance levels in the range K [0, L-1] is a discrete function as

$$h(l_k) = n_k \tag{3}$$

Where l_k is the k^{th} luminance level in K and n_k represents the number of pixels having luminance level l_k. So we generate the histogram of image as shown below.

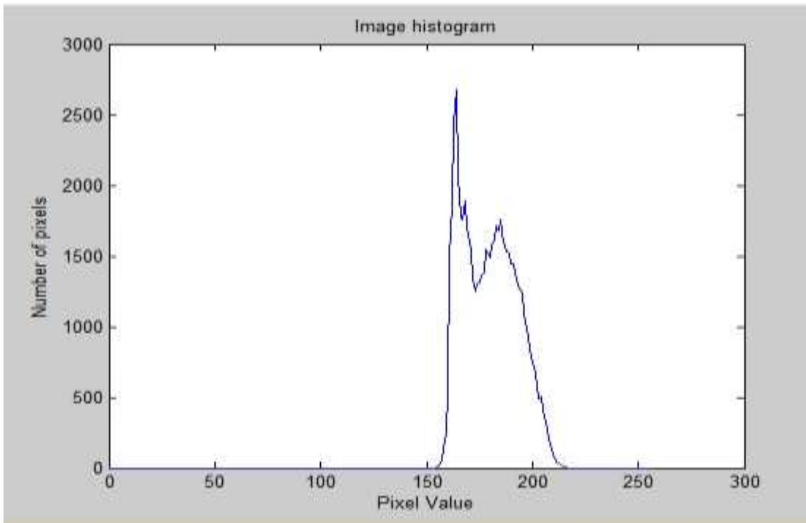

Fig. 3 Generating histogram for image

Smoothing the histogram to avoid spikes that lead to strong repelling fixed points, a smoothness constraint can be added to the objective. The backward-difference of the histogram, i.e.,$h[i] - h[i-1]$ can be used to measure its smoothness. A smooth modified histogram will tend to have less spikes since they are essentially abrupt changes in the histogram. Although histogram smoothing is successful in avoiding histogram spikes, it has a shortcoming. The ringing-artifact pixels that have intensities less than the background pixels are mapped to even darker intensities.

In the histogram, a ridge shape with some consecutive luminance levels can be regarded as the feature area of an image. To globally distinguish between ridges and valleys and remove their ripples, we smooth the histogram [6] [14] like as follows:

$$hg\ (l_k) = h\ (l_k) * g\ (l_k) \tag{4}$$

Where, $g\ (x) = e^{-x^2}$ is a Gaussian function, x is the corresponding location to a bin of the histogram, and coefficients of the Gaussian filter are normalized.

Boosting minor areas: This is a key strategy of proposed contrast enhancement to suppress quantum jump. First, the peak value in the smoothed histogram $h_g\ (l_k)$ is found as

$$p(k) = max_{k \in K}\{h_g(I_k)\} \tag{5}$$

Second, the ridges between valleys are searched and boosted. Ridge boundary is defined as the bins between the first point of the positive slope and the last point of the negative slope. We find the constant factor of enhancement and then find the local minor areas of histogram. We check for local maxima, if it is found it means a peak value is found and we need to enhance it and store value to new histogram.

Slantwise clipping: The clipping technique is used as it effectively suppresses the quantum jump. We find the mean of newly generated histogram and then find the mid value and then we gather the residual from local and global clipping. It will reduce higher components.

Generating new image: Find the normalised cumulative histogram and replace the values with new equalised values.

$$h= (cdf- cdf(min)/MN- cdf(min)) * 255 \tag{6}$$

Detail or fine enhancement is done by using Gaussian function

GAUSSIAN FUNCTION

The Gauss filter is a local convolution with a filter kernel defined by samples of the 2D Gauss function. This function is the product of two 1D Gauss functions defined as follows:

$$G\sigma, \mu x, \mu y\ (x, y) = \frac{1}{2\pi\sigma^2} \exp\left(-\frac{(x-\mu x)^2 + (y-\mu y)^2}{2\sigma^2}\right)$$

$$= \frac{1}{2\pi\sigma^2} e^{-\frac{(x-\mu x)^2}{2\sigma^2}} . e^{-\frac{(y-\mu y)^2}{2\sigma^2}} \tag{7}$$

where *(μ_x,μ_y)* combines the expected values for *x*- and *y*-components, σ is the standard deviation (σ^2 is the variance), which is also called the *radius* of this function, and *e* is the Euler number. The standard deviation σ is also called the *scale.*
So f1 enhances lower components of image while f2 enhances higher components of image. Then Combine all the level of pyramids to get the final Gaussian enhanced image. After that, add the Gaussian and Laplacian images to get the final enhanced images.

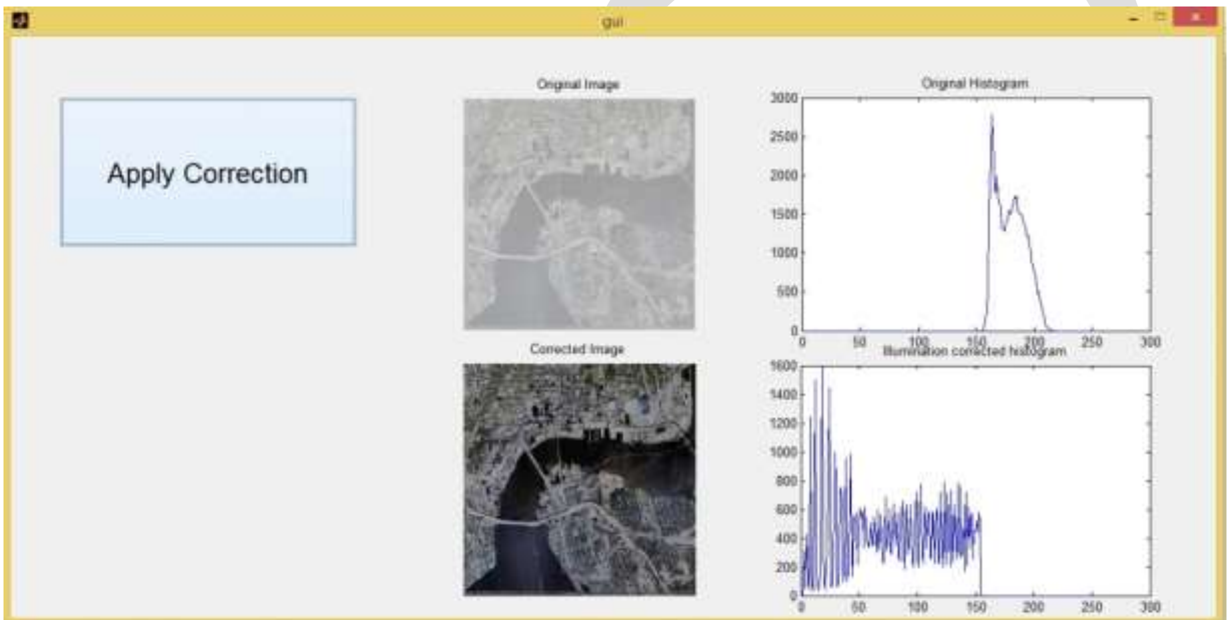

Fig. 4 GUI for illumination normalization using Laplacian and Gaussian pyramid

HISTOGRAM SIMILARITY OF ILLUMINATION IMAGES

Now we can compare illumination images for evaluating illumination consistency. For a group of images, we firstly compute the mean histogram of them, and then compare each histogram to the mean histogram [1]. The formulation is

$$p = 1-\frac{\sum_{i=1}^{k}\sum_{j=0}^{255} |\mathrm{Gi(j)} - \mathrm{A(j)}|\mathrm{Wj}}{\mathrm{k \cdot N \cdot Wmax}} \tag{8}$$

where k is the number of the images i.e.5. Gi is a vector indicating the histogram of ith image. Gi(j) is the number of pixels whose value is j. A is the mean histogram, the value is 0.96. A(j) is the number of pixels whose intensity value is j. Wj = |M− j| + 1.N is the size of images. Wmax = max(|M− j|) is the weight when illumination difference is huge, such as black image and white image. In their experiments Wmax is set to be 128. The parameter p is between 0 and 1, which can quantitatively evaluate illumination consistency of images. The bigger p is, the more consistent images are.

EXPERIMENTS AND ANALYSIS

The method can normalize the illumination of any amount of images but due to space available in GUI window we processed single image at a time. We perform the algorithm on 5 different remote sensing images and calculate mean histogram value as 0.96 then compare proposed approach with original image, Singular Value Equalization, Singular Value Decomposition and Discrete Wavelet Transform and Zhang et al.'s method. The result of our experiment is shown below by bar graph.

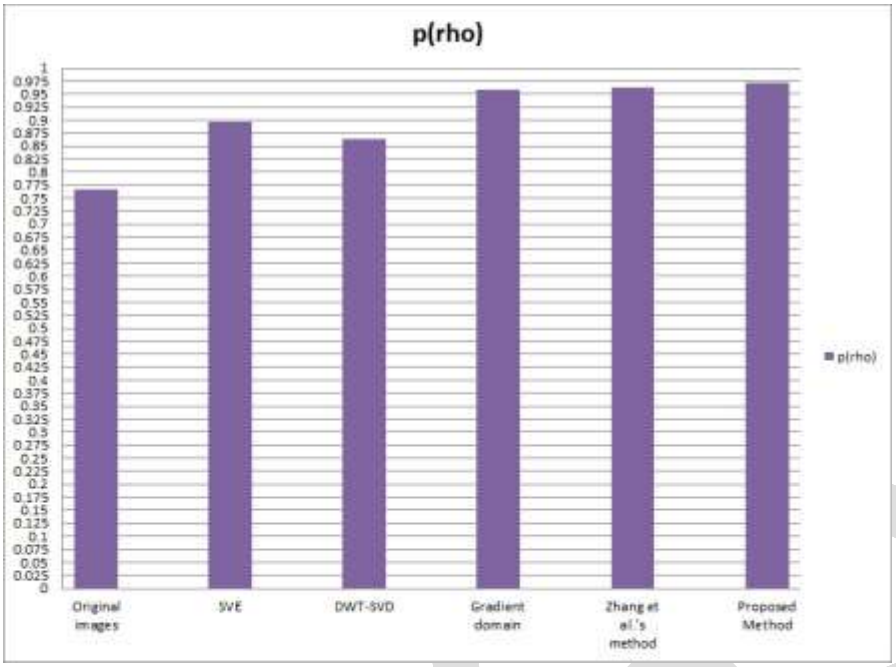

Fig. 5 Graph showing p(rho)values of different methods

The above figure shows the graphical representation of p(rho) values of different methods used before for illumination normalization. From the above figure it is clear that with the proposed method we improve the value of p(rho) compare to other methods which indicates the illumination consistency.

Table 1 Comparison between different methods for p(rho) value

Method	*p(rho)*
Original images	**0.7663**
SVE	**0.8974**
DWT-SVD	**0.8641**
Gradient domain	**0.9576**
Zhang *et al.*'s method	**0.9628**
Proposed Method	**0.9707**

The above table gives the complete details about p(rho) values of different methods used before for illumination normalization. From the above table it is clear that with the p(rho) value of previous used method of Zhang et al.'s method is above of all before method in our proposed method we improve its value greater than Zhang et al.'s method.

QUALITY MEASURES

We computed other image quality measures like mean square error (MSE), normalized absolute error (NAE) in our experiment and compared with other conventional methods of image enhancement like Histogram equalization (HE), Gamma correction.

Mean square error (MSE): It deals with the values obtained by an estimator thus calculating the divergence between estimator values and optimum values of estimated quantity. MSE quantifies the average of squares of the "errors" .The higher value of MSE the better**.**

$$\mathrm{MSE} = \frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N}(x(i,j) - y(i,j))^2 \quad (9)$$

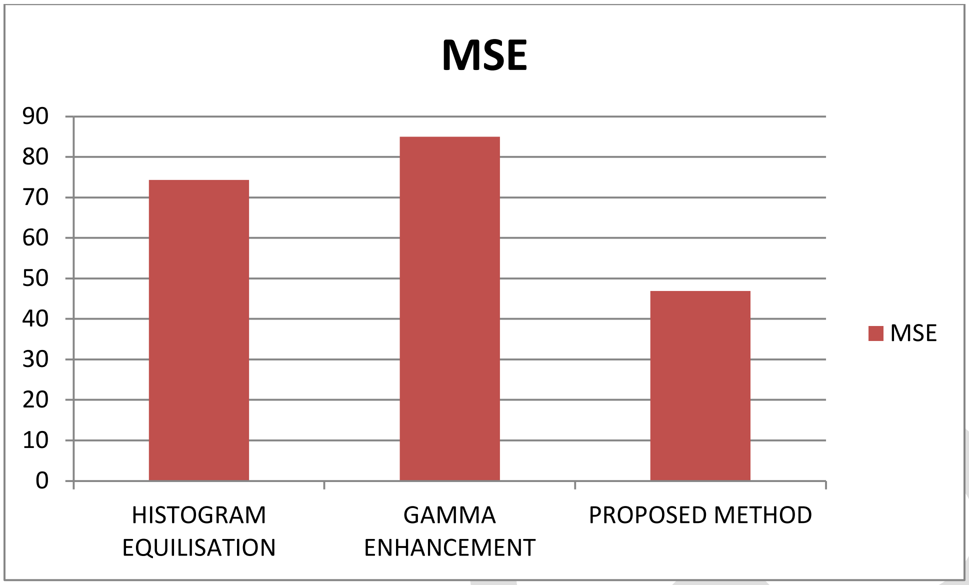

Fig. 6 Graph showing MSE Comparison with other methods

Normalized absolute error (NAE): Normalized absolute error is a measure of how far is the reconstructed image from the original image with the value of zero being the perfect fit. Large value of Normalised absolute error indicates poor quality of the image, small value of Normalised absolute error gives good quality image.

$$NAE = \frac{\sum_{i=1}^{M}\sum_{j=1}^{N}(x(i,j)-y(i,j))}{\sum_{i=1}^{M}\sum_{j=1}^{N}(x(i,j))} \quad (10)$$

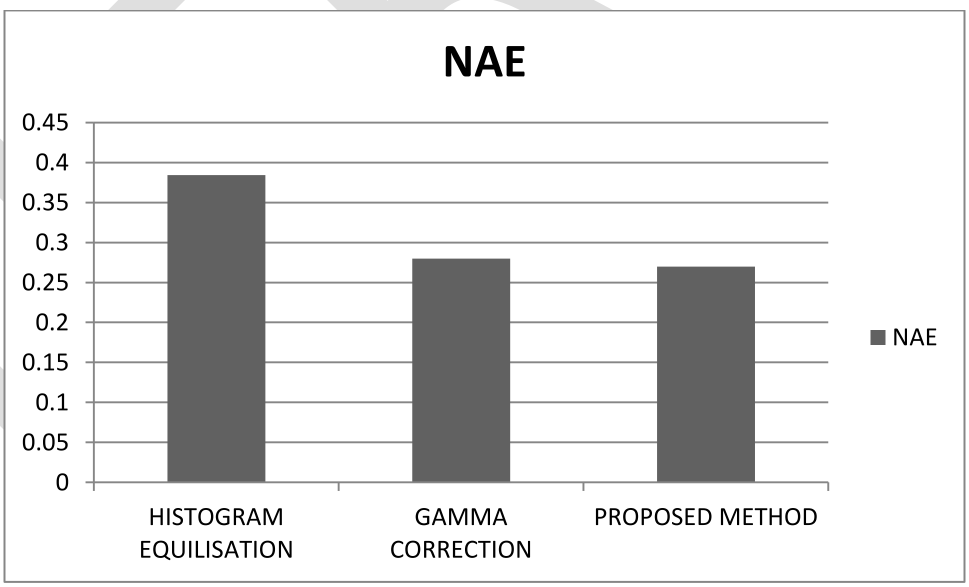

Fig. 7 Graph showing NAE Comparison with other methods

The fig. 6 and fig. 7 shows the graphical representation of MSE and NAE values of different methods. We have compared the proposed approach with HE and Gamma correction. From the above figures it is clear that with the proposed method we found that MSE and NAE value of proposed method is less than HE and Gamma correction method.

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CONCLUSION

This paper is an effort to implement a Laplacian and Gaussian pyramid method is proposed for remote sensing images. The satellite images will get illumination normalized. It is observed that the combined approach of Laplacian and Gaussian pyramid is able to enhance the satellite images in terms of image quality measures satisfactorily. It can be useful to determine the MTF, with three pairs of images acquired on different dates. The method needs all images at same illumination conditions. The Modulation Transfer Function (MTF) is a fundamental imaging system design specification and system quality metric often used in remote sensing. This automatic illumination normalization of remote sensing images method is useful to describe how the sensor optics and electronics modulate the original signal (image).

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