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Selection of Optimal Denoising Filter using Quality Assessment for Potentially Lethal Optical Wound images

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Abstract

The objective of this paper is to select the best filter for the camera-captured digital wound image pre-processing. Wound images give the most essential information about the wound. The information may be size, status of the wound, tissue composition and rate of healing. These images are most often corrupted by impulse or random noises while capturing them. Corrupted images often suffer from sharpness, chrominance and luminance. Application of several filtering schemes such as linear and non-linear filtering suppresses noise and improves the image quality. In this paper, a comparative study of five filters has been performed using mathematical morphology operations for removing the impulse/random noise. These five filters were applied on seventy-five randomly selected wound images from the developed image database as well as online chronic wound image database. In order to assess the quality of the filtered image, seven quality measures have been applied. Local first order statistics (LFOS) is the best and efficient filter in the context of reduced mean square error (MSE) and high peak signal to noise ratio (PSNR) between the reference original and the filtered image.

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Keywords: Image quality assessment, filter, structural similarity, chronic wound.

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1. Introduction

Optical images of wound investigation fascinates many research disciplines including medical to material science. Optical wound imaging (OWI) is a non-invasive, non-contact and cost effective technique for chronic wound (CW) assessment[1, 2]. However, image quality suffers badly due to random/impulse and banding noise. Sometimes impulse is referred to as ISO noise which depends on the shutter speed of the camera[3]. These badly affected noisy images need to be processed to filter out the noise in them. There are many de-noising filters for noise removal. To choose the best filter among the used filters, one needs to examine the quality of the image. The image quality evaluation can be broadly categorized into objective and subjective[4]. Subjective assessment involves visual ability of human beings and objective evaluation involves human visual mimic. Human vision color perception varies from man to man. Different color perception sensitivity such as brightness, contrast, pixel location, and color frequency may vary subjectively and it plays a very crucial role in scene quality analysis. Visual quality evaluation is one of the techniques which consider variations in such peculiarities with respect to the original image. The assessment is based on comparison between reference and processed image.

In this paper, the aim is to explore best filter amongst all used filters based on quality assessment of CW images. The camera images often suffer from impulse noise. Impulse noise is independent and uncorrelated[5]. The pixel intensities of the image are unevenly distributed over the image. For an image corrupted by random noise, all the image pixels are not noisy. Few pixels will be noise-corrupted and few pixels will be noise-free. The impulse noise introduced in an image may be salt and pepper noise or random-valued impulse noise[6]. These noises are to be removed for better quality of image for further processing. In this paper, five despeckle filters are applied and evaluated on the basis of seven different quality measures. The seven quality measures are namely: mean squared error (MSE), peak signal noise to ratio (PSNR), negative absolute error (NAE), mean absolute error (MAE), maximum difference (MD), Mean Structural Similarity Index Measurement (MSSIM), and Universal image quality index (UIQI) [7-9].

The organization of paper is as follows: Section 2 presents overview of used speckle filters in the paper. Section 3 discusses about methodology and experimentation. Section 4 deals with result and discussion followed by conclusion which falls under Section 5.

2. Denoising filters for OWI

Most of the denoising filters emerge from aerospace and radar communication and have been extensively used in medical imaging field. In this paper, the performance of six different filters has been evaluated. Here, we assume that the original image corrupted by noise as g(a, b) and S(p, q) represents the set of coordinates in a rectangular sub-image window (neighborhood) of size m × n, which is centered at a point (p, q). The filtered image is represented by f (p, q). The filters used in the comparative study are described as follows:

2.1. First order statistics filter (fosf)

To decide filtering strategy, most denoising algorithms in literatures use local statistic filter around neighborhood of filter to determine transformed pixel characteristics. This filter uses the first order statistics of the neighborhood of the center pixel in the sub-image S(p, q). The filter function is defined as,

$$f(p,q) = \bar{g}(p,q) + k(p,q)\left\{g(p,q) - \bar{g}(p,q)\right\} \tag{1}$$

Where, f(p, q) is the estimated impulse noise reduced value of pixels at location (p, q) on the image with a original value g(p, q). $\bar{g}(p,q)$ is the local mean of the m × n

$f(p,q)=\bar{g}$ Neighborhood around and including g(p, q). $k(p,q)$ is the weight factor with kϵ[0, 1]. The factor $k(p,q)$ is a function of local statistics and it is calculated as,

$$k(p,q)=\frac{1-\bar{g}^2(p,q)\sigma^2(p,q)}{\sigma^2(p,q)\left(1+\sigma^2\right)} \quad (2)$$

Where, $\sigma^2(p,q)$ is the local noise variance in the moving window (W = m ×n) and σ^2 is the variance of noise in the whole image respectively. Hence the noise variance of the whole image is computed as,

$$\sigma^2=\sum_{x,y}\frac{\sigma^2(p,q)}{\bar{g}^2(p,q)} \quad (3)$$

2.2. Midpoint filter (mf)

Midpoint filter is combination of order and mean filter. The mf computes the mid-point between minimum and maximum values within the window given by S (p, q). Therefore, the value of reinstated image f at point (p, q) is calculated by,

$$f(p,q)=\frac{1}{2}\left[\max_{(a,b)\in S(p,q)}\{g(a,b)\}+\min_{(a,b)\in S(p,q)}\{g(a,b)\}\right] \quad (1)$$

The mf filter combination local order statistics with averaging filters and display better result for randomly distributed noise structures like Gaussian and uniform noise[11, 12].

2.3. High boost filter (hbf)

High boost filter[13] has the capability of preserving the high frequency components of the image which represents the details of the image without eliminating low frequency components [1]. For sharpening the image we have to consider a mask for this filter. The total filtering process consists of blurring the original image, subtracting the blurred image from the original and finally adds the resultant mask with the original. Let $f^1(x,y)$ denotes the blurred image. Hence the mask is as follows,

$$g_{mask}(x,y)=f(x,y)-f^1(x,y) \quad (2)$$

Hence the final output would be,

$$g(x,y)=f(x,y)+k*g_{mask}(x,y) \quad (3)$$

k is a weight factor; When $k>1$, the process is called High boost filtering. The symbol, * represents convolution.

2.4. Laplacian filter (lf)

The lf sharpens the image by superimposing Laplacian image over the original image. Here, Laplacian filter[11] is defined as,

$$g(p,q)=f(p,q)+c[\nabla^2 f(p,q)] \quad (4)$$

Where, ∇ represents the second derivate.

2.5. Adaptive median filter (amf)

Adaptive median filter[13] can handle impulse noise with higher probabilities. Amf not only smoothes the non-impulse noises present in an image, but also preserves all edge detailed of an image. Unlike all traditional filters this filter changes the size of sub image Sxy during the filter, depending on certain conditions. Let, Z_{min}, Z_{max} *and* Z_{med}, be minimum, maximum, and median of intensities in Sxy. Z_{xy} *and* S_{max} be intensity value at (x,y) and maximum window size of Sxy. The amf algorithm works in two stages.

Stage 1: If A1>0 and A2<0, go to stage 2. Here $A1 = Z_{med} - Z_{min}$ and $A2 = Z_{med} - Z_{max}$. If specified condition is not satisfied then increase the window size. Stage 1 is repeated, if window size is less than S_{max} else output will be Z_{med}.

Stage 2: If B1>0 and B2<0 output is Zxy, otherwise output is Zmed. Here, B1= Zxy - Zmin and B2= Zxy – Zmax.

3. Material and Methodology

3.1. Material

A set of seventy five randomly selected potentially lethal wound images were selected for study. The images were captured in different lighting conditions. The distance between camera and wound region varies with subjects. Proper Ethical clearance and patients consent were obtained prior to study. Subjects have given consent to use the images on condition of anonymity. The images were captured strictly for academic and research work only.

3.2. Camera Specifications

The images were obtained using Sony W520 cyber shot camera. Flash was turned off during grabbing to avoid banding noise. All the images were having original size of 1280×720 pixels. However images were cropped for unwanted processing of background instead of wound area of interest. For the work, all the images were transferred to PC and were stored in jpeg format with average compression ratio of 6:1.

3.3. Proposed Methodology for optimum filter selection

The proposed methodology for optimal denoising filter selection is shown in Fig.1. The handheld camera captured RGB image of lethal wound suffers from light intensity variations. These variations are due to variable lighting conditions in Out-patients department. Flash light introduces banding noise, hence to avoid mixing of it, all the images were obtained without flash light.

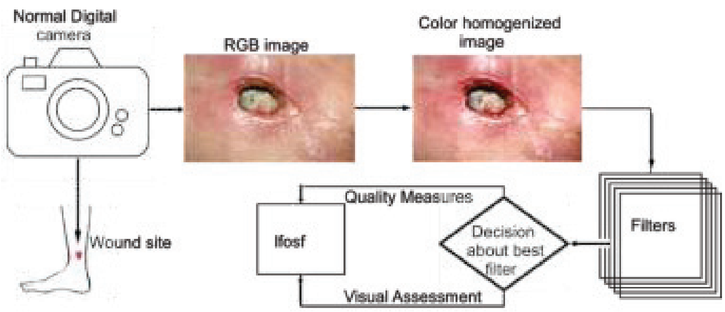

Fig. 1. Proposed framework for optimal filter selection

The color homogenization is done using hybrid approach grey world assumption (GRA) and Retinex theory (RT)[14, 15]. GRA is based on equalization of average intensities of red, blue and green. RT is based upon maximization of intensity value in three color channels. The hybrid approach i.e. quadratic approach preserves the strength of two independent approach[16]. The quadratic approach can be represented in matrix form as:

$$\begin{bmatrix} \sum\sum I_r^2 & \sum\sum I_r \\ \max I_r^2 & \max I_r \end{bmatrix} \begin{bmatrix} \mu \\ v \end{bmatrix} = \begin{bmatrix} \sum\sum I_g \\ \max I_g \end{bmatrix} \tag{5}$$

Here, (μ, v) are the parameters for automatic color correction.

3.4. Quantitative performance measures for image quality assessment

The preprocessing steps considered here are in accordance with seven different quantitative performance measures on five different filters as well as enhancement criteria. We have followed common representation of original camera image as g(p, q) and the filtered image as f(p, q).

Mean square error (MSE)
Mean square error is a peculiar risk function which is used to estimate the difference in quality between the original image and pre-processed image.

$$MSE = \frac{1}{MN}\sum_{p=1}^{M}\sum_{q=1}^{N}[g(p,q) - f(p,q)]^2 \tag{6}$$

Maximum difference (MD)**.**
Maximum difference (MD)[17, 18] computes the maximum difference in the intensity values of the original image and filtered image. Larger MD indicates that filtered image is of poor quality and has sufficient amount of noise.

$$MD = max|g(x,y) - f(x,y)| \tag{7}$$

Peak signal to noise ratio (PSNR)
Peak signal to noise ratio is used to calculate the ratio of the maximum possible power present in an image signal to the power of corrupting noise which affects the fidelity of its representation. However this ratio is an approximation to human perception of reconstruction quality. PSNR is formed as,

$$PSNR = 10\log_{10}\left(\frac{(\max I)^2}{MSE}\right) \tag{8}$$

Here 'max I' is representation of the maximum possible pixel value image (in between 0-255 range of gray values).

Mean absolute error (MAE)
If β=1, then MAE is referred as Minkowski metric. MAE calculates the difference between the original image and filtered image[17, 18]. The lower value of MAE indicates that more noise is removed from the image. MAE is computed as,

$$MAE = \frac{1}{MN}\sum_{p=1}^{M}\sum_{q=1}^{N}[g^2(p,q) + f^2(p,q)] \tag{9}$$

Normalized absolute error (NAE)

Normalized absolute error (NAE)[10] helps to find out how much the filtered image is similar to the original image i.e. how much noise is removed from the image. So, larger value of NAE attests poor quality of filtered image. Here, NAE is computed as,

$$NAE = \frac{\sum_{p=1}^{M}\sum_{q=1}^{N}|(g(p,q)-f(p,q))|}{\sum_{p=1}^{M}\sum_{q=1}^{N}|g(p,q)|} \tag{10}$$

Universal image quality index (UIQI)
The universal image quality index (Q) is modelling of image distortion as a combination of three basic factors of the original and enhanced images i.e. loss of correlation, luminance distortion and contrast distortion.

$$Q = \frac{1}{K}\sum_{p=1}^{K} Q_p \tag{11}$$

Where,

$$Q_p = \frac{\sigma_{k,f_g}}{\sigma_{k,f}\sigma_{k,g}} \cdot \frac{\overline{2f_k}\ \overline{g_k}}{\overline{f_k^2} + \overline{g_k^2}} \cdot \frac{2\sigma_{k,f}\sigma_{k,g}}{\sigma_{k,f}^2 + \sigma_{k,g}^2}$$

$\bar{g}_k$ and $\bar{f}_k$ are the mean of sub image window for original and enhanced image, $\sigma_{k,f}$ and $\sigma_{k,g}$ represent the standard deviation of k^{th} sub image window 'W' for original and enhanced image, σ_{k,f_g} is the covariance between them. Here window size taken is 5×5.

Mean Structural Similarity Index (MSSIM)
MSSIM is used to measure distortion in an image[8, 12]. For image quality assessment MSSIM algorithm is applied locally rather than globally. Localized quality measure was applied to provide more understanding about the image quality degradation. MSSIM can be represented as,

$$MSSIM = \frac{1}{K}\sum_{k-1}^{K} SSIM_k(g_k, f_k) \tag{12}$$

$$SSIM_k(g_k, f_k) = \frac{(2\overline{f_k}\overline{g_k} - c_1)(2\sigma_{k,f_g} + c_2)}{(\overline{f_k}^2 + \overline{g_k}^2 + c_1)(\sigma^2{}_{k,f} + \sigma^2{}_{k,g} + c_2)} \tag{13}$$

K is the number of local windows. $\overline{f_k}$ and $\overline{g_k}$ are the mean intensities of input and filtered images of wounds. $\sigma_{k,f}$ and $\sigma_{k,g}$ are the standard deviation of intensity levels of input and filtered images respectively. The constant value $c_1 = 0.01l$ and $c_2 = 0.03l$ are taken as default value, where l is the dynamic range of gray value content in an image. We have taken l=255. Here, for optical wound image application, we use 11×11 circular symmetric Gaussian weighting function w with standard deviation 1.5 of samples and weights normalized to unit sum. Hence, local statistics of sub image window W_k, in the original image are computed as,

$$\overline{g_k} = \sum_{(M,N)\in W} W_{M,N}\, g_{M,N} \tag{14}$$

$$\sigma_{k,g} = (\sum_{(M,N)\in W} W_{M,N}(f_{M,N} - \overline{g_k}^2)^{\frac{1}{2}} \tag{15}$$

Similarly, these measures are also computed for the enhanced filtered image. Finally their covariance between the local windows of the original and filtered image is calculated as,

$$\sigma_{k,fg} = \left(\sum_{(M,N)\in W} W_{M,N}(f_{M,N} - \overline{f_k})(g_{M,N} - \overline{g_k})\right) \tag{16}$$

The range of value of MSSIM varies from -1 to 1(worst to best condition respectively).

4. Result and discussion

In this section, we present result of five denoising filters on OWI. The results of three images are shown in Fig. 2. The findings are informatively represented in Fig.3. Visual assessment of these images and filter by four different experts was also discussed in the following section.

4.1. Image quality evaluation

The original RGB images firstly underwent illumination correction using quadratic approach. This approach preserves the strength of RT and GWA. The color-corrected image is then assessed for different filters. Total of five filters were implemented. Most of them use mathematical morphology operations. 5×5 square structuring elements were used. These five filters were applied on 75 randomly selected wound images from our database as well as online chronic wound image database. These five best filters are namely Local first order statistics, adaptive median filter, mid-point filter, Laplacian filter and high boost filter. Fig. 2 shows various filters applied on color-corrected images. Original images is also shown besides each color-corrected image.

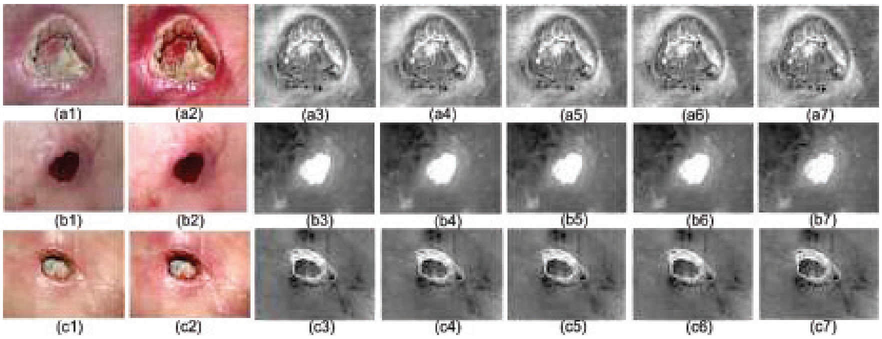

Fig. 2. Different filter outputs. (a1, b1, c1) Original images, (a2, b2, c2) color homogenized images, (a3, b3, c3) amf, (a4, b4, c4) lfosf, (a5, b5, c5) mf, (a6, b6, c6) hbf and (a7, b7, c7) lf.

In order to access the quality of the image, seven quality measures are defined as MSE, PSNR, NAE, MAE, MD, MSSIM, and UIQI. Lower value of MSE, NAE, MD and MAE indicates the fact that there is very small change in gray level scale between the original and the filtered image. On the contrary, higher value of PSNR reports to the same direction. The value of MSSIM and UIQI closer to 1 indicates the best possible image quality as well as intact structural similarity. From Fig.3, it is found that MSSIM and UIQI of lfosf and hbf shows value closer to 1, whereas lfosf, mf and hbf shows lowest NAE and PSNR. The MD of amf, lfosf, midpoint, hbf and lf is below 0.30. The lowest NAE can be observed in lfosf and mf. Least MSE is reported for mf (0.36) and lfosf (0.03). The highest PSNR (62.82) can be seen in lfosf. Amf shows PSNR of 44.76. From all the discussion above, it can be concluded that ranking wise lfosf scores highest in terms of preference of pre-processing followed by mf, lf, amf and hbf.

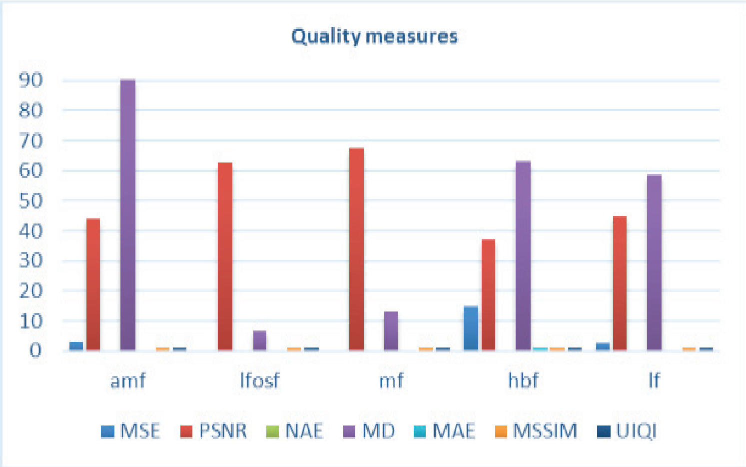

Fig. 3. Comparison of filter performance on basis of average value of quality measure

4.2. Visual assessment by experts

Four different experts have assessed the filtered image results. All the experts were from the department of dermatology. According to experts, sharpness of a wound healing edge is preserved in **hbf**, **amf, lfosf and lf**. Background uniform noise removal is prominent in **mf** and **lf.** Compared to other methods, tissue details are preserved in **lfosf**. Majority of the experts feels that **lfosf** gives better visualization followed by **mf.** However, some experts were unable to justify the performance of **lfosf.**

5. Conclusion

Denoising filters are important for image enhancement in OWI. In this study, it can be seen that out of five applied filters, lfosf performs best and can be effectively used for noise removal. As far as subjective assessment is concerned, lfosf performs well but some of the experts were unable to justify this claim. The area of filtering is being further examined for development of more robust technique.

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