Linear Regression Model for Gaussian Noise Estimation and Removal for Medical Ultrasound Images

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ABSTRACT
Ultrasound imaging is widely used in the field of medicine. It is used for imaging soft tissues in organs like liver, kidney, spleen, uterus, heart, brain etc. The common problem in ultrasound image is speckle noise which is caused by the imaging technique used, that may be based on coherent waves such as acoustic to laser imaging. The denoising is to be performed to improve the image quality for more accurate diagnosis. The objective of the paper is to propose a novel linear regression model for Gaussian representation of speckle noise in medical ultrasound images. The speckle noise is modelled as a Gaussian noise, with estimated mean and standard deviation based on PSNR of the ultrasound image, using the proposed linear model for Gaussian noise estimation and removal. The experimental results demonstrate the efficacy of the proposed method.

General Terms
Gaussian noise removal, Speckle noise.

Keywords
Medical ultrasound image, Despeckling, Gaussian noise estimation, Linear regression model.

1. INTRODUCTION
Among the medical imaging modalities, currently available on the medical equipment market, ultrasound imaging systems are considered to be non-invasive, portable, accurate, practically harmless to the human body, and relatively low-cost imaging modality. These features make the ultrasonography the most prevalent diagnostic tool in hospitals around the world. It is used for imaging soft tissues in organs like liver, kidney, spleen, uterus, heart, brain etc. The main disadvantage of medical ultrasonography is the poor quality of images, which are affected by multiplicative speckle noise [1-2]. Speckle is a random interference pattern present in all images obtained using coherent radiation in a medium containing sub resolution scatterers. In particular, it is important to reduce speckle in medical images since its presence affects the tasks of human expert interpretation and diagnosis. Several methods have been proposed in the past for removing speckle. In [3-4], a survey of different digital image processing techniques used in enhancing the quality and information content in ultrasound image is presented.

In [5], a novel Bayesian multi-scale method for speckle reduction has proposed. The logarithmic transform of the original image is analyzed into the multi-scale wavelet domain. The mean of the log-transformed image is considered in which Cauchy and Gaussian distribution is used to model the speckle noise. The main disadvantage of this method is, time taken for execution is high.

In [6], a speckle reduction through multi-scale nonlinear processing, which presents an algorithm for speckle reduction is proposed. This speckle reduction method is based on, soft-thresholding the wavelet coefficients of the logarithmically transformed medical ultrasound image. Shrinkage of wavelet coefficients using soft-thresholding is performed for finer levels of scale and then hard-thresholding of wavelet coefficients is applied within selected (mid-range) spatial-frequency levels of analysis is done to preserve the features to eliminate the noise. Then inverse discrete wavelet transformation is performed to reconstruct the de-noised image. Then exponential transformation is applied. The main disadvantage of this method is that the parameters that are used for wavelet shrinkage for de-noising were adjusted by the trial and error method. The computational time is high.

In [7], the despeckling medical ultrasound images using wavelet transform and Bayes' thresholding is proposed. The wavelet transform is well adapted to point singularities, so it has a problem with orientation selectivity. This is a major drawback for wavelet based image denoising technique. The contourlet transform has been recently developed in [8] to overcome the limitations of wavelets. It is based on an efficient two-dimensional multiscale and directional filter bank that can deal effectively with images having smooth contours.

In [9] the despeckling medical ultrasound images using contourlet transform is presented. The proposed method consists of the log transformed original ultrasound image being subjected to contourlet transform, to obtain contourlet coefficients. The transformed image is denoised by applying thresholding techniques on individual band pass sub bands using a Bayes shrinkage rule. In [10] authors have tested and compared three multi-scale methods for despeckling medical ultrasound images. These methods are proven to be very efficient to treat multiplicative noise and reduce speckle in ultrasound images. The performance evaluation of the three methods is done interms of variance, MSE, SNR, PSNR correlation coefficient (CC) are computed from despeckled image. This study proves that contourlet transform using hard thresholding is an excellent tool for despeckling medical ultrasound images. Further, it is found that, 2-level of Laplacian pyramidal decomposition and 6 directional bandpass subbands using hard thresholding with Bayes' shrinkage rule yields optimal results for speckle reduction. The contourlet transform based despeckling method produces better quality ultrasound images for subsequent computer-assisted image analysis by medical experts.

In [11-12] nonlinear diffusion equations called as an anisotropic diffusion algorithm have been proposed for Gaussian noise removal. In [13] a bilateral filter to remove

Gaussian noise is proposed. In [14] a robust estimation based filter to remove Gaussian noise with detail preservation is presented. In [15] a window based linear regression filter for echocardiographic image denoising is proposed. The filter has the ability to replace the additive Gaussian noise, since nearby points compute very nearly the same underlying value, averaging can reduce the level of noise without biasing the value obtained. The filtering technique manages to provide smoothing without loss of resolution. The main draw backs of the above algorithms are, it takes much computation time and complex circuit to implement.

The objective of the paper is to propose a linear regression model for Gaussian noise representation of speckle noise for medical ultrasound images. The speckle noise is modeled as a Gaussian noise, with estimated mean and standard deviation based on PSNR of the ultrasound image. Our experimental results show significant improvements of the proposed method as compared to that of cycle spinning using contourlet transform based despeckling [16] in terms of PSNR and also in visual effect.

This paper is organized into four sections. The section 2 describes the proposed method, and the section 3 describes the experimental results and discussion. Finally section 4 reports conclusion.

2. PROPOSED METHOD

We consider a medical ultrasound image X and the corresponding despeckled image Y obtained by using the contourlet transform with cycle spinning [16]. The subtracted image Z=X-Y is the error image containing speckle noise. We find the mean m and standard deviation σ of Z and then simulate Gaussian noise G with these values of m and σ. The removal of this Gaussian noise G from despeckled image Y yields the new despeckled image $\hat{Y}$, i.e. $\hat{Y}$=Y-G, which is further subtracted from the original image X to obtain the new error image Z containing the residual speckle noise. This procedure is repeated until the percentage of black pixels in error image Z reaches 99.9. We determine the maximum value of PSNR and the corresponding values of mean m and standard deviation σ using the iterated despeckled images $\hat{Y}$. This procedure is applied for all the medical ultrasound images X_i , i=1,..., N, in the dataset, yielding the two sets of data points ($PSNR_i$,m_i) and ($PSNR_i$, σ_i) , i=1,...,N exhibits linear correlation. Using the method of least square errors, we obtain the lines of best fit for these data, namely:

$$m = a * PSNR + b \quad (1)$$

$$\sigma = c * PSNR + d \quad (2)$$

where a, b, c and d are constants. The Eqs. (1) and (2) represent the linear regression model for Gaussian representation of speckle noise in the medical ultrasound image. The algorithm for this procedure is given below.

Algorithm 1: Linear regression model for Gaussian representation of speckle noise.

Input : Medical ultrasound image.

Output: Linear regression model parameters for Gaussian representation of speckle noise.

Step 1: Input medical ultrasound image X.

Step 2: Input despeckled ultrasound image Y obtained by using contourlet transform with cycle spinning.

Step 3: Find the error image Z as subtraction between X and Y (i.e. Z = X – Y).

Step 4: Find the percentage of black pixels in Z.

Step 5: Find the mean (m) and standard deviation (σ) of Z.

Step 6: Simulate the Gaussian noise G using mean m and standard deviation σ calculated in the Step 5.

Step 7: Subtract simulated Gaussian noise G from despeckled image Y to obtain the resultant image $\hat{Y}$, i. e. $\hat{Y}$ =Y-G.

Step 8: Find the PSNR, mean and standard deviation of the resultant image $\hat{Y}$ of Step 7. Set Y = $\hat{Y}$.

Step 9: Repeat the Steps 3-8 until the percentage of black pixels in Z reach 99.9%.

Step 10: Find the maximum PSNR among the iterated images $\hat{Y}$ and the corresponding values of m and σ.

Step 11: The Gaussian noise with mean m and standard deviation σ determined in Step 10 is the modeled Gaussian noise for image X

Step 12: Repeat Steps 1-11 for all the ultrasound images X and Y in the data set.

Step 13: Obtain the lines of best fit for the both PSNR vs. m and PSNR vs. σ obtained for all the ultrasound images using the method of least square error. The lines are represented by,

$$m = a * PSNR + b \quad (3)$$

$$\sigma = c * PSNR + d \quad (4)$$

where a, b, c and d are the regression model parameters. These lines of best fit form the linear regression model for representing the speckle noise in ultrasound image as Gaussian noise.

Step 14: Output linear regression model parameters a, b, c and d.

In the data set used for building regression model for Gaussian representation of speckle noise, we select a reference image X_{ref} for which the PSNR value is minimum. Given an arbitrary input medical ultrasound image X, we compute the PSNR of X with respect to the reference image X_{ref}. Using linear regression model, we estimate the values of mean m and standard deviation σ of the Gaussian noise, which is removed from the input original image. The resultant image is the despeckled image.

3. EXPERIMENTAL RESULTS AND DISCUSSION

The experimentation is carried out using 63 medical ultrasound images of size 512 X 512 (43 kidney images and 20 liver images). These images are acquired using the instrument GE LOGIQ 3 Expert system with 5-MHz transducer frequency, in JPEG format. The proposed algorithm has been implemented on the Core2Duo system with 1GB RAM @2.53GHz using MATLAB 7.9. The linear regression model parameters a, b, c and d for Gaussian representation of speckle noise are computed for this dataset of 63 ultrasound images and the linear regression model equations are

$$m = a * PSNR + b \quad (5)$$

$$\sigma = c * PSNR + d \quad (6)$$

where a=-6.129e-007, b=2.742e-005, c=-0.0002192, d=0.01004, with the measures of 'best fit' are SSE=4.682e-009, RMSE=8.833e-006 for mean vs. PSNR and SSE=0.0006471, RMSE=0.003284 for standard deviation vs. PSNR.

The Fig. (1 and 2) show the lines of best fit for mean vs. PSNR and standard deviation vs. PSNR respectively, which are used for Gaussian noise estimation and removal. The Fig. 3 shows a sample medical ultrasound image, its despeckled image using contourlet transform with cycle spin and the denoised image based on proposed method respectively. The proposed model has been experimented with all the 63 images. The comparison of the results of the proposed method with the contourlet transform method (with cycle spinning) is given in the Table 1. It is observed that the image quality enhancement obtained by the proposed method is better than the contourlet transform method in terms of PSNR and computational time required for denoising.

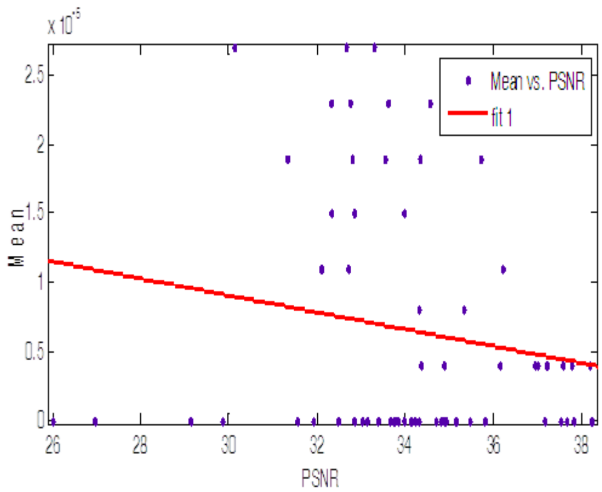


Fig. 1 Linear regression of mean on PSNR

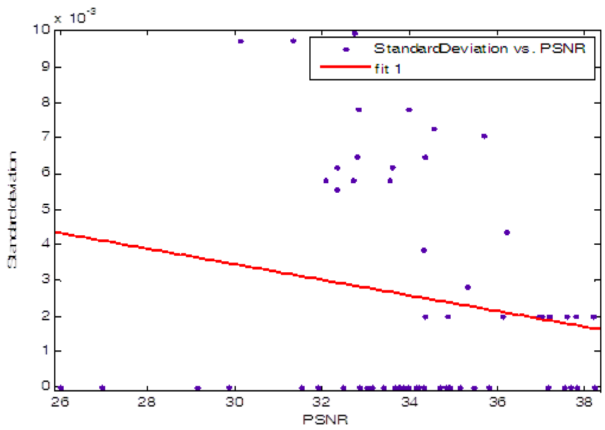


Fig. 2 Linear regression of standard deviation on PSNR

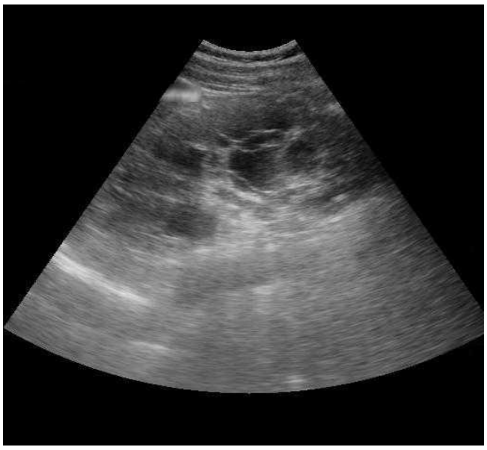
Table 1. Comparison of performance of despeckling based on contourlet transform and proposed method based on linear regression model

Denoising methods	PSNR (in dB)	Computational Time (in seconds)
Contourlet transform using cycle spinning	33.8821	8.5678
Proposed method based on linear regression model	36.4825	0.3517

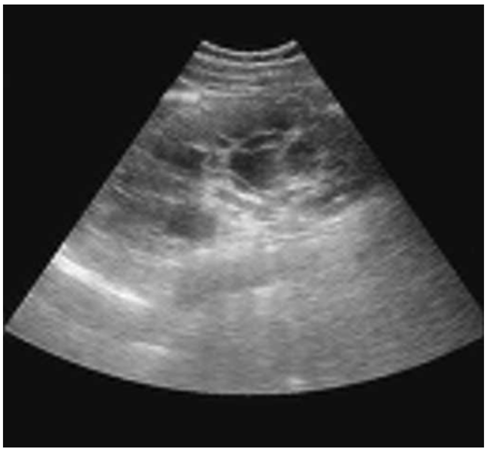
Further, the visual quality of image enhancement can also be observed from the sample image and its denoised image shown in the Fig. 3. The anatomical structures are more clearly visible in the Fig. 3 (c) than that in Fig. 3 (b). The proposed method estimates the Gaussian noise content in the input medical ultrasound image for denoising the image efficiently. Hence, it is easily amendable for building embedded system for ultrasound imaging equipments in order to display the high quality images, which help the physician in the diagnosis with greater accuracy.

4. CONCLUSION

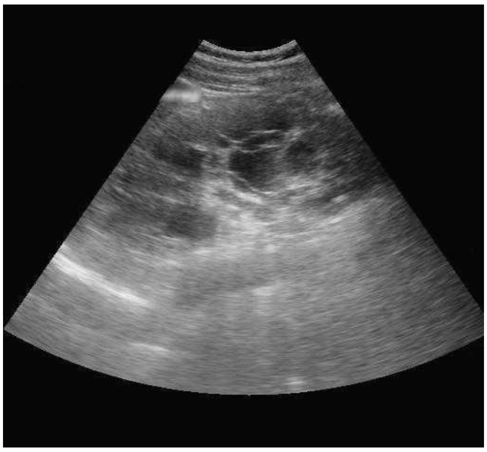
In this paper, we have proposed a novel linear regression model for Gaussian noise estimation and removal in despeckling medical ultrasound images. The experimentation is carried out on ultrasound images of liver and kidney. The speckle noise is modeled as a Gaussian noise, with estimated mean and standard deviation based on PSNR of the ultrasound image, using the proposed linear regression model. The experimental results demonstrate its efficacy both interms of speckle reduction and computational time required for denoising. Hence, it is easily amendable for building embedded system for ultrasound imaging equipments in order to display the high quality images, which help the physician in the diagnosis with greater accuracy. In future work, we propose to generalize the regression model for noise in the ultrasound scanned images of other anatomical structures of the human body.



(a)



(b)



(c)

Fig. 3 (a) Original image (b) Despeckled image using contourlet transform with cycle spinning (c) Denoised image using proposed method.

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