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Overview of Particle Swarm Optimization (PSWO) Method, Architecture, and Obstacles

Rajesh Nayaak, Yamini
Department of Mathematics,

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ABSTRACT

Particle Swarm Optimization (PSO) is a biologically inspired computational search and optimization method developed in 1995 by Eberhart and Kennedy based on the social behaviors of birds flocking or fish schooling. A number of basic variations have been developed due to improve speed of convergence and quality of solution found by the PSO. On the other hand, basic PSO is more appropriate to process static, simple optimization problem. Modification PSO is developed for solving the basic PSO problem. The observation and review 46 related studies in the period between 2002 and 2010 focusing on function of PSO, advantages and disadvantages of PSO, the basic variant of PSO, Modification of PSO and applications that have implemented using PSO. The application can show which one the modified or variant PSO that haven't been made and which one the modified or variant PSO that will be developed.

Keywords

Particle Swarm Optimization (PSO), Variant PSO, Modification PSO, Basic PSO problem, Bird Flocking, Evolutionary Optimization, biologically inspired computational search.

1. INTRODUCTION

Theory of particle swarm optimization (PSO) has been growing rapidly. PSO has been used by many applications of several problems. The algorithm of PSO emulates from behavior of animals societies that don't have any leader in their group or swarm, such as bird flocking and fish schooling. Typically, a flock of animals that have no leaders will find food by random, follow one of the members of the group that has the closest position with a food source (potential solution). The flocks achieve their best condition simultaneously through communication among members who already have a better situation. Animal which has a better condition will inform it to its flocks and the others will move simultaneously to that place. This would happen repeatedly until the best conditions or a food source discovered. The process of PSO algorithm in finding optimal values follows the work of this animal society. Particle swarm optimization consists of a swarm of particles, where particle represent a potential solution. Recently, there are several modifications from original PSO. It modifies to accelerate the achieving of the best conditions. The development will provide new advantages and also the diversity of problems to be resolved. Study on the development of PSO is necessary to do to know how far its development, its advantages and disadvantages and how much use this method to settle a problem. Tutorial and theoretical of PSO has made about what is PSO [1], [2], those describe about what PSO is, simple data tested, and comparison with others evolutionary computations.

This paper will describe what for the modifications, advantages and disadvantages each modification of PSO and make a conclusion from those. In section 2 describes about basic PSO, basic variation of PSO, and modification of PSO, and section 3 observation, and the last section 4 describe about summary and future work.

2. VARIANT OF PSO

Exploration is the ability of a search algorithm to explore different region of the search space in order to locate a good optimum. Exploitation, on the other hand, is the ability to concentrate the search around a promising area in order to refine a candidate solution[3].With their exploration and exploitation, the particle of the swarm fly through hyperspace and have two essential reasoning capabilities: their memory of their own best position - *local best (lb)* and knowledge of the global or their neighborhood's best - *global best (gb)*.

with $x_i(0) \sim U(x_{min}, x_{max})$, acceleration coefficient c_1 and c_2, and random vector and . Simple example of PSO, there is a function [3]:

$$\text{Min } f(x) \quad r_1 \quad r_2$$

where $x(B) \leq x < x(A)$

Denote $x(B)$ as a lower limit and $x(A)$ as an upper limit. So, PSO procedure can be described by the following steps: *First*, Assume that the size of the group of particle is N. It is necessary that the size N is not too large, but also not too small, so that there are many possible positions toward the best solution or optimal. *Second*, generate initial population x with range $x(B)$ and $x(A)$ by random order to get the $x_1, x_2, \ldots, x_n$. It is necessary if the overall value of the particle is uniformly in the search area.

After that, the particle j and the velocity at iteration i are denoted as and thus, these initial particles will be . Vector $x_j(0), j = 1,2,\ldots,n$ is called a particle or vector coordinates of the particle. (Such as: chromosomes in genetic algorithms). Evaluation of the objective $x_1(0), x_2(0), \ldots, x_n(0)$ function value for each particle and expressed by $f[x_1(0)], f[x_2(0)], \ldots, f|x_n(0)|$

Then calculate the speed of all particles. All particles move towards the optimal point with a velocity. Initially all of the particle velocity is assumed to be zero. Set iteration $i = 1$.

At the i^{th} iteration, find the two important parameters for each particle j that is:

a. The best value of $x_j(i)$ (the coordinates of particle j at iteration i) and declare as , with the lowest value of objective function (minimization case), $P_{best}(j) = f|x_j(i)|$, which found a particle at all previous iteration. The best value for all particles which found up to the i^{th} iteration, G_{best} with the value function the smallest goal / minimum among all particles for all the previous iterations, $f|x_j(i)|$.
b. Calculate the velocity of particle j at iteration i using the following formula using formula (2): $v_j(i)$
   Where c_1 and c_2, respectively, are learning rates for individual ability (cognitive) and social influence (group), and r_1 and r_2 uniformly random numbers are distributed in the interval 0 and 1. So the parameters c_1 and c_2 represent weight of memory (position) of a particle towards memory (position) of the groups (swarm). The value of c_1 and c_2 is usually 2, so multiply $c_1 r_1$ and $c_2 r_2$ ensure that the particles will approach the target about half of the difference
c. Calculate the position or coordinates of particle j at the i^{th} iteration by : $x_i(t+1) = x_i(t) + v_i(t+1)$

Evaluation of the objective function value for each particle and expressed as: $f[x_1(i)], f[x_2(i)], \ldots, f[x_n(i)]$

The last step, check whether the current solution is convergent. If the positions of all particles leading to an equal value, then this is called convergence. If not convergent then step 4 is repeated by updating iterations $i = i + 1$, by calculating new values from $P_{best}(j)$ and G_{best}. This iteration process continues until all particles convergence the same solution. Usually be determined by the termination criteria (Stopping criterion), for example the amount of the excess solution with a solution now previously been very small. If the current solution is convergent, then the iteration will stop. We do not know whether the final value is the best value. Below are the stopping criteria conditions for the iteration: *First*, terminate when a maximum number of iterations, or FEs, has been exceeded. *Second*, Terminate when an acceptable solution has been found, *Third*, Terminate when no improvement is observed over a number of iteration. *Fourth*, terminate when the normalized swarm radius is close to zero. *Fifth*, terminate when the objective function slope is approximately zero. Although the particle has stopped, we do not know whether the particle will pitch on local optima, local minima, global optima or global optima.

In the original particle swarm optimization, there has also a lack of solution, because it is very easy to move to *local optima.* In certain circumstances, where a new position of the particle equal to global best and local best then the particle will not change its position. If that particle is the global best of the entire swarm then all the other particles will tend to move in the direction of this particle. The end of result is the swarm converging prematurely to a local optimum. If the new position of the particle pretty far from global best and local best then the velocity will changing quickly turned into a great value. This will directly affect the particle's position in the next step. For now the particle will have an updated position of great value, as a result, the particle may be out of bounds the search area.

In analysis, PSO has advantages and disadvantages [4]. Advantages of the basic particle swarm optimization algorithm: PSO is based on the intelligence. It can be applied into both scientific research and engineering use. Then PSO have no overlapping and mutation calculation. The search can be carried out by the speed of the particle. During the development of several generations, only the most optimist particle can transmit information onto the other particles, and the speed of the researching is very fast. After that the calculation in PSO is very simple. Compared with the other developing calculations, it occupies the bigger optimization ability and it can be completed easily. The last one is PSO adopts the real number code, and it is decided directly by the solution. The number of the dimension is equal to the constant of the solution.

On the other hands, disadvantages of the basic particle swarm optimization algorithm are the method easily suffers from the partial optimism, which causes the less exact at the regulation of its speed and the direction. Then the method cannot work out the problems of scattering and optimization and the method cannot work out the problems of non-coordinate system, such as the solution to the energy field and the moving rules of the particles in the energy field.

2.1 Basic Variants of PSO

The lacks of PSO have been reduced with a variation of PSO. Many variations have been developed to improve speed of convergence and quality of solution found by the PSO. The variation is influenced by a number of control parameters, namely the dimension of the problem, the number of particles (swarm size), acceleration coefficients (The acceleration coefficient, c_1 and c_2, together with random vector r1 and r2, control the stochastic influence), inertia weight, neighborhood size, number of iteration, and the random values which scale the contribution of the cognitive and social component.

$$\phi = \phi_1 + \phi_2$$
$$\phi_1 = c_1 r_1$$
$$\phi_2 = c_2 r_2$$

$$v_{ij} = \begin{cases} v'_{ij}(t+1), if\ v_{ij}(t+1) < v_{max}(J) \\ v_{max}(j)\ \ otherwise \end{cases} \quad (3)$$

High value of $v_{max}\ (j)$ will cause global exploration, whereas lower values result in local exploration. $v_{max}\ (j)$ will control the movement of the particle and aspect of exploration and exploitation. Velocity clamping did not influence the position of the particle. This only reduces the size of the step velocity. Changes in the search direction not only can make a particle to perform a better exploration but also has negative effects and the optimum value cannot be found.
The following equation [2] is used to initialize the max and min velocity to the solution:

$$v_{max,j} = \delta\ (x_{max,j} - x_{min,j}) \quad (4)$$
$$v_{min,j} = \delta\ (x_{min,j} - x_{max,j}) \quad (5)$$

Where as $x_{max,j}$ and $x_{min,j}$ are the minimum and maximum positions of the particle in the j^{th} dimension. δ is a constant factor and is taken from 0 until 1. The problem is if all the velocity becomes equal to v_{max} the particle will continue to conduct searches within a hypercube and will probably remain in the optima but will not converge in the local area.

There are some researchers that have develop velocity clamping method, such as : [5], [6]

a. Inertia weight

It is a mechanism to control an exploration and exploitation abilities of the swarm, and as mechanism to eliminate the need of velocity clamping. The inertia weight, w, controls the momentum of the particle by weighing the contribution of the previous velocity – basically controlling how much memory of the previous flight direction will influence the new velocity. For the $gbest$ PSO, the velocity equation [5] changes from equation:

$$v_{ij}(t+1) = wv_{ij}(t) + c_1 r_1(t)\left(y_{ij}(t) - x_{ij}(t)\right) + c_2 r_2(t)\left(\hat{y}_j(t) - x_{ij}(t)\right) \quad (6)$$

A similar change is made from the- PSO. Inertia weight presenting how much the amount of memory from the previous flight direction will affect the new velocity. If $w > 1$, then the velocity will decrease with time, the particle will accelerate to maximum velocity and the swarm will be divergent. If $w < 1$, then the velocity of particle will decrease until it reaches zero. The larger value of w will facilitate an exploration, rather small values will promote the exploitation.There are some researchers that have develop inertia weight application, such as :[7], [8], [9], [10]

$lbest$

b. Constriction Coefficient

Velocity update equation that using constriction coefficient changes to:

$$v_{ij}(t+1) = x[v_{ij}(t) + \emptyset_1(y_{ij}(t) - x_{ij}(t) + \emptyset_2(\hat{y}_j(t) - x_{ij}(t)] \quad (7)$$

Equation above is used under the constraints that $\emptyset \geq 4\ and\ k \in [0,1]$. The constriction approach was developed as a natural, dynamic way to ensure convergence to a stable point, without the need for velocity clamping. Condition $\emptyset \geq 4$ and $k \in [0,1]$ of the swarm is guaranteed to convergence. There are some researchers that have develop constriction coefficient , such as : [11], [12].

c. Synchronous Versus Asynchronous Updates

Synchronous Updates [13] are done separately from the particle (personal best and neighborhood bests) position updates, only given one feedback per iteration update, slower feedback and better for $gbest$. While asynchronous is better for $lbest$, updates calculate the new best positions after each particle position update and have the advantage that immediate feedback is given about the best region of search space. There are some researchers that have develop this method, such as : [14], [15], [16], [17], [18], [19], [20].

2.2. Modification of PSO

The modification in PSO consists of three categories: extension of field searching space, adjustment the parameters, and hybrid with another technique. The modifications of PSO can enhance its performance.

a. Single Solution PSO

A large number of PSO variations can be found to locate single solutions. These PSO implementations were specially developed to obtain single solutions to continuous-valued, unconstrained, static, single-objective, optimization problem, most of these algorithm can also be applied to other problem types.

b. Niching with PSO

In the EC field, algorithms that locate multiple solutions are refers to as niching algorithm. The process of finding multiple solution or niche is generally referred to as speciation. Niching algorithms model yet another natural process, where large numbers of individuals compete

for the use of limited resources on physical environment.
Nieces are partitions of an environment while species are partitions of computational optimization, a niece represents one solutions to the problem, while a species refers to the group of individuals (particle in the context of PSO) that convergence on a single niece.

c. Constraint Optimization using PSO
Constraint reduces the feasible space where in solution to the problem can be found. Optimization algorithms need to ensure that a feasible solution is found. That is the optimization algorithm should find a solution that both optimizes the objective function satisfies all constraints. If it is not possible to satisfy all constrains, the algorithm has to balance the trades off between optimal objective function value and number of constrain violated.

d. Multi-objective optimization with PSO
Many real world optimization problems require the simultaneous optimization of a number of objectives (multi-objectives). Using the notation, the multi-objectives optimization problem is defined as:

$$\begin{aligned} &minimize \quad f(x), \quad x = (x_1, x_2, \dots, x_n) \\ &subject\ to \quad g_m \le 0, \qquad m = 1, \dots, n_g \\ &\qquad\qquad h_m = 0, \qquad m = n_g + 1, \dots, n_g + n_h \end{aligned} \tag{8}$$

The main objective of MOO algorithms is to find a set of solution which optimally balance the trade-offs among the objective of a MOP. It is different with the basic PSO that return only one solution.

e. Dynamic Environment With PSO
In dynamic Environments, PSO should be fast to allow quick re-optimization. It is desirable to find a good solution before the next environment change. In original PSO, it is impossible to convergence to an equilibrium state in its first goal to locate the optimum.
There are several solutions for dynamic environment. Such as: a. Environment change detection, It is to allow timeous and efficient tracking of optimum, b. Response to environment changes, c. Changing the inertia weight update, d. Reinitialize Particle Solution, e. Limit Memory, f. Local Search, g. Split adaptive PSO,
h. Fine-Grained, i. charged Swarm, The changed PSO charges the velocity equation by adding a particle acceleration, a_i , to the standard equation, That is:

$$\begin{aligned} v_i(t+1) = &\left(\omega \otimes v_i(t)\right) \circ \left(c_1 r_1(t)\left(y_i(t)\right) \ominus x_i(t)\right) \circ \\ &\left(\left(c_1 r_1(t)\left(\hat{y}_i(t)\right) \ominus x_i(t)\right)\right. \end{aligned} \tag{12}$$

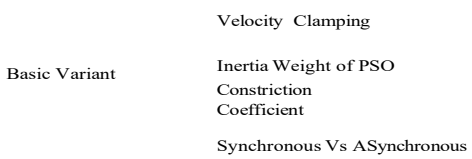
Position update: first, all velocities are normalized to the range [0,1] by dividing the velocities by the maximum range of the corresponding dimensions,

$$\begin{aligned} x_i(t+1) &= x_i(t) \oplus v_i(t+1) \\ &= \left(\omega \otimes v_i(t)\right) \end{aligned} \tag{13}$$

Then, each position determines if there is a swap with probability v_{ij}. Last, if a swap has to be executed, the affected position of the particle change to that of the global best (or local best) position.

3. OBSERVATION AND REVIEW

Particle swarm optimization (PSO) is a biologically inspired computational search and optimization method developed in 1995 by Eberhart and Kennedy based on the social behaviors of birds flocking or fish schooling. Recently, there are many variants of PSO, and it may always grow rapidly. Figure 1 describes the variants of particle swarm.



$$v_{ij}(t+1) = \omega v_{ij}(t) + c_1 r_1(t)\left[y_{ij}(t) - x_{ij}(t)\right] + c_2 r_2(t)\left[\hat{y}_j(t) - x_{ij}(t)\right] + a_{ij}(t)$$

Where: $a_i(t) = \sum_{l=1, i\neq l}^{n_s} a_{il}$ (9)

f. Discrete PSO

PSO was originally developed for continuous-valued spaces. Many problems are, however, defined for discrete value. Fortunately, the PSO is easily adaptable to discrete-value spaces.

Table1. The Basic Variant of PSO

Basic Variant	Function	Advantages	Disadvantages
Velocity Clamping	Control the global exploration of the particle Reduces the size of the step velocity, so that the particles remain in the search area, but it cannot change the search direction of the particle	VC reduces the size of the step velocity so it will control the movement of the particle	If all the velocity becomes equal to v_{max} the particle will continue to conduct searches within a hypercube and will probably remain in the optima but will not converge in the local area.
Inertia Weight	Controls the momentum of the particle by weighing the contribution of the previous velocity,	A larger inertia weight in the end of search will foster the convergence ability.	Achieve optimality convergence strongly influenced by the inertia weight
Constriction Coefficient	To ensure the stable convergence of the PSO algorithm [21]	Similar with inertia weight	when the algorithm converges, the fixed values of the parameters might cause the unnecessary fluctuation of particles
Synchronous and Asynchronous Updates	Optimization in parallel processing	Improved convergence rate	Higher throughput: More sophisticated finite element formulations Higher accuracy (mesh densities)

Table 2.Characteristic Modifications of PSO

Variant PSO	Utilities	Methods
Single Solution of PSO	Obtain single solutions to continuous-valued, unconstrained, static, single-objective, optimization problem	Social network structure, hybrid algorithm, sub-swarm-based, revealing methods, memetic PSO multi-start PSO
Niching with PSO	Niching (speciation) techniques have the ability to locate multiple solutions in multimodal domains	Quasi-sequential niching, Parallel niching algorithm, Objective function stretching, Sequential niching
Constra-int Optimization using PSO	Find a solution that both optimizes the objective function satisfies all constraints. If it is not possible to satisfy all constrains, the algorithm has to balance the trades off between optimal objective function value and number of constrain violated	convert to unconstrained problem, Repair method, Boundary constrain, Pareto ranking, Preserving feasible
Multi-objective optimization (MOO)	Find a set of solution among the objective of a multi optimization problem.	Criterion-based methods, dominance-base;
Dynamic Environment of PSO	Have an ability to solve an optimization in the dynamic real-world problems although if it is in multi objective optimization	Environment change detection, Response to environment changes, Changing the inertia weight update, Reinitialize Particle Solution, Limit Memory, Local Search, Split adaptive PSO, Fine-Grained, Charged Swarm
Discrete PSO	Find an optimization problem that operate on binary search space	Binary PSO, General Discrete PSO

With the characteristic of modification of PSO, there are several application areas that can develop, such as scheduling, searching, forecasting, feature selection, classification, production rate and functions problem. Table 3 described the distribution of article for every function of PSO.

Table 3.Distribution of article for every function of PSO

	Optimized Scheduling	Optimized Local Search	Optimized Multi Search	Optimized Forecasting	Optimized Function Problem	Optimized Feature Selection	Optimized Classification	Optimized Production Rate
Single Solution of PSO	[22] [23]	[24], [25] [26], [27]	[28]	[29]	[30]		[31]	
Niching With PSO		[32]	[33], [34] [35]		[36]			
Constrain Optimzed using PSO		[37]	[38]		[39] [40]			[41]
Multi Objective Optima zation	[42]	[43] [10]	[44]	[45]	[46]		[47] [48] [49]	[50]
Dinamic Environment of PSO	[51]	[52] [53]			[54], [55] [51]	[56], [51] [57]		[58], [59] [60]
Discrete PSO	[61]				[62]	[63]	[64]	

Modification of particle swarm optimization problems have implemented in several areas, i.e. Searching, Optimization mathematical function, Classification problem, Feature selection, Scheduling, and etc. Although the method of modification PSO has

developed in many variant, it is very conducive to the creation of a new method of variation PSO because there are others area that can be implemented by modification PSO.

4. SUMMARY

In its search for optimum values, the PSO algorithm mimics the behaviour of a non-hierarchical animal community. Each "particle" in a swarm of particles represents a possible solution or improved state in particle swarm optimisation. To locate the optimal location, the particle will traverse a three-dimensional search space, where optimal positions might be anywhere between the two extremes of the spectrum. This article provides a comprehensive overview of the various PSO algorithm techniques. There are pros and cons to using basic particle swarm optimisation to make up for PSO's shortcomings. Many different versions of PSO exist. Controlling the velocity and steady convergence have been aided by the fundamental versions stated before. In contrast, the basic PSO is unable to handle certain situations; however, modified variation PSO can.

This study and analysis aims to demonstrate the absolute function of PSO, its pros and cons, the most fundamental form of PSO, its modifications, and the applications that have made use of it. The app may display the versions of PSOs that have been improved or upgraded, as well as the ones that are still in the planning stages.

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