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Review on Different Evolutionary Computing Techniques In Particle swarm Optimization

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Particle swarm optimization, Inertia weight, Velocity Clamping, Multi phase PSO (MPPSO), Distribution vector PSO (DVPSO)

Abstract

Particle swarm optimization (PSO) technique is used mainly for non linear functions. The different types of PSO method are described in this paper. Implementations of different PSO methods are discussed and compared. Relationships between particle swarm optimization and both artificial life and evolutionary computation are reviewed. This paper describes the engineering and computer science aspects of applications, and resources related to particle swarm optimization. PSO is originated in 1995.This paper presents the review of development of PSO as well as recent development in the PSO.

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Introduction

In continuous and differential functions, for finding the optimum solution and unconstrained maxima or minima, the classical optimization techniques are used. [1] These classical methods have limited scope for practical operations. PSO is suitable for non-continuous and non differentiable objective functions.PSO theory is growing rapidly now a days and this is a very prominent results of PSO algorithm. . Finally, this powerful tool for optimization.PSO is a population based stochastic evolutionary technique.[2] It is introduced by Dr. Kennedy and Dr. Eberhart in 1995.This is basically inspired by the social behavior of animals and birds. From the 1995 to Recent years, there are several modifications has been done in original PSO.This paper provides a review and discussion on the most paper gives different types of improved versions and the future research issues are also given.

Particle Swarm Optimization

James Kennedy and Russell C. Eberhart [3] originally proposed the PSO algorithm for complex non-linear optimization problem by imitating the nature of birds flock. PSO soon became a very popular global optimizer, mainly in objective space.

The algorithm required for evolution depends mainly on three factors first parent representation, second selection of individuals and the third one is the fine tuning of the parameters. Since PSO does not adopt an unambiguous selection function. By use of leaders, the PSO is compensated in case of the absence of selection mechanism, for the guidance of search. Normally PSO has two basic algorithm one is the Global Best (*gbest*) and another is Local Best (*lbest*) PSO.They may differ in the size of their neighborhoods. These PSO algorithms are explained below sections respectively.

Global Best PSO

In the global best PSO or *gbest PSO* [5] the every particle is subjective by the best-fit particle in the whole swarm family. In this method mainly star social information topology is used in which all social information is collected from all particle exist in the swarm family. In search space each particular particle has current velocity (V_i) best position (x_i) and personal best position ($P_{best\ i}$).Amongst all the personal best $P_{best\ I}$, which position has minimum value is called the global best position and it is denoted as G_{best}.

Local Best PSO

Local best PSO or *lbest* PSO method [5] only permits each particle to be subjective by the best-fit particle selected from it neighborhood and this indicate the ring social topology. In this algorithm the information is being collected by the neighborhood particle hence it is based on knowledge of the environment.

Parameters Of PSO Algorithm

The performance of the algorithm of PSO can be affected by the some parameters. These parameters value put large effect on the efficiency on the optimization. In PSO some parameters put very small or no effect on the optimization process.

There are some parameters are discussed below

(i) **Size of the Swarm: -** The number of particle present in the swarm is called the size of the swarm. This also known as the population (n) of the swarm. If the population of swarm is large, the less number of iteration is required to obtain the good result of the optimization. Oppositely, the large number of particles may increase the computation complexity per iteration and also consumes the time.

(ii) **The number of Iteration: -** The good result of the optimization is depending on the number of iteration. If the number of iteration is very less, then search process may stop prematurely. While if number of iteration is too large, then computation complexity will arise and this may need more time.

(iii) **Velocity Components:-**The velocity components are required to determine and update the particle's velocity. In equation three terms are describes the particle velocity.

(a) V_{ij}^t is the inertia component by which we can obtain the memory of the previous flight direction. This is the momentum component and it protect the drastically change in direction of the particle and also tend the particle to the current direction.

(b) $C_1r_{1j}^t\ [P^t_{best,i} - X_{ij}^t\ ]$ is known as cognitive component which continuously calculate the particles performance relative to the previous performance This component shows the particular memory lbest which is position of the particle. This cognitive component is taken as recollection of the particle.

(c) For gbest PSO term $C_2r_2{}^t{}_j[Gbest - xij^t]$ a for lbest PSO term $C_2r_2{}^t{}_j[Lbesti - xij^t]$ is known as social component. This component calculate the performance execution of the particles with respect to the swarm group or neighbors.

Coefficients of Acceleration

C_1 and C_2 are the coefficients of acceleration; when C1 and C2 combine with random values r_1 and r_2; they control the effect of cognitive and social components of the particles velocity respectively.

C_1 represents the confidence of own particle & C_2 represents the confidence or believe on neighbor particle.

(i) If $C_1 = C_2 = 0$, then all particles go through on their current speed up to they hit the search space's boundary.

Hence the new velocity equation can be given by $V_{ij}^{t+1} = V_{ij}^t$

(ii) When $C_1 > 0$ & $C_2 = 0$; all particles are free. The new velocity equation

$V_{ij}^{t+1} = V_{ij}^t + C_1r_1{}^tj\ [P^tbesti - xij^t]$.

If $C_2 > 0$ & $C_1 = 0$particles will attracted towards single point [ie. Gbest] and new velocity.

$V_{ij}^{t+1} = V_{ij}^t + C_2r_2j^t\ [Gbest - x_{ij}{}^t]$ for gbest PSO

$$V_{ij}^{t+1} = V_{ij}^{t} + C_2 r_2 j^t \, [Lbest - x_{ij}^{t}] \text{ for Lbest PSO}$$

If $C_1 = C_2$, all particles move to average of P^tbesti and Gbest.

If $C_1 > C_2$, each particle is highly affected to its best position on the other hand if $C_2 > C_1$ all particles are affected by the global best position because of that all particles move to prematurely tp the maxima. [4] [11].

Refinement in rate of convergence

For PSO, the velocity is the key criterion. Because each & every particle. is move by adjusting & controlling the velocity, and each particle can move in any direction of the search space. In this regard two terms can be defined i.e. exploration and exploitation.

Exploration means, the capability to explore an identify the new areas in the search space for better optimization & exploitation means the capability to focus the search across a search space for improvement in optimistic solution. For better optimization algorithm these two qualities (i.e. Exploration & Exploitation)should have proper balance.

Velocity Clamping

This velocity clamping is mainly introduced by Eberhart & Kennedy. With the help of velocity clamping the particles can live in the boundary without clamping the position of particle changes very frequently and rapidly. By velocity clamping the better balance between global exploration and local exploitation .

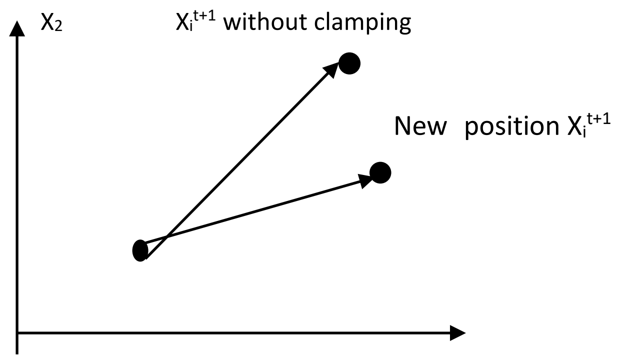

Fig:1.For two dimensional space search effect of velocity clamping

Fig shows that the effect of velocity clamping on the changes of step size and also the search direction.

Inertia weight

The Inertia weight is designated by 'ω' and at every step, w is multiplied by velocity at the previous time step.[6] The inertia weight is given as Shi by Eberhart in 1999. They use that to deduct the velocities overtime, so that the exploration and exploitation both can be control for the swarm family. It makes the swarm accurate and efficient. Either fixed value or dynamically changing value of the inertia weight can be established.[7]

Boundary Conditions

Many times, the search space is bounded & limited so the erupt of swarm can be prevented.[4] Sometimes particles may fly beyond the specified space search and can produce the invalid solution. The velocity clamping is apply to control the velocities of the particle to the maximum value Vmax. The constriction coefficient γ, inertia weight ω and maximum velocity Vmax, confine the particle in the search space, Besides some particles still escapes from the search space even though all values chosen for good optimization.

To prevent and overcome this situation, some instructions are implemented and it is called boundary conditions of PSO algorithm, it is very reliable in worst condition.

Some PSO techniques are discussed below.

Multi start PSO

In multi-start PSO, the main aim is to increase the diversity so that the more parts of the search space can be explored.

Earlier kennedy & Eberhart given the advantages of randomly reinitialization of particles.

Velocity vector and randomly initializing of position vector can able to enhance the diversity of swarm. But the big question is that when and how reinitialize the particle Reinitialize.

The convergence technique can be used to decide when the particles can reinitialize. In this technique particles are allowed to exploit their local regions. When particles do not enhance the the overtime, then at that time all particles initiates the reinitialization. The variations calculate the particle fitness for the current swarm, if variation is too small means the particles are very near to the gbest position.

Multi phase PSO (MPPSO)

In this technique the main group of swarm particles is divided into sub-swarms or subgroups. In which each subgroups perform the different work and each sub-swarm posses the different behavior. [11]

In two phase PSO there are two possible phases.

1. **Attraction Phase**

   In this PSO phase particles are moved towards the global best position corresponding to sub-swarm.

2. **Repulsion Phase**

   In this phase particles are moved away from the gbest position corresponding to sub-swarm. In MPPSO algorithm, the fitness of particles never changes, but the flying speed and direction of search space can be changed according to the adaptive velocity strategy. Therefore the MPPSO is guide more accurate solution as compared to basic PSO.

Multiobjective PSO

In multi objective optimization several objective functions are optimized at the same time. For the multi-objective problem. [9]There are several set of solutions which are normally cannot be compared with each other. Such types of solutions are known as Pareto optimal solution only when, in any objective functions no improvement is possible. The set of non-dominated solutions of problem in the search space is called the

Pareto optimal set. The main task in Pareto optimality to identify the all Pareto optimal solutions and it is possible that Pareto optimal set may be infinite in numbers and it will create computational problem which may be time consuming and space too.[8]

Distribution vector PSO

In PSO when the search process is going on , the distribution of the particle continuously charging. So the distribution arrangement of the particles can be given by the distribution vector d.

$Di=\max(X_{ij})-\min(X_{ij})/abs(\max(X_{ij}))+abs(\min(X_{ij}))$

(i=1, 2…………m)

Here

m=Particles dimension

n=Size of population

The distribution vectors (d) components have the values between the 0 to 1.

When the constriction factor updates, the velocity of each particles will also rearrange, so the distribution vector d depends on the numerical values and the direction of particle.

The PSO method which is applied with the distribution vector is called DVPSO (distribution vector particle swarm optimization).

Landscape adaptive PSO

In landscape adaptive PSO (LAPSO), the distribution of the particle in the search space can be alone properly because in LAPSO by the distribution of the present particle the velocity of the next step can be generated.[10]

For prevention the local convergence and unsettled oscillation. Hence the limitation of distribution vector can be overcome in the LAPSO.

Conclusion

This paper presented some fundamental and basic PSO techniques acceleration coefficients, topologies and velocity updates. The inertia weight velocity clamping construction coefficient set of convergence techniques and boundary conditions also discussed.

All these techniques can be utilized to enhance the speed of convergence and control the exploitation and exploration capabilities of the swarm. The Multi start PSO, Multi objective PSO, Distribution vector PSO, were analyzed & reviewed which are very helpful to solve the different types of optimization problems. The MSPSO, identity the lack of diversity and restarts the algorithm with new position of the particle. The MPPSO algorithm divide the main swarm group into the sub-swarm or sub-group to perform the different task. The MOPSO is helpful for several objective functions.

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