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Fuzzy performance evaluation of Evolutionary Algorithms based on extreme learning classifier

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ABSTRACT

In current decades, various Evolutionary Algorithms(EAs) raise as well as many kinds of benchmarks are popular in evaluations of EAs' performances. Since there exists randomness in EAs' performances, the evaluations are made by a large number of runs in simulations or experiments in order to present a relatively fair comparison. However, there still exit several problems that have not been well explained. Does it make sense to deem two algorithms have equal ability if they have same final results? Is it convinced to decide winners or losers in comparisons just by tiny difference in performances? Besides the final results, how to compare algorithms' performances during the optimization iterations? In this paper, a neural network classifier based on extreme learning machine (ELM) is proposed to solve these problems. A novel role of classifier is first proposed to convince the differences between algorithms. If the classifier succeeds to classify algorithms based on their performances recorded in all generations, we deem the two algorithms have so convinced difference that comparisons of two algorithms can reflect algorithms' disparity. Therefore, the conclusions to judge the two algorithms are feasible and acceptable. Otherwise, if classifiers cannot distinguish two algorithms, we deem the two have similar performances so that it is meaningless to differ two algorithms just by tiny differences. By employing a set of classical benchmarks and six EAs, the simulations and computations are conducted. According to the analysis results, the proposed classifier can provide more information to reflect true abilities of algorithms, which is a novel view to compare EAs.

1. Introduction

In current decades, Evolutionary Algorithms (EAs) play an active role in optimization [1]. Besides several classic algorithms such as Genetic Algorithm, Particle Swarm Optimization, Ant Colony Optimization, increasing number of novel algorithms raise, which are inspired by various natural phenomena. Gravitational Search Algorithm is inspired from the gravity phenomenon [2]. Ant Bee Colony algorithm mimics the foraging of bee colony [3]. Biogeography-Based Optimization simulates the migration of species among islands [4,5]. All of the novel algorithms have enriched the researches related to EAs. However, according the conclusions in [6], none of EAs can outperform all others for all possible problems since the average performances of EAs are equal. Therefore, in front of so many EAs, it is very necessary to choose a suitable one for a specific problem. As an important way to investigate algorithms' performances, empirical simulation is often employed to test algorithms' abilities. One of the famous international conference, Conference of Evolutionary Computation (CEC), proposes several topics about benchmarks per year and numerous EAs take part in the competition. The winner algorithm shows poses its specific ability in dealing with corresponding benchmarks. Since most EAs have probabilistic operators, randomness in performances is inevitable. To pursue a fair comparison, a huge number of runs are employed to eliminate the effects of randomness. In comparisons, the popular metrics involve "Best Result" which is on behalf of the best performance in all runs, "Mean Result" which presents an average performance in all runs, and some other metrics such as "Medium Result", "Worst Result", and "Std" [7]. In general, none of the above metrics can be only used in estimation, but an ensemble of metrics. However, three problems remain. First, the usage of ensemble may leads to a dilemma. For example, an algorithm wins for some metrics and loses lose for other metrics so that it is hard to estimate the algorithm's effectiveness in optimization say which algorithm is better. Second, for algorithms that have similar performances, the

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little difference caused by randomness is not convictive evidence to judge which algorithm is better. Third, there lacks comparison for algorithms' dynamical performances, which means that although two algorithms have similar performances in "Best Result", "Mean Result", etc., they may still have big difference in first hitting time (FHT), convergence ability, solutions distribution and so on [8,9].

To solve the problems, we utilize the idea of classifiers to deal with evaluations of EAs. As a hot topic of machine learning, classifiers are used to distinguish objects into two or more categories [10,11]. The extreme learning machine (ELM) is a fast learning and simple structured single hidden layer network which has been well used in classification problems [12–14]. In the application of classifier to evaluation, On one hand, a high accuracy rate for classification means that two EAs have a big difference in their performances. Therefore, the evaluations to differ the two EAs are reasonable. On the other hand, a low accuracy rate means that the two EAs' performances are similar and the evaluations to differ the EAs are meaningless. In addition, considering that in classification, the data are recorded from all iterations of EAs, the proposed method is feasible to differ algorithms' dynamics including FHT, convergency abilities, solutions distribution, etc. Since the accuracy rate for classification belongs to $[0,1]$, to quantify the differences of EAs, a fuzzy approach is employed as a measurement in differing EAs. In classical set theory, the membership of elements in a set is assessed in binary terms according to a bivalent condition an element either belongs or does not belong to the set. By contrast, fuzzy set theory permits the gradual assessment of the membership of elements in a set; this is described with the aid of a membership function valued in the real unit interval $[0,1]$. By calculating the fuzzy classification accuracy, we review the algorithms' performance so that we can filter the randomness in algorithms' performance and differ algorithms by algorithms's dynamical performances, which provide a new view to evaluate EAs and help users choose a suitable algorithm in applications.

The rest of this paper is organized as follows. The preliminaries for Evolutionary Algorithms, Extreme Learning Machine and Fuzzy System are introduced in Section 2. In Section 3, a neural network classifier is designed based on extreme learning neural network to distinguish algorithms. The steps are illustrated in this section in detail. The simulations and discussion are presented in Section 4. Besides, we also compare Non-Parametric Statistical Test (NPST) with the proposed method. We conclude this paper in Section 5 and present our future work.

2. Preliminaries and related works

2.1. Evolutionary Algorithms

In researches of artificial intelligence, EAs has been explored and exploited in both of theory and practice. The mechanisms of EAs are often inspired from biological principles or phenomena. By recombination operator, mutation operator and selecting operator over candidate solutions, the solutions' qualities improve, which the optimization process is analogous to biological evolutions. Genetic Algorithm (GA), as a very famous EA, mimics the biological process through producing generations of chromosomes [15]. The idea of Particle Swarm Optimization (PSO) comes from the flocking behavior of birds [16]. Ant Colony Optimization (ACO) simulates the ecological behavior of ants in foraging [17]. Artificial Bee Colony (ABC) was inspired by the behavior of honeybees in collecting nectar [3]. Biogeography based Optimization inspired the science of biogeography mimics species' migration in geographic space. Besides, several hybrid methods have been proposed as well [18–20].

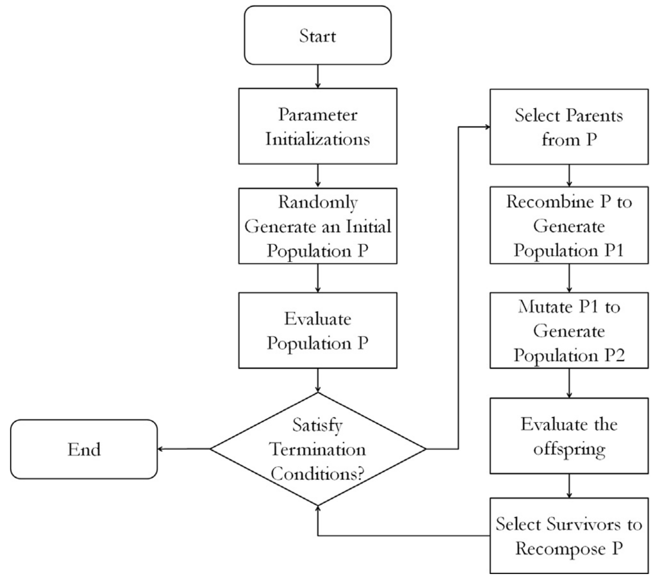

Fig. 1. Generalized flowchart of Evolutionary Algorithm.

EAs have a wide range of applications since they are implemented well in approximation solutions to all types of problems without considering assumption with respective to the fitness landscape [21]. The successful achievements cover fields as diverse as daily life, economics, finances, engineering, science, biology and so on. A classic framework of EAs is shown in Fig. 1. The main differences among EAs are the operators of "Selection", "Recombination" and "Mutation". In particular, the mechanism of recombination modular is inspired from nature and play an active role to affect algorithms' performances. In this paper, we employ six EAs involving Genetic Algorithm (GA), Particle Swarm Optimization (PSO), Ant Colony Optimization (ACO), Differential Evolution (DE), Evolutionary Strategy (ES) and Biogeography-based Optimization (BBO). The details of the algorithms can be found in [4,16,17,22,23].

2.2. Extreme learning machine

Machine learning is an important topic in artificial intelligence, and has already been implemented in various applications [27,28,29,30,31]. As a very attractive machine learning method, Extreme Learning Machine (ELM) was first proposed by Huang [12], which is such a single hidden layer feed forward network (SLFN) that chooses weights for hidden neurons and generates the output weights. Compared with traditional classifiers, such as Support Vector Machine (SVM), ELM can provide a comparable performance and a much faster learning speed. Due to ELM's attractive properties including simple structure, extreme learning speed, rare tuning of parameters, favorable generalization and super ability in approximation, its developments have spread in various kinds of researches and applications.

In ELM, assuming that in single hidden layer feedforward networks (SLFNs), there are N arbitrary distinct samples (x_i, t_i), where $x_i = [x_{i1}, x_{i2}, \ldots, x_{in}]^T \in R^n$ and $t_i = [t_{i1}, t_{i2}, \ldots, t_{im}] \in R^m$. Then the SLFNs with $\hat{N}$ hidden nodes can be formulated as follows:

$$\sum_{i=1}^{\hat{N}} \beta_i g(W_i \cdot X_j + b_i) = o_j, \tag{1}$$

where $j = 1,\ldots,N$, $g(\cdot)$ is an activation function. $W_i = [w_{i,1}, w_{i,2}, \ldots, w_{i,n}]^T$ is the weights of inputs, β_i is the weights of outputs, b_i the bias of ith hidden unit. $W_i \cdot X_j$ denotes that the inner product of W_i and X_j.