

Comprehensive Study on Image Restoration Model Based on Improved Non Localized Method

Er. Neha ¹, Er. Deepti Gupta ², Er. Richa Aggarwal ³

Computer Science & Engineering Dept, SDDIET College of Engineering and Technology, India ^{1,2}

Electronics & Communication Engineering Dept, SRMIET College of Engineering and Technology, India ³

Abstract: Image processing plays a vital role in the field of biomedical, science, engineering, defence etc. Digital image becomes omnipresent and this desirable change made possible by science. Various steps include image acquisition, image restoration, image enhancement and image segmentation etc. An image signal gets corrupted with noise during acquisition, communication, storage and retrieval processes. It includes various noises like salt & pepper, Gaussian & speckle noise. To remove the noise in digital images we use various filters like mean filter, median filter, LMS adaptive filter and also various techniques. But these techniques can not improve the image quality. So that we use the sparse representation in this we can minimize the difference between the sparse codes of degraded image and the sparse code of unknown original image so that we can improve the performance of sparsity based image restoration. In this we use parameters PSNR, SSIM and noise sigma.

Keywords: Image acquisition, image restoration, image enhancement and image segmentation, parameters PSNR, SSIM and noise sigma.

I. INTRODUCTION

Images are common and easy method to convey and transmit the information. But the quality of image is degraded or image became blurred during transmission due to the noise introduced.

So that to get the original image back we use image restoration. In this we will reduce the noise to get the original image and is called image denoising.

1.1 DIFFERENT TYPES OF NOISE

In image processing, noise is undesired information that contaminates the image. In the image denoising process, information about the type of noise present in the original image plays a significant role.

Typical images are corrupted with noise modeled with either a Gaussian, uniform, or salt or pepper distribution.

1.1.1 Speckle Noise

Speckle noise is a multiplicative noise. This type of noise occurs in almost all coherent imaging systems such as laser, acoustics and SAR (Synthetic Aperture Radar) imagery.

The source of this noise is attributed to random interference between the coherent returns. Fully developed speckle noise has the characteristic of multiplicative noise. It follows the gamma distribution and is given:

$$F(g) = \frac{g^{\alpha-1}}{(\alpha-1)! \alpha^\alpha} e^{-g/\alpha} \quad (1.1)$$

1.1.2 Gaussian Noise

Gaussian noise is evenly distributed over the signal. This means that each pixel in the noisy image is the sum of the true pixel value and a random Gaussian distributed noise value. It has zero mean and 0.05 variance.

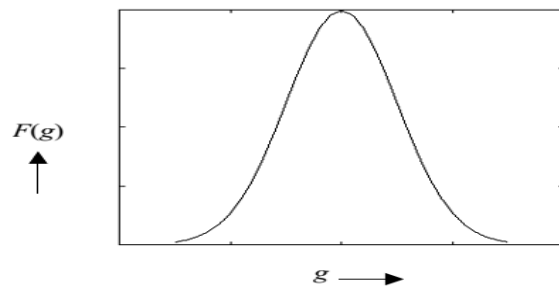


Figure 1.1: Gaussian Distribution Response [5]

1.1.3 Salt and Pepper Noise

Salt and pepper noise is an impulse type of noise, which is also referred to as intensity spikes. This is caused generally due to errors in data transmission. It has only two possible values a and b. The probability of each is typically less than 0.1. The corrupted pixels are set alternatively to the minimum or to the maximum value, giving the image a “salt and pepper” like appearance. Unaffected pixels remain unchanged. For an 8-bit image, the typical value for pepper noise is 0 and for salt noise 255. The salt and pepper noise is generally caused by malfunctioning of pixel elements in the camera sensors, faulty memory locations, or timing errors in the digitization process.

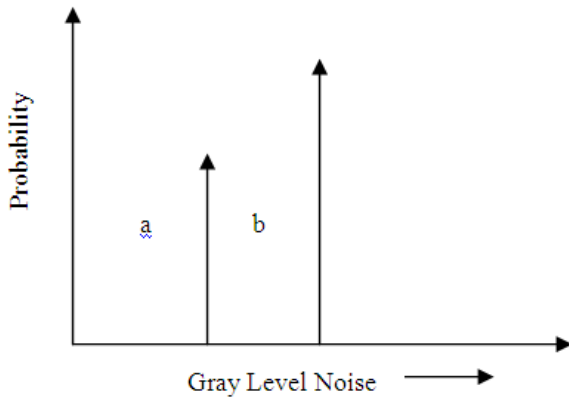


Figure 1.2: Salt and pepper noise

1.2 Filtering Approach for Image Denoising

Filters play a major role in the image restoration process. The basic concept behind image restoration using linear filters is digital convolution and moving window principle. Let $w(x)$ is the input signal subjected to filtering, and $z(x)$ be the filtered output. If the filter satisfies certain conditions such as linearity and shift invariance, then the output filter can be expressed mathematically in simple form as

$$z(x) = \int w(t)h(x - t)dt \quad (1.2)$$

Where $h(t)$ is called the point spread function or impulse response and is a function that completely characterizes the filter.

1.2.1 Mean Filters

A mean filter [Um98] acts on an image by smoothing it; that is, it reduces the intensity variation between adjacent pixels. The mean filter is nothing but a simple sliding window spatial filter that replaces the center value in the window with the average of all the neighboring pixel values including it. By doing this, it replaces pixels that are unrepresentative of their surroundings. It is implemented with a convolution mask, which provides a result that is a weighted sum of the values of a pixel and its neighbors. It is also called a linear filter. The mask or kernel is a square. Often a 3×3 square kernel is used. If the coefficients of the mask sum up to one, then the average brightness of the image is not changed. If the coefficients sum to zero, the average brightness is lost, and it returns a dark image. The mean or average filter works on the shift-multiply-sum principle.

1.2.2 LMS Adaptive Filter

An adaptive filter does a better job of denoising images compared to the averaging filter. The fundamental difference between the mean filter and the adaptive filter lies in the fact that the weight matrix varies after each iteration in the adaptive filter while it remains constant throughout the iterations in the mean filter. Adaptive filters are capable of denoising non-stationary images, that is, images that have abrupt changes in intensity. Such filters are known for their ability in automatically tracking an unknown circumstance or when a signal is variable

with little a priori knowledge about the signal to be processed. In general, an adaptive filter iteratively adjusts its parameters during scanning the image to match the image generating mechanism. This mechanism is more significant in practical images, which tend to be non-stationary.



Figure 1.3: Input and Output Images of LMS Filter [3]

II. SYSTM MODEL

The above block diagram describe the how can we remove the noise from blurred and noisy image and get the denoisy image. In the first step we take an original image that is known as read input image. After that we define the noise level we add the level of noise (e.g. 5, 10, 15 etc.) and the set parameters like PSNR, Noise Sigma etc. After that we train our image by adding noisy components and our image get blurred.

We use k-means and PCA concepts in which iterations performed to reduce the noise level. With the increasing of PSNR value our noise level will reduced and give the SSIM (Structural Similarity Index Matrices) that tells the similarity of denoisy image with Original image and at last we get a recovered image that is almost similar to original image.

2.1 Image denoising

It is the process of removing a noise from blurred image while preserving an edge. It is mostly used in the field of photography where an image is somehow degraded and need to be improved before it is printed so that clarity of image is improved. The image denoising process is opposite of image degradation process. It involves the manipulation of the image data to produce the visually high quality image.

2.2 PCA (Principle Component Analysis)

It is also known as Karhunen-Loeve Transformation. It belongs to the linear transformation based on statistical techniques. It is used in image enhancement, analysis and pattern recognition. It used mathematical principle to transfer number of possibly correlated variable into smaller number of variables called principle components.

It is used in the data dimension reduction or data de-correlation. The application of PCA consists in image color reduction while three color components are reduced into one containing the major part of information. It is the way to identify the pattern in data in such a way so that it can find out similarity and difference in patterns.

2.2.1 PCA use for image compression

The main task of image processing is data volume reduction. Algorithms related to color image reduction is lossy but results of these algorithms are still acceptable in many applications. The image transformation from color to grey level is based on weighted sum of three color components R, G, B.

$$I = w_1R + w_2G + w_3B \tag{3.1}$$

It contains three colour components and w_i determined with possibility of human perception.

2.3 K Means Concept

The images are grouped together on the basis of features such as colour, texture, shapes etc. contained in images in the form of pixels.

2.3.1 Clustering: It is applied in image processing, data mining etc. in information retrieval clustering is enhance the performance of retrieving the information from internet. It is defined as the cluster in which the objects have high degree of similarity, but dissimilarity between different groups of clusters.

Data points in each cluster are calculated with the data points in the cluster, similar data points brought in one cluster.

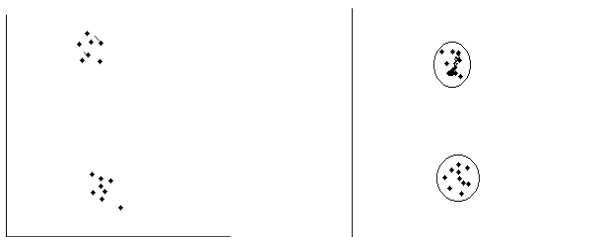


Figure 2.2: Clustering of Data Points [4]

2.3.2 K Mean Clustering

It is most popular partition based clustering technique. In this we choose the centroid and then compare the centroid with each data point based on their characteristics and find the distance, the data points that are similar to the centroid are assigned to cluster having centroid. New 'k' centroid is calculated and k-cluster is created by finding nearest data points.

Steps of K-Mean algorithms:

1. Choose k number of points randomly and make the initial centroid.
2. Select a data point from collection, compare with each centroid and if data point is similar to centroid then assign it into cluster of that centroid.
3. When each point has been assigned one of the cluster, re calculate the value of centroid for each k number of clusters.
4. Repeat step 2 and 3 until no data point move from its previous cluster to some other cluster (termination criterion has been satisfied).

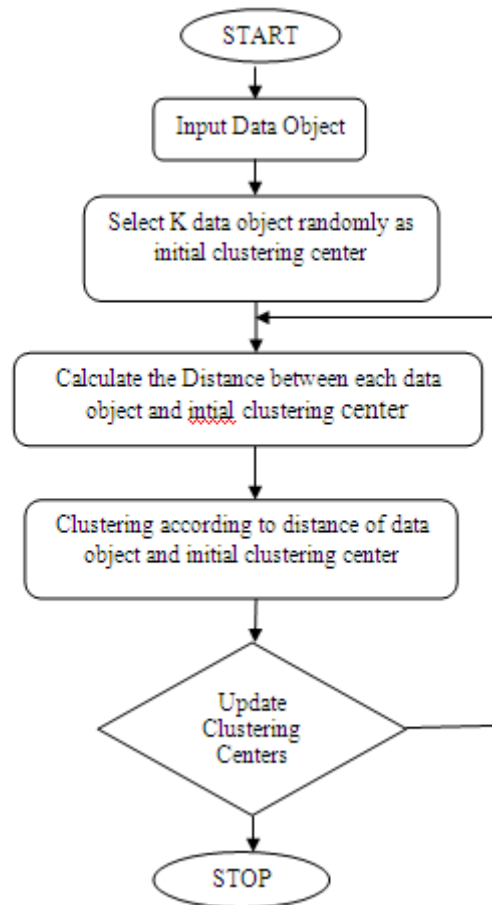


Figure 2.3: K-Mean Flow Chart [4]

2.4 Parameters used

- PSNR: It is used to compute the Peak Signal to Noise signal in decibels within two images. It is the ration between the maximum possible power signal and power of corrupting noise that can affects the quality of image. If the PSNR value is high it means the quality of image is high.

The mean squared error (MSE) and peak signal to noise signal (PSNR) are the two metrics used to compare the quality of the image. If the value of MSE is lower it means there is lower number of error. To calculate the PSNR, we first calculate MSE using the following equation:

$$MSE = \frac{1}{mn} \sum_{i=0}^{m-1} \sum_{j=0}^{n-1} [I(i, j) - K(i, j)]^2 \tag{2.1}$$

PSNR (in db) is defined as:

$$PSNR = 10 \cdot \log_{10} \left(\frac{MAX_I^2}{MSE} \right) \tag{2.2}$$

$$= 20 \cdot \log_{10} \left(\frac{MAX_I}{\sqrt{MSE}} \right) \tag{2.3}$$

$$= 20 \cdot \log_{10}(MAX_I) - 10 \cdot \log_{10}(MSE) \tag{2.4}$$

Here, MAX_I is the maximum possible value of the image and MSE is the sum over all squared value difference divided b image size or by three.

- SSIM (Structural Similarity Index): It is the method used to measure the similarity between two

images. It requires two images from same capture: a reference image and a processed image. The measurement or prediction of image quality is depending upon the uncompressed or noise free image. The difference from other techniques like MSE and PSNR is that this technique gives absolute error. It is perception-based model it consider image degradation as perceived change in structural information. It satisfies the condition of symmetry. SSIM is widely used in video industry and photography. The SSIM is calculated on various windows of image. The measure between two windows x and y of common size N*N is:

$$SSIM(x, y) = \frac{(2\mu_x\mu_y + c_1)(2\sigma_{xy} + c_2)}{(\mu_x^2 + \mu_y^2 + c_1)(\sigma_x^2 + \sigma_y^2 + c_2)} \quad (2.5)$$

Where:

μ_x is the average of x.

μ_y is the average of y.

σ_x^2 is the variance of x.

σ_y^2 is the variance of y.

σ_{xy} is the covariance of x and y.

c_1 and c_2 two variables stabilize the division with weak denominator.

SSIM satisfies the condition of symmetry: $SSIM(x, y) = SSIM(y, x)$

III. RESULT

In this chapter the results of the proposed system is being discussed. The chapter shows the simulation results for various cases and examples in the descriptive manner. Here, the testing and training results of the noisy and clear images are also figured out. The original Image is:



Figure 3.1: Original image



Figure 3.2(a): Image with Noise Level 5 (b) Denoisy Image

Table 3.1: Results of System with Noise Level 5

| Noise level = 5 | | |
|-------------------|--------------|-------------|
| No. of Iterations | PSNR (34.15) | Noise sigma |
| 1 | 39.01 | 5 |
| 2 | 39.23 | 0.84 |
| 3 | 39.42 | 0.81 |
| 4 | 39.60 | 0.78 |
| 5 | 39.74 | 0.74 |
| 6 | 39.84 | 0.70 |
| 7 | 39.88 | 0.65 |
| 8 | 39.89 | 0.60 |
| 9 | 39.90 | 0.56 |

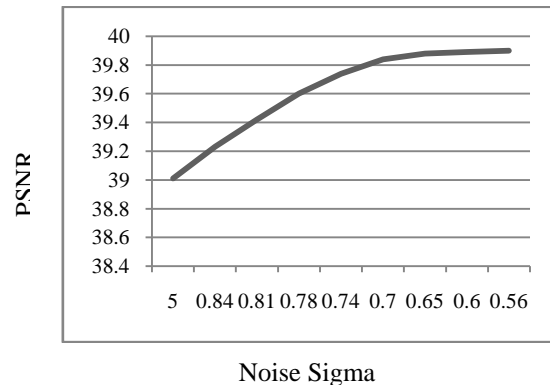


Figure 3.3: Noise Sigma and PSNR Graph for 9 Iterations

The graph (Figure 5.4) is corresponding to table (Table 5.1) in which PSNR value is increasing with Decreasing Noise Sigma. For Noise Level 5 we get PSNR value 39.90, Noise Sigma 0.56 and SSIM 0.95.



Figure 3.4(a) Image with Noise Level 20(b) Denoisy Image

| Noise Level = 20 | | |
|-------------------|--------------|-------------|
| No. of Iterations | PSNR (22.15) | Noise Sigma |
| 1 | 29.94 | 20 |
| 2 | 32.63 | 5.44 |
| 3 | 33.69 | 4.21 |
| 4 | 33.65 | 3.03 |
| 5 | 33.64 | 2.05 |
| 6 | 33.62 | 1.71 |
| 7 | 33.75 | 1.55 |
| 8 | 33.75 | 1.40 |
| 9 | 33.75 | 1.37 |

Table 3.2: Results of System with Noise Level 20

The graph (Figure 5.13) is corresponding to table (Table 5.4) in which PSNR value is increasing with Decreasing Noise Sigma. For Noise Level 20 we get PSNR value 33.75, Noise Sigma 1.37 and SSIM 0.86.

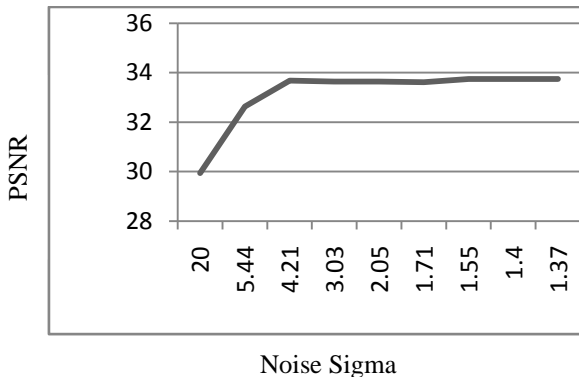


Figure 3.5: Noise Sigma and PSNR Graph for 9 Iterations

| Lena.tif | | | |
|-------------|-------------------|----------------------------|-----------------|
| Noise Sigma | Soft Thresholding | SWT + [Spatial Domain] [4] | Proposed Method |
| 10 | 32.3 | 34.3 | 35.30 |
| 20 | 28.7 | 31.75 | 32.41 |
| 40 | 24.85 | 27.80 | 27.97 |
| Barbara.tif | | | |
| 10 | 29.9 | 33.34 | 35.03 |
| 20 | 26.26 | 29.00 | 31.55 |
| 40 | 22.87 | 25.30 | 28.31 |

Table 3.3: PSNR Comparison of Existing and Proposed Technique [3]

IV. CONCLUSION

Image restoration is a fundamental topic in image processing and computer vision applications, and it has been widely studied. In this work, it presents a novel non-locally centralized sparse representation model for image restoration. The sparse coding noise (SCN), which is defined as the difference between the sparse code of the degraded image and the sparse code of the unknown original image, should be minimized to improve the performance of sparsity-based image restoration. To this end, we proposed a centralized sparse constraint, which exploits the image nonlocal redundancy, to reduce the SCN. The basic idea behind this dissertation is the estimation of the uncorrupted image from the distorted or noisy image, and is also referred to as image “denoising”. There are various methods to help restore an image from noisy distortions. Selecting the appropriate method plays a major role in getting the desired image. The denoising methods tend to be problem specific. The main task of image restoration is to capture a noisy image and estimating the original image. The process is used to denoise the image by use of k-means process. The PSNR, SSIM and noise sigma value are calculated under different values of noise levels. This process is tested on different types of images and results are evaluated.

V. FUTURE SCOPE

One possible improvement to our Gaussian process method may reduce the pixilation effects experienced at high-noise levels in image denoising resulting from

discontinuities between the predictions of adjacent patches. When processing each patch/partition of an image (or microarray), instead of ignoring all the data outside of the patch, one could incorporate certain statistics computed from all other patches. Presumably, global trends (in the spatially-dependent component) extending beyond single patches could then be more easily inferred, without increasing the amount of training data significantly. Speeding up our algorithm for large image/micro-array datasets is of considerable practical importance.

REFERENCES

- [1] Gonzalez, R.C., Woods, R., “Digital Image Processing”, 2nd Edition, Prentice-Hall, (2002).
- [2] R. Gonzalez, R. Woods and S. Eddins “Digital Image Processing Using Matlab”, 2004, Prentice Hall.
- [3] Aravind B. N, K. V. Suresh, “An Improved Image Denoising Using Wavelet Transform”, IEEE, 2015.
- [4] Kaneria Avni, “Image Denoising Techniques: A Brief Survey”, The SIJ Transactions on Computer Science Engineering & its Applications (CSEA), Vol. 3, No. 2, February 2015.
- [5] YIN Lei, DI Xiaoguang, “Image Blind Restoration Based on Blur Identification and Quality Assessment of Restored Image”, IEEE Chinese Control Conference July 28-30, 2015, Hangzhou, China.
- [6] Shi ya ping, “Image Restoration Algorithm of Smoothness Constraints Constructed by Adaptive Fuzzy Edge Evaluation Function”, IEEE Seventh International Conference on Measuring Technology and Mechatronics Automation, 2015.
- [7] Changhun Cho, Jaehwan Jeon, “Real-Time Spatially Adaptive Image Restoration Using Truncated Constrained Least Squares Filter”, IEEE International Conference on Consumer Electronics, 2014.
- [8] Yifan Zhang, “An EM- and wavelet-based multi-band imagerestoration approach”, IEEE 19th International Conference on Digital Signal Processing, 2014.
- [9] K.Sakthidasan, V.Nagarajan, “Non Local Image Restoration Using Iterative Method”, IEEE International Conference on Communication and Signal Processing, 2014.
- [10] Tian Chen, Xin Yi, “Image Restoration Method Self-Adaptive To The Dielectric Layer Color”, IEEE 2014.
- [11] Weisheng Dong, Lei Zhang, “Non-locally Centralized Sparse Representation IEEE Transactions On Image Processing, Vol. 22, No. 4, April 2013.
- [12] M. A. O. Marques and C. O. A. Freitas, “Document Decipherment-restoration: Stripshredded Document Reconstruction Based on Color”, IEEE Latin America Transactions, Vol. 11, No. 6, December 2013.
- [13] S.OudayaCoulmal, P .Rajesh, “Image Restoration Using Filters And Image Quality Assessment Using Reduced Reference Metrics”, IEEE 2013.
- [14] Jyotsna Patil, Sunita Jadhav, “A Comparative Study of Image Denoising Techniques”, International Journal of Innovative Research in Science, Engineering and Technology”, Vol. 2, Issue 3, March 2013.
- [15] Shoulie Xie, Susanto Rahardja, “Alternating Direction Method for Balanced Image Restoration”, IEEE Transactions on Image Processing, Vol. 21, No. 11, November 2012.
- [16] Liwei Zhang, Yaping Zhang, “A New Color Image Restoration Algorithm Based On LAB and RBF Neural Network”, IEEE International Conference on Mechatronics and Automation, 2012.
- [17] Tanveer Ahsan, Lei Zhang, “Patch Group Based Nonlocal Self-Similarity Prior Learning for Image Denoising”, IEEE 2011.
- [18] Haichao Zhang, Jianchao Yang, Yanning Zhang, “Close the Loop: Joint Blind Image Restoration and Recognition with Sparse Representation Prior”, IEEE International Conference on Computer Vision 2011.
- [19] Oleg V. Michailovich, “An Iterative Shrinkage Approach to Total-Variation Image Restoration”, IEEE Transactions On Image Processing, Vol. 20, No. 5, May 2011.
- [20] Ryu Nagayasu, Naoto Hosoda, Nari Tanabe, “Restoration Method For Degraded Images Using Two-Dimensional Block Kalman Filter With Colored Driving Source”, IEEE 2011.