# PSO Aided Neuro Fuzzy Inference System for Ultrasound Image Segmentation

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## ABSTRACT
Individual micro calcifications are difficult to be detected as they are variable in shape and size and may be embedded in areas of dense parenchymal tissues. One of the most important problems of medical diagnosis, in general, is the subjectivity of the pattern recognition by diagnosis experts. This is due to the fact that the results are depended on the interpretation of the input from the patients but not on systematic procedure. In this paper, an adaptive neuro-fuzzy model optimized by PSO algorithms has been proposed. The symptoms and signs are gathered and the fuzzy membership values are defined. Feed forward multilayer networks are used to accept the fuzzy input values and is trained using back-propagation algorithm. The system is tested for detecting the micro-calcifications in breast sonograms. Later the results are compared for its performance.

## General Terms
Pattern Recognition, PSO Algorithms, Image Processing, Ultrasound Image, Segmentation

## Keywords
Sonograms; micro-calcifications; fuzzy systems; neural networks

## 1. INTRODUCTION

### 1.1. Micro-calcifications in Breast Sonograms
About 25% of all cancers diagnosed in women are breast cancers. It is the leading cause of death due to cancer in women [1]. Breast ultrasound is the use of ultrasonic sound waves (sounds that cannot be heard by humans) to produce an image of breast tissue. Breast sonogram images show whether the lump is solid or fluid-filled [5]. Breast ultrasound may be used with mammography or by itself. There are no risks associated with breast ultrasound. Ultra-sonography may be used to detect and classify breast lesions in the following types of women [3]: Women with dense breasts, fibrocystic breast disease, a lesion that cannot be well classified by mammography.Young women with masses, Pregnant women with masses, and Women who do not prefer x-ray [4]. Results of the breast sonography indicate patterns of :

- Cysts
- Benign lesions
- Malignant lesions (breast cancer)

### 1.2. Artificial Neuro-Fuzzy Networks (ANFN)
ANFN are widely used in the areas medical imaging [1]. The motivation to use Neuro-Fuzzy systems is based on different observations: (1) In most of the cases biological data exhibit a priori unknown statistical properties [2]. Therefore, trainable classification algorithms are based on some kind of learning procedure promise better performance than non-adaptive classifiers such as the Bayes classifier or the KNN classifier. (2) Neuro-Fuzzy systems use a learning procedure to determine an appropriate set of Fuzzy membership functions (msf). This set of membership functions can be expressed in linguistically and hence provides an understanding about the properties of the classification problem. (3) Fuzzy system allows toincorporate a priori knowledge into the classification process which enables to include some of the experience of the physician into the classifier [6].

### 1.3. Particle Swarm Optimization algorithm
Particle swarm optimization (PSO) is a population based stochastic optimization technique developed by Dr. Eberhart and Dr. Kennedy in 1995, inspired by social behavior of birds. The system is initialized with a population of random solutions and searches for optima by updating generations. The potential solutions, called particles, fly through the problem space by following the current optimum particles. The advantages of PSO are that PSO is easy to implement and there are few parameters to adjust [10]. PSO has been successfully applied in many areas: function optimization, artificial neural network training [18], fuzzy system control, and other areas where GA can be applied.

Here, we have proposed the system to diagnose the cancer from sonogram images using ANF model and optimize using PSO [9].

## 2. EXISTING SYSTEM

### 2.1. Existing ANFN Models in Ultrasound Imaging
In [16] deals specifically with skin cancer diagnosis. The system has been divided into two main parts: feature selection, using the Greedy feature flip algorithm (G-flip), and Classification method using ANFIS algorithm. The ANFIS algorithm could be trained with the back propagation gradient descent method in combination with the least squares method. Three different types of skin lesions were introduced in this diagnosis system and the performance of the ANFIS model was evaluated in terms of

training performance and classification accuracies. In [12] the images are normalized and then fuzzification of the normalized images based on the maximum entropy principle has been applied. Edge and textural information are extracted to describe the lesion features and the scattering phenomenon of US images and the contrast ratio measuring the degree of enhancement is computed and modified. The defuzzification process is used to obtain the enhanced US images. [11] explores a novel dynamic programming (DP) based optimal technique in ultrasound image (USI) edge detection, which is less constrained than the previous. Dynamic programming is an optimal approach in multistage decision-making. In an image segmentation system, the global optimal contour with connectedness and closeness is found. The DP algorithms process the object image to get the minimum cumulative cost matrix to trace a global optimal edge [7].

## 2.2. Existing PSO models in Ultrasound Imaging

In [13] a novel automatic segmentation algorithm based on the characteristics of breast tissue and the eliminating particle swarm optimization (EPSO) clustering analysis. The characteristics of mammary gland in breast ultrasound (BUS) images are analyzed and utilized, and a method based on step-down threshold technique is employed to locate the mammary gland area. The EPSO clustering algorithm employs the idea of "survival of the superior and weeding out the inferior". The experimental results demonstrate that the proposed approach can segment BUS image with high accuracy and low computational time. In [14] the PSO is to maximize an objective fitness criterion in order to enhance the contrast and detail in an image by adapting the parameters of a novel extension to a local enhancement technique. The feasibility of this method is demonstrated and compared with Genetic Algorithms (GAs) based image enhancement technique.

# 3. PROPOSED SYSTEM

## 3.1 Image Enhancement

Breast ultrasound images have low contrast and some degree of fuzziness such as indistinct cyst borders, ill-defined mass shapes, and different tumor densities. Image enhancement is used to improve the quality of the image and to correct deficiencies of the contrast. We implement an algorithm for mammary gland image enhancement based on Evolutionary Neuro-Fuzzy Filters [15]. After the mammary gland images are enhanced, the contrast is improved and the boundaries of the regions much distinct, which is better for segmentation.

## 3.2. Artificial Neuro Fuzzy Network Model

In this paper, for the segmentation method the ANFN model was used in order to detect the cancerous cells. Therefore, the system is organized as two parts like fuzzy systems the first part and the second part is the conclusion part, that are connected to each other by rules, in the network form.

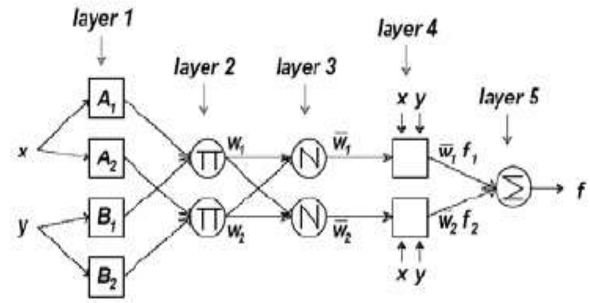


**Figure 1 Artificial Neuro-Fuzzy Feed Forward Network with 5 layers.**

ANFN is described as a multi-layered neural network as shown in Figure 1 [16] where the first layer executes a fuzzification process, the second layer executes the fuzzy AND of the antecedent part of the fuzzy rules, the third layer normalizes the membership functions (MFs), the fourth layer executes the consequent part of the fuzzy rules, and finally the last layer computes the output of fuzzy system by summing up the outputs of fourth layer. Here for ANFN structure two inputs and two labels for each input are considered. The inputs are the fuzzy values.

## 3.3. Image Segmentation

PSO has a fitness evaluation function to compute each position's fitness value [8]. The position with the highest fitness value in the entire run is called the global best solution PBest.. Each particle tracks its highest fitness value. The location of this value is called the personal best solution Pi. The algorithm involves casting a population of particles over the search space and remembering the best solution encountered. For each iteration, all particles adjusts its velocity vector based on its momentum, and the effect of both its best solution and the global best solution of its neighbors. The EPSO is based on the idea of "survival of the superior and weeding out the inferior" [9]. N particles whose velocities and positions are updated accordingly are initialized, and the positions' fitness values are calculated and sorted in a list in descending order. Then, L particles whose fitness values are in the last L positions of the list are eliminated. This reduces the computational time, while the accuracy of the solution is not affected. The process iterates until the maximum iteration number is reached or the minimum error condition is satisfied. EPSO clustering is an algorithm based on ANFN clustering and the EPSO algorithm [10]. The centers of the clusters are considered as the particle's positions, and the EPSO algorithm is employed to search the optimum solution by eliminating the "weakest" particles to speed up the computation. ANFN is utilized to update the positions of particles. Because the intensities of the pixels belonging to a lesion are very low, the group of pixels with the lowest intensities can be regarded the lesion-like pixels. The mammary gland region is located by the following formula:

$$bw(i,j) = \begin{cases} 0 & g(i,j) \in C_1 \\ 255 & otherwise \end{cases} \quad \textbf{\textit{(1)}}$$

where g (i , j ) is the pixel in mammary gland region at the location (i , j ) , and in equation (1) C1 is the cluster with the lowest intensities. bw is the binary mammary gland image after segmentation. After the mammary gland is segmented, the round-like regions are reserved as the lesion-like regions and others are eliminated [17]. The centers of the clusters are considered as the particles positions, and PSO algorithm is employed to search the optimum solution by eliminating the "weakest" particles to speed up the computation. The procedure of generalized algorithm of PSO model is given in Figure 2(a). Let Pi represent the ith particle, whose velocity vid and position xid are defined in a d-dimensional space as:

$$V_{id}(t) = \omega V_{id}(t-1) + c_1 rand()(P_{id}(t-1) - X_i(t-1)) + c_2 rand()(P_{ig}(t-1) - X_i(t-1)) \quad (2)$$

$$X_{id}(t) = X_{id}(t-1) + V_{id}(t-1) \quad (3)$$

Where xid (t) is the position of the ith particle, in a d-dimensional space at time step t, vid is the velocity of Pid(t). Pid and Pig represent the dth and gth position of the ith particle. Parameters c1 and c2 are learning factors where c1=c2=2. ω is the interia weight, ω=0.1 and rand() is the function to generate a random variable.

The procedure for clustering based on EPSO and ANFN is given below:

(1) Select $_M$ particles, and put them into the primary swarm $s(1) = \{P_1, P_1, \ldots, P_M\}$and initialize the positions $x_{id}$ of swarm s using ANFN clustering;

(2) Randomly initialize the velocities $v_{id};$

(3) Evaluate the fitness of each particle Fit ($x_{id}$ $(t)$);

(4) Compare the personal best of each particle in the new swarm $s(t+1)$ with its current fitness value, and set $P_{id}(t)$ to better performance.

(5) Set the global best $P_{gd}(t+1)$ to the position of the particle with the best fitness in the swarm;

(6) Sort the particles according to the fitness values.

(7) A new swarm $s(t+1)$ is obtained by eliminating the $L$ particles whose fitness values are in the last $L$ positions of the list;

(8) Optimize the position of each particle in the new swarm $s(t+1)$ according to ANFN clustering;

*(9)* Change the velocity vector $v_{id}$ $(t+1)$ for each particle according to Eq. (2)Update each particle position in $s(t+1);$

(10) Go to step (3), and repeat the process until the maximum iteration number or the minimum error is reached.

*For each particle*
Initialize particle
*For each particle*
Calculate fitness value
If the fitness value is better than the best fitness value ($p_{best}$) in history
Set current value as new $p_{best}$
*End*
Choose the particle with the best fitness value of all the particles as $g_{best}$
For each particle
Calculate particle velocity according to Eq. 2
Update particle position according to Eq. 2
*End*
*Continue while maximum iterations or minimum error criteria is not attained*

**Figure 2 (a) PSO Algorithm**

After the mammary gland is segmented, the round-like regions are reserved as the lesion-like regions and others are eliminated. The complete steps of the segmentation process are given in Figure. 2 (b).

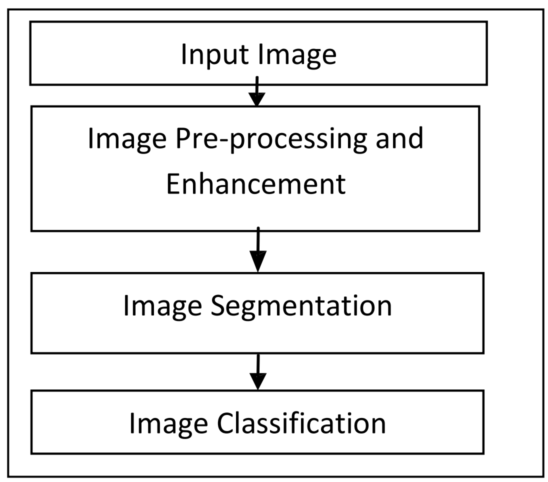


**Figure 2 (b) CAD System**

## 4. EXPERIMENTAL RESULTS

The proposed segmentation method was tested on breast ultrasound images database, experimental results are presented to demonstrate the performance of the proposed method. In Figures 3(a) Original US image, in which most of the bright areas are the breast and muscle tissues, and the suspicious tumor areas are corrupted by speckle noise [18]. In Figures 3(b) through 3(f) are the segmentation results by the proposed expert system.

The proposed segmentation algorithm is less sensitive to noise because of the utilization of an effective speckle reduction algorithm. Furthermore, the EPSO clustering method reduces the computational time by 32.75% compared with the standard PSO clustering algorithm. EPSO clustering was implemented using

Matlab 7.1, and the program was executed on a PC with a single processing unit AMD Athlon 64GHz and 2GB RAM. The average execution time was 157 second per image with an average size of 500 X 600, while the average execution time using the conventional PSO clustering algorithm was 233 second per image. After segmentation, lesions can be detected and classified easier and better. The match rate (MR) between the manually determined areas [18] and the automatically located lesions by the proposed algorithm is used to quantitatively evaluate the performance of the proposed algorithm. The MR is defined as:

$$MR = \frac{A_m \cap A_a}{A_m} \quad (4)$$

Where Am and Aa is the area of the tumor determined manually by radiologists and the area of the lesion determined automatically by the proposed algorithm. The average match rate (MR) of the proposed algorithm was 0.9639 and the values are tabulated below in Table 1.

**Table 1 MR Values of Segmentation**

| Image Data Sets | **MR value of Proposed System** | |
|---|---|---|
| | After Speckle Reduction and Enhancement | With-out Speckle Reduction and Enhancement |
| Sample 1 | 0.9627 | 0.8932 |
| Sample 2 | 0.9832 | 0.9503 |
| Sample 3 | 0.9582 | 0.8774 |
| Sample 4 | 0.9623 | 0.8832 |
| Sample 5 | 0.9529 | 0.8563 |
| **AVERAGE MR** | **0.9639** | **0.8921** |

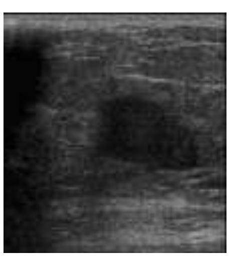

**Fig. 3. (a) Original Image**

**Fig. 3. (b) Segmentation**

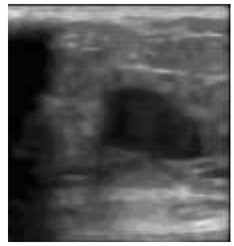

**Fig. 3. (c) After Denoising**

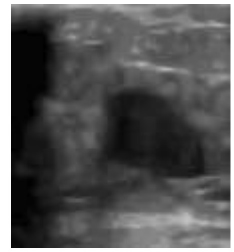

**Fig. 3. (d) Feature Selection**

**Fig. 3. (e) Feature Extraction**

**Fig. 3. (f) Extracted Segment**

## 5. CONCLUSION

Breast cancer is one of the most common factors for mortality rate among young women [4]. In this paper a BUS image segmentation based on Artifical neuro-fuzzy system (ANFN) and EPSO as a diagnosis system for biomedical problems is proposed. The EPSO clustering method reduces the computational time by 32.75% compared with the standard PSO clustering algorithm.

The major advantage of the proposed algorithm is that it can handle the entire image automatically and accurately instead of focusing exclusively on ROIs, since it utilizes the characteristics of mammary gland of the BUS images. Also, the algorithm has very low computational time and complexity. The proposed approach may find wide applications in automatic lesion classification and CAD systems for breast cancer detection.

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