Removal of the Noise And Blurriness using Global & Local Image Enhancement Equalization Techniques

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Abstract- The research paper encompasses the extraction of the noise and blurriness factors by deploying the global and local approach methodologies. On receiving an image analyze it. Divide an image on the number of sources (in case of local approach only). Confirm on the base of assumptions for noise test cases whether same noise is added in the whole image, same noise with different values or even different noise of different values then applies the related systematic model including the median filter techniques by parts along with equalization and concatenation of all images. The same system models with little modification (using Weiner & other blur removal Filters) will deploy for the blur test cases both in local and global methodologies. The description about the histogram, PDF & probabilities of a received and resultant image has provided and calculated as well. The most supportive factor of this paper is that it can also designate as to secure an image from the other parties and make it confidential as well from source to destination with the same parameters.

Keywords: Median, GIE, Noise, Blurriness, Image, Equalization, Weiner, Local, Global.

1 Introduction

The digital photos are constantly impacted by multifarious corrupted in the imaging frameworks used to create them. Image blur and noise are the essential sources for these degradations which decrease the quality of the image [1]. Nadeem et al. [2] observed that an image restore technique plays a significant role in image processing like blur and noise removal. In the proposed method, the Fuzzy logic technique used with random valued impulse noise to remove noise and restore the image. The suggested method converted large scale impulse area of an image into various small size area. These small size regions represented lines, edges, and texture of an image with their neighbors. Fuzzy rules provide suitable results for the detection of texture and edge of an image. The fuzzification phase classifies a particular pixel of an image like a noisy image and a noisy free image. Directional fuzzy rules are introduced in this approach for the removal of noise and blurriness of an image. Matlab tool is used for the validation of the suggested technique and a large amount of dataset of images is used to obtain the results. The results presented that the presented technique is better as compared with other existing approaches.

Zhang et al. [3]described that learning model is being used rapidly due to its performance an effectiveness. The authors presented a novel technique based on feed-forward convolutional neural network to remove noise and blur from an image. The suggested model trained with Gaussian at particular noise level. The researchers implemented DnCNN model that was able to deal denoising and removal blur in the different hidden layers. The current research foucued on the denoiseing from the images.

Tian et al. [4] presented a novel network model named batch-renormalization denoising network (BRDNet) that based on two different network to increase the performance of denoising. Using Deep learning technique enhances the quality of the image. The experimental results of the proposed model are effective and accurate while comparing with other existing methods. Jin et al. [5]presented a structure based vector filter to remove noise from the image. The researchers used local estimation method and noise classifer based on Convolution neural networl. Local pattern technique is used for this purpose. Although in this method more computational time is required for the processing pupose but for the solution of this problem , researchers proposed theorem that converts quaternion frequency domain (QFD) computation into spatial domain computation. The windows size is determine on the based of Local orientation and its size and strength. The obtainted results showed that the proposed model has the superiority on the exisintg models and the model is used for both noise removal and the image structure preservation.

Gowthami et al. [6] proposed auto-encoding-based deep Gaussian mixture model (ADGMM) to obtain sharp image from blurred images. The proposed model consisting of two parts one is dimensionality reducation and other is feature estimation that is used to classify mixture membership. The outcomes of suggested model are effective and efficient.
Radlak et al. [7] presented a switching filter based on deep neural network for the removal of noise form the color images. In the proposed model, the researchers introduced a filtering architecture that used modified version of Deep convoluational neural network for pixel detection form the images. The fileter 512 x 512 size remove noise and graphic processing unit is used in the simulation to obtain the experimental results of the proposed model. The switching filter need not any adjusting parameters and this proposed filter also applied on the image contamination mass. Due to this characteristic of the proposed model can applied in different denoising situations which no user's involment is need. The simulation results of the proposed model are accurate and effective. The review of previous studies shows that Several techiques to remove noise and blur are used but there is no perfect technique that can be called perfect in every aspect and there is always a chance for improvement. It is a more complex and challenging to remove noise and blur from the images.In addition, removal techniques are based on the accuracy and detection in the images. Therefore, accuracy and estimation play an important role in the detection of noise and blur removal. Further research is needed in noise and blur removal form the images to fil the gap in research.

2 Literatur Review

People saved memorable moments of their lives in the shape of digital images. While capturing images, they cannot be clear due to noise, blurring, hazing, fogging, barcode de-blurring, etc. The type of such effects may occur due to a lot of causes. The image can be blurred when the picture is being taken with the camera movement. The blurred image needs to be de-blurring with different algorithms and techniques. De-blurring algorithms divide into two types. There are two types of blur kernel known and unknown. Furthermore, Blind image de-blurring can be dividing into two parts. One is Kernel estimation and the second is image de-blurring. Kernel estimation plays an important role in improving blurred images. To improve the quality of blurred images and blind images kernel estimation is used. The assessment in the kernel can increase the image quality. During the estimation of the kernel, the problem of over-smoothing can occur in case of a lack of local object textures. Dawood et. al., proposed a new model known as Probability Weighted Moments Regularization (PWMR) owns the capacity to save the local texture structure during minimizing the artifacts that rely on the Probability Weighted Moments (PWM) for kernel estimation. This model has also the ability to compare and save information between neighbor pixels in a small size window. In this study, the researchers discuss the kernel estimation on blind image de-blurring. Kernel estimated by PWMR is the source of recovering the best quality image. Blind image de-blurring effectively functional in various domains like audio, astrophysical, and biomedical image processing. PWMR shows the effectiveness and accuracy while compared to existing blind image de-blurring methods. The proposed study focused only on blind image de-blurring. Furthermore, the study can help enhance the global textures and local textures of the images for better estimation of the kernel [8]. The other approach presented by Kang et al. [9]that hyperspectral image has a lot of information about spectral. The hyperspectral image comprises hundreds of spectral bands that can provide a better quality thought of the approach including objects. It leads to beneficial, precise presentations of environment control, objects discovery, and classification. But, the extraordinary quantity of hyperspectral data faces novel trials in image systems and storage. It is not possible to present a hyperspectral data set that consists of many spectral bands utilizing typical methods. Researchers are working to overcome this problem with visualization algorithms that are using two approaches, i.e., the band selection based and transform-based approaches. The researchers proposed an edge protective filtering and basic component assessment based visualizing techniques. Kang et. el., suggested a method that consists of edge-preserving filtering and principal component analysis (PCA) based visualization. Global and local image information of hyperspectral images is part of the proposed method. A visualization framework is presented based on global and local information. First, average-based image fusion (AIF) is used to decrease the band of the genuine image. After it, the edge-preserving filter applied to the dimension of the image. The Edge-preserving filter consists of two covers. The base layer has a huge amount of boundary information and is attached to the PCA. A

comprehensive layer having middle and small level edges and textures and is attached to the weighted sum method. Consequently, the histogram equalization applied to the fused detail layer and united with the fused base layers to envision the hyperspectral image. The precisions obtained from the original hyperspectral data sets show that the suggested method accomplishes act as a comparison of other existing latest visualization methods. The proposed method needs to address its three parameters using the trial and error approach. In the future, an algorithm could be developed to adjust these parameters in a better way.
Yu et. al. [10] described that image segmentation is a pillar of the image and vision field. Segmentation is a very critical and sensitive research topic in the field of image processing. Low resolution, high noise, and blurry boundaries are the main factors distressing segmentation. To split and separate an image is the major activity of image segmentation. The segment of the images, region-based models is extensively being used in the current scenario. Most of the models currently used are making use of the Gaussian method to strain images. Many researchers presented different methods for image segmentation consisting of different approaches. In the recent era, convolutional neural networks (CNN) have adopted in the field image processing. However, CNN needs more training data and energy consumption for better results. Because of storage and cost issues, there is a need for an approach for image segmentation that consists of model-based. The researchers presented a novel range-based adaptive bilateral filter local region (RABFLR) model for segmenting noisy images. The model consists of there phases. In the first phase, RABFLR is used to preserved edge features and resisted noise. In the next phase, the energy model based on data-driven is used native area information centered at every pixel to find strengths in and outside of the circular contour. This approximate approach is used to increase the accuracy of the noisy image. In the last phase, a regularization function is used to converge speed and smoothen the segmentation contour. In the end, the researchers solve the energy function minimize using descent method. To analyses different synthetic and real images dataset the proposed model was used and implemented in Matlab 2017 on a personal computer having core i5, CPU 3.30ghz, 16gb ram. Some parameters have been used in this paper to assign different values for the images. Precisions obtained from the testing and real images show that the suggested approach is much accurate and efficient while compared with four existing region-based models.
Liu et. al. [11] stated that infrared image approaches are utilized often in the army and civil environment for different purposes consisting of these areas like audio and video surveillance, satellite images, and automatic target recognition. IR images tainted by force bias and lines that disturb the quality of images. It is a big task to remove nonuniformity noise having less texture infrared images. The present research, They proposed a novel model that works on both exclusive bias correction and destraping through two sparsity limitations. One constraint of the model is responsible to produce accurate results as possible for the intensity bias. For this purpose, a bivariate polynomial model is constructed for the global smoothness of the strength of bias. The second constraint stays responsible to represent direction characteristic of stripe noise. The unidirectional variational sparse model manages this work for the second constraint. Complex problems handle by an exclusively efficient numerical algorithm based on split Bregman. The researchers analyzed after comparing split Bregman with other latest methods for optimization that it is effective and more efficient in a numerical environment. The purpose of the suggested model was to optimize two different variables consecutively that can be used in minimizing scheme in a better way. According to the results of the suggested study analysis, it can be observed that the proposed method is forceful to both techniques intensity bias and stripe. Its performance is more accurate and authentic. The assessment of the presentation of visual observation is not sufficient in quantitative evaluation. It is also necessary for the sequence of stripes. The proposed method stays different from the recent state-of-the-art denoising techniques. Significant results are obtained from the simulated and real images using this method. Precisions show that the accuracy and efficiency of the proposed model are better for both qualitative and quantitative comparisons with the existing approaches. Chang [12] discussed that in the last few years, computer technology and its different branches widely used in various scientific fields. Computer vision is one of them that is used for image processing. Computer vision has a branch called Human motion recognition. This branch belongs to categorize human motion in motion images. There are quite some issues in human motion recognition techniques. How motion information has been extracted and distinguished from the images? How complex information of human motion provided and affected in images? When the

data size is small then how deep learning models handle a higher human motion recognition rate? Human motion as a significant part of computer vision is basically to characterize human motion data moving pictures accurately. It has extraordinary criticalness in wise observing and security, human-PC communication, motion investigation, and different fields. At present, there are still a few issues in human motion techniques. Right off the bat, how to extricate and show the motion data in pictures has been one of the troubles in this field. When the measure of test information is little, how to utilize the profound learning system model to accomplish a higher human motion recognition rate? In light of UTD-MHAD database, The authors intends the human motion recognition of RGB picture and insight picture caught all the while by Kinect, and does relevant conversation and investigation on the above issues, utilizing reduced scale inertial sensors (MTi-G-700 created by Xsens and Android cell phones, tablets and other individual cell phones accompany MEMS whirligigs what's more, accelerometers) to address the picture to motion unclear, form another numerical model, utilize the inertial information got by MIMU in a brief timeframe to assess the position, conduct and speed of camera motion, right the picture pixel position, perform picture de-motion obscure preparing, and afterward perform picture handling, for example, denoising to take care of the picture motion obscure issue. Focusing on the issue of fuzzy picture recognition, extraordinary from the normal deblurring reorganization algorithm, and the calculation of extricating fuzzy invariant descriptors, this paper proposes another algorithm of fuzzy image recognization dependent on move learning. Simultaneously, the invariance of the fuzzy area of extricating highlights dependent on profound learning convolutional neural organize is considered. The precisions are quite better while comparing with other existing methods. Yang et. al.,[1] stated that an image restoration is a significant task in engineering fields. For this purpose, Gaussian noise, Multiplicative noise as well as impulse noise can be handle with different existing denoising techniques. Besides this, there are other noises i.e. Cauchy noise, Rician noise, and Gamma noise that presents biomedical images and synthetic aperture radar images. There are different methods available to remove Cauchy noise from images. The authors [13] proposed a new method to repair an image that was ruined by blur and Cauchy noise. The suggested method removes Cauchy noise from TV high-order TV. This method predicts and assesses the weights of the image taken from all kinds of resolutions. The proposed model consisted of total variation and high-order total variation including data fidelity. The main purpose of the total variation is to provide accurate edges of the images. On the other hand, high-order resolution removed staircase impressions from the image. The suggested method can evaluate the strength of an image, so this model is helpful in the prevention of sharp edges during retaining the levelness in the flat area. Furthermore, the authors presented an approach for the selection of parameters. It was experimental that values of parameters were large in homogeneous regions and were small in detail and texture regions. The proposed model based on an algorithm named Alternating Direction Method of Multipliers (ADMM) that can handle restored and secure edges and reduce staircase impressions. With the help of this algorithm, images get recover preserving edges and reduce staircase impressions during the maintenance of the flatness in the area. The proposed model compared with other existing numerical solutions that show the supremacy of the presented model in the case of visual quality and quantitative approaches. In the present study, authors focused only to restore images that belong to medical images and unreal images that consist of radar. The proposed model focuses on gray images that make it simple.

3 Methodology / Proposed System Model

An image received consisting of the four parts coming from four sources in one frame. Below are the system diagrams. There are three system models for this paper. First one simply shows the flow of steps. Second and third will display both approaches deployed in different cases.

Here is the figure consisting of three system models. The first model (a) is the standard approach for both global and local methods [14], which have deployed. F (x, y) is the source side of images, F/ (x, y) is the final output. The system model (b) is responsible for removing the noise/blur using Global approach[15]. H (x, y) is showing the source side, H/ (x, y) is the final output.

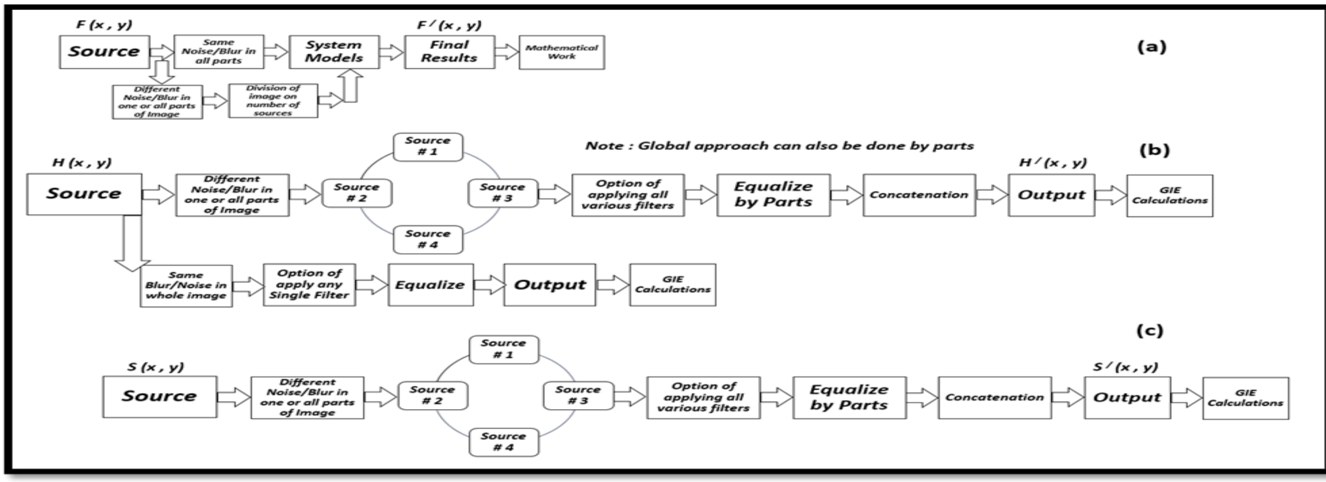


Table 1. Proposed Model Removal of the Noise & Blurriness using Global & Local Image Enhancement Equalization Techniques

The system model (c) is responsible for removing the noise/blur using a local approach. S (x, y) is the initial side of receiving images and defining the input image same as for the S/ (x, y) which is the final output. The purpose of this paper has clearly defined now, this portion encompasses the proposed algorithm step by step. Before this, there must be an understandability that there are two approaches which have deployed in terms of different test cases for the removal of noise & blurriness as well.

3.1 Local Approach Description for Noise Removal

Receive an image from the source. Analyze it whether it is a single image or consisting of the multiple images along with the determination that is image consisting of same noise in the whole image or differs in some parts of the image. Divide the image on the number of sources like if the image is consisting of 2 different screenshots then make it into two equal portions in such a way that not a single pixel of the image has cropped and all the images must be divided properly as the actual size of every portion. Move forward to the noise removal, remember to remove the noise by parts, extraction of the noise must be done separately using the median filter techniques [16]. Equalize [17]every part of the image in this way, getting the better contrast and brightness. Getting the equalization of all parts, it is time to again rejoin the image to its original form, so concatenate all images. At last, step make calculations of the Problem density function (PDF), Probabilities and histograms of all images including the all original image and received images.

3.2 Global Approach Description for Noise Removal

Receive an image from the source. Analyze it whether is it a single image or consisting of the multiple images along with the determination that is an image consisting of same noise in the whole image or differs in some parts of the image and remember there must be same type & same values of noise in the whole image to implement this approach logically. Do not divide an image, even if an image is consisting of multiple images then still consider it in one frame. Apply median filter methodology on the complete image. Equalize the image. There is the final output and obviously, there is no need for the concatenation of images. At last, step, calculate the Problem density function (PDF), Probabilities and histograms of the original and received images.Same algorithms have to deploy for the blurriness removal. The only difference is that these methodologies have to use blur removal techniques instead of noise removal like in this case deploy the Weiner Filters [18] mostly (other techniques can also be used but in blur case, Weiner gives the best results in 3D images) where remaining steps goes the same. The decision to take whether the received image consisting of the noise or blur, it will be on observations and assumptions but certainly, it is very clear in the received attachments.

4 Simulation Results and Discussion

MATLAB 2017b has implemented for this research paper.

4.1 Hardware Specification

- Windows 10
- Intel Core i5
- 64 - bit OS
- 8 GB RAM).

4.2 Noise removal Test Cases with respective mathematical calculatio.

4.2.1 Case 1: Same Noise in all parts of an image with the same values

There are four pictures designated as (a, b, c & d). (a) is the original image which has received. (b) is the noise removal using the GLOBAL approach, (c) is the noise removal by deploying LOCAL approach. Where (d) is also the result by LOCAL approach but first, same noise has added in an image collectively then divide an image and applies the local algorithm. So, in other words, get the same result as in (c) where noise has added independently. The only difference is the change of position of noise dots but almost the output is the same so the conclusion is that.

"Whether adding noise collectively or adding noise separately, by using the LOCAL approach, get the same results at the end but only in the current test case".

Figure 1

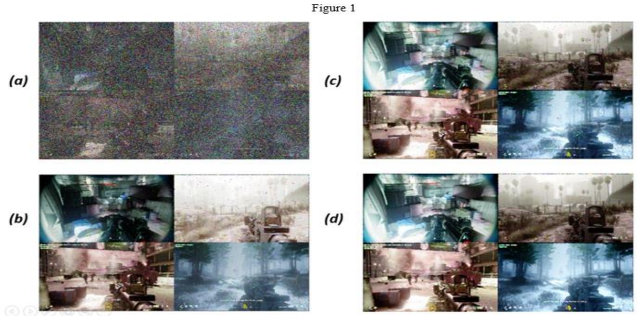


Figure 1.1

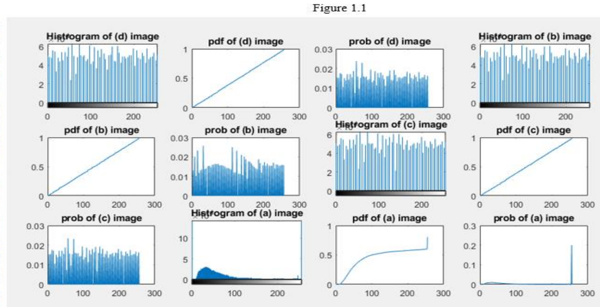


Figure 1 consists of final results & figure 1.1 contains Histogram, Pdf and Probabilities of all images

4.2.2 Case 2: Same Noise in all parts of an image with different values

The added noise has different values so removed the noise using the LOCAL approach in (c) where deployed GLOBAL approach in (b).

Figure 2

Figure 2.1

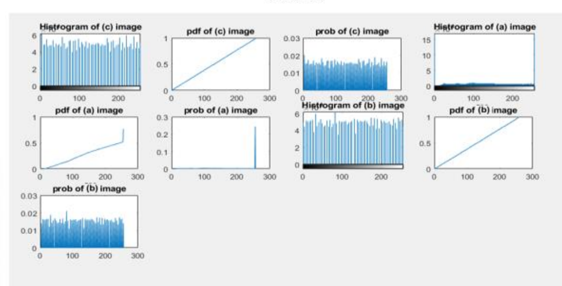


Figure 2 consists of final results and figure 2.1 contains Histogram, PDF & Probabilities of all images

Now due to different values of noise, different windows sizes of median filters [19] have utilized like in the first portion the deployed window size is (3,3),(5,5) in second, (9,9) in third & (4,4) in the last portion of an image. The reason for using (9,9) size is (higher the noise value higher should the median size filter). Now in case of (b) just to get the third portion of the image focused, (9,9) size deployed for every part of an image as it is a GLOBAL approach that's why the output is consisting of blur images.

4.2.3 Case 3: Different Noise in all parts of an image with the same values

Same values of different noise using the LOCAL approach in (b), results are more prominent and clearer as compare to the GLOBAL technique. The names of added noises are salt n pepper, Gaussian, Poisson & speckle.

Figure 3

Figure 3.1

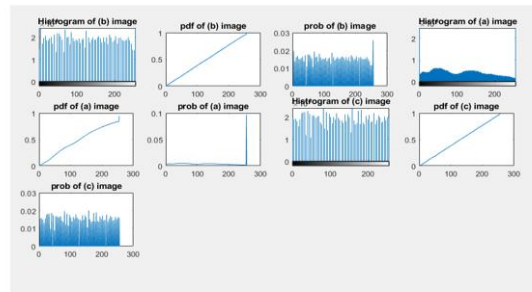


Figure 3 consists of final results and 3.1 contains Histogram, PDF and probabilities of all images

4.2.4 Case 4: Different Noise in all parts of an image with different values

Different type of noise there with different values so by removing noise using LOCAL approach (b) results are again more prominent and clearer as compare to the GLOBAL technique. Where the names of added noises are salt n pepper, Gaussian, Poisson & speckle. (a) is the original image whereas (b) is LOCAL and (c) is GLOBAL resultant.

Figure 4

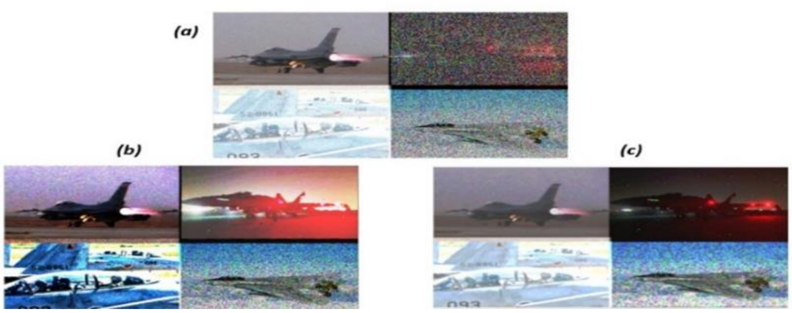


Figure 4.1

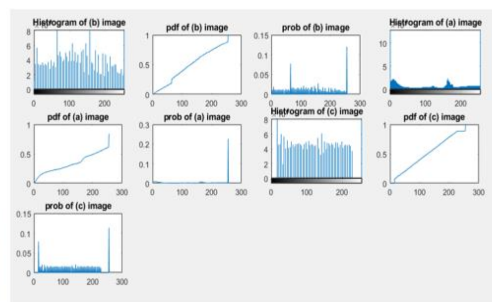


Figure 4 consists of the final results and figure 4.1 contaons Histogram, PDF and probabilities of all images

4.3 Blur Removal Test Cases with respective mathematical calculations

4.3.1 Case:5 Same Blur in the whole image

The case as above for the (same noise removal). Every part is consisting of the "motion" blur and removed by Weiner Filters collectively. Figure 5 is displaying two original images designated as (a) & (c) whereas their resultants are (b) & (d) using GLOBAL approach.

Figure 5

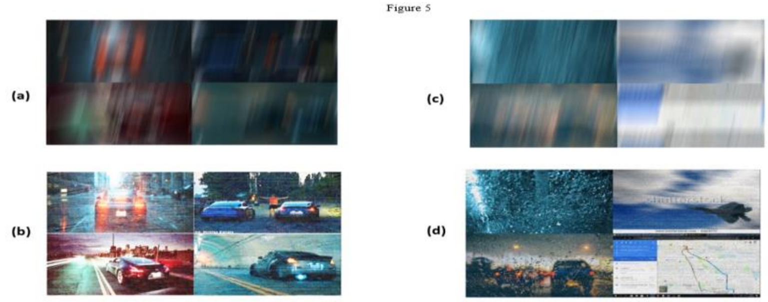


Figure 5.1

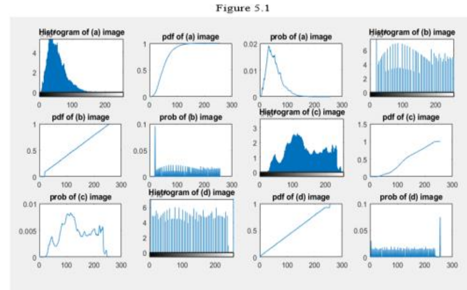


Figure 5 consists of final results and figure 5.1 contains Histogram, PDF & Probablities of all images

4.3.2 Case:6 Same Blur in whole the image (added independently) & removing individually

Every part is consisting of the "motion" blur and removed by Weiner Filters individually. Figure 6 is displaying two original images designated as (a) & (c) whereas their resultants are (b) & (d) using LOCAL approach.

It is observed that results are better by deploying local approach.

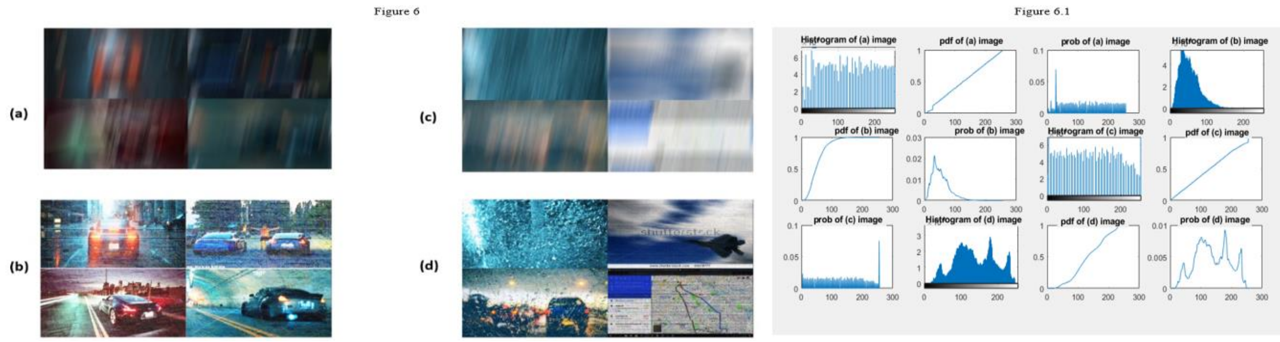


Figure 6 consists of the final results & Figure 6.1 contains the Histogram, PDF & Probabilities of all images

Repeating case 6 with different blur in every portion of an image. In (a) noise of the first portion is reduced by the blind convolution method, second by Lucy Richardson, third by regularized filter and the last one is by Weiner and this is the actual significance why division of an image takes place before applying system models as it is quite clear if applying system model directly on an image then there is only one option of applying blur removal filter.

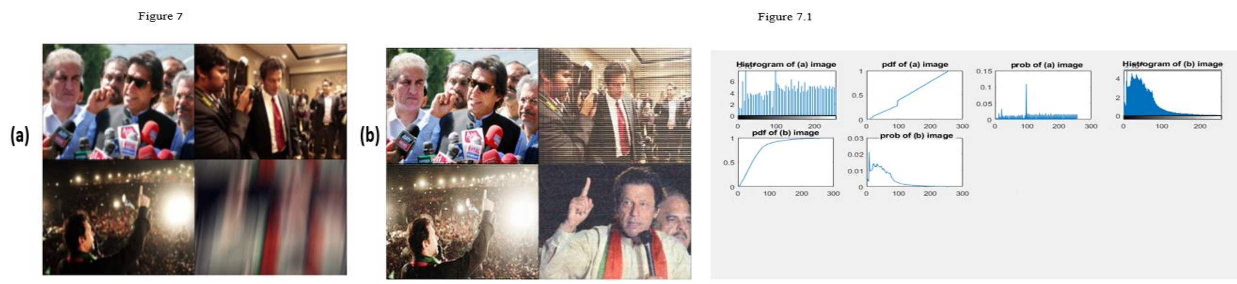


Figure 7 consists of the final results & Figure 7.1 contains the Histogram, PDF & Probabilities of all images

4.3.3 Case:7 Getting a mixture of noise & blur at the same time within the received image

This is another solid significance of image division as the existence of the noise & blur at the same time so definitely, there is a requirement of making portions of an image at any cost. Get error generations on not dividing the image as noise & blur codes are not compatible with each other.

Figure 8 consists of the final results & Figure 8.1 contains the Histogram, PDF & Probabilities of all images

4.3.4 Case:8 Maintaining the confidentiality of the received images

The best ever argument on the division of an image will be in terms of confidentiality when there is a need of securing some portions of the image as per requirement.

Figure 9

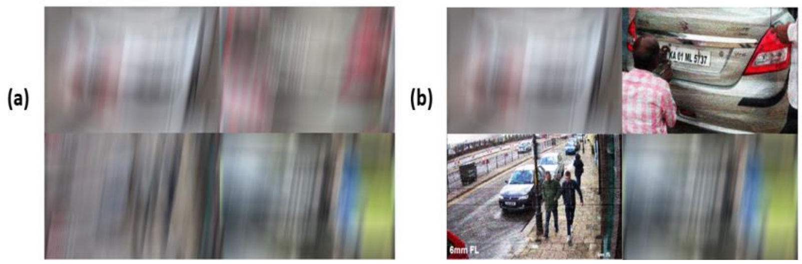


Figure 9.1

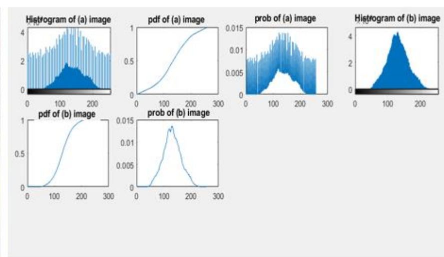


Figure 9 consists of the final results & Figure 9.1 contains the Histogram, PDF & Probabilities of all images

4.4 Results of the Noise and Blurrness Removel in Term of the Medical Field

Many variables are associated with the response in a multiple regression model, including irrelevant variables that show the impact on complexity in a resulting model. So we have to interpret those variables corresponding to the coefficient estimate tends to zero. But there are no possibilities to consider estimates exactly zero in the least-squares. This portion will have to perform feature selection excluding irrelevant variables in a multi regression model.

4.5 Results of without Blur-Noise

Figure 10

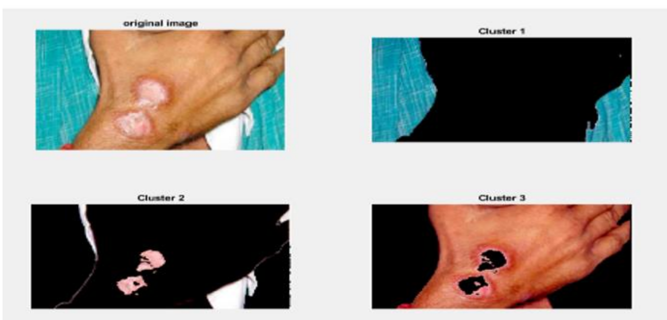


Figure 10.1

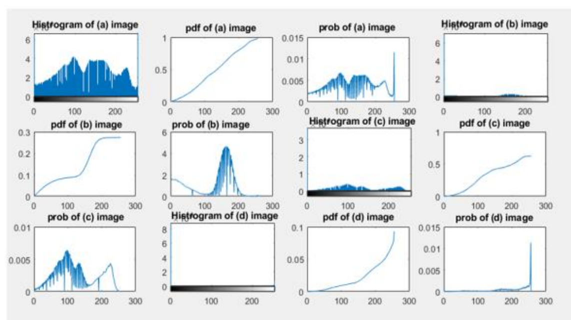


Figure 10 consists of the final results & Figure 10.1 contains the Histogram, PDF & Probabilities of all images

LOCAL approach system model has deployed before running their respective algorithm, the reason is that an image received consists of four portions in order to equalize & applies algorithm locally.

Figure 11

Figure 11.1

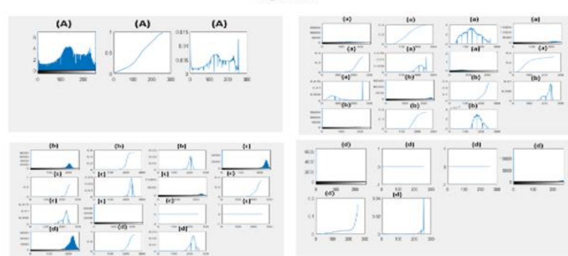
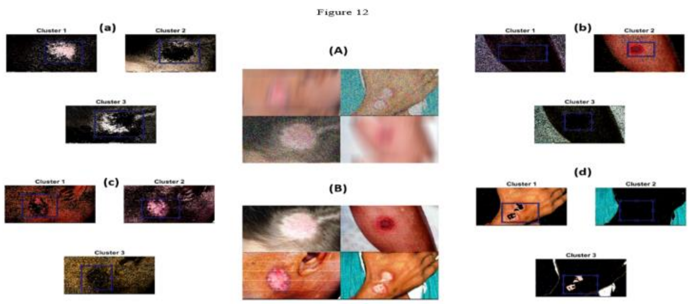


Figure 11 consists of the final results & Figure 11.1 contains the Histogram, PDF & Probabilities of all images

LOCAL approach system model has deployed before running their respective algorithm, the reason is that an image received consists of four portions with the addition of both noise & blur.



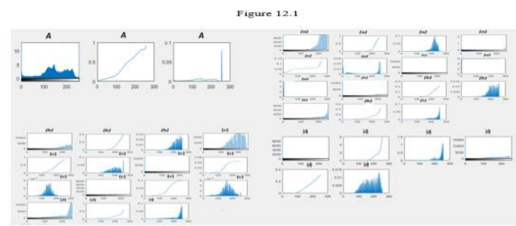


Figure 12 consists of the final results & Figure 12.1 contains the Histogram, PDF & Probabilities of all images

Removal of noise & blur must be done before implementing the medical system models. There is also an edge detection in all clusters identified by blur color on the original images designated.

6 Conclusion

A novel Global & Local Image Enhancement Equalization Techniques for removal noise and blurriness form the images. The experimental results of all test cases of noise and blur removal, the final outputs quite effective, efficient, prominent, clear, more equalized & much better which have deployed using the Local approach as compared to Global approach and other existing techniques. The reason is that from every portion of an image noise & blur have removed individually and independently and at the same time, all parts of the received image are equalized locally and then concatenate with each other after successfully applies the system models with the respective algorithm. This declared the designed local algorithm more supportive for deblurring & making the images noise free. The study is limited to remove noise and blurriness from small size of data. In the future, other approaches may be implemented on large amount of dataset for detection of noisy pixels in the tainted image to improve the performance of the proposed technique.

7 References

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