Neurocomputing 167 (2015) 558–568

Contents lists available at ScienceDirect

Neurocomputing

journal homepage: www.elsevier.com/locate/neucom

A new data-driven neural fuzzy system with collaborative fuzzy clustering mechanism

M. Prasad [a,*], Y.Y. Lin [b], C.T. Lin [c], M.J. Er [d], O.K. Prasad [e]

[a] Department of Computer Science, National Chiao Tung University, Hsinchu, Taiwan
[b] Brain Research Center, National Chiao Tung University, Hsinchu, Taiwan
[c] Department of Electrical Engineering, National Chiao Tung University, Hsinchu, Taiwan
[d] School of Electrical and Electronic Engineering, Nanyang Technological University, Singapore, Singapore
[e] EECS International Graduate Program, National Chiao Tung University, Hsinchu, Taiwan

ARTICLE INFO

Article history:
Received 23 December 2014
Received in revised form
28 February 2015
Accepted 15 April 2015
Communicated by Ning Wang
Available online 27 May 2015

Keywords:
Neural networks
Fuzzy system
Big-data
Privacy and security
Collaborative technique
On-line learning system
Time series prediction

ABSTRACT

In this paper, a novel fuzzy rule transfer mechanism for self-constructing neural fuzzy inference networks is being proposed. The features of the proposed method, termed data-driven neural fuzzy system with collaborative fuzzy clustering mechanism (DDNFS-CFCM) are; (1) Fuzzy rules are generated facilely by fuzzy *c*-means (FCM) and then adapted by the preprocessed collaborative fuzzy clustering (PCFC) technique, and (2) Structure and parameter learning are performed simultaneously without selecting the initial parameters. The DDNFS-CFCM can be applied to deal with big data problems by the virtue of the PCFC technique, which is capable of dealing with immense datasets while preserving the privacy and security of datasets. Initially, the entire dataset is organized into two individual datasets for the PCFC procedure, where each of the dataset is clustered separately. The knowledge of prototype variables (cluster centers) and the matrix of just one halve of the dataset through collaborative technique are deployed. The DDNFS-CFCM is able to achieve consistency in the presence of collective knowledge of the PCFC and boost the system modeling process by parameter learning ability of the self-constructing neural fuzzy inference networks (SONFIN). The proposed method outperforms other existing methods for time series prediction problems.

1. Introduction

Neural networks and fuzzy systems [1] are two important technologies which play a pivotal role towards realization of machine learning and artificial intelligence [2]. The integration of fuzzy inference systems (FISs) and artificial neural networks (ANNs) has been widely pursued by many researchers due to the requisite of adaptive intelligent systems for solving real-world problems. The integrated technology, called neural fuzzy technique, has been applied frequently in many disciplines related to engineering. Consequently, many researchers have focused on system modeling by using neural fuzzy techniques [3–5], because it possesses the advantages of both neural networks and fuzzy systems. Moreover, structure identification and parameter learning of neural fuzzy networks help prevailing over the incapability of fuzzy systems with parameter learning and neural networks unable to do interpretation of human-like intelligence. In neural fuzzy systems, several data-driven strategies to generate appropriate numbers of fuzzy rules have been introduced [6–8].

Rong and Sundarajan [9] proposed a sequential adaptive fuzzy inference system (SAFIS) based on the functional equivalence between a radial basis function network and a fuzzy inference system (FIS). In this method, if there is no admission to the new fuzzy rule by input data, then only the parameters of the nearest rule are updated by using an extended Kalman filter (EKF) scheme. Dovzan and Skrjan [10] proposed an on-line TSK-type fuzzy model, which can be used for modeling control system or robotics by combination of a recursive fuzzy *c*-means and least squares. This method needs more computational cost than the SAFIS because of the fuzzy covariance matrix. However, the memory requirements are stationary due to the inelastic number of clusters. Wang and Lee [11] proposed a self-adaptive neuro-fuzzy inference system (SANFIS), which is adequate for self-adapting and self-organizing its domestic structure to obtain an economical rule base for illustrating the internal structure from input training dataset of the system. An online sliding-window-based self-organizing fuzzy neural network (SOFNN) was proposed by Leng and Prasad [12], which is suitable for machine learning and also it is applicable for cognitive reasoning in smart home environment. Er and Wu [13] proposed a learning algorithm for dynamic fuzzy neural networks

* Corresponding author.
E-mail addresses: mukeshnctu.cs99g@nctu.edu.tw (M. Prasad), oliver.yylin@gmail.com (Y.Y. Lin), ctlin@mail.nctu.edu.tw (C.T. Lin), EMJER@ntu.edu.sg (M.J. Er), omg.eo02g@nctu.edu.tw (O.K. Prasad).

http://dx.doi.org/10.1016/j.neucom.2015.04.034
0925-2312/

(DFNN) based on extended radial basis function (RBF) neural networks. The features of DFNN approach evolve around free parameters that can be adjusted and structure learning mechanism associated with self-adaptive operation through a pruning technique.

Wang [14] proposed a generalized-ellipsoidal-basis-function-based online self-constructing fuzzy neural network (GEBF-OSFNN), which enlarges the ellipsoidal basis function (EBF)-based fuzzy neural networks (FNNs) by allowing the input variables to be modeled by dissymmetrical Gaussian functions (DGFs). Han [15] proposed a novel growing-and-pruning (GP) approach, which improves the formation of fuzzy neural networks (FNNs). The GP-FNN is based on RBFN, where neither the parameters nor the numbers of neurons in the hidden layer requires, all values are allocated during the learning process. Reinforcement evolutionary learning algorithm (REL) was proposed by Lin and Chen [16] for self-evolving neural fuzzy inference networks (SENFIN). The proposed REL consists of parameter learning and structure learning which are used to adjust the parameters of the SENFIN and determine the number of fuzzy rules. The merits of the SENFIN-REL technique include that it can dynamically design the structure of SENFIN and adjust free parameters of SENFIN whose consequent part is a nonlinear combination of input variables. Malek [17] proposed three new hybrid learning algorithms for Takagi–Sugeno–Kang fuzzy systems by using three kinds of manners, including the K-nearest neighbor, mean-shift procedure and space partitioning, which are more effective in terms of accuracy and requires fewer rules because of the simplicity of the algorithms with lower computational cost and approximate nonlinear functions. It has been shown that fixing the variance value for the Gaussian fuzzy sets reduces the number of parameters and there is no need for parameter tuning.

The existing fuzzy neural networks (FNNs) have two factions. The first faction is fuzzy systems with self-tuning ability but it requires initialization of the number of fuzzy rules. The second faction of neural fuzzy networks is the capability to dynamically determine the fuzzy rules from the given dataset. However, most of the existing fuzzy neural systems confronted some problems such as a priori computation to determine the number of clusters, inconsistent rule-base and heuristically defined node operations. Taking all deficiencies into consideration, a novel fuzzy rule transfer mechanism for self-constructing neural fuzzy inference networks, where transfer fuzzy rule is used as a substitute for the rule generation strategy of the SONFIN is proposed in this study. The proposed method not only promotes our learning process but also provides a stable and excellent performance. In order to demonstrate the feasibility and effectiveness of the proposed method, several examples, including the Mackey Glass time series prediction problem and a nonlinear dynamic system, are used to determine the network's performance. Experimental results demonstrate that the proposed method outperforms other methods on given sets of benchmark data with comparatively fewer rules.

The rest of the paper is organized as follows: Section 2 gives a brief introduction of SONFIN, FCM, CFC, PCFC and an overview on the proposed method and its architecture. Section 3 shows the experimental results on two different time-series datasets and finally conclusions are drawn in Section 4.

2. Proposed method

2.1. Self constructing neural fuzzy inference networks

A self-constructing neural fuzzy inference networks (SONFIN) [18] was proposed by Juang and Lin, which has been applied to various applications [19–24]. The SONFIN always brings an effective network structure and speeds up the learning process with well-defined modeling capability compared to common neural networks.

The SONFIN consists of multiple layers, each of which has a finite fan-in of connections that are represented by weight values from other nodes and a fan-out of connections to other nodes. The function provides the net input for node is denoted as follows:

$$net-input = f[u_1^{(k)}, u_2^{(k)}, \ldots, u_n^{(k)}; w_1^{(k)}, w_2^{(k)}, \ldots, w_n^{(k)}] \tag{1}$$

where $u_1^{(k)}, u_2^{(k)}, \ldots, u_n^{(k)}$ are inputs to this node and $w_1^{(k)}, w_2^{(k)}, \ldots, w_n^{(k)}$ are the associated link weights. The superscript (k) indicates the layer number. The output of each node is an activation function value of its net input given by:

$$output = o_i^{(k)} = a(net-input) = a(f) \tag{2}$$

where $a(.)$ denotes tha activation function. The functions of the nodes in each of the five layers of the SONFIN structure are briefly described as follows:

Layer 1. No computation is performed in this layer, the input values are directly transmited to the next layer.

$$f = u_i^{(1)} \text{ and } a^{(1)} = f \tag{3}$$

Layer 2. Using the Gaussian membership function the output of Layer 1 is calculated as follows:

$$f[u_{ij}^{(2)}] = -\frac{[u_{ij}^{(2)} - \mu_{ij}]^2}{\sigma_{ij}^2} \text{ and } a^{(2)} = e^f \tag{4}$$

where μ_{ij} is the mean and σ_{ij} is the variance of the Gaussian membership function of the ith input variable u_{ij} for the jth partition.

Layer 3. One fuzzy logic rule is represented by a node in this layer and it performs a precondition matching of a rule with an AND operation as follows:

$$f[u_i^{(3)}] = \prod_{i=1}^{n} u_i^{(3)} \text{ and } a^{(3)} = f \tag{5}$$

where n is the number of Layer 2 nodes participating in the IF part of the rule.

Layer 4. Normalized firing strength is calculated in Layer 3 and number of nodes in this layer is equal to that in Layer 3.

$$f[u_i^{(4)}] = \sum_{i=1}^{r} u_i^{(4)} \text{ and } a^{(4)}(f) = \frac{u_i^{(4)}}{f} \tag{6}$$

where r is the number of rule nodes in Layer 3.

Layer 5. The node integrates all the actions recommended in Layer 5 and acts as a defuzzifier. Each node in this layer corresponds to one output variable.

$$f[u_i^{(5)}] = \sum_i w_i u_i^{(5)}, \; a^{(5)}(f) = f \tag{7}$$

For details on structure and parameter learning of the SONFIN, users can refer to [18].

2.2. Fuzzy c-means clustering

Bezdek introduced fuzzy c-means (FCM) [25], which allows each data point exhibits to one or more clusters that are specified by a membership function. The minimization of objective which decides the performance of FCM is defined as shown in Eq. (8).

$$J_M = \sum_{i=1}^{N} \sum_{j=1}^{c} u_{ij}^m ||x_i - v_j||^2 \tag{8}$$

where M is real number great than 1, u_{ij} is the degree of membership of x_i in the cluster j, x_i is the ith data point of d-dimension dataset, v_j is the d-dimension of the cluster and $||*||$ is any norm expressing the similarity between any measured data and the center.