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An Ultrasound Image Preprocessing System Using Memetic ANFIS Method

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***Abstract*— Ultrasound images are corrupted with speckle noise which makes it impossible for diagnosis. A novel memetic based approach to optimize neuro fuzzy system for reducing this speckle noise in sonogram images has been proposed. The system uses a 5 layer feed forward neural network with 5 input parameters representing the 5×5 window pixel. These are the fuzzy values which are optimized by memetic algorithm (MA) and fed into the system as input parameters. The population generations used in the system are optimized fuzzified input parameters. Fuzzification is based on IF THEN rules. The efficiency is improvised on adding weights in between the input and hidden layer. Then, the amplitude is measured. The system is compared with traditional adaptive mean and adaptive weighted mean methods. The results were 32% better and the computation time was less.**

Keywords- neural networks; fuzzy logic; sonogram images; speckle noise reduction; memetic algorithm;

I. INTRODUCTION

A. Ultrasound Images

The non-persistent character, cheap cost, portable nature and real-time image formation make ultrasound images essential tool for medical diagnosis [1]. The common usages are image restoration, preprocessing, enhancement techniques, segmentation, and classifications. The ultrasound devices acquire high quality, real-time images but are corrupted with speckle noise. Speckle noise degrades the quality of the images for identifying the edges, patterns in images [10]. Speckle noise produces artificial edges, echoes the patterns in the images and etc., this hinders the diagnosis of disease. In such cases simple evolutionary algorithms do not perform well to identify edges and patterns. Hence, preprocessing the artifacts in US images becomes mandatory [3] using the evolutionary neuro-fuzzy model.

B. Neuro-Fuzzy Models

Neural Networks and Fuzzy Logic systems are dynamic, parallel processing systems which estimate the input-output functions [12]. Fuzzy logic systems are able of modeling ambiguity, supervising uncertainty and also to support manual interpretation. Whereas, neural-networks are capable of learning from scratch, without any prior intervention, but are provided with sufficient data which are available or measureable. The neuro-fuzzy system is the hybridization in terms of the number of practical real time algorithms. In NFS, the fuzzy system is the main focal point of the combination procedure and the neural-network includes the learning capability to the inference engine [5].

C. Evolutionary Neuro-Fuzzy Models

Evolutionary neuro-fuzzy (ENF) system is the consequence of adding evolutionary search practices to the system, integrating fuzzy-logic-computing and neural learning. With these techniques we can overcome the limitations of the existing hybrid systems. The main objective and the drawback of the NFS is that, the learning technique is based on the gradient descent optimization technique [6]. That is, in back-propagation, training will not converge and tuning of the membership function parameters through neural learning is not guaranteed. The algorithm will be trapped in local minima. With this kind of system, the global solution is impossible to found.

Memetic Algorithms (MA) is inspired by Darwins' idea of a 'meme' [2], which is the element that forms the chromosome. MAs are comparable with GAs. The distinctive feature of the MA algorithm is that, all the chromosomes and their off-springs are allowed to gain adequate experience, by a process of local searching, before involving in the evolutionary process. The first population is created at random which is similar to the population generation procedure in GA. Later, a global search is performed on each individual member to improvise its experience and thus obtain a population of local optimum solutions. Then, crossover and mutation operations are performed to reproduce the off-springs. These off-springs are then subjected to the local search so that local optimality is always maintained in the system.

In this paper, we have proposed a novel method using Memetic Algorithms based neuro-fuzzy to harness the power of fuzzy reasoning and the learning capabilities of neural networks.

II. PROPOSED METHOD

The difficulty in the existing neuro-fuzzy or fuzzy-neuro systems is that they fail to quantify the rules or the membership functions. Integrating these evolutionary approaches into the NFS or FNS systems optimizes the structure and parameters of the fuzzy rules. In this paper we discuss about optimizing the parameters.

A. Strucutre of the System

In our NFS system, the capability of the Memetic algorithm is supplemented with existing system. Memetic algorithm is used to optimize and set the neuro-fuzzy parameters. This feature acts as a filter in despeckling and smoothing the US images.

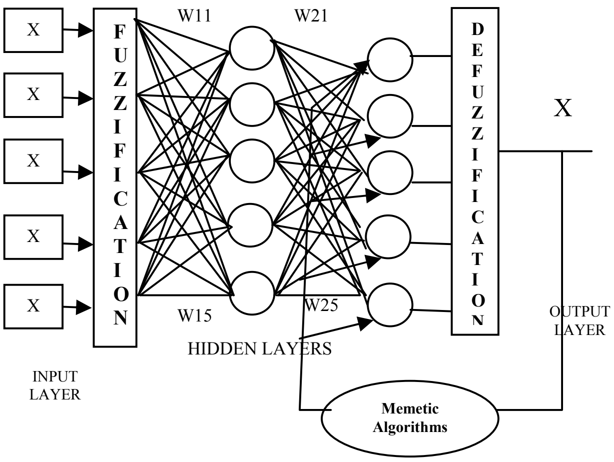

Figure 1. Strucutre of the MA Neuro Fuzzy System

The filter that is recommended and implemented is a self-organized adaptive neuro-fuzzy filter which is based on neuro-fuzzy and evolutionary learning. The system uses the neural network ability to train and the knowledge for this is fed into the system in fuzzy format. In the network a 5-layer feed forward network (Figure 1) is used. Where, the first layer performs the fuzzification process, the second layer performs the Fuzzy AND of the predecessor operation of the fuzzy rules. The third layer regulates the membership function, the fourth layer performs the resultant part of the fuzzy rules and lastly, the fifth layer computes the output of fuzzy system by summing up the outputs of the fourth layer [7]. The speckle noise is deducted on based on the local statistical characters and uses the fuzzy knowledge for it. Here, memetic algorithm is used to decide and optimize the parameters to the network [13].

The fuzzy model experimented used is the basic Sugeno_type fuzzy model, which is a single network to filter the speckle noises [11]. The input parameters that are fed into the system are the fuzzy values based on the difference between the main pixel and its neighboring window pixels. The window size is determined by the number of input layer nodes in the system. In this system we have used a 5×5 window sizes, hence we have 5 input nodes. Each node in the input layer is coupled with its neighboring window pixel. Therefore, the input data which used in this layer are fuzzy data. The hidden layers of arrangement supply information to the system based on the fuzzy rules and its implications [14]. The conclusion to the system is dependant on the fuzzy IF-THEN rules which engross the parameters of the system. The weights are then supplemented to the network connecting the input layers and the hidden layers. The weights are binary threshold values. To progress the efficiency of this encoding system a set of 5 binary weights which recognize the pattern on pixels is used. In the usage of this 5-bit encoding technique, a substring is evolved. These 5-bit substrings result in three different patterns of rotation of 90, 180, and 270 degrees are evolved. Then, optimization of the non-zero elements in weighted sets, which assist in identifying patterns in the neighboring window [15] is done. Binary weights in the queen string are optimized while training the system. Evaluation of the speckle noise amplitude in the neighboring patterns is applied in the same manner as local statistics [17].

B. Optimized Pattern Learning

MA-based search-process is chosen, as it is belongs to set of algorithms as Genetic algorithm for maximization of member functions [9]. MA explores the characters of the error functions and does not guarantee the parameter space. MA uses the mechanism of natural selection and genetics to its population of solutions. It involves:

- Global optimization,
- Stochastic searching and
- Selection is based on good features.

The general features of MA which make it suitable for the likelihood of choosing the operators is given in Figure2. The initial population which is chosen by the EA algorithms is the one individual string which is defined as the 'queen' string. The generations are generated by conducting mutation operations on these strings. These strings contain the membership function (msf) width-parameter *P* and the threshold weights have to be applied between the input and hidden layers. The descriptions of the steps of the evolutionary algorithm are discussed as:

1. Randomly generate the individual string (queen string).
2. Initialize the queen string to the bit string of 0's and 1's.
3. Child string is generated using the mutation operator.
4. Then, the mutation points are chosen at random.
5. For each string, perform the following:
   a. Interpret the parameter values.
   b. Assign to the neuro-fuzzy filter.
6. Stop the process after 100 generations.

III. Experimental Results

We have chosen to use a 5 layered NFS which is trained individually. The system output, which is the noise-value is filtered from the neighbor pixel window. Speckle noise reduction is a low pass filtering operation [18]. Our system reduces the noise and makes it acceptable for preprocessing. The experiment is conducted on 50 Breast Sonogram images which are trained in the neural network based on fuzzy values for 100 epochs [19]. The input parameters are adjusted accordingly. System performance is tested of its error value based on Mean Square Error (MSE) [16]. The results are compared with the simulations of the existing models adaptive mean filter [4] and adaptive weighted mean filters. It is observed that the projected noise reduction system is a dynamic system when compared to the standard systems. Ultrasound images used are 2d gray images which have 256 levels and are best compared based on visual observation [20]. The experiment is simulated and compared with existing models (Figure 3) using Matlab 7.3 on Athol processor based system with 1 GB RAM.

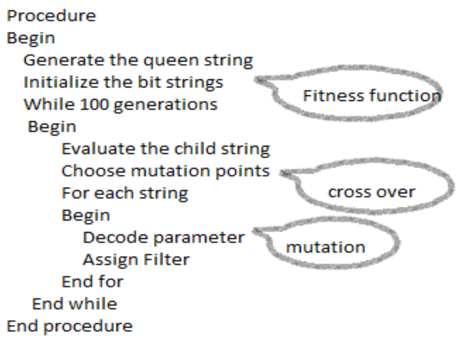

Figure 2. MA Algorithm for Parameters Optimization

In Figure 4(a) refers the typical diagnostic image, in Figure 4(b) noisy image corrupted by speckle noise, in Figure 4(c) MA based Neuro-fuzzy system after speckle reduction and Figure 4(d) compared with the standard adaptive mean filter and in Fig.4.(e) adaptive weighted mean filter. The table 1 summarizes the various MSE results:

TABLE I. COMPARISION OF NOISE MEAN SQUARE ERROR

Method	**Epochs**	
	50	***100***
Adaptive Mean	0.540029	0.530682
Adaptive Weighted Mean	0.512929	0.510502
GA Based Method	0.532629	0.532202
MA Based Method	0.499929	0.499502

IV. CONCLUSION

In this paper we have proposed two dynamic soft computing tools namely-neural networks, and fuzzy logic using genetic and memetic algorithms. The intention of this paper was to harness the power of the individual system by substituting its drawbacks with the power of other system. This type of system is evolutionary neuro-fuzzy system.

In the proposed system we have suggested a Memetic based approach to optimize neuro-fuzzy system for speckle reduction in breast sonograms. We have used the neural networks for learning and fuzzy parameter for knowledge development. The inputs to the system are fuzzy inputs which optimizes the output. Based on these parameters the MA learning is performed. The system outperforms the traditional system [8] in terms of MSE ratio and the computation time is considerably reduced.

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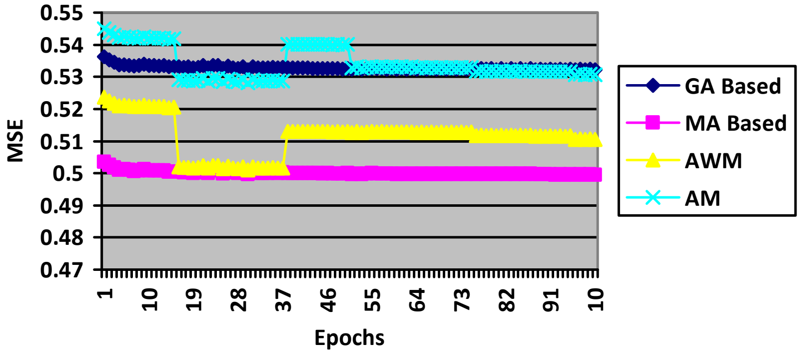

Figure 3. Comparision of Different Models

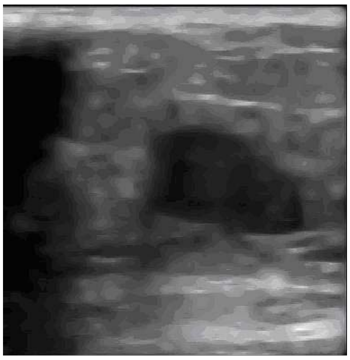

Figure.4.(a) Original Image

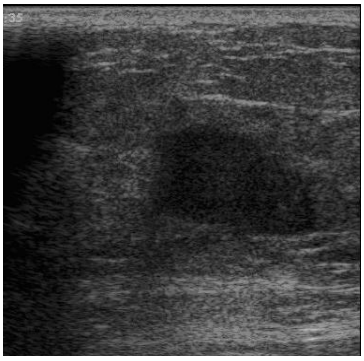

Figure.4.(b) Noisy Image Corrupted by Speckle Noise

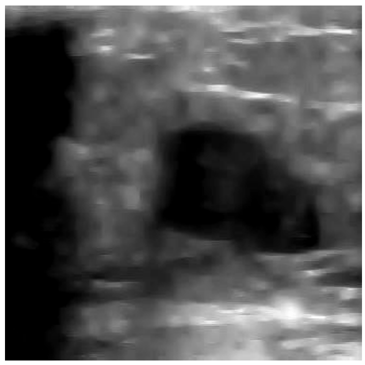

Figure.4.(c) Proposed MA Method

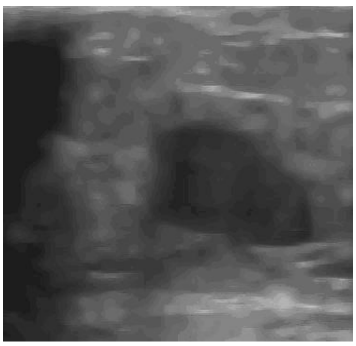

Figure.4.(d) Adaptive Mean Filter

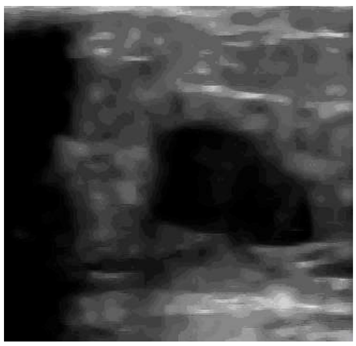

Figure.4.(e) Adaptive Weighted Mean Filter