Texture Enhanced Image denoising Using Gradient Histogram preservation

Mr. Harshal kumar Patel[1], Mrs. J.H.Patil[2]
(E&TC Dept. D.N.Patel College of Engineering, Shahada, Maharashtra)

Abstract - General framework based on gradient histogram preservation based image denoising is discussed. In this framework, denoising is posed as an optimization problem that minimizes a cost function. Gradient histogram preservation based image denoising is an effective technique for image enhancement. However, conventional histogram equalization and Sparse Representation based denoising methods usually results in excessive contrast enhancement, which in turn gives the processed image an unnatural look and creates visual artifacts. By introducing specifically designed penalty terms, the level of image enhancement can be adjusted; noise robustness, white/black stretching and mean-brightness preservation may easily be incorporated into the optimization.

Keywords: Histogram, sparse representation, image denoising and enhancement.

1. INTRODUCTION

Contrast enhancement plays a crucial role in image processing applications, such as digital photography, medical image analysis, remote sensing, LCD display processing, and scientific visualization. Image enhancement is a technique which reduces image noise, remove artifacts, and preserve details. Its purpose is to amplify certain image features for analysis, diagnosis and display.

Contrast enhancement increases the total contrast of an image by making light colors lighter and dark colors darker at the same time. It does this by setting all color components below a specified lower bound to zero, and all color components above a specified upper bound to the maximum intensity (that is, 255). Color components between the upper and lower bounds are set to a linear ramp of values between 0 and 255. Because the upper bound must be greater than the lower bound, the lower bound must be between 0 and 254, and the upper bound must be between 1 and 255. Some users describe the enhanced image that if a curtain of fog has been removed from the image .

There are several reasons for an image/video to have poor contrast:

- the poor quality of the used imaging device,
- lack of expertise of the operator, and
- The adverse external conditions at the time of acquisition.

These effects result in under-utilization of the offered dynamic range. As a result, such images and videos may not reveal all the details in the captured scene, and may have a washed-out and unnatural look.

2. IMAGE ENHANCEMENT

Image enhancement processed consist of a collection of techniques that seek to improve the visual appearance of an image or to convert the image to a form better suited for analysis by a human or machine. Enhancement of an image can be implemented by using different operations of brightness increment, sharpening, blurring or noise removal. Unfortunately, there is no general theory for determining what 'good' image enhancement, when it comes to human perception. If it looks good, it is good! While categorizing Image Enhancement operations can be divided in two categories:

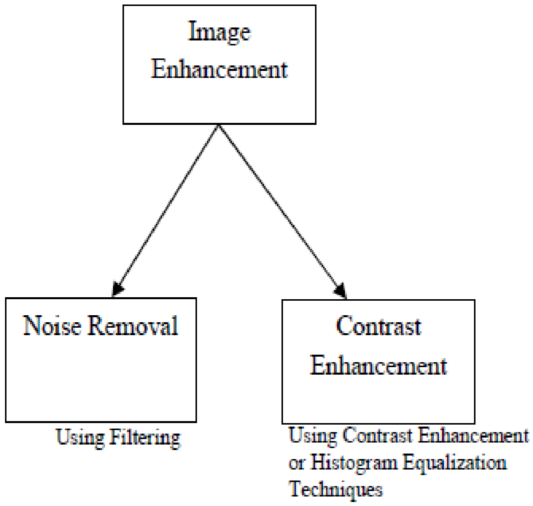


Figure 1.1: Operations of Image Enhancement

As shown in Fig. 1.1, image enhancement can be implemented by Noise removal or Contrast Enhancement. Noise Removal is an operation to remove unwanted details from an image. This detail gets attached to an image while capturing or acquisition process. Noise may be due to environment particles, capturing device inability, lack of experience of machine computer operator or some other reason. Noise removal helps an image processing system to extract necessary information only.

Other operation of Image Enhancement is Contrast Improvement. This process is used to make the image brighter, visual and detail worth full. Contrast Enhancement is the major area of this study and represents various methodologies being used for this process.

2.1TECHNIQUES OF IMAGE ENHANCEMENT

These techniques can be broadly categorized into two groups:

- direct methods and,
- Indirect methods.

2.1.1 Direct method

In direct method of contrast enhancement, a contrast measure is first defined, which is then modified by a mapping function to generate the pixel value of the enhanced image. Various mapping functions such as the square root function, the exponential function, etc., have been introduced for the contrast measure modification. However, these functions do not produce satisfactory contrast enhancement results and are usually sensitive to noise and digitization effects [4]. In addition, they are computationally complex from the point of view of implementation. The polynomial function is ready to implement on digital computers and provides very satisfactory contrast enhancement.

2.1.2 Indirect method

Indirect methods, on the other hand, improve the contrast through exploiting the underutilized regions of the dynamic range without defining a specific contrast term. Most methods in the literature fall into the second group. Indirect methods can further be divided into several subgroups:

 Techniques that decompose an image into high and low frequency signals for manipulation, e.g., homomorphic filtering,
 Histogram modification techniques, and
 Transform-based techniques.

Out of these three subgroups, the second subgroup received the most attention due to its straightforward and intuitive implementation qualities.

2.1.3 Histogram Equalization methods

Contrast enhancement techniques in the second subgroup modify the image through some pixel mapping such that the histogram of the processed image is more spread than that of the original image. Techniques in this subgroup either enhance the contrast globally or locally. If a single mapping derived from the image is used then it is a global method; if the neighborhood of each pixel is used to obtain a local mapping function then it is a local method.

The histogram in the context of image processing is the operation by which the occurrence of each intensity value in the image is shown. Normally, the histogram is a graph showing the number of pixels in an image at each different intensity value found in that image. For an 8- bit grayscale image there are 256 different possible intensities, and so the histogram will graphically display 256 numbers showing the distribution of pixels amongst those grayscale values. Histogram equalization is the technique by which the dynamic range of the histogram of an image is increased. HE assigns the intensity values of pixels in the input image such that the output image contains a uniform distribution of intensities. It improves contrast and the goal of HE is to obtain a uniform histogram.

3. CSR AND PROPOSED GHP BASED METHOD:

3.1 Centralized Sparse Representation Based Method

Local and nonlocal image models have supplied complementary views toward the regularity in natural images the former attempts to construct or learn a dictionary of basic functions that promotes the sparsity; while the latter connects the sparsity with the self-similarity of the image source by clustering.

The basic idea behind our CSR model is to treat the local and nonlocal sparsity constraints (associated with dictionary learning and structural clustering respectively) as peers and incorporate them into a unified variational framework. The new regularization term can be viewed as a plausible formalization of joint/group sparsity.

3.1.1 CSR Algorithm:

1. Initialization: X = Y;
2. Outer loop (dictionary learning): for i = 1, 2, ..., I
3. Update Φ via k-means and PCA;
4. Inner loop (structural clustering): for j = 1, 2, ..., J
5. Iterative regularization: $\tilde{X} = \hat{X} + \delta(Y - \hat{X})$;
6. Regularization parameter update: obtain new estimate of τ_1, τ_2 ;
7. Centroid estimate update: obtain new estimate of β_k 's via knn clustering
8. Image estimate update: obtain new estimate of X by $\hat{X} = D \, o \, S \, o \, R\tilde{X}$

3.2 Gradient Histogram Preservation Based Method

Image denoising model by gradient histogram preservation with sparse nonlocal regularization, and then present an effective histogram specification algorithm to solve the proposed model for texture enhanced image denoising.

3.2.1 Proposed Algorithm:

a) GHP Algorithm:

1. Initialize $k = 0, x^{(k)} = y$
2. Iterate on $k = 0,1,2,\ldots,J$
3. Update g:
$$g = F(\nabla x)$$
4. Update x:
$$x^{(k+1)/2} = x^{(k)} + \delta\begin{pmatrix}\frac{1}{2\sigma^2}(y - x^{(k)}) + \\ \mu\nabla^T(g - \nabla x^{(k)})\end{pmatrix}$$
5. Update the coding coefficients of each patch:
$$\alpha_i^{(k+1/2)} = D^T R_i x^{(k+1/2)}$$
6. Update the nonlocal mean of coding vector:
$$\beta_i = \sum_q w_i^q \alpha_i^q$$
7. Update α:
$$\alpha_i^{(k+1)} = S_{\lambda/d}\left(\alpha_i^{(k+1/2)} - \beta_i\right) + \beta_i$$
8. Update x:
$$x^{(k+1)} = D \circ \alpha^{(k+1)}$$
9. $k \longleftarrow k + 1$
10. $x = x^{(k)} + \delta\left(\mu\nabla^T(g - \nabla x^{(k)})\right)$

4. EXPERIMENTAL RESULTS

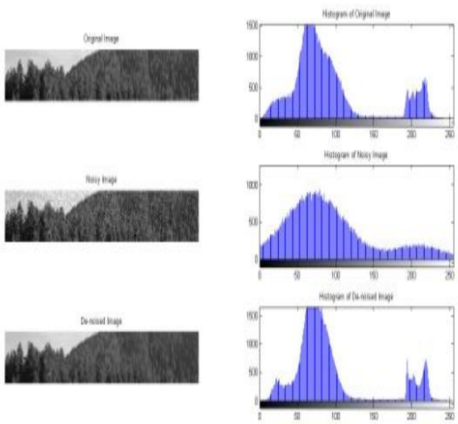
To verify the performance of the proposed Gradient Histogram Preservation (GHP) based image denoising method, we apply it to natural images with various texture structures, whose scenes are shown in Figure. All the test images are gray-scale images with gray level ranging from 0 to 255.

Also for comparison Centralised Sparse Representation (CSR) based image denoising method is applied to same images.

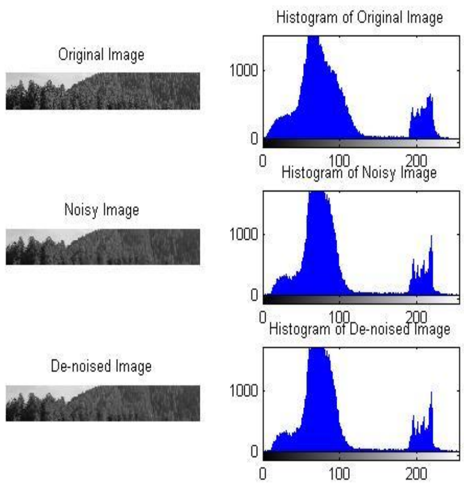
Finally, experiments are conducted to validate its performance in comparison with the CSR denoising algorithms.

4.1 Comparisons of Results:

Following figures shows comparison of GHP and CSR method with histograms.



(a)



(b)

Figure 4.1: Result for Trees image using (a) GHP method (b) CSR method.

These methods are applied to more images and the resulting denoised images are shown in figures bellow.

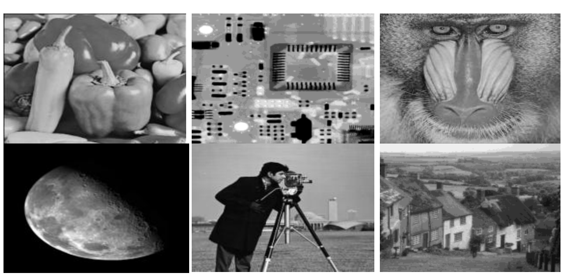


Figure 4.2: Original noiseless images.

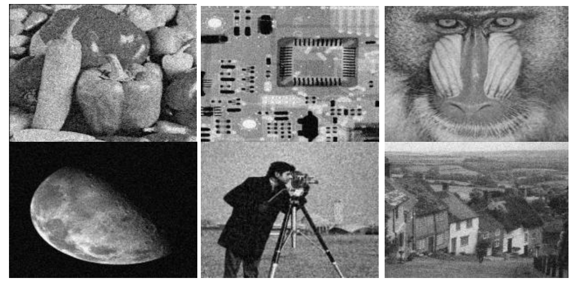


Figure 4.3: Noisy images.

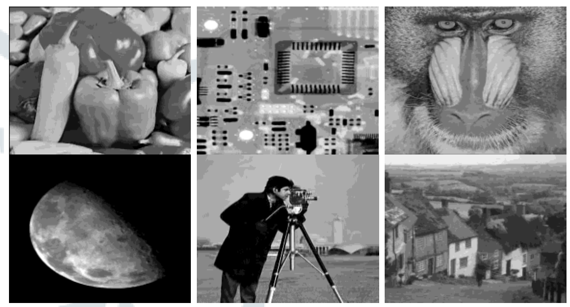


Figure 4.4: Denoised images using CSR Method.

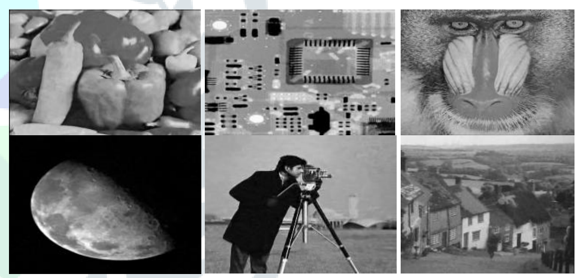


Figure 4.5: Denoised images using GHP Method.

4.2 Comparisons of obtained parameter values:

Image	Iter-ations	Noise level	PSNR	Average PSNR	Time
Trees	1	28.66	25.497315	25.7890	6.24 min
	2	4.66	25.693808		
	3	4.56	25.825020		
	4	4.45	25.951427		
	5	4.26	25.977771		

Table 4.1 PSNR with respect to noise level and Time required for GHP method.

Image	Iter-ations	Noise level	PSNR	Average PSNR	Time
Trees	1	30.0	24.675479	25.5185	9.11 min
	2	5.17	25.179103		
	3	4.83	25.597019		
	4	4.42	25.975387		
	5	3.86	26.165906		

Table 4.2 PSNR with respect to noise level and Time required for CSR method.

Parame-ters → / Images ↓	Average PSNR (for nsig = 30)		Time (min)	
	CSR	GHP	CSR	GHP
Trees	25.51	25.789	9.11	6.24
Peppers	34.11	28.94	22.19	15.04
Cktboard	28.47	28.86	19.05	17.49
Monkey	24.36	24.45	24.22	10.19
Moon	32.43	31.69	14.02	20.54
Cameraman	27.95	28.34	18.34	12.17
Hill	28.17	28.69	24.56	20.19

Table 4.3 Comparisons of PSNR using GHP and CSR Methods and Time for denoise image.

5. CONCLUSIONS

5.1 Conclusions

In this paper, we presented a gradient histogram preservation (GHP) model for texture-enhanced imaged noising. An efficient iterative histogram specification algorithm was developed to implement the GHP model.GHP achieves promising results in enhancing the texture structure while removing random noise. The experimental results demonstrated the effectiveness of GHP in texture enhanced image denoising. GHP leads to PSNR measures to the state-of-the-art denoising method. However, it leads to more natural and visually pleasant denoising results by better preserving the image texture areas. Limitations of GHP are that it cannot be directly applied to non-additive noise removal.

5.2 Advantage:

1) A simple but theoretically solid model.
2) Enhancing the texture structure while removing noise.
3) Less time consuming method.
4) Better image contrast enhancement, images looks more natural as original.

5.3 Disadvantage:

1) Limitation of system is that it cannot be directly applied to non-additive noise removal.
2) Need to study more general models and algorithms for non-additive noise removal with texture enhancement.
3) Not Suitable for Colour Quality Measures.

5.4 Applications

1) Medical images: many diseases are diagnosed by medical images.
2) Crime prevention: face recognition systems, used by police forces.
3) Geographical information system.
4) Digital photography.

6. REFERENCES

[1] WangmengZuo, Lei Zhang, Chunwei song, David Zhang and huijunGao. 2014. Gradient Histogram Estimation and Preservation for Texture Enhanced Image Denoising. IEEE trans. Image process. Vol.23, No 6, June.

[2] M. Elad and M. Aharon. 2006. Image denoising via sparse and redundant representations over learned dictionaries. IEEE Trans. Image Process. Vol. 15, no. 12, pp. 3736–3745, December.

[3] J. Mairal, F. Bach, J. Ponce, G. Sapiro and A. Zisserman. 2009. Non-local sparse models for image restoration. In: Proc. Int. Conf. Comput. Vis., Sep./Oct. pp. 2272–2279.

[4] W. Dong, L. Zhang, G. Shi and X. Li. 2013. Nonlocally centralized sparse representation for image restoration. IEEE Trans. Image Process. Vol. 22, no. 4, pp. 1620–1630, April.

[5] J. Jancsary, S. Nowozin and C. Rother. 2012. Lossspecific training of nonparametric image restoration models: A new state of the art. In: Proc. 12th ECCV, pp. 112–125.

[6] I. Daubechies, M. Defriese and C. De Mol. 2004. An iterative thresholding algorithm for linear inverse problems with a sparsity constraint," Commun. Pure Appl. Math. Vol. 57, No. 11, pp. 1413–1457, November.
[7] J. Bioucas-Dias and M. Figueiredo. 2010. Multiplicative noise removal using variable splitting and constrained optimization," IEEE Trans. Image Process. Vol. 19, No. 7, pp. 1720–1730, July.
[8] M. Afonso, J. Bioucas-Dias and M. Figueiredo. 2010. Fast image recovery using variable splitting and constrained optimization. IEEE Trans. Image Process., Vol. 19, No. 9, pp. 2345–2356, September.
[8] H. Attouch, J. Bolte, P. Redont, and A. Soubeyran. Proximal alternating minimization and projection methods for nonconvex problems: An approach based on the Kurdyka- Lojasiewicz inequality. *Mathematics of Operations Research*, 35(2):438–457, 2010.
[9] A. Buades, B. Coll, and J. Morel. A review of image denoising methods, with a new one. *Multiscale Model. Simul.*, 4(2):490–530, 2005.
[10] M. Elad and M. Aharon. Image denoising via sparse and redundant representations over learned dictionaries. *IEEE T-IP*, 15(12):3736–3745, 2006.
[11] T. S. Cho, N. Joshi, C. L. Zitnick, S. B. Kang, R. Szeliski, and W. T. Freeman. A content-aware image prior. *Proc. CVPR*, 2010.
[12] T. S. Cho, C. L. Zitnick, N. Joshi, S. B. Kang, R. Szeliski, and W. T. Freeman. Image restoration by matching gradient distributions. *IEEE T-PAMI*, 34(4):683–694, 2012.
[13] V. Katkovnik, A. Foi, K. Egiazarian, and J. Astola. From local kernel to nonlocal multiple-model image denoising.*IJCV*, 86(1):1–32, 2010.
[14] W. Dong, L. Zhang, and G. Shi. Centralized sparse representation for image restoration. *Proc. ICCV*, 2011.
[15] W Dong L. Zhang G. Shi and X. Wu.Image deblurring and super-resolution by adaptive sparse domain selection and adaptive regularization. *IEEE T-IP*, 20(7):1838–1857, 2011.
[16] M. Elad and M. Aharon. Image denoising via sparse and redundant representations over learned dictionaries. *IEEE T-IP*, 15(12):3736–3745, 2006.
[17] D. Krishnan and R. Fergus. Fast image deconvolution using hyper-laplacian priors. *Proc. NIPS*, 2009.
[18] J. K. Patel and C. B. Read. Handbook of the normal distribution. *New York: Marcel Dekker*, 1982.
[19] L. Rudin, S. Osher, and E. Fatemi. Nonlinear total variation based noise removal algorithms. *Physica D*, 60(1-4):259–268, 1992.
[20] K. Suzuki, I. Horiba, and N. Sugie. Efficient approximation of neural filters for removing quantum noise from images. *IEEE T-SP*, 50(7):1787–1799, 2002.
[21] M. Varma and A. Zisserman. A statistical approach to texture classification from single images. *IJCV*, 62(1-2):61–81, 2005.
[22] M. Wainwright and S. Simoncelli. Scale mixtures of Gaussians and the statistics of natural images. *Proc. NIPS*, 1999.