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A global-best guided phase based optimization algorithm for scalable optimization problems and its application

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ABSTRACT

Large scale optimization problems are more representative of real-world problems and remain one of the most challenging tasks for the design of new type of evolutionary algorithms. Very recently, a new meta-heuristic algorithm named Phase Based Optimization (PBO) inspired by the different motional features of individuals under three different phases (gas phase, liquid phase and solid phase) was proposed. In order to improve PBO for solving large scale optimization problems, an effective search strategy combining complete stochastic search (the diffusion operator) and global-best guided search (the improved perturbation operator) is utilized. The proposed strategy can provide well-balanced compromise between the population diversity (diversification) and convergence speed (intensification) especially in solving large scale optimization problems. We term the improved algorithm as Global-best guided PBO (GPBO) to avoid ambiguity. Seven well-known scalable benchmark functions and a real-world large scale transmission pricing problem are used to validate the performance of GPBO compared with some state-of-the-art algorithms. The experimental results demonstrate that GPBO can provide better solution accuracy and convergence ability in both large scale benchmark functions and real-world optimization problem.

1. Introduction

Large scale optimization problems have achieved more and more attentions in evolutionary computation and swarm intelligence [1–3], because some real industry problems may have hundreds and even thousands of variables and those large scale problems bring high complex challenging tasks in the optimization process such as strong interaction variables and high multimodality [4–8]. With the increasing of the number of decision variables, as well as the change that some problems suffer from their own features with dimensions [2,9], the solution space of the problem also increases exponentially, the performance of most optimization algorithms deteriorate rapidly[10]. That is to say, a previously successful search strategy may become less effective in finding the optimal solution as the dimensionality of the search space increases. All these difficulties motivate us to deeply analyze the scalable features of large scale problems and to further develop more effective optimization algorithms to tackle problems with hundreds of variables.

There are several factors that cause the difficulties in solving large scale optimization problems listed above. Firstly, the difficulty of large scale optimization problem mainly lies in that it is high-dimensional, and the solution space of one problem will increase exponentially with the problem dimension, i.e. curse of dimensionality. It needs more effective search strategies to explore all promising regions in given computational resources or number of fitness evaluation cost. Secondly, in the high-dimensional space, the direction of a good individual has the low probability to point to the global optimum, so it is difficult to determine which direction of the good individual is better in fixed number of fitness evaluations. In the field of evolutionary computation and swarm intelligence, an individual is evaluated on the whole dimensions, even the individual is updated on only one dimension. The update of an individual deviates from the combination of several vectors, such as the current individual, the difference between current individual and previous best individual, the difference between current individual and neighbor best individual, or the difference between two random individuals, etc. The direction of these vectors combination has the high probability to point to the global optimum in the low dimensional space [9], but this scheme is not necessarily suitable for high dimensional space. Thirdly, the strong interaction between variables increases the difficulty to search the global optimum in tackling high-dimensional problems.

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In above three factors, the most crucial task of an evolutionary algorithm is how to deal with the complex search space resulted from high dimensionality [11]. About the above difficulties, many effective algorithms with particular mechanisms have been proposed. There are mainly two categories of algorithms which are Cooperative Coevolution (CC) based algorithms and non-decomposition-based algorithms.

The first category is CC-based algorithms with specific decomposition strategies which adopt the divide-and-conquer approach to decompose large scale problems into multiple low dimensional subcomponents [12]. After Potter and De Jong firstly incorporated CC into Genetic Algorithm (GA) by decomposing one n-dimensional problem into n 1-D problems for function optimization [13], there are many decomposition strategies utilizing the CC-based methods to decompose a high dimensional problem into a number of low dimensional problems for the purpose of solving the whole problem, such as Random Grouping [14,33], Delta Grouping [15], Variable Interactive Learning [16], Differential Grouping [17], Multilevel CC [18], High Dimensional Model Representation [19]. Cooperative coevolution with different forms has obtained better performance and great successful for separable problems. However, if the variables are fully non-separable, all the CC-based algorithms will lose the functionality [20]. Besides, in CC-based algorithms, many issues like robustness and efficiency of grouping strategies should also be considered in reasonable computational cost.

Non-decomposition-based algorithms are the second category of algorithms which are devised with effective operators or combined with other optimization algorithms to solve a large scale problem as a whole [8]. Without divide-and-conquer strategy, the non-decomposition-based algorithms focus on the especial alteration mechanisms or methods, such as efficient population utilization strategy [21], dynamic multi-swarm strategy [22], competitive mechanism [23], social learning mechanism [24,25], opposition-based learning [26], sampling operators [27,28], hybridization [29], restarting strategy [10], local search [30], hybrid metaheuristic strategies[31], and etc. All those algorithms have also obtained good results for separable and non-separable large scale problems, but there is still no universal algorithm to perfectly solve all large scale optimization problems [32]. In addition, from the standpoint of utilization, many algorithms required especial burden, such as parameter tuning, population initialization [33], it will be a very tedious and trivial task. In this study, we mainly concern the second category of non-decomposition-based algorithms.

Most recently, a new meta-heuristic termed Phase Based Optimization (PBO) was proposed by authors [34]. PBO is inspired by the different motional features of individuals with three different phases in nature (gas phase, liquid phase and solid phase) and it exhibits good performance on big optimization problems [3]. Thus, in this paper, we will further investigate the performance of PBO in large scale optimization problems, and attempt to improve PBO to better adapt to more complex high-dimensional problems. In this study, based on the original PBO, an improved PBO with an effective strategy combining complete stochastic search and global-best guided search which is termed Global-bestguided PBO (GPBO) for solving large scale optimization problems is proposed.

In this paper, firstly, we propose an effective strategy combining complete stochastic search and global-best guided search that shows the better performance in small scale optimization problems (100-D and 500-D). The basic idea of this strategy is that the more the dimensions of the problem are, the more effective the global search and scalable capability of the search algorithm needs. Therefore, under the premise of maintaining good diversity (diversification), when positioning to the approximate position of the optimal solution, the strategy should be diverted to strengthen the local search and fine-tune capability (intensification). Secondly, the strategy is further validated by seven well-known large scale benchmark functions (1000-D). Finally, the proposed GPBO is applied to large scale transmission pricing problem. By introducing the effective strategy combining complete stochastic search and global-best guided search into PBO, PBO has been greatly improved through experimental study not only on large scale benchmark functions, but also on real-world complex optimization problem in engineering and science.

The remainder of this paper is organized as follows. In Section 2, we briefly provide a review of phase based optimization algorithm. In Section 3, the global-best guided phase based optimization algorithm is described in detail, and followed by the analyses about the dynamic search process of GPBO. In Section 4 the experimental results and comparisons with other six algorithms are demonstrated. A case analysis about large scale transmission pricing using GPBO is given in Section 5. Finally, Section 6 draws the conclusion.

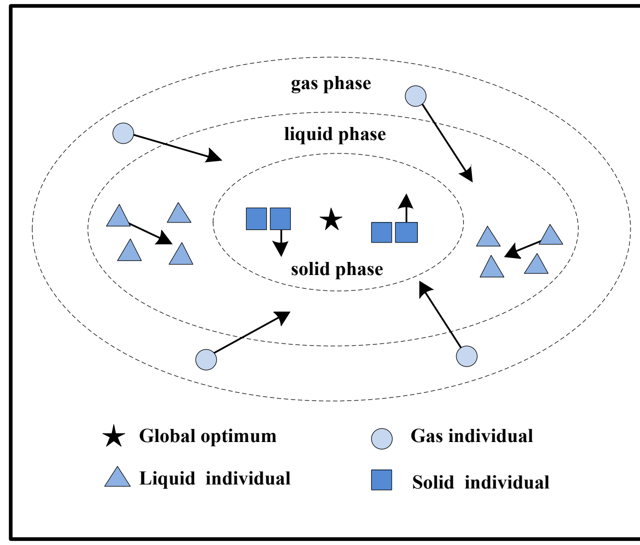

Fig 1. Search process of PBO.

2. A brief review of PBO algorithm

2.1. Basic idea

PBO is a newly developed population-based stochastic search algorithm proposed by authors [34], which mainly simulates three types of motional features of individuals with three completely different phases which are gas phase, liquid phase and solid phase in nature. The simplified search process of PBO is shown in Fig. 1.

In Fig. 1, the label of star presents the global optimum to be searched for. The labels of square in the nearer region with the global optimum indicate the individuals of solid phase, and the labels of circle in the farther region from the global optimum represent the individuals of gas phase, and the labels of triangle is the individuals of liquid phase. In an iterative process, three phases of individuals respectively move in the search space according to their corresponding rules. The individual of gas phase moves freely towards a casual position in an arbitrary direction, this motional characteristic of gas phase is adopted to act as the global divergence in PBO. The individual of liquid phase moves in its neighborhood range towards the individual with lower temperature, hence we adopt this motional characteristic of liquid phase to play an important role of convergence. On the contrary, the individual of solid phase slightly vibrates at its original location in a very regular mode, so this motional characteristic of solid phase is utilized to act as a fine-tuning local search.