An Approach For Image Removal Blurring Using Gauss-Total In Optical Communications

Utkarsh Shukla
Assistant Professor and HOD, Dept of Computer Science & Engineering
Sunrise Institute of Engineering Technology & Management, Kanpur, Uttar Pradesh, INDIA.

Abstract- *In video and still image camera noise and blurring of images is often seen. Image noises can be removed using various classes of filters. In case of mixed noises filter cannot eliminate noise completely. To remove such noises pdf estimation of noises becomes important. Blurring of images is another degrading factor and when image is corrupted with both blurring and mixed noises de- noising and de-blurring of image is very difficult. In this paper, Gauss-Total Variation model (G-TV model) is discussed and results are presented and it is shown that blurring of image is completely removed using G-TV model, however, image corrupted with blurring and mixed noise cannot be completely recovered.*

Keywords- Blurring, Image compression.

I. INTRODUCTION

For the past recent decades, Image denoising has been analysed in many fields such as computer vision, statistical signal and image processing. It facilitates a appropriate base for the analysis of natural image models and signal separation algorithms. Moreover, it also turns into an essential part to digital image acquiring systems to improve qualities of image. These two directions are vital and will be examined in this paper.

Among the present work of image denoising, a major portion assumes additive white Gaussian noise (a.k.a. AWGN) and taken off the noise independent of RGB channels. Although, the level and type of the noise produced by digital cameras are not known if the camera brand and series along with settings of the camera (ISO, speed, shutter, aperture and flash on/off) are unknown, e.g., digital pictures with exchangeable image file format (EXIF) metadata lost. In the mean time, the color noise statistics is dependent of the RGB channels due to the demosaic process embedded in cameras. Hence, the present denoising way are not genuinely automatic and are not able to remove color noise in an effective way. This avoids the techniques of noise removal from being basically applied to digital image denoising and improving applications.

It is required by some image denoising software that the user specifies a number of smooth image regions for the estimation of the noise level. This inspired us to adopt a segmentation-based method to automatically evaluate the level of noise from a single image. The image brightness is a factor on which noise level depends, and we propose the evaluation of the upper bound of a noise level function (NLF) from the image. The partition of image is done into piecewise smooth regions in which the standard deviation is an overestimate of noise level and the mean is the estimate of brightness. The initial of the noise level functions are understood by simulating the digital camera imaging process, and are utilized to help assessing the curve effectively at the missing data.

As separating signal and noise from a distinct input is fully under-constrained, it is in theory not possible to totally resume the original image from the noise corrupted observation.

The fundamental criterion in the denoising of image is therefore to safeguard image features to the maximum possibility while the noise elimination. There are various principles we need to coordinate in designing image denoising algorithms.

(a) The smoothness of the perceptually flat regions should be maximum. Noise should be totally expelled from these regions.
(b) The boundaries of image should be well preserved. This implies the boundary should not be either sharpened or blurred.
(c) The details of the texture should be preserved. This is one of the extremely hardest criteria to match. As image denoise algorithm constantly tends to smooth the image, it is quite easy to lose details of the texture in denoising.
(d) The preservation of global contrast should be maintained, or the low-frequencies of the denoised and input images should be similar.
(e) Artifacts should not be produced in the denoised image.

The global contrast is most likely the simplest to match, though a portion of the rest principles are nearly incompatible. For instance, (a) and (c) are extremely hard to be tuned together as a lot of denoised algorithms couldn't recognize flat and texture regions from a single input image. Principle (e) is of very importance. For example, wavelet-based denoising algorithms have a tendency to create ringing artifacts In an ideal way, the very same image model should be used for both denoising and noise estimation.

The tunsharp image area created by subject movement or camera, inaccurate focusing, or the use of an aperture that provides shallow depth of field is termed as blur. The Blur impacts are filters that smooth transitions and reduce contrast by averaging the pixels next to hard edges of defined lines and areas where there are valuable color transition.

Gaussian Blur

Gaussian Blur is that pixel weights aren't equal - according to a bell-shaped curve, they decrease from kernel center to edges .The effect of Gaussian Blur is a filter that blends a particular number of pixels incrementally, that follows a bell-shaped curve. The blurring is dense in the center while at the edge is feathers.

Frequently, digital cameras have very little noise in their pictures. Some are worse as compared to others, yet it's there. Here I'll illustrate you an approach to dispose of that noise by making use of the selective Gaussian blur filter.

The fundamental idea behind specific Gaussian blur is that the photo areas with contrast below a certain threshold get blurred.

The composition of paper is as follows: We provide a statistical interpretation of the ROF model in Section 2 and propose a Gauss-Total Variation model (G-TV model). We explain the ROF model statistically and few statistical control parameters of noise emerge automatically, at this point one can notice that these parameters rely on the noise may take a similar part of the regularization parameter.

II. RUDIN-OSHER-FATEMI (ROF) MODEL

A novel version of the popular Rudin-Osher-Fatemi (ROF) model is presented in this work to restore image. The crucial point of the model is that it could recreate images with blur and non-uniform distributed noise.

In numerous applications, the images we acquire are contaminated by added blur and noise. This procedure is frequently modeled by

$$g(x) = (k * f)(x) + n(x) \qquad (1)$$

where $f(x)$ is the original clean image, $g(x)$ is the noticed noisy blurred image, k is the point spread function (PSF) and also termed as the blur kernel, $n(x)$ is the additive noise and *refers to the usual convolution.

The issue of reconstruction of image is to recover $f(x)$ from the degraded image $g(x)$. Traditional image recovery approaches are chiefly on the basis of variational techniques [2, 3, 4,6, 8, 9, 10, 11, 13, 17], of which the most renowned one is the ROF model, proposed by Rudin, Osher and E.Fatemi [3, 17]. A regularized solution is obtained in that model by minimizing the energy functional

$$T(f) = \frac{1}{2}\|k * f - g\|^2 + \lambda J_\beta(f) \qquad (2)$$

$$J_\beta(f) = \int \sqrt{|\nabla f|^2 + \beta}\, dx \qquad (3)$$

k is a known blur kernel, $\beta > 0$ is referred to as the stabilizing parameter, and $\lambda > 0$ is the regularization parameter. A number of experimental results (ref.[3, 4, 10, 12, 17]) have illustrated the impact of these processes in eliminating Gaussian and uniform distributed white additive noise. Although, indeed, images are generally degraded by mixed noise with different variances, means, and even distributions. The traditional methods (e.g., ROF model) may not work well in this case.

It is quite clear from the above experiments that the ROF model can't work effectively when the blurred images are further degraded by mixed Gaussian noise. Therefore in order to enhance the reconstructed images quality, more information about such specific noise should be employed.

A new approach is proposed in this paper which incorporates some statistical information of noise. With the adaptive updating of the statistical control parameters of noise, we could adjust the effects of denoising and deblurring and hence get a improved reconstruction. In the mean time, we propose a process of how one can adaptively find out the statistical parameters of noise for the restoration of the image.

III. GAUSS-TOTAL VARIATION MODEL (G-TVMODEL).

A new interpretation of the ROF model is developed in this section that based on statistical approaches. In the following, we consider that the noise intensity $n(x)$ or $(k*f)(x)-g(x)$ is a random var able and all these random variables are not dependent and identically- distributed (i.i.d.)as a Gaussian distribution N(0, 2), i.e.,

$$g(x) = (k * f)(x) + n(x) \tag{4}$$

$$p\left((k*f)(x) - g(x) / \sigma\right) = \frac{1}{\sqrt{2\pi\sigma^2}} \exp - \left\{ \frac{|(k*f)(x) - g(x)|^2}{2\sigma^2} \right\} \tag{5}$$

$$L(f,\sigma^2) = \Pi_{x\in\Omega} \frac{1}{\sqrt{2\pi\sigma^2}} \exp - \left\{ \frac{|(k*f)(x) - g(x)|^2}{2\sigma^2} \right\} \tag{6}$$

Minimizing log-likelihood function

$$E_1(f,\sigma^2) = \frac{1}{2}\int_\Omega \left\{ \frac{|(k*f)(x) - g(x)|^2}{\sigma^2} \right\} dx + \frac{1}{2}\int_\Omega \ln(\sigma^2) dx \tag{7}$$

Where, σ^2 is unknown constant. Minimumizing the above equation is equivalent to minimizing the residual

$$\frac{1}{2}\|k * f - g\|^2_{L^2} \tag{8}$$

The minimization problem defined above is ill-possed, hence we incorporate a regularization term and gets the following cost functional

$$E(f,\sigma^2) = E_1(f,\boldsymbol{\sigma}^2) + \lambda J(f) \tag{9}$$

Considering TV regularization term as

$$J(f) = \int_\Omega \sqrt{|\nabla f|^2 + \beta}\, dx \tag{10}$$

$$E(f,\sigma^2) = \frac{1}{2}\int_\Omega \left\{ \frac{|(k*f)(x) - g(x)|^2}{\sigma^2} \right\} dx + \frac{1}{2}\int_\Omega \ln(\sigma^2) dx + \lambda \int_\Omega \sqrt{|\nabla f|^2 + \beta}\, dx \tag{11}$$

Algorithm 1

Choose initial values of f^0 and $(\sigma^2)^0$. For different values of n=1,2,3,4…….so on

1. Evaluate f^{n+1}, under the condition

$$f^{n+1} = \arg\min E(f, (\sigma^2)^n)$$

2. Evaluate $(\sigma^2)^{n+1}$, under the condition

$$(\sigma^2)^{n+1} = \arg\min E(f^{n+1}, (\sigma^2))$$

3. Check for the convergence, if converges STOP, else go to STEP 1.

IV. RESULTS

Original Lena image considered in the experiment is shown in figure 1, this image is corrupted with Gaussian Blur with mean 25, and variance as 1, 5 and 7 respectively and obtained images are shown in Figure

Fig.1 Original Lena image

(a) (b) (c)

Fig.2 Blurred Lena image

(a) (b)

Fig.3(a) Blurred and (b)Recovered Lena image

(a) (b)

Fig.4(a) Blurred and (b)Recovered Lena image

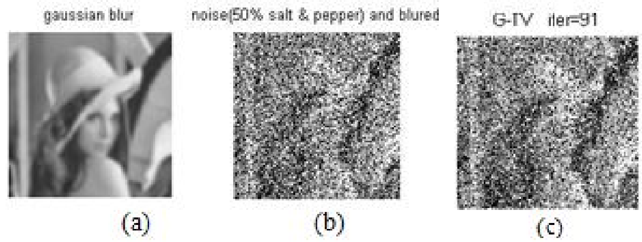

Fig.5(a) Blurred and (b) Blurred and Noisy image (c) recovered image with G-TV model with 91 iterations

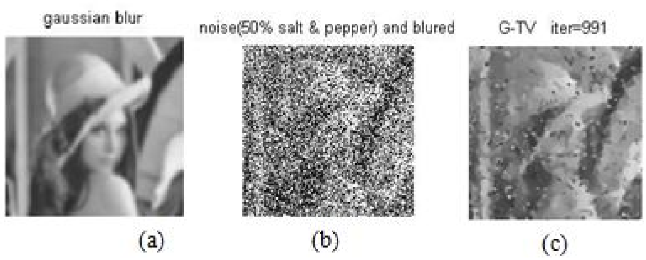

Fig.6(a) Blurred and (b) Blurred and Noisy image (c) recovered image with G-TV model with 991 iterations

In figure 3, Lena image is corrupted with Gaussian blur with mean 25 and variance 3 and image is free from any other noise. The simulation was run for 600 iterations, and after 91 iterations significant improvement was found in the blurred image (Fig 3(b)).

In figure 4, Lena image is corrupted with Gaussian blur with mean 25 and variance 5 and image is free from any other noise. The simulation was run for 600 iterations, and after 391 iterations significant improvement was found in the blurred image (Fig 4(b)). But improvement is much lesser in comparison to fig 3(b).

In figure 5, Lena image is corrupted with Gaussian blur with mean 25 and variance 3 and image is corrupted with salt and pepper noise (50%). The simulation was run for 200 iterations, and after 91 iterations no significant improvement was found in the blurred image (Fig 4(b)). In figure 6(c) results are obtained after 991 iterations and still improvement is very less. However, recovered image is much better in comparison to 91 iterations.

V. CONCLUSION

The above G-TV model is quite effective in reconstructing images with blur and uniform distributed noise without changing the regularization parameter □ directly. However, it still could not work well when the image is contaminated with blur and mixed noise. As the number of iterations are increased obtained results improves. Moreover, with lesser Gaussian blur variance, image recovered in lesser iterations. However, as the variance increases number of iterations also increases which required to recover images.

REFERENCES

[1] Bilmes, J. (1998). A Gentle Tutorial of the EM Algorithm and its Application to Parameter Estimation for Gaussian Mixture and Hidden Markov Models. Available at http://citeseer.ist.psu.edu/bilmes98gentle.html.

[2] Acar, R., & Vogel, C. (1994). Analysis of Total Variation Penalty Methods. Inverse Problems, 10 , 1217-1229.

[3] Rudin, L., & Osher, S. (1994). Total Variation Based Image Restoration with Free Local Constraints. Proc.IEEE ICIP, 1, 31-35. Austin TX, USA.

[4] Vogel, C., & Oman, M. (1998). Fast, Robust Total Variation- based Reconstruction of Noisy, Blurred Images. IEEE Transactions on Image Processing, 7, 813-824.

[5] Redner, R., & Walker, H. (1984). Mixture Densities Maximum Likelihood and the EM Algorithm. SIAM Review, 26(2), 195-239.

[6] Chan, R., Ho, C., & Nikolova, M. (2005). Salt-and-Pepper Noise Removal by Mediantype Noise Detectors and Detail-preserving Regularization. IEEE Transactions on Image Processing, 14(10), 1479-1485.

[7] Chan, T., & Wong, C. (1998). Total Variation Blind Deconvolution. IEEE Trans. Image Processing, 7, 370-375.

[8] Nikolova, M. (2004). A Variational Approach to Remove Outliers and Impulse Noise.
Journal of Mathematical Imaging and Vision, 20, 99-120.

[9] Bar, L., Kiryati, N., & Sochen, N. (2006). Image Deblurring in the Presence of Impulsive Noise. International Journal of Computer Vision, 70, 279-298.

[10] Shi, Y., & Chang, Q. (2007). Acceleration methods for image restoration problem with different boundary conditions. Applied Numerical Mathematics, 58(5) 602-614.

[11] Bect, J., Blanc-F´eraud, L., Aubert, J., & Chambolle, A. (2004). A l1-Unified Variational Framework for Image Restoration. Proc. ECCV’2004, Prague, Czech Republic, Part IV: LNCS 3024, 1-13

[12] Michael, K., Chan, H., & Tang, W. (1999). A fast algorithm for deblurring models with neumann boundary conditions. SIAM J.SCI.Comput, 21(3), 851-866.

[13] Vogel, R. (2002). Computational Methods for Inverse Problems. SIAM.

[14] McLachlan, G., & Krishnan, H. (1997). The EM Algorithm and Extensions, JOHN WILEY & SONS, INC, New York.

[15] He, L., Marquina, A., & Osher, J. (2005). Blind Deconvolution Using TV Regularization and Bregman

Iteration. Wiley Periodicals, Inc.Int J Imaging Syst Technol, 15, 74-83.

[16] Shi, Y., & Chang, Q. (2006). New time dependent model for image restoration. Applied Mathematics and Computation, 179 (1) 121-134.

[17] Rudin, L., Osher, S., & Fatemi, E. (1992). Nonlinear total variation based noise removal algorithms. Phys. D, 60, 259-268.

[18] Lagendijk, R., & Biemond, J. (1988). Regularized iterative image restoration with ringing reduction. IEEE Transaction on Acoustics, Speech, and Signal Processing, 36(12)