Fuzzy performance evaluation of Evolutionary Algorithms based on extreme learning classifier

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ABSTRACT

In current decades, various Evolutionary Algorithms (EAs) are proposed 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.

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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 arise, 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 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
little difference caused by randomness is not convicive 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, clas-
sifiers 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,
convergacy abilities, solutions distribution, etc. Since the accu-

racy rate for classification belongs to [0, 1], to quantify the differ-
ces 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 con-

dition 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 algo-

rithms’ 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 recombi-
nation operator, mutation operator and selecting operator over can-
didate solutions, the solutions’ qualities improve, which the optimi-
ization 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].

EAs have a wide range of applications since they are implemen-
ted well in approximation solutions to all types of problems
without considering assertion with respective to the fitness
landscape [21]. The successful achievements offer 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”, “Recombi-
nation” 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 net-
works (SLFNs), there are N arbitrary distinct samples (xi, ti), where
x_i = [x_i1, x_i2, ..., x_in] \in \mathbb{R}^n \quad \text{and} \quad t_i = [t_i1, t_i2, ..., t_in] \in \mathbb{R}^m.
Then the SLFNs with N hidden nodes can be formulated as follows:

\[ \sum_{i=1}^{N} \beta_i g(W_j \cdot X_j + b_i) = t_i, \]

where j = 1, ..., N, g(\cdot) is an activation function. W_j = [w_{j1}, w_{j2}, ..., w_{jn}] is the weights of inputs, \beta_i is the weights of outputs, b_i the
bias of ith hidden unit. W_j \cdot X_j denotes that the inner product of W_j
and X_j.
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