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Optimization of quantum-inspired neural network using memetic algorithm for function approximation and chaotic time series prediction

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ABSTRACT

Heuristic and deterministic optimization methods are extensively applied for the training of artificial neural networks. Both of these methods have their own advantages and disadvantages. Heuristic stochastic optimization methods like genetic algorithm perform global search, but they suffer from the problem of slow convergence rate near global optimum. On the other hand deterministic methods like gradient descent exhibit a fast convergence rate around global optimum but may get stuck in a local optimum. Motivated by these problems, a hybrid learning algorithm combining genetic algorithm (GA) with gradient descent (GD), called HGAGD, is proposed in this paper. The new algorithm combines the global exploration ability of GA with the accurate local exploitation ability of GD to achieve a faster convergence and also a better accuracy of final solution. The HGAGD is then employed as a new training method to optimize the parameters of a quantum-inspired neural network (QINN) for two different applications. Firstly, two benchmark functions are chosen to demonstrate the potential of the proposed QINN with the HGAGD algorithm in dealing with function approximation problems. Next, the performance of the proposed method in forecasting Mackey–Glass time series and Lorenz attractor is studied. The results of these studies show the superiority of the introduced approach over other published approaches.

1. Introduction

A variety of learning algorithms have been developed for artificial neural networks (ANNs). Stochastic and deterministic optimization techniques are among the most popular learning algorithms for ANNs [1–5]. Both techniques have their own advantages and disadvantage. Stochastic search algorithms such as genetic algorithm (GA) [1,2], shuffled frog-leaping algorithm (SFLA) [3] and particle swarm optimization (PSO) [4] perform global search but they suffer from the problem of slow convergence rate near global optimum. On the other hand deterministic search algorithms like gradient descent [5] exhibit a fast convergence rate around global optimum but may get stuck in a local optimum. Furthermore, the weight initialization of the back-propagation neural network can significantly affect the speed of convergence, the probability of convergence and the generalization. From the point of speed of convergence, the number of iterations of the training algorithm and the convergence time will vary depending on the weight initialization. If the initial values of the weights are close to the solution, the algorithm needs a small number of iterations to achieve an acceptable solution. But, if the initial values of the weights are far from the solution, searching the best solution takes a very long time during the training process of networks.

The memetic algorithm (MA) is a combination of global search and local search algorithms that exploit the advantages of both algorithms [6]. MAs are also called genetic local search, Lamarckian evolutionary algorithms, cultural algorithms, and hybrid evolutionary algorithms. In recent years, memetic algorithms have been proven to be powerful in solving the complex optimization problems in wide areas of engineering fields [7–11]. For example, in [7] the computation of global structural balance was solved as an optimization problem by using the memetic algorithm. In their work, the optimization algorithm combines genetic algorithm and a greedy strategy as the local search procedure. A memetic algorithm based on genetic algorithm with two different local search strategies was proposed to maximize the modularity density in [8]. In the proposed methodology, one local search strategy was simulated annealing (SA), and the other one was tightness greedy optimization (TGO). A fractional particle swarm optimization-based memetic algorithm (FPSOMA) to solve optimization problem using fractional calculus concept was introduced in [9]. In the proposed algorithm the FPSOMA accomplishes

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Nomenclature

ψ	qubit state
α, β	probability amplitude
ξ	controlled input parameter
z	neuron state
φ	phase parameter
w	weight connection parameter
λ	threshold parameter
δ	reversal parameter
g	sigmoid function
x	input variable
L	number of neurons in input layer
M	number of neurons in hidden layer
y_N	network output
N_p	number of population
X	chromosome vector
y_d	desired output
P_c	probability of crossover
r, ρ	random numbers
P_m	probability of mutation
J	objective function
γ	learning rate
η	momentum rate
D_{final}	number of patterns
T_{final}	number of elite individuals
G_{final}	number of generation

Abbreviations

ANFIS	adaptive neuro-fuzzy inference systems
ANN	artificial neural network
ARMA	autoregressive moving average
BP	back propagation
BS	backward selection
CCRNN	cooperative coevolution recurrent neural networks
CICC	competitive island-based cooperative coevolution
CLPSO-MA	comprehensive learning particle swarm optimization-based memetic algorithm
ESN	echo state network
EKF	extended Kalman filter
EP	evolutionary programming
FNT	flexible neural tree
FPSOMA	fractional particle swarm optimization-based memetic algorithm
GA	genetic algorithm
GD	gradient descent
GSA	gravitational search algorithm
HGAGD	hybrid genetic algorithm and gradient descent
HLA	hybrid learning algorithm
LLS	linear least square
LS	least-squares
MA	memetic algorithm
MDE	modified differential evolution
PSO	particle swarm optimization
QC	quantum computing
QINN	quantum-inspired neural network
QNN	quantum neural network
RBF	radial basis function
RMSE	root mean square error
RNN	recurrent neural network
ROLS	recursive orthogonal least square
RPNN	recurrent predictor neural network
SA	simulated annealing
SFLA	shuffled frog-leaping algorithm
TGO	tightness greedy optimization
WT	wavelet transform

global search over the whole search space through PSO whereas local search was performed by PSO with fractional order velocity to alter the memory of best location of the particles. To optimize the urban transit network a memetic algorithm was proposed in [10]. In the proposed algorithm four types of local search operators were embedded in the classical genetic algorithm with the aim of improving the computational performance. In [11] a comprehensive learning particle swarm optimization (CLPSO)-based memetic algorithm (CLPSO-MA) was developed for short-term load forecasting. In the proposed CLPSO-MA algorithm, CLPSO was applied to explore the solution space, while a problem-specific local search was used for conducting individual learning.

MAs have recently gained much importance for learning of artificial neural network (ANN) because they offer more advantages over the conventional learning algorithms used individually. Many researchers such as the authors in [12–15] have applied the MAs to examine their proposed algorithms in learning of ANN. In [12] an automatic search methodology for the optimization of the parameters and performance of neural networks was proposed. In the proposed methodology, a combination of evolution strategies, particle swarm optimization, and genetic algorithm was performed to build a hybrid method capable of seeking near-optimal or even optimal neural networks. A hybrid of PSO and gravitational search algorithm (GSA) was introduced as new training method for feedforward neural networks in [13]. The objective of the study was to investigate the efficiencies of the GSA and PSOGSA in reducing the problems of trapping in local minima and the slow convergence rate of current evolutionary learning algorithms. In [14] a combined genetic algorithm and gradient descent was proposed for the complex permittivity determination of arbitrary shaped materials. In the proposed algorithm the final solution obtained by the GA was the start point for the GD. A two-step learning scheme for radial basis function (RBF) neural networks, which combines the genetic algorithm (GA) with the hybrid learning algorithm (HLA), was proposed in [15]. In their work, the parameters of an RBF neural network were first optimized by a genetic algorithm. Then a hybrid learning process which combines the gradient paradigm and the linear least square (LLS) paradigm was used to modify the weights and continue adjusting the parameters.

In recent years, several researches have been looking for better ways to design neural networks for chaotic time series prediction [16,17]. A new methodology to model and predict chaotic time series based on a new recurrent predictor neural network (RPNN) was proposed in [16]. In this study a long-term prediction by making accurate multistep predictions was realized. In [17] by combining the advantage of the Bayesian framework and the echo state mechanisms, a novel echo state network (ESN) was proposed for chaotic time series prediction.

Quantum-inspired neural networks (QINNs) model is based on the combination of quantum computing with the properties of neural networks that can be implemented on a classical computer. Quantum computing based on the quantum mechanical nature of physics [18] is a good candidate for enhancing the computational efficiency of the classical neural networks. It should be noted that the quantum-inspired neural networks mistakenly called as quantum neural networks (QNNs) in some literatures. More complete details on this problem can be found in [19,20]. Several previous studies have considered a QINNs model to solve problems such as image compression, approximation, time series prediction, identification and system controlling [21–25]. The performance of the