CHAPTER 6

Computational Analysis of Cloud Removal Techniques

6.1 Introduction

Clouds are common features of visible and infrared remotely-sensed images collected from many tropical, humid, mountainous, and coastal regions of the world. The Landsat cloud-free scenes for analyses of current land cover and land-cover change is developed using cloud removal approach. Landsat data have been used for high temporal resolution analyses of land-cover changes related to urban expansion, regeneration of forest over abandoned agricultural land, estimation of forested area, identification of forests types and current land-cover classification, a key component for mapping habitats and biodiversity.

Remote sensing is an interesting field which plays a major role in economic development of the country. It is suitable for study and analysis of changes in the environment with higher impact on defense [69]. Remote sensing is closely related with satellite imaging where images are sensitive with resolution and other image features [70]. Images can be acquired by using different satellites such as ikonos, Landsat, Quick bird and each satellite is used for different purposes like defense (change detection in regions), agriculture (for analysis of agriculture) etc. [72]. Image quality is one of the most important factors in satellite images because every object in a satellite image is essential for accurate processing. Quality of satellite image is always questionable when there is higher influence of clouds in an image. Presence of these clouds in satellite image is unavoidable during image acquisition and it also causes many problems in the study of satellite image based applications [73]. Removing cloud as a noise from an image will be helpful for better analysis of satellite imaging applications. Removal of cloud cover region is a challenging task because each region in satellite image is an essential one [74, 75].

Pixels in most of the cloud cover regions will have higher brightness than other pixels. These regions can be identified and removed by discriminating pixel resolution.

Algorithms such as, Mean, Second Highest (SH) value, Modified Maximum Average (MMA) and Hybrid method which is combination of mean and MMA [69] are currently in use for cloud analysis and these algorithms are primarily based on pixel properties.

Existing methods are more suitable for static images and less cloud cover regions. Development of new method is needed for most of the applications to improve the accuracy and better predictions [75].

Main aim of this research work is to remove low and high brightness clouds without losing quality of the images. Proposed method is designed in such a way that it will be applicable to all types of satellite images which are taken by using various satellites.

A modified Neighborhood similar pixel interpolator (NSPI) helps to remove the cloud from the satellite images. In the NSPI approach, it predicts the spectral value of the target pixels from its neighboring similar pixels. It employs the threshold to identify the similar pixels. The weight between the similar pixels and target pixels can be calculated by using the Euclidean distance. It has the major drawback such as cloudy images may sometime replace as the similar pixels. Due to the varying size & random shape of the clouds similar pixel replacement can reflect the cloudy appearance. Thus the modified NSPI method is used and it overcomes those problems. In the modified NSPI method the time series images are used to replace the cloud area. The detailed descriptions of the steps that are different from the original NSPI approach are given as follows:

The cloud masking is the first step used in this method where thick clouds are brighter in the visible band and lighter in thermal bands than the land surface. The second step is searching the similar pixel. In a modified NSPI method, it helps to search the spectrally similar pixels around the cloud. The third step is the gap-filling, in which the data has to fill in the area where the cloud masked [79-78]. In the cloud-removal process, the distance between a cloudy and its similar pixels may vary greatly.

If the target pixel is located near the cloud center then the spectro-temporal information is more consistent because the spectro-spatial information becomes less useful around the cloud center where the target pixel is farther to its similar pixels. The cloud center is computed by averaging the coordinates of the pixel.

6.2. Multi-Spectral Image Enhancement

Image enhancement is basically improving the Interpretability or perception of information in images for human viewers and providing better input for other automated image processing techniques [79]. There exist many techniques that can enhance a digital image without spoiling it. The enhancement methods can broadly be divided into the following two categories:

1. Spatial Domain Methods
2. Frequency Domain Methods

In spatial domain techniques, we directly deal with the image pixels. The pixel values are manipulated to achieve desired enhancement. In frequency domain methods, the image is first transferred into frequency domain. It means that, the Fourier Transform of the image is computed first. All the enhancement operations are performed on the Fourier transform of the image and then the Inverse Fourier transform is performed to get the resultant image. Image enhancement is applied in every field where images ought to be understood and analyzed. For example, medical image analysis, analysis of images from satellites etc. In this section we briefly describe the various image enhancement techniques.

6.2.1. Contrast Stretching

Contrast stretching technique is used to stretch the dynamic range of an image. Dynamic range is the range between the minimum intensity value and the maximum intensity value of an image. Mathematically, Contrast Stretching is given by [80],

$$I^{'}(x,y)=\frac{d}{I_{\max}-I_{\min}}X\left(I(x,y)-I_{\min}\right)+I_0$$

Where, $I^{'}(x,y)$ is the new dynamic range image, d is the new dynamic range value, $I(x,y)$ is the input image, $I_{\min}$ is the minimum intensity value of the input image,

I_{max} is the maximum intensity value of the input image, and I_0 is the offset point of the new dynamic range for $I(x,y)$. This transformation will provide good visual representation of the original scene but some of the detail may be lost due to saturation and clipping as well as due to poor visibility in under-exposure regions of the image.

6.2.2 Histogram Equalization

Histogram Equalization (HE) [79] is a technique that makes contrast adjustment using image's histogram. This technique is based on the idea of remapping the histogram of the scene to a histogram that has a near-uniform probability density function. Histogram Equalization redistributes intensity distribution. If the histogram of any image has many peaks and valleys, it will have peaks and valleys after equalization but the peaks and valleys will be shifted. This technique improves contrast and the goal of Histogram Equalization is to obtain a uniform histogram. In general, Histogram Equalization can be divided into three types, Global Histogram Equalization (GHE), Adaptive Histogram Equalization (AHE), and Block-based Histogram Equalization (BHE) [81]. In Global Histogram Equalization (GHE), each pixel is assigned a new intensity value based on previous cumulative distribution function. To perform Global Histogram Equalization (GHE), the original histogram of the gray-scale image needs to be equalized. The cumulative histogram from the input image needs to be equalized to 255 by creating the new intensity value by applying [81];

$$I^{'}(x) = \frac{d}{C_{max} - C_{min}} X\left(C(x) - I_{min}\right) + I_0$$

Where, $I^{'}(x)$ is the new intensity level, d is the new dynamic range value, I_0 is the offset point of new dynamic range for $I^{'}(x)$, $C(x)$ is the normalized cumulative value, C_{max} is the maximum value in normalized cumulative value, and C_{min} is the minimum value in normalized cumulative value. Lastly, the normalized cumulative histogram is used as the mapping functions of the original image. This technique increased the contrast of the image but lighting condition under uneven illumination may sometimes turn to be more uneven. The source of the Reference and subject images are [85, 86]

(a) (b) (c)

Fig. 6.1: (a) Subject Image (b) Reference image (c) Cloud-free image

6.2.3 Homomorphic Filter

The illumination component of an image is generally characterized by slow spatial variation while the reflectance component of an image tends to vary abruptly. These characteristics lead to associating the low frequencies of the Fourier transform of the natural log of an image with illumination and high frequencies with reflectance. Even though these assumptions are approximation at best, a good deal of control can be gained over the illumination and reflectance components with a homomorphic filter. Homomorphic filtering is a method in which the illumination and reflectance components can be filtered individually. The basic model is shown below:

Homomorphic Filtering [80], is sometimes used for image enhancement. It simultaneously normalizes the brightness across an image and increases the contrast. Here, Homomorphic Filtering is used to remove multiplicative noise. Illumination and reflectance are not separable, but their approximate locations in the frequency domain may be located. Since illumination and reflectance are combined multiplicatively, the component are made additive by taking the logarithm of the image intensity, so that these lie linearly in the frequency domain. Illumination variations can be thought of as a multiplicative noise, and can be reduced by filtering in the log domain.

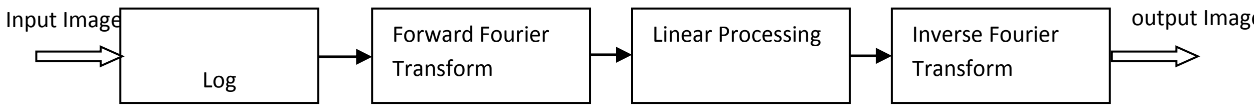


Fig 6.2: Homomorphic Filtering

6.3 Different Cloud Removal Approach

6.3.1 Mean

Mean based cloud removal is a traditional method which will detect and remove the cloud based on mean intensity value of cloud regions. The strength of mean based method is easy and simple to implement but major constraint of this algorithm is that this method is suggestible only for removal of less brightness clouds and it is not good for high or medium brightness clouds. Mean is a mathematical concept which is used for finding mean value of an array or a vector. Equation for calculating mean is,

$$A = \frac{\text{Sum of the pixel values of the vector / array}}{\text{Sum of the total number of pixels in the vector / array}} \tag{1}$$

Calculated mean value will be used for removal of cloud by comparing mean value with respect to each pixel value of an image. Pixels which are lesser than mean value will be categorized as non cloud regions otherwise pixels will be considered as cloud cover region. This method is not an efficient one when an image has non cloud regions with higher pixel value than mean [84].

6.3.2 Modified Maximum Averaging

Modified Maximum Averaging (MMA) will detect and remove cloud regions better than mean. These algorithms will support only for low-level brightness clouds. MMA is one of the enhanced algorithms used to remove high brightness clouds. Procedure used for MMA algorithm is as follows;

Step1: First step is to assume image as a vector.

Step2: Find mean for whole vector.

Step3: The subset of the pixel is extracted by comparing pixel values to the mean value of an image [14].

Step3: If the pixel value is higher than mean then eliminate the pixel values and remaining values of pixel is considered as cloud free region.

Step4: Repeat the process until entire cloud region has been detected.

6.3.3 Radiometric Normalization

Relative radiometric correction is aimed towards reducing atmospheric and other unexpected variation among multiple images by adjusting the radiometric properties of target images to match a base image [83], thus it is also called relative radiometric normalization. Relative radiometric normalization is an image based correction method achieved by setting the multi-temporal images into a common scale without extra parameters from other measurements. In this method, reflectance of invariant targets within multiple scenes can be used to render the scenes to appear as if they were acquired with the same sensor, with the same calibration, and under identical atmospheric condition without the need to be absolutely corrected to surface reflectance.

In normalization procedure first reference image and subject is divided into block of size 16×16 pixels. A block of reference image is placed over block centered on the same coordinates in the other image. Then normalized correlation between two corresponding blocks is done by using frequency domain. This operation is repeated for all blocks. After this, we applied a threshold criterion, in order to select no change pixels used to find normalization coefficients. The correlation can be calculated as,

$$f(m,n) o w(m,n) = F^{-1}\left[F(u,v)W^{*}(u,v\right] \tag{2}$$

Where,

$f(m,n)$ is the block of 16×16 pixels of reference image $w(m,n)$ is the block of 16×16 pixels of cloudy image (m, n) are the special coordinates.

$F(u,v)$ and $W(u,v)$ are the Fourier transform of $f(m,n)$ and $w(m,n)$ respectively. 'o' is the correlation. The Normalization correlation is derived from following equation,

$$NC = F^{-1}\left[F(u,v)W^{*}(u,v\right] \tag{3}$$

The normalization coefficients can be obtained by,

$$a_k = \frac{Syk^{(nc)}}{Sxk^{(nc)}}, \quad b_k = y_k^{-(nc)-a_k x_k^{-(nc)}} \tag{4}$$

Where, $x_k^{-(nc)}$ and $y_k^{-(nc)}$ are the means. Sample variance and covariance for subset NC on two dates can be determined using equations

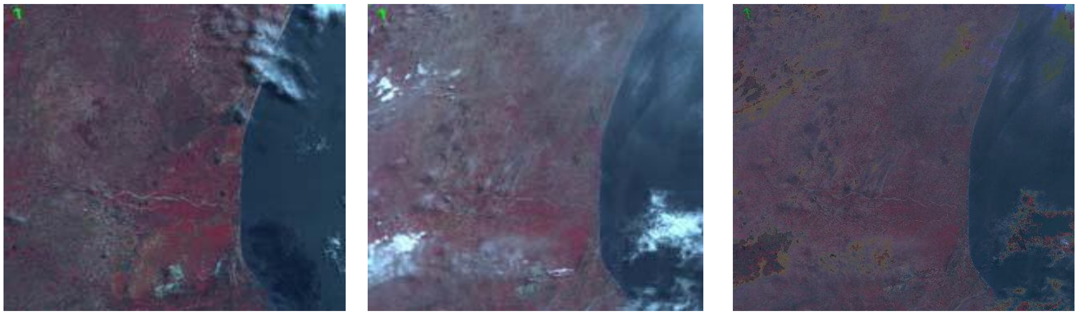
$$S^{(nc)} y_k x_k = \frac{1}{|NC|} \Sigma NC(X_k - X_k^{-(NC)})^2 \tag{5}$$

$$S^{(nc)} x_k y_k = \frac{1}{|NC|} \Sigma NC(X_k - X_k^{-(NC)})^{1/2} (y_k - y_k^{-(NC)})^{1/2} \tag{6}$$

A block is assumed to belong to no- change set if it has normalized correlation is greater than 0.9. If normalized correlation is greater than 0.9 then for normalized image select no change set of cloudy image otherwise select pixels set of reference image. This operation is repeated for all blocks and this procedure is repeated for whole images [84].

The Fig. 3(a) Shows Reference image Fig. 3(b) Subject Image and Fig.3(c). shows Normalized Image after cloud removal.

The source of the Reference and subject images are [85, 86]



(a) (b) (c)

Fig 6.3: (a) Reference Image, (b) Subject Image, (c) Normalized Image after cloud removal

6.4 Comparison of Different Techniques

Sl	Enhancement Technique/Algorithm	Domain	Measuring Parameters	Advantages	Disadvantages
1	Contrast Stretching [71]	Spatial	-	Good visual representation of the original scene.	some of the detail maybe loss due to saturation and clipping.
2	Histogram Equalization [70, 72]	Spatial	RMSE-53.17 PSNR (dB)-31.27	Image has uniform histogram Produce optimal contrast Fast	Cannot adapt the local information of the image and preserve the brightness of the original image.
3	Contrast Limited Adaptive Histogram Equalization [70,72]	Spatial	RMSE - 102.05 PSNR (dB)-18.23	Enhanced local contrast	Noise amplification in flat region and ring artifacts at strong edges.
4	Homoporphic Filtering [71, 73]	Frequency	RMSE - 125.44 PSNR (dB)-14.10	Remove multiplicative Noise Simultaneous gray-level range compression and contrast enhancement	Problem of bleaching of the image
5	Multi Scale Retinex [75, 76]	Frequency	PSNR (dB)-37.8	Provides dynamic range compression Preserve most of the detail	Unnatural color rendition ‘Washed out’ appearance but less than SSR

Table 6.1: Comparison between different color image enhancement techniques