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A novel approach to fuzzy wavelet neural network modeling and optimization

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ABSTRACT

In this paper, an efficient approach of combining Takagi–Sugeno–Kang fuzzy system with wavelet based neural network is presented. The model replaces the constant or a linear function of inputs in conclusion part of traditional TSK fuzzy model with wavelet neural network (WNN), thus each rule uses fuzzy set to separate the input space into subspaces spanned by different wavelet functions. For finding the optimal values for parameters of our proposed fuzzy wavelet neural network (proposed-FWNN), a hybrid learning algorithm integrating an improved particle swarm optimization (PSO) and gradient descent algorithm is employed. The two-layer inline-PSO process is proposed in this paper, whose adjustment scheme is more fitting the consequent pattern learning based gradient descent optimization and will locate a good region in the search space. Simulation examples are given to test the efficiency of proposed-FWNN model for identification of the dynamic plants. It is seen that our modeling and optimization approach results in a better performance.

Introduction

Recently, the concepts of neural network, fuzzy logic, wavelet technology have got a lot of attention by researchers. In the field of artificial intelligence, neural networks have been widely used on account of its ability of nonlinear approximation and advantage of easy realization [1–3]. Due to the ability of wavelet transformation for revealing the property of function in localize region, different types of wavelet neural network (WNN) which combine wavelets with neural networks have been proposed [4–6]. In WNN, the wavelets were introduced as activation functions of the hidden neurons in traditional feedforward neural networks with a linear output neuron. There are two different WNN architectures: one type has fixed wavelet bases possessing fixed dilation and translation parameters. In this one only the output layer weights are adjustable. Another type has the variable wavelet base whose dilation and translation parameters and output layer weights are adjustable. Several WNN models have been proposed in the literatures. In [7], a four-layer self-constructing wavelet network (SCWN) controller for nonlinear systems control is described and the orthogonal wavelet functions are adopted as its node functions. In [8], a local linear wavelet neural network (LLWNN) is presented whose connection weights between the hidden layer and output layer of conventional WNN are replaced by a local linear model. In [9], a model of multiwavelet-based neural networks is proposed. The structure of this network is similar to that of the wavelet network, except that the orthonormal scaling functions are replaced by orthonormal multiscaling functions.

Fuzzy logic systems are often used to deal with complex nonlinear systems with ill-defined conditions and uncertain factors [10,11]. Compared with the difficulty to understand the meaning associated with each neuron and each weight in the neural network, fuzzy logic uses linguistic terms and the structure of if-then rules. The traditional Takagi–Sugeno–Kang (TSK) fuzzy model consist of a set of rules, and each rule uses fuzzy set to separate the input space into local fuzzy regions. As the form of combining the benefits of neural network and fuzzy systems, fuzzy neural networks have emerged as a powerful approach to solving many problems [12–15]. In [12], a fuzzy modeling method using fuzzy neural networks with the backpropagation algorithm is presented which can identify the fuzzy model of a nonlinear system automatically. In [13], a hybrid neural fuzzy inference system (HyFIS) for building and optimizing fuzzy models is proposed which is applied to an on-line incremental adaptive learning for the prediction and control of nonlinear dynamical systems. In [14], the adaptive neural fuzzy inference system is used as classifier of fault in power distribution system and makes good performance. In [15], a

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self-organizing complex neuro-fuzzy system is presented and applied to the problem of time series forecasting.

Taking account of the neural networks' self learning ability, fuzzy logic's handling uncertainty capacity and wavelet transforms' analyzing local details superiority, several researchers have made a synthesis model of a fuzzy wavelet neural network (FWNN) [16–20]. In [16], a fuzzy wavelet network is proposed for approximating arbitrary nonlinear functions. Each rule of network corresponding to a sub-wavelet neural network consists of single-scaling wavelets. In [17], a dynamic time-delay fuzzy wavelet neural network model is presented for nonparametric identification of structures using the nonlinear autoregressive moving average with exogenous inputs approach. In [18], the proposed fuzzy wavelet neural network is used for the identification and the control of the dynamic plants. Each rule in FWNN includes a wavelet function in the consequent part of the rule and multi-dimensional wavelet functions are the summation form. In [19], the genetic algorithm (GA) approach is used to adjust the FWNN parameters of dilation, translation, weights, and membership functions. In [20], a hybrid adaptive wavelet-neuro-fuzzy system is proposed using wavelets as membership functions in the antecedent part as well as the activation functions in the consequent part of fuzzy rules.

Inspired by social behavior of bird flocking or fish schooling, particle swarm optimization (PSO) was firstly introduced by Kennedy and Eberhart in 1995 [21,22]. After several years of development, PSO and its modified forms have evolved as an important branch of stochastic techniques to explore the search space for optimization, which have been successfully applied in many areas: function optimization, artificial network training, fuzzy system control and so on [23–27]. The attractive features of PSO include ease of implementation and the fact that no gradient information is required. However, PSO does exhibits some disadvantages: like other heuristic algorithms, it takes more calculation time than traditional gradient descent method when you want to achieve similar accuracy; it sometimes is easy to be trapped in local optima, and the convergence rate decreased considerably in the later period of evolution; when reaching a near optimal solution, the algorithm stops optimizing, and thus the accuracy the algorithm can achieve is limited.

In this paper, a novel fuzzy wavelet neural network is proposed, which use the concepts of fuzzy logic in combination with WNN. In our proposed fuzzy wavelet neural network (proposed-FWNN), each fuzzy rule corresponds to a WNN consisting of several wavelets with adjustable translation and dilation parameters. In the aspect of optimizing the proposed-FWNN, in order to avoid the trial-and-error process and the impact coming from random initialization, we adopt a hybrid learning algorithm. Firstly, an inline-PSO algorithm is proposed to find a relative good initial value of adjustable parameters. The inline-PSO shows a faster convergence than the basic PSO and the updating scheme of the velocity and position of particles are more coordinating with the following pattern learning based gradient descent algorithm. Secondly, the gradient descent algorithm is adopted to adjust parameters in the proposed-FWNN. For getting a more reasonable model, the performance criterion of training and testing signals during learning are both investigated.

The rest of the paper is organized as follows. The proposed-FWNN is introduced in Section "The proposed fuzzy wavelet neural network modeling". A hybrid learning algorithm for training proposed-FWNN is described in Section "Hybrid learning algorithm to optimize the proposed-FWNN". In Section "Simulation examples", two simulation examples of system identification are given to demonstrate the better performance of proposed-FWNN. Finally, a brief conclusion is drawn in Section "Conclusion".

The proposed fuzzy wavelet neural network modeling

Motivated by the reason stated in Section "Introduction", we present a novel type of fuzzy wavelet-based model. TSK fuzzy models are employed to describe the proposed-FWNN by some fuzzy rules, and WNNs consisting of several wavelets with adjustable translation and dilation parameters form the consequent parts of each fuzzy rules.

Takagi–Sugeno–Kang fuzzy system

In a TSK fuzzy model, the domain interval of each input is separated into fuzzy regions and each region shows a membership function in the IF part of the fuzzy rules. A constant or a linear function of inputs is used in the THEN part of the rules. That is, the IF-THEN rules are as follows [10]:

$$\begin{aligned} R_k\text{: IF } x_1 \text{ is } A_{k1} \text{ AND } x_2 \text{ is } A_{k2} \text{ AND } \cdots \text{ AND } x_n \text{ is } A_{kn} \\ \text{THEN } y_k = a_{k0} + a_{k1}x_1 + \cdots + a_{kn}x_n, \end{aligned} \tag{1}$$

where R_k represents the kth fuzzy inference rule, x_j and A_{kj} are fuzzy variables and fuzzy sets with membership functions.

The fuzzy membership functions of A_{kj} are Gaussian function defined by (2):

$$\mu_{kj}(x_j) = \exp\left(-\left(\frac{x_j - c_{kj}}{\sigma_{kj}}\right)^2\right), \tag{2}$$

where c_{kj} denote the centers and σ_{kj} denote the standard deviation for membership function associated with rule k. The output of TSK fuzzy system with M rules is aggregated as (3):

$$y = \frac{\sum_{k=1}^{M} y_k \prod_{j=1}^{n} \mu_{kj}(x_j)}{\sum_{k=1}^{M} \prod_{j=1}^{n} \mu_{kj}(x_j)}. \tag{3}$$

The TSK fuzzy model is based on a fuzzy partition of input space and it can be viewed as expansion of a piecewise linear partition.

Wavelet neural network

Wavelets in the following form:

$$\psi_{a,b} = |a|^{-1/2}\psi\left(\frac{x-b}{a}\right), (a, b \in R, a \neq 0) \tag{4}$$

are a family of functions generated from one single function $\psi(x)$ by the operation of dilation and translation. $\psi(x) \in L^2(R)$ is called a mother wavelet function that satisfies the admissibility condition:

$$C_\psi = \int_0^{+\infty} \frac{|\hat{\psi}(\omega)|^2}{\omega} d\omega < +\infty, \tag{5}$$

where $\hat{\psi}(\omega)$ is the Fourier transform of $\psi(x)$ [28,29].

Grossmann and Morlet [30] proved that any function $f(x)$ in $L^2(R)$ can be represented by (6):

$$f(x) = \frac{1}{C_\psi} \iint Wf(a,b)|a|^{-1/2}\psi\left(\frac{x-b}{a}\right)\frac{1}{a^2} dadb, \tag{6}$$

where $Wf(a,b)$ given by (7):

$$Wf(a,b) = |a|^{-1/2}\int_{-\infty}^{+\infty} \psi\left(\frac{x-b}{a}\right) f(x)dx \tag{7}$$

is the continuous wavelet transform of $f(x)$.

Superior to conventional Fourier transform, the wavelet transform (WT) in its continuous form provides a flexible time–frequency window, which narrows when observing high frequency phenomena and widens when analyzing low frequency behavior. Thus, time resolution becomes arbitrarily good at high frequencies,