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Particle Swarm Optimisation, Fundamental Concepts, Basic Variants and Applications

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Abstract: There are a lot of optimization problems in various areas of sciences and technologies. For solving them, there exist so many optimization techniques. Among optimization techniques, particle swarm optimization (PSO) has proved to be so promising. In this paper, fundamental concepts of PSO are introduced, basic PSO variants are explained and analysed and some applications of PSO in different areas are mentioned. The authors believe that this paper can be useful for researchers who intend to apply PSO to optimisation problems.
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1. Introduction

There are so many optimisation problems in various areas of science and engineering. For solving them, there exist twofold approaches; classical approaches and heuristic approaches. Classical approaches such as linear programming and non-linear programming are not efficient enough in solving optimisation problems. Since they suffer from curse of dimensionality and also require preconditions such as continuity and differentiability of objective function that usually are not met.

Heuristic approaches which are usually bio-inspired include a lot of approaches such as genetic algorithms, evolution strategies, differential evolution and so on. Heuristics do not expose most of the drawbacks of classical and technical approaches. Among heuristics, particle swarm optimisation (PSO) has shown more promising behavior.

PSO is a stochastic, population-based optimisation technique introduced by Kennedy and Eberhart in 1995 (Kennedy & Eberhart, 1995). It belongs to the family of swarm intelligence computational techniques and is inspired of social interaction in human beings and animals.

Some PSO features that make it so efficient in solving optimisation problems are the followings:

- In comparison with other heuristics, it has less parameters to be tuned by user.
- Its underlying concepts are so simple. Also its coding is so easy.
- It provides fast convergence.
- It requires less computational burden in comparison with most other heuristics.
- It provides high accuracy.
- Roughly, initial solutions do not affect its computational behavior.
- Its behavior is not highly affected by increase in dimensionality.
- It is efficient in tackling multi-objectives, multi-modalities, constraints, discrete/integer variables.
- There exist many efficient strategies in PSO for mitigating “premature convergence.” Thus, its success rate is so high.

However, typical PSO variants are merely applicable to static optimisation problems while many real-world optimization problems are dynamic. Dynamic problem is a problem whose objective function and/or constraints of a dynamic problem vary over time. Therefore, for solving dynamic problems, typical PSO variants should be modified. In this paper various PSO variants specially designed for dynamic problems are analysed in details. Moreover, their pros and cons are mentioned. According to the author’s knowledge, in literature, there is no comprehensive analysis on PSO variants for dynamic problems. The paper is organised as follows; in section 2, fundamental concepts and basic variants of PSO are introduced. In section 3, some applications of PSO are mentioned. Finally, drawing conclusions is implemented in section 4.

2. Fundamental Concepts and Basic Variants of PSO

PSO launches with the random initialisation of a population (swarm) of individuals (particles) in the n-dimensional search space (n is the dimension of problem in hand). The particles fly over search space with adjusted velocities. In PSO, each particle keeps two values in its memory; its own best experience, that is, the one with the best fitness value (best fitness value corresponds to least objective value since fitness function is conversely proportional to objective function) whose position and objective value are called P_i and P_{best} respectively and the best experience of the whole swarm, whose position and objective value are called P_g and g_{best} respectively. Let denote the position and velocity of particle i with the following vectors:

$$X_i = (X_{i1}, X_{i2}, \dots, X_{id}, \dots, X_{in})$$

$$V_i = (V_{i1}, V_{i2}, \dots, V_{id}, \dots, V_{in})$$

The velocities and positions of particles are updated in each time step according to the following equations:

$$V_{id}(t+1) = V_{id}(t) + C_1 r_{1d}(P_{id} - X_{id}) + C_2 r_{2d}(P_{gd} - X_{id}) \qquad (1)$$

$$X_{id}(t+1) = X_{id}(t) + V_{id}(t+1) \qquad (2)$$

Where C_1 and C_2 are two positive numbers and r_{1d} and r_{2d} are two random numbers with uniform distribution in the interval [0,1]. Here, according to (1), there are three following terms in velocity update equation:

The first term this models the tendency of a particle to remain in the same direction it has traversing and is called “inertia,” “habit,” or “momentum.”

The second term is a linear attraction toward the particle’s own best experience scaled by a random weight $C_1 r_{1d}$. This term is called “memory,” “nostalgia,” or “self-knowledge.”

The third term is a linear attraction toward the best experience of the all particles in the swarm, scaled by a random weight $C_2 r_{2d}$. This term is called “cooperation,” “shared information,” or “social knowledge.”

The procedure for implementation of PSO is as follows:

1) Particles’ velocities and positions are Initialised randomly, the objective value of all particles are calculated, the position and objective of each particle are set as its P_i and P_{best} respectively and also the position and objective of the particle with the best fitness (least objective) is set as P_g and g_{best} respectively.
2) Particles’ velocities and positions are updated according to equations (1) and (2).
3) Each particle’s P_{best} and P_i are updated, that is, if the current fitness of the particle is better than its P_{best} , P_{best} and P_i are replaced with current objective value and position vector respectively.
4) P_g and g_{best} are updated, that is, if the current best fitness of the whole swarm is fitter than g_{best}, g_{best} and P_g are replaced with current best objective and its corresponding position vector respectively.
5) Steps 2-4 are repeated until stopping criterion (usually a prespecified number of iterations or a quality threshold for objective value) is reached.

It should be mentioned that since the velocity update equations are stochastic, the velocities may become too high, so that the particles become uncontrolled and exceed search space. Therefore, velocities are bounded to a maximum value V_{max}, that is (Eberhart, Shi, & Kennedy, 2001)

$$\text{If } |V_{id}| > V_{max} \text{ then } V_{id} = \text{sign}(V_{id})V_{max} \qquad (3)$$

Where sign represents sign function.

However, primary PSO characterised by (1) and (2) does not work desirably; especially since it possess no strategy for adjusting the trade-off between explorative and exploitative capabilities of PSO. Therefore, the inertia weight PSO is introduced to remove this drawback. In inertia-weight PSO, which is the most commonly-used PSO variant, the velocities of particles in previous time step is multiplied by a parameter called inertia weight. The corresponding velocity update equations are as follows (Shi & Eberhart, 1998; Shi & Eberhart, 1999)

$$V_{id}(t+1) = \omega V_{id}(t) + C_1 r_{1d}(P_i - X_{id}) + C_2 r_{2d}(P_{gd} - X_{id})$$

$$X_{id}(t+1) = X_{id}(t) + V_{id}(t+1) \qquad (4)$$

Inertia weight adjusts the trade-off between exploration and exploitation capabilities of PSO. The less the inertia weight is, the more the exploration capability of PSO will be and vice versa. Commonly, it is decreased linearly during the course of the run, so that the search effort is mainly focused on exploration at initial stages and is focused more on exploitation at latter stages of the run. The flowchart of linearly decreasing inertia weight PSO which is usually called conventional PSO, is depicted is Figure 1.

2.1 Constricted PSO

Constricted PSO, like inertia weight PSO, was invented to enhance the exploration capability of PSO and to hinder explosion of swarm. Velocity update equations in this variant are as follows (Clerc, and Kennedy, 2002):

$$V_{id}(t+1) = \chi\left(V_{id}(t) + C_1 r_{1d}(P_{id} - X_{id}) + C_2 r_{2d}\left(P_{gd} - X_{id}\right)\right) \qquad (5)$$

$$X_{id}(t+1) = X_{id}(t) + V_{id}(t+1)$$

Where

$$\chi = \frac{2}{\left(2 - C - \sqrt{(C^2 - 4C)}\right)} \quad \text{and} \quad C = C_1 + C_2 \qquad (6)$$

Usually, C is set to 4.1 and so χ=0.729.

2.2 Cognitive Only PSO

In velocity update equations of PSO in (1) and (2), if the value of social acceleration coefficient is set to zero (C_2=0), each particle is solely attracted to the best experience of itself and is not affected by other particles, that is, social interaction and information sharing does not exist. This variant is called cognitive-only PSO and has been used rarely in PSO applications.

$$V_{id}(t+1) = V_{id}(t) + C_1 r_{1d}(P_i - X_{id}) \qquad (7)$$

$$X_{id}(t+1) = X_{id}(t) + V_{id}(t+1)$$

2.3 Social Only PSO

In PSO's velocity update equations in (1) and (2), if the value of cognitive acceleration coefficient is set to zero (C_1=0), the particles are solely attracted to the best experience of the whole swarm and not their own best experience. This variant is called cognitive-only PSO and has been used rarely in PSO applications.

$$V_{id}(t+1) = V_{id}(t) + C_2 r_{2d}\left(P_{gd} - X_{id}\right) \qquad (8)$$

$$X_{id}(t+1) = X_{id}(t) + V_{id}(t+1)$$

2.3.1 Bare-Bone (Velocity-free) PSO

Bare-bones PSO is a version of PSO in which position update equations are replaced by a procedure that samples a parametric probability density function. In this variant, the concept of velocity is missing. A particle's position update equation is as follows (Kennedy, 2003)

$$X_{id}(t+1) = N\left(\mu_{id}(t),\ \sigma_{id}(t)\right) \qquad (9)$$

$$\mu_{id}(t) = \frac{P_{id} + P_{gd}}{2} \qquad (10)$$

$$\sigma_{id}(t) = \sqrt{\left|P_{id\,(t)} - P_{gd\,(t)}\right|} \qquad (11)$$

Where N stands for a Normal distribution.

3. Applications of PSO

The areas of PSO applications is extremely wide. For instance, it has been applied in medicine (Chen, Wang et al. ; Gandhi, Karnan et al. ; Kessentini, Barchiesi et al. ; Yang and Zhang ; Zabidi, Lee Yoot et al. ; Nakib, Roman et al. 2007; Liman, Haiming et al. 2008), chemistry (Qiang, Wen-cong et al.), economy (Ernawati and Subanar ; An-Pin, Chien-Hsun et al. 2009), geology (Dianfeng, Yaolin et al. ; Jen-Chih and Chen ; Han and Wang 2009; Liang, Guangming et al. 2009), mechanical engineering (Bin, Hangxia et al. ; Jianghui and Wenjun ; Mukesh, Lingadurai et al. ; Qiang and Fang 2006; Hushan, Shengdun et al. 2008; Changlin, Heyan et al. 2009; Youxin and Xiaoyi 2009), biology (Chengwei and Jianhua 2008), geography (Hua-sheng, Long et al. ; Wenyu, Xuan et al. 2009), civil (Huawang and Wanqing 2008; Min and Fang-Fang 2009), computer science (Geetha and Sathya ; Guosheng, Jianxun et al. ; Shuzhi, Ping et al. ; Toreini and Mehrnejad ; Youssef ; van der Merwe and Engelbrecht 2003; Alam, Dobbie et al. 2008; Xueping, Qingzhou et al.

2008), electrical power engineering (Amanifar ; Ghanbarzadeh, Goleijani et al. ; Iyer, Xiaomin et al. ; Nabavi, Hajforoosh et al. ; Sundareswaran, Nayak et al. ; Slochanal, Saravanan et al. 2005; Sadati, Hajian et al. 2007; Das, Prasai et al. 2009; El-Gammal and El-Samahy 2009; Zhao, Zhan et al. 2009).

4. Conclusions

In this paper, fundamental concepts of PSO have been introduced, basic PSO variants have been explained and analysed. Furthermore, some applications of PSO in different areas have been mentioned. The authors believe that this paper can be useful for researchers in related areas.

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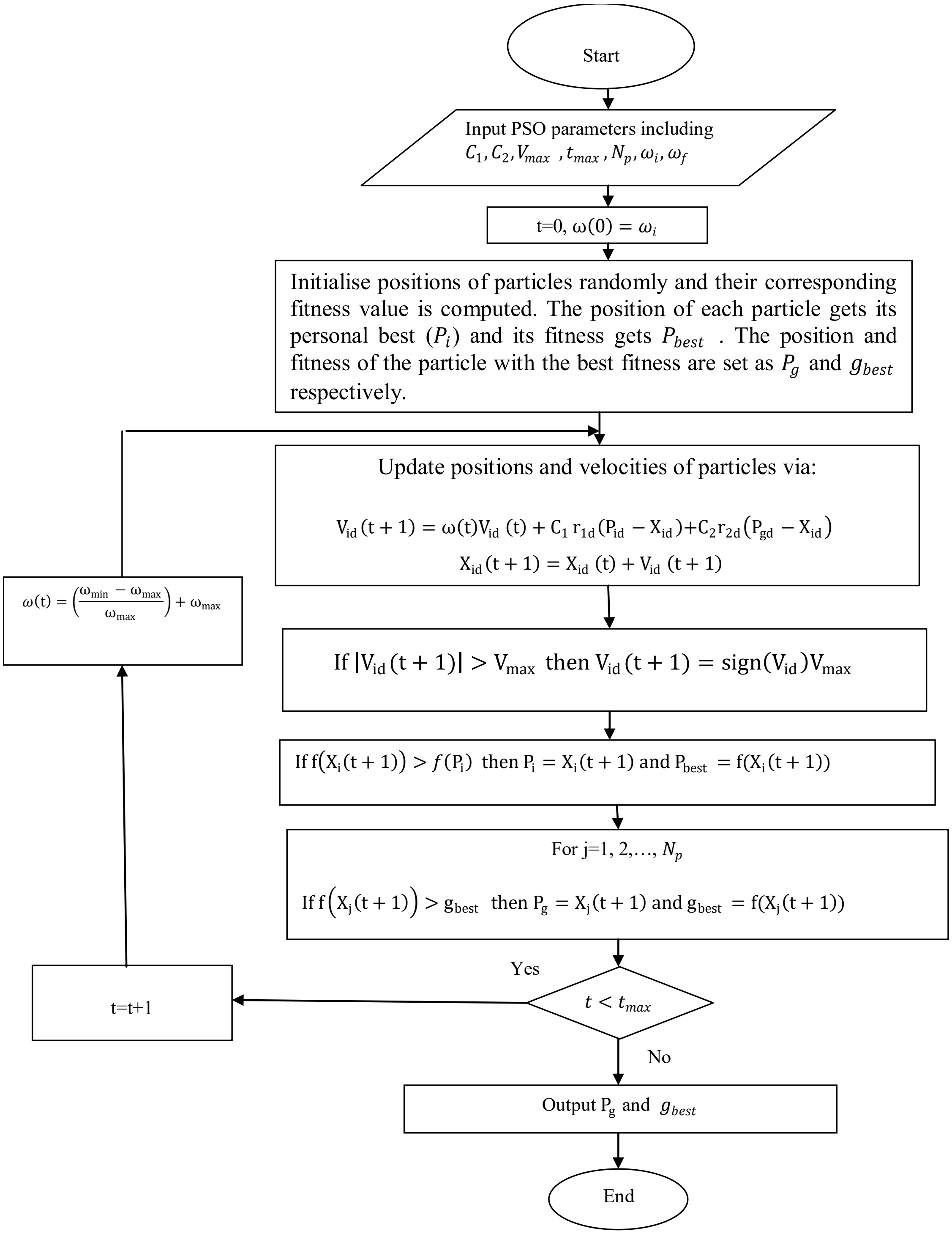

Fig.1 Flowchart of conventional PSO

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