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Technical note

Adaptive speckle reduction in ultrasound images using fuzzy logic on Coefficient of Variation

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ABSTRACT

Speckle reduction is an important pre-processing stage for ultrasound medical image processing. In this paper, an adaptive fuzzy logic approach for speckle noise reduction in ultrasound images is presented. In the proposed method, adaptiveness is incorporated at two levels. In the first level, applying fuzzy logic on the coefficients of variation computed from the noisy image, image regions are classified. The best suitable filter for the particular image region is adaptively selected by the system yielding appreciable improvement in noise suppression and preservation of image structural details. At the second level, to distinguish between edges and noise, the proposed method uses a weighted averaging filter. The structural similarity measure, which depends on the nature of image and quantity of noise present in the image, is used as the tuning parameter. Thus with two levels of adaptiveness, the proposed method has better edge preservation compared to existing methods. Experimental results of the proposed method for natural images, Field II simulated images and real ultrasound images, show that proposed denoising algorithm has better noise suppression and is able to preserve edges and image structural details compared with existing methods.

1. Introduction

Ultrasound imaging is predominantly used for diagnosis of thyroid diseases compared to X-ray, computed tomography and magnetic resonance imaging as it is non-invasive, utilises non-ionising radiation and is cost effective. However, the main disadvantage of medical ultrasonography is the poor image quality due to backscattered echo signals called speckle [1]. Therefore, it is not only difficult for the physician to analyse and diagnose the image in the presence of speckle noise but it is also difficult for feature extraction, analysis, and recognition [2]. Hence, speckle filtering is a critical pre-processing step. Researchers have proposed a number of methods for speckle reduction. Lee [3], Frost et al. [4], and Kuan et al. [5] have proposed spatial domain filters based on the local statistics of the image. These methods achieve good speckle reduction in homogeneous areas but ignore the speckle noise in areas close to the edges and lines. Perona and Malik [6] developed a method called anisotropic diffusion based on heat equation. This technique works well in homogenous areas with edge preservation for images corrupted by additive noise but the performance is poor for the multiplicative speckle noise. Yu and Acton [7] proposed a method called speckle reduction anisotropic diffusion (SRAD). In this method, a diffusion coefficient is defined based on the ratio of local standard deviation to mean using four nearest neighbour window. However, smoothening of the edges and structural content occurs in this method.

Achim et al. [8] proposed a speckle reduction based on homomorphic filtering and modelled the wavelet coefficients as a non-Gaussian model. However, this approach is computationally expensive, as it requires the extraction of distribution parameters. Yue et al. [9] developed a non-linear multiscale wavelet diffusion algorithm for speckle suppression. This technique not only preserves edges but also enhances edges by inhibiting diffusion across edges. Pizurica et al. [10] proposed a generalised likelihood (GenLik) method in which wavelet coefficients are denoised by likelihood ratio using local neighbours following non-homomorphic filtering technique. An adaptive wavelet thresholding technique was proposed in [11] based on Bayesian maximum aposteriori probability (MAP) by modelling the noise free signal coefficients as symmetric normal inverse Gaussian and noisy coefficients as Gaussian distribution. From this, an adaptive threshold is obtained to reduce the speckle noise in ultrasound images. An adaptive bilateral filtering algorithm was developed in [12] by estimating the range parameter using intensity homogeneity measurements and denoising was performed iteratively. Nonsubsampled Contourlet Transform

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(NSCT) developed by Cunha et al. [13] tested the transform on image corrupted with additive white Gaussian noise (AWGN) and applied hard thresholding. This method gives better performance than the undecimated wavelet transform in image enhancement as well as in filtering AWGN noise. Cheng et al. [14] proposed speckle reduction of synthetic aperture radar images based on fuzzy logic. This technique computes fuzzy edges for each pixel in the filter window and uses these to weight the contributions of neighbouring pixels to perform fuzzy filtering. Nevertheless, this iterative filter has the drawback that it is suitable only for images with large homogenous area. Zhang et al. [15] proposed a fuzzy sub pixel fractional partial difference method for ultrasound speckle reduction. In this, the Euler Lagrange equation is employed and filtering is done in an iterative manner by which image contrast is improved. Nevertheless, calculation of parameters for image fuzzification at every iteration is the limitation of this scheme. Kwan et al. [16,17] proposed symmetrical and asymmetrical triangle fuzzy filters based on median and average filters. However, the fuzzy based median or average filters tend to smoothen the fine details causing poor edge preservation. Binaee et al. [18] developed a fuzzy filter based on local gradient of the image and used fuzzy inference to categorise the image regions and structural information. Weights were found based on a similarity window by non-local means filtering process. Nevertheless, the method is computationally intensive as it takes much iterations to locate the similarity window. Guo et al. [19] proposed a despeckling filter based on modified non local means algorithm. This method consists of two steps, first noise free pixel has been estimated using maximum likelihood estimator and a non-local means algorithm has been applied to restore details. The noise variance parameters in maximum likelihood estimator is directly related with exponential function in non-local means algorithm; hence optimisation of this parameter is difficult and this algorithm is time consuming. Damodaran et al. [20] developed an algorithm based on discrete topological derivative. This algorithm is able to reduce speckle noise and contrast of the image has been improved at the cost of more computational time. Tsakalakis et al. [21] developed a denoising filter based on novel multi-transducer architecture. Despeckling technique has been employed by combining frequency and spatial compounding along with despeckling super resolution algorithm. The main drawback is that image registration step is required as images are captured from different sensors with different frequencies.

This paper presents a novel fuzzy based filter for speckle noise reduction based on Coefficient of Variation parameter derived from the noisy image. Using this parameter, the structural information of the images is characterised. This proposed method incorporates adaptiveness at two levels. In the first level, using fuzzy logic, image regions are classified based on Coefficient of Variation parameter and the system adaptively selects the best suitable filtering technique for the particular region of the image. By applying appropriate filters on the corrupted pixels, appreciable improvement in noise suppression and preservation of image structural details is achieved. At the second level, to distinguish between edges and noise the proposed method uses a weighted averaging filter. Using the structural similarity index for computing the tuning parameter the proposed technique adapts with the nature of image and amount of noise present in the image. Thus with two levels of adaptiveness using Coefficient of Variation and structural similarity, the proposed method has better edge preservation compared to existing methods. The performance of the proposed method is studied with natural images, Field II simulated images, real ultrasound images and compared with existing methods.

The paper is organised as follows: Section 1 describes the related works, their limitations, and the objective of the paper. Section 2 discusses the fuzzy logic model for speckle noise reduction with Coefficient of Variation, design of the adaptive weighted averaging filter and the despeckling algorithm. Section 3 describes the experimental results and Section 4 summarises the conclusions of the study.

2. Proposed method

Most of the existing denoising techniques have considered only noise suppression and failed in the preservation of important details in an image. In addition, the methods are not able to distinguish between edge information and noise, thereby suppressing the edges assuming them as noise. Therefore, there is a need for a method that not only preserves the image details but also adapts the degree of smoothing based on the noise present in the image. This paper proposes an algorithm based on the concept of fuzzy logic to classify the different noisy pixels into classes such as homogenous, details and edges using parameters derived from the noisy image itself. Based on this inference, the proposed method adaptively applies appropriate filtering methods to different regions of same image and hence is able to preserve edges and details.

2.1. Noise model

Speckle noise corrupts the information content of the ultrasound image. Speckle noise occurs due to the interaction of the ultrasound waves with objects that are comparable to its wavelength [22]. In order to derive an efficient despeckle filter, there is a need for a speckle noise model. Let $R(x, y)$ be the observed ultrasound image with size $M \times N$. The speckle noise is multiplicative in nature and hence the output of the ultrasound imaging system may be defined as:

$$R(x, y) = I(x, y) . n(x, y) + \eta(x, y) \quad (1)$$

where (x, y) denote the pixel of observed image, $I(x, y)$ represents the noise free image, $n(x, y)$ and $\eta(x, y)$ represent the multiplicative and additive noise respectively. Since the effect of additive noise is negligible compared to multiplicative noise, Eq. (1) becomes

$$R(x, y) = I(x, y) . n(x, y) \quad (2)$$

The proposed method utilises homomorphic filtering approach by which logarithmic transformation is carried out to convert the multiplicative model to an additive model. Therefore, Eq. (2) can be written as

$$R'(x, y) = \log[I(x, y)] + \log[n(x, y)] \quad (3)$$

where $R'(x, y)$ is the log-transformed image.

2.2. Adaptive fuzzy logic model

In ultrasound images, speckle noise affects the image pixels and image regions can be grouped as homogenous, detail or edge regions. Each region has its distinguished characteristic features. Based on this, each pixel can have different degree of membership. Therefore, to classify each pixel, there is a need for an appropriate reasoning method. As ultrasound images have fuzziness caused by speckle noise, fuzzy logic can be considered as a simple way to arrive at a definite output from ambiguous, imprecise, or noise input information. Hence, fuzzy logic is used to classify the noisy pixel to belong to several classes based on the membership degree. The proposed fuzzy filtering process has two stages: detection and filtering. The detection stage involves classifying the noisy pixel into various classes. The image parameter, Coefficient of Variation has been utilised to categorise each pixel for detection. In the filtering process, three filters are applied on the classified pixels to suppress noise and enhance the ultrasound image.

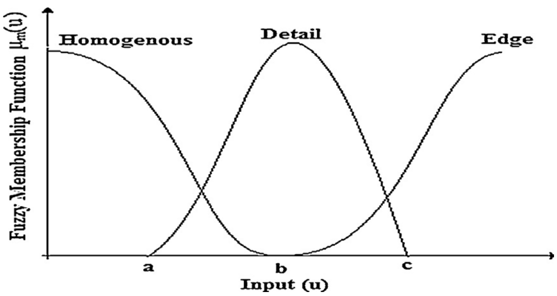

Fig. 1. Gaussian membership functions with different classes.

2.2.1. Detection using coefficient of variation

Coefficient of Variation (CV) is a normalised measure of distribution of data and it is defined as ratio of standard deviation to the mean. As edges have variation, high CV values correspond to edges. Similarly, a pixel with lower CV value indicates that it is belongs to the homogenous region. The intermediate values belong to detail region. Based on this principle, noisy pixels have been characterised into 'Homogenous', 'Detail' and 'Edges'. During image filtering process, pixels cannot be eliminated, as noise is spread over all the pixels in an image. Hence, for defining the degree of membership in a fuzzy system, the Gaussian membership function has been used.

The Gaussian membership function given in Eq. (4) has the property that it approaches zero only after a few standard deviations. The main advantage that this membership function is symmetric about its mean and nonzero over the entire real axis is utilised for the proposed design of fuzzy filter. So the CV values computed for the noisy image are mapped to the fuzzy domain using the Gaussian membership function:

$$\mu_m^i(u) = e^{\left((-(u-c_i)^2/2\sigma_i^2\right)} \tag{4}$$

where $i = 1, 2,$ and 3.

In Eq. (4) μ_m^i is the fuzzy set for the group of pixels $W \times W$ with mean C_i and variance σ_i^2 represents the three different regions in noisy images and $W \times W$ is the square window. Fig. 1 shows the Gaussian membership function for the three regions.

To define the three classes namely, 'Homogenous', 'Detail' and 'Edge', threshold values a, b, c are determined as given in the following equation:

$$\mu_m^i(u) = \begin{cases} \text{homogenous}, & u < b \\ \text{detail}, & u \geq a \text{ and } u \leq c \\ \text{edge}, & u > b \end{cases} \tag{5}$$

The pixels with lower CV value belong to uniform or homogenous region. Hence, a threshold point a is needed to define the intermediate detail region. To define the threshold a, the peak value of CV calculated for the log-transformed image $R'(x, y)$ is selected. Pixels with high CV correspond to edges. For defining the transition to the edge region, the threshold 'c' is to be determined. As gradient operation is efficient in distinguishing edges, gradient of the log-transformed image $R'(x, y)$ is found for which CV is computed. Then peak value of CV is selected as threshold 'c'. The threshold 'b' is taken as the average of 'a' and 'b'.

Eqs. (6)–(10) give the threshold calculation equations:

$$a = \text{peak}\left[R_{\text{cv}}\right] \tag{6}$$

where

$$R_{\text{cv}} = \text{CV}\left[R'(x, y)\right]_{W \times W} \tag{7}$$

$$C = \text{peak}\left[R'_{\text{cv}}\right] \tag{8}$$

Table 1
Thresholds a, b, c for the Gaussian membership function for different levels of noise.

Image	Parameter	Standard deviation of noise (σ_n)		
		0.4	0.7	1
Lena	a	0.0314	0.0784	0.1686
	b	0.1314	0.1549	0.2078
	c	0.2314	0.2314	0.2471
House	a	0.0275	0.0745	0.1608
	b	0.1373	0.1588	0.1922
	c	0.2471	0.2431	0.2235

where

$$R'_{\text{cv}} = \text{CV}\left[\text{grad}R'(x, y)\right]_{W \times W} \tag{9}$$

$$b = \text{average}\left[a, c\right] \tag{10}$$

Hence depending upon the amount of noise added to the image, thresholds a, b, c adaptively varies, and input noisy pixel is classified accordingly. Table 1 gives the thresholds computed for two different natural images for different levels of noise.

This is graphically shown in Fig. 2. Hence, by adaptively changing the threshold with the noise, the pixels are correctly classified. This allows the most suitable filter to be applied for denoising at the same time preserving the edges and detail information.

2.2.2. Fuzzy IF–THEN rules for noisy pixel classification

Fuzzy rules are formed to classify the noisy pixel as 'Homogenous', 'Detail' and 'Edge'. The class 'Homogenous', 'Detail' and 'Edge' are defined in terms of CV value. 'Small' and 'Large' represents the degree of membership function in each class. Five rules based on CV are used for classification as given below.

Rule 1:

If $\mu_m^1(u)$ is large and $\mu_m^2(u)$ is small and $\mu_m^3(u)$ is small then noisy pixel in homogenous class

Rule 2:

If $\mu_m^1(u)$ is small and $\mu_m^2(u)$ is large and $\mu_m^3(u)$ is small then noisy pixel in detail class

Rule 3:

If $\mu_m^1(u)$ is small and $\mu_m^2(u)$ is small and $\mu_m^3(u)$ is large then noisy pixel in edge class

Rule 4:

If $\mu_m^1(u)$ is large and $\mu_m^2(u)$ is large and $\mu_m^3(u)$ is small then noisy pixel in detail class

Rule 5:

If $\mu_m^1(u)$ is small and $\mu_m^2(u)$ is large and $\mu_m^3(u)$ is large then noisy pixel in edge class

To avoid complexity of the fuzzy algorithm, the number of fuzzy rules has been reduced to five. With these rules, it is possible to distinguish all the possible classes of pixels efficiently and effective fuzzy inference can be made.

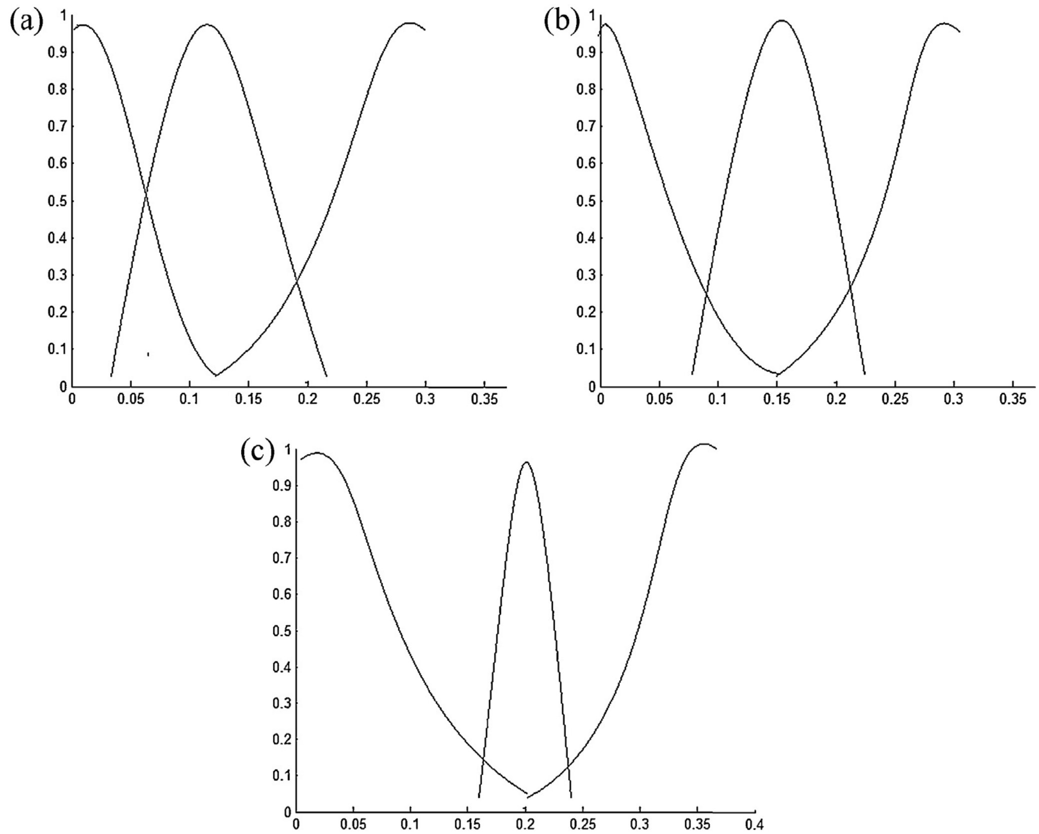

Fig. 2. Gaussian membership function for Lena image, (a) noise with standard deviation 0.4, (b) noise with standard deviation 0.7 and (c) noise with standard deviation 1.0.

2.3. Speckle denoising filters

In the fuzzy detection process, each pixel in a noisy image is mapped into fuzzy membership function based on CV. Each pixel in fuzzy domain is analyzed and characterised into homogenous region, detail and edge region in the fuzzy reasoning stage. For denoising, an appropriate filter is required, which should eliminate the noise without affecting the structural content of the image. So suitable filters are applied on the three regions classified using fuzzy inference technique.

2.3.1. Homogenous region

For the pixels in the Homogenous region, a smoothening filter which takes average of pixels in a moving window of size $(2K+1)\times(2K+1)$ is sufficient. $F(x, y)$, the new replaced pixel value after the averaging process, is given by

$$F(x,y)=\frac{1}{(2K+1)^2}\sum_{r=-k}^{K}\sum_{s=-K}^{K}R'(x+r,y+s)\quad \text{where}\quad K=1,2,\ldots \text{is an integer} \tag{11}$$

2.3.2. Detail region

For the pixels classified as Detail region, the average filter cannot be applied, as the structural information needs to be preserved. Hence, an edge preserving non-linear filter, the median filter that retains the desirable features instead of dislocating them is utilised. Due to this, desirable details of the image are preserved. The median filter is given by Eq. (12) for the moving window of size $(2K+1)\times(2K+1)$:

$$F(x,y)=\text{median}\left(R'(x+r,y+s)\right),\quad \text{where}\quad -K\le(r,s)\le K \text{ and } K=1,2,\ldots \text{ is an interger} \tag{12}$$

2.3.3. Edge region

The fuzzy inference technique classifies the pixels with high CV as edges. In this class, there is the possibility to have pure edges or noise. Therefore, there is a requirement for a filter to denoise the noisy pixel and to preserve edges without affecting the original content of image. As the main objective of the proposed method is edge preservation of denoised image, an adaptive weighted average filter given in Eq. (13) is designed based on the following observation. Edge pixels are clustered and continuous in nature so larger weight is assigned to the neighbouring coefficient with similar magnitude. On the other hand, noisy pixels with larger coefficient value are isolated and discontinuous in nature, so small weight is assigned to the neighbouring coefficient with dissimilar magnitude. The value of weight $w(x,y)$ for each neighbouring coefficient is defined by Eq. (14):

$$F(x,y)=\frac{\sum_{r=-k}^{K}\sum_{s=-k}^{K}w(r,s)\times R'(x+r,y+s)}{\sum_{r=-k}^{K}\sum_{s=-k}^{K}w(r,s)} \tag{13}$$

$$w(x,y)=m(x,y)\times s(x,y) \tag{14}$$

where $m(x,y)$ and $s(x, y)$ are the magnitude similarity and spatial similarity respectively defined as in [23].

$$m(x,y)=\exp\left(-\left(\frac{R'(x,y)-R'(x+r,y+s)}{\delta}\right)^2\right) \tag{15}$$

$$s(x,y)=\exp\left(-\left(\frac{r^2+s^2}{(2K+1)^2}\right)\right) \tag{16}$$

where $R'(x, y)$ and $R'(x+r,y+s)$ are center pixel and its neighbouring pixel respectively in a local window of size $(2K+1)\times(2K+1)$ and $r, s \in [-K \text{ to } K]$. $\delta=C\hat{\sigma}_n$ is an important parameter that distinguishes noisy and edge pixels. 'C' is called tuning parameter and $\hat{\sigma}_n$ is the noise variance.

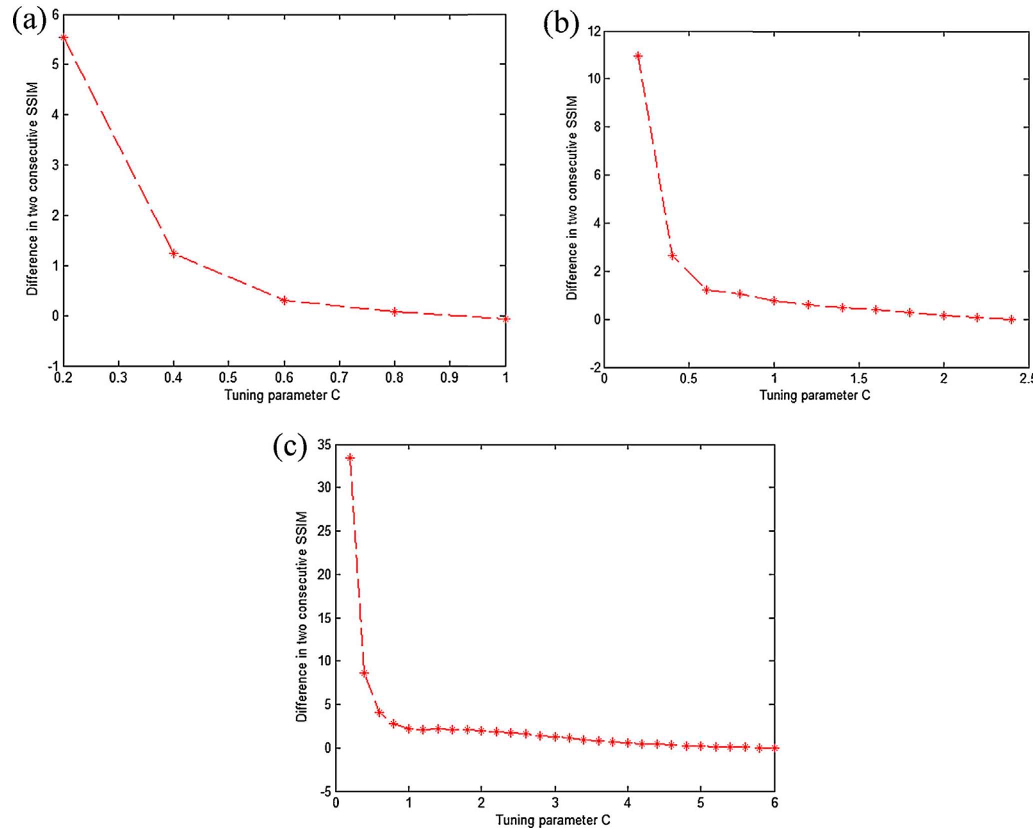

Fig. 3. Relative difference of SSIM for Lena image. (a)–(c) Relative difference of SSIM with noise standard deviation 0.4, 0.7 and 1 respectively.

To obtain efficient filtering, the tuning parameter '*C*' has to be suitably selected. In this paper, '*C*' is computed based on the relative difference in Structural Similarity Index Measure (SSIM), which is defined as follows:

Relative difference of SSIM

$$\rho = \frac{\mathrm{SSIM}\,(n+1) - \mathrm{SSIM}\,(n)}{\mathrm{SSIM}\,(n)} \tag{17}$$

and '*n*' is iteration index. As SSIM indicates the degree of similarity between denoised and original image it is selected. In addition, SSIM varies with the nature of the image and magnitude of noise in the image.

The optimum tuning parameter C_{opt} is computed iteratively. Fig. 3 shows the plot of iteratively varying tuning parameter '*C*' and relative difference in SSIM calculated for Lena image with noise standard deviation of 0.4, 0.7, and 1. It is observed that the relative difference in SSIM decreases for each iteration of '*C*'. The value of '*C*' at which relative SSIM difference becomes less than zero is chosen as C_{opt}.

The optimum '*C*' value for different natural images with various noise standard deviations are shown in Table 2. Thus, the designed weighted averaging filter changes the weights used adapting to the type of image and quantity of noise affecting the image.

Table 2
Optimum tuning parameter '*C*', for various images with different noise levels.

Image	Standard deviation of noise (σ_n)		
	0.4	0.7	1
Lena	1	2.4	6
House	0.8	2.8	7.2

2.4. Despeckling algorithm

Detection
1. Compute logarithmic transformation on input image $R(x, y)$ of size $M \times N$ to obtain $R'(x, y)$
2. Compute $\mathrm{CV}[R'(x,y)]_{w\times w}$, where $w \in [M,N]$
3. Compute thresholds *a*, *b* and *c* using Eqs. (6)–(10).
4. Calculate Fuzzy degree of membership $\mu_m^i(u)$ to each class using Eq. (4).
5. Classify each pixel in fuzzy domain into homogenous region, detail and edge region using fuzzy reasoning.

Filtering
6 Set initial tuning parameter '*C*' = 0
7 for $i = 1{:}M$
{
for $j = 1{:}N$
{
if $R'(i,j)$ in homogenous region
{

$$F(i,j) = \frac{1}{(2K+1)^2} \sum_{r=-K}^{K} \sum_{S=-K}^{k} R'(i+r, j+s)$$

}
elseif $R'(i,j)$ in homogenous region
{
$F(i,j) = \mathrm{median}(R'(i+r, j+s))$
}
elseif $R'(i,j)$ in edge or noisy region
{

$$F(i,j) = \frac{\sum_{r=-K}^{K} \sum_{s=-K}^{K} W(r,s) \times R'(i+r,j+s)}{\sum_{r=-K}^{K} \sum_{s=-K}^{K} W(r,s)}$$

}
}
}

8. Take inverse logarithmic transform on $F(i,j)$ to get denoised image $\hat{F}(x, y)$.

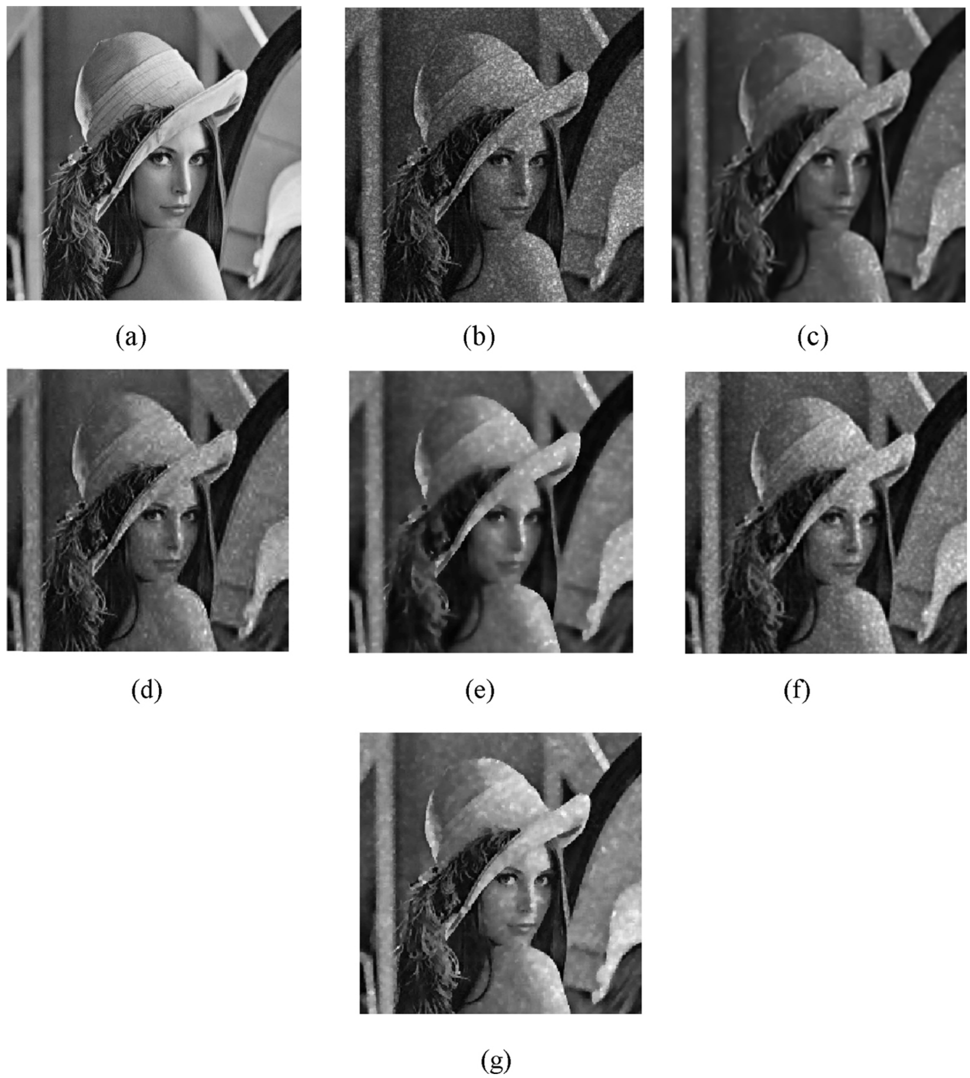

Fig. 4. Comparison of various despeckling methods. (a) Noise free Lena image, (b) noisy image of noise standard deviation 0.7. Denoised image obtained by using (c) GenLik [10], (d) SNIG I [11], (e) adaptive bilateral filter [12], (f) ATMAV [16], and (g) proposed adaptive fuzzy logic filter based on CV.

9. Find SSIM for $\hat{F}(x, y)$ and obtain the relative difference in SSIM, ρ using Eq. (17).

10. If $\rho(n+1)-\rho(n)<0$ then $c=c_{\mathrm{opt}}$ Stop Iteration, else increment

c and repeat steps 7 to 9.

The advantage of this proposed method is that the algorithm applies fuzzification on the CV values obtained from the log-transformed image and applies appropriate filtering to different regions of the same image. In addition, to distinguish between edge and noise, the algorithm iteratively selects the optimum tuning parameter value 'C' based on SSIM that varies in accordance with the nature of image and amount of noise in the image.

3. Experimental results

The proposed despeckling method is implemented in MATLAB 8 in a Intel core i3 processor and experimental results are presented. The performance is compared with GenLik [10], SNIGI [11], Adaptive bilateral filter [12], and Asymmetric Triangle Fuzzy Filter with Moving Average (ATMAV) [16]. Speckled image is obtained by first generating complex Gaussian random field of image size that is filtered by a low pass filter of size 3×3. The magnitude of filtered output is then taken which is multiplied with the noise free image [10]. The performance of proposed fuzzy logic based adaptive filter in noisy images were compared in terms of SSIM, Edge Preservation Index (EPI) [24], SNR and Ultrasound Despeckling Assessment Index (USDAI) for natural images and Field II [25] simulated image. In order to evaluate the performance of despeckling filter more realistic speckle simulation (Field II) has been utilised for study and the parameters used for this simulation are as in [26].

In detection stage, CV has been implemented to classify each pixel into different class. All the methods used for comparison have been implemented for the purpose of comparison with the proposed work. GenLik results are obtained by using quadratic spline wavelet transform with four level decomposition, 5×5 size window and tuning factor (k) of 3 as mentioned by the author [10]. SNIG I method is implemented on orthogonal DWT with four level decomposition using symlet wavelet of order 8 and parameters as mentioned by the author [11]. Adaptive bilateral filter is implemented as per [12] using 5×5 size window and proportionality factor of 0.008. Fuzzy filter based on average filter (ATMAV) [16] is implemented using 3×3 size moving window. For visual quality comparison, the despeckled outputs of noisy images with standard deviation 0.7 are shown in Fig. 4. After applying various denoising schemes, it is observed that the proposed adaptive fuzzy

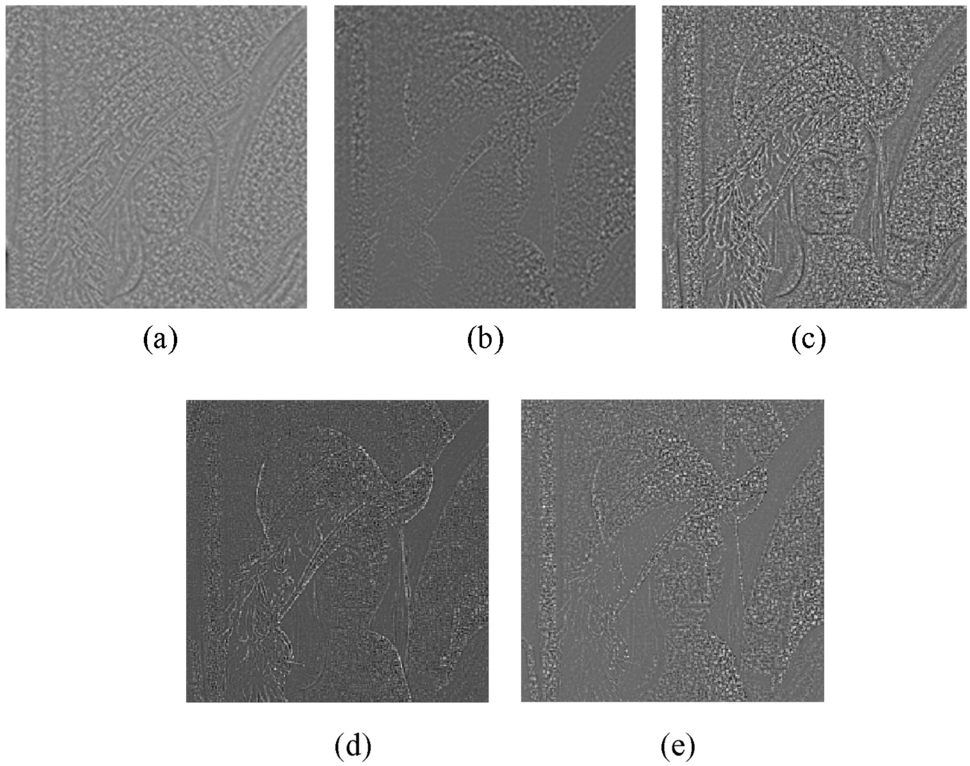

Fig. 5. Noise removed from image by using (a) GenLik, (b) SNIG I, (c) adaptive bilateral filter, (d) ATMAV, and (e) proposed adaptive fuzzy logic filter based on CV.

method based on CV performs better than the existing methods by suppressing speckle noise and preserving important details in an image. In addition to that, the contrast of the image is improved by the proposed fuzzy filtering scheme compared to the existing methods. This is clearly shown in Fig. 4.

For further validation of the proposed method, the amount of noise removed and preservation of edges and important details in image by the various methods is shown in Fig. 5. From this it is clearly observed that, GenLik (a) filters more information than noise while SNIG I method (b) filters lesser noise. The Adaptive Bilateral filter 5(c) has removed not only noise but also edge and fine details of the image. ATMAV method (d) filters important structures in the image. The proposed adaptive fuzzy method (e) based on CV filters more amount of noise and preserves image structures compared to other methods.

In order to validate the result quantitatively, Table 3 shows the results of Edge Preservation Index β [24] for various denoising methods with noise variance 0.7. The values of β calculated for the denoised image by the proposed fuzzy logic filter indicates better performance than the existing methods in preserving edges.

Performances of the various methods are analysed in terms of Signal to Noise Ratio (SNR), which is given by

$$\mathrm{SNR} = 10\log_{10}\left(\frac{\sigma_I}{\sigma_D}\right) \tag{23}$$

where σ_I represents the variance of noise free image $I(x,y)$ and σ_D represents the variance of the error in the despeckled image. i.e. $D = I(X, Y) - \hat{F}(X, Y)$, where $\hat{F}(X, Y)$ is the despeckled image. Table 4 shows the SNR values calculated for different denoising methods with various noise standard deviations. It shows that proposed adaptive fuzzy filtering method based on CV performs better in all cases than the ATMAV, Adaptive Bilateral filter, SNIG I and GenLik methods with an average improvement of 1.676, 2.615 dB, 3.792 dB and 3.737 dB respectively.

To evaluate the despeckling performance of proposed Adaptive Fuzzy logic filter full contrast stretched eight bit image template is used as ideal noise free image. Field II simulation [25] is used to obtain simulated B mode ultrasound image and this is shown in Fig. 6(a) and (b) respectively. Fig. 6 shows the performance of various despeckling algorithm for Field II simulated image. GenLik and SNIG I denoising methods are based on estimation and for Field II simulated image both the methods perform poorly. The Adaptive bilateral method also has low performance in denoising the simulated image. ATMAV method is based on asymmetrical triangle fuzzy moving average filter, which smoothens the image and is poor in edge preservation. On the other hand, the proposed adaptive fuzzy logic based filtering method performs better than the other method in denoising the simulated image, which is shown in Fig. 6. Table 5 shows the quantitative analysis of various methods discussed. From this, it is observed that proposed method performs better than the other methods in terms of SSIM and USDAI

A qualitative analysis was done on the various methods in real ultrasound images. Figs. 7 and 8 present the performance

Table 3
Comparison of EPI (β) values for various methods with σ_n.

Image	GenLik [10]	SNIG I [11]	Adaptive bilateral [12]	ATMAV [16]	Proposed adaptive fuzzy logic filter
Lena	0.6443	0.7565	0.6569	0.4833	0.8017
House	0.7304	0.7000	0.7476	0.6445	0.7468

Table 4
Comparison of SNR (in dB) values for various methods.

Image	Method	Standard deviation of noise σ_n				
		0.6	0.7	0.8	0.9	1
Lena (256 × 256)	GenLik	14.39	13.29	12.38	11.47	10.61
	SNIG shrink I	14.60	13.66	12.77	12.01	11.44
	Adaptive bilateral	14.77	13.99	12.93	12.48	11.82
	ATMAV	15.36	14.93	14.39	13.83	13.34
	Proposed adaptive fuzzy logic filter	17.49	16.80	16.19	15.55	14.99
House (256 × 256)	GenLik	13.53	12.07	11.27	10.15	9.63
	SNIG shrink I	12.57	11.40	10.72	9.97	9.10
	Adaptive bilateral	14.16	13.42	12.74	12.08	11.62
	ATMAV	15.42	14.42	13.48	12.51	11.72
	Proposed adaptive fuzzy logic filter	16.74	15.81	14.97	14.16	13.46

of different denoising technique on real ultrasound thyroid images containing important features. The ultrasound thyroid images are obtained from the websites, www.radiology.rsna.org and www.medison.ru/uzi/eho139. The outputs show that GenLik method over smoothens the uniform area whereas SNIG I denoises around the edges. Adaptive bilateral filter preserves edges and features but the amount of filtering of speckle noise is less. On comparison, the proposed method based on fuzzy logic applied on Coefficient of Variation and adaptive weighted averaging filter enhances the contrast of the image with better preservation of edge and important details. This is clearly shown in Figs. 9 and 10, which shows the removed noise from the ultrasound thyroid images using the various methods.

From Figs. 9 and 10 it is observed that in the case of real ultrasound images, GenLik, SNIG and Adaptive Bilateral methods

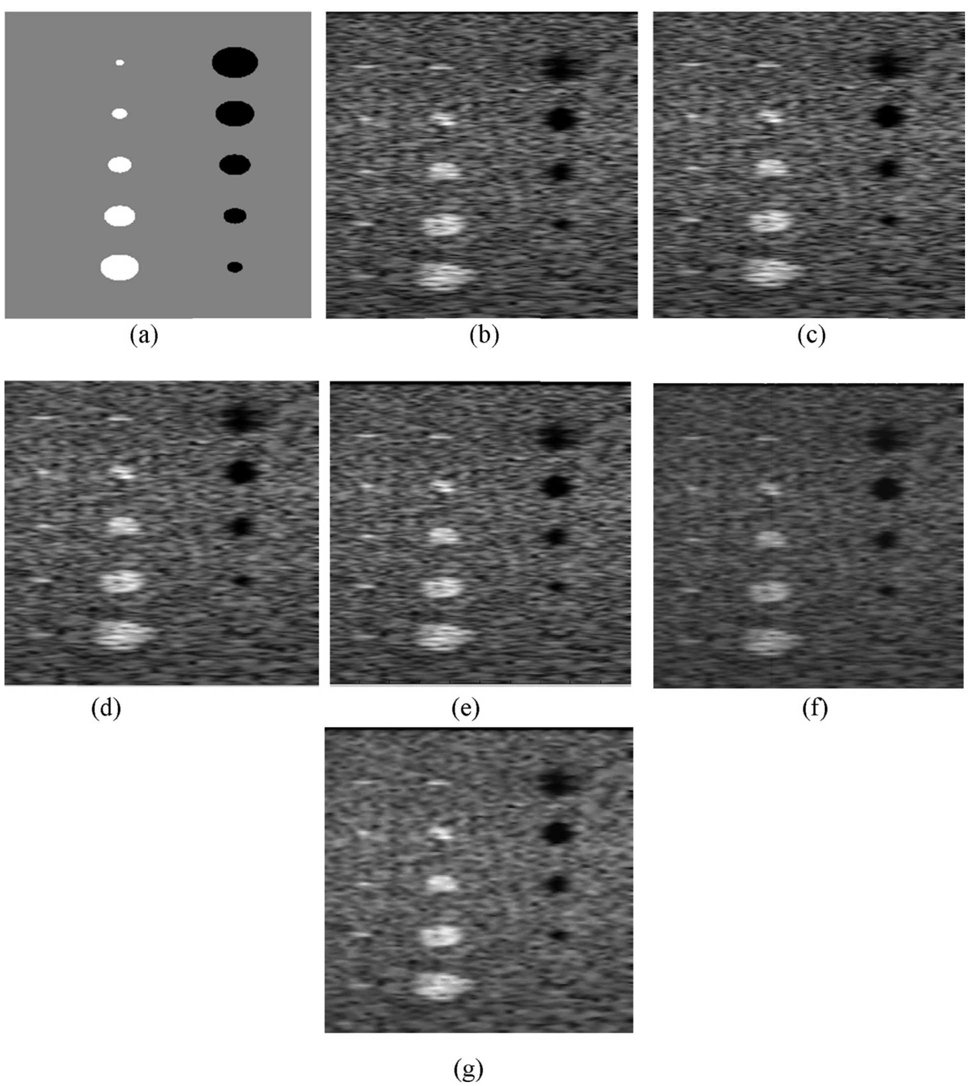

Fig. 6. Comparison of various despeckling methods on Field II simulated image.(a) Noise free Cyst phantom, (b) Field II simulated Cyst phantom, (c) GenLik [10], (d) SNIG I [11], (e) adaptive bilateral filter [12], (f) ATMAV [16], and (g) proposed adaptive fuzzy logic filter based on CV.

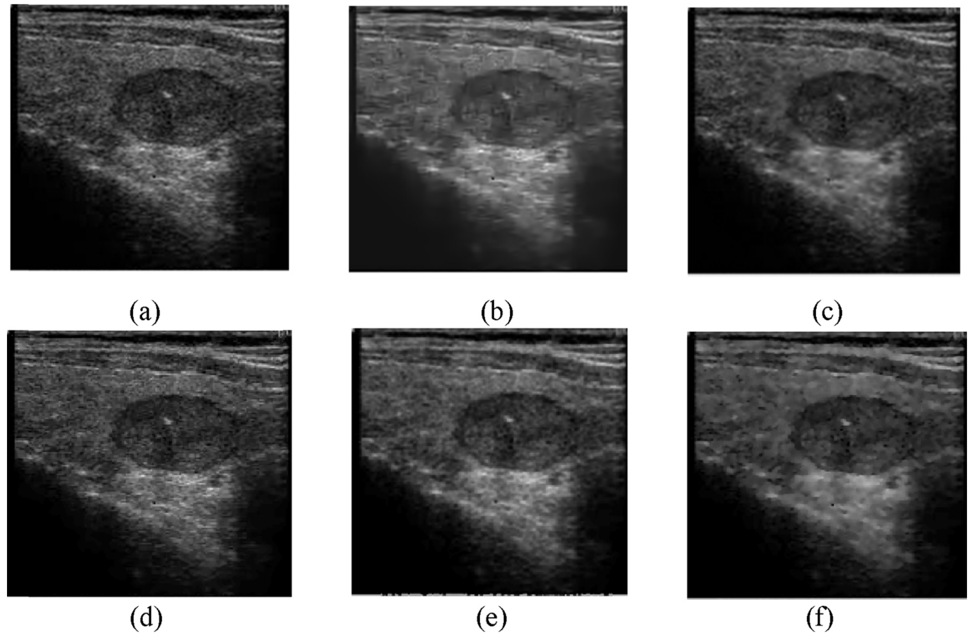

Fig. 7. Various denoising methods applied on ultrasound thyroid image containing nodule (a) ultrasound thyroid image and corresponding denoised image using, (b) GenLik, (c) SNIG I, (d) adaptive bilateral filter, (e) ATMAV, (f) proposed adaptive fuzzy logic filter based on CV.

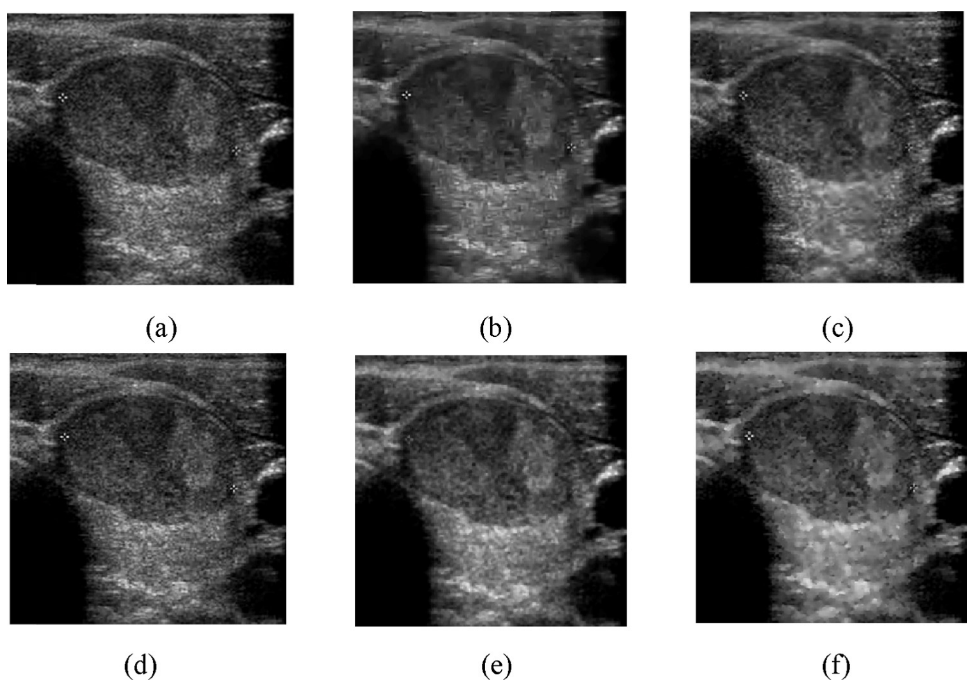

Fig. 8. Various denoising methods applied on ultrasound thyroid image containing nodule (a) ultrasound thyroid image and corresponding denoised image using, (b) GenLik, (c) SNIG I, (d) adaptive bilateral filter, (e) ATMAV, and (f) proposed adaptive fuzzy logic filter based on CV.

Table 5
Comparison of SSIM and USDAI values for various methods for Field II simulated image.

Method	USDAI	SSIM
GenLik	1.0662	0.3528
SNIG shrink I	1.0027	0.3137
Adaptive bilateral	1.2357	0.5764
ATMAV	1.1941	0.4737
Proposed adaptive fuzzy logic filter	1.3914	0.6041

filter noise and information details both in and around the thyroid nodules present in ultrasound image. This results in losing useful information details of the ultrasound image. On the other hand, the proposed Adaptive Fuzzy logic filter based on CV has the advantage that it denoises the speckle present around the nodules present in ultrasound image while filtering less in the nodule structure thereby preserving the information details of the nodules of the thyroid image. This is clearly shown in Figs. 9(e) and 10(e).

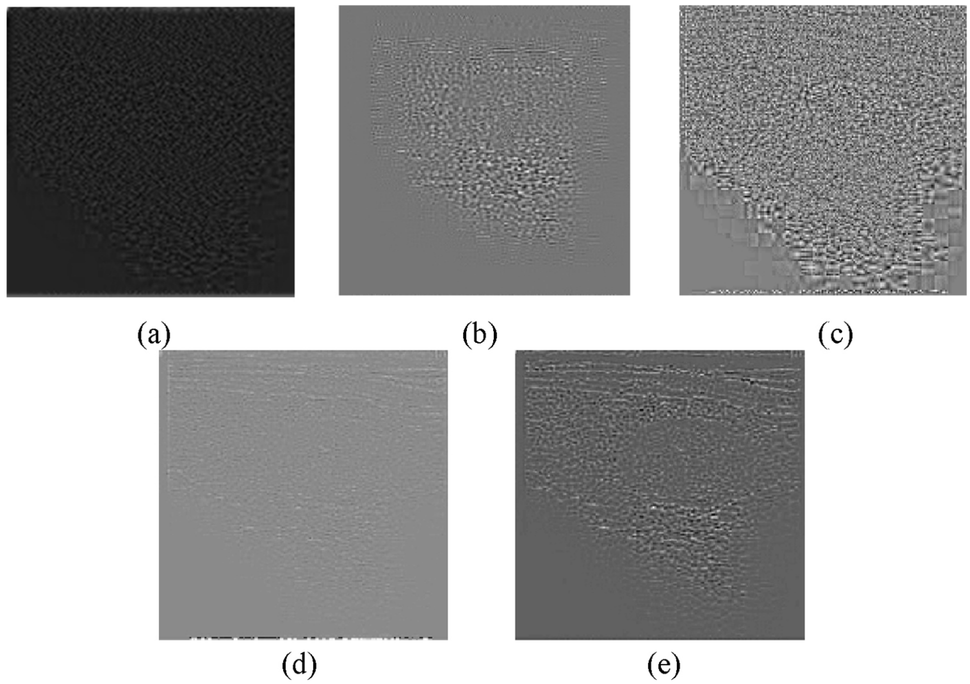

Fig. 9. Noise removed from the ultrasound thyroid image by implementing (a) GenLik, (b) SNIG I, (c) adaptive bilateral filter, (d) ATMAV and (e) proposed adaptive fuzzy logic filter based on CV.

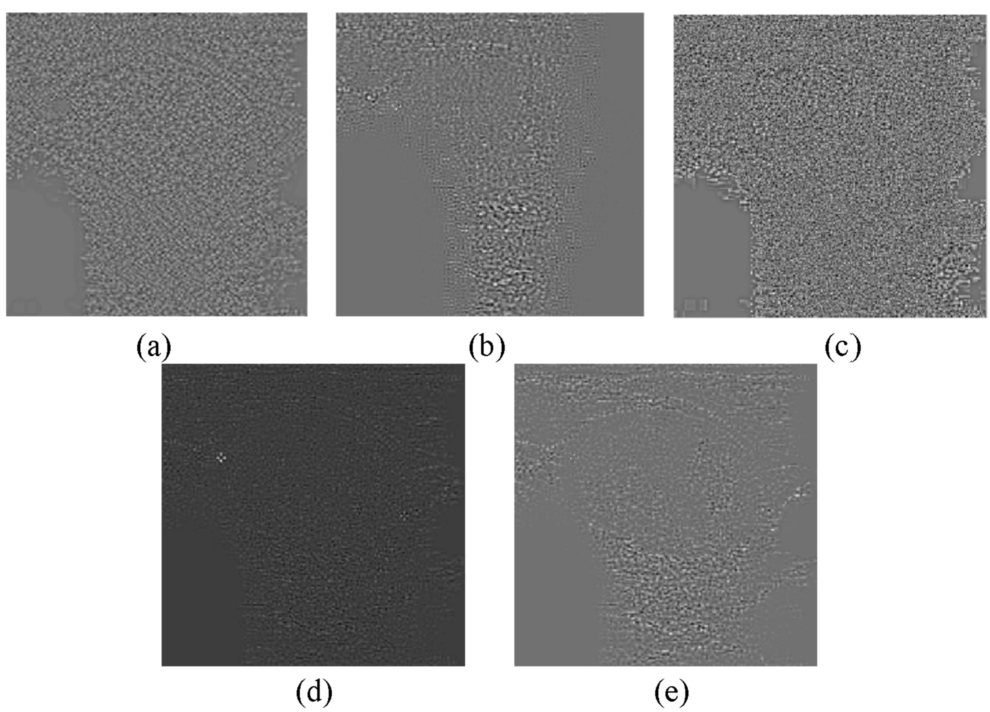

Fig. 10. Noise removed from the ultrasound thyroid image by implementing (a) GenLik, (b) SNIG I, (c) adaptive bilateral filter, (d) ATMAV, and (e) proposed adaptive fuzzy logic filter based on CV.

4. Conclusion

In this paper, an adaptive fuzzy logic filter based image denoising for speckle reduction in ultrasound images is proposed. This method is based on fuzzy logic. Adaptation to nature of image and quantity of noise in the image is done at two levels, namely detection and filtering. In detection stage, the image parameter Coefficient of Variation has been implemented. Based on this parameter each pixel is classified into three different classes. For each defined class, appropriate filter has been applied and speckle noise filtering is achieved. For edge preservation, adaptive weighted average filter is used based on relative difference of similarity measure. Experiments are conducted on artificially speckled images, Field II simulated image and for real ultrasound images. Through experiments, the proposed adaptive fuzzy logic filter method outperforms the existing techniques and retains important details for better diagnostics of ultrasound images. In this work, the values of CV and SSIM are dependent on image types and hence the algorithm adaptively changes the threshold value depending on nature of image and magnitude of noise in the image. Experimental studies indicate that proposed adaptive fuzzy logic filter using Coefficient of Variation and SSIM performs better in terms of SNR and Edge Preservation Index.

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