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THE PARTICLE SWARM OPTIMIZATION ALGORITHM

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Abstract: *The particle swarm optimization (PSO) is a possible optimization technique which works on the basis of population .This method was introduced by Dr. Abrheart and Dr. Kendy in 1995 and its main idea was inspired by the collective behaviour of the fish or birds when searching for food. A flock of birds are randomly searching for food in an area. There is only one piece of food in the area in question. None of the birds know the place of the food. One of the best strategies can be to follow the bird which is closest to the food. In fact, this strategy is the basis of the PSO Algorithm.*

Keywords: *Particle Swarm Optimization, Bird Flocking, Basic PSO problem, Evolutionary Optimization*

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1. INTRODUCTION

In the PSO Algorithm, every solution which is called a particle is equivalent to a bird in the birds swarm algorithm. Every particle has a competence value which is calculated by a competence function. The closer the particle is to the target – food in the birds' movement model – the more competence it has. In addition, the particle has a speed which is responsible for directing the movement of the particle. Every particle continues its movement in the question area by following the optimal particles in the current situation [1].

2. PSO ALGORITHM IN STATIC ENVIRONMENTS

PSO is one of the evolutionary calculations techniques which have been invented by imitating bird flights and information interchange between them. In PSO, every solution is only a bird in the search area and is called a member. All the birds have a competence value which is evaluated by the competence function which must be optimized. In addition, every i bird has a situation in the D dimensional area of the question which, in the t frequency, is shown by a vector in the following way:

$$X_i^t = (x^t{}_{i1}, x^t{}_{i2}, \ldots, x^t{}_{iD})$$

This bird has also a speed which directs its flight and is shown by the following :

$$V_i^t = (v^t{}_{i1}, v^t{}_{i2}, \ldots, v^t{}_{iD})$$

Vector in the t frequency: and in every frequency, this bird has also a memory from its best previous situation which is shown by the P vector:

$$P_i^t = (p^t{}_{i1}, p^t{}_{i2}, \ldots, p^t{}_{iD})$$

In every search repetition, every member is updated by considering the two best values. The first one is related to the best situation which the bird has experienced till now (the competence value of this best solution is also stored.). This value is called the best P or the so-called Pbest. The second one which is followed by the PSO is the best situation which has been obtained in the population so far. This optimal value is general and is called the so-called Gbest. When a member considers part of the population as its neighbours' topology, the best value is the local best and is called Lbest. After the best two values were found, the situation and speed of every member are updated by the following:

$$V_i(t+1) = wV_i(t) + c_1 r_{1,i}(t)(P_i(t) - X_i(t)) + c_2 r_{2,i}(t)(P_g(t) - X_i(t))$$

$$X_i(t+1) = X_i(t) + V_i(t+1)$$

In the aforesaid formulas, t indicates the number of frequency and the variables c_1 and c_2 are the learning factors. Often c_1=c_2=2 which controls the degree of movement of a bird in one time frequency. r_1 and r_2 are two steady random numbers in the range of 1 and 0. w is an algebraic weight which is typically valued in the range of 1 and 0. A larger algebraic weight facilitates a general exploration and a smaller algebraic weight facilitates a local exploration [2].

In the PSO algorithm, the population standard is valued by random solutions and until reaching the end condition , the population competence is repetitiously calculated, the values are *Pbest* and *Gbest*, the speed and the situation are updated respectively. In the end, *Gbest* and its competence value are expressed as output. The end condition can be to reach the maximum of the number of the generations or to reach a certain amount of competence in *Gbest*.

3. THE PSO ALGORITHM IN DYNAMIC ENVIRONMENTS

The PSO change causes this model to be developed for searching multi-faceted environments and tracing a peak in the dynamic environment. Dynamic multi-faceted environments can change in several ways: the peaks may shift in the surroundings or the shape or the height of the peaks changes [3].

In multi-faceted environment which is completely dynamic, the height of the global best peak may decrease whereas the height of the local best peak is increasing. A peak may disappear when another peak with a great height appears above it or a peak may completely appear or disappear.

The dynamic multi-peak environment needs a technique which allows the development of several subpopulations in a parallel way. Some of such techniques are the following:

- ✓ Allowing the particles to do an impartial search for local best
- ✓ Encouraging the particles to find several peaks
- ✓ Presenting a natural method for particles to join the subpopulations for the division and forming the subpopulations

- ✓ Preventing from centralization of a lot of particles in small peaks so that other particles continue searching and find other peaks.

These requirements are the characteristics of the algorithm which is explained and uses them for making several subpopulations in a parallel way and every subpopulation tries to trace and extract the local peak. These subpopulations or clusters are placed in the centre of the particle with the best situation in a local area which is defined as a form of a sphere with radius *r* in the centre of a particle with the best privilege[1].

All the particles which belong to a cluster *Pbest*[2] choose the central particle as their *Gbest*[3]. Therefore, the candidates of membership in a cluster are defined in such a way that every x particle which its distance to the central particle (*d*) is shorter than the radius of the cluster (*r*) is the member of that cluster:

$$d(x, s) \leq r$$

Which *d(x,y)* is defined by the Euclidean distance between the two points from *n*-dimension in the following way:

$$d(x, s) = \sqrt{\sum_{i=1}^{n}(x_i - s_i)^2}$$

If a particle is a candidate of membership in two clusters, this particle belongs to the cluster which has better privilege. By using this mechanism, every particle is either a central particle (even the cluster which has only one member and that member is its centre) or a member of another particle. In every generation repetition, the clusters may be reconstructed, and they are often different from the centre and a set of members which already belonged to another cluster.

A mechanism is still needed to prevent the particles from gathering on a peak. In a dynamic environment, it is necessary that tracing is not only following the current global best because maybe in the near future, the current local best turns into a global best. To do this, we consider a value for the maximum of the number of the population of every cluster called *pmax*, and so only the *pmax* of the particle which has the best privilege in a range will become the member of that range (this number also includes the central particle itself). In this case, those particles which have small privilege and do not belong to that cluster are valued from the beginning and are spread in the question area to become the member of

1- fitness
2- The best memory of every particle which has gained the most privilege there
3- The best memory of a group which one of the particles has gained the most privilege of the group there

other particles. In this case, gathering of the particles in certain areas is prevented and the particles are encouraged to explore the whole question area [4].

Each of the particles , regarding its geographical situation and the memory of the best situation which they have already gained (*pbest*) and communication with their neighbours to find the best situation which has been obtained by other particles (*gbest*) , continues to move.

Using these cases, the particles gain their speed for the next update and so gain the global best.

The equations which calculate these cases are standard like PSO. The pseudo code and flowchart of the suggested method can be seen in figure 1 and figure 2.

```
For  each particle
   Initialize particle
End For
Do
   For each particle
      Calculate fitness value of the particle fp
      /*updating  particle's best fitness value so far)*/
       If fp is better than pBest
          set current value as the new pBest
   End For
    /*updating  population's best fitness value so far)*/
   Set gBest to the best fitness value of all particles
   For each particle
      Calculate particle velocity according equation (1)
      Update particle position according equation (2)
   End For
While maximum iterations OR
        Minimum error criteria is not attained
```

Figure 1: Pseudo-Code of PSO algorithm

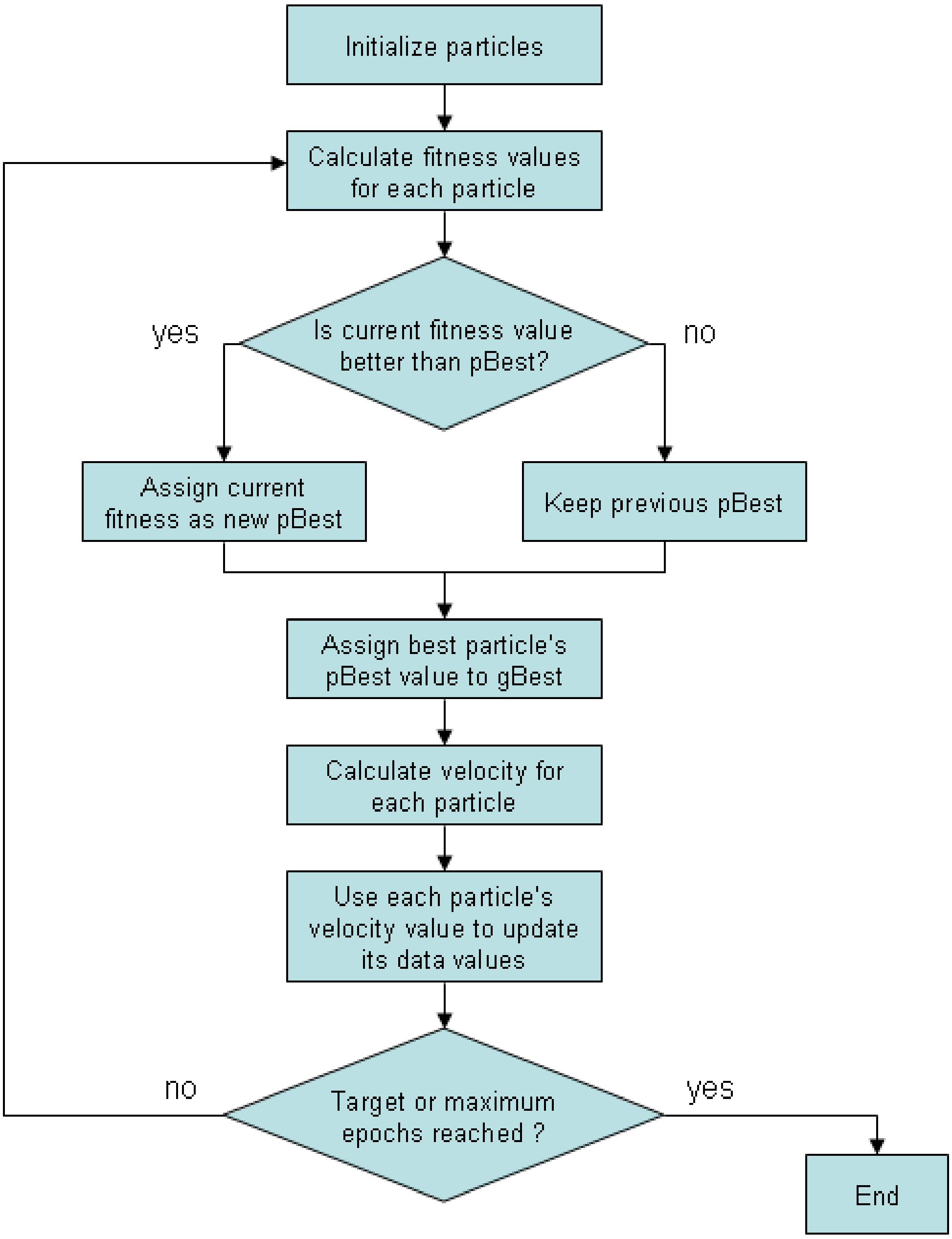

Figure 2: flowchart of PSO

4. THE BINARY MODEL OF PSO

It was presented to solve the discrete mathematics questions in 1997 by the standard algorithm presenters. In this model, the situation of each particle in every dimension is specified by one of the values of 1 or 0. So, the particle moves in an area limited to 0 and 1 and the speed of the particle in every dimension will be equal to the possibility of oneness of the situation of the particle in that dimension [5]. The speed is also updated according to the previous equations. Then, at first the speed gained in every dimension is transferred in the range of [0,1] by using the sigmoid function and then the new situation of the particle in every dimension is calculated according to the following equation.

If (rand() < sigmoid(v_{id}(t+1)) then

$x_{id}(t+1) = 1$

else

$x_{id}(t+1) = 0$

In which rand() is a random number in the range of [0,1].

5. CONCLUSION

The main advantages of PSO, being applicable to problems with discrete functions, problems with discrete solution space, high speed answers, high strength at finding the general solution (which is probably a bit of traveling without falling into the trap of local optimum, of course, depends on the superconducting the parameters are set properly), the number of parameters for the control algorithm is low, very low, and thus the amount of memory and processing complexity is much less than the others.

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