Applied Soft Computing 33 (2015) 328–336

Contents lists available at ScienceDirect

Applied Soft Computing

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

A Metacognitive Fully Complex Valued Functional Link Network for solving real valued classification problems

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ARTICLE INFO

Article history:
Received 7 July 2014
Received in revised form 5 April 2015
Accepted 6 April 2015
Available online 29 April 2015

Keywords:
Meta-cognitive complex valued functional link networks
UCI repository
Real valued data

ABSTRACT

In this paper, a sequential learning based meta-cognitive fully complex valued functional link network (Mc-FCFLN) is developed for solving complex real world problems. Mc-FCFLN network consists of two components: a cognitive component and a meta-cognitive one. A fully complex-valued functional link network (FCFLN) is a cognitive component and the self-regulatory learning method is its meta-cognitive component. As the network does not possess hidden layers, the multi-variable polynomials are represented in the input layer for capturing the nonlinear relationship between the input and the output sample. Moreover, when the sample is presented to the Mc-FCFLN network, the meta-cognitive component decides what to learn, when to learn, and how to learn depending on the knowledge gained by the FCFLN network and the novel information present in the sample. The network can learn sample one after the other and thus the drawback existing with the batch learning strategy can be eliminated while orthogonal least square principle is used for selecting the best polynomial and the recursive least square update is used for tuning the network. Multi-category and binary datasets chosen from the UCI machine learning repository is used for the validation of the proposed classifier. Lastly, a performance comparison of the Mc-FCFLN applied for classification problems shows better classification ability when compared with the other existing classifiers in the literature.

1. Introduction

Nowadays, Artificial neural networks have become the potential field of research [1–3], and they are applied in areas like system identification and control, communication, pattern recognition systems, classification [4] and prediction [5,6]. The physical properties and the non linear transformations of the signals used in these applications can be preserved by representing them in the complex domain. Recently, researchers have begun to develop algorithms for the complex valued neural networks and it has been shown that these algorithms have a better computational power than the real-valued networks [7] and due to the presence of orthogonal decision boundaries [8] these networks act as better decision makers when compared to their real-valued counterparts. This decision making ability has motivated the researchers in developing efficient classifiers for real world applications. A major challenge faced during the development of the complex-valued neural network is the absence of an entire and a bounded activation function as the *Liouville's theorem* states that an entire and a bounded function is a constant in the Complex domain [9]. Initially, this limitation was overcome by processing the real part and imaginary part of the complex valued signals separately [10]. However, the separation of the complex-valued sample into two parts does not form a better representation and therefore it results in a significant loss of information during processing [11]. Hence, the desired properties of a complex-valued activation function to be analytic and bounded *almost everywhere* [12] has been reduced. In addition, a set of elementary transcendental functions with singularities has been recommended by Kim et al., [13] as the activation functions for the fully complex-valued multi-layer perceptron networks. The effect of their singularities and the convergence of these activation functions have been experimentally studied and reported in [14].

Some of the classifiers developed in the Complex domain include the Multi Layered Network with Multi Valued Neurons (MLMVN) [15], the single layered complex-valued classifier referred to as, "Phase Encoded Complex-valued Neural Network (PE-CVNN)" [16], the Bilinear Branchcut Complex-valued Extreme Learning Machine (BB-CELM), the Phase Encoded Complex-valued Extreme Learning Machine (PE-CELM) [17], the Fully Complex-valued Radial Basis Function network (FC-RBF) classifier [18] and

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http://dx.doi.org/10.1016/j.asoc.2015.04.022
1568-4946/

the Circular Complex-valued Extreme Learning Machine (CC-ELM) [19].

The multi-layered network with multi-valued neurons [15] is the first classifier that has been developed in the Complex domain. The MLMVN uses multi-valued neurons which employ a piecewise continuous activation function for mapping the complex-valued inputs to C discrete class labels (i.e. C-valued threshold logic, where C is the number of classes). In MLMVN, the real-valued input features (x) are mapped to a unit circle with the help of $exp(i2\pi x)$ transformation and the class labels are encoded in the complex plane by the roots of unity and MLMVN requires significant computational effort during the training process.

In the single layered phase encoded complex-valued neural network [16,20], the real-valued input features (x) are phase encoded in the region of $[0, \pi]$ (unique transformation) and they employ the '$exp(i\pi x)$' transformation for obtaining the complex-valued input features. However, this network uses an activation function similar to the activation function used in the split type complex-valued neural networks and a gradient descent based learning algorithm is used to calculate the parameters of the network. Thus, it requires a massive computational effort for training.

A multi-layer neural classifier, namely 'Fully Complex-valued Radial Basis Function classifier (FC-RBF)' has been introduced in [18]. FC-RBF classifier employs gradient descent batch learning algorithm for estimating the parameters of the network. It also requires a large computational effort during training. Hence, two fast learning classifiers, indicated as, 'Bilinear Branch-cut Complex-valued Extreme Learning Machine (BB-CELM)' and the 'Phase Encoded Complex-valued Extreme Learning Machine (PE-CELM)' were introduced in [17]. These classifiers have one input layer, one hidden layer and a single output layer. In the BB-CELM network, a bilinear transformation using a branchcut around 2π was used at the input layer for transforming the real-valued input features into the complex domain, whereas in PE-CELM, the neurons in the input layer employ the phase encoded type transformation. The fully complex-valued '*sech*' function is used at the hidden layer and the linear neurons are used in the output layer. Even though these classifiers are fast they use a fully complex-valued activation function in the hidden layer. The BB-CELM and PE-CELM neural classifiers use a bilinear transformation and phase encoding type transformation is employed in MLMVN classifier and PE-CVNN classifier, respectively. The transformation used in the BB-CELM classifier and the PE-CELM classifier does not fully exploit the orthogonal decision boundaries of a fully complex-valued classifier. Hence, a circular transformation mapping that maps the real-valued input feature vectors to all of the four quadrants of the complex domain has been developed in a 'Circular Complex-valued Extreme Learning Machine (CC-ELM)' [19], and this transformation has also been used in [21,22]. To overcome the drawback existing with the sech function, two new activation functions are proposed in [23]. Recently, Kartick [24] proposed a complex valued neuro fuzzy algorithm for solving real world problems. Moreover, the same author has developed a complex valued neuro fuzzy based classifiers [25] for solving real valued classification problems as well as addressed prediction problems. For the complete details of the complex-valued neural networks in the literature, one must refer to [26–28].

Some of applications in this domain are presented in [29,30]. The main bottleneck of these networks is the use of complex valued activation functions with singularities in the hidden layer. Apart from this bottleneck, the presence of hidden layers in the real valued as well as in the complex valued neural networks results in a computationally intensive network. Recently, networks without hidden layers, namely Functional link networks [FLN] [31] have become predominant to overcome the aforesaid difficulty. In these networks, the nonlinearity can be introduced by the functional expansion of attributes in the input layer. The trigonometric functions, orthogonal basis functions, polynomials etc., can be used for the functional expansion at the input layer. FLNs can be grouped depending upon the various functional expansion methods and they are (i) Random Vector FLNs, (ii) FLNs with multivariate polynomial as basis functions, (iii) FLNs with trigonometric basis functions and (iv) orthogonal polynomials based FLNs. All FLNs do not possess the property of universal approximation like Multi layer perceptron networks. Only the random vector FLNs act as efficient universal approximators.

In the MLP network, hidden layers provide mapping from lower dimensional plane to a higher dimensional one for enhancing the representation of original input using supervised learning. However, the learning suffers from limitations like slow convergence, initial weight dependency, local minima and saturation of activation function. The process of improving the input representation in FLNs is similar to Multilayer Perceptron (MLP) networks. In FLNs, the improvement is carried out from the input layer in a linearly independent way. This approach has a remarkable effect in learning and makes the problem simpler in MLPs. The major difference between FLNs and MLPs is that in the MLPs, enhancement of the input at the hidden layer results in learning process whereas in FLNs without learning the variables are enhanced at the input layer. However, choosing proper functional expansion can result in a better network. The real valued functional link networks are applied in the area of control, communication and pattern recognition. Only few work has been carried out to process complex valued signals. In [32] the real and imaginary components are processed separately. This method of processing cannot utilise the natural properties of complex valued neural networks and it will not result as an efficient method.

In this paper, a meta-cognitive fully complex valued functional link network (Mc-FCFLN) for solving classification problem is presented. The nonlinear relationship is captured between input and the output using samples of multivariate polynomials. Computations performed are easier with the polynomial when compared to elementary transcendental functions with singularities [13]. As the total terms (or monomials) in the multivariate polynomial exponentially grow with the degree value and the number of input variable, it is essential that only significant monomials are to be chosen in the FCFLN and it is obtained by Orthogonal Least Squares Method (OLS) [33]. The polynomial degree is incremented until there is no improvement observed from the increment. In the above cited paper, the network has been developed to deal with function approximation problems.

The FCFLN network involves batch learning method for training process. It assumes that the complete training samples will be available in prior for calculating the output weights. There arises a problem when only a few samples are available in prior for training. Learning of similar samples also constitutes one of the major issues that exists in complex valued functional link networks. The algorithm applied in the above said network requires the ability to evaluate its knowledge with respect to the environment and its own knowledge. Hence, the algorithms assume even sharing of information in the training dataset and learn the entire samples in the sequence in which it is been presented. So getting trained with similar samples will result in overtraining.

In order to overcome the aforesaid issue existing in the FCFLN network, this paper introduces a meta-cognitive fully complex valued functional link network (Mc-FCFLN) which can process data in a sequential manner. Recently, it is found that the human learning literature with self-regulated learning capable of assessing what-to-learn, when-to-learn and how-to-learn is the best learning strategy. First Flavell [34] defined meta-cognition as knowledge concerning one's own cognitive processes and products or anything related to them. Nowadays research works focusing on combining the commonsense and the emotional reasoning power with