Fitness Estimation Strategy Assisted Competitive Swarm Optimizer for High Dimensional Expensive Problems

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ABSTRACT

Surrogate-assisted meta-heuristic algorithms are promising methods for solving computationally expensive optimization problems. It is usually assumed that the computational effort required for building and using surrogates is much less than that for calculating the fitness using the real fitness function. Different surrogate models, such as polynomials, kriging (also known as Gaussian process) and neural networks, have been proposed to assist population based meta-heuristics to solve computationally expensive problems [4][3][2]. In many cases, surrogates are meant for approximating the global fitness profile during the optimization, which however, may become infeasible, especially when the input dimension of the objective function, i.e., the number of decision variables, becomes high. Due to the limited number of training samples, global surrogates will become inaccurate and may introduce false optimums, which can mislead the evolutionary search. By contrast, local surrogate models aim to approximate a small region of the objective function, which is relatively easier to achieve with a limited number of training data. Although quite a large number of surrogate assisted meta-heuristic algorithms have been proposed, most of them work only for relatively low dimensional optimization problems. This might be attributed to the fact that it is extremely challenging to train an accurate surrogate model when the computational budget is limited for high dimensional problems. As far as we know, the maximum dimension of optimization problems solved by surrogate-assisted evolutionary algorithm is 50, which was reported in Liu et al. [5]. The authors proposed a Gaussian process surrogate model assisted differential evolution for medium-size computationally expensive optimization problems, in which principal component analysis was used to reduce the dimension.

In this paper, we aim to develop a surrogate assisted evolutionary algorithm for solving large scale optimization problems having up to 500 decision variables. To this end, we adopted a recently proposed meta-heuristics, termed competitive swarm optimizer (CSO) [1] that was developed for large scale optimization. Since local surrogate models can more reliably approximate the fitness values than global ones, in this paper, we develop a new fitness inheritance technique, which can be seen a specific local surrogate model, to assist the CSO. Fitness inheritance was originally proposed for genetic algorithms [6] and was extended to PSO by Sun et al. [8], called FESPSO. In FESPSO, if the fitness of a particle is known, the fitness of its closest neighbour will be estimated according to the positional relationship between the two particles. Later on, a similarity measure was introduced into FESPSO in order to further reduce the number of expensive fitness evaluations [7]. Compared with computational model based surrogates, fitness estimation techniques proposed in [8] and [7] have the following advantages. First, these fitness estimation strategies do not require an external archive to save the historical information. Second, they are computationally much more efficient than most model based surrogate techniques. Finally, fit-

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ness estimate techniques are less sensitive to the number of decision variables. For these reasons, this paper proposes a fitness approximation assisted competitive swarm optimizer (FAACSO) by extending the fitness estimation technique proposed in FESPSO to the competitive swarm optimizer [1] to speed up convergence in solving large scale expensive optimization problems with limited computational resources. Different from the typical surrogate models, the fitness approximation strategy proposed in this paper is based on the positional relationships between the individuals according to the updating mechanism in CSO. Despite its simplicity in algorithmic implementation, FAACSO has been shown to perform well on large scale optimization problems, outperforming the original CSO and a PSO with a similar fitness approximation strategy. We conducted experiments on 100-D and 500-D problems. The overall goal is to see whether the proposed FAACSO can obtain better solutions under a limited number of fitness evaluations than the compared approaches. To the best of our knowledge, this is the first time that a surrogate assisted meta-heuristic algorithm has been tested on large scale optimization problems.

In addition, the following two observations can be made from the obtained experimental results. First, as a local surrogate model, fitness estimation strategy can help improve the convergence speed, although it cannot help the search algorithm escape from local optimums. Second, as the real expensive fitness evaluation is replaced by the cheap fitness approximation, in which the approximated values are supposed to be close to the real fitness, the swarm has more chance to obtain better solutions, as more iterations of search can be afforded under the same number of fitness evaluations using the real fitness function. It should be noted that we assume that the computational cost for fitness estimation is negligible in comparison with that of calculating the fitness using the real fitness function.

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