New Particle Swarm Optimization Variant with Modified Neighborhood Structure

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Abstract

Numerous particle swarm optimization (PSO) variants were proposed in past decades to tackle different types optimization problems more robustly. Nevertheless, the imbalance of explorative and exploitative search behaviors remains as an on-going research challenge that can restrict the performance of PSO. In this paper, a new variant known as PSO with time-varying topology connectivity (PSO-TVTC) is proposed. A time-varying topology connectivity (TVTC) module is designed to achieve the proper regulation on explorative and exploitative behaviors of PSO via dynamic modifications of particle's topology connectivity throughout the optimization process. Experimental results reveal that the proposed PSO-TVTC has exhibited prominent performance among its competitors by producing 7 best mean fitness out of 8 benchmark functions.

Keywords: global optimization, modified neighborhood structure, metaheuristic, particle swarm optimization

1. Introduction

Various real-world engineering problems such as energy management[1], material machining[2], pattern recognition[3] etc. can be formulated as complex optimization problems that are not feasible to solve with conventional methods. Recently, metaheuristic search algorithms (MSAs) inspired by different natural phenomena have emerged as the popular approaches to solve these complex problems.

Motivated by bird flocking behaviors to locate food sources, particle swarm optimization (PSO) is a popular MSAs used to solve various optimization problems due to its desirable characteristics such as the simplicity in implementation and fast convergence speed. Similar with most MSAs, original PSO tends to suffer with premature convergence when solving complex problems.[4] Numerous methods such as parameter adaptation[5,6], modified neighborhood structure[4,7,8], modified learning strategies[9,10,11,12] etc. were introduced to enhance the performance of PSO. Despite of improvement achieved, some new PSO variants might suffer with undesirable drawbacks such as high complexity and manual tuning of new parameters. Appropriate strategies used to balance the exploration and exploitation searches of PSO for solving different types of optimization problems effectively remain as an on-going research challenge.

In this paper, a PSO with time-varying topology connectively (PSO-TVTC) is designed by leveraging the capability of a novel TVTC module to adjust the exploration and exploitation strengths of particles via dynamic modification of their neighborhood structures. This is because each particle behaves more explorative when connected with less neighbors and vice versa.[4] The Shuffling and perturbation mechanisms are also designed for PSO-TVTC to handle premature convergence issue.

2. Basic PSO

Each PSO particle serves as a potential solution for an optimization problem with D-dimensional size. The current state of each i-th particle is associated with the velocity and position vectors of $V_i = [V_{i,1}, \ldots, V_{i,d}, \ldots, V_{i,D}]$ and $X_i = [X_{i,1}, \ldots, X_{i,d}, \ldots, X_{i,D}]$, respectively, where $d = 1,\ldots, D$ refers to a dimension index. Each i-th particle is also able to memorize the best solutions ever achieved by itself and population in the personal best position of $P_i = [P_{i,1}, \ldots, P_{i,d}, \ldots, P_{i,D}]$ and global best position of $P_g = [P_{g,1}, \ldots, P_{g,d}, \ldots, P_{g,D}]$, respectively. In the $(t+1)$-th iteration of search process, the velocity and position of each i-th particle in d-th dimension can be updated as:

$$V_{i,d}(t+1) = \omega V_{i,d}(t) + c_1 r_1 (P_{i,d}(t) - X_{i,d}(t)) + c_2 r_2 (P_{g,d}(t) - X_{i,d}(t)) \quad (1)$$

$$X_{i,d}(t+1) = X_{i,d}(t) + V_{i,d}(t+1) \quad (2)$$

where $i = 1,\ldots,S$ and S is the population size; ω is inertia weight used to control the influence of previous velocity; r_1 and r_2 are two random numbers generated between 0 to 1; c_1 and c_2 are acceleration coefficients.

3. Proposed PSO-TVTC

3.1. *TVTC Module*

Previous studies reported that PSO with smaller topology connectivity can perform well in multimodal problems with numerous local optima due to its more explorative nature, whereas PSO with large connectivity has stronger exploitation strength and able to exhibit fast convergence speed in solving unimodal problems[4]. Therefore, a TVTC module is proposed in this paper to regulate the exploration and exploitation strengths of each particle via the dynamic adjustment of its topology connectivity with time. At the beginning stage of optimization process, the topology connectivity of each i-th particle is set as $TC_i = 1$ to connect with a randomly selected particle. The connection between particles is not bidirectional as shown in Fig. 1. For instance, if the i-th particle has chosen to connect with j-th particle, the latter particle might select the other k-th particle as its neighbor instead.

Suppose that $TC_{min} = 1$ and $TC_{max} = S - 1$ refers to the minimum and maximum topology connectivity assigned to each particle, respectively, whereas FE_{max} is the maximum fitness evaluation numbers. The TVTC module is designed to increase the topology connectivity TC_i of each i-th particle linearly with the current fitness evaluation numbers (FEs) of k as follow:

$$TC_i = \lfloor TC_{\min} + TC_{\max}[(k-1)/(FE_{\max}-1)] \rfloor \quad (3)$$

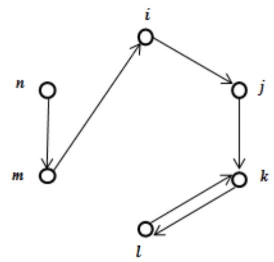

Fig. 1. Initial topology connectivity of PSO-TVTC particles.

This topology modification strategy of TVTC module cam gradually increase exploitation strengths of particles for fine tuning the promising solution regions found.

A shuffling mechanism is further incorporated into TVTC module to address the premature convergence issue. When the i-th particle is unable to improve the global best fitness $f(P_g)$ for M successive FEs, it is trapped into local optima. The TVTC module is executed to discard all existing neighbors of i-th particle and then randomly reassign another TC_i new neighbors as shown in Fig. 2. The new topology information is expected to offer new directional information for stagnated particle and guide it to escape from local optima. A random perturbation process is also performed on the P_g to provide additional momentum for it to jump out of local optima. For the randomly selected d-th dimension of P_g, i.e., $P_{g,d}$, the perturbed component $P_{g,d}^{per}$ is produced as:

$$P_{g,d}^{per} = r_3 P_{g,d} + (1 - r_3)(P_{x,d} - P_{y,d}) \quad (4)$$

where r_3 is a randomly generated number between 0 to 1; $P_{x,d}$ and $P_{y,d}$ are personal best positions of two randomly selected particles. Current P_g is replaced by its perturbed counterpart P_g^{per} if the latter particle is more superior.

The overall mechanisms of TVTC module are shown in Fig. 3. For each i-th particle, a flag variable $fc(i)$ is used to record the number of successive FEs for i-th particle fails to update $f(P_g)$. When $fc(i) > M$, both shuffling and perturbation mechanisms are triggered. The parameter

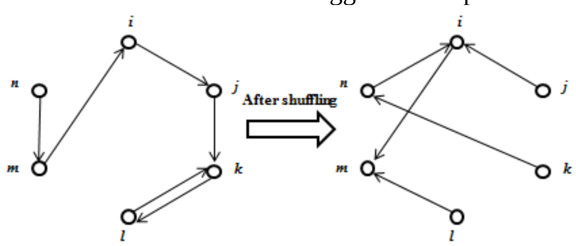

Fig. 2. Shuffling mechanisms triggered by TVTC module if the i-th particle fails to update the $f(P_g)$ for M successive FEs.

TVTC_module($fc(i)$, $mode$, P_g, k, TC_i)

$TC_{old} = TC_i$
Calculate current TC_i using Eq. (3);
if current $TC \neq TC_{old}$ **then**
    Randomly select TC_i - TC_{old} particles as neighbor;
else
    if $fc(i) > M$ **then**
        Randomly select TC particles as neighbors;
        Perform perturbation on P_g using Eq. (4);
        Update P_g if P_g^{per} has better fitness;
        $k = k + 1$;
        $fc(i) = 0$;
    end if
end if

Fig.3. Implementation of TVTC module.

value of M = 5 is set to achieve better tradeoff in term of solution accuracy and convergence speed.

3.2. *Complete PSO-TVTC*

The complete framework of PSO-TVTC is shown in Fig. 4. Unlike basic PSO that relies on both P_i and P_g, the proposed PSO-TVTC leverages the promising direction information of P_i and $P_{n,i}$ (i.e., best neighbor of i-th particle) in updating the velocity of each i-th particle with better diversity for $d = 1,\ldots,D$ as:

$$V_{i,d}(t+1) = \omega V_{i,d}(t) + c_1 r_1 (P_{i,d}(t) - X_{i,d}(t)) + c_2 r_2 (P_{n,d}(t) - X_{i,d}(t)) \tag{5}$$

The search process of PSO-TVTC using Eqs. (5) and (2) along with TVTC module is iterated until the termination condition of $k > FE_{max}$ is satisfied.

4. Performance Evaluation

4.1. *Simulation Settings*

Eight scalable benchmark functions with dimensional sizes of D = 50 are used for performance evaluation. These include F1 Sphere with range of $[-100, 100]^D$, F2 Step with range of $[-100, 100]^D$, F3 Rosenbrock with range of $[-2.048, 2.048]^D$, F4 Rastrigin with range of $[-5.12, 5.12]^D$, F5 Noncontinuous Rastrigin with range of $[-5.12, 5.12]^D$, F6 Grienwank with range of $[-600, 600]^D$, F7 Ackley with range of $[-32, 32]^D$ and F8 Salomon with range of $[-100, 100]^D$. Five well-established PSO variants known as BPSO[6], FlexiPSO[10], FIPSO[9], FLPSO-QIW[5] and FPSO[8] are used to compare with PSO-TVTC. All algorithms are simulated with S = 30 and FE_{max} = 30,0000 for fair comparisons.

PSO-TVTC

Initialize population of PSO-TVTC
$TC = 1$, $k = 0$;
for each particle i **do**
    randomly select 1 particle as neighbor;
    $fc(i) = 0$;
end for
while $k < FE_{max}$ **do**
    for each particle i **do**
        Perform **TVTC_module (Refer Fig. 3)**;
        Identified the best neighbor $P_n(i)$;
        Update V_i with Eq. (5) and X_i with Eq. (2);
        Evaluate the fitness of updated X_i;
        $k = k + 1$;
        Update the P_i and P_g;
        if P_g is improved **then**
            $fc(i) = 0$;
        else
            $fc(i) = fc(i) + 1$;
        end if
    end for
end while

Fig.4. Complete framework of PSO-TVTC.

4.2. *Comparisons of PSO Variants*

The search accuracies of all PSO variants are evaluated in terms of the mean fitness value (F_{mean}) and standard deviation (SD). Smaller F_{mean} and SD values are more desirable because it indicates the errors between P_g and actual global optimum are consistently smaller. The F_{mean} and SD values produced by the compared PSO variants when solving all benchmark functions are shown in Table 1 and the best results are represented in bold fonts. From Table 1, PSO-TVTC can outperforms its peers with large margin when solving majority of tested problems, implying the excellent search accuracy of the proposed algorithm. PSO-TVTC produces the best (i.e., smallest) F_{mean} values for all benchmark functions except for F3. PSO-TVTC is also the only PSO variant that is able to locate the global or near global optima of F1, F2, and F4 to F8. Majority of compared PSO variants exhibit relatively poor performance in F3 because the global optimum of Rosenbrock function locates in a valley with long narrow parabolic shape. While most algorithms can find the valley regions, it is extremely challenging for them to converge towards the global optimum, hence leading to poor F_{mean} values.

5. Conclusions

A new variant of PSO-TVTC is proposed in this paper, where a TVTC module is designed to attain better

Table 1. Simulation results of F_{mean} and SD for solving 50-D benchmark functions

f	Metric	FLPSO-QIW	FlexiPSO	FPSO	FIPSO	BPSO	PSO-TVTC
F1	F_{min}	2.90E-81	1.78E-04	7.02E+01	2.96E-01	4.67E+03	**0.00E+00**
	SD	5.97E-81	5.23E-05	6.98E+01	8.06E-01	7.30E+03	0.00E+00
F2	F_{min}	3.33E-02	8.50E+03	8.48E+01	3.03E+00	3.33E+03	**0.00E+00**
	SD	1.83E-01	3.09E+03	6.97E+01	1.14E+01	5.47E+03	0.00E+00
F3	F_{min}	**4.22E+01**	4.48E+01	5.68E+01	4.77E+01	2.10E+02	4.74E+01
	SD	2.39E-01	1.04E+00	7.08E+00	8.44E-01	4.34E+02	5.79E-01
F4	F_{min}	2.60E+00	2.12E-04	1.85E+01	1.57E+00	1.15E+02	**1.68E-10**
	SD	1.52E+00	6.24E-05	1.02E+01	3.71E+00	7.78E+01	2.72E-10
F5	F_{min}	5.58E+00	2.07E-04	1.60E+01	5.70E-01	1.14E+02	**1.68E-10**
	SD	2.36E+00	7.51E-05	9.56E+00	8.65E-01	5.81E+01	2.01E-10
F6	F_{min}	5.75E-04	8.34E-03	1.86E+00	1.93E-01	3.92E+01	**0.00E+00**
	SD	2.21E-03	9.48E-03	9.28E-01	3.47E-01	7.00E+01	0.00E+00
F7	F_{min}	3.43E-14	3.55E-03	1.80E+00	1.70E-01	1.21E+01	**0.00E+00**
	SD	1.07E-14	5.36E-04	1.10E+00	3.38E-01	5.99E+00	0.00E+00
F8	F_{min}	2.33E-01	1.22E+00	1.32E+00	3.33E-02	5.43E+00	**0.00E+00**
	SD	4.79E-02	1.51E-01	8.01E-01	1.30E-01	5.65E+00	0.00E+00

balancing of exploration and exploitation searches via the dynamic adjustment of particles' topology connectivity. Shuffling and perturbation mechanisms are also used by TVTC module to reduce the likelihood of premature convergence. Simulation results show that PSO-TVTC can outperforms its peers in term of search accuracy.

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