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RESEARCH PAPER

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A NOVELMETAHEURISTIC ALGORITHM BASED ON WAVE FUNCTION

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Abstract: Aiming at the phenomenon of slow convergence rate and low accuracy of some meta heuristic algorithms , a novel meta heuristic algorithm based on wave function and swarm intelligence is proposed. Swarm intelligence is a collective intelligence of groups of simple agents deals with collective behaviors of decentralized and self-organized swarms, which result from the local interactions of individual components with one another and with their environment. Wave function is introduced to accelerate the convergence speed of proposed algorithm. Standard deviation can ensure the dispersion of the population to prevent premature convergence. The simulation results using Benchmark functions show that the proposed algorithm is effective.

Keywords: meta heuristic; wave function; swarm; standard deviation; Pso;

1. INTRODUCTION

Meta heuristics are a class of intelligent self-learning algorithms forfinding near -optimum solutions to hard optimization problems, mimicking intelligent processes and behaviors observed from nature, sociology, thinking, and other disciplines. Meta heuristics may be nature-inspired paradigms, stochastic, or probabilistic algorithms. Meta heuristics-based search and optimization are widely used for fully automated decision-making and problem-solving.

Two major components of any meta heuristic algorithms are: selection of the best solutions and randomization. The selection of the best ensures that the solutions will converge to the optimality, while the randomization avoids the solutions being trapped at local optima and, at the same, increase the diversity of the solutions. The good combination of these two components will usually ensure that the global optimality is achievable.

Meta heuristic algorithms can be classified in many ways. One way is to classify them as: population-based and trajectory-based. For example, genetic algorithms are population-based as they use a set of strings, so is the particle swarm optimization (PSO) which uses multiple agents or particles. PSO is also referred to as agent-based algorithms. On the other hand, simulated annealing uses a single agent or solution which moves through the design space or search space in a piecewise style. A better move or solution is always accepted, while a not-so-good move can be accepted with certain probability. The steps or moves trace a trajectory in the search space, with a non-zero probability that this trajectory can reach the global optimum.

Now a days, since the evolutionary algorithm can solve some problem that the traditional optimization algorithm cannot do easy, the evolutionary algorithm ,most meta heuristic algorithms are nature-inspired as they have been developed based on some abstraction of nature. Nature has evolved over millions of years and has found perfect solutions to almost all the problems she met for example, particles swarms optimization (PSO) [1], firefly algorithm (FA) [2,3], artificial chemical reaction optimization algorithm (ACROA) [4], glowworm swarms optimization (GSO) [5], invasive weed optimization (IWO) [6], differential evolution (DE) [7, 8], bat algorithm (BA) [2, 9], and so on [10–14]. Some researchers have proposed their hybrid versions by combining two or more algorithms.

Wave Function Algorithm (WFA) is a novel meta heuristic algorithm based on wave function. Developing it comes from wave function and swarm intelligence.

The definitaon of swarm intelligence was introduced in 1989, in the context of cellular robotic systems [15]. Swarm intelligence is a collective intelligence of groups of simple agents [16].Swarm intelligence deals with collective behaviors of decent ralized and self-organized swarms, which result from the local interactions of individual components with one another and with their environment [16]. Although there is normally no centralized control structure dictating how individual agents should behave, local interactions among such agents often lead to the emergence of global behavior.

Most species of animals show social behaviors. Biological entities often engage in a rich repertoire of social interaction that could range from altruistic cooperation to open conflict. The well-known examples for swarms are bird flocks, herds of quadrupeds, bacteria molds, fish schools for vertebrates, and the colony of social insects such as termites, ants, bees, and cockroaches that perform collective behavior. Through flocking, individuals gain a number of advantages, such as having reduced chances of being captured by predators, following migration routes in a precise and robust way through collective sensing, having improved energy efficiency during the travel, and the opportunity of mating.

The rest of the paper is organized as follows: the proposed algorithm is discussed in Section 2. We will introduce analysis in Section 3, includes original PSO and proposed algorithm through results of experiment.. Finally, the conclusion and future work is presented in the last section.

2. THE PROPOSED ALGORITHM

The proposed algorithm aims to achieve rapid convergence rate and high accuracy to find the optimal value in the optimization problem. suppose a group of birds is searching for food in an area, only one piece of food is available. Birds do not have any knowledge about the location of food. A flying bird has a position and velocity at any time t. through in searching for food, the bird change its position and velocity. The velocity changes based on his past experience and also the feedbacks received from its neighbor. Each solution is considered as bird. All birds have fitness value. The fitness value can be calculated using objective function. all birds preserve their individual best performance and best performance of the group.

Each bird adjust its position and velocity according to the following equations.

$$v_{i+1} = a\, v_i + b\, r_1(xbest_i - x_i) + c\, r_2(xglobal_i - x_i) \quad (1)$$

$$x_{i+1} = x_i + A\sin(\theta)+v_{i+1} \quad 0 \le \theta \le 2\pi \quad (2)$$

$$, A \in [0,2]$$

Where x_i *and* v_i are the position and velocity of the bird at time i. $xbest_i$ *and* $xglobal_i$ represent the individual best performance and best performance of the group. during an evolutionary algorithm , the maintenance of population diversity is important. Therefore , standard deviation used in the algorithm to control the diversity of the population of birds.

Definition: (population position standard deviation)

If birds of a population S=$(X_1, X_2, X_3, \ldots\ldots, X_N)$ get their positions $X_1(t), \ldots\ldots X_N(t)$ at generation t and $X_i(t)$ can be expressed as a vector $(X_{i1}(t), X_{i2}(t), \ldots\ldots, X_{iD}(t))$, i=1,2,….., N, let $\bar{X}(t) = \left(\bar{X}^1(t), \bar{X}^2(t), \ldots\ldots, \bar{X}^D(t)\right)$, and $\bar{X}^j(t) = {}^1/_N \sum_{i=1}^{N} X_{ij}(t)$.

The population position standard deviation for generation t can be computed by

Std-positon (t)=$(std^1(t), std^2(t), \ldots\ldots, std^D(t))$,

$$std^j(t) = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N}\left(X_{ij}(t) - \bar{X}^j(t)\right)^2} \quad (3)$$

Then with respect to searching locally, a new solution generated according to the equation:

$$X_L = X_{i+1} + \sin(\theta) \;,\; 0 \le \theta \le 2\pi \quad (4)$$

The procedure of the algorithm is :

1- Objective function $f(x), x = [x_1, x_2, \ldots\ldots, x_3]^T$.
2- Randomly Initialize the birds population x_i, $1 \le i \le n$ *and* v_i .
3- Initialize the parameters of the equations (1) and (2).
4- Compute the standard deviation for populations using equation (3).
5- While (iter$\le$ *Max number of iterations*)
6- Generate new solutions by equations (1) and (2) for each bird in the population.
7- For each bird , generate local solution using equation (4) .
8- If (iter %10 ==0)
9- Using equation (3) compute the standard deviation for every dimension, if the value is less than before ,compute new solution using (1) and (2) but change random value A to be one of {2A,3A,4A,5A} in equation (2) in this dimension and the other dimensions use the (1) and (2) without change.
10- Rank the birds and determine the best solution
11- End while

3. ANALYSIS

This paper examined the proposed algorithm and particle swarm optimization (pso) when solving benchmark functions. These benchmark functions are Sphere, Schaffer F6, Rosenbrock.

Number of generations are 4000, number of birds N=10, and the process repeated 50 times.

After executing the proposed algorithm and pso to solve benchmark functions :

1- Sphere :
$f(\vec{x}) = \sum_{i=1}^{n} x_i^2$, $|x_i| < 10$. The optimal value is oat (o,o,….o). and n is the dimensions.

2- Schaffer F6 :

$$f(\vec{x}) = \frac{sin^2\sqrt{x_i^2 + x_2^2} - 0.5}{[1 + 0.001(x_1^2 + x_2^2)]^2} - 0.5\,, |x_i| < 10$$

The optimal value is 0 at (o.o).

3- Rosenbrock :
$f(\vec{x}) = \sum_{i=1}^{n-1}[\,(1 - x_i)^2 + 100(x_{i+1}) - x_i^{2^2}]$, $|x_i| < 10$
The optimal value is 0 at (1,1,….1) .

Then getting results that are in table 1. From results we find that the mean values got by proposed algorithm are obvious better than PSO for functions sphere and Rosenbrock. But for Schaffer F6 , pso is better.

For the standard deviation , for the sphere function the values nearly equal. for Rosenbrock function , the proposed algorithm is better than pso. And for Schaffer F6 , pso is better.

4. CONCLUSION

By analyzing the advantage and disadvantage of the standard PSO, algorithm based on Swarm intelligence and Sine wave is proposed in this paper. Although PSO has a fast convergence rate, it is likely to trap into the local optimum, and can't guarantee converge to the global optimum. Proposed algorithm introduces Sine wave into the position update equation in order to increase the probability of jumping out of the local optimum. Proposed algorithm used standard deviation to measure the dispersion to increase it every 10 generations by generating new solution away from the current solutions. experiment was tested on 3 benchmark functions. From the experimental results of these functions, it can be seen that the Proposed algorithm performed much better than PSO on the most of selected problems. Although Proposed algorithm needs more time to perform convergence. Further research will focus on testing the performance of Proposed algorithm on higher dimensional problems in order to find whether proposed algorithm would scale up well for the large function

Table 1.

Function	Algorithm	Mean	Standard deviation
Sphere n=30	Proposed Pso	0.69431e-2 2.06121	0.21124 0.23452
Schaffer F6 n=2	Proposed Pso	0.072 1.1541e-11	0.042 5.409e-13
Rosenbrock n=30	Proposed Pso	6.54105e-24 4.2852e-10	4.2541e-24 1.978581e-10

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