Advance in Electronic and Electric Engineering.
ISSN 2231-1297, Volume 3, Number 8 (2013), pp. 1063-1070

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Image Restoration using Modified Lucy Richardson Algorithm in the Presence of Gaussian and Motion Blur

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Abstract

Image restoration is the process of reconstruction or recovering an image that has been corrupted by some degradation phenomenon. Degradation may occur due to motion blur, Gaussian blur, noise and camera mismatch. In this paper corrupted image have been recovered using Modified Lucy Richardson algorithm in the presence of Gaussian blur and motion blur. The performance of this algorithm has been compared with Wiener filter, Constraint Least Square method and Lucy Richardson algorithm. The performance comparison done on the based on peak signal-to-noise ratio (PSNR).The result shows that Modified Lucy Richardson method is better than Wiener filter, Constraint Least Square method and Lucy Richardson algorithm.

Keywords: Wiener filter, Constraint Least Square Method, Lucy Richardson Algorithm, Gaussian blur, Motion blur, Peak Signal to Noise Ratio (PSNR).

1. Introduction

Images are produced to record the useful information. Due to imperfections in the imaging and capturing process, however, the recorded image invariably represents a degraded version of the original scene. The degradation results in image blur, affecting identification and extraction of the useful information in the images. It can be caused by relative motion between the camera and the original scene, by an out of focus of optical system, atmospheric turbulences and aberrations in the optical system [1][2][4]. Noise introduced by the medium through which the image is created can also cause degradation. The degradation phenomenon of the acquired imagescauses serious economic loss. Therefore, restoring thedegraded images is an urgent task in order to expand uses ofthe images.In general there are two types of restoration methods are used. One is non-blind restoration in which we need prior knowledge of h(x,y). In this case three filtering techniques are generally used [4]: Wiener filtering, Constraint least square filtering and Lucy Richardson algorithm which are discussed in section 2. Other one is Blind Restoration in which we do not need any prior knowledge of h(x,y) [4].

The image restoration model is shown in figure 1. It consist of taking a non-blurred image f(x,y), creating a known blurring function or point spread function h(x,y) and then filtering the image with this function so as to add blur into it.This image is further corrupted additive Gaussian noise to get the degraded image g(x, y). This degraded image is passed through a restoration filter R(x,y) to get the restored image$\hat{f}(x,y)$.

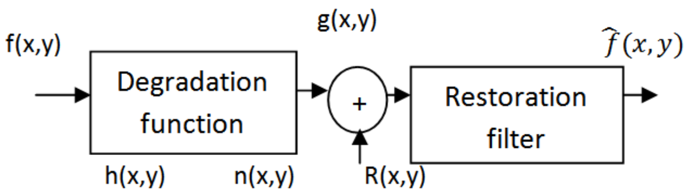

Figure 1: Image restoration process model.

In this paper we are focussing on non-blind restoration methods. We have restored the degraded image by using proposed modified Lucy Richardson Algorithm.Since DWT has excellent spatial localization and multi-resolution characteristics, which are similar to the theoretical models of the human visual system it is widely used in image processing [5][6][7][8]. In theproposed modified LR algorithm we have taken the DWT of degraded image and then apply LR algorithm to it. Further the performance of the proposed algorithm is compared with wiener filter, constraint least square method, LR method.The rest of the paper is organized as follows. Section 2 consists of the important deblurring algorithms and their brief characteristics. In Section 3 we have discussed the proposed modified LR Algorithm. Section 4 consists of simulation set up and the results. Conclusions are drawn in Section 4.

2. Non-Blind Restoration Methods

In this section we have discussed various non-blind methods: Wiener filter, constrained least squares filter (CLS) and Lucy Richardson(LR) algorithm. It is assumed that the characteristics of thedegrading system and the noise are known a priori.

2.1 Wiener Filter

Wiener filter is an efficient method for restoration of degraded image because it minimizes the mean square error between the estimated random process and the desired process.With reference to figure 1,the problem statement is:For given$g(x,y)$, some knowledge about $h(x,y)$, some knowledge about$n(x,y)$and some knowledge about$f(x,y)$, obtain the estimate $\hat{f}$ of original image f such that mean square errormse between them is minimum where $\mathrm{mse} = \mathrm{E}\{(\mathrm{f} - \hat{\mathrm{f}})^\wedge 2\}$and E is a mean value operator. The solution of this expression in the frequency domain is given by

$$R(u,v) = \frac{|H(u,v)|^2}{H(u,v)\left[|H(u,v)|^2 + \frac{S_n}{S_f}\right]} \quad (1)$$

Clearly, wiener filter requires the knowledge of PSF h(x,y), power spectra of noiseS_n and power spectra of image S_f to be known. When they arenot known the ratio is approximated by user and is determinedby trial to minimize the error.

2.2 Constraint Least Square Filter

The constrained least-squares filter (CLS) is anotherapproach for overcoming some of the difficulties of the Wiener filtersas it is required to have a priori knowledge about mean and varianceof the noise only. The CLS algorithm is based on finding a directsolution using a criterion*C*, which ensures optimal smoothnessof the degraded image.From figure 1, we can express linear degradation in vector matrix vector form as$\mathrm{G} = \mathrm{HF} + \mathrm{N}$

The problem statement is: To minimize the smoothness function Csubjected to the constraint $\left\|\mathrm{G} - \mathrm{H}\hat{\mathrm{F}}\right\|^2 = \|\mathrm{N}\|^2$

$$C = \sum_{x=0}^{M-1} \sum_{y=0}^{M-1} [\nabla^2 f(x,y)]^2 \quad (2)$$

The frequency domain solution is given by

$$\hat{\mathrm{F}}(\mathrm{U},\mathrm{V}) = \frac{1}{\mathrm{H}(\mathrm{U},\mathrm{V})}\left[\frac{|\mathrm{H}(\mathrm{U},\mathrm{V})|^2}{|\mathrm{H}(\mathrm{U},\mathrm{V})|^2 + \gamma|\mathrm{P}(\mathrm{U},\mathrm{V})|^2}\right]\mathrm{G}(\mathrm{U},\mathrm{V}) \quad (3)$$

Where γ is a parameteradjusted so that constrained is satisfied, |P(U,V)|is the Fourier Transform of $p(x,y) = \begin{bmatrix} 0 & 1 & 0 \\ 1 & -4 & 1 \\ 0 & 1 & 0 \end{bmatrix}$

Clearly, CLS method requires the knowledge of only PSF h(x,y) and γ which can be found is we know $\|\mathrm{N}\|^2$.

2.3 **Lucy Richardson Algorithm**

The restoration methods which are discussed above are linear. They are also direct in the sense that, once therestoration filter is specified, the solution is obtained in one go. During the past two decades, non-liner iterative methods have been gaining there acceptance as restoration tool that often yield result better than those obtained with linear methods.The Lucy Richardson (LR) algorithm is an iterative nonlinear restoration method.The L-R algorithm arises from maximum likelihood formulation in which image is modelled with poison statistics. Maximizing the likelihood function of the model yield an equation that is satisfied when following iteration converges:

$$\hat{f}_{k+1}(x,y) = \hat{f}_k(x,y)\left[h(-x,-y) * \frac{g(x,y)}{h(x,y)*\hat{f}_k(x,y)}\right] \quad (4)$$

While using this method, there arises an obvious question ofwhere to stop. It is difficult to claim any specific value for thenumber of iterations; a good solution depends on the size andcomplexity of the PSF matrix. The algorithm usually reaches astable solution very quickly (few steps) with a small PSF matrix.But if one stops after a very few iterations then the image maybe very smooth. On the other hand, increasing the number of iterations not only slows down the computational process, butalso amplifies noise and introduces the *ringing effect.* Some additional methods for ringing reduction are given in [9]. Thus for the "good" quality of restored image,the optimal number of iterations are determined manually fore very image as per the PSF size.

3. Proposed Modified Lucy Richardson Algorithm

In the proposed method we have taken the DWT of degraded image, so we will discuss the properties of DWT in brief. DWT has excellent spatial localization and multi-resolution characteristics, which are similar to the theoretical models of the human visual system. The original image is decomposed into four sub-band images by DWT: three high frequency parts (HL, LH and HH, named detail sub images) and one low frequency part (LL, named approximate sub-image). The detail sub-images contain the fringe information while the approximate sub-image is the convergence of strength of original image. Relative to the detail sub-images, approximate sub image is much more stable, since the majority of image energy concentrates here. Therefore, we will apply Lucy Richardson algorithm to LL sub-band image.

1) Take a non-blurred image **f**of size 512x512.
2) Add Gaussian or Motion Blur to it to produce blurred image **bf**.
3) Now add Gaussian noise to **bf**to produce degraded image **G.**
4) DWT is applied to degraded image **G**to decompose it into four sub-bands **LL, HL , LH** and **HH** each of size 256x256.
5) Choose **LL** sub-band and then apply LR method to it to produce the restored low frequency band **LLM**
6) Apply thresholding to remaining sub images i.e. **HL, LH, HH**.
7) Apply inverse DWT to **LLM, HL, LH** and **HH** to get the restored image$\hat{\boldsymbol{f}}$.

4. Simulation Set Up & Results

We have tested the proposed scheme on gray scale image of size 512 × 512. The proposed scheme was tested in the presence of Gaussian blur and motion blur. We have taken two performance evaluation metrics: PSNR (Peak Signal to Noise Ratio) and MSE (Mean Square Error) which are defined as follows:

$$\mathrm{PSNR(dB)} = 10\log_{10}\frac{255\times255}{MSE} \& \mathrm{MSE} = \frac{1}{M*N}\sum_{x=1}^{M}\sum_{y=1}^{N}\left(\mathrm{f}(\mathrm{x},\mathrm{y}) - \hat{\mathrm{f}}(\mathrm{x},\mathrm{y})\right)^2$$

Where M X N denotesthe size of the image, $\mathrm{f}(\mathrm{x},\mathrm{y})$ *and* $\hat{\mathrm{f}}(\mathrm{x},\mathrm{y})$ denotes the pixel values at $(x,y)^{th}$ location of original and restored image respectively.The PSNR has been utilized to calculate similarity between the original image and the restored image.The higher the PSNR and lower the MSE inthe deblurred image, the better is its quality.

Figure 1 shows the non-blurred image, figure 2 shows Gaussian blurred &noisy image. Inthe presence of Gaussian Blur figure 3 shows the restored image using wiener filter,figure 4 shows the restored image usingCLS method,figure 5 shows the restored image using LR methodand figure 6 shows the restored image using modifiedLR method.






Figure1 Figure 2 Figure 3 Figure 4 Figure 5 Figure 6

Figure 7shows the non-blurred image, figure 8 shows Motion blurred & noisy image. In the presence of Motion Blur,figure 9 shows the restored image using wiener filter,figure 10 shows the restored image using CLS method,figure 11 shows the restored image using LR method and figure 12 shows the restored image using modified LR method.




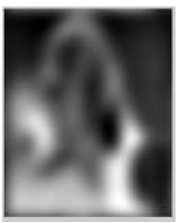

Figure 7 Figure 8 Figure 9 Figure 10 Figure 11 Figure 12

Table 1: PSNR Comparison in the presence of Gaussian Blur.

Filter Type	MSE	PSNR (dB)
Wiener Filter	1.0754e+004	17.9947
Constraint Least Square Filter	579.3914	47.2055
Lucy Richardson method	485.7005	48.9693
Modified Lucy Richardson method	421.8640	50.3784

Table 2: PSNR Comparison in the presence of Motion Blur.

Filter Type	MSE	PSNR (dB)
Wiener Filter	2.2033e+003	33.8482
Constraint Least Square Filter	1.1289e+003	40.5354
Lucy Richardson method	956.1066	42.1966
Modified Lucy Richardson method	882.0553	43.0027

Table 1& Table 2 show the PSNR& MSE calculation between the non-degraded image and restored image in the presence of Gaussian blur& Motion blurusing modified LR method, LR method, CLS method and Wiener method.

5. Conclusion

In this paper, the performance of proposed modified LR method is compared with various deblurringtechniques. The proposed algorithm has high value of PSNR than the other deblurring methods in the presence of both Gaussian blur as well as motion blur. Furthermore, the proposed algorithm has low value of mean square error than the other deblurring methods in the presence of both Gaussian Blur as well as motion blur. In other words modified LR method restores the seriously blurred and noisy image in real life better than the Wiener filter, CLS method and LR method.

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