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Satellite Image Enhancement Using Contrast Limited Adaptive Histogram Equalization

Shaik Asha[1], Dr. G. Sreenivasulu[2]

[1]M.Tech, Electronics and Communication Engineering Department, Sri Venkateswara University, Tirupathi, Andhra Pradesh, India

[2]Department of Electronics and Communication Engineering Sri Venkateswara University, Tirupathi, Andhra Pradesh, India

ABSTRACT

The satellite Images that are captured from the satellites are blurred by optical system and atmospheric effects and also corrupted by additive noise, the image restoration method known as Weiner deconvolution intervenes to estimate from the degraded image an image as close as possible to the original image . Recently different approaches have been used to reduce the noise in the satellite images. This paper proposed based on genetic approach to the Weiner deconvolution for the satellite image restoration. Our future work is based on different types of filters used to remove the noise completely from the satellite images. The performance can be evaluated using the metrics like PSNR,SNR and comparing it with the existing approaches. Experimental results give the better performance than the other methods and provide valid and accurate results.

Keywords : Additive Noise, Weiner Deconvolution, Genetic Approach, Image Restoration, PSNR, SNR

I. INTRODUCTION

Image Restoration is the operation of taking a corrupt/noisy image and estimating the clean, original image. Corruption may come in many forms such as motion blur, noise and camera mis-focus.[1] Image restoration is performed by reversing the process that blurred the image and such is performed by imaging a point source and use the point source image, which is called the Point Spread Function (PSF) to restore the image information lost to the blurring process.

The objective of image restoration techniques is to reduce noise and recover resolution loss. Image processing techniques are performed either in the image domain or the frequency domain. The most straightforward and a conventional technique for image restoration is deconvolution, which is performed in the frequency domain and after computing the Fourier transform of both the image and the PSF and undo the resolution loss caused by the blurring factors. This deconvolution technique, because of its direct inversion of the PSF which typically has poor matrix condition number, amplifies noise and creates an imperfect deblurred image. Also, conventionally the blurring process is assumed to be shift-invariant. Hence more sophisticated techniques, such as regularized deblurring, have been developed to offer robust recovery under different types of noises and blurring functions.

In mathematics, Wiener deconvolution is an application of the Wiener filter to the noise problems inherent in deconvolution. It works in the frequency domain, attempting to minimize the impact of deconvolved noise at frequencies which have a poor signal-to-noise ratio.

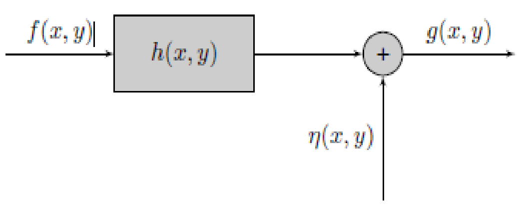
The Wiener deconvolution method has widespread use in imaged convolution applications, as the frequency spectrum of most visual images is fairly well behaved and may be estimated easily.

Most images are affected to some extent by noise that is unexplained variation in data: disturbances in image intensity which are either uninterruptable or not of interest. Image analysis is often simplified if this noise can be filtered out. In an analogous way filters are used in chemistry to free liquids from suspended impurities by passing them through a layer of sand or charcoal. Engineers working in signal processing have extended the meaning of the term filter to include operations which accentuate features of interest in data. Employing this broader definition, image filters may be used to emphasize edges — that is, boundaries between objects or parts of objects in images. Filters provide an aid to visual interpretation of images, and can also be used as a precursor to further digital processing, such as segmentation.

II. RELATED WORK

Satellite Image Degradation

The degradation can be caused in many ways, such as subject movement, out-of-focus lenses, or atmosphericturbulence. The modelling of degradations suffered bythe observed image is an essential step in order that therestoration takes place in good conditions. And thus, thedegradation process of a satellite image subjected to spatiallyinvariant blur and additive noise is modelled by



Model of image degradation by spatially invariant blur and additive noise

In the spatial domain, the modelling shown in figure is denoted as follows:

g(x, y) = f(x, y) h(x, y) + η(x, y)

Whereg represents the degraded image, f is the original image,denotes the convolution operator, and h is the degradation function which is also known as the Point Spread Function (PSF) and η (x, y) is the Gaussian additive noise.

Image quality (often **Image Quality Assessment, IQA**) is a characteristic of an image that measures the perceived image degradation (typically, compared to an ideal or perfect image). Imaging systems may introduce some amounts of distortion or artifacts in the signal – for example by transcoding –, which affects the subjectively experienced quality and Quality of Experience for end users.

An (image) is formed on the image plane of the camera and then measured electronically or chemically to produce the photograph. The image formation process may be described by the ideal pinhole camera model, where only light rays from the depicted scene that pass through the camera aperture can fall on the image plane. In reality, this ideal model is only an approximation of the image formation process, and image quality may be described in terms of how well the camera approximates the pinhole model.

Genetic algorithm for image processing:

In agenetic algorithm(GA) is a meta heuristic inspired by the process of natural selection that belongs to the larger class of evolutionary algorithms(EA) Genetic algorithms are commonly used to generate high-quality solutions to optimization and search problems by relying on bio-inspired operators such as mutation, crossover and selection. In a genetic algorithm, a population of candidate solutions(called individuals, creatures, or phenotypes) to an optimization problem is evolved toward better solutions. Each candidate solution has a set of properties (its chromosomes or genotype) which can be mutated and altered; traditionally, solutions are represented in binary as strings of 0s and 1s, but other encodings are also possible.

Genetic Algorithms (GAs) are adaptive computational procedures modelled on the mechanics of natural genetic systems. They express their ability by efficiently exploiting the historical information to speculate on new offspring with expected improved performance. GAs are executed iteratively on a set of coded solutions, called population, with three basic operators: selection/reproduction, crossover and mutation. They use only the payoff (objective function) information and probabilistic transition rules for moving to the next iteration. They are different from most of the normal optimization and search procedures in four ways:

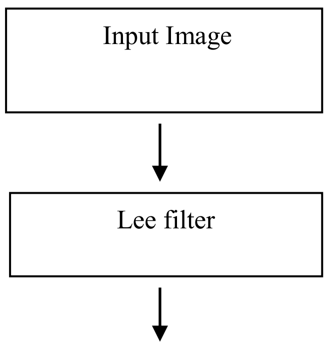
- ✓ GAs work with the coding of the parameter set, not with the parameter themselves.
- ✓ GAs work simultaneously with multiple points, and not a single point.
- ✓ GAs search via sampling (a blind search) using only the payoff information.
- ✓ GAs search using stochastic operators, not deterministic rules

III. METHODOLOGY

The methodology of the proposed method is as follows

Input Image

Input (prompt) displays the prompt string on the screen, waits for input from the keyboard, evaluates any expressions in the input, and returns the result. To evaluate expressions, the input function can use variables in the current workspace.



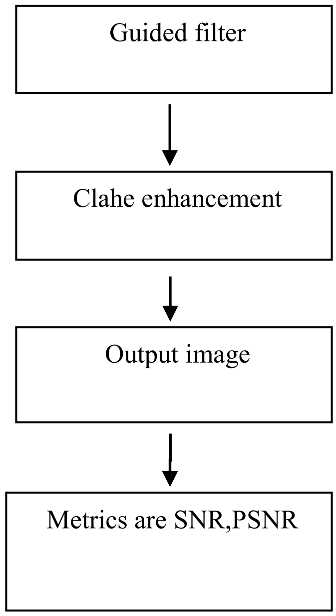


Figure 1. Block Diagram of Proposed Method

Lee Filter

Lee Filters is a maker of shading channels and shading gels for the diversion lighting, film and photography enterprises. Their shading gels for arrange lighting are the business standard in Europe while contending with different brands, for example, Rosco.The organization was established in 1967 as a feature of the gathering that ended up plainly Lee International. Lee Filters is currently claimed by Panavision. In 1980, the organization was granted the Bert Easey Technical Award of the British Society of Cinematographersfor "the improvement of film channels and control mediums".

Guided Filter

Guided filter Performs edge-preserving smoothing on an image, utilizing the substance of a moment picture, called a guidance image, to impact the separating. The direction image can be simply the image, an alternate form of the image, or a totally unique image. Guided imagefiltering is an area operation, as other sifting operations, yet considers the measurements of a locale in the relating spatial neighborhood in the direction image.The filtering output at a pixel is expressed as a weighted average.

where

$$J(x) = I$$

The weighted average is given as $q_i = \sum_j w_{ij}(j(x)P_J)$ (7)

where i and j are pixel indexes. The filter kernel Wij is a function of the guidance image j(x) and independent of p. This filter is linear with respect to p. A concrete example of such a filter is the joint bilateral filter . The bilateral filtering kernel w_{bf} is given by

$$w_{ij}^{bf}(j(x)) = \frac{1}{k_i} exp\left(-\frac{|X_i X_j|^2}{\sigma_n^2}\right) exp\left(-\frac{|X_i - X_j|^2}{\sigma_r^2}\right) (8)$$

Now we define the guided filter and its kernel. The key assumption of the guided filter is a local linear model between the guidance j(x) and the filter output q.

The solution for linear regression is given by a_k , b_k

$$a_k = \frac{1}{|w|} \sum_i w_k j(x)_i p_i - \mu_k \widehat{p_k} \ (9)$$

$$b_k = \widehat{p_k} - a_k . \mu_k (10)$$

Here, μk and σ2 k are the mean and variance of j(x) in ωk, |ω| is the number of pixels in w_k, and $\widehat{p_k}$ = 1 |ω| j(x)∈w_k pi is the mean of p in w_k.

The guided filter output is given by $q_i = \frac{1}{|w|} \sum_{k:i \in w_k} (a_k j(x)_i + b_k$

$$= \widehat{a}_i j(x)_i + \widehat{b}_i (11)$$

Finally the guided filter output and the kernel weights can be explicitly expressed as

$$w_{ij}\big(j(x)\big) = \frac{1}{|w|^2} \sum_{k(i,j) \in w_k} \left(j(x) + \frac{(j(x)_I - \mu_k)(j(x) - \mu_K)}{\sigma_K^2 + \epsilon}\right) (12)$$

Some further computations show that Wij (I) = 1. No extra effort is needed to normalize the weights.

Clahe Enhancement

Contrast Limited Adaptive Histogram Equalization

Histogram evening out is a dark scale change for difference improvement. The point is to get a picture with consistently circulated force levels over the entire power scale. Histogram levelling may deliver the outcome that is more terrible than the first picture since the histogram of the subsequent picture turns out to be roughly level. Vast tops in the histogram can be created by uninteresting range. Along these lines, histogram evening out might prompt an expanded deceivability of undesirable picture clamours. This implies it doesn't adjust to neighbourhood differentiate necessity; minor complexity contrasts can be completely missed when the quantity of pixels falling in a specific dim range is generally little.

A versatile technique to stay away from this downside is square based handling of histogram levelling. In this strategy, picture is separated into sub-pictures or squares, and histogram balance is performed to each sub-pictures or pieces. At that point, blocking antiques among neighbouring pieces are limited by sifting or bilinear addition.

The CLAHE acquainted clasp restrains with defeat the commotion issue. As far as possible the intensification by cut-out the histogram at a predefined esteem before figuring the CDF. This confines the incline of the CDF and subsequently of the change work. The incentive, at which the histogram is cut, the alleged clasp restrain, relies on upon the standardization of the histogram and in this manner on the measure of the area locale. The redistribution will push a few containers over as far as possible once more, bringing about a successful clasp confine that is bigger than as far as possible and the correct estimation of which relies on upon the picture.

The CLAHE has two key parameters: piece size and clasp restrain. These parameters are utilized to control picture quality. Nonetheless, itemized strategy to decide these parameters was not given, and they were heuristically picked by clients. At the point when a client decides unseemly parameters, the aftereffects of the CLAHE would be more awful than that of HIM. Figure demonstrates the outcome pictures of the

CLAHE with various clasp cutoff and square size, and the outcome pictures of HIM.

Signal to Noise Ratio (SNR)

The signal-to-noise ratio is used in imaging as a physical measure of the sensitivity of a imaging system. Industry standards measure SNR in decibels(dB) of power and therefore apply the 10 log rule to the "pure" SNR ratio (a ratio of 1:1 yields 0 decibels, for instance). In turn, yielding the sensitivity. Industry standards measure and define sensitivity in terms of the ISO film speed equivalent; SNR: 32.04 dB = excellent image quality and SNR: 20 dB = acceptable image quality.

PSNR(Peak Signal to Noise Ratio)

Peak signal-to-noise ratio, often abbreviated PSNR, is an engineering term for the ratio between the maximum possible power of a signal and the power of corrupting noise that affects the fidelity of its representation. Because many signals have a very wide dynamic range, PSNR is usually expressed in terms of the logarithmic decibel scale.

PSNR is most commonly used to measure the quality of reconstruction of lossy compression codes (e.g., for image compression). The signal in this case is the original data, and the noise is the error introduced by compression. When comparing compression codes, PSNR is an approximation to human perception of reconstruction quality. Although a higher PSNR generally indicates that the reconstruction is of higher quality.

$$PSNR = 10 \cdot \log_{10}\left(\frac{MAX_I^2}{MSE}\right)$$

IV. RESULTS

Figure 1. Original Image

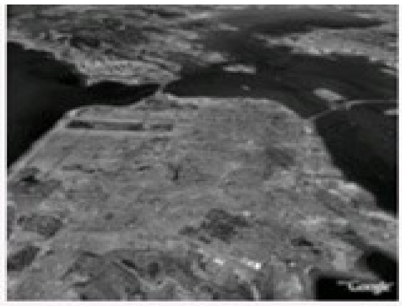


Figure 2. Lee filter

Figure 3. Guided Filter

Figure 4. CLAHE Enhanced Image

Table 1. Comparison Between the Existing and Proposed method

GA	SNR	PSNR
Weiner filter	12.6891	21.1503
Lee filter	17.4857	25.9705
Guided filter	21.2537	29.1926
CLAHE	24.1728	33.9826

V. CONCLUSION

In this paper, by using the CLAHE method the satellite images gets more enhanced than the other methods. Our results are compared using the metrics like PSNR and SNR .experimental results prove to be the better. This method provides valid and accurate methods than the other state of art methods.

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