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Research Paper

# Analysis of image quality metric for ROI using image restoration techniques

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**Abstract**

Analysis of an image plays vital role in the image processing field, which leads to the inventions of applications in the area of telemedicine, remote sensing via satellites and other spacecrafts, radar, sonar and acoustic image processing etc. This concept is a key factor in research field. One of the common image analysis is use of Region of Interest (ROI) image, which is an effortless way of analyzing images. This paper proposes a method to analyze the Image Quality Metric (IQM) for a ROI based color image. IQM is accomplished by the use of the three image restoration algorithms such as Blind deconvolution algorithm, Wiener Filtering algorithm and Lucy – Richardson algorithm.

***Keywords***: *Blind Deconvolution, Lucy Richardson, Point Spread Function, Region of Interest, Image Quality Metric, Wiener Filter*.

## 1. Introduction

Image restoration is to recover or restore an image that has been degraded by using a priori knowledge of the degradation phenomenon [1]. Restoration techniques are oriented to develop degrading modeling and applying the inverse process to obtain an optimal estimation of the desired outputs. The degraded image is modeled based on the convolution of an original image with additive noise. The linear, spatial invariant process can be used to develop the degraded model in the spatial domain as shown below:

$$m(x, y) = h(x, y) * g(x, y) + \eta(x, y) \tag{1}$$

Where: $m(x, y)$ = degraded model
$g(x, y)$ = original image,
$h(x, y)$ = point spread function (PSF) in the spatial domain,
$*$ = convolution
$\eta(x, y)$ = additive noise [1].
PSF is the point of light to obtain the characteristics of degradation of any type of input. Based on the known and unknown PSF, images are restored by applying algorithms. This paper deals with three different restoration algorithms, which are applied to restore the images. The performances of restoring algorithms [4] are evaluated with different IQM parameters.
This paper is organized as follows: Section 2 describes the three different algorithm concepts, Section 3 presents image quality metrics, and Section 4 presents experimental results and finally Section 5 describes conclusion and future directives.

## 2. Methodology and system design

The main objective of this paper is to analyze an image based on the user specified Region of Interest. The user has the freedom to choose a desired ROI of image using polygonal shape of ROI tool. After selection of ROI, the proposed algorithm is applied to construct the iterative images which are based on image restoration algorithms and their corresponding image quality metric values.

## 2.1. Image restoration algorithms

This section deals with the basic concepts of three different algorithms.

### 2.1.1. Blind deconvolution algorithm

The main objective of this algorithm is to restore an object of blurred and noisy image, which doesn't have the prior knowledge of Point Spread Function (PSF)[1].As we know, blurred image comprises of distortion factor (ie.PSF) of an original image, along with additive noise. To apply this algorithm, PSF would be extracted by an image itself and it helps to perform the algorithm by iteratively and non-iteratively to obtain a better image [2].

### 2.1.2. Wiener filtering algorithm

The Wiener Filter is working based on Fourier transform. It minimizes the mean square error between observed image and the original image. To find a desired solution, it takes minimum computational time. This algorithm can work with any type of image with relatively high – signal to noise ratio [3].
The objective of this algorithm is to filter out noise from a corrupted signal. It is working under the assumption of knowledge about the spectral properties of the original image and the noise which seeks the linear time-invariant filter that produces output as close to the original image.

### 2.1.3. Lucy – Richardson algorithm

In this method the image restoration is being done iteratively with known PSF from blurred image. Here, PSF represents the pixel of observed image as an undegraded image [2]. The undegraded image equation is given as follows:

$$q_i = \sum_j p_{ij} s_j \tag{2}$$

Where: $p_{ij}$ = the point spread function
$s_j$ = is the pixel value at location j in the undegraded image
$q_i$ = the observed value at pixel location i.
Here Poisson distribution is applied to obtain the statistical values of $s_j$, which is appropriate for photon noise in the data. The main concept of this algorithm is to compute the most likely $s_j$ from the observed $q_i$ and known $p_{ij}$. This leads to an equation for $s_j$ which can be solved iteratively according to pixels in the observed image and can be represented in terms of the point spread function of the undegraded image as shown in (3):

$$s_j^{(k+1)} = s_j^{(k)} \sum_i \frac{q_i}{v_i} p_{ij} \tag{3}$$

Where: $v_i$ is given as follows:

$$v_i = \sum_j p_{ij} s_j^{(k)} \tag{4}$$

It has been shown in (3), this iteration converges to maximum likelihood result for $s_j$.

# 3. Image quality metric

The following IQM factors [5] were analyzed in a particular ROI image in the respective three algorithms mentioned above.

## 3.1. Average difference (AD)

It provides the average difference between the original image and distorted images as mentioned in (5).

$$AD = \frac{1}{m*n} \sum_{i=1}^{n} \sum_{j=1}^{n} [O(i,j) - D(i,j)] \tag{5}$$

## 3.2. Mean square error (MSE)

It measures the average square errors between distorted image and original image. The output values deliver details of distorted image analysis. Mean Square Error values are computed on the Red, Green and Blue channels using the following formula (6).

$$MSE = \frac{1}{m*n}\sum_{i=1}^{n}\sum_{j=1}^{n}[O(i,j)-D(i,j)]^2 \tag{6}$$

### 3.3. Peak signal noise ratio (PSNR)

It measures the maximum possible pixel value of an image and the power of corrupting noise of an image. It is used to represent the quality of an image. PSNR values are computed on the three channels of color image using the following formula (7):

$$PSNR = 10\log_{10}\left(\frac{MAX_i^2}{MSE}\right) \tag{7}$$

### 3.4. Normalized cross correlation

This metric gives the template matching between the images in a spatial domain[6][7]. It is computed with based on the following formula in Matlab 7.0. The same is shown in (8).

$$NCC = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n}[O(i,j)D(i,j)]}{\sum_{i=1}^{n}O(i,j)^2} \tag{8}$$

### 3.5. Structural content

It gives the image structural information which is not influenced by the factors like lighting, texture and image colors [4].The computation of structural content is given as follows in (9):

$$SC = \frac{\sum_{i=1}^{n}O(i,j)^2}{\sum_{i=1}^{n}D(i,j)^2} \tag{9}$$

## 4. Experimental results

These are the main results of the paper. This portion describes the performance of each algorithm separately and IQM comparison of three algorithms.

### 4.1. Blind deconvolution algorithm:

In this algorithm, original image [8] is reconstructed based on the undersize PSF, oversize PSF and initial PSF. The resultant images are shown in the Fig 1. The IQM for this is represented in Table 1. If we compare original and reconstructed image, the IQM for reconstructed with oversize PSF produces 27.1671dB PSNR but INIT PSF produces 35.dB PSNR.

**Table 1:** IQM for Bind Deconvolution Algorithm

| Input Images | IQM | | | | |
|---|---|---|---|---|---|
| | AD | MSE | PSNR | NCC | SC |
| Original,blurred | -3.6667 | 20.5317 | 35.0065 | 0.9576 | 1.0576 |
| Blurred, underpsf | 195.5556 | 13.941 | 36.6879 | 1.0127 | 0.9564 |
| Blurred, OverPSF | 2.36E+04 | 124.8445 | 27.1671 | 0.9935 | 0.8485 |
| Blurred, InitPSF | 9.39E+03 | 57.0355 | 35.0065 | 1.0168 | 0.8911 |

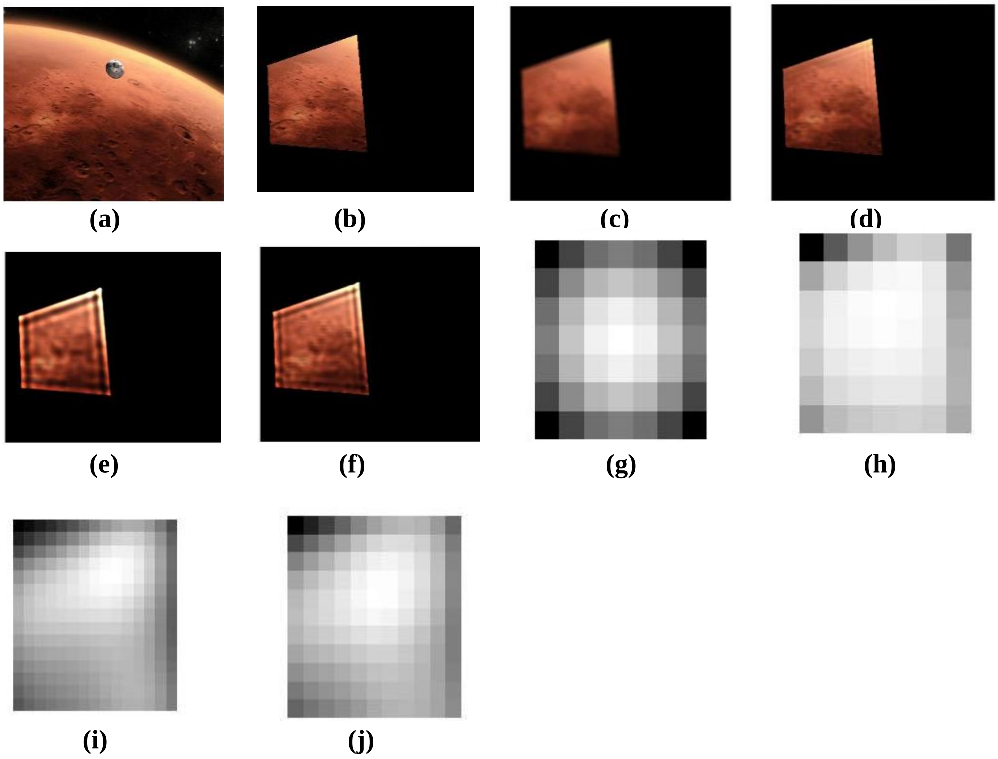


**Fig. 1:** (L to R) (a) Original Image. (b) Selected ROI (c) ROI with Blurred. d) Reconstructed ROI with Undersized PSF. (e) Reconstructed ROI with Oversized PSF (f) Reconstructed ROI with INITPSF. (g) True PSF. (h) Reconstructed Undersized PSF. (i) Reconstructed Oversized PSF. (j) Reconstructed INIT PSF

## 4.2. Wiener filter algorithm

The Table 2 illustrates the IQM values for different input images of Wiener Filter Algorithm. The first row is representing the comparison of IQM for original ROI with blurred ROI. Blurred image is obtained after applying PSF. Row two describes first iteration of wiener filter with zero noise signal ratio, third row represents original ROI with blurred and noisy which is the added noise in original. The fourth row of value implicates the restoration of Blurred and Noisy Image with zero noise to signal ratio, the fifth row shows the results of restoration of Blurred and Noisy Image using estimated NSR. The sixth and seventh rows show restoration of Blurred and Quantization of Image with zero NSR, restoration of Blurred Quantization Image with NSR respectively. Blurred and Quantization image is considered because sometime even a visually unnoticeable noise can affect the result.

**Table 2:** IQM for Wiener Filter Algorithm

| Input images | IQM | | | | |
|---|---|---|---|---|---|
| | AD | MSE | PSNR | NCC | SC |
| Original , Blurred | 5 | 32.5593 | 33.0041 | 0.9371 | 1.0883 |
| Blurred , wnr1 | -2.00E+04 | 34.1763 | 32.7936 | 1.0208 | 0.9114 |
| Original,Blurred_Noisy | -1.98E+04 | 33.8918 | 32.8299 | 0.9373 | 1.0842 |
| Blurred_Noisy ,wnr2 | -3.97E+05 | 559.8399 | 20.6502 | 1.0898 | 0.4737 |
| Blurred_Noisy ,wnr3 | -3.96E+05 | 557.3405 | 20.6696 | 1.0895 | 0.4745 |
| Blurred_QuanI,wnr4 | -2.00E+04 | 34.1763 | 32.7936 | 1.0208 | 0.9114 |
| Blurred_Quan ,wnr5 | -1.88E+04 | 33.1279 | 32.9289 | 1.0207 | 0.9133 |

As per the IQM values, if we compare the row number three and five, with estimated NSR of this algorithm reproduces the image with 20.6696dB of PSNR and 1.0895 Normalized cross correlation but structural content of an image is low as compared to row three. The following Fig 2 illustrates the resultant images of Wiener Filter Algorithm.

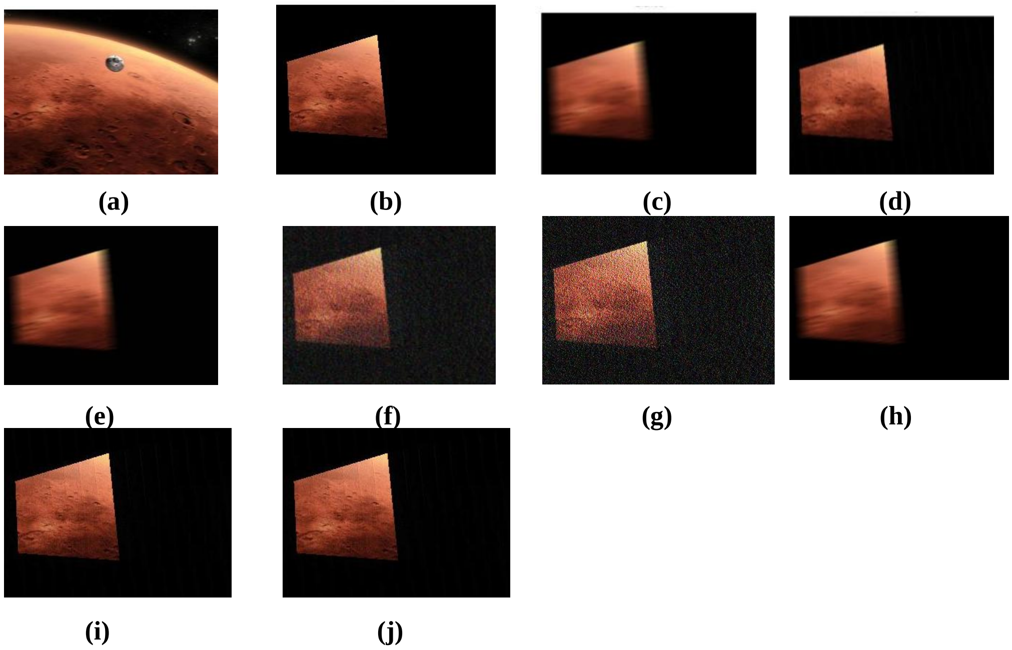


**Fig. 2:** (L To R) (a) Original Image (b) Selected ROI (c) ROI with Blurred (d) Reconstructed ROI From Blurred (e)ROI with Blurred & Noisy (f) Reconstructed ROI with NSR 0 (g) Reconstructed ROI with NSR (h) Blurred with Quantization (i)Reconstructed ROI with NSR 0 (j) Reconstructed ROI with NSR From Blurred Quantization.

## 4.3. Lucy Richardson algorithm

In this algorithm, blurred image is obtained based on the Gaussian filter PSF and this blurred image is compared with original ROI with IQM as shown in Table 3. Then, blurred image is simulated with Gaussian noise of V variance and it produced blurred and noisy image. The algorithm is applied with iteration 5 to obtain a restored image. The IQM values for this is represented in row two of Table 3, row four describes the comparison between blurred and noisy image and restoration image of iteration 15. Taking into consideration of speckled appearance of restored image, damping is applied to smoothen the image; IQM for this is mentioned in the last row of the table.
If we compare IQM values for this algorithm as given in the row number three and six, this algorithm reproduces the image with 26.2762dB of PSNR and 0.9801 Normalized cross correlation, but structural content of an image is low as compared to row three. The resultant images of LRA are shown below in Fig 3.

**Table 3:** IQM for Lucy Richardson Algorithm

| Input Images | IQM | | | | |
|---|---|---|---|---|---|
| | AD | MSE | PSNR | NCC | SC |
| Original,blurred | -2.8889 | 14.702 | 36.457 | 0.9689 | 1.0416 |
| Blurred, lcr1 | 246 | 5.9932 | 40.3542 | 1.0097 | 0.9729 |
| Original ,blurredNoisy | -9.11E+04 | 40.8687 | 32.0169 | 0.9686 | 0.9815 |
| BlurredNoisy,luc2 | 510.8889 | 24.3839 | 34.2598 | 1.0048 | 0.9448 |
| BlurredNoisy,luc3 | 3.09E+03 | 149.9965 | 26.37 | 0.9857 | 0.7895 |
| BlurredNoisy,luc4 | -8.53E+04 | 157.4066 | 26.2762 | 0.9801 | 0.7646 |

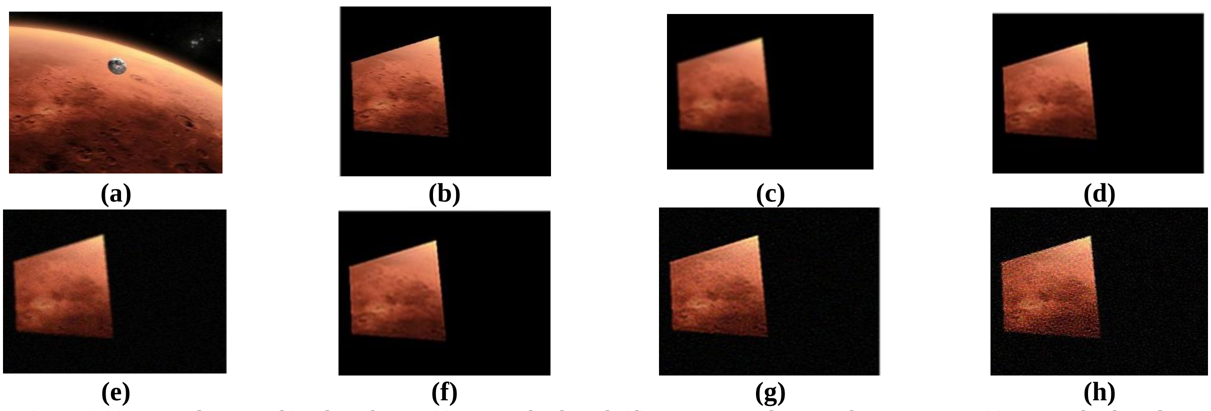


**Fig. 3:** (L to R) (a) Original Image. (b) Selected ROI. (c) ROI with Blurred. (d) Reconstructed ROI with NUMIT = 5. (e) ROI with Blurred & Noisy. (f) Reconstructed ROI with NUMIT =5. (g) Reconstructed ROI with NUMIT=15. (h) Reconstructed ROI with NUMIT=125

## 4.4. Comparison of three algorithms

The first iteration in all algorithms as per Table 1, 2 and 3 for restoration from blurred image are compared and the result is shown in Table 4. As per the observation, Lucy Richardson algorithm produces high PSNR and low MSE as compared to other two algorithms. This algorithm also reproduces an image with high SC value as compared to other two algorithms.

**Table 4**: Reconstruction from Blurred Image

| IQM | BDC | WFA | LRA |
|---|---|---|---|
| AD | 195.5556 | -2.00E+04 | 246 |
| MSE | 13.941 | 34.1763 | 5.9932 |
| PSNR | 36.6879 | 32.7936 | 40.3542 |
| NCC | 1.0127 | 1.0208 | 1.0097 |
| SC | 0.9564 | 0.9114 | 0.9729 |

Table 5 shows restoration from blurred noisy image. Results indicate Lucy Richardson produces better reconstructed IQM values, even though PSNR is moderate, as compared to blind deconvolution, as we know BDC is reconstructing the image with known PSF.

**Table 5:** Reconstruction from Blurred Noisy Image

| IQM | BDC | WFA | LRA |
|---|---|---|---|
| AD | 9.39E+03 | -3.96E+05 | -8.53E+04 |
| MSE | 57.0355 | 557.3405 | 157.4066 |
| PSNR | 35.0065 | 20.6696 | 26.2762 |
| NCC | 1.0168 | 1.0895 | 0.9801 |
| SC | 0.8911 | 0.4745 | 0.7646 |

# 5. Conclusion

## 5.1. Conclusion

This paper mainly focuses the analysis for different IQM values of reconstructed ROI based color images. As per our discussion in the results Lucy Richardson is a better algorithm for reproducing the images. This proposed method is useful for the users who would apply the concepts to analyze the IQM values for any image with user specified ROIs. This proposed method is also helpful for the users to choose their own iterations for Lucy Richardson to get optimum results.

## 5.2. Future scope

This paper is addressed to analyze the IQM values for remote sensing images, this method can be enhanced to analyze the medical images in future with an additional IQM factors which are helpful for telemedicine.

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