Information Sciences 239 (2013) 165–190

Contents lists available at SciVerse ScienceDirect

Information Sciences

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

Memetic multiobjective particle swarm optimization-based radial basis function network for classification problems

Sultan Noman Qasem [a,b,*], Siti Mariyam Shamsuddin [c], Siti Zaiton Mohd Hashim [c], Maslina Darus [d], Eiman Al-Shammari [e]

[a] Computer Science Department, College of Computer and Information Sciences, Al-Imam Muhammad ibn Saud Islamic University, Riyadh, Saudi Arabia
[b] Computer Science Department, Faculty of Applied Science, Taiz University, Taiz, Yemen
[c] Soft Computing Research Group, Faculty of Computer Science and Information System, Universiti Teknologi Malaysia, 81310 Skudai, Johor, Malaysia
[d] School of Mathematical Sciences, Faculty of Science and Technology, Universiti Kebangsaan Malaysia, Malaysia
[e] Information Science Department, College of Computing Sciences and Engineering, Kuwait University, Kuwait

A R T I C L E I N F O

Article history:
Received 5 November 2010
Received in revised form 4 March 2013
Accepted 10 March 2013
Available online 20 March 2013

Keywords:
Pareto optimization
Particle swarm optimization
Hybrid learning
Radial basis function network

A B S T R A C T

This paper presents a new multiobjective evolutionary algorithm applied to a radial basis function (RBF) network design based on multiobjective particle swarm optimization augmented with local search features. The algorithm is named the memetic multiobjective particle swarm optimization RBF network (MPSON) because it integrates the accuracy and structure of an RBF network. The proposed algorithm is implemented on two-class and multiclass pattern classification problems with one complex real problem. The experimental results indicate that the proposed algorithm is viable, and provides an effective means to design multiobjective RBF networks with good generalization capability and compact network structure. The accuracy and complexity of the network obtained by the proposed algorithm are compared with the memetic non-dominated sorting genetic algorithm based RBF network (MGAN) through statistical tests. This study shows that MPSON generates RBF networks coming with an appropriate balance between accuracy and simplicity, outperforming the other algorithms considered.

1. Introduction

Artificial neural networks (ANNs) represent an information-processing paradigm that is inspired by the way biological nervous systems process information. ANNs [8] have been an object of interest in statistics and computer science. They found applications in classification and pattern recognition problems. Radial basis function (RBF) networks are typical ANNs, and they were introduced into neural network literature by Broomhead and Lowe [9] as a means to observe local responses in biological neurons. RBF networks have a number of advantages over other types of ANNs, and these include better approximation capabilities, simpler network structures and faster learning algorithms. Fundamentally, there are many important aspects that influence the quality of an RBF network such as its structure and generalization capability. However, the construction of a quality RBF network to reduce generalization error can be a time-consuming process as the modeler must select both a suitable set of inputs – the inputs are given in the problem and a suitable RBF network structure.

* Corresponding author at: Computer Science Department, College of Computer and Information Sciences, Al-Imam Muhammad ibn Saud Islamic University, Riyadh, Saudi Arabia. Tel.: +966 535289679.

E-mail addresses: sultann.noman@ccis.imamu.edu.sa (S.N. Qasem), mariyam@utm.my (S.M. Shamsuddin), sitizaiton@utm.my (S.Z.M. Hashim), maslina@ukm.my (M. Darus), dr.eiman@ku.edu.kw (E. Al-Shammari).

0020-0255/$ - see front matter
http://dx.doi.org/10.1016/j.ins.2013.03.021

Because some of the traditional algorithms such as back-propagation (BP) still suffer from slow convergence and long training time [2,3,10], there is a clear need to develop sophisticated solutions to improve learning characteristics. In addition, BP and its variants are based on gradient-descent convergence algorithms and can easily become stuck at a local minimum [2]. The key problem with BP and other traditional learning algorithms is the choice of a correct architecture (i.e., number of hidden nodes). Hence, evolutionary algorithms (EAs) are used to train ANNs (that use a single error function) to solve the above problems. An EA still has a number of parameters to tune, similar to tuning BP algorithm parameters. The advantage of using EAs instead of BP is not in reducing the number of parameters to tune. A major advantage of using an EA is its ability to escape from local minimum, its robustness and its ability to adapt itself to a changing environment. Selecting the structure of ANNs is a difficult issue. The major disadvantage of using EAs in ANN applications is high computational cost. Therefore, hybrid algorithms are used to speed up the convergence by augmenting EAs with a local search feature such as BP (also known as a memetic approach). The literature on use of EAs in ANNs does not emphasize the trade-off between the structure and the generalization ability of an EA network. A network with more hidden nodes may learn a training set more quickly, but it may not generalize well on a testing set. This trade-off is a well-known problem in the multiobjective optimization problem (MOP) where a trade-off exists between the structure of the network and generalization error. Multiobjective techniques offer the potential advantage of helping a learning algorithm to escape a local minimum, therefore improving the accuracy of the learning model [3,53].

There are numerous studies in the literature that addressing the problem of ANN training and structure optimization, with majority focusing on feed-forward models. A general framework for using EAs to evolve ANNs was provided in [61]. Other authors have used single-objective EAs to evolve sets of networks of different sizes in the same population. Currently, Pareto-based multiobjective algorithms have been proposed as more promising algorithms to train and optimize the size of a neural network. For example, multiobjective approaches may force the search process to find a set of optimal solutions instead of a single one. Furthermore, a Pareto-based approach may be preferred to a linear weight aggregation procedure since the weight aggregation algorithm may entail some undesirable characteristics when combining different error measures such as those mentioned in [26]. Considering the set of Pareto-based multiobjective procedures [16,19], population-based multi-objective algorithms might be preferred since these may speed up the search and optimization process [22].

Pareto-based multiobjective algorithms have been adopted to evolve the training and structure of neural networks simultaneously. For example, multiobjective algorithms have been used to co-evolve ensembles to build feed-forward networks [27,28]. Liu and kadirkamanathan studied the benefits of multiobjective optimization for identifying nonlinear systems while optimizing the size of neural networks [49]. Locerda et al. [46] have provided one of the first approximations for optimizing the size and parameters of RBF networks. In addition, González et al. [30] used multiobjective optimization to find the best RBF, number of hidden units, centers, and widths of RBF networks. Abbass and Sarker [5] have proposed multiobjective algorithm that includes differential evolution to find the optimal number of hidden units and to train the network as a single-layer perceptron. Multiobjective Pareto ANN (MPANN), a multiobjective algorithm that combines Pareto-based multiobjective algorithms with a local search, was proposed in [1] to optimize the number of hidden nodes and to train ANNs. In addition, Abbass [2] applied MPANN to diagnose breast cancer with promising results. Abbass [3] also studied the benefits of hybridizing Pareto differential evolution with the BP training algorithm to speed up slow convergence and long training time. MPANN was considered in [4] with ANN ensembles to improve network learning performance using different formulations for multiobjective optimization. Other studies have focused on the problem of multiobjective optimization of ANNs to regularize a network's complexity [36]. In this case, the number of network connections is minimized to optimize the network structure. Jin and Sendhoff [37] included a local search in the evolutionary process to improve the generalization capabilities of the networks and their interpretability, described in [32,39], respectively. Although, many studies offer competitive solutions to simplify feed-forward ANNs, this is not the case for an RBF network, where hybrid learning increases the complexity of the network.

Current work provides training in RBF networks based on multiobjective evolutionary algorithms (MOEAs). Kokshenev and Braga [43] proposed a deterministic global solution to a multiobjective problem of supervised learning applied to an RBF network using nonlinear programming. A multiobjective optimization algorithm [42] has been applied to the problem of inductive supervised learning based on smoothness of apparent complexity measures for RBF networks. However, the computational complexity of their algorithm is high in comparison with other state-of-the-art machine learning algorithms. A multiobjective genetic algorithm based design procedure for the RBF network has been proposed in [62]. In addition, a hierarchical rank density genetic algorithm (HRDGA) has been developed to evolve both the neural network's topology and its parameters simultaneously. An RBF network ensemble [44] has been constructed from a Pareto-optimal set obtained by multiobjective evolutionary computation. A Pareto-optimal set of RBF networks was based on three criteria: model complexity, representation ability and model smoothness. An EA, RBF-Gene, was applied to optimize RBF networks [47]. Unlike other works, this algorithm can evolve both the structure and the numerical parameters of the network. In fact, it can evolve a number of neurons and their weights.

González et al. [31] presented RBF network optimization from training examples as a multiobjective problem and proposed an EA to solve it. This algorithm incorporates mutation operators to guide the search towards good solutions. An algorithm of obtaining a Pareto-optimal RBF network set based on MOEAs has been proposed in [45]. On the other hand, Ferreira et al. [25] proposed a multiobjective genetic algorithm for use with RBF network models of humidity and temperature in a greenhouse. Two combinations of performance and complexity criteria were used to steer the selection of model structures, resulting in distinct sets of solutions. Qasem and Shamsuddin [50] proposed time variant particle swarm optimization