Novel Genetic-Neuro-Fuzzy Filter for Speckle Reduction from Sonography Images

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Edge-preserving speckle noise reduction is essential to computer-aided ultrasound image processing and understanding. A new class of genetic-neuro-fuzzy filter is proposed to optimize the trade-off between speckle noise removal and edge preservation. The proposed approach combines the advantages of the fuzzy, neural, and genetic paradigms. Neuro-fuzzy approaches are very promising for nonlinear filtering of noisy images. Fuzzy reasoning embedded into the network structure aims at reducing errors while fine details are being processed.

The learning method based on the real-time genetic algorithms (GAs) performs an effective training of the network from a collection of training data and yields satisfactory results after a few generations. The performance of the proposed filter has been compared with that of the commonly used median and Wiener filters in reducing speckle noises on ultrasound images. We evaluate this filter by passing the filter's output to the edge detection algorithm and observing its ability to detect edge pixels.

Experimental results show that the proposed genetic-neuro-fuzzy technique is very effective in speckle noise reduction as well as detail preserving even in the presence of highly noise corrupted data, and it works significantly better than other well-known conventional methods in the literature.

KEY WORDS: Ultrasound, speckle, real-time genetic algorithm, neuro-fuzzy, genetic-neuro-fuzzy

ULTRASONOGRAPHY has been considered one of the most powerful techniques for imaging organs and soft tissue structures in the human body. It is often preferred to other medical imaging modalities because it is non-invasive, portable, and versatile, it does not use ionizing radiation, and it is relatively low-cost. However, the presence of random speckle noises, caused by the interference of reflected ultrasound wavefronts, makes computer-aided

ultrasound image processing and interpretation a difficult task. Such wavefronts appear when a coherent source and a noncoherent detector are used to interrogate a medium, which is rough on the scale of the wavelength. The main disadvantage of medical ultrasonography is the poor quality of images, which are affected by this multiplicative noise.¹⁻⁸ Thus, it seems necessary to remove speckle noise from the images prior to further processes such as feature extraction, analysis, and recognition from medical imagery measurements.

Multiple methods are used to remove speckle noise from ultrasound medical images. Linear filters such as mean filters are not suitable for the speckle noise of ultrasound images, because they eliminate the high frequencies and thereby tend to smooth out the image edges. Temporal averaging methods are effective for noise reduction, although tissue motion, caused by external force, and hard spatially object adjustment in multiimages are drawbacks of such method.^{3,4}

Median filters are among the best methods for accomplishing speckle reduction.⁹⁻¹⁶ The adaptive weighed median filter can effectively

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suppress speckle, but it fails to preserve many useful details, being merely a low-pass filter. Chirungrueng and Suvichakorn² suggested a new filter, referred to as the 2-D weighted Savitzky-Golay, filter, which could achieve at least the same level of speckle reduction as the median filter, but with far less computational time. This filter is suitable for filtering problems with large windows. Jain⁵ developed a homomorphic approach, in which he took the logarithm of the image, converted the multiplicative into additive noise, and then applied the Wiener filter.

Recently, there has been considerable interest in using the wavelet transform as a powerful tool to recover signals from noisy data. These methods are generally referred to as *wavelet shrinkage technique*.² Zong et al used a logarithmic transform to separate the noise from the original image. They adopted regularized soft thresholding (wavelet shrinkage) to remove noise energy within the finer scales and nonlinear processing of feature energy for contrast enhancement.¹⁷ Choice of the threshold and the matching of specific distributions of the signal and noise at different scales are two drawbacks of thresholding methods.

Husbey et al.⁷ recommended a new filter, based on Markov random field and bayesian statistical methods. They described a model for the scattering distribution of homogeneous tissue. The model is used in algorithms to restore speckle ultrasound images and shows that this filter is better than the Wiener filter. Both filters have limitation on quasi-periodic components and specular structure.

Compounding techniques provide other speckle reduction methods. These techniques are based on assumption that the ensemble average of speckle image is the same as incoherent average of the original object. Spatial, frequency, and strain compounding are different compounding states.⁶

In this article, a new adaptive filter based on a genetic-neuro-fuzzy system for sonography image speckle reduction is proposed. This filter is constructed from a feedforward multilayer network that integrates the basic elements and functions of a traditional fuzzy system into a connectionist structure. In this filter linguistic information is about the input-output rela-

tionship and is usually expressed as *fuzzy if-then rules*.¹⁸⁻²⁵ This filter uses a real-time genetic algorithm to adapt network parameters.³¹ GAs, that search for the optimal solution of a problem by applying the mechanisms of natural selection and natural genetics, in fact, have been demonstrated to be very effective for training the neuro-fuzzy systems.^{22,29} The neuro-fuzzy filters are used as a nonlinear filtering for noise cancellation in removal of impulse, gaussian, and uniform noises, but still had not been used for speckle noise reduction.

MATERIALS AND METHODS

Speckle Noise

Speckle noise affects all coherent imaging systems including laser, SAR (Synthetic Aperture Radar) imagery, and ultrasound. Speckle may appear distinct in different imaging systems, but it is always manifested in a granular pattern due to image formation under coherent waves. Goodman has described the basic properties of speckle.⁴ A general model for speckle noise proposed by Jain⁵ was also used by Zong.¹⁷ In the following, we will formulate the ultrasound speckle model. Denote by $N(x,y)$ a noisy recorded ultrasound image, $M(x,y)$ the noise-free image that has to be recovered and by $S_m(x,y)$ and $S_a(x,y)$, the corrupting multiplicative and additive speckle noise components, respectively. One can write:

$$N(x,y) = M(x,y)S_m(x,y) + S_a(x,y). \quad (1)$$

Generally, the effect of the additive component of the speckle in ultrasound images is less significant than the effect of the multiplicative component. Thus, ignoring the term, one can rewrite eq. (1) as

$$N(x,y) = M(x,y)S_m(x,y). \quad (2)$$

Genetic-Neuro-Fuzzy Structure

Genetic-neuro-fuzzy systems belong to a newly developed class of hybrid intelligence systems, that combine the main features of artificial neural networks with those of fuzzy logic and genetic algorithm. The goal here is to circumvent difficulties encountered in applying fuzzy logic for systems represented by numerical knowledge (data sets), or in applying neural networks for systems represented by linguistic information (fuzzy sets).²⁴ Genetic algorithm is used to optimize and update network and fuzzy parameters. The structure of the genetic-neuro-fuzzy system is shown in Figure 1. Let's suppose we must deal with digitized images having L gray levels. Let X be the pixel luminance that must be processed in the noisy image and let $\{X_1, X_2, X_3, X_4, X_5, X_6, X_7, X_8\}$ be the set of neighboring pixels which belong to a 3×3 window (Fig 2). The network aims at producing a

Fig 1. Genetic-neuro-fuzzy system.

Fig 2. 3 × 3 neighborhood window.

correction term ΔX , which when added to X yields the resulting pixel luminance in the output image. The filter is recursive, ie, the new value is assigned to pixels in the noisy image at the end of the processing.

As depicted in Figure 3, the neural fuzzy system includes two symmetrical subnetworks. These subnetworks are designed to deal with positive and negative fuzzy sets, respectively. The operation performed by the different layers is described in the paragraphs that follow.

Input Layer

There are eight nodes in this input layer. The differences between main pixel and neighborhood window pixels are entered to this layer. Data fuzzification is constructed by means of triangle membership function.²⁶ Let $O_{ij}^{(1)}$ be the output of the i th node in the j th subnetwork. The node function is expressed as:

$$\Delta X_i = X_i - X \quad (3)$$

$$O_{i1}^{(1)} = \mu_p(\Delta X_i) \quad (4)$$

$$O_{i2}^{(1)} = \mu_n(\Delta X_i) \quad i = 1, \dots, 8. \quad (5)$$

μ_p and μ_n are positive and negative triangle membership functions, respectively (Fig 4). $O_{i1}^{(1)}$ is the output of i th node in first subnetwork and $O_{ij}^{(1)}$ is the output of i th node in second subnetwork. $O_{ij}^{(1)}$.

First Aggregation Layer

The weights between the input layer and the first fuzzy aggregation layer are binary, which represents the strength of the 2-node connection. The same set of weights is used for both subnetworks. We can improve the efficiency of the encoding scheme by taking care of the symmetry processing. In fact, a set of eight binary weights directly identifies a specific pattern of pixels. Thus, an 8-bit genetic substring can be used to automatically encode this pattern and three related patterns obtained by 90, 180, and 270 rotations. Fuzzy rules are constructed by means of these patterns. For the sake of simplicity, let us consider the first set of binary weights in the first subnetwork: $\{W_{ij}, i, j = 1, \dots, 8\}$. The nonzero elements in this set identify a pattern of pixels in the neighborhood window. For example, let the weights for one node of first hidden layer $W = \{0, 1, 0, 1, 1, 1, 0, 0\}$, the rotated weights $W_{90} = \{0, 1, 0, 1, 0, 0, 1, 1\}$, $W_{180} = \{0, 0, 1, 1, 1, 0, 1, 0\}$ and $W_{270} = \{1, 1, 0, 0, 1, 0, 1, 0\}$. These patterns are shown in Figure 5. Fuzzy rules for this example are explained as follow:

$$\begin{aligned} &\text{IF } (X_3, X_4, X_5, X_7) \text{ IS } P \text{ THEN } \Delta X \text{ IS } P \\ &\text{IF } (X_1, X_2, X_5, X_7) \text{ IS } P \text{ THEN } \Delta X \text{ IS } P \\ &\text{IF } (X_2, X_4, X_5, X_6) \text{ IS } P \text{ THEN } \Delta X \text{ IS } P \\ &\text{IF } (X_2, X_4, X_7, X_8) \text{ IS } P \text{ THEN } \Delta X \text{ IS } P \\ &\text{IF } (X_3, X_4, X_5, X_7) \text{ IS } N \text{ THEN } \Delta X \text{ IS } N \\ &\text{IF } (X_1, X_2, X_5, X_7) \text{ IS } N \text{ THEN } \Delta X \text{ IS } N \\ &\tilde{X} = X - \Delta X \\ &\text{IF } (X_2, X_4, X_5, X_6) \text{ IS } N \text{ THEN } \Delta X \text{ IS } N \\ &\text{IF } (X_2, X_4, X_7, X_8) \text{ IS } N \text{ THEN } \Delta X \text{ IS } N \end{aligned} \quad (11)$$

$$O_{i1}^{(2)} = \min_{l=1}^4 \left(\text{AVE}_{k=1}^8 \left(O_{k1}^{(1)} W_{ki}^l \right) \right), \quad i = 1, \dots, 8 \quad (6)$$

$$O_{i2}^{(2)} = \min_{l=1}^4 \left(\text{AVE}_{k=1}^8 \left(O_{k2}^{(1)} W_{ki}^l \right) \right), \quad i = 1, \dots, 8 \quad (7)$$

The following relations yield the node functions:

$O_{i1}^{(2)}$ and $O_{i2}^{(2)}$ are outputs of i th node in first hidden layer, $O_{k1}^{(2)}$ and $O_{k2}^{(2)}$ are outputs of k th node in input layer for positive and negative subnetworks, respectively. W_{ki}^l is the weight between the i th node of the first hidden layer, and the k th node of the input layer for the l th pattern (a 4 pattern is used). Aggregation between patterns is replaced by averaging operators, and minimum operation is used for node aggregation. Weights that are binary (0 or 1) in genetic string are optimized in training steps.

Second Aggregation Layer

The second aggregation layer adopts second aggregation connectives in order to combine the information coming from the previous layer. According to the choice of the maximum operator for aggregation, this layer selects the patterns that are most appropriate for the processing. Each subnetwork in this layer has a node, and outputs of nodes

Fig 3. Genetic-neuro-fuzzy filter structure for speckle noise reduction.

Fig 4. Triangle membership function.

Fig 5. An example of neighborhood pattern and 90, 180, and 270 degree rotated patterns.

input variables, and its width relative to P . The output of this layer is defined by following relation:

$$\Delta X = \frac{P(O_1^{(3)} - O_2^{(3)})}{(O_1^{(3)} + O_2^{(3)})}, \quad (10)$$

where ΔX is filter output that is the noise amplitude estimation. $O_1^{(3)}$ is positive subnetwork output, $O_2^{(3)}$ is negative subnetwork output and P is membership function parameters, which is between 0 to 255 and is an 8-bit number in genetic binary string. Filter output then is subtracted from main pixel in image such as the following relation:

$$\tilde{x} \text{ is edited pixel, } X \text{ is noisy pixel and } \Delta X \text{ is noise amplitude.} \quad (10)$$

Real-Time Genetic Algorithm

Genetic algorithms are a class of algorithms for function maximization. They do not rely on the existence of a continuous parameter space or differentiability of the error function, but they do exploit features of the error function. The GAs are techniques that search for the optimal solution of a problem by applying the mechanisms of natural selection and natural genetics to a population of possible solu-

are estimations of positive and negative noise amplitude. The node functions are defined by:

$$O_1^{(3)} = \max_{i=1}^8 (O_{i1}^{(2)}) \quad (8)$$

$$O_2^{(3)} = \max_{i=1}^8 (O_{i2}^{(2)}), \quad (9)$$

where $O_1^{(3)}$ is positive subnetwork output and $O_2^{(3)}$ is negative subnetwork output, both of which are estimation of noises amplitude.

Output Layer

The output layer is a defuzzification layer. Output of two subnetworks is entered into this layer, and noise amplitude is yielded by using the center of average defuzzification method. Output membership function is triangular, with

Fig 6. Genetic string encoding.

Fig 7. Real-time GA in a genetic-neuro-fuzzy filter.

Fig 8. Mutation operator in real-time GA.

chosen for refinement randomly, with the probability of selection enhanced by the solution quality ("fit-ness"). We pose using GAs for the neuro-fuzzy filter parameters optimization problem, which satisfies the following features:

- It performs global optimization and avoids local optimization
- It is parallel, so that it combines good features of multiple solutions.

Most GAs are multi-individual.²⁷⁻³¹ We arrived at a simple GA approach that is a real-time algorithm with a single individual.³¹ This individual (string) is defined as a *queen*. The next generation is created by using only the mutation operator. Saifpour³¹ performed a study of real-time GA, and with a Markov chain showed that this algorithm is adapted to provide the best solution.

The genetic string includes a membership function width parameter (P) and binary weights between the input and first hidden layers (Fig 6). The GA begins by randomly generating an individual (string). It is initialized at random to a bit string of 0's and 1's. Then, a subsequent string (designated the *son*) is generated by using a genetic mutation operator. Real-time GA is shown in Figure 7. Mutation is the occasional alternation of binary values in the particle part of the string (Fig 8). The best results are yielded by 3–10 percent of the string bit mutation (ie, 2–7 bits in a 72-bit string). Mutation places are given randomly.

For each string, the set of parameter values is decoded and assigned to the neuro-fuzzy filter. A noisy image is used as input data. A performance index is then evaluated by considering the inverse mean-square error (IMSE) between the filtered data and the original noise-free image. The string that has the best performance indexes (ie, the largest IMSE) is selected as a queen to generate the next generation. IMSE is yielded by the following relation:

$$\text{IMSE} = \frac{n_1 n_2}{\sum_{i=1}^{n_1 n_2} (x_i - \tilde{x}_i)^2}, \quad (12)$$

tions. Hence, GAs are well suited for the training of neuro-fuzzy architectures that typically adopt the minimum and maximum operators. It is stochastic that solutions are

Table 1. MSE Values for Ultrasound Test Images

	0.3 speckle	0.2 speckle	0.03 speckle
Main noisy image	860.02	585.3	132.22
Median filter output (3 × 3)	393.76	299.99	92.96
Median filter output (5 × 5)	515.88	465.2	104.05
Wiener filter output (3 × 3)	484.59	329.3	101.37
Wiener filter output (5 × 5)	453.58	318.1	99.9
Proposed filter output	247.21	182.08	65.23

where X_i is the pixel intensity of the test free noise image, $\hat{X}_i$ is the pixel intensity obtained from the filtering operation, and n_1, n_2 are the numbers of pixels in column and row of the image. The process typically stops after an assigned number of generations. This algorithm is faster than our previous method, which used 50 strings in populations with a similar degree of precision.^{29,30}

EXPREMENTAL RESULTS

We trained our proposed genetic-neuro-fuzzy speckle suppressing algorithm on ultrasound images. The training data were obtained by corrupting the sonography images having 256 gray levels. To simulate the speckle noise effect, we multiply each pixel of the original test image by a random value generated according to the Rayleigh probability distribution of mean one, as shown in expression (2). In our experiments, we considered three different variance levels (0.03, 0.2, and 0.3) of simulated speckle noise.

To perform real-time genetic learning, we have encoded the binary weights, fuzzy membership function parameter by means of a 72-bit binary string. We have adopted a simple genetic algorithm dealing with a population of 1 string, and have chosen the mutation bit rate 4% (3 bits in a 72-bit string). For each filtering operation, we measure its ability to reduce speckle noise by MSE function. The MSE values obtained from the genetic-neuro-fuzzy filter during the training process are graphically depicted in Figure 9. Satisfactory results have been obtained after 46 generations. The algorithm is implemented in Matlab software and run on a 800-MHz Duran AMD PC. As a result, for 640×480 pixel images, the overall training process (150 generations) requires about 30 minutes.

We compared the results of our approach with other speckle reduction techniques including median filtering and homomorphic Wiener filtering. These are classical nonlinear

Fig 9. MSE values obtained during the training process.

filters that are typically adopted for the removal of speckle noise. These filters were applied using the Matlab image-processing toolbox, version 6. For the median filter we used a 3×3 mask and the homomorphic Wiener filter was implemented using a window of 3×3 pixels size.

The performance of the genetic-neuro-fuzzy filter has been evaluated by using data different from those adopted during the training process. In order to validate the proposed method, corrupting the test pictures with the same noise distributions has generated a different array of noisy data. The performance of the proposed technique and other operators has been evaluated by considering the MSE of the processed data with respect to the original uncorrupted images. The list of MSE values is shown in Table 1 and a sample of the processed images is shown in Figure 10 for visual inspection.

Figure 10 shows a representative result from the processing of the noisy trimester fetus and yolk sac image. The simulated speckle image shown in Figure 10(b) corresponds to an MSE value of 653.8. The median and homomorphic Wiener filters resulted in the images shown in Figure 10(c) and 10(d). Our proposed genetic-neuro-fuzzy filter result is shown in Figure 10(e).

Indeed, the problem with the MSE is its connection to the visual interpretation of a human observer. A radiologist, in analyzing ultrasound images, does not compute the above measure. Hence, in order to visually study the

Fig 10. (a) Ultrasound trimester fetus and yolk sac main image. (b) Speckle noisy image (c) Wiener filter output, (d) Median filter output, (e) Proposed genetic-neuro-fuzzy filter ouput.

merit of the proposed genetic-neuro-fuzzy filter, we chose a noisy ultrasound image, applied the algorithm without artificially adding noise, and visually evaluated the denoised image. The results of this experiment are shown in Figure 11.

To investigate the effectiveness of genetic-neuro-fuzzy filter in preserving image edges when compared with the other filters; we transformed the results obtained from all filters as inputs to Canny's edge detector³² and investigated the quality of the detected edges. We show in Figure 11(a) the ultrasound noisy image where it is passed from all filters. This image allows us to evaluate the performance of all filters because it contains edges with high contrast characteristics, ranging from sharp distinctive edges to almost indiscernible edges. Figure 11(b)—11(d) depicts the resultant images obtained from the output of the median, the Wiener, and the genetic-neuro-fuzzy filters, respectively. The corresponding edges of these four images are portrayed in Figure 11 (e)—11(h).

DISCUSSION

In the previous section, the genetic-neuro-fuzzy results were compared with those of the median and Weiner filters. It is apparent from

table 1 that the proposed genetic-neuro-fuzzy technique significantly outperforms conventional methods. Indeed, the proposed method is able to effectively remove speckle noises even with different levels of noise, while preserving the quality of fine details in the image data.

Figure 10 shows a representative result from the processing of the noisy trimester fetus and yolk sac image. For this noise level, the genetic-neuro-fuzzy filter achieved good speckle suppression. The median and homomorphic Wiener filters lose many of the signal details, and the resulting images are blurred. Clearly, as can be seen in Figure 10(e), our proposed genetic-neuro-fuzzy filter effectively reduces speckle; it preserves step edges and enhances fine signal details better than other methods.

Figure 11(a) illustrates the ultrasound noisy image where it passed from all filters. The images derived from the edge detector are then visually judged by comparing with the bowel boundary depicted as white-solid lines in Figure 11(a). Figure 11(e) portrays the edges derived by applying Canny's edge detector directly to the bowel test image without any filtering. It appears to contain numerous noise edges masking the real bowel boundary, thus, making it impossible to segment the bowel from the

Fig 11. (a) Ultrasound bowel main noisy image, (b) Wiener filter output, (d) Median filter output, (e) Proposed genetic-neuro-fuzzy filter, (f—h) Edges derived by Canny edge detector for images (a—d), respectively.

background. The results of the edge detector obtained from images preprocessed by the median and Wiener filters are shown in Figure 11(f)—11(g). It appears that these images contain some noisy edges.

Inspecting the results of the edge detector obtained from the images preprocessed by the genetic-neuro-fuzzy filter, as shown in Figure 11(h), is most convenient for segmentation. Note that the boundary edges of the bowel are clearly preserved while noise edges are mostly removed. Notice that even though the resultant images from the filters appear similar, the edges obtained from the genetic-neuro-fuzzy filter are much closer to the ideal edges than those obtained from the other filters.

CONCLUSION

In this article, we introduce a novel genetic-neuro-fuzzy filter for speckle suppression in ultrasound images. The combination of the neural and fuzzy paradigms permits us to exploit the effectiveness of fuzzy reasoning and the ability to learn from examples. Key aspects of the proposed design are the adoption of 2-D fuzzy sets and the use of trainable fuzzy aggregators. The learning

method based on real-time GAs has demonstrated that it is possible to perform an effective high-speed training of the network, yielding satisfactory results after a few generations.

Validation of the method has been carried out by considering groups of different ultrasound images corrupted by speckle noise. An in-depth analysis of the filtering behavior has been proposed by taking into consideration the IMSE evaluated on different classes of pixels and has shown that this filter is effective in noise reduction and edge preservation. Experimental results have shown that the genetic-neuro-fuzzy filter is able to outperform a number of well-known methods in the literature. Our method can easily be extended to multiple dimensions and used for multidimensional filtering, enhancement, segmentation, and visualization applications. Research in this direction is under way and will be presented in a future report.

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REFERENCES

1. Achim AL, Bezerianos AN, Tsakalides PA: Novel bayesian multiscale method for speckle removal in medical ultrasound images. *IEEE Trans On Medical Imaging* 20:772-783, 2001
2. Chirungrueng CH, Suvichakorn AI: Fast edge processing noise reduction for ultrasound images. *IEEE Trans Nuclear Science* 48(3):849-854, 2001
3. Abbott JG, Thurstone FL: Acoustic speckle: theory and experimental analysis. *Ultrason. Imag* 1:303-324, 1979
4. Goodman JW: Some fundamental properties of speckle. *J. Opt. Soc. Am* 66:1145-1150, 1976
5. Jain AN: *Fundamentals of Digital Image Processing* NJ, Prentice-Hall: Englewood Cliffs, 1989
6. Li P-C, Chen M-J: Strain compounding, a new approach for speckle reduction. *IEEE Trans. Ultr. Ferroelectronic Freq. Cont.* 49:39-46, 2002
7. Husbey OD, Lie TO, Longo TH: Bayesian 2-D deconvolution, a model for diffuse ultrasound scattering. *IEEE Trans. Ultr. Ferroelectronic Freq. Cont* 48:121-130, 2001
8. KHZ Abd-Elmoniem, Ya M Kadad, AB BA M Youssef: Real time ultrasound speckle reduction and coherent enhancement. In *International Conference on Image Processing*, 10—13 Sept. 2000: Image Processing Proceeding, 2000 IEEE, Vol 1, pp. 172—175
9. Ioannidis AL, Kazakos DA, Watson DD: Application of median filtering on nuclear medicine scintigram images. In: *Proceedings of the 7th International Conference on Pattern Recognition*, Montreal, Canada, pp. 33—36, 1984
10. Ritenour ER, Nelson TR, Raff UO: Application of the median filter to digital radiographic images. *Proc. IEEE Int. Conf. Acoust. Speech, Signal Processing* :2311-2314, 1998
11. Loupas TA, McDicken WN, Allan PL: An adaptive weighted median filter for speckle suppression in medical ultrasonic images. *IEEE Trans. Circuits Syst.* 36:129-135, 1989
12. Czerwinsky RN, Jones DL Jr, O'Brien WD: Ultrasound speckle reduction by directional median filtering. *Proc. Int. Conf. Image Processing* 1:358-361, 1995
13. Hu, J, Hu, X (1994) "Application of median filter to speckle suppression in intravascular ultrasound images" *Intelligent Information Systems* 1994. In: *Proc. 1994 2nd IEEE Australian and New Zealand Conf. Intelligent Information Systems*, 29 Nov—2 Dec 1994, pp 302—306
14. Yin L, Yang R, Gabbou M, Neuvo Y: Weighted median filters: a tutorial. *IEEE Trans. Circuits Syst. II* 43:157-192, 1996
15. Huang TS, Yang GY, Tang GY: A fast two-dimensional median filtering algorithm. *IEEE Trans. Acoust. Speech, Signal Processing ASSP*-27:13-18, 1979
16. Pitas I, Venetsanopolous AN: *Nonlinear Digital Filter-Principles and Applications* Norwell, MA: Kluwer Academic, 1990
17. Zong X, Laine AF, Geiser EA: Speckle reduction and contrast enhancement of echocardiograms via multiscale nonlinear processing. *IEEE Trans. Med. Imag* 17:532-540, 1998
18. Lin CT, Juang CF: An adaptive neural fuzzy filter and its applications. *IEEE Trans Systems, Man, and Cybernetics—Part b: Cybernetics* 27:635-656, 1997
19. Russo F: A Evolutionary neural fuzzy system for data filtering. *IEEE Inst. Meas. Tech. Conf. St Paul Minnesola* 826-831, 1998 MAY 18—21
20. Cojbasic F, Nikolic VD: An approach to neuro-fuzzy filtering for communications and control. In: *5th IEEE International Conference on Telecommunications in Modern Satellite, Cable and Broadcasting Service, TELSIKS* 2001, Vol. 2, pp. 719—722, 2001
21. Hong X, Harris C, Wilson PA: Neurofuzzy state identification using prefiltering. *IEE Proc. Cont. Theory Appl.* 146:234-240, 1999
22. Russo F: Evolutionary neural fuzzy systems for noise cancellation in image data. *IEEE Trans Instr Meas* 48:915-920, 1999
23. Wong HS, Guan L: A neural learning approach for adaptive image restoration using a fuzzy model-based network architecture. *IEEE Trans Neural Networks* 12:516-531, 2001
24. Sinha SK, Karray F: Classification of underground pipe scanned images using feature extraction and neuro-fuzzy algorithm. *IEEE Trans Neural Networks* 13:393-401, 2002
25. Boskovitz V, Guterman H: An adaptive neuro-fuzzy system for automam tic image segmentation and edge detection. *IEEE Trans Fuzzy Systems* 10:247-262, 2002
26. Russo M: Genetic fuzzy learning. *IEEE Trans Evol Comput* 4:259-273, 2000
27. Durant EA, Wakefield GH: Efficient model fitting using a genetic algorithm: pole-zero approximations of HRTFs. *IEEE Trans Speech Audio Processing* 10:18-27, 2002
28. Goldberg DE: Genetic algorithms. In: *Search, Optimization and Machine Learning*. Reading, MA: Addison-Wesley, 1989
29. Rafiee Kerachi A, Moradi MH, Farzaneh MR: Impulse noise reduction in sonography images by using neuro-fuzzy filters. *Second Iranian Conference on Machine Vision, Image Processing & Applications, MVIP* 2003, Khajeh Nasir Al-Din Toosi University Tehran, Iran, 2003
30. Rafiee A: Sonography images enhancement by neuro-fuzzy algorithms. Ph.D. Thesis, Research and Science campus, Islamic Azad University, Tehran, Iran, 2003
31. Saifipour N: On-line genetic algorithm in optimization and control. Ph.D. Thesis Amirkabir University, Tehran, Iran, 2002
32. Canny J: A computational approach to edge detector. *IEEE Trans. Pattern Anal. Machine Intel.* Vol. PAMI-8: 679-697, 1986