ARTICLE IN PRESS

Neurocomputing ∎ (∎∎∎∎) ∎∎∎–∎∎∎

Contents lists available at ScienceDirect

Neurocomputing

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

Unified granular neural networks for pattern classification

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ARTICLE INFO

Article history:
Received 30 September 2015
Received in revised form
10 June 2016
Accepted 20 July 2016
Communicated by Zidong Wang

Keywords:
Pattern recognition
Information granulation
Neural networks
Fuzzy sets
Multiple decision system

ABSTRACT

Motivation in the development of granular neural network (GNN) with the principle of granular computing (GrC) is to obtain possible degree of transparency in the network architecture and its operational steps, which are bottleneck for conventional neural network (NN). In addition, GNN provides improved performance and at the same time poses less computational burden compared to conventional NN and fuzzy NN (FNN). Topologically, the nodes of different layers of FNNs are fully connected whereas it is partial in case of GNNs. Further, the architectures of GNN is determined based on the extracted rules from the domain information. However, selection of relevant rules for GNN is a tedious task. To mitigate this, the present paper aims to develop a pattern classification model in the framework of unification of GNNs and tries to avoid the searching of optimum number of rules and the best combination of rules. The unified model thus works with a set of different rules-based GNNs and derives the final decision from the individual GNN. Each of these GNNs takes the class-supportive fuzzy granulated features of the input in order to preserve the feature-wise belonging information to different classes. These granulated features provide improved class discriminatory information for the classification of data sets with ill-defined and overlapping class boundaries. The proposed model thus explores mutually the advantages of class-supportive fuzzy granulation of features, informative rules-based GNNs and unification of GNNs. Superiority of the model to similar other methods are justified in terms of various performance measurement indexes using different benchmark data sets including remote sensing imagery.

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1. Introduction

Human beings follow a structural and hierarchical approach to solve various pattern recognition problems in order to achieve high rate of success. In this process, human brain initially tries to experience the task through the acquired knowledge and stores them in the form of synaptic weights. These information are then used for reasoning and interpreting the new tasks. Artificial neural networks (NNs) [1] are evolved with these inspirational steps of human brain to solve real-time complex pattern classification problems. The advantages of a NN that make it popular includes; network's adaptivity to a changing environment, fault tolerance to missing or noisy information, speed with massive parallelism, ruggedness to failure of nodes/links, and optimality as regards to error rates in classification tasks [1,2]. In spite of several merits, the bottleneck for these NNs are the transparency in processing of information. This characteristic restricts the user to gain knowledge about the network architecture that effects the decision taking capability of NNs. Further, NN can only process the numerical input and becomes unfit for linguistic/symbolic/categorical data. Several attempts have been made in order to overcome these issues of NNs using neuro-fuzzy (NF) networks [3–8]. In a NF network, the input to NN is fuzzified using fuzzy set theory [9] that provide certain extent of transparency at the network-input. The fuzzification process also handles the uncertainty and imprecise nature of the problem, and can take care of linguistic or symbolic inputs. Although, NF networks provide transparency at the input, looking inside into the operational steps of the network is still a challenging task. To mitigate this, GNNs [10,11] are developed in the framework of granular computing (GrC) [12] that provide ample scopes for editing network's processing steps, and at the same time can handle uncertain and imprecise information efficiently.

GrC is a problem solving paradigm that works with the basic element called granules. Significance of a granule in GrC is similar to any subset, class, object, or cluster of a universe. The granules are composed of elements that are drawn together by indiscernibility, similarity, and functionality [13]. Each of these granules according to its shape and size, and with a certain level of

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http://dx.doi.org/10.1016/j.neucom.2016.07.034
0925-2312/© 2016 Published by Elsevier B.V.

Please cite this article as: D. Arun Kumar, et al., Unified granular neural networks for pattern classification, Neurocomputing (2016), http://dx.doi.org/10.1016/j.neucom.2016.07.034

granularity may reflect a specific aspect of the problem. Granulation is the process of construction, representation, and interpretation of these granules. Computation with granules at a certain level of granulation is the basis of GrC. With this framework various GNNs are developed [11,14–17] to solve complex problems. However, these networks are fully connected among the connecting layers and their nodes. In the present study, we have used GNNs, where the network is not fully connected. Similar types of GNNs are developed by Vasilakos and Stathakis [18,19] to classify land cover classes of remote sensing imagery. Performance of these GNNs depends on the fuzzy granulated input information and different rules-based network architecture that leads to improved performance. However, fuzzy granulation method (as adopted in these GNNs) with three linguistic fuzzy sets (*low*, *medium* and *high*), does not take care of the class belonging information of feature spaces and make the network less-effective. To mitigate this, we have proposed to use the class-supportive fuzzy granulation method that preserves class-wise belonging information of each feature to all classes in order to improve the efficacy of a network. Further, the authors in [18,19] have derived empirical rules to construct GNNs and demonstrated their efficiency. However, extraction of these rules is a difficult task for the user with the increase in number of samples, features and class labels. The process thus demands the intervention of domain specific experts, which is expensive and time consuming. To overcome this issue, we have proposed to use rule extraction method, as described by Kasabov [20]. Kasabov rule extraction (KRE) method derives meaningful rules from the fuzzy granulated input data and then the NN is trained using these granulated information. The method works adaptively and extracts fuzzy rules from an adaptive fuzzy NN with fully connected nodes. The network is trained for certain number of iterations using back propagation algorithm [1] and the required knowledge is stored in the form of updated weights between the nodes. Based on the significance of weights, node-to-node connectivity is determined and the NN is designed.

From the experimental study, it is seen that the proposed GNN with extracted rules using KRE method, works better with the increase in number of rules per class. This poses a tricky issue in determining optimum number of rules for a class. In addition, one should take the appropriate combination of rules for improved performance. This becomes a hurdle for the user to decide the best set of rules. In the quest of a classification model that overcomes the above-mentioned problems, we have proposed a unified framework that unifies multiple number of GNNs and the final decision depends on the strategic combination of these networks. Functioning of the proposed model is similar to the process of taking decision by considering individuals opinion of a group of experts [21–26]. Different types of decision combination strategies, such as *majority voting*, aggregation operators like *mean, median, product, sum, minimum* and *maximum* are used to get a combined and better decision. The model thus avoids the searching process for optimum number of rules per output class and the best combination of rules. Superiority of the proposed model to similar other methods with individual and combination of rules for classification tasks is experimentally demonstrated and verified with different indexes, such as overall accuracy, producer accuracy, user accuracy, kappa coefficient, and measure of dispersion estimation. Experimental results with four data sets showed that the proposed model can preserve and even improve the classification performance while at the same time avoid the task of searching the best GNN with an informative set of rules, for improved performance.

1.1. Motivation for the proposed pattern classification model

Development of the proposed classification model is motivated by four factors; (i) Conventional NN does not provide a transparent platform, i.e., it restricts the user to interpret and reason the processing steps of input information. In addition, conventional NN fails to handle symbolic and linguistic inputs. As a result, performance improvement with the exploitation of information processing steps in a diverse domain of inputs becomes a bottleneck for the network developer. This motivated us to explore the significance of GNN that provides a fairly transparent network, and can deal with both numeric and symbolic or linguistic inputs and justifies its potential role in a pattern classification task. (ii) Design of GNN requires different rules for each of the output classes and more informative a rule is, better is the performance. We got the motivation from this factor and aims to extract informative rules from the data using KRE method to design efficient GNN. (iii) Again, the performance of a network highly depends on the available input information and better decision can be expected from a network with more discriminative input information. This motivated us to exploit the input feature space using class-supportive fuzzy granulation method that provides class-wise belonging of each feature to different classes. (iv) With all these phases of operation, it is still a difficult task for the user to obtain potential decisions from a GNN, because selection of optimum number of informative rules for each of the classes and their appropriate combination play important role for improved performance. Finally, in order to avoid the confusion in deciding the number of rules and types of their combination, we got motivated and proposed a unified framework that unifies the decision of individual GNN to provide the final result. Potentiality of the proposed classification model is validated in terms of various performance measurement indexes using different data sets with overlapping and ill-defined class boundaries.

2. Preliminaries of granular neural network

Granular neural network (GNN) is a derived version of the conventional neural network (NN) and its development is motivated by the challenging factors encountered by NN. For example, NN, with its complete network structure becomes very complex and triggers huge computational burden while dealing with the data set having large number of samples and features. Due to the complex and considerable size, NN takes more training time and becomes infeasible for online data processing. Further, most of the parameters of NN are determined empirically and thus it tries different methods to learn from the mistakes. Often, NN provides satisfactory results however, it is difficult to explain the reasons for its success through the overabundance number of network parameters, such as synaptic weights and large number of nodes between the layers of NN. Generally, such trait is referred as the "black box" phenomenon. This factor motivates to develop models that aim to interpret the operational steps and network structure more effectively in order to improve the overall performance. Most often, data sets for complex problems are symbolic / linguistic or/ and heterogeneous in nature rather than only numerical. These types of data sets become a severe challenge for NNs, as they are incapable to process them. To mitigate this issue, fuzzy sets [9] has been extensively used that can appropriately handle symbolic or linguistic data sets.

However, fuzzy systems alone lack the capabilities of machine learning and NN- type memory. As a result, integration of NN and fuzzy logic that provides a hybrid paradigm called neuro-fuzzy (NF) network [3,4,7,8] are being used extensively among all other integrations in soft computing. Such integration of concepts generally aims to design more intelligent systems than the individual one to deal with real-life complex decision making problems. Fuzzy set theory also describes the concept of information granulation that formulates the process of fuzzy information granulation (FIG). FIG

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