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A Novel Preprocessing System using Evolutionary Neuro Fuzzy System

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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 is 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, Memetic Algorithms, Sonograms and Noise Reduction.

1. INTRODUCTION

1.1 Ultrasound Images

The non-persistent nature, low cost, portability and real-time image formation make ultrasound images and essential tool for medical diagnosis [1]. The common applications are image registration, preprocessing, enhancement, segmentation, classifications. The US images allow high acquisition rates and provide real-time images but are corrupted with speckle noise. Speckle noise degrades the quality of the images for identifying the edges, patterns in the images [9]. Speckle noise produces artificial edges, echoes the patterns in the image and etc, this corrupts the images for easy diagnosis. In such cases evolutionary algorithms do not perform well to identify edges and patterns. Hence, preprocessing the artifacts in US images is mandatory [3].

1.2 Neuro-Fuzzy Models

Neural networks and fuzzy systems are dynamical, parallel processing systems that approximation input-output functions [12]. Fuzzy logic is capable of modeling ambiguity, handling vagueness and supporting human-type reasoning. Whereas, neural-networks are capable of learning from scratch, without needing any a priori involvement provided that sufficient data are available or measurable. The neuro-fuzzy systems are the most prominent legislature of hybridizations in terms of the number of practical implementations. In NFS, the fuzzy inference system is the main subject of the hybridization; neural-network adds learning to an inference engine [5].

1.3 Neuro-Fuzzy Evolutionary Models

An evolutionary neuro-fuzzy system (ENFS) is the result of adding evolutionary hunt procedures to systems, integrating fuzzy logic computing and neural learning. With these techniques we can overcome some the boundaries of the existing hybrid systems. The main problem with NFS, is that, the learning algorithm is based on a steepest plunge optimization technique minimizing the error function [6]. That is, in back-propagation training is not guaranteed to converge. The algorithm may be trapped in a local minimum. It can never find the global solution. The tuning of the membership function parameters through neural learning is also not guaranteed. Memetic Algorithm (MA) is inspired by Dawkins' notion of a meme [2]. MAs are similar to GAs but the elements that form a chromosome are called "memes". The unique aspect of the MAs algorithm is that all chromosomes and off-springs are allowed to gain some experience, through a local search, before being involved in the evolutionary process. Similar to the GAs, an initial population is created at random. Afterwards, a global search is performed on each population member to improve its experience and thus obtain a population of local optimum solutions. Then, crossover and mutation operators are applied, similar to GAs, to produce off-springs. These off-springs are then subjected to the local search so that local optimality is always maintained.

In this paper, have proposed a method using Hyrid Memetic Algorithms based Neuro-Fuzzy system to harness the power of the fuzzy reasoning and the learning capabilities of neural networks.

2. PROPOSED METHOD

The problem with the existing Neuro-Fuzzy or Fuzzy-Neuro methods is that it fails to determine the number of rules or the membership functions (MSF) [11]. While integrating evolutionary approach into these systems it optimizes the structure and parameters of the fuzzy rules. This paper discusses about optimizing the parameters.

2.1. Structure of the System

In the system NFS the capabilities are added to Evolutionary Algorithm: Hybrid Memetic Algorithm. Hybrid Memetic algorithm is used to optimize and set the neuro-fuzzy parameters. This acts as a filter to despeckle the ultrasound image. The filter which is suggested is a self-organized adaptive neuro-fuzzy filter which is based on neuro-fuzzy and memetic learning. The system uses the neural network ability to learn and knowledge in the system is in fuzzy form.

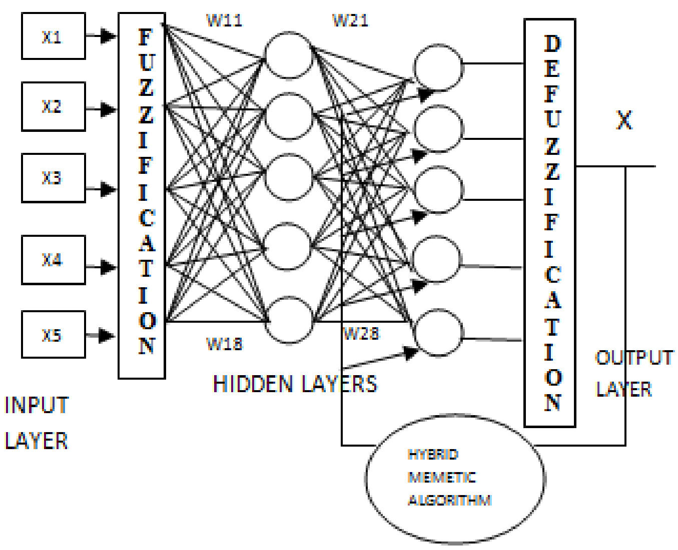

Figure 1. Structure of the MA Neuro-Fuzzy System

The network used is a feed-forward 5 layered network Fig.1 [10], 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 [7]. The noise is detected based on local statistical features and uses the fuzzy knowledge. Here, the hybrid memetic algorithm is used to decide and optimize the parameters to the network [13].

The basic Sugeno_type fuzzy model is used which is a single network to filter the speckle noises [11]. The input parameters are the fuzzy values based on the difference between the main pixel and its neighboring window pixels. The window size is number of input layers nodes in the system. This system uses a 5×5 window sizes hence five input nodes. Each node of the input layer is coupled with its neighboring window pixel and therefore the data used in this layer are fuzzy data. The hidden layers in the system provide knowledge to the system based on the fuzzy rules and their implications [14]. The inferences to the system are based on the fuzzy IF-THEN rules, which involve the parameters of the system. The weights are added to the network between the input layers and the hidden layers which are binary values. To improve the efficiency of the encoding system a set of five binary weights which identify the pattern of pixels is used. With this encoding mechanism a five bit substring is evolved. These 5-bit substrings result in three patterns of 90, 180 and 270 degree rotations. Optimization is done to the non-zero elements in weight-sets which identify a pattern in the neighboring window [15]. Binary weights in the genetic string are optimized in training steps. Estimation of the noise amplitude in the neighboring patterns is applied the same manner as applying the local statistics [17].

2.2. Optimized Parameter Learning

MA is chosen, as it is a class of algorithm for maximization of functions [8]. 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. Hence, it is more suitable to train the NFS than the GAs. The features of MA which make it suitable for the probability of selection of operators are given in Fig. 2:

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

An algorithm with one individual string which is defined as the 'queen' string is chosen. The generation is generated by performing mutation on this string. This string contains the msf width parameter P and the weights which have to be applied between the input and hidden layers. The steps of the algorithm are:

1. Randomly generate the individual string (queen string).
2. Initialize it to the bit string of 0's and 1's.
3. Child string is generated using the multi-point guided mutation operator.

4. Mutation points are chosen randomly.
5. For each string,
    a. Decode the parameter values.
    b. Assign to the neuro-fuzzy filter.
6. Stop the process after 100 generations.

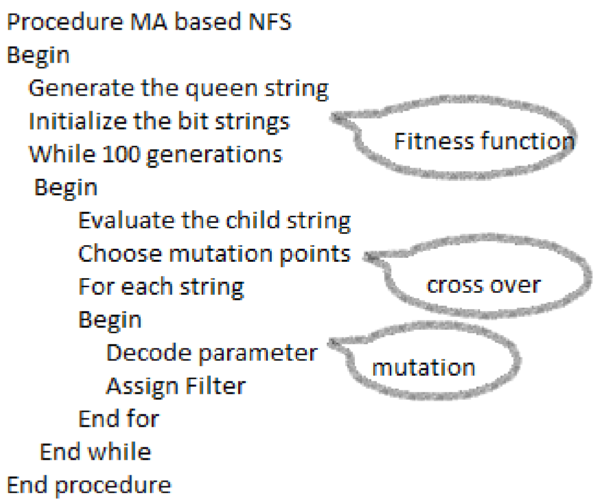

Figure 2. Application of HMA Parameters

3. EXPERIMENTAL RESULTS

A 5 layered NFS which is trained individually is used. 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 available 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 adaptive mean filter [4] and adaptive weighted mean filters. It is observed that the 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 using Matlab 7.5 on Athol processor based system with 1 GB RAM. In Fig.4.(a) the typical diagnostic image, in Fig.4.(b) noisy image corrupted by speckle noise, in Fig.4.(c) proposed MA based Neuro-fuzzy system after speckle reduction, compared with the standard adaptive mean filter in Fig.4.(d) and adaptive weighted mean filter in Fig.4.(e). The table 1 summarizes the various MSE results:

Table 1 Comparison of the Noise Mean Square Error (MSE)

Method	50 epochs	100 epochs
Adaptive Mean	0.540029	0.530682
Adaptive Weighted Mean	0.512929	0.510502
Proposed Method	0.499929	0.499502

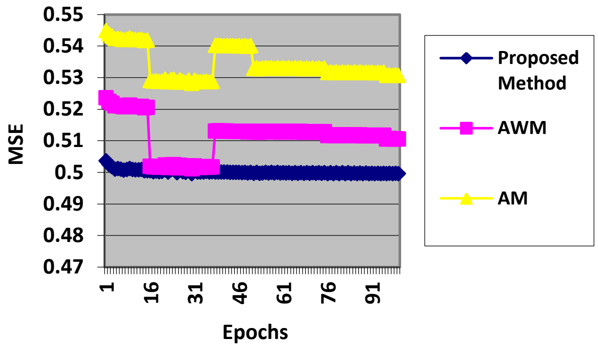

Figure 3. Comparison of Three Methods

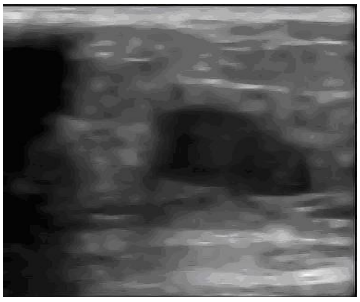

Figure.4.(a) Original Image

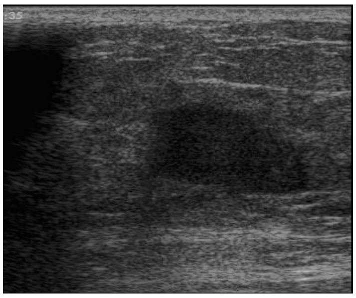

Figure.4.(b) Noisy Image Corrupted by Speckle Noise

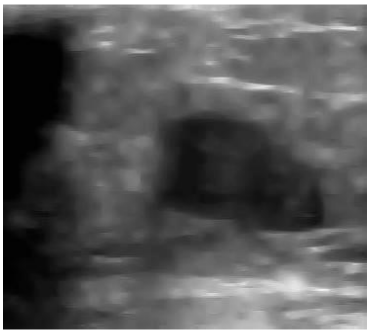

Figure.4.(c) Proposed Method

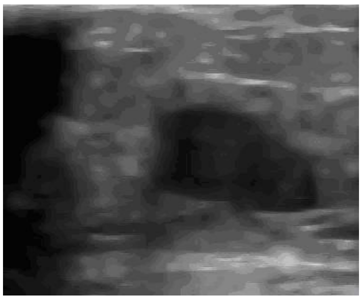

Figure.4.(d) Adaptive Mean Filter

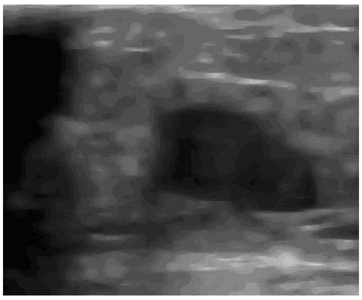

Figure.4.(e) Adaptive Weighted Mean Filter

4. CONCLUSION

This paper discusses about three dynamic soft computing tools namely, neural networks, fuzzy logic, 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.

The proposed system suggests a Hybrid Memetic based approach to optimize neuro-fuzzy system for speckle reduction in breast sonograms. Neural networks for learning and fuzzy parameter for knowledge development are used. The inputs to the system are fuzzy parameters optimizes the output. Based on these parameters MA learning is performed. The system outperforms the traditional systems by 34.5 % in terms of MSE ratio and the computation time is reduced considerably.

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