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Multi-population cooperative bat algorithm-based optimization of artificial neural network model

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A B S T R A C T

The performance of an artificial neural network (ANN) depends on the connection weights and network structure. Many optimization algorithms have been applied for ANN model selection. This paper presents an optimization algorithm based on the cooperative bat-inspired algorithm. The advantage of the bat algorithm lies in the combination of a population-based algorithm and local search; however, it is more powerful in local search. Therefore to better balance exploration and exploitation in the population some modifications to the velocity equation of the standard bat algorithm are applied. In addition, we propose two new topologies for cooperation between subpopulations to further improve the algorithm's capability to maintain the diversity of bats in the population. The first is a combination of two known mechanisms (Ring and Master–Slave), and the second inserts a Coevolving strategy of slave subpopulations in the Master–Slave strategy. The proposed methods are applied for the selection of an ANN model, where both the structure of the ANN and its weights are optimized by the method. Six classification and two time series prediction benchmark datasets are tested and the performance of the proposed algorithms is evaluated and compared with other methods in the literature. Statistical analysis shows that for the classification problem there is a significant improvement in the bat algorithm with Ring and Master–Slave strategies cooperation compared to the other methods in the literature in terms of classification error for three cases out of five and a significant enhancement in the number of connection weights in the network. The analysis also shows that for time series prediction there is a significant improvement in the prediction error for all the cases.

1. Introduction

Intelligent system techniques are contained in a number of computing concepts, such as fuzzy set theory, the artificial neural network (ANN), approximate reasoning and optimization techniques such as metaheuristic algorithms. The most important advantage of an ANN is its ability to learn by instances, which makes it attractive as a model for intelligent systems. The structure of an ANN has biological root which is expressed in several interconnections (weights) of processing units (nodes) with one or more hidden layers of nodes between the input layer and output layer. In recent years, optimization algorithms have been applied to optimize the structure or weights of the ANN model. Among the vast number of methods that have been used for ANN training [29,30,39], the most simple is that based on a fixed number of nodes and

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layers (commonly a three-layered structure). A number of researchers have employed optimization algorithms to train neural network models [8,9,16,22,23,27,46,49] and a family of multi-layer self-organizing neural networks has been studied [33–36]. Also, a few methods [26,42,46] have been applied to attempt to optimize both the weights and the structure of the neural network simultaneously.

The major aim in the optimization process is to find the global optimum solution. The key mechanism to achieve this is a significant interaction between global diverse exploration and local intensive exploitation, the success of which is affected by the efficiency of the algorithm. However, there is no set method for balancing these components. Hence more attempts should focus on the diverse exploration phase so that the best solutions obtained by the algorithm can be globally optimal. The most common strategy used to maintain the diversity of the solutions in the population of the algorithm is a cooperative strategy between subpopulations in the population.

Many researchers have shown that the multi-population cooperative scheme influences and maintains the diversity of the solutions and approaches the global optimum. A cooperative approach for particle swarm optimization (CPSO-S) was proposed in [41], which is based on splitting the solution vector into smaller vectors where each sub-vector is optimized by a separate swarm. The complete solution vector is built using the best solutions found by each swarm. This method is based on one that was initially proposed using a genetic algorithm [37]. Later, in [4] an approach was proposed that involves two swarms searching in parallel for a solution with frequent message passing of information (regarding the global bests of the two swarms). In [31] a Master–Slave multi-population for particle swarm optimization (PSO) was proposed to maintain the diversity of the particles. Other works include [44], which uses cooperating swarms that exchange information based on a diversity strategy; [47], which proposed a parallel PSO with an adaptive asynchronous migration strategy; [48], which employed a fuzzy multi-population cooperative genetic algorithm for multi-objective transportation; [11], which presented a discrete cooperative PSO for FPGA placement; and [12], which proposed a cooperative particle swarm optimizer with migration of heterogeneous probabilistic models. A cooperative approach to bee swarm optimization was proposed in [2] while in [15] a multi-population cooperative cultural algorithm was proposed that embedded the competition cooperative genetic algorithm into the population space of the cultural algorithm.

In this paper, we propose a modified bat algorithm with multi-population cooperation for ANN training. The original bat algorithm was introduced by [43]. The advantage of the bat algorithm lies in the combination of a population-based algorithm and local search which is one step toward balancing exploration and exploitation. To enhance performance, first a modification of the velocity equation of the algorithm using the *pbest* effect in the movement of bats is performed. In this work, we generate a chaotic sequence with the aid of a chaotic map to use it instead of random numbers in the algorithm. To achieve our goal of maintaining the diversity of the bats in the population, we propose two multi-population cooperative strategies for the bat algorithm. One is a combination of the Ring strategy [3,11,12] and Master–Slave strategy [11,32] while the second includes a Coevolving strategy of slave subpopulations in the Master–Slave strategy. The idea of a Coevolving strategy is similar to [25,38,45]. An experimental study is carried out to test the proposed algorithms on six classification problems and two time series prediction problems. To assess their performance, the results are compared with those of other similar approaches in the literature.

Section 2 provides an overview of the bat algorithm and Section 3 presents our proposed modifications to improve the balance between exploration and exploitation. Section 4 explains the different cooperative strategies that are developed to maintain diversity. Section 5 illustrates and discusses the results of our experiments using the proposed strategies. Finally, Section 6 contains our conclusion and the direction of our future research.

2. Bat algorithm

The bat algorithm is a novel swarm intelligence method proposed by [43]. This optimization algorithm is inspired by the echolocation behavior of bats when sensing distances. Bats release a very loud sound pulse and pay attention to the echo that returns from objects. Bats fly randomly using frequency, velocity and position to search for prey. Their pulses differ in properties depending on the variety of the bats. The bat algorithm is formulated to imitate the ability of bats to find their prey. Each bat in bat algorithm represents a solution in the population. In this algorithm, the frequency, velocity and position of each bat in the population are updated for further movements. It means that the bat algorithm uses a frequency tuning technique to provide the diversity of the solutions in the population. The bat algorithm has the advantage of combining a population-based algorithm with local search. The role of pulse rate and loudness in this algorithm is to control the balanced combination of population-based and local search processes. This algorithm employs the variations of pulse rates and loudness of bats to try to balance the exploration and exploitation during the search process. The bat algorithm follows many simplifications and idealization rules of bat behavior that are considered and proposed by Yang [43]. The algorithm involves a progression of iterations, where a set of solutions alters through random change of the signal bandwidth which is increased using harmonics. The loudness and pulse rate are updated when the new solution is accepted. The frequency, velocity and position of the solutions are computed based on following formulas:

$$f_i = f_{\min} + (f_{\max} - f_{\min})\beta \quad (1)$$

$$v_i^t = v_i^{t-1} + (x_i^{t-1} - x_{gbest}^t) f_i \quad (2)$$

$$x_i^t = x_i^{t-1} + v_i^t \quad (3)$$