Indian Journal of Science and Technology, *Vol 9(34), DOI: 10.17485/ijst/2016/v9i34/96766, September 2016*
ISSN (Print) : 0974-6846
ISSN (Online) : 0974-5645

A Comparative Analysis on Image Quality Assessment for Real Time Satellite Images

S. Rajkumar* and G. Malathi

School of Computing Science and Engineering, VIT University, Chennai - 600127, Tamil Nadu, India; rajkumar.srinivasan@vit.ac.in, malathi.g@vit.ac.in

Abstract

Objectives: The objective of this paper is to analyze the different image quality metrics by testing and comparing with different distorted set of satellite images. **Methods/Statistical Analysis:** In this paper, we propose the methods for analyzing the quality of real time images that are corrupted due to different distortions. The several quality metrics are applied and ultimately the best metrics are derived based on the type of degradation. Different metrics such as metric based on single image and metric based on two images have been tested with different real time satellite images from NASA data sets. **Findings:** This framework will help to identify the metrics in order to prove the proposed filtering schemes that are applied to the corrupted images. Based on the results, we have concluded the characteristics of different quality metrics and further we successfully identified the quality metric appropriate to various distortions. **Application/Improvements:** The proposed quality metric analysis is used to estimate the performance of any filtering schemes which are used to enhance the quality of any real time images such as remote sensing field.

Keywords: Assessment, Blur, Gaussian, Metrics, Quality, Satellite Images, Salt and Pepper

1. Introduction

The importance of Image Quality Assessment (IQA) lies in its emerging multidisciplinary topics that widely include image and signal processing, computer vision, visual psychophysics, neural physiology, information theory, machine learning, design of image acquisition, communication and display systems. The proposed model in[1], measures the quality of the image based on the human visual system and this model also combines the stereo pair image features with cyclopean features which in turn it predicts the quality of 3D image. A novel framework is derived in[2] is used to assess the image quality of tone mapped images. The experimental resultin[2] examines the structural information of tone mapped images. The proposed method in[3] yields better performance for tone mapped images in terms of the metrics mean and computational complexity. In[4], the edge information and singular value decomposition methods are used to assess the quality of the image and compared the proposed model with traditional methods. The proposed metrics in[5] is used for fusing the images. If the original image is available, then the performance of the image fusion is evaluated using the metrics root mean square error, Peak Signal Noise Ratio and Mean Absolute Error. If the original image is not available, then the performance of the fused image is evaluated using the metrics standard deviation and entropy etc. In[6], a four stage perceptual Image quality metric is derived from the Gabor features.

The mutual information is converted in to quality store that measures the quality of the image. An user-friendly and non-intrusive approach is proposed in[7], is used to improve the security of biometric system thereby to distinguish between legitimate and impostor samples. The experimental results reveals in[7] focused about fake traits. The Gaussian of Log filter is used in[8], to measure the performance of Blind Image Quality (BIQ).The proposed model in[8], aims to examine the degraded image quality without the need of original image or the reference image. The image quality assessment model using Hue Value Saturation (HVS) and non HVS methods is proposed in[9], and proved that the IQA performs well at

**Author for correspondence*

predicting human judgments. In[10], the definition of the image quality and assessment is focused on full reference image. The proposed approach in[11], deals the noise by the external means and use of degradation model.

The model in[12], deals the importance of image quality index value. The quality of the image can be dynamically controlled and adjusted using these measurements, the range of values can be studied in[13,14] are used to understand the arrangement of pixels in the image, the contrast, the amount of noise degrading the quality of image and eventually use the metrics to set standards.

The compression quality metrics are developed in[15], to measure the quality of decompressed images. The signal is the original data, and the noise is the error introduced by transmission and reception of images in networks. The proposed approach in[16,17]**,** discusses the range of validity of PSNR in image and video. It is one of the simplest metrics to compute along with Mean Square Error (MSE). Higher the value of the PSNR, better the quality of the reconstructed image. An effective method in[17], is used to increase the PSNR value of an image is using Stationary Wavelet Transform (SWT). The MAE in[18,19], are used in measuring the difference in the predicted outcome with that of expected outcome.

To explore the statistical behavior of an image, the model in[20], deals with the mean and Variance information. The average intensity or the mean has a role to play in the contrast of an image, higher the value better the image. Also the Mean value gives the contribution of individual pixel intensity for the entire image, where as the variance is in general describes how each pixel varies from the neighboring pixel (or center pixel) and in used in classify into different regions. It gives how far a given set of pixel values are spread out. An optimized novel approach in[21], was proposed for de-focused images such as short and long exposure images. This framework can produce visually appealing High Dynamic Range (HDR) image. The large and small exposure images are used as the inputs in the work. In the first step, the shaken/movement pixels between the images are identified. The blur pixels are eliminated and optimal quality image is attained by combining the large and small exposure images. An efficient framework using hybrid statistical approach in[22], was developed for identifying and removing the noise pixels in images that are corrupted with Impulse, Gaussian and mix of any Random noise. In[23], the quality of the image is assessed by partial information of the image. The partial information is extracted from the original image at the originating point and the received image at the evaluating point. A successful quality aware image system was proposed and that provides more robustness and accurate. In this approach, certain features of an original image were extracted using steerable pyramid decomposition and the quality of the image is assessed by using the Reduced Reference (RR) method. In[24,] a spatial domain enhancement filter is proposed and the Peak Signal to Noise Ratio is used as a measurement to assess the quality of the algorithm.

This paper analyses the application of a wide variety of measurements on image sets covering more range of pixels. Also an acute examine of the range of values gives a clear idea on variation it imposes on the respective images. This paper covers maximum number of metrics and a vivid idea on the obtained outputs depicting the quality of the images. Since, much effort has not been taken in this area we aim to give the significance of the different image quality metrics through this paper.

This paper has been organized in the following manner. In Section II, we elaborated the Image Quality Analysis using different Image Assessment metrics**.** Section III, brief the data sets used in this paper. The Section IV, deals with the implementation results of different metrics and further we discuss the inferences obtained on the results to give the idea of suggesting the suitable metric for the different images to the researcher. Section V summarizes the conclusion. Finally, the Section VI presents the Future enhancements of the proposed work.

2. Image Quality Analysis using Different Image Assessment Metrics

The quality analysis characterizes the content of an Image and its texture. Basically, the assessment metrics can be classified in to first order, second order and higher order measures. The first order metric is focusing the properties such as mean intensity, standard deviation and variance. It means that the first order metric is operating only on individual pixels of an image. The first order metric is not considering the spatial relationship between the pixels thereby leaving the neighborhood relationship. On the other hand, the second and higher order metrics measures the properties of 2 or more pixels occurring at specific locations relative to each other.

2.1 Mean Square Error (MSE)

The MSE is used in measuring the difference in the predicted outcome with that of expected outcome. This metric is the dispersion metric and it can be used to measure the quality of the image enhancement algorithm in which it is applied to removal of noise and blur. Also in real time this metric can be applied to satellite, seismic and medical applications. If the MSE value increases, then the image degradation increases. When MSE value reaches zero then pixel by pixel matching of images becomes perfect.

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

Where M is the number of pixels in horizontal direction, N is the number of pixels in vertical direction, x(i,j) is the filtered image at i and j co-ordinates and y(i,j) is the noisy image at i and j co-ordinates.

2.2 Peak Signal to Noise Ratio (PSNR)

The PSNR is the important metric which is used to measure the quality of the restored image when it is corrupted due to noise and blur. This metric performs well in LAND-SAT images. Higher the value of PSNR, indicates higher the quality rate. The MSE decides the PSNR value. When comparing the two images, PSNR is calculated by taking the Mean Squared Error (MSE) between the pixel intensities and taking the ratio of the maximum possible intensity to the result of the calculation. The standard value of PSNR is 35 to 40 db. In general, a higher PSNR value corresponds to a better quality image. The PSNR standard value is subjected to correlative analysis and is depends on MSE. MSE is indirectly proportional to the PSNR. The histogram represents the frequency of differences in intensity between the two compared images. The histogram values spread from 30 to 40 db shows more signal. However, the PSNR result is unbounded. PSNR can be computed by using the following relation:

$$\text{PSNR} = 10\log_{10}\frac{MaxI^2}{\text{MSE}} \quad (2)$$

Where n is the maximum pixel value of the image and MSE is in II a.

2.3 Mean Absolute Error (MAE)

Higher value of MAE, signifies the lower the quality of the image. This is the conventional measure and it can be used to detect the blurring effect present in any real time images. The MAE metric, most extensively applied to assess the quality of satellite imaging. Usually, the satellite images are blurred due to atmospheric turbulence and aperture effects of the camera. Due to these limitations, the quality of the image becomes degraded. In this situation, the MAE measure gives better idea to the researcher to update the de-blurring scheme.

$$\text{MAE} = \frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N}|(x(i,j) - y(i,j)| \quad (3)$$

Where M is the number of pixels in horizontal direction, N is the number of pixels in vertical direction, x(i, j) is the filtered image at i and j co-ordinates and y(i, j) is the noisy image at i and j co-ordinates.

2.4 Average or Mean Intensity

The Average intensity or the mean has a role to play in the contrast of an image, higher the value better the image. Mean value gives the contribution of individual pixel intensity for the entire image. This measure is applicable to almost all the areas of Image processing field and is exclusively used in Synthetic Aperture Radar (SAR) images. The Mean Intensity deals all the color components of the image. It gives how far a given set of pixel values are spread out. It also describes the statistical behavior of an image. The application includes photographs with poor contrast due to glare and is used to measure the intensity strength of any pictures taken in real time. This measure is very important, if the application focus towards the contrast and the histogram based approach is relies on intensity value concentrations. The Mean Intensity is the "central statistic" measure of an image.

$$\text{Average or Mean Intensity} = \frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N}|(x(i,j)| \quad (4)$$

Where M is the number of pixels in horizontal direction, N is the number of pixels in vertical direction and x(i, j) is the filtered image at i and j co-ordinates.

2.5 Average Difference (AD)

The average difference is the pixel difference between the filtered image and its corresponding degraded image.

This quantitative measure is exclusively used in object detection and recognition applications and it can also be applicable to any image processing applications where we find the average difference between 2 images. Larger value of the AD, specifies the poor quality of the image.

Average Difference =

$$\frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N}(x(i,j)-y(i,j)) \quad (5)$$

Where M is the number of pixels in horizontal direction, N is the number of pixels in vertical direction, x (i, j) is the filtered image at i and j co-ordinates and y (i, j) is the noisy image at i and j co-ordinates.

2.6 Maximum Difference (MD)

It is directly proportional to contrast giving the dynamic range of an image. It is performed by passing an image to a low pass filter as sharp edges corresponds to the higher frequency elements in an image, which gets suppressed by the low pass filter).Higher the value of Maximum Difference indicates that the image is poor quality. As similar to AD, the Maximum Difference metric can also works well in object detection and recognition fields.

$$\text{Maximum Difference} = \text{Max}\,|x(i,j)-y(i,j)| \quad (6)$$

Where x(i, j) is the filtered image at i and j co-ordinates and y(i, j) is the noisy image at i and j co-ordinates.

2.7 Structural Content (SC)

The structural content deals with spatial arrangements of pixels in an image. It measures the closeness of two digital images which also can be done in terms of correlation function. This metric brings out the similarity between two images. It takes out the closely association of two images and implies on the fact no human eye can differentiate the two images. Higher the value of structural content specifies poor the quality of the image. When two same images are compared to each other its structural content metric value comes to 1(maximum) and the hidden data length comes to zero, hence the images are identical to each other. Two images of values within an almost same range say 0.90 to 0.95will appear same to a human eye but they are not closer degree of similarity. The hidden data gives the measurements of dissimilarity and a structural content value of 1 shows no dissimilarity in an image set, no stego image. This metric can be used in radar and steganography applications. Structural content can be given as:

$$\text{Structural Content} = \frac{\sum_{i=1}^{M}\sum_{j=1}^{N}(y(i,j))^2}{\sum_{i=1}^{M}\sum_{j=1}^{N}(x(i,j))^2} \quad (7)$$

Where M is the number of pixels in horizontal direction, N is the number of pixels in vertical direction, x(i, j) is the filtered image at i and j co-ordinates and y(i, j) is the noisy image at i and j co-ordinates.

2.8 Fidelity

The fidelity measures the closeness of an image to its ideal image. It measures the visual information of an image and also it measures the relativity of distortion image information to its reference image information. It gives a prediction of the quality betterment due to contrast enhancements. This metric is the most significant metric in the field of image fusion and watermarking applications.

$$\text{Fidelity} = 1 - \frac{\sum_{i=1}^{M}\sum_{j=1}^{N}(x(i,j)-y(i,j))^2}{\sum_{i=1}^{M}\sum_{j=1}^{N}x(i,j)} \quad (8)$$

Where M is the number of pixels in horizontal direction, N is the number of pixels in vertical direction, x(i, j) is the filtered image at i and j co-ordinates and y(i, j) is the noisy image at i and j co-ordinates.

2.9 Variance

The variance metric describes how each pixel varies from the neighboring pixel (or center pixel) and is used in classify into different regions. It also describes the statistical behavior of an image. This is the important metric which is used to assess the quality of the restored images and it can be used in diverse applications where the image is degraded due to different distributions. The Variance metric can be used to improvise the filtering techniques where it can be applied in space craft images.

$$\text{Variance} = \frac{1}{Totalno.of pixels}\sum_{i=1}^{M}\sum_{j=1}^{N}(x_{i,j}-\mu)^2 \quad (9)$$

Where, M is the number of pixels in horizontal direction, N is the number of pixels in vertical direction, $x_{i,j}$ is the filtered image at i and j co-ordinates andμ is the calculated mean of the image.

2.10 Standard Deviation (SD)

The SD quantifies the amount of variation in an image. This is the optimal metric to assess the quality of restored images and it can be used in applications where the image is degraded due to distribution such as Gaussian and impulse noises. This metric can be extensively used in real time applications such as Satellite and Medical imaging fields.

Standard Deviation =

$$\sqrt{\frac{1}{Total no.of pixels}\sum_{i=1}^{M}\sum_{j=1}^{N}(x_{i,j}-\mu)^2} \quad (10)$$

Where, M is the number of pixels in horizontal direction, N is the number of pixels in vertical direction, $x_{i,j}$ is the filtered image andµ is the calculated mean of the image.

2.11 Normalized Cross Correlation (NCC or NK)

The NCC is the measure of similarity between two set of images. In image-processing applications where the brightness of the image can vary due to lighting and exposure conditions, the images can be first normalized. It is used in finding the incidences of a pattern or an object in an image. The application of this metric widely used in image registration areas. It can also be used to assess the quality of deconvolution algorithms. The standard values of NCC range from –1 to 1. –1 indicates perfect correlation and 1 indicates perfect anti-correlation.

$$\text{NCC or NK} = \frac{\sum_{i=1}^{M}\sum_{j=1}^{N} x(i,j)\, X y(i,j)}{\sum_{i=1}^{M}\sum_{j=1}^{N}(x(i,j))^2} \quad (11)$$

Where, M is the number of pixels in the horizontal direction, N is number of pixels in the vertical direction, x(i, j) is the filtered image at i and j co-ordinates and y(i, j) is the noisy image at i and j co-ordinates.

2.12 Structural Similarity Index Metric (SSIM)

In order to bring betterment to these metrics SSIM is introduced. SSIM is defined as a function of luminance comparison, contrast and structural comparison term. The value lies from 0 to 1.SSIM is a perception-based model that considers the image degradation as perceived change in structural information where, structural information is the idea that the pixels have strong inter-dependencies especially when they are spatially close. The linear dependence factor is computed using the correlation coefficient in SSIM index. Blurring operation on an image causes fading of the sharp edges of an image. SSIM has a high significance on blurred images with high consistency. In real time, this metric can be widely used in bio-medical applications especially in mammographic diagnosis and cancer detection fields. It is the universal metric where we can apply this metric to assess the quality of any images. Since this metric is operating on luminance, contrast and structural information in images.

$$\text{SSIM} = \frac{(2\,\mu_x+\mu_y)(2\,\sigma_{xy})}{(\mu_x{}^2+\mu_y{}^2)(\sigma_x{}^2+\sigma_y{}^2)} \quad (12)$$

Where,

$$\mu_x = \frac{1}{N}\sum_{i=1}^{N} x_i$$

$$\mu_y = \frac{1}{N}\sum_{i=1}^{N} y_i$$

$$\sigma_x = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N}(x_i-\mu_x)^2}$$

$$\sigma_y = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N}(y_i-\mu_y)^2}$$

$$\sigma_{xy} = \frac{1}{N-1}\sum_{i=1}^{N}(x_i-\mu_x)(y_i-\mu_y)$$

N is the total number of pixels in the image. $x_{i,j}$ is the filtered image at i and j co-ordinates and $y_{i,j}$ is the noisy image at i and j co-ordinates.

2.13 Mean Luminance

The Luminance is a measure of the luminous intensity per unit area of light travelling in a given direction.

It affects the brightness quality of a picture. The mean luminance of an image slightly differs from the mean intensity of an image. The mean luminance factor is only sensitive to RGB components of an image. The Mean Luminance can be widely used in Computer vision and LANDSAT applications.

$$\text{Mean Luminance} = \frac{1}{N}\sum_{i=1}^{M} Luminance \quad (13)$$

Where, Luminance = 0.299 * Red + 0.587 * Green + 0.114 * Blue and N is the total number of pixels.

3. Datasets

This work is tested with different LANDSAT images taken from the NASA database. Few of the sample input study area imageries are extracted here for demonstration purpose and is shown in Figure1, 3 and 5.

4. Results and Discussion

The Image quality assessment is vital part of many image and signal processing applications which in turn proves the quality of the any image enhancement algorithm. In order to measure the performance of the any filtering schemes such as spatial or frequency domain filters, we conduct the experiment on all the different data sets. The Table 1 gives the results of quality metrics that depends on single image. The Table 2 gives the results of quality metrics that depends on two images.

In our experiment, First we consider the Gaussian noisy satellite image (noisy level=20)of size 360 x 264as shown in Figure 1. The corresponding filtered image is shown in Figure 2.

The blurred image is of size 1031 x 589 is shown Figure 3 and the de-blurred image is shown in Figure 4. The salt and pepper satellite noisy image of size 1031 x 589 is shown in Figure 5 and the corresponding enhanced image is shown in Figure 6.

This work is tested with the different LANDSAT images taken from the NASA database. Few of the sample input study area imageries are shown in Figures 1, 3 and 5.

The Figure 7 shows the graphical representations of the different measures operating on single image. The other metrics such as MAE, AD, MD, MSE, PSNR, SC,

Table 1. Metrics depends on single Image

S.No	Fig. No	Image Type	Mean	Variance	SD	Mean Luminance
1	**Refer Fig.1**	**Gaussian Noisy Satellite Image = 20**	98.6	1542	39. 3	98.54
2	**Refer Fig.2**	**Filtered Image**	99.2	1333	36.5	99.14
3	**Refer Fig.3**	**Blurred Satellite Image**	113	1482	38.5	113.52
4	**Refer Fig.4**	**Filtered Image**	114	2938	54.2	114.51
5	**Refer Fig.5**	**Salt and Pepper Noisy Satellite Image**	110	1350	36.7	110.42
6	**Refer Fig.6**	**Filtered Image**	111	1305	36.1	110.91

Table 2. Metrics depends on two Images

S. No	Fig. No	Image Type	MAE	AD	MD	MSE	PSNR	SC	Fidelity	NK	SSIM
1	**Refer Fig.1**	**Gaussian Noisy Satellite Image=20**	12	-0.6	85	234	24	1	-1.37	1	1
2	**Refer Fig.2**	**Filtered Image**									
3	**Refer Fig.3**	**Blurred Satellite Image**	19	-1	158	819	19	1.1	-6.22	0.9	0.9
4	**Refer Fig.4**	**Filtered Image**									
5	**Refer Fig.5**	**Salt and Pepper Noisy Satellite Image**	11	-0.5	141	251	24	1	-1.27	1	1
6	**Refer Fig.6**	**Filtered Image**									

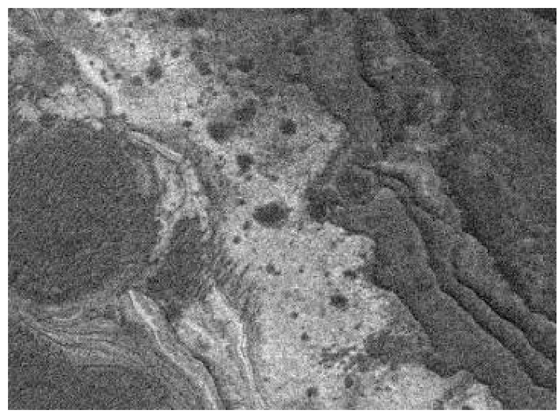

Figure 1. Gaussian Noisy Satellite Image = 20.

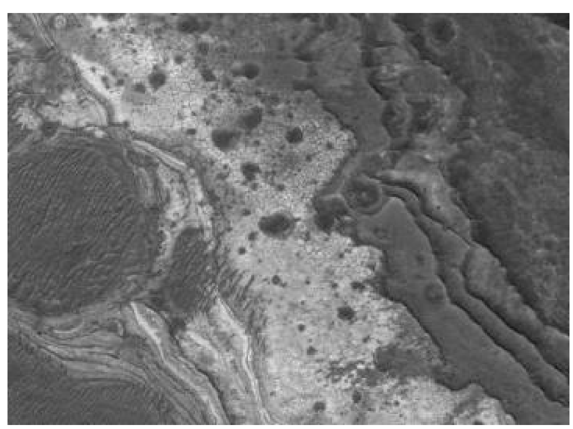

Figure 2. Filtered Image.

Figure 3. Blurred Satellite Image.

Figure 4. Filtered Image.

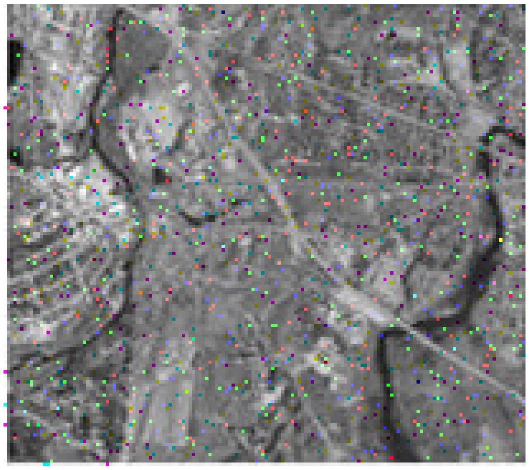

Figure 5. Salt and Pepper Noisy Satellite Image.

Figure 6. Filtered Image.

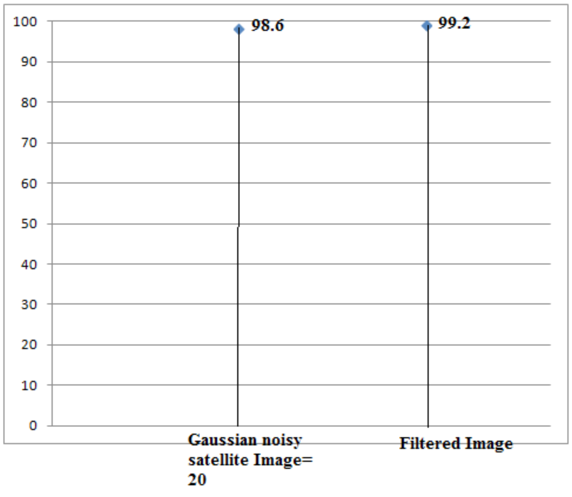

Figure 7.1. Graphical representation of Mean value for Gaussian and filtered Satellite image.

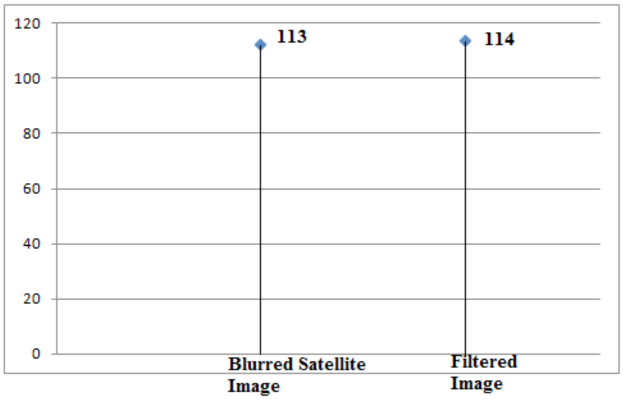

Figure 7.2. Graphical representation of Mean value for blurred and filtered Satellite image.

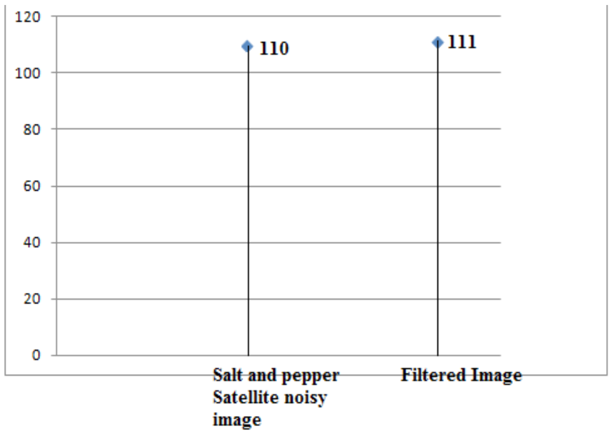

Figure 7.3. Graphical representation of Mean value for Salt and pepper and filtered Satellite image.

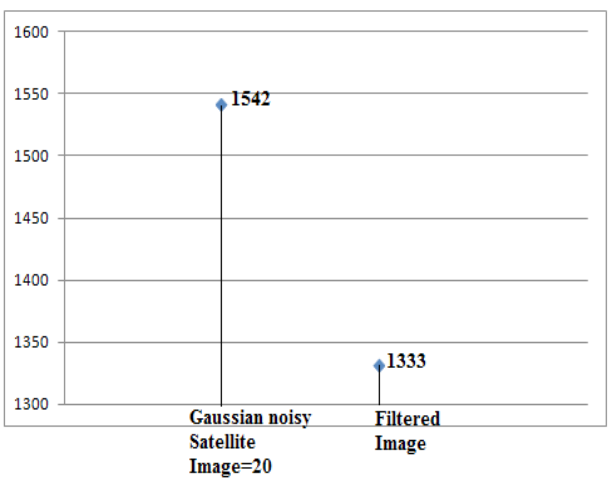

Figure 7.4. Graphical representation of Variance value for Gaussian and filtered Satellite image.

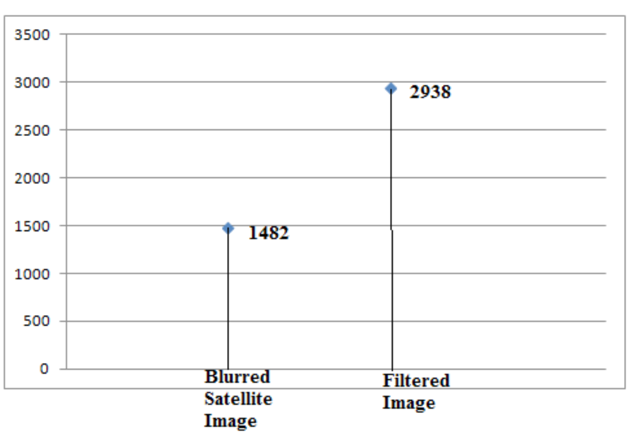

Figure 7.5. Graphical representation of Variance value for Blurred and filtered Satellite image.

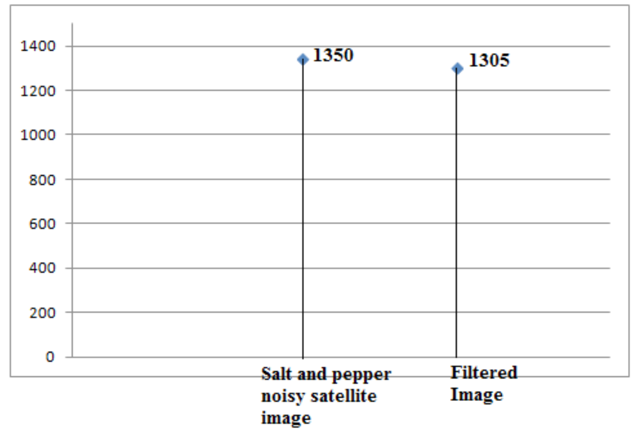

Figure 7.6. Graphical representation of Variance value for Salt and pepper and filtered Satellite image.

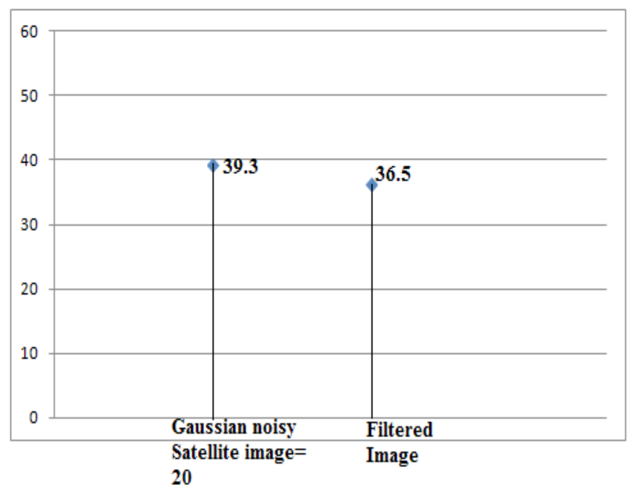

Figure 7.7. Graphical representation of Standard deviation value for Gaussian and filtered Satellite image.

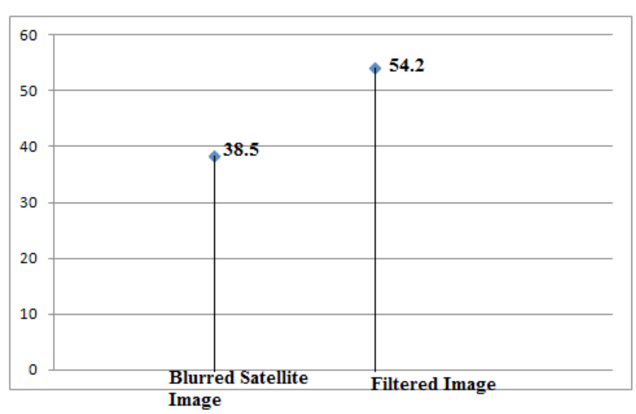

Figure 7.8. Graphical representation of Standard deviation value for blurred and filtered Satellite image.

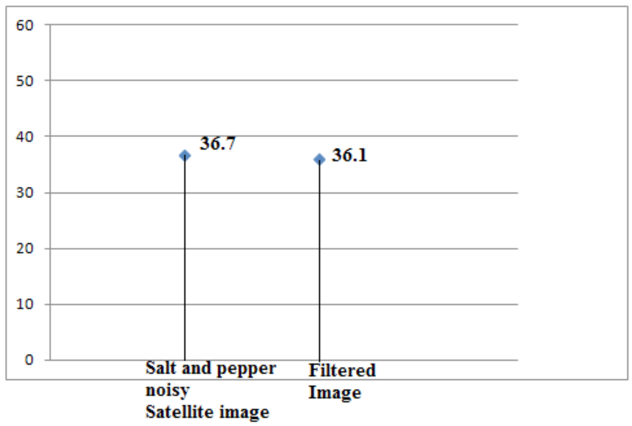

Figure 7.9. Graphical representation of Standard deviation value for Salt and pepper and filtered Satellite image.

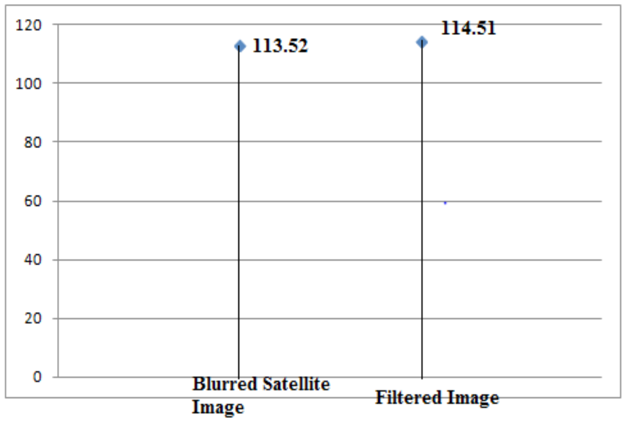

Figure 7.11. Graphical representation of Mean Luminance value for Blurred and filtered Satellite image.

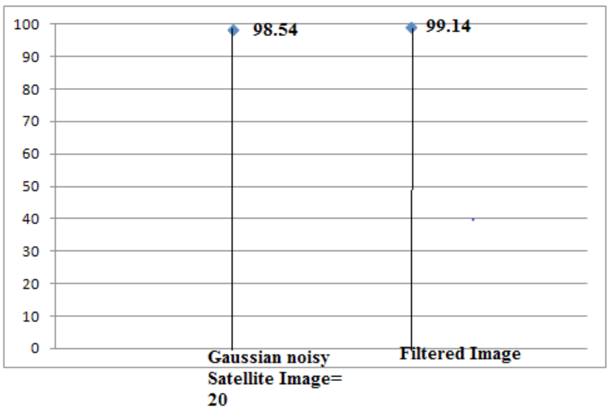

Figure 7.10. Graphical representation of Mean Luminance value for Gaussian and filtered Satellite image.

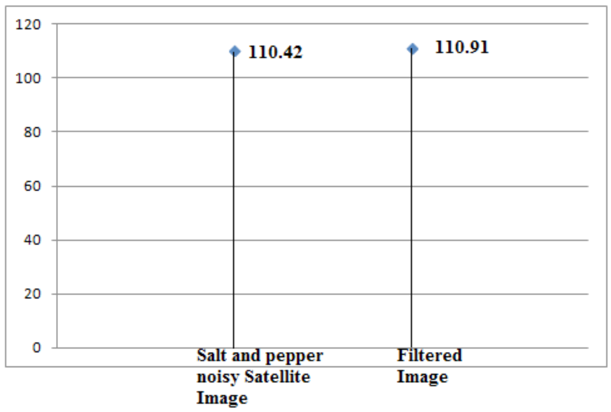

Figure 7.12. Graphical representation of Mean Luminace value for Salt and pepper and filtered image.

Fidelity, NCC, SSIM are depends on two images. Therefore the graphical representation can be shown only for the metrics which are operating on single image.

5. Conclusion

This paper gives a comparative analysis of various image quality metrics. Different metrics such as metric based on single image and metric based on two images have been tested with different real time satellite images from NASA data sets. Each metric has a role to play in the control of the image quality. As discussed and shown in the results, three different sets of degraded images such as Gaussian, blurred and Salt and pepper satellite images are extracted for demonstration purpose in this paper. All the image quality metrics described in this paper have been computed for all three types of image sets. The metrics such as mean, standard deviation, variance and mean luminance are operating on one image. Using these metrics alone, we cannot quantify the quality of the image. Other metrics such as MAE, AD, MD, MSE, PSNR, SC, Fidelity, NCC and SSIM plays the vital role to assess the quality of the images and these metrics are functioning in both degraded image and the filtered image.

As based on the results obtained, metrics depends on single image such as Average Intensity, Variance, Standard deviation and Mean Luminance are the appropriate metrics to assess the quality the image if the image is corrupted due to Gaussian noise. If the image is corrupted due to Gaussian noise and if there is an increase in average intensity and mean luminance and decrease in variance and standard deviation after the filtering, indicates that the quality of the image is good. Therefore the Average Intensity, Variance, Standard deviation and Mean Luminance are the best measures to analyze the quality of the images that are corrupted due to Gaussian noise.

According to the results obtained, the Mean Intensity is also the optimal measure to assess the quality of deblurred image. But the variance and standard deviation will not produce accurate results on the deblurred image. Hence, we conclude that the metrics depends on single image will not be suitable to assess the quality of the image if the effect of the degradation is blur. Hence, we further used extensive metrics to prove the quality of images which are corrupted due to other degradations.

As based on the experimental results, the metrics depends on two images such as MAE, MSE and PSNR are yielding good results to assess the quality of the image if it is corrupted due to Gaussian noise, Salt and pepper noise and blur. The above three measures provides simple, more convenient, easy to implement and less time complexity. The characteristic of the above metrics assess the quality of the image objectively.

The MD gives good results for noisy images and according to the results, this metric works outstanding to analyze the blurred images. As similar to MD, the AD is more sensitive metric for blurred and noisy images.

According to the results, the Fidelity factor is the best measure for assessing the quality of excessive contrast images and is exclusively used in Image Fusion applications where we can combine the best features of multiple images to produce the fused image. Therefore this metric is not a suitable measure for assessing the quality of noisy and blurred images. Higher the value of the Fidelity indicates, higher the contrast of the reconstructed image.

The Normalized Noise Correlation is another optimal metric to assess the quality of the images which are corrupted due to any noise and blur. According to the results, the NK values are almost close to the value one for all the different image sets. Therefore all the values of NK indicate that the filtered image is moderately correlated.

The Structural content is the correlation based metric. This metric gives the similarity between filtered image and degraded image. As based on the results, the structural content is a good measure to analyze the quality of deblurred image.

The SSIM is the exclusive and consistent metric that provides the information about the similarity in two images. It is the perfect measure for assessing the quality of deblurred images and it also handles the extensive Gaussian noisy images.

6. Future Enhancement

In this paper, we assessed the quality of satellite images which are corrupted due to different unwanted degradations. In future, we plan to continue to demonstrate how this framework may be used for analyzing the quality of any other real time images such as medical and ultrasound images.

7. Acknowledgement

We wish to express our sincere gratitude and thanks to the reviewers for their constructive comments and valuable suggestions.

8. References

1. Zhang Y, Chandler DM. 3D-MAD: A Full Reference Stereoscopic Image Quality Estimator Based on Binocular Lightness and Contrast Perception. IEEE Transactions on Image Processing. 2015; 24(11):3810–25.
2. Lee J, Park R-H. Image Quality Assessment of Tone mapped Image. International Journal on Computer Graphics and Animation (IJCGA). 2015; 5(2):9–20.
3. Liu X, Zhang L, Li H et al. Integrating visual saliency information into objective quality assessment of tone-mapped images. 10th Proceedings International Conference on Intelligent Computing, Taiyuan, China. 2014. p. 376–86.
4. Li J, Wang C, Li M, Guo P. An Image Quality Assessment Algorithm on the basis of edge information and singular value decomposition. International Journal of Signal Processing, Image Processing and Pattern Recognition. 2015; 8(6):283–88.
5. Jagalingam P, Hegde AV. A Review of Quality Metrics for Fused Image. International Conference on Water Resources, Coastal and Ocean Engineering (ICWRCOE-2015). 2015. p. 133–42.
6. Ding Y, Zhang Y et al. Perceptual Image Quality assessment metric using mutual information of Gabor features. Springer Journal. 2014; 57(3):1–9.
7. Galbally J, Marcel S, Fierraz J. Image Quality Assessment for Fake Biometric Detection: Application to Iris, Fingerprint, and Face Recognition. IEEE Transactions on Image Processing. 2014; 23(2):710–24.

8. Xue W, Mou X, Zhang L et al. Blind Image Quality Assessment using Joint Statistics of Gradient Magnitude and Laplacian Features. IEEE Transactions on Image Processing. 2014; 23(11):4850–62.
9. Chandler DM. Seven Challenges in Image Quality Assessment: Past, Present, and Future Research. ISRN Signal Processing. 2013; 2013:1–54.
10. Thung KH, Raveendran P. A Survey of Image quality measures, IEEE International Conference for Technical Post Graduates (TECHPOS), Kuala Lumpur. 2009. p. 1–4.
11. Damera-Venkata N, Kite TD, Geisler WS, Evans BL, Bovik AC. Image Quality Assessment based on a Degradation Model. IEEE Transactions on Image Processing. 2000; 9(4):639–50.
12. Wang Z, Bovik AC. A Universal Image Quality Index. IEEE Signal Processing Letters. 2002; 9(3):81–4.
13. Wang Z, Bovik AC, Sheikh HR, Simoncelli EP. Image Quality Assessment: From Error Visibility to Structural Similarity. IEEE Transactions of Image Processing. 2004; 13(4):600–12.
14. Silva EA, Panetta K, Agaian SS. Quantify similarity with measurement of enhancement by entropy, Proceedings: Mobile Multimedia/Image Processing for Security Applications, SPIE Security Symposium, 2007.
15. David S. Data Compression: The Complete Reference, (4 ed) Springer-Verlag: London, 2007.
16. Huynh-Thu Q, Ghanbari M. Scope of validity of PSNR in image/video qualityassessment. Electronics Letters. 2008; 44(13):800–1.
17. Naveen Kumar N, Ramakrishna S. An Impressive Method to Get Better Peak Signal Noise Ratio (PSNR), Mean Square Error (MSE) Values Using Stationary Wavelet Transform (SWT). Global Journal of Computer Science and Technology Graphics andVision. 2012; 12(12):35–40.
18. Wang Z, Sheikh HR, Bovet AC. Objective video quality assessment, in the Handbook of Video Databases: Design and Applications, B. Furht and O. Marques, Eds. CRC Press: Boca Raton, FL. 2003; 1041–78.
19. Peli E. Contrast in complex images. J Opt Soc Amer A. 1990; 7(10):2032–40.
20. Kumar R, Rattan M. Analysis of Various Quality Metrics for Medical Image Processing. International Journal of Advanced Research in Computer Sciences and Software Engineering. 2012; 2(11):137–44.
21. Rajkumar S, Malathi G. A Novel approach for the recovery of de-focused color Images. International Journal on Recent Researches in Science, Engineering and Technology (IJRRSET). 2015; 3(5).
22. Rajkumar S. A Novel Approach for the Recovery of ill conditioned color images. Proceedings 6th National Conference on Convergence of Computer and Information Engineering, (NCCCIE'06), PSG College of Technology, Coimbatore, India. 2006; 12 pp.
23. Rajkumar S. An Advanced Technique for the Analysis of Image Quality Assessment for Distorted Images in the Field of Image Processing Application, Karunya University, Coimbatore, India. 2008; 84–8.
24. Janani P, Premaladha J, Ravichandran KS. Image Enhancement Techniques: A Study. Indian Journal of Science and Technology. 2015; 8(22):1–12.