Evaluating the Effect of Various Speckle Reduction Filters on Ultrasound Liver Cancer Images

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Abstract

The main goal of Ultrasound (US) image pre-processing is to reduce noise of an image. It helps consecutive stages of image analysis like classifications or segmentation of liver cancers to differentiate easier and efficiently. In pre-processing stage filtering is the key process used for reducing signal depended noise, so called speckle. The optimal filter model has the main objective of reducing speckle noise by enhancing contrast, smoothing and sharpening of the image signal. Several noise filters are introduced for different capacities and purposes with its own advantages and disadvantages. This paper describes the evaluation and performance analysis of five image filtering techniques, namely Kuan, Frost, Mean, Median and Speckle reducing anisotropic diffusion filter (SRAD) from the spatial filtering process for liver US data. An application of US hepatic liver cancer image was chosen and selected denoising algorithms are applied to estimate the impact on the US speckle image signal. Experiments are investigated based on Peak Signal-to-Noise Ratio (PSNR), Mean Structural Similarity (MSSIM) and Mean square error (MSE). The result shows that SRAD filter performs better than other denoising filters with a PSNR =31.11 dB, MSE=31.07, MSSIM=0.895.

Keywords: Image Processing; Ultrasound; Liver cancer; Speckle noise; Image filters.

1. Introduction

At present, the researchers are more interested in developing an effective automated Computer Aided Diagnosis (CAD) system that helps the radiologists to classify different liver cancer images for an accurate diagnosis for US signal. An automated CAD system has several stages [1] as follows: Data preprocessing, image segmentation, feature extraction, selection, and finally classification. The first step is preprocessing, which perform different quantization and sampling rate for digitizing the image signal. However, in CAD US image processing interpretation a difficult goal due to the presence of multiplicative speckled noise [2], which degrades the US image quality to poor. Thus, it makes CAD system to classify or provide proper diagnosis for various types of liver cancers [3-4]. Hence, it's necessary to denoise speckle prior to further processing stages.

In this study, we selected five well known filtering techniques namely Kuan [5], Frost [6], Mean [7], Median filter [8] and Speckle reducing anisotropic diffusion(SRAD) [9] from spatial filtering process which, uses local statistics intensity of the image [10]. The main objective of the paper is to analyze the performance, denoising ability on multiplicative speckle noise and the impact to the application on US liver cancer images. We evaluated and compared algorithms by calculating quantitative parameters like PSNR, MSE, MSSIM [11] and suggests the best filter that suits for our application by reducing multiplicative noise meanwhile preventing edges and features of US images.

This paper further organized as follows: section 2 discuss about five spatial filtering Process. The discussion on experimental analysis and denoised images are shown in section 3. Finally, Concluded in section 4.

2. Filtering Techniques

2.1. Kuan Filter

The Kuan filter [5] used to reduce speckle by preserving edges in US images and it's depend on Minimum Mean Square Error (MMSE) [5].At first, MMSE metric implemented as $y = x + n$ an additive noise signal model. Then considered multiplicative noise model under the form $y = x + (n-1)x$ from which the corresponding linear filter is presumed. It also transforms additive noise model from the multiplicative noise signal and it utilize an alternative weighting function. The Kuan filter has more advantage if the detected intensities and scene are Gaussian distributed. The pixel value estimate $\bar{x}$ is defined in eq.(1) by assuming unit-mean noise.

$$\bar{x} = y + \frac{\sigma_x^2 (y - y)}{\sigma_x^2 + (y^2 + \sigma_x^2)/L} \quad (1)$$

Where , $\sigma_x^2 = \frac{L\sigma_y^2 - y^2}{L+1}$ and $\bar{x} = y$ for the pathological cases which measures yields $\sigma_x^2 < 0$.

2.2. Frost filter

The Frost filter [6] is the most robust and exponentially damped symmetrically circular filter based on local statistics (the coefficient of variation) which is the local standard deviation proportion to local mean of the noisy image.

In this filter the interest pixels are replaced with a weighted sum calculated values within exponential impulse response m. That can be defined as:

$$m = \sum_{nXn} k\alpha \exp^{-\alpha|t|} \quad (2)$$

Where, $\alpha = \left(\frac{4}{n\sigma^2}\right)\left(\frac{\sigma}{I^2}\right)$, K is filter parameter, α is the location of the processed pixel, n represent moving kernel, σ and σ represents local variance and image coefficient of variation value respectively . local mean is defined as I and $|t|$ is the distance measured from pixel α .The scene reflectivity x assumed from an autoregressive exponential model assumed of impulse response.

2.3. Mean filter

The mean filter [7] is the simple noise reduction algorithm but instead of removing speckle between adjacent pixels, it averages the intensity variation. In simple which replaces the center value in the pixel with the average of all the neighboring pixel values including itself. so, that it replaces pixel windows that are unfamiliar to their surroundings. It is also called as linear filter, since implemented with a convolutions mask. Where, weighted sum of the values of a pixel and neighbors provides results. The working principle of mean or average filter based on shift multiply sum. The main disadvantage with algorithm results in loss of resolution and details while reducing speckle.

2.4. Median filter

The Median filter [8] also a simple algorithm to remove spike or pulse noises. It follows sliding window spatial filter and use 3X3 or 5X5 or 7X7 window. However, it replaces into median of all the pixel values from center value in window. This makes image resolution reduce without losing the edges but results in blurred image. The other drawback is that it takes more computational time to sort the intensity value of all pixels set.

2.5. Speckle reducing anisotropic diffusion (SRAD)

SRAD [9] is an effective technique for removing noise by balancing speckle suppression and preserving feature. In [12] author's developed the solution of nonlinear partial differential equation (PDE) for smoothing image on a continuous domain of transient permeability for 2D domain:

$$\begin{cases} \frac{\partial I}{\partial t} = div(\nabla I . d(|\nabla I|)), \\ I(x, y, 0) = g(x, y) \end{cases} \quad (3)$$

Where ∇ represents gradient operator, divergence operator denoted as , $g(x, y)$ is the original noisy image, || represent magnitude and $d(x)$ are diffusion coefficient. The two diffusion coefficients suggested by [12] authors are:

$$d(x) = \frac{1}{1 + (x/k)^2} \quad (4)$$

$$d(x) = \exp[-(x/k)^2] \quad (5)$$

Here k is magnitude edge parameter.

The gradient strength increases by decreasing diffusion coefficients and at the edges diffusion will be stopped. This is effective well in Gaussian additive noise. However, SRAD proposed to reduce noise image without logarithmic compression by exploiting the continues variation of coefficients which performs as edge detector in speckled images. Thus function enhance and preserve by exhibits high values at edges and preserving by producing low values in homogeneous region.

3. Experiment Results

In this sections, we implemented the above five filtering algorithms using MATLAB to estimate the noise reduction on US liver images. For this experiment we used 256 X 256-pixel hepatic liver cancer image and tested with two different noise level variance as 0.10 and 0.20. To test the performance of algorithm, we computed PSNR, MSE, MSSIM values [11] between noisy and recovered image. The quantitative parameters are defined as follows:

$$PSNR = 10 \log_{10} \frac{255}{MSE} \quad (6)$$

Where, 255 is the maximum fluctuations in the input image, estimated by $(2^n - 1)$ .Here, n=8 since components of pixels are encoded on 8 bits. MSE: denotes the mean square error, given by:

$$MSE = \frac{1}{MN}\sum_{i=1}^{N}\sum_{j=1}^{M}\left|X'(i,j) - Y'(\hat{i,j})\right|^2 \qquad (7)$$

where $X'(i,j)$:the original image, $Y'(\hat{i,j})$:the restored image.

$$MSSIM = \frac{1}{N}\sum_{i=1}^{N}\left[l'\left(\hat{j},k\right)\right]^{\alpha}.\left[c'\left(\hat{j},k\right)\right]^{\beta}.\left[s'\left(\hat{j},k\right)\right]^{\gamma} \quad (8)$$

Where, $l'(\hat{j},k)$ define luminance, $c'(\hat{j},k)$ for contrast and $s'(\hat{j},k)$ define structure comparison functions. The three components α,β,γ are weighted parameters that used to adjust the relative importance.

Fig. 1 depicts despeckle of US images obtained from Kuan, Frost, Mean, 3X3 Median and SRAD filters. For better perception view, we zoomed into particular part of image to visualize more details. It's visible that mean and median methods decreases the resolutions of image by more smoothing. Kuan and Frost denoised technique poorly represent texture details but SRAD image has smooth edges and preserved texture details compared to other methods.

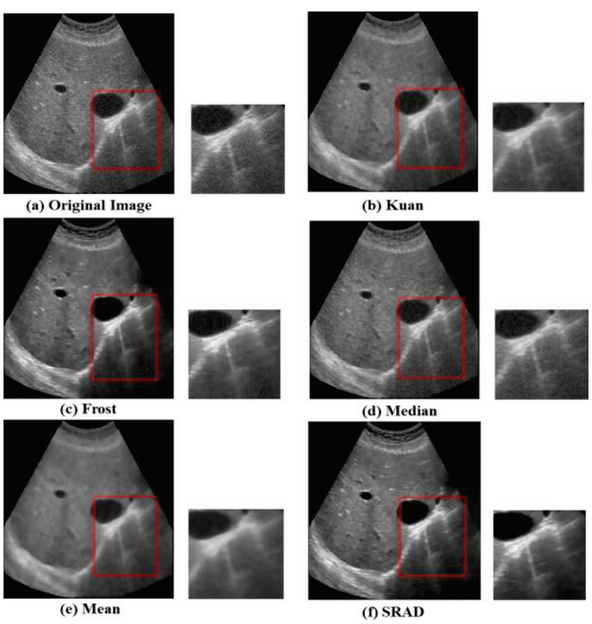

Fig.1: Comparison results of reducing speckle by applying different filtering methods on US hepatic cyst cancer images.

Table 1 shows numerical results of images analysis for two different noise variance level σ =0.10 and σ =0.20 respectively. The quantitative performance results clearly show that image recovered from SRAD method comparatively has better PSNR value than rest of the techniques used for analysis.

Table 1: The numerical guidelines of despeckle algorithms for different methods.

Filtering Methods	σ =0.10			σ =0.20		
	PSNR(dB)	MSE	MSSIM	PSNR(dB)	MSE	MSSIM
Mean	21.23	38.25	0.617	17.65	27.45	0.492
Median	22.19	36.27	0.642	18.86	22.69	0.511
Frost	29.36	30.41	0.831	23.26	24.18	0.698
Kuan	28.14	28.22	0.797	21.73	22.67	0.624
SRAD	**31.11**	31.07	0.895	**25.16**	24.95	0.705

Fig.2 shows as the raw profile of original image and SRAD denoised image taken from a selected pixels range which represented in blue dashed line. In fig.2 (b) shows the rapidly moving of objects create more noise and distort the image leads to more sharp peaks. Meanwhile fig.2 (d) we can see that SRAD significantly recovered and preserved image by improving the texture and edge details. The intensity graph of selected pixels is smoother compared to original image. This makes clearer that SRAD filtering techniques have more advantages on US liver images.

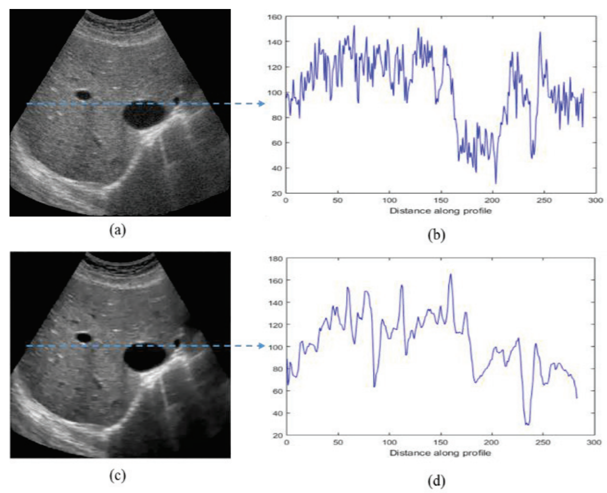

Fig.2: (a) Origianl speckled image. (b) Raw profile of original image(raw=300). (c) Restored by SRAD filter. (d) Raw profile of restored image.

4. Conclusion

In this paper we proposed a study on spatial based filtering process includes Kuan, Frost, Mean, Median and SRAD filters. The idea is to compare and evaluate the performance of this algorithms on hepatic cyst image signals obtained from US device. The effect of the denoising techniques on preprocessing stage of the CAD system was investigated by PSNR, MSE, MSSIM. The experimental results on a real US images shows that

SRAD filter has good impact on denoising US image with a PSNR of 31.11 dB with noise variance of 0.10 compared with other methods while preserving the presence of structured region, edges and texture information. It is also observed from the simulations that mean and median filters smooth the image extensively and can be used only when resolution of US image are not being considered. On the other hand, using filters like Frost and Kuan also have a comparatively good PSNR but details and edge preserving is poor than SRAD which lead to negative effect on image segmentation stage.

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References

[1] M. Y. Jabarulla and H. N. Lee, "Computer aided diagnostic system for ultrasound liver images: A systematic review," Optik (Stuttg)., vol. 140, pp. 1114–1126, 2017.

[2] J. W. Goodman, "Some fundamental properties of speckle," J. Opt. Soc. Am., vol. 66, no. 11, p. 1145, 1976.

[3] H. Yoshida, D. D. Casalino, B. Keserci, A. Coskun, O. Ozturk, and A. Savranlar, "Wavelet-packet-based texture analysis for differentiation between benign and malignant liver tumours in ultrasound images.," Phys. Med. Biol., vol. 48, no. 22, pp. 3735–53, Nov. 2003.

[4] G. Xian, "An identification method of malignant and benign liver tumors from ultrasonography based on GLCM texture features and fuzzy SVM," Expert Syst. Appl., vol. 37, no. 10, pp. 6737–6741, 2010.

[5] D. T. Kuan, Sawchuk, T. C. Strand, and P. Chavel, "Adaptive noise smoothing filter for images with signal-dependent noise.," IEEE Trans. Pattern Anal. Mach. Intell., vol. 7, no. 2, pp. 165–177, 1985.

[6] V. S. Frost, J. A. Stiles, K. S. Shanmugan, and J. C. Holtzman, "A model for radar images and its application to adaptive digital filtering of multiplicative noise.," IEEE Trans. Pattern Anal. Mach. Intell., vol. 4, no. 2, pp. 157–66, Feb. 1982.

[7] R. C. Gonzalez and R. E. Woods, "Digital Image Processing," Addison-Wesley Publ. Co., 2002.

[8] W. N. M. and P. L. A. T. Loupas, "An Adaptive Weighted Median Filter for Speckle Suppression in Medical Ultrasound Images," IEEE Trans. Circuits Syst., vol. Vol. 36., no. January, p. 129–135., 1989.

[9] S. T. Acton, "Deconvolutional speckle reducing anisotropic diffusion," Proc. - Int. Conf. Image Process. ICIP, vol. 1, no. 11, pp. 5–8, 2005.

[10] J.-S. Lee, "Digital Image Enhancement and Noise Filtering by Use of Local Statistics," IEEE Trans. Pattern Anal. Mach. Intell., vol. PAMI-2, no. 2, pp. 165–168, Mar. 1980.

[11] Z. Wang, A. Bovik, H. Sheikh, and E. Simoncelli, "Image quality assessment: from error visibility to structural similarity," IEEE Trans Image Process, vol. 4, no. 13, pp. 600–12, 2004.

[12] P. Perona and J. Malik, "Scale-space and edge detection using anisotropic diffusion," IEEE Trans. Pattern Anal. Mach. Intell., vol. 12, no. 7, pp. 629–639, Jul. 1990.