Hybrid Swarm of Particle Swarm with Firefly for Complex Function Optimization

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ABSTRACT

Swarm intelligence is rather a simple implementation but has a good performance in function optimization. There are a variety of instances of swarm model and has its inherent dynamic property. In this study, we consider a hybrid swarm model where agents complement each other using its native property. Employing popular swarm intelligence model Particle swarm and Firefly, we consider hybridization methods in this study. This paper presents a hybridization that agents in Particle swarm selected by a simple rule or a random choice are changing its property to Firefly. Numerical studies are carried out by using complex function optimization benchmarks, the proposed method gives better performance compared with standard PSO.

CCS CONCEPTS

• **Theory of computation** → *Evolutionary algorithms*; **Bio-inspired optimization**;

KEYWORDS

Swarm intelligence, hybrid swarm, continous function optimization

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1 INTRODUCTION

Evolutionary computation and swarm intelligence are practical methods to black-box function optimization. Especially swarm intelligence family has spread due to its simple implementation by difference equations representation, a variety of algorithms have been developed in this two decades.Even though these swarm models have common properties and inherent characteristics. Thus, understanding the role of a part of models mathematically is an important point to develop, improve, and apply the swarm model to actual optimization problems. However, it is difficult to analyze each swarm model mathematically because of analysis of such set of difference equations where the system is consisted of many agents having nonlinear properties is a hard problem in mathematics.

On the other hand, population-based optimization methods require keeping its population diversity. To achieve this requirement, swarm models have a kind of attractive effect and a kind of diffusion effect. By parameter tuning for these opposed effects, each swarm model is able to improve its performance. For example, in PSO each particle is attracted by the global best position and by using inertia factor each particle essentially vibrate, note that a vibration behavior depends on parameters setting. In Firefly algorithm, each firefly is attracted by brighter ones and is diffused by a random walk. A vibration and a random walk look like similar behavior, however, there is a significant difference between them in a degree of freedom about searchable space.

From this point of view, we consider a hybrid algorithm of swarm intelligence based on PSO [1] and FA [2] in this study. Since there is a difference between these two swarm models, it is expected to improve the search performance by making a good combination of agents property. Previously, we have proposed several hybridization methods. A mixed swarm of Particle swarm and Firefly [3] achieved better search performance than the original PSO and FA. Then, a stochastic property change mechanism has introduced, it also showed better performance than the original PSO and FA [4].

Then in this paper, we present a novel hybrid method, in which almost agents follow PSO model but the agent that has the global best memory follows FA model and randomly selected agents also follow FA model. We tested the hybrid algorithm on complex function optimization benchmark problems, the numerical simulation results show that the proposed mechanism has better search performance in comparison with the original PSO and the standard PSO [5] that is a baseline in a performance test.

2 SWARM MODELS

Here, x_i^t denotes i^{th} agent in the swarm at t^{th} step, v_i^{t+1} denotes its movement, and n denotes the number of agents. An original particle swarm model is described by the following equations,

$$\begin{cases} v_i^{t+1} = wv_i^t + c_1 r_1 (p_{best,i}^t - x_i^t) + c_2 r_2 (g_{best}^t - x_i^t) \\ x_i^{t+1} = x_i^t + v_i^{t+1}. \end{cases} \tag{1}$$

Where w is an inertia weight, c_1, c_2 are constants, r_1, r_2 are randomly selected from the uniform distribution over [0,1]. Two memories are used in PSO model, $p_{best,i}^t$ represents the personal best position of i^{th} agent, and g_{best}^t represents a shared memory over the swarm, that is defined as the best position for all $p_{best,i}^t$, $i = 1, 2, \ldots, n$.

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Table 1: Pseudo code of PSO-FA hybrid algorithm

Step1	Initialize the agents' position
Step2	Evaluate the agents and set the global best and personal best
Step3	Update
	If agent has the global best position or randomly selected move as firefly according to (2) (as Firefly)
	Else
	The agent move as a particle according to (1) (as Particle)
Step4	Evaluate the agents and set the global best and personal best
Step5	Repeat from Step 3 until terminate conditions are satisfied

While, a firefly model in FA is described by the following equations,

$$x_i^{t+1} = x_i^t + \beta \exp[-\gamma r_{ij}^2](x_j^t - x_i^t) + \alpha_t \varepsilon^t. \tag{2}$$

Where, α_t is a parameter controlling the step size, ε^t is a vector to determine the direction of random walk. The second term of (2) represents that each firefly moves to more attractive fireflies. Here, β and γ are contol parameters for attractiveness. We can easily understand that memories are important in PSO and current objective function value has more dominant effect in FA. Additionary a random walk also has an important role in FA.

3 HYBRID ALGORITHM

As it is a common problem in a stochastic population based search, how to ensure the diversity of agents may be considered in a hybrid algorithm. That means how to make the different properties cooperate with each other is a key point in hybridization, as there are different properties exist in the basic model to affect the movement of an agent. And property changing mechanism will help agent to change a personal moving style. Since a weakness of PSO is that it is limited the searchable dimension since there is no random factor, especially the particle that memories the global best position does not have rich movement direction. Thus, we introduce two hybridization rules in this paper. The first rule is that the particle that memories the global best position will change its property to Firefly. This leads particle to move randomly and to move more prosperous region if there are better particles. The second one is randomly selected particle will change its property to Firefly, this makes swarm aggregate to a prosperous region. A pseudo code of the proposed hybrid algorithm is shown in Table 1.

4 NUMERICAL EXPERIMENTS

To evaluate the performance of the proposed hybrid algorithm, numerical studies are carried by a benchmark suite of the bound-constrained single-objective computationally expensive numerical optimization problems presented at CEC2015 [6]. This benchmark consists of 15 functions, including simple multimodal functions and composited functions of some popular benchmarks.

The experimental configuration is presented in Table. 2. Due to page limitation, here we show the results for one simple multimodal function (f_1) and 5 composited functions of some popular benchmarks (f_{10}–f_{14}) in this paper. The typical convergence curves of 10 times trials for some functions are shown in Figure 1. and 2. A green line indicates a convergence curve for the proposed algorithm, red dot, and blue dot lines indicate the original PSO and the standard PSO [5], respectively. As shown in Figure 1 and 2, the proposed algorithm shows better convergence speed than the original PSO and the standard PSO proposed by M. Clerc as a baseline for performance improvement. For other benchmark functions, the proposed algorithm shows better or equivalent performance in comparison with the original PSO and the standard PSO.

Table 2: Parameter setting

Agent numbers	50
PSO parameter	c_1=1.4, c_2=1.4, w=0.7
FA parameter	α=0.2, β=1.0, γ=0.05
Iteration numbers	100
Dimension	30
Search space range	[-100, 100]

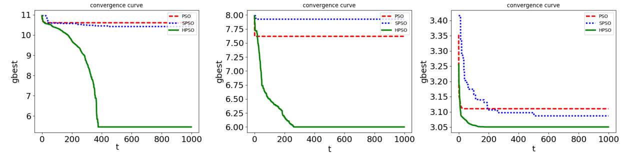

Figure 1: convergence curves for f_1, f_{10}, f_{11}

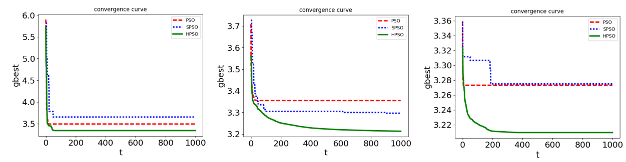

Figure 2: convergence curves for f_{12}, f_{13}, f_{14}

5 CONCLUSION

In this paper, we have proposed a hybrid algorithm of PSO and FA. Based on a consideration of properties of swarm model, two hybridization rules are used. The proposed algorithm is a simple combination of these two models however the search performance is better than standard PSO2011 that is a baseline for improvement. Whole experimental results will be shown at a presentation and we will discuss why such hybridization well works.

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