COMBINATION OF BREEDING SWARM OPTIMIZATION AND BACKPROPAGATION ALGORITHM FOR TRAINING RECURRENT FUZZY NEURAL NETWORK

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Abstract: The usage of recurrent fuzzy neural network has been increased recently. These networks can approximate the behaviour of the dynamical systems because of their feedback structure. The Backpropagation of error has usually been used for training this network. In this paper, a novel approach for learning the parameters of RFNN is proposed using combination of the backpropagation and breeding particle swarm optimization. A comparison of this approach with previous methods is also made to demonstrate the effectiveness of this algorithm. Particle swarm is a derivative free, globally optimizing approach that makes the training of the network easier. These can solve the problems of gradient based method, which are instability, local minima and complexity of differentiating.

1 INTRODUCTION

Fuzzy neural network (FNN) was introduced to fuse fuzzy systems and neural networks into an integrated system to reap the benefits of both (Ku, 1995). The major drawback of the FNN is its limited application domain to static problems, due to the feedforward network structure, thus it is inefficient in dealing with temporal applications.

Recurrent neural network systems learn and memorize information implicitly with weights embedded in them. A recurrent fuzzy neural network (RFNN) was proposed based on supervised learning, which is a dynamic mapping network and it is more suitable for describing dynamic systems than the FNN (Lee, 2000). Of particular interest is that it can deal with time-varying input or output through its own natural temporal operation (Williams, 1989). Ability of temporarily storing information simplifies the network structure and fewer nodes are required for system identification. Because of the complexity in back propagation (BP) learning approach, only diagonal fuzzy rules have been implemented (Ku, 1995). This limiting feature restricts users to employ a more completed fuzzy rule base.

In this paper a novel approach is proposed as a solution to this problem. We combined original BP used in previous works (Lee, 2000) with a breeding particle swarm optimization (BPSO) to train the network more easily and without the complexity of differentiating. The BPSO approach is an derivative-free, global optimizing algorithm that is a combination of genetic algorithm (GA) (Surmann, 2001) and particle swarm optimization (PSO) (Engelbrecht, 2002, Angeline 1994, and Kennedy, 1995) which was first used for training RNN (Settles, 2005).

This paper is organized as follows. In section 2, the RFNN structure is introduced and a comparison between the FNN and the RFNN is described. Section 3 briefly introduces BPSO. The training architecture of the network is presented in section 4 and simulation results are discussed in section 5. Finally, in section 6 we summarize the result of this approach.

2 NETWORK STRUCTURE

The key aspects of the RFNN are dynamic mapping capability, temporal information storage, universal approximation, and the fuzzy inference system. The

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RFNN possesses the same advantages as recurrent neural networks and extend the application domain of the FNN to temporal problems. A schematic diagram of the proposed RFNN structure is shown in Fig. 1 which indicates the signal propagation and the operation functions of the nodes in each layer. In the following description, u_i^k denotes i-th input of a node in the k-th layer; o_i^k denotes the i-th node output in the k-th layer. For the sake of brevity, a brief description of the RFNN is introduced. Interested readers are referred to reference (Lee, 2005).

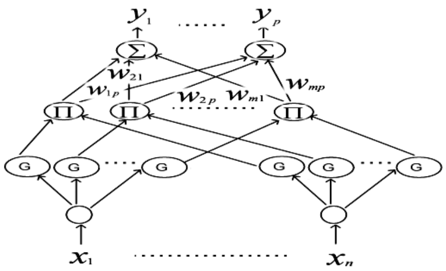


Figure 1: structure of RFNN.

Layer 1: Input Layer:

$$o_i^1 = u_i^1 \tag{1}$$

Layer 2: Membership Layer: The Gaussian function is adopted here as a membership function:

$$o_{ij}^2 = \exp\left\{-\frac{(u_{ij}^2 - m_{ij})^2}{(\sigma_{ij})^2}\right\} \tag{2}$$

where m_{ij} and σ_{ij} are the center (or mean) and the width (or standard deviation—STD) of the Gaussian membership function. The subscript ij indicates the j-th term of the i-th input. In addition, the inputs of this layer for discrete time k can be denoted by

$$u_{ij}^2(k) = o_i^1(k) + o_{ij}^f(k) \tag{3}$$

where $o_{ij}^f(k) = o_{ij}^2(k-1) \times \theta_{ij}$ and θ_{ij} denotes the link weight of the feedback unit. It is clear that the input of this layer contains the memory terms $o_{ij}^2(k-1)$, which store the past information of the network. Each node in this layer has three adjustable parameters: m_{ij}, σ_{ij}, and θ_{ij}.

Layer 3: Rule Layer:

$$\begin{aligned} o_i^3 &= \prod_i u_i^3 = \\ &\exp\left\{-\left[D_i(u_i^2 - m_i)\right]^T \left[D_i(u_i^2 - m_i)\right]\right\} \end{aligned} \tag{4}$$

Where

$$\begin{aligned} D_i &= diag\left\{\frac{1}{\sigma_{1i}}, \frac{1}{\sigma_{2i}}, \ldots, \frac{1}{\sigma_{ni}}\right\}, \\ u_i &= \left[u_{1i}, u_{2i}, \ldots, u_{ni}\right]^T, m_i = \left[m_{1i}, m_{2i}, \ldots, m_{ni}\right]^T \end{aligned} \tag{5}$$

Layer 4: Output Layer:

$$y_p = o_p^4 = \sum_{j=1}^{m} u_j^4 w_{jp}^4 \tag{6}$$

where $u_j^4 = o_j^3$ and w_{ji}^4 (the link weight) is the output action strength of the i-th output associated with the j-th rule. w_{ji}^4 are the tuning factors of this layer. Finally, the overall representation of input x and the p-th output is

$$\begin{aligned} y_p(k) &= o_p^4 = \sum_{j=1}^{m} w_{jp}^4 \times \\ &\prod_{i=1}^{n} \exp\left[-\frac{(x_i(k) + o_{ij}^2(k-1) \times \theta_{ij} - m_{ij})^2}{(\sigma_{ij})^2}\right] \end{aligned} \tag{7}$$

Where

$$\begin{aligned} &o_{ij}^2(k-1) = \\ &\exp\left[-\frac{(x_i(k-1) + o_{ij}^2(k-2) \times \theta_{ij} - m_{ij})^2}{(\sigma_{ij})^2}\right] \end{aligned} \tag{8}$$

Obviously, using the RFNN, the same inputs at different times yield different outputs. The proposed RFNN can be shown to be a universal uniform approximator for continuous functions over compact sets if it satisfies a certain condition (Lee, 2000).

3 BPSO

With correct combination of GA and PSO, the hybrid can outperform, or perform as well as, both the standard PSO and GA models (Settles, 2005). The hybrid algorithm combines the standard velocity and position update rules of PSOs with the ideas of selection, crossover and mutation from GAs. An additional parameter, the breeding ratio (Ψ), determines the proportion of the population which undergoes breeding (selection, crossover and mutation) in the current generation. Values for the breeding ratio parameter range from (0.0:1.0).

In each generation, after the fitness values of all the individuals in the same population are calculated, the bottom (N · Ψ) are discarded and removed from the population where N is the population size. The remaining individual's velocity vectors are updated, acquiring new information from the population. The next generation is then created by updating the position vectors of these individuals to fill (N · (1 − Ψ)) individuals in the next generation. The (N · Ψ) individuals needed to fill the population are selected from the individuals whose velocity is updated to undergo VPAC crossover and mutation and the process is repeated. For clarity, the flow of these operations is illustrated in Figure 1 where k = (N · (1 − Ψ)).

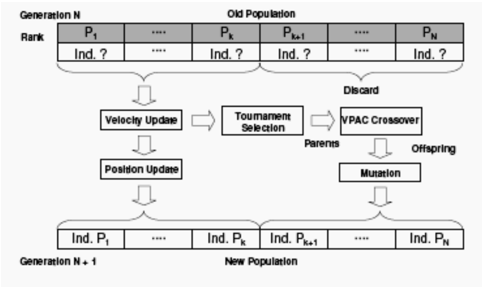


Figure 2: BPSO.

Here, we developed crossover operator to utilize information available in the Breeding Swarm algorithm, but not available in the standard GA implementation. The new crossover operator, velocity propelled averaged crossover (VPAC), incorporates the PSO velocity vector. The goal is creating two new child particles whose position is between the parent's positions, but accelerated away from the parent's current direction (negative velocity) in order to increase diversity in the population. Equations (8) show how the new child position vectors are calculated using VPAC.

$$\begin{cases} c1(x_i) = \dfrac{p1(x_i) + p2(x_i)}{2.0} - \varphi 1\, p1(v_i) \\ c2(x_i) = \dfrac{p1(x_i) + p2(x_i)}{2.0} - \varphi 2\, p2(v_i) \end{cases} \tag{9}$$

In these equations, $c_1(x_i)$ and $c_2(x_i)$ are the positions of child 1 and 2 in dimension *i*, respectively. $p_1(x_i)$ and $p_2(x_i)$ are the positions of parents 1 and 2 in dimension *i*, respectively. $p_1(v_i)$ and $p_2(v_i)$ are the velocities of parents 1 and 2 in dimension *i*, respectively. φ is a uniform random variable in the range [0.0:1.0]. Towards the end of a typical PSO run, the population tends to be highly concentrated in a small portion of the search space, effectively reducing the search space. With the addition of the VPAC crossover operator, a portion of the population is always pushed away from the group, increasing the diversity of the population and the effective search space.

The child particles retain their parents's velocity vector $c_1(\vec{v}) = p_1(\vec{v}),\ c_2(\vec{v}) = p_2(\vec{v})$. The previous best vector is set to the new position vector, restarting the child's memory by replacing new $c_1(\vec{p}) = p_1(\vec{x}),\ c_2(\vec{p}) = p_2(\vec{x})$. The velocity and position update rules remain unchanged from the standard inertial implementation of the PSO. The social parameters are set to 2.0 while inertia is linearly decreased from 0.7 to 0.4 and a maximum velocity (Vmax) of ±1 was allowed. The breeding ratio was set to an arbitrary 0.3. Tournament selection, with a tournament size of 2, is used to select individuals as parents for crossover. The used mutation operator is Gaussian mutation, with mean 0.0 and variance reduced linearly in each generation from 1.0 to 0.0. Each weight in the chromosome has probability of mutation 0.1.

4 NETWORK TRAINING

BP approach, as mentioned, has been mostly used for training RFNN in previous works. This approach is not easy to implement, when faced with the case of a complete or a non-diagonal fuzzy rule base. As we can see in Fig. 1, each rule of layer 3 is made by only a diagonal variables, i.e. the *i-th* rule are made by multiplication of the *i-th* outputs of layer 2. However, if we want to use complete or non-diagonal fuzzy rule base, it will make learning of parameters in layer 2 totally complicated. In this paper we propose Breeding Particle Swarm Optimization for tuning parameters of layer 2 ($m_{ij}, \sigma_{ij}, \theta_{ij}$) and original BP for tuning w_{jp}. These two approaches are used simultaneously. Pseudo code of the algorithm used in this study for training RFNN parameters is shown in Fig. 3. The proposed combination has various benefits for training RFNN. First of all, there is no need to differentiate those complex derivations for training the parameters of the 2nd layer. The proposed algorithm utilizes BPSO as a derivative-free approach for training these parameters. The method is also a global optimization approach that prevents training parameters from converging to local minima. Because of simplicity and high speed convergence, the parameters of 4th layer is learned by BP. Note that using a complete fuzzy rule base doesn't affect the tuning of w_{jp} by BP and will not increase its complexity.

Initialize
While $error > \xi$
apply BPSO for tuning m_{ij}, σ_{ij}, *and* θ_{ij}
apply BP for tuning w_{jp}

Figure 3: Pseudo code of the proposed tuning algorithm.

5 SIMULATION RESULTS

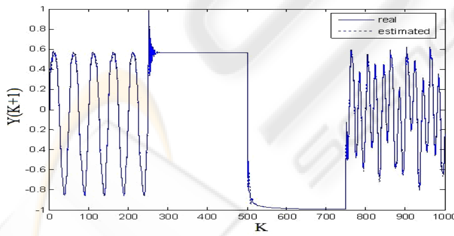
Suppose the following nonlinear dynamical system:

$$y_p(k+1) = f(y_p(k), y_p(k-1), y_p(k-2), u(k), u(k-1)) \quad (10)$$

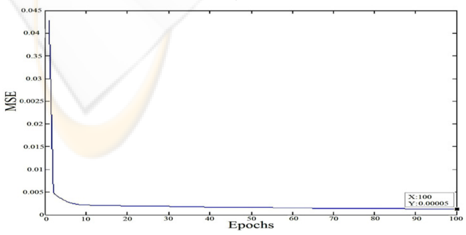
Where,

$$f(x_1, x_2, x_3, x_4, x_5) = \frac{x_1 x_2 x_3 x_5 (x_3 - 1) + x_4}{1 + x_2^2 + x_3^2} \quad (11)$$

In this system the output value depended on the previous values of the output and the previous values of the input. We use RFNN to identify this system. Because of dynamical characteristics of RFNN, it is not necessary to use all complete samples of the previous inputs and outputs. So just y(k) and u(k) are used for estimating y(k+1). The parameters of the 2nd layer of the RFNN is tuned by BPSO and the output weights, w_{jp} is tuned with BP simultaneous. The same input signal that was used in (Lee, 2000) is used here for testing. Fig. 4 illustrates that learning of the network is successfully done. This method leads to better identification than the previous ones. The MSE parameter was 0.00013 in original method while our proposed method converges to 0.00005.



a)



b)

Figure 4: training RFNN parameters with cooperation of the BPSO and BP. a) Identification. b) MSE.

6 CONCLUSIONS

In this study a novel approach for training RFNN was proposed. BP algorithm suffers from complexity of differentiating and converging to local minima. Our proposed method utilizes BPSO with combination of BP. As the simulation results show, applying this algorithm improves the performance of training RFNN. This improvement is gained by globally optimizing the feature of PSO that prevents training to be entrapped in local minima. The complexity of differentiating for gradient based methods is more serious when a complete or a non-diagonal fuzzy rule base is used. This algorithm solves this problem too and one can use it more frequently.

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