FUZZY-BASED BOUNDARY ENHANCEMENT FOR ECHOCARDIOGRAM USING LOCAL IMAGE CHARACTERISTICS

***Sheila Chan*[1], *Gopalakrishnan Sainarayanan*[2]**
[1] School of Engineering and Information Technology,
Universiti Malaysia Sabah, Locked Bag No. 2073, 88999 Kota Kinabalu, Sabah, Malaysia.
E-mail: sheilachan_oiyip@yahoo.com
[2] School of Engineering and Information Technology
Universiti Malaysia Sabah, Locked Bag No. 2073, 88999 Kota Kinabalu, Sabah, Malaysia.
E-mail: jgksai@ums.edu.my

ABSTRACT

Speckle noise and artifacts in echocardiogram may cause edges to manifest themselves in different manners. As a result, edges in echocardiogram are identified with ambiguous definitions and they pose challenges for conventional gradient approximations that typically characterize an edge as an abrupt change in gray-level. Therefore, an approach using fuzzy reasoning that works on a different notion from the typical edge definition is introduced to enhance the boundary of echocardiogram. The fuzzy reasoning employed in the proposed method defines edges by local image characteristics computed based on local statistics of the image. The proposed method addresses the challenge in two levels. Initially, noise suppression is applied without incurring over-blurring across the boundaries. Subsequently, fuzzy reasoning is employed to determine the edginess of each pixel of the enhanced echocardiogram to detect the boundaries. For performance measure, the results of the proposed method are compared to that of a conventional method, qualitatively and quantitatively.

***Keywords:* Boundary enhancement, Echocardiogram, Edge detection, Noise suppression, Fuzzy reasoning, and Local image characteristics.**

1.0 INTRODUCTION

Ultrasound imaging allows direct visualization of the heart in motion. Image sequences of standard cross-sectional views through the heart provide insight of the functional performance of different segments of the left ventricular wall. It is widely recognized that quantitative analysis of echocardiogram is preferable over qualitative interpretation, in particular for wall motion and volume estimation [1].

However, artifacts such as speckle, grating lobes, and shadowing that are caused by some degradation factors in ultrasound can hamper human interpretation and impede automated analysis. Speckle is the interference pattern resulting from constructive and destructive interference of echoes returning simultaneously from many scatterers within the propagating ultrasound pulse at any instant that gives ultrasound a grainy appearance [2]. Grating lobes are additional beams emitted from an array transducer that are stronger than the side lobes of individual elements. When grating lobes encounter a strong reflector (e.g. bone or gas), their echoes may well be imaged and appear at incorrect locations [2]. Shadowing is the reduction in echo amplitude caused by reflectors that lie behind a strongly reflecting or attenuating structure such as calcified plaque and bone. A strongly attenuating or reflecting structure weakens the sound distal to it, i.e. the sound away from the structure, causing echoes from the distal region, i.e. the region away from the structure, to be weak and thus appear darker, like a shadow [2].

Artifacts in echocardiogram may cause edges to manifest themselves in different manners. As a result, edges in echocardiogram are identified with ambiguous definitions and they pose challenges for conventional gradient approximations that typically characterize an edge as an abrupt change in gray-level. Thus, classical edge detectors that are based on conventional edge definition to search for abrupt change in intensity do not work well on echocardiogram. Inadequacies of classical edge detectors such as Sobel and Prewitt operators on echocardiogram are shown in [3]. This problem has led researchers to develop various methods of noise suppression and edge detection for speckle tarnished images.

A common approach favored by some researchers is to use local image characteristics. Local image characteristics are defined by operators based on local statistics of the image. Since speckle noise is often modeled as being at least weakly multiplicative [4], edge detectors based on ratios may perform better than edge detectors that look for large derivative magnitude to determine gradient. The ratio of mean to variance is an example of local characteristic to measure the uniformity of an area in the adaptive-weighted median filter for speckle suppression in medical ultrasonic images introduced by Loupas et al. [5]. The algorithm is capable of applying smoothing based on local statistics, which is an improvement over the conventional block median filter. However, the method uses an operator with fixed size and shape which means two points at an equal distance from the central pixel receive identical weight. This characteristic can cause difficulty in enhancing features such as line segments [6].

Another example of local image characteristic is the ratio-of-averages (RoA). Bovik [7] proposed to use a RoA operator in conjunction with the LoG operator to detect edges in speckle imagery. The image gradient using the RoA operator is approximated by computing the root mean square (rms) value of the maximum ratio of neighborhood averages taken along two orthogonal directions. By applying the RoA edge detector only at the zero crossings on the LoG convolved image, the edge output corresponds well to detect step discontinuities in noisy images. However, this approach and the other conventional edge detectors are not suitable to detect the boundaries of ultrasonic images that typically appear as bright streaks between similar intensity regions, rather than demarcations regions of differing contrast [4].

Based on the conventional RoA edge detector proposed by Bovik [7], many more techniques have been derived for preserving edges and smoothing speckle noise such as the Modified RoA (MRoA) and Ratio-and-Gradient-of Averages (RGoA) edge detectors [8], the Maximum Strength Edge Pruning RoA (MSP-RoA) [9], and the modified RoA algorithm using improved Hough transform [10]. However, each of these methods has its drawback and limitation. The MRoA and RGoA methods tend to generate thick edge maps while the MSP-RoA introduced yet another parameter that must be determined by referring to a given image and defined carefully in order to get the best results [9]. Although the modified RoA algorithm using improved Hough transform performs relatively better than the conventional RoA algorithm in detecting linear features, it has to incur costly execution time due to the complex computation [10].

There are many other methods available, for examples, global thresholding, active contour model, and Markov random field (MRF). Ohyama et al. [11] proposed an automatic detection of left ventricular endocardium in echocardiogram using ternary thresholding method. The use of global thresholding in this method requires domain knowledge about the standard ultrasound images. Furthermore, global thresholds have been shown to be unstable because of noise and dropout from rib-shadowing [3]. Using a different approach, Chalana et al. [12] developed a boundary detection method on echocardiographic sequences by employing active contour model. Nevertheless, the algorithm requires manual initialization where a human operator is needed to identify the starting position for the contour. Another example is a method proposed by Hokland and Kelly [13] using MRF to restore medical ultrasound images. The algorithm is based on a statistical image model that includes descriptions of both diffuse scattering and specular reflectors, as well as spatial smoothness constraints implemented through a tissue-label MRF. However, this method is prone to noise modeling error which can cause the global scaling parameter to be wrongly estimated.

Therefore, a method employing fuzzy reasoning based on local image characteristics is proposed in this paper to enhance the boundaries of echocardiogram. By employing fuzzy reasoning, the proposed boundary enhancement method does not require any initialization and spares users from making tedious fine-tuning exercise via time-consuming trial-and-error (as would be required in fixed scale operators) to achieve satisfactory results. The proposed method also reduces trade-off between noise suppression, edge detection and edge localization that usually limits the performance of edge detectors that operate in fixed-scale space and depend on hard threshold value.

The next section describes the noise suppression employed in the proposed method. Section 3 provides the definitions for the local image characteristics employed in fuzzy reasoning. Subsequently, Section 4 describes the Fuzzy Inference System (FIS) employed in the proposed system. Finally, a comparison is made for the results obtained using the proposed method with that of a standard edge detector in Section 5.

2.0 NOISE SUPPRESSION

The proposed boundary enhancement method is comprised of two functions, i.e. noise suppression and edge detection. Fig. 1 shows the block diagram for the proposed boundary enhancement method for echocardiogram.

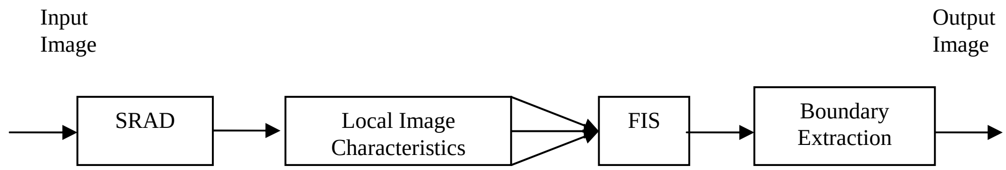


Fig. 1: The proposed boundary enhancement method for echocardiogram

Ultrasound images represent a very difficult and demanding application area for noise reduction algorithms because, although they are heavily corrupted by noise, they possess sharp contrast which should be retained. In addition, they contain structures such as small blood vessels with dimensions comparable to the average speckle size and, more importantly, boundaries between areas of slightly different gray-scale level which enable the physician to detect abnormalities such as tumors. Thus, linear filters are not suitable for this type of images because they introduce severe blurring and loss of diagnostically significant information [5].

Therefore, in the proposed method, Speckle Reducing Anisotropic Diffusion (SRAD) introduced by Yu and Acton [14] is employed for initial noise suppression. SRAD [14] uses an operator, namely the instantaneous coefficient of variation (ICOV), which is a function of the local gradient magnitude and Laplacian operators to reduce speckle noise. Using an approach analogous to heat conduction process, SRAD is able to reduce the inevitable trade-off between edge detection and edge localization that comes from using linear filtering. The nonlinear filter also encourages intra-region smoothing in preference to inter-region smoothing, thus preserving edges and suppressing noise efficiently.

Given an intensity image $I_0(x,y)$ having finite power and no zero values over the image support Ω, the output image $I(x,y;t)$ is evolved according to the following PDE (partial differential equations):

$$\begin{cases} \partial I(x,y;t)/\partial t = div\left[c(q)\nabla I(x,y;t)\right] \\ I(x,y;0) = I_0(x,y) \quad , \quad \left(\partial I(x,y;t)/\partial\vec{\eta}\right)\Big|_{\partial\Omega} = 0 \end{cases} \tag{1}$$

where $\partial\Omega$ denotes the border of Ω and $\vec{\eta}$ is the outer normal to the $\partial\Omega$. The diffusion coefficient in SRAD is given as

$$c(q) = \exp\left\{-\left[q^2(x,y;t) - q_0^2(t)\right] / \left[q_0^2(t)\left(1+q_0^2(t)\right)\right]\right\} \tag{2}$$

or $$c(q) = \frac{1}{1+\left[q^2(x,y;t) - q_0^2(t)\right] / \left[q_0^2(t)\left(1+q_0^2(t)\right)\right]} \tag{3}$$

where Equation 2 privileges high contrast edges over low contrast ones while Equation 3 privileges wide regions over smaller ones. Equation 2 is used throughout the proposed method. $q(x,y;t)$ is the ICoV determined by

$$q(x,y;t) = \sqrt{\frac{(1/2)\left(|\nabla I|/I\right)^2 - \left(1/4^2\right)\left(\nabla^2 I/I\right)^2}{\left[1+(1/4)\left(\nabla^2 I/I\right)\right]^2}} \tag{4}$$

and $q_0(t)$ is the speckle scale function approximated by

$$q_0(t) \approx q_0 \exp[-\rho t] \tag{5}$$

where ρ is a constant, and q_0 is the speckle coefficient of variation in the observed image. For fully developed speckle, $q_0 = 1$ for ultrasound intensity data and $\rho = 1/6$ [14].

3.0 DEFINITION OF LOCAL IMAGE CHARACTERISTICS

In the proposed method, local image characteristics “steepness” and “symmetry” are used to determine the image gradient. The local image characteristics are motivated from an existing edge detection method using fuzzy reasoning. The method proposed by Law et al. [15] to detect edges in images of real scenes (pictures of people, animals and sceneries) is modified in the proposed method to specifically detect edges in echocardiogram.

Consequently, some feature characterizations such as corner points and triple points (junctions) in [15] are not considered in the proposed method when evaluating edge fuzzy membership values because their appearance is not common in the echocardiogram boundaries of concern. Furthermore, the edge tracing and assembly procedures in the final stage of Law’s method are found to be unsuitable for echocardiogram. The edge tracing algorithm in [15] compares the edginess of the pixel with the edginess of its two neighboring pixels according to the direction of the edge. When applied on echocardiogram, Law’s edge tracing algorithm produces severely fragmented edge segments. And in turn, connection in the final structure assembly encounters difficulties because the tracing procedure fails to produce a decent and basic edge skeleton.

Similar to the gradient notion in [15], the gradient magnitude of the pixel concern, i.e. the pixel (x, y) in the center of the 3X3 window in Fig. 2, is determined by the characteristics of two neighboring regions on both sides of edge direction crossing the center pixel (x, y).

(x-1,y+1)	(x,y+1)	(x+1,y+1)
(x-1,y)	(x,y)	(x+1,y)
(x-1,y-1)	(x,y-1)	(x+1,y-1)

Fig. 2: A 3X3 window for steepness and symmetry evaluation

Pixels that lie directly on the crossing of each steepness component are ignored to disregard noise effect as much as possible. For example, in Fig. 2, pixels (x,y+1) and (x,y-1) are ignored when calculating the horizontal component of steepness for pixel (x,y). Likewise, pixels (x-1,y) and (x+1,y) are ignored when calculating the vertical component of steepness. Thus, the horizontal component of steepness takes the absolute difference given as

$$S_h(x, y) = |R(x, y) - L(x, y)| \tag{6}$$

where $R(x, y)$ and $L(x, y)$ are the average intensity values of neighborhoods immediately to the right and left of pixel (x,y) respectively. The value of steepness used for fuzzy reasoning is estimated by

$$S(x, y) = \left[S_h^2(x, y) + S_v^2(x, y)\right]^{1/2} \tag{7}$$

where S_v is the corresponding vertical component of steepness $S(x, y)$.

Likewise, symmetry is measured by horizontal and vertical components also. In a 3X3 window, there are only two pairs of pixels to be compared for each component. For example, along the horizontal steepness track, the corresponding symmetry component compares pixel (x-1,y+1) and (x-1,y-1) in one pair and pixels (x+1,y+1) and (x+1,y-1) in the other. The symmetry component is thus the sum of absolute differences of both pairs. To make the sum a positive value which increases with symmetry, it is subtracted from the largest possible value.

$$M_h(x, y) = M_{\max} - \sum_{i=1}^{2} P_i(x, y) \tag{8}$$

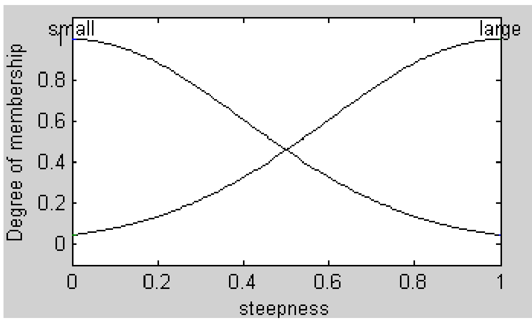
where $M_h(x, y)$ is the horizontal symmetry component and $P(x, y)$ is the absolute difference of a pixel pair in comparison. The overall value of symmetry taken for fuzzy reasoning is approximated by

$$M(x,y) = \left[M_h^2(x,y) + M_v^2(x,y)\right]^{1/2} \tag{9}$$

where $M_v(x,y)$ is the corresponding vertical component of symmetry $M(x,y)$.

4.0 EDGE DETECTION USING FUZZY REASONING

The fuzzy inference system (FIS) in the proposed system employs the Mamdani model. The Mamdani-type inference is implemented using Matlab [16]. For each fuzzy input, two Gaussian membership functions are assigned, i.e. small and large for steepness, and low and high for symmetry. Fig. 3 shows the input and output membership functions employed in the FIS.



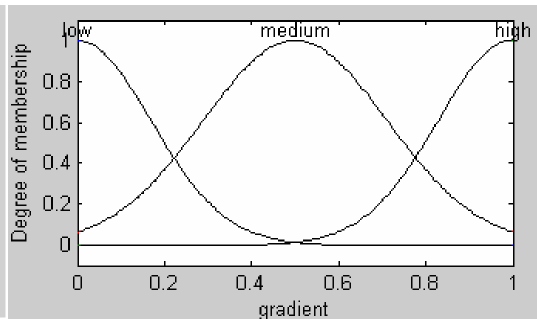


Fig. 3 (a): Input membership function Fig. 3 (b): Output membership function

The fuzzy If-Then rules employed in the proposed system are shown in Table 1. The fuzzy operator used for the antecedents is "And" which applies the minimum function. The output of the fuzzy system is obtained via centroid defuzzication.

Table 1: FIS input/output of the proposed method

Input 1 **Steepness**	**Input 2** **Symmetry**	**Output** **Gradient**
Small	Low	Low
Small	High	Low
Large	Low	Medium
Large	High	High

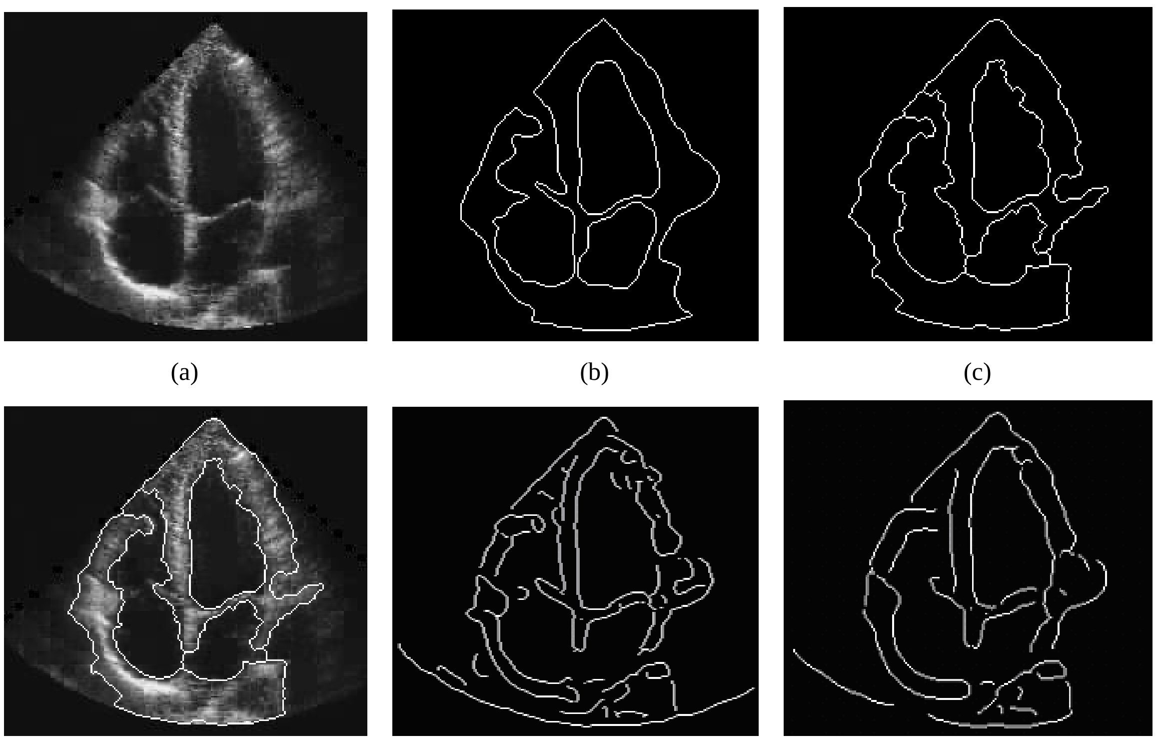
Finally, the output from the FIS is channeled through the final component of the proposed system for boundary extraction. The procedures for boundary extraction follow the sequence of intensity adjustment, hysteresis thresholding, morphological reconstruction, thinning, perimeter determination, and spur-edges removal. All operations and values of thresholds are determined empirically and remain constant for all test data.

5.0 COMPARISON OF RESULTS

This section analyzes the performance of the proposed method, qualitatively and quantitatively, by comparing the results to that of a standard operator, i.e. the Canny edge detector. The Canny edge images are obtained using Matlab [17]. Twenty images which form four sets of test data (five images per data set) from three echocardiogram videos are used for the comparison. Ten sequential images are extracted from the first video and five sequential images from the second and third video respectively. Fig. 4 shows the results of a particular frame chosen arbitrarily from the data sets for qualitative comparison.

The results are compared quantitatively using Pratt's Figure of Merit (FOM) [18]. FOM ranges between 0 and 1, with unity for ideal edge detection. The FOM computations are based on comparison with the desired edge images generated manually using computer graphic tools. FOM is taken from the average reading of 5 sequential images of each data set.

The Canny edge images are obtained by using hysteresis thresholding where the low threshold is set empirically as 40% of the high threshold. Generally, the results using higher σ value ($\sigma = 3$) show less noise, reasonable edge detection and better edge linking compared to lower σ value ($\sigma = 2$), as can be seen in Fig. 4(e) and Fig. 4(f). The parameter σ is the standard deviation of the Gaussian function in Canny edge detector. The results of higher σ value are also favored by better FOM measurement. Table 2 tabulates the average FOM readings obtained using the Canny edge detector and the proposed system. Therefore Canny edge image of higher σ value ($\sigma = 3$) serves as a better comparison to the proposed method.



(a) (b) (c)

(d) (e) (f)

Fig. 4: (a) Raw echocardiogram, (b) desired edge image generated using computer graphic tool, (c) boundary detected using the proposed method, (d) boundary detected using the proposed method superimposed on the raw echocardiogram, (e) Canny edge image ($\sigma = 2$) and (f) Canny edge image ($\sigma = 3$)

Table 2: Average FOM for quantitative comparison

Data set (5 in each set)	**Average FOM**		
	Canny edge detector ($\sigma = 2$)	**Canny edge detector ($\sigma = 3$)**	**Proposed system**
Data set 1	0.60635	0.67481	0.71022
Data set 2	0.56320	0.64588	0.72258
Data set 3	0.46675	0.52740	0.73537
Data set 4	0.38894	0.46935	0.54342

It can be seen that the proposed system in Fig. 4(c) produced results with closer representation to the desired edge image in Fig. 4(b). The output of the proposed method in Fig. 4(c) is superimposed on the raw echocardiogram in Fig. 4(d) to view how well the detected boundary matches the actual boundaries. Furthermore, the results of the proposed method have better edge linking and less false edges compared to the Canny edge images. From the calculated FOM, the proposed boundary enhancement method also shows better average measurement for all data sets.

5.1 Recommendations for Improvements in Future Works

Although the proposed method produced results with better representation and improved FOM measurement, the edges detected by the proposed method are not as smooth as the Canny edge output. The less smooth edges may be caused by the small window size (3X3) employed in the proposed method in evaluating the local statistics. Therefore, a larger window size (5X5 or 7X7) may be employed to improve the smoothness of the boundaries detected. However, using a larger window to compute the local image characteristics may implicate heavier computations.

Nevertheless, the proposed approach is versatile and holds potentials for further developments. For example, the fuzzy system in the proposed method may be replaced with a neuro-fuzzy system such as the Adaptive Neuro-Fuzzy Inference System (ANFIS) [19]. The modification allows the recommended method to adapt to the desired output with its learning capabilities while retaining simple computation based on a small window size.

Furthermore, by employing a fuzzy-based approach, the proposed method is automated and requires no initialization. And the proposed method does not have to tolerate bias that may result from variability between observers. This may also be achieved in the recommended modification aforementioned by using training images generated by different observers.

6.0 CONCLUSION

By employing fuzzy reasoning based on local image characteristics, a method that is able to handle ambiguous edge definitions attributed to inherent noise and artifacts has been proposed for echocardiogram boundary enhancement. The proposed method is user-friendly because it does not require constant fine-tuning and time-consuming manual initialization. The boundaries detected by the proposed method are also well-linked. Moreover, the proposed approach is flexible and holds potentials for further developments. Although the proposed method has shown favorable results thus far, qualitatively and quantitatively, edge localization and boundary smoothness need to be improved. For future work, a neuro-fuzzy system with learning capabilities may be employed to optimize the proposed method.

REFERENCES

[1] J. G. Bosch, S. C. Mitchell, B. P. F. Lelieveldt, F. Nijland, O. Kamp, M. Sonka, and J. H. C. Reiber, “Automatic Segmentation of Echocardiographic Sequences by Active Appearance Motion Models,” *IEEE Trans. Medical Imaging*, Vol. 21, No. 11, 2002, pp. 1374-1383.

[2] F. W. Kremkau, *Diagnostic Ultrasound: Principles and Instrument*, ed. 6, London, W.B. Saunders Com, 2002.

[3] J. Manivannan, M. R. Reddy, S. Thanikachalam, and R. Varghese, “Endocardial Edge Detection by Fuzzy Inference System,” in *Proceeding of IEEE TENCON 2003, Conference on Convergent Technologies for the Asia-Pacific Region*, Bangolore, 2003, pp. 3–5.

[4] R. N. Czerwinski, D. L. Jones, and W. D. Jr. O’Brien, “An Approach to Boundary Detection in Ultrasound Imaging,” in *IEEE Ultrasonics Symposium*, Baltimore, MD, 1993, pp. 951-955.

[5] T. Loupas, W. N. McDicken, P. L. and Allan, “An Adaptive Weighted Median Filter for Speckle Suppression in Medical Ultrasonic Images,” *IEEE Trans. Circuits and Systems*, Vol. 36, No. 1, 1989, pp. 129-135.

[6] R. N. Czerwinski, D. L. Jones, and W. D. Jr. O'Brien, "Ultrasound Speckle Reduction by Directional Median Filtering," in *Proceeding of International Conference on Image Processing*, Washington, D. C, 1995, pp. 358-360.

[7] A. C. Bovik, "On Detecting Edges in Speckle Imagery," *IEEE Trans Acoustics, Speech, and Signal Procesing*, Vol. 36, No. 10, 1988, pp. 1618-1627.

[8] M. R. Zaman and C. R. Moloney, "A Comparison of Adaptive Filters For Edge-Preserving Smoothing of Speckle Noise," in *IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, Minneapolis, USA, 1993, pp. V77-80.

[9] S. S. Ganugapati and C. R. Moloney, "A Ratio Edge Detector for Speckle Images Based on Maximum Strength Edge Pruning," in *Int. Conf. Image Processing (ICIP'95)*, Washington, DC, USA., 1995, pp. 165-168.

[10] H. Sun, F. Su, and Y. Zhang, "Modified Algorithm Applied to Extract Linear Features in SAR Images," in *1st International Symposium on Systems and Control in Aerospace and Astronautics (ISSCAA)*, Harbin, China, 2006, pp. 1209-1213.

[11] W. Ohyama, T. Wakabayashi, F. Kimura, S. Tsuruoka, and K. Sekioka, "Automatic Left Ventricular Endocardium Detection in Echocardiograms Based on Ternary Thresholding Method," in *15th International Conference on Pattern Recognition (ICPR'00)*, Barcelona, Spain, 2000, pp. 320-323.

[12] V. Chalana, D. T. Linker, D. R. Haynor, and Y. Kim, "A Multiple Active Contour Model for Cardiac Boundary Detection on Echocardiographic Sequences," *IEEE Trans. Medical Imaging*, Vol. 15, No. 3, 1996, pp. 290-298.

[13] J. H. Hokland and P. A. Kelly, "Markov Models of Specular and Diffuse Scattering in Restoration of Medical Ultrasound Images," *IEEE Trans Ultrasonics, Ferroelectrics, and Frequency Control*, Vol. 43, No. 4, 1996, pp. 660-669.

[14] Y. Yu and S. T. Acton, "Speckle Reducing Anisotropic Diffusion," *IEEE Trans Image Processing*, Vol. 11, No. 11, 2002, pp. 1260-1270.

[15] T. Law, H. Itoh, and H. Seki, "Image Filtering, Edge Detection, and Edge Tracing using Fuzzy Reasoning," *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 18, No. 5, 1996, pp. 481-491.

[16] The MathWorks, Inc., *Fuzzy Logic Toolbox User's Guide*, 2006.

[17] The MathWorks, Inc., *Image Processing Toolbox User's Guide*, 2005.

[18] A. K. Jain, *Fundamentals of Digital Image Processing*, New Jersey, Prentice-Hall, Inc., 1989.

[19] J-S. R. Jang, "ANFIS: Adaptive-Network-Based Fuzzy Inference System," *IEEE Trans. Systems, Man, and Cybernetics*, Vol. 23, No. 3, 1993, pp. 665-685.

BIOGRAPHY

Sheila Chan received her B. Eng degree in Electrical and Electronics Engineering in Universiti Malaysia Sabah (UMS), Malaysia, in 2002. Currently, she is a master student in the School of Engineering and Information Technology, UMS. Her research is focused on medical image processing.

Gopalakrishnan Sainarayanan is currently a lecturer in the field of Electrical and Electronics Engineering in Universiti Malaysia Sabah, Malaysia. He received his B.E., M.E., and Ph.D. degrees, respectively, from Annamali University, India, Bharathiar University, India, and Universiti Malaysia Sabah, Malaysia, in 1998, 2000, and 2002. His research interests are in the areas of vision rehabilitation, medical imaging and intelligent control.