International Journal of Pure and Applied Mathematics
Volume 117 No. 20 2017, 773-784
ISSN: 1311-8080 (printed version); ISSN: 1314-3395 (on-line version)
url: http://www.ijpam.eu
Special Issue
ijpam.eu

Fuzzy Application Based Despeckling Algorithm for Ultrasound Images

[1]P. Nageswari, [2]S. Rajan and [3]K. Manivel

[1]Department of Mathematics,
Erode Arts and Science College,
Erode, Tamilnadu, India.

[2]Department of Mathematics,
Erode Arts and Science College,
Erode, Tamilnadu, India.

[3]Department of ECE,
Mahendra Engineering College,
Namakkal, Tamilnadu, India.

Abstract

The speckle noise removal is an essential preprocessing step in medical image processing. In this paper, fuzzy rules based algorithm is proposed for despeckling the ultrasound images. The proposed algorithm consists of two levels. In the first level, image areas are classified into three different regions by applying fuzzy rules on the normalized image. In the second level, the proposed algorithm adaptively uses suitable filtering techniques for filtering the classified pixels of the normalized image. Experimental results indicate the development over other existing filtering techniques for speckle noise removal in an ultrasound image.

Key Words: Fuzzy logic, speckle noise, normalization, membership function.

1. Introduction

Medical image processing is used to generate human body images for the purposes of clinical or medical science. Techniques such as Ultrasound imaging, magnetic resonance imaging, computed tomography scan and X- ray are acts as a powerful tool in medical imaging. Among these techniques, Ultrasound imaging is considered as the most important one. A major advantage of Ultrasound imaging is that its waves are not dangerous for the human body. However, the poor image quality is the main drawback in Ultrasound imaging. This is due to the fact that it is suffered by a particular kind of noise called speckle. Hence, diagnose and analyze of speckle corrupted image is very difficult for a physician. Therefore, detecting and filtering of speckle noise is an important preprocessing stage in Ultrasound imaging.

2. Related Works

Nowadays, different types of methods have been presented for the speckle reduction in Ultrasound images. Based on local statistics, spatial domain filters for Ultrasound images have been presented by [1-3]. These filters effectively reduce the speckle noise in the homogeneous region however, they are failed to detect the speckle noise present near to edge like regions. Similarly based on heat equation, anisotropic diffusion has been developed by [4]. This method performs well for additive noise removal, but it makes poor performance for the removal of multiplicative speckle noise. [5] Introduced a speckle reduction an isotropic diffusion for Ultrasound imaging. This method used the ratio of local standard deviation to mean for defining the diffusion coefficient. Homomorphic filtering based speckle reduction method has been proposed by [6]. In this method, wavelet coefficients are modeled as a non Gaussian model. [7] Presented an algorithm for the speckle reduction in Ultrasound imaging. This algorithm works well for preserving image edges; however, it enhanced the edges by restraining diffusion crosswise edges. A Bayesian maximum aposteriori probability based wavelet thresholding method has been proposed in [8]. In this method, the noise free signal coefficient and the noisy coefficients are modeled by using symmetric normal inverse Gaussian and Gaussian distribution. By using this modification a threshold value is acquired for denoising the speckle Ultrasound images.

Nowadays, fuzzy techniques are used in different areas but they are widely used for removing speckle noise in synthetic aperture radar images and medical images. These techniques can efficiently handle the ambiguity and vagueness present in the images. Fuzzy logic can easily manage the human information as fuzzy if then rules. The filters based on fuzzy rules are providing an alternative solution for the classical logical system [9]. Most of the fuzzy-based filters are used to remove impulse noise in digital images. An adaptive fuzzy filter for impulse detection has been introduced by [10]. Fuzzy two-step filter and fuzzy impulse noise detection and reduction method are proposed in [11, 12] for impulse noise pixels. Different fuzzy technique based methods have been also developed for speckle noise images. Fuzzy logic based speckle reduction in synthetic radar images has been proposed by [13]. However, this technique is suitable only for filtering noise in homogeneous regions. Mean and median based triangular fuzzy filters have been developed in [14, 15]. However, these mean and median-based filters are not performs well in case of edge preservation. Local gradient based fuzzy filter is introduced in [16] for enhancement of ultrasound images. This filter used fuzzy if -then rules for classifying the image pixels as edge, noisy and homogeneous regions. Though, this method takes a lot of iterations to establish the similarity window. A non local means algorithm is proposed in [17] for Ultrasound images. In this technique, initially the noise free pixels are estimated by using maximum likelihood estimator. After that the non local means algorithm is applied for restoring the image details. Nevertheless, the optimization of noise variance parameters is difficult due the fact that these parameters are directly linked with exponential function in the proposed algorithm. Topological derivative based algorithm has been developed in [18]. This proposed algorithm performs well for speckle reduction, but it takes much computational time for improving the contrast of the image.

3. Proposed Method

Different types of despeckling filters have been considered to remove noise in ultrasound images. But these filters are not able to differentiate edge facts, noise and to protect the significant details present in the image. This is the main drawback of these existing filters. Hence, a new algorithm based on fuzzy rules is proposed for speckle reduction in ultrasound images. Initially, the range of image pixel intensity values are normalized and then fuzzy rules are applied to the normalized image for classifying the image regions into three different regions such as low, medium and high affected regions. Finally, the proposed algorithm adaptively chooses the suitable filter for filtering the classified pixels.

Normalization

Normalization is a process that changes the range of pixel intensity values between [0,255]. Generally, high pixel intensity values of the normalized image correspond to the high affected or edge region and low pixel intensity values correspond to the low affected or homogeneous region. Also the in-between values of the normalized image belong to medium affected or detail region. On the basis of this principle, the noisy pixels belong to the normalized image are classified into high, medium and low. Let X (m, n) is an observed speckle noise ultrasound image with size P×Q. Then the normalization of X (m, n) is represented as N[X (m, n)] and is given by

$$N[X(m,n)] = \frac{X(m,n) - X_{min}}{X_{max} - X_{min}} \times 255$$

Where, X_{max} and X_{min} are the maximum and minimum intensity values of the original observed image. X (m, n) is the intensity value of the pixel (m, n).

Defining Membership Functions

During the process of image filtering, the noisy pixels cannot be removed, as it is widen over all in an image. Hence, the degree of membership has been defined in a fuzzy system by using the fuzzy membership function. Gaussian membership function is one of the most used membership function in ultrasound images. So, it is used to map the normalized image into the fuzzy domain.

$$\mu_{mf}^{k}(z) = \exp\left[-(z - r_k)^2 \big/ 2\sigma_k^2 \right], \quad k = 1,2 \text{ and } 3.$$

In the above equations, μ^k_{mf} is the fuzzy set for the group of pixels with size K×K. r_k and σ_k^2 are the mean and variance of three different regions in the noisy image. Next, the threshold values p, q, r are calculated for defining three different regions such as high, medium and low. The values of p, q, and r are given by

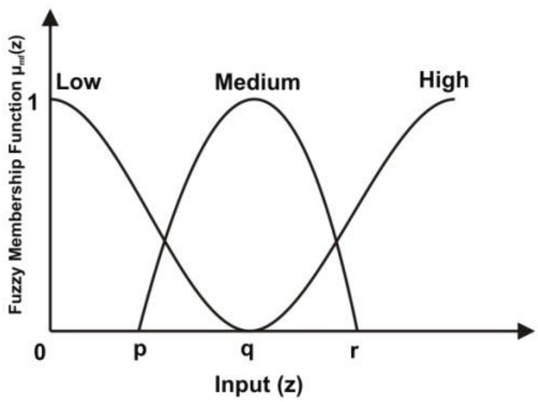


Figure 1: Fuzzy Membership Function

$$\mu_{mf}^{k} = \begin{cases} \text{low} & \text{if } z < q \\ \text{medium} & \text{if } z \geq p\ , z \leq r \\ \text{high} & \text{if } z > q \end{cases}$$

Where p = maximum intensity value of $N[X(m,n)]$

r = maximum value of $G[N(X(m,n))]$, G is the gradient value.

$$q = \frac{p+r}{2}$$

The threshold value ‘p’ is determined by the concept that the low pixel intensity values correspond to uniform or the low affected region. Note that the gradient calculation is effective in differentiating edges. So the value of ‘r’ is determined by the gradient of the normalized image. The threshold ‘q’ is determined as the mean of p, r. Hence, the variation in threshold values and classification of noisy pixels were depends upon the various levels of noise included in the image. Figure 1 shows the fuzzy membership function for the low, medium and high regions. Table 1 and figure 2 gives the computed threshold values and fuzzy membership function for pepper and boat in lake images for 0.7 noise level.

Table 1: Threshold Values for the Gaussian Membership Function

Image	Noise level	Parameter		
		p	q	r
Pepper	0.7	0.0874	0.1647	0.3213
Boat in lake	0.7	0.0854	0.1687	0.3416

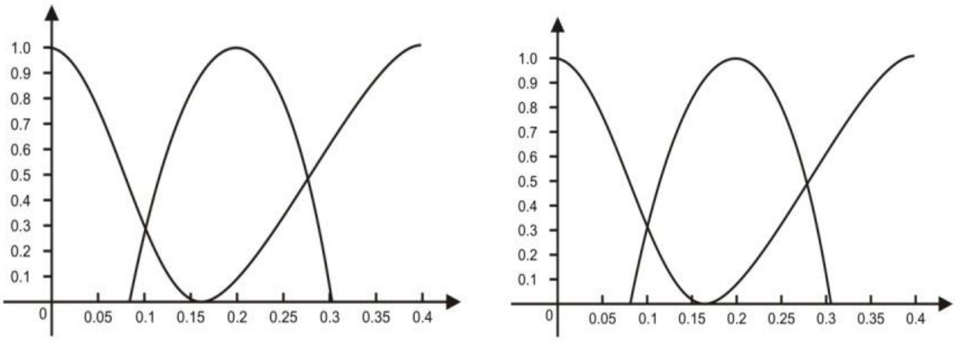


Figure 2: Fuzzy Membership Function (a) Pepper Image (b) Boat in Lake Image

Fuzzy Rules for Classification of Noisy Pixels

Fuzzy rules are used for classification of the noisy pixel as high, medium and low affected region. 'Large' and 'Small' denotes the membership function degree in each class. The rules are defined as follows.

$$FR_1 = \mathrm{Large}(\mu_{mf}^1).\ \mathrm{Large}(\mu_{mf}^2).\ \mathrm{Small}(\mu_{mf}^3)$$
$$FR_2 = \mathrm{Large}(\mu_{mf}^1).\ \mathrm{Small}(\mu_{mf}^2).\ \mathrm{Small}(\mu_{mf}^3)$$
$$FR_3 = \mathrm{Small}(\mu_{mf}^1).\ \mathrm{Small}(\mu_{mf}^2).\ \mathrm{Large}(\mu_{mf}^3)$$
$$FR_4 = \mathrm{Small}(\mu_{mf}^1).\ \mathrm{Large}(\mu_{mf}^2).\ \mathrm{Large}(\mu_{mf}^3)$$
$$FR_5 = \mathrm{Small}(\mu_{mf}^1).\ \mathrm{Large}(\mu_{mf}^2).\ \mathrm{Small}(\mu_{mf}^3)$$

In the above rules, the product inference mechanism is employed to recognize the fuzzy reasoning. The use of fuzzy rules is reduced to five for ignoring the computational complexity of the proposed method. Within this rules, the proposed technique efficiently differentiate the noisy pixels as three different regions. The following three cases are continued after obtaining all FR_m, m=1, 2, 3, 4, 5.

Filtering Process for Classified Pixels

Case (i)

If FR_2 occurs, the noisy pixel present in the homogeneous or low affected region. A smoothening filter is simply enough for filtering the pixels which are classified as homogenous. It takes the average value of pixels in a window of size $(2M+1)\times(2M+1)$ and is given by

$$F(m,n)=\frac{\sum_{u=-M}^{M}\sum_{v=-M}^{M} N[X(m+u,n+v)]}{(2M+1)^2}$$

Where m is an integer.

Case (ii)

If FR_1, FR_5 occurs, the noisy pixel present in detail or the medium affected region. An average filter is not sufficient for filtering the pixels which are differentiated as detail. Because the image structural facts were required to be protect. Hence, the standard median filter is defined for the window of size $(2M+1)\times(2M+1)$ and is given by

$$F(m,n)=MED\left[N(m+u,n+v)\right]$$

Where M is an integer and $-M \le (u, v) \le M$.

Case (iii)

If FR_3, FR_4 occurs, the noisy pixel present in the edge or high affected region. By using the fuzzy inference mechanism, the pixels with maximum intensity values are grouped as edges. Hence, an efficient filter is required for filtering the noisy pixel and for edge preservation without changing the unique fact of the image. A modified adaptive weighted filter is designed and denoted by

$$F(m,n)=\frac{\sum_{u=-M}^{M}\sum_{v=-M}^{M} N[X(m+u,n+v)]\times W(m+u,n+v)}{\sum_{u=-M}^{M}\sum_{v=-M}^{M} W(m+u,n+v)}\times(1-W(m,n)+W(m,n)\times N[X(m,n)]$$

Where, $N[X(m,n)]$ and $[X(m+u,n+v)]$ are the centre pixel and its neighboring pixel in a window of size $(2M+1)\times(2M+1)$, $W(m,n)$

Represents the weight corresponds to every pixel in that window. Finally, we obtained the denoised image $\hat{F}(m,n)$.

Algorithm for the Proposed Method

Classification of noisy input pixels

(i) Compute normalization $N[X(m,n)]$ for the observed $X(m, n)$ of size P×Q.

(ii) Calculate the threshold values p, q, and r.

(iii) Compute membership function degree μ_{mf}^{K} to three different regions.

(iv) By using fuzzy rules, classify the pixels in fuzzy domain as low, medium and high effected regions.

Filtering process for classified pixels

(v) For r = 1: P
{
For s = 1: Q
{
if $N[X(m, n)]$ in the low affected region
{

$$F(r, s) = \sum_{u=-M}^{M} \sum_{v=-M}^{M} \frac{N[X(r+u, s+v)]}{(2M+1)^2}$$

}
else if $N[X(m, n)]$ in the medium affected region
{

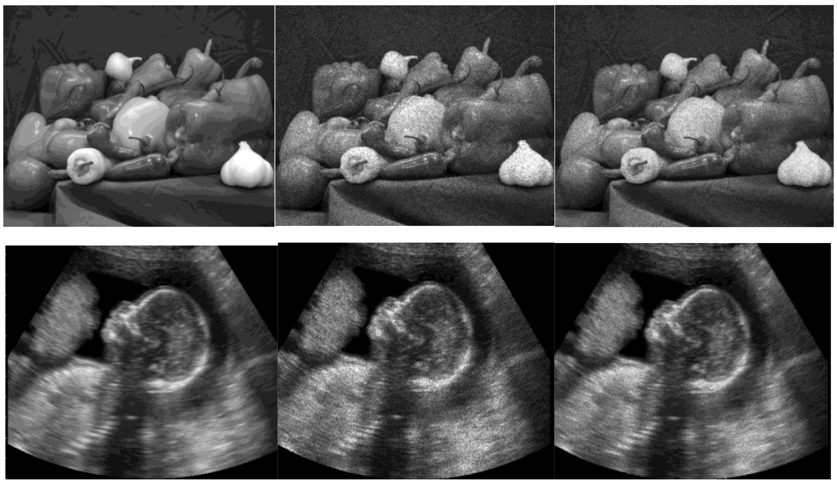
$$F(r, s) = MED[N(r+u, s+v))]$$

}
else if $N[X(m, n)]$ in the high affected region
{

$$F(r,s) = \frac{\sum_{u=-M}^{M} \sum_{v=-M}^{M} N[X(r+u, s+v)] \times W[r+u, s+v]}{\sum_{u=-M}^{M} \sum_{v=-M}^{M} W(r+u, s+v)} \times (1 - W(r, s)) + W(r,s) \times N[X(r,s)]$$

}
}
}

(vi) Obtain the denoised image $\hat{F}(m, n)$.



(a) (b) (c)

Figure 3: (a) Noise Free Pepper and Ultrasound Fetal Image, (b) Noisy Image of Noise Standard Deviation 0.5 and (c) Denoised Image Obtained by using Proposed Method

4. Experimental Results

The proposed images were adopted as the trial images with 50% speckle noise. The performance of the proposed method fuzzy based speckle noise reduction method is implemented in MATLAB12 and experimental results are presented. The well-known pepper image and ultrasound fetal image is evaluated by the following parameters such as the signal to noise ratio (SNR) and Structural Similarity Index Measure (SSIM) and is given as

$$\text{SNR} = 10\log_{10}\left(\frac{\sigma_N}{\sigma_D}\right)$$

$$\text{SSIM} = l\left[N(x(m,n)),\hat{F}(m,n)\right].C\left(N(x(m,n)),\hat{F}(m,n)\right).S\left(N(x(m,n)),\hat{F}(m,n)\right)$$

Here, σ_N denotes the variance of noise free input image, and σ_D denotes the variance of the error in the denoised image ie., D = $N(x(m,n))-\hat{F}(m,n)$. Also, $S(\cdot)$, $C(\cdot)$ and $l(\cdot)$ are comparison functions of structure components, contrast, and luminance of the two images respectively. For more detail about SSIM, the reader is referred to [19]. Figure 3 shows the speckle noise removal ability of the proposed method when the standard deviation of the noisy image is equal to 0.5.In order to evaluate the capability of the proposed method, the experimental results were compared with different despeckling methods. The table 2 and table 3 show that the proposed method performs well than the other existing methods in terms of SNR and SSIM.

Table 2: Comparison of SNR Values for Various Despeckling Methods

Noise level/Method	**SNR**			
	σ **=0.1**	σ **= 0.2**	σ **= 0.4**	σ **= 0.8**
Noisy image	52.86	38.74	25.16	13.92
LEE Filtering Method	69.86	64.57	54.26	42.78
Anisotropic Diffusion Method	61.75	57.22	45.72	37.36
Fuzzy Anisotropic Diffusion Method	63.13	60.76	43.28	32.67
Non Local Means Method	63.56	61.84	47.18	37.63
Bayesian Non Local Mean Based Method	72.66	63.28	52.34	41.69
Proposed Method	75.36	69.25	57.32	47.38

Table 3: Comparison of SSIM Values for Various Despeckling Methods

Noise level/Method	**SSIM**			
	σ **= 0.1**	σ **= 0.2**	σ **= 0.4**	σ **= 0.8**
Noisy image	0.4632	0.2383	0.1734	0.1125
LEE Filtering Method	0.8917	0.7713	0.5032	0.3584
Anisotropic Diffusion Method	0.8982	0.6312	0.5011	0.3250
Fuzzy Anisotropic Diffusion Method	0.8256	0.6234	0.4358	0.2976
Non Local Means Method	0.7974	0.6213	0.3690	0.2074
Bayesian Non Local Mean Based Method	0.8995	0.7421	0.4977	0.3472
Proposed Method	0.9932	0.7957	0.5576	0.3981

Figure 4 and figure 5 shows the comparison of SNR and SSIM values for various despeckling methods with different noise levels.

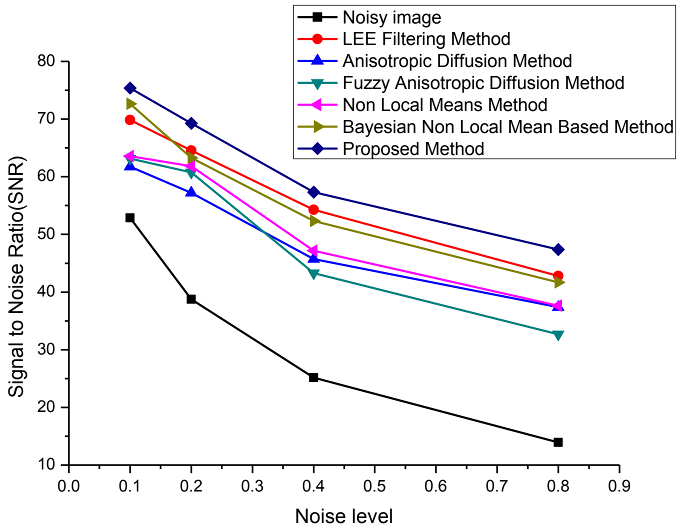


Figure 4: Graphical Representation of Comparison of SNR Values between the Proposed Method and other Existing Methods at Different Noise Levels

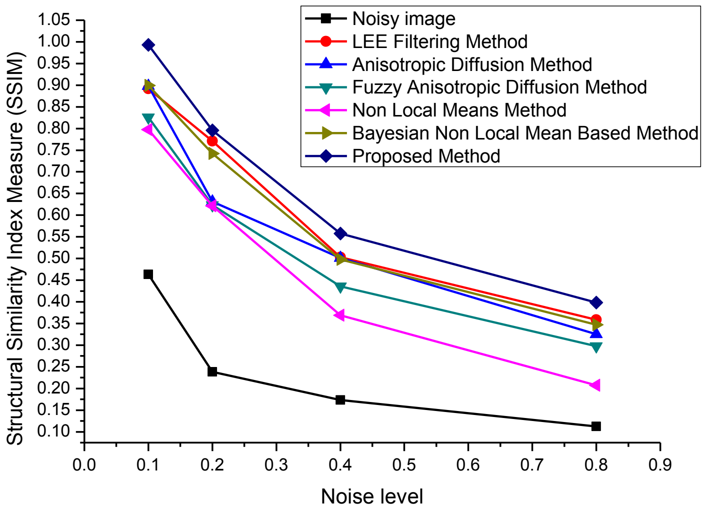


Figure 5: Graphical Representation of Comparison of SNR Values Between the Proposed Method and other Existing Methods at Different Noise Densities

5. Conclusion

In this paper, fuzzy based speckle noise reduction algorithm for ultrasound images is presented. The proposed algorithm has two levels. By using fuzzy rules, the normalized image areas are classified into three different regions in the first level. In the second level, for each different region, suitable filtering technique has been applied and despeckling image is achieved. Experimental results show that the proposed method performed well than the other existing methods in terms of SNR and SSIM.

References

[1] Lee J., Digital image enhancement and noise filtering using local statistics, IEEE Trans. Pattern Anal. Mach. Intell., 2 (2) (1980), 165–168.

[2] Frost V., Stiles J., Shanmugan K.S., Holtzman J., A model for radar images and its application to adaptive digital filtering of multiplicative noise, IEEE Trans. Pattern Anal. Mach. Intell., 4 (2) (1982), 157–166.

[3] Kuan D.T., Sawchuk A.A., Strand T.C., Chavel P., Adaptive noise smoothing filter with signal-dependent noise, IEEE Trans. Pattern Anal. Mach. Intell., 7 (2) (1985), 165–177.

[4] Perona P., Malik J., Scale-Space and edge detection using anisotropic diffusion, IEEE Trans. Pattern Anal. Mach. Intell., 12 (7) (1990), 629–639.

[5] Yu Y., Acton S.T., Speckle reducing anisotropic diffusion, IEEE Trans. Image Process., 11 (11) (2002), 1260–1270.

[6] Achim A., Bezerianos A., Tsakalides P., Novel Bayesian multi scale method for speckle removal in medical ultrasound images, IEEE Trans. Med. Imaging 20 (8) (2001), 772–783.

[7] Yong Y., Croitoru M.M., Bidani A., Zwischenberger J.B., John W.C., Nonlinear multi scale wavelet diffusion for speckle suppression and edge enhancement in ultrasound images, IEEE Trans. Med. Imaging 25 (3) (2006), 297–311.

[8] Bhuiyan M.I.H., Ahmad M.O., Swamy M.N.S., Spatially adaptive thresholding in wavelet domain for despeckling of ultrasound images, IET Image Proc., 3 (3) (2009), 147–162.

[9] Yager Ronald R., Lotfi A.Z., An Introduction to Fuzzy Logic Applications in Intelligent Systems, Kluwer Academic Publishers Norwell, MA, USA, (1992).

[10] Kam H.S., Tan W.H., Impulse Detection Adaptive Fuzzy (IDAF) filter, Int. Conf. Comput. Technol. Dev., 2 (2009), 355–359.

[11] Schulte S., De Witte V., Nachtegael M., Van Der W., Dietrich E.E.K., Fuzzy two-step filter for impulse noise reduction from color images, IEEE Trans. Image Process., 15 (11) (2006), 3567–3578.

[12] Schulte S., Nachtegael M., De Witte V., Van Der Weken D., Kerre E.E., A fuzzy impulse noise detection and reduction method, IEEE Trans. Image Process., 15 (5) (2006), 1153–1162.

[13] Cheng H., Tian J., Speckle reduction of synthetic aperture radar images based on fuzzy logic, in: First International Workshop on Education Technology and Computer Science, IEEE Computer Society, Wuhan, Hubei (2009), 933–937.

[14] Kwan H.K., Fuzzy filters for noise reduction in images, in: Fuzzy Filters for Image Processing, Springer, Berlin Heidelberg, Germany (2003), 25–53.

[15] Kwan H.K., Cai F.Y., Fuzzy filters for image filtering, in: In the 45th Midwest Symposium on Circuits and Systems 3 (2002), 672–675.

[16] Binaee K., Hasanzadeh R.P.R., An ultrasound image enhancement method using local gradient based fuzzy similarity, Biomed. Signal Process. Control 13 (2014), 89–101.

[17] Guo Y., Wang Y., Hou T., Speckle filtering of ultrasonic images using a modified non local-based algorithm, Biomed. Signal Process. Control 6 (2011), 129–138.

[18] Damodaran N., Ramamurthy S., Velusamy S., Manickam G.K., Speckle noise reduction in ultrasound biomedical b-scan images using discrete topological derivative, Ultrasound Med. Biol. 38 (2) (2012), 276–286.

[19] Hore A., Ziou D., Image quality metrics: PSNR vs. SSIM, in: International Con-ference on Pattern Recognition (ICPR) (2010), 2366–2369.