Inverse Techniques for Efficient Corneal Image Restoration

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Abstract— **This paper presents two proposed approaches for digital restoration of corneal images. The first algorithm is based on Wiener Restoration approach. The second algorithm depends on regularized image restoration. As corneal images are usually acquired with confocal microscopes. Hence if the corneal layer is outside the focus of the microscopes, the image will be blurred. To solve this problem, the restoration process can be applied on the corneal image. Both Linear Minimum Mean Square Error (LMMSE) and regularized restoration are implemented. The evaluation metrics used to test the performance of the proposed restoration approaches are mean square error (MSE), peak signal to noise ratio (PSNR) and correlation coefficient. Simulations results reveal good success in restoration of corneal images refer to the mentioned evaluation metrics and appearance view.**

1. Introduction

Generally, the principally purpose of the restoration of the image is to return the genuine image from a degraded version. Hence, the corneal image restoration is the removal or reduction of degradations which are included during the acquisition of corneal images. Many corneal image degradation problems can be formed as a linear blur in the existence of additive noise [1-2]. The degradation due to blur and noise generally makes the analysis of the genuine corneal image difficult. The inverse of the blur operator may be non-unique, and the noise move to be amplified in admissible [3-4]. Blurring of corneal images caused when object in the corneal image is outside the camera's depth of confocal microscopes through the exposure. In cases where the corneal image is corrupted by noise, the best we may hope to do is to compensate for the degradation it caused [5-6].

Different algorithms have been used to restore the degradation image like Wiener restoration technique, regularization of image restoration, Histogram Adaptive Fuzzy filter, Min-max Detector Based filter and Centre etc [7-8]. These techniques depend on reducing the blurred point spread function PSF. In many applications it is not simply to get information about degraded image and it is too be hard to measure the degradation [9]. In such cases, info regarding the degradation should be extracted from the determined image either expressly or implicitly. This task is termed blind image restoration [11-12].

In this article we will implement two techniques. Firstly, LMMSE restoration approach (Wiener restoration approach) is one among the foremost common techniques for image restoration. The LMMSE technique attacks the restoration downside directly and proposes a criterion that expressly evaluates however shut the restoration is to the first object intensity distribution.

Secondly, Regularization of image restoration which was basically introduced by Tikhonov and Miller provides a formal basis for the development of regularized solutions of ill posed problems. The stabilizing function approach is one in all the fundamental methodologies for the event of regular solutions. Depending on this approach, the problem of the restoration process can be constrained by choosing the regularization operator and regularized parameter

The rest of this paper is listed as follows: Section 2 summarizes the corneal image degradation model. The proposed methods are listed in section 3. The results of simulation are denoted in section 4. Concluding remarks are demonstrated in section 5.

2. Corneal Image Degradation Model

While taking images there are many factors that affect image quality, so it is important to reestablish that corrupted images. Generally, main reasons of degradation are blurring, noising, and motion. The image restoration may be a terribly massive challenge within the field of image process. To recover the image there should have data of degradation. Restoration method improves the looks of the image. Reconstruction of the image may be performed using two forms of model (i) Degradation Model (ii) Restoration Model

In Figure 1 there are 2 pictures shown. Figure 2(a) is imperfect because of varied reasons delineate during this paper. Figure 2(b) shows the clear image that is obtained by differing kinds of restoration techniques. Generally, degradation caused at the instant of image acquisition and transformation of the image from one device to a different device.

$$\mathbf{g} = \mathbf{Hf} + \mathbf{n} \tag{1}$$

In above Equation (1) **f** is an original corneal image which is degraded by PSF (Point Spread Function) **H** and additive noise **n.** So, we demand to restore it restoration function. Finally, restored corneal image $\hat{\mathbf{f}}$ is obtained.

3. Proposed Restoration Algorithms for Corneal Images

3.1 The first proposed approach

This approach is based on wiener restoration. One among the foremost common techniques for image restoration is LMMSE restoration approach and also called Wiener restoration approach. The main concept of wiener restoration is how to close the error between the original and the estimated corneal image. This approach assume that the signal and noise are static with spectral properties.

The image degradation model is described in eq. (1) [10-11]:

$$\mathbf{g} = \mathbf{Hf} + \mathbf{n}$$

Using the LMMSE approach, we can estimate the corneal image $\mathbf{f}$. This estimate is called $\hat{\mathbf{f}}$. The error of this estimate is defined as [2]:

$$\boldsymbol{\varepsilon} = \mathbf{f} - \hat{\mathbf{f}} \tag{2}$$

The following equation represents the formula of wiener algorithm which minimizes the error $\boldsymbol{\varepsilon}$:

$$\mathbf{L} = \mathbf{R_f H^t (H R_f H^t + R_n)}^{-1} \tag{3}$$

where $\mathbf{L}$ represents wiener filter, $\mathbf{R_f}$ is the power spectrum of the original image, $\mathbf{R_n}$ presents power spectrum of noise.

3.2 The second proposed approach

This approach based on regularized image restoration. The application of the regularized approach depends mainly on the regularization operator and a regularization parameter choice. The restoration problem in this case can be fixed either iteratively or non-iteratively. The regularized restoration technique can be achieved for single as well as multi-channel image restoration cases.

Due to the regularization theory, the solution result of Eq. (1) is achieved by minimize the cost function [3]:

$$\Psi(\hat{\mathbf{f}}) = \left\| \mathbf{g} - \mathbf{H}\hat{\mathbf{f}} \right\|^2 + \lambda \left\| \mathbf{C}\hat{\mathbf{f}} \right\|^2 \tag{4}$$

Where $\mathbf{C}$ is the regularize operator and λ is the regularize parameter.
Apply the derivative function to minimize the cost function [3]:

$$\frac{\partial \Psi(\hat{\mathbf{f}})}{\partial \hat{\mathbf{f}}} = \mathbf{0} = 2\mathbf{H}^t(\mathbf{g} - \mathbf{H}\hat{\mathbf{f}}) - 2\lambda \mathbf{C}^t \mathbf{C}\hat{\mathbf{f}} \tag{5}$$

Then,

$$\hat{\mathbf{f}} = (\mathbf{H}^t\mathbf{H} + \lambda \mathbf{C}^t\mathbf{C})^{-1}\mathbf{H}^t\mathbf{g} = \mathbf{A}(\lambda)\mathbf{g} \tag{6}$$

Where,

$$\mathbf{A}(\lambda) = (\mathbf{H}^t\mathbf{H} + \lambda \mathbf{C}^t\mathbf{C})^{-1}\mathbf{H}^t \tag{7}$$

The main concept of the regularization operator $\mathbf{C}$ is to make the small eigenvalues of $\mathbf{H}$ far from zero and don't change the large eigenvalues. Changing these eigenvalues depends on the value of regularize parameter λ .
Equation (6) can be expressed as follow [4]:

$$\hat{F}(u,v) = \frac{H^*(u,v)}{|H(u,v)|^2 + \lambda |C(u,v)|^2} G(u,v) = D(u,v,\lambda)G(u,v) \tag{8}$$

where C(u,v) is the regularization operator Fourier transform.

$$D(u,v,\lambda) = \frac{H^*(u,v)}{|H(u,v)|^2 + \lambda |C(u,v)|^2} \tag{9}$$

where D(u,v,λ) is the 2-D regularized filter transfer function.

4. Simulation Results

In this section, wiener and Regularized image restoration approaches are tested for single restoration of corneal images. Part (a) shown the original corneal image in Fig. (2). Part (b) to Part (e) shown the degraded images for both blur of 7X7 operator and additive noise with different SNR= -10,0,10,20,30 dB that are given in Fig. (2).

Firstly, the wiener restoration is implemented on the fifth degraded corneal image mentioned above. These experiments illustrate the effect of signal to noise ratio (SNR) on the MSE, PSNR and Correlation Coefficient in the restored corneal images.

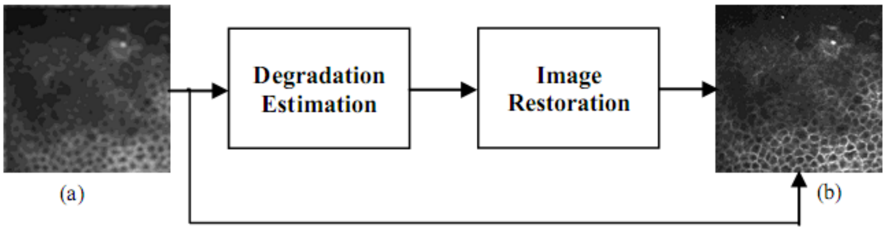

Fig. (1). Degradation and restoration model for corneal image

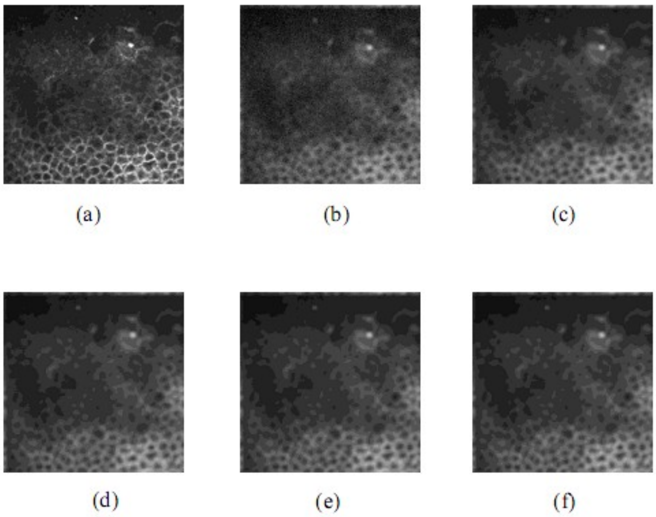

Fig. (2) (a) original corneal image (b) degraded Image for SNR= -10 dB (c) degraded Image for SNR= 0 dB (d) degraded Image for SNR= 10 dB (e) degraded Image for SNR= 20 dB (f) degraded Image for SNR= 30 dB

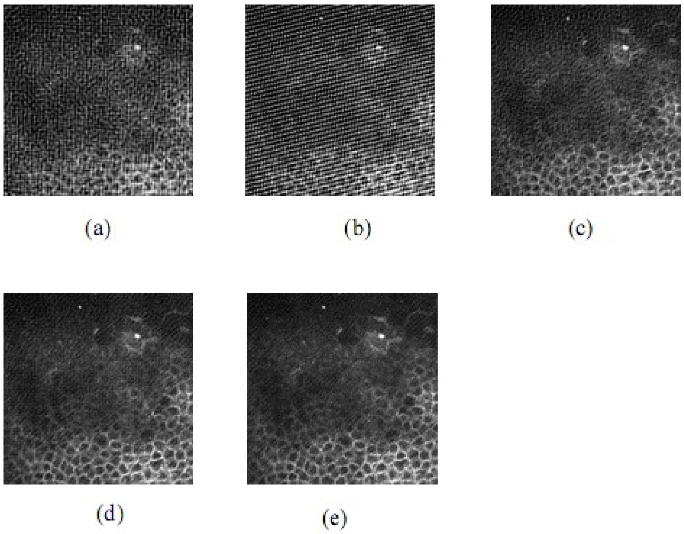

Fig. (3) The results for corneal image using Wiener Filter restoration
(a) Restored Image for SNR= -10 dB (b) Restored Image for SNR= 0 dB
(c) Restored Image for SNR= 10 dB (d) Restored Image for SNR= 20 dB
(e) Restored Image for SNR= 30 dB

Table (1) MSE, PSNR and Correlation Coefficient for different restorations using the Wiener restoration approach.

SNR	-10 dB	0 dB	10 dB	20 dB	30 dB
MSE	0.08	0.0390	0.0076	0.0031	0.0015
PSNR	10.9679	14.0919	21.1816	25.1316	28.316
Correlation Coefficient	0.5453	0.6551	0.8066	0.9020	0.9548

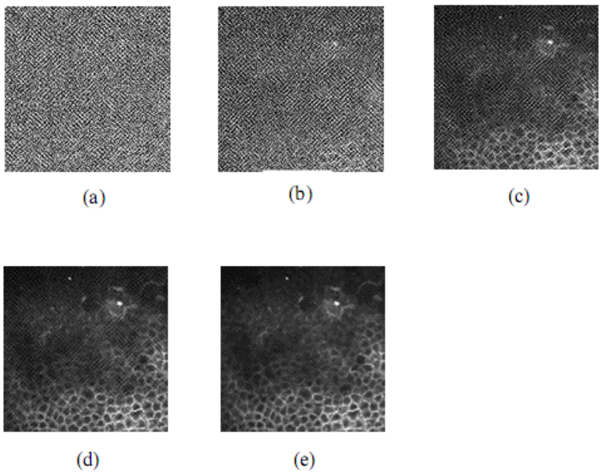

Fig. (4) The results for corneal image using Regularized Restoration
(a) Restored Image for SNR= -10 dB (b) Restored Image for SNR= 0 dB
(c) Restored Image for SNR= 10 dB (d) Restored Image for SNR= 20 dB
(e) Restored Image for SNR= 30 dB

Table (2) MSE, PSNR and Correlation Coefficient for different restorations using the Regularized restoration approach.

SNR	-10 dB	0 dB	10 dB	20 dB	30 dB
MSE	7.1378	0.7145	0.0715	0.0072	0.0008
PSNR	-8.535	1.459	11.455	21.422	31.131
Correlation Coefficient	0.0386	0.129	0.423	0.821	0.9747

The restoration results are illustrated in Part (a) to Part (e) shown Fig. (3). The MSE, PSNR and Correlation Coefficient in each result are tabulated in table (1). From the results tabulated in the table, it is clear that the best restoration result is obtained for high SNR. As the SNR decreases, the performance of the LMMSE restoration approach deteriorates giving higher MSE with lower PSNR and Correlation Coefficient.

In the next experiment, the Regularized image restoration is implemented on the fifth degraded corneal image mentioned above with regularized parameter $\lambda = 0.0000001$. The restoration results of these degraded corneal images are given in Part (a) to Part (e) shown Fig. (4). The MSE, PSNR and Correlation Coefficient in each result are tabulated in table (2). From the results tabulated in the table, it is clear that the best result is obtained for the highest SNR. While the SNR decreases, the performance of the Regularized restoration technique is deteriorating.

5. Conclusion

This paper investigated the effect of the blurring and noise introduced for corneal image processing. Two proposed approach for restoration of corneal image have been presented. The first algorithm is based on Wiener restoration approach. The second algorithm used the regularized image restoration.

The evaluation metrics and visual appearance ensured that the LMMSE restoration is suitable for low SNR. While Regularized restoration achieved high quality due to the constraints given in the solution especially at high SNR.

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