CHAPTER 3
SPECKLE NOISE REDUCTION USING MEMETIC ADAPTIVE NEURO FUZZY INFERENCE SYSTEM

3.1. OVERVIEW

Noise and artifacts are gained while acquisition or during transmission and cause image and signal degradation. Image degradation has an impact on image quality and affects the interpretation and accuracy of detection methods. Reduced image quality deteriorates the analysis, quantitative measurements and feature extraction techniques. The method improves the accuracy and reliability of image processing algorithms for qualitative and quantitative problems. The main objective of the techniques is to remove the noise and retain the significant features.

Ultrasound imaging is a widely used medical imaging procedure as it is economical, safe, transferable, and adaptable. One of its main shortcomings is the poor quality of images, affected due to speckle noise. The existence of speckle degrades image quality and affects the tasks of individual interpretation and diagnosis. Speckle filtering is a vital pre-processing step, in a report by Radhika et al (2002), for feature extraction, analysis and recognition from medical images.

A number of algorithms have been proposed for speckle mitigation in the past. Chang et al (2005), adopted the top-hat filter to find bright spots and used four 2-D criteria to select the spots as candidate microcalcifications.
An appropriate method for speckle reduction is to enhance the signal to noise ratio (SNR) by conserving the edges and lines in the image. Filtering techniques are used as a preface action before segmentation and classification. Statistical Weiner filter in spectral domain is designed primarily for additive noise suppression. Adaptive filter takes a moving filter window and estimates the statistical information of all pixels’ grey value; local mean and local variance. The central pixel’s output value is dependent on the statistical information. Adaptive filters adapt themselves to the local texture information surrounding a central pixel in order to calculate a new pixel value. Adaptive filters generally incorporate the Kuan filter, Lee filter, Frost filter, Gamma MAP filters. Adaptive filters preserve the image sharpness and details by suppressing the speckle noise.

3.2. SPECKLE NOISE IN ULTRASOUND IMAGES

In the medical literature, speckle noise is referred as “texture” and possibly contains diagnostic information. The acquired image is corrupt with random granular speckle pattern that delays the interpretation of image content. Parthiban et al (2006), despeckled and edge preserved medical US images using Contourlets giving a better performance in terms of SNR.

Mariana Carmen Nicolae et al (2010), recommended the difference between noise reduction and the preservation of actual image features using Contourlets and Wavelets. The speckle noise is modeled as in Equation (3.1) and it is necessary to develop noise filter to conserve the features of interest.

\[ v = f * g \]  

(3.1)

where, \( v = \{v_1, v_2, ..., v_n\} \) speckle noise,
\( f = \{f_1, f_2, ..., f_n\} \) noise-free ideal image, and
\[ \mathcal{g} = \{g_1, g_2, \ldots, g_n\} \] unit mean random field.

3.3. **NEURO-FUZZY SYSTEMS**

Fuzzy logic, the science of thinking and reasoning have been studied by Jang et al (2007), it is an extension of binary theory using the concept of fuzziness. The properties of the Artificial Neural Network (ANN) in tuning rule based fuzzy system imitate human reasoning. The synergy between ANN and fuzzy logic is known as NFS.

The development of a methodology using Neural-Fuzzy Systems (NFS) is an activity of two decades. Benecchi (2009), suggested an artificial neural fuzzy network for prostate cancer detection. Segmentation is based on neuro-fuzzy classifier with feed forward network. The cancer lesion is extracted and distinguished from normal cells. Ali Rafiee et al (2004), suggested a design for 2-D fuzzy sets and the use of trainable fuzzy aggregators on ultrasound images corrupted by speckle noise. The analysis of the filter is done using Inverse Mean Square Error. The motivation is based on the observations of Jang and Sun (1997) to use soft computing techniques to Neuro-Fuzzy systems for various applications for pattern recognition and signal processing.

(1) Biological data exhibit prior unknown statistical properties. Trainable classification algorithms are based on learning procedure and promise better performance than non-adaptive classifiers.

(2) Neuro-Fuzzy systems use learning procedures to determine the appropriate set of Fuzzy membership functions. The set of membership functions is expressed linguistically and provides
an understanding about the properties of the classification problem.

(3) Fuzzy systems allow incorporating prior knowledge into the classification process by enabling the experience of the physician into the classifier.

The task of fuzzy classification is to generate an appropriate fuzzy partition of the feature space and optimize the rule base by deleting unused rules.

3.4. MEMETIC ALGORITHM

Nature inspired algorithms are stochastic search methods impersonating the metaphor of natural biological evolution and the social behavior of species is studied by Ali Rafiee et al (2004). In the area of computer science, artificial neural network, genetic algorithm and swarm intelligence solve hard problems by imitating mechanisms in nature. Researchers have developed expert systems seeking fast and robust solutions to complex NP-hard problems. Youngjun Ahn et al (2010), presented a novel implementation of the Memetic Algorithm (MA) with Genetic Algorithm (GA) and Mesh Adaptive Direct Search (MADS) and applied to the optimal design methodology of electric machines.

The Memetic Algorithm (MA) is population based heuristic approach based on evolution. MA is intrinsically concerned with exploiting all available knowledge about the problem under study. The adjective ‘memetic’ is derived from the term ‘meme’, coined by R. Dawkins. The algorithm maintains a pool of population solutions termed as ‘individuals’.
The applications of MA in medical image processing extend from feature selection to pattern matching and clustering of image elements.

The unique aspect of the MA algorithm is that all chromosomes and off-springs are allowed to gain some experience in a study by Youngjun Ahn et al (2007), through a local search, before being involved in the evolutionary process. The flow chart for MA is given in Figure 3.1 and the algorithm steps are:

1. Start: Randomly generate a population of N chromosomes.
2. Fitness: Evaluate the fitness of all chromosomes.
3. Create a new population:
   a. Selection: Select 2 chromosomes from the population.
   b. Local search: Search for the best chromosome, ‘queen string’.
   c. Crossover: Perform 2 point crossover on the chromosomes selected.
   d. Local search: Search for the best chromosomes.
   e. Mutation: Perform mutation on the chromosomes obtained with small probability as in figure 3.4.2.
4. Replace: Replace the current population with the new population.
5. Test: The termination condition is the number of iterations. If it is satisfied, stop. If not, return the best solution in current population and go to Step 2.
An initial population is created at random. A local search is performed on each population member to improve the experience and obtain a population of local optimum solutions. The off-springs are produced as a result of crossover and mutation operators. Areibi (2005), proposed to perform local search through a pair-wise interchange heuristic. In this method, the local-search neighborhood is defined as the set of all solutions reached from the current solution by swapping two elements (memes), Figure 3.2, in
the chromosome. For a chromosome of length n, the neighborhood size for the local search as in Equation (3.2).

\[ N = \frac{1}{2} \times n \times (n - 1) \] (3.2)

The number of swaps and consequently the size of the neighborhood grows quadratically with the chromosome length (problem variables). In order to reduce processing time, Areibi (2005), suggested stopping the pair-wise interchange after performing the first swap by enhancing the objective function of the current chromosome. The objective function is evaluated based on local-search algorithm to suit the problem nature. The change is kept if the chromosome’s performance improves otherwise, the change is ignored. The parameters involved are population size, number of generations, crossover rate, and mutation rate in addition to a local-search mechanism.

![Figure 3.2 Searching by Pair-Wise Interchange Heuristic](image)

**Figure 3.2** Searching by Pair-Wise Interchange Heuristic

### 3.5. MEMETIC ADAPTIVE NEURO FUZZY INFERENCE SYSTEM

Neuro-Fuzzy or Adaptive Neuro Fuzzy Inference System (ANFIS) methods fail to determine the number of rules or the membership functions. Integrating evolutionary approach into the system optimises the structure and parameters of the fuzzy rules. Russo (1995), recommended a speckle noise
filter using the combination of fuzzy, neural and memetic paradigms. The structure acquires knowledge automatically by analyzing the decisions of a prior level to the architecture and to be utilized through fuzzy logic theory and artificial neural network.

3.5.1. **Structure of the System**

The system is designed to use neural networks to realise the Sugeno fuzzy model to implement the membership function in the precondition and the inference functions in the consequents. The neural network in the precondition learns the membership functions and in the consequent learns the proper action of rule as studied by Jang (1993). The fuzzy inference rules, $R^j$, in the neural network-driven fuzzy reasoning have the following equation 3.3,

$$R^j: \text{IF } x_1 \text{ is } A^i_1 \text{ AND } x_2 \text{ is } A^i_2 \text{ AND } \ldots \text{ AND } x_n \text{ is } A^i_n, \text{ THEN } y \text{ is } f_j = a^i_0 + a^i_1 x_1 + a^i_2 x_2 + \cdots + a^i_n x_n \quad (3.3)$$

where $x_i$ is an input variable, $y$ and $f_j$ are the output variables, $a^i_j$ are the consequent parameters, $A^i_l$ are linguistic terms of the precondition part with membership functions $\mu^i_{A^i_l}(x_i)$, $A^i_l \in \mathbb{R}$ for $j=1, 2, \ldots, m$, and $i=1, 2, \ldots, n$. For the given input values $x_1, x_2, \ldots, x_n$ the inferred output $y^*$ is computed by the Equation (3.4),

$$y^* = \frac{w_1f_1 + w_2f_2 + \cdots + w_mf_m}{w_1 + w_2 + \cdots + w_m} \quad (3.4)$$

where $w_j$ are strengths of $R^j$, $j=1, 2, \ldots, m$, and is given by Equation (3.5)

$$w_j = \mu^i_{A^i_1}(x_1) + \mu^i_{A^i_2}(x_2) + \cdots + \mu^i_{A^i_n}(x_i) \quad i = 1, 2, \ldots, n \quad (3.5)$$
The system uses product inference and the architecture as in Figure 3.3, consisting of layers with the following functions and outputs: Layer 1 is an input node. A 2×2 window pixels are the inputs coupled with its neighboring window pixel to transfer input signals to the next layer. Layer 2 consists of nodes operating as membership functions and the parameters in the layer are precondition parameters. Layer 3 includes nodes to multiply the incoming signals, and the product represents the strength of a rule. Layer 4 has nodes to calculate the normalised weights of a rule given by Equation (3.6).

\[
\bar{w}_j = \frac{w_j}{w_1+w_2+\cdots+w_j} \quad j = 0,1, \ldots, n
\]  

(3.6)

Layer 5 consists of nodes to calculate the weighted consequent parameters are given in Equation (3.7) and the summation is given in Equation (3.8).

\[
\bar{w}_j f_i = \bar{w}_j (a_0^i + a_1^i x_1 + a_2^i x_2 + \cdots + a_n^i x_n)
\]  

(3.7)

\[
\sum_j \bar{w}_j f_i = \frac{\sum_i \bar{w}_j f_i}{\sum_i \bar{w}_j} \quad j = 0,1, \ldots, n
\]  

(3.8)

The membership function of every node is chosen to be bell-shaped and is computed by Equation (3.9).

\[
\mu_{A_1}(x_j) = \frac{1}{1 + \left(\frac{x_j - m_j}{\sigma_j}\right)^{2b_j}} \quad j = 0,1, \ldots, n
\]  

(3.9)

where \(m_j, \sigma_j, b_j\) is the tuning parameter using MA to optimize and set the neuro fuzzy parameters. This acts as a filter to despeckle the ultrasound image.
3.5.2. Optimized Parameter Learning

MA is chosen as it is a class of algorithm for maximization of functions. It exploits the features of the error functions and does not rely on the parameter space. MA applies the mechanism of natural selection and genetics to its population of solutions and is suitable to train the NFS as adopted in literature Areibi (2005).

The meme optimization procedure is an iterative process to improve the individuals by reducing the number of population selected and by enhancing the classification accuracy. It is described as follows:

i. Improve the number of classified patterns by reducing the subset size. A neighbour is obtained by changing 1 to 0 in a gene.

ii. The inputs are:
   a. The chromosome to be optimised
   b. Lists of associated neighbours
c. The list of identifiers of the instances removed without a sufficient gain according to the threshold value

iii. The list of Nearest Neighbourhood (NN) of each identifier of the instances is considered.

iv. The search of the NN of each instance is needed when the instance is removed from the subset selected. It is upgraded in order to contain more than one neighbour per instance.

3.6. EXPERIMENTAL RESULTS

Speckle noise reduction is a low pass filtering operation on ultrasound mammary carcinoma images and makes it available for preprocessing. The system is simulated using Matlab and is experimented on 2D grey scale ultrasound mammary carcinoma images having 256 levels. The diagnostic image as in Figure 3.4, corrupt with speckle noise is chosen.

![Selecting the ultrasound image](image.png)

*Figure 3.4 Selecting the ultrasound image*

The system has two input layers and one output layer shown in Figure 3.5 and algorithm is repeated for 50 iterations as in Figure 3.6.
Figure 3.5 ANFIS editor

Figure 3.6 Iterations

The system uses a 5 layer feed-forward neural network as in Figure 3.7. Layer 1 is an input node with 2×2 window pixels as inputs coupled with its neighboring window pixel to transfer input signals to the next layer. Layer 2 has 8 membership functions and parameters in this layer are
precondition parameters. Layer 3 multiplies the incoming signals using prodmf with 16 rules.

Figure 3.7 ANFIS model structure

Layer 4 has nodes to calculate the normalized weights of a rule by applying a threshold weight of 0.5 as in Figure 3.8 and the parameters are tuned using MA.

Figure 3.8 Rule editor
Layer 5 consists of nodes to calculate the weighted consequent value where parameters are consequent parameters. The membership function of every node in each layer is chosen as bell-shaped, Figures 3.9 and 3.10. The output function is given as in Figure 3.11.

**Figure 3.9**  Input 1 membership function

**Figure 3.10**  Input 2 membership function
Figure 3.11 Output membership function

The rule viewer and surface viewer are shown in Figures 3.12 and 3.13 the input parameters are adjusted accordingly.

Figure 3.12 Rule viewer structure
The standard median filter and memetic ANFIS are the methods used in the system. The system is tested for its performance based on Peak Signal to Noise Ratio (PSNR) and Mean Squared Error (MSE) of the original image $A_{ij}$ and altered image $B_{ij}$ where $x$ and $y$ are width and height of image. PSNR and MSE are calculated using formula in Equation (3.10) and (3.11),

$$PSNR = 10 \log_{10} \left( \frac{255^2}{MSE} \right)$$  \hspace{1cm} (3.10) $$MSE = \sum_{i=1}^{x} \sum_{j=1}^{y} \frac{(A_{ij}-B_{ij})^2}{x \times y}.$$  \hspace{1cm} (3.11)

Tables 3.1 and 3.2 summarize the various MSE and PSNR values computed for all types of mammary carcinoma. The table is grouped in two columns Median Filter and Memetic ANFIS. For each column it shows the reduction and accuracy in training with respective to MSE and PSNR. The rows compute the MSE and PSNR obtained on each image for both the methods described. Figures 3.14 and 3.15 are the graph for the comparison of two methods.
Table 3.1  Comparison of memetic ANFIS and median filter using mean square error

<table>
<thead>
<tr>
<th>Ultrasound Images</th>
<th>Mean Square Error</th>
<th>Memetic ANFIS</th>
<th>Median filter</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>79.6856</td>
<td>273.7119</td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>116.9318</td>
<td>363.4691</td>
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<td>3</td>
<td>31.2592</td>
<td>17.3200</td>
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<td>10</td>
<td>22.6832</td>
<td>32.2915</td>
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Figure 3.14  Comparison of memetic ANFIS and median filter using mean square error
Table 3.2  Comparison of memetic ANFIS and median filter using peak signal to noise ratio

<table>
<thead>
<tr>
<th>Ultrasound Images</th>
<th>Peak Signal To Noise Ratio</th>
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<td></td>
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<tr>
<td>10</td>
<td>44.5738</td>
</tr>
</tbody>
</table>

Figure 3.15  Comparison of memetic ANFIS and median filter using peak signal to noise ratio

Figure 3.16 shows the original input image, noise induced image, median filtered image and resultant MA-ANFIS despeckled image.
3.7. INFERENCES

This chapter presents ultrasound speckle noise reduction algorithm based on the Memetic ANFIS. In the proposed algorithm, to discriminate speckle from the useful signal, noise is induced and information from the image is obtained. The fuzzy logic requires many MFs and the number of rules determines the operational speed and the stability of the system. The goal to reduce the number of rules is achieved. The training corresponds to the THEN part of the fuzzy inference rule. The checking data input values are substituted and the MSE and PSNR are obtained. The experimental results show that the proposed algorithm improves the subjective image quality with better performance compared with the existing schemes. The algorithm was tested and found to be effective for detecting malignant carcinoma.