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Hybridizing Particle Swarm Optimization with Signal-to-Noise Ratio for numerical optimization

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ABSTRACT

This paper hybridized the Particle Swarm Optimization (PSO) with Signal-to-Noise Ratio (SNR) to solve the numerical optimization problems. PSO has the ability of both global and local searches, where improper parameter settings could cause the algorithm to converge at the local optimum. SNR, on the other hand, has the ability to evaluate "existence possibility of optimal value". Integration of PSO and SNR thus becomes more robust, statistically sound and efficient than PSO. In this paper, fifteen standard test functions (benchmark problems) with a large number of local optimal solutions and high dimension (30 or 100 dimension) are used for examples and solved by the proposed algorithm. The results show that the proposed algorithm by this study can effectively obtain the global optimal solutions or close-to-optimal solutions.

1. Introduction

Global optimization problem has become increasingly important, in fields of science, engineering, trading, management and many natural behaviors. The main challenge in global optimization problems is that the solving process is more likely to fall in the local optimum of problems, especially when the dimension is very high. Most of optimization problems cannot be resolved analytically; therefore, numerical algorithms are used for solution. Evolutional Computation is a common model in solving optimization problems among numerical algorithms.

In fact, some evolutional algorithms have been applied to solving optimization problems. A chaotic bee colony algorithm was presented to solve global numerical optimization (Alatas, 2010). A hybrid genetic algorithm based quantum computing was proposed for numerical optimization and parameter estimation (Wang, Tang, & Wu, 2005). Wang and Huang presented a self-adaptive harmony search algorithm to solve the optimized problems (Wang & Huang, 2010). An improved genetic algorithm based on potential offspring production strategies was proposed for global numerical optimization (Hsieh, Sun, & Liu, 2009). An improved Genetic Algorithms were designed for the global optimization of multi-minima functions (Leung & Wang, 2001; Xing, Chen, & Cai, 2006; Zhang & Leung, 1999). Tsai et al. proposed the hybrid Taguchi-genetic algorithm in the numerical optimization search (Lin & Hsieh, 2009; Tsai, Liu, & Chou, 2004). A few of improved evolutionary algorithms were proposed for numerical optimization (Liu, Zhong, & Jiao, 2007; Zhao, Wang, & Wang, 2008). An Improved immune algorithm was proposed for global numerical optimization and job-shop scheduling problems (Tsai, Ho, Liu, & Chou, 2007). Evolutional Computations simulate the behavioral characteristics of natural organisms, and utilize the solution set of problems to be solved by numerous individuals to carry out the solution search. The solution characteristics of evolutional algorithm are different from the traditional gradient descend, where the individuals of evolution can obtain highly adaptive offspring through evolution mechanism, such as the position updated of individuals to continue on searching, Particle Swarm Optimization (PSO) proposed.

Particle Swarm Optimization (PSO) had been proposed by Dr. Eberhart and Dr. Kennedy in 1995 (Shi & Eberhart, 1999). By observing the foraging behaviors of birds and fish, PSO can apply the activity characteristics of biotic populations to optimization problems. When birds or fish forage, they not only refer to their own experiences, but also learn from the most efficient individual in the group. They learn and exchange their experiences, and pass this experience on until the whole population reaches the optimum condition. The advantage of PSO algorithm is that individuals can converge to the optimal solution rapidly within permissible range through a small number of evolution iterations, and it also has a faster convergence rate. PSO has been successfully applied to problems in optimal search and in engineering problems. Ali and Kaelo proposed an improved particle swarm algorithm for global optimization (Ali & Kaelo, 2008). Combining particle algorithm

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and ant colony algorithm was proposed to improve the continuous optimization (Shelokar, Siarry, Jayaraman, & Kulkarni, 2007). Gaussian quantum-behaved Particle Swarm Optimization approaches for constrained engineering design problems was proposed to solve the numerical problems (Coelho, 2010). Xincho presented a perturb swarm algorithm for numerical optimization (Xincho, 2010). Pal and Maiti developed a binary Particle Swarm Optimization for dimensionality reduction (Pal & Maiti, 2010). A binary Particle Swarm Optimization was developed to solve the unit commitment problem (Yuan, Nie, Su, Wang, & Yuan, 2009). PSO had been successfully improved and developed to research more complicated problems.

Although PSO can expedite the solution process, the search space is relatively small, and it is likely to fall into local optimum. Therefore, this study proposed an improved Particle Swarm Optimization (PSO), which is called Particle Swarm Optimization with Signal-to-Noise Ratio (PSO/SNR). This new method integrates PSO and SNR (Phillip, 1988), and applies SNR to the initialization of PSO in order to turn infinite solution problems into finite solution problems. Furthermore, SNR is also used in Local Search in order to refine the quality of solution.

2. Preliminary

Most of practical engineering applications can be formulated as a global optimization problem, however in which the objective function is not convex and contains many local minima in the solution space.

2.1. Problem definition

The global optimization problem is defined by

$$\begin{aligned} &\text{minimize} \quad f(X) \\ &\text{subjectto} \quad l \leqslant X \leqslant u \end{aligned} \tag{1}$$

In the above equation, $X = (x_1, x_2, \ldots, x_i, \ldots, x_N)$ is the variable vector in R^N space. $f(X)$ is the objective function and the feasible solution space is composed of vector $l = (l_1, l_2, \ldots, l_i, \ldots, l_N)$ and vector $u = (u_1, u_2, \ldots, u_i, \ldots, u_N)$. Therefore, the domain of x_i is designated by $[l_i, u_i]$, while the feasible solution space is bounded by $[l, u]$.

2.2. Particle Swarm Optimization

When birds forage, they communicate information to find targets efficiently. Individuals provide messages to the population, thus influence the group behavior, which is a normal social phenomenon in nature. If the message provided by an individual is regarded as local solution, the foraging process could be regarded as solving the global optimal solution. PSO has been successfully applied to optimization problem search, neural network training, fuzzy system control, and other engineering problems.

PSO is similar to random search methods, but it does not contain complicated mechanisms such as crossover or mutation. PSO generates a set of initial solution, known as particles, through the initialization mechanism, and then searches the optimal value through iteration evolution. More importantly, every particle has a memory capacity, and can provide one-way message to the population. Thus, the search process of PSO is the process of following current optimal solution. For example, if food distance is known to the population but location is unknown, the simplest way to find the food is to search the peripheral regions of the birds that are closest to the food.

The proposed algorithm first sets the end condition (number of iterations or error values of solution), and obtains the optimal solution lastly. PSO can have several solutions at the same time, each

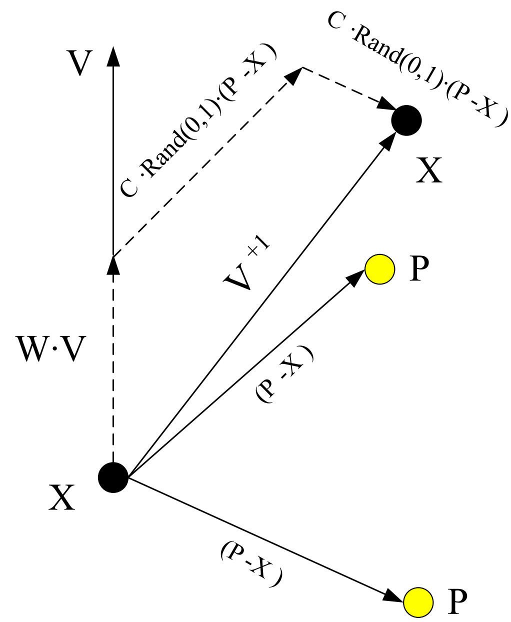

Fig. 1. PSO illustration.

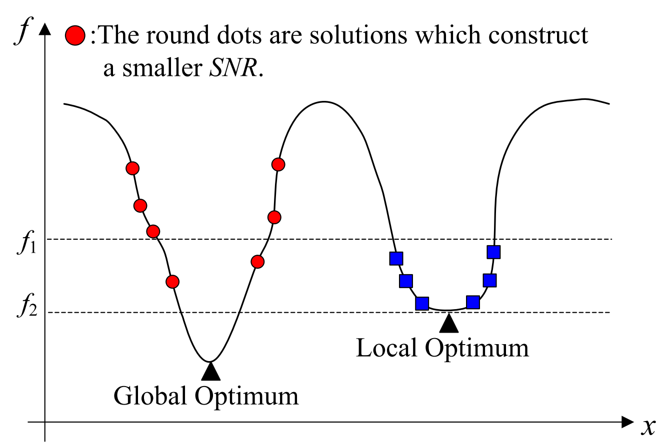

Fig. 2. SNR legend.

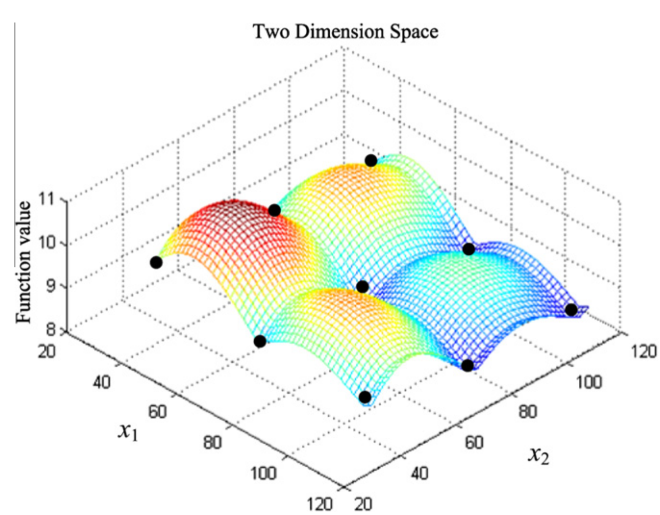

Fig. 3. The two dimensions space.