Speed-Constrained Multi-Objective PSO for Optimization of Problem

Prachi Gupta¹, Dr. Ramachandra Pujeri²

¹Post Graduate Student, Computer Engineering Department, MIT COE, Pune, India

²Vice Principal, MIT COE, Pune, India

Abstract: In this work we represent a new algorithm multi-objective particle swarm optimization algorithm (PSO) characterized by the use of a strategy to limit the velocity of the particles. So that the Speed-constrained Multi-objective PSO (SMPSO) allows to produce new effective particle positions in those cases where the velocity becomes too high or too low. SMPSO also have other feature polynomial mutation as turbulence factor and an swarm archive to store the non-dominated solutions found during the search.

Keywords: PSO, SMPSO, metaheuristic.

1. Introduction

Particle Swarm Optimization (PSO) is a metaheuristic algorithm, it is inspired by the social behaviour of bird flocking or fish schooling [1] which has become popular to solve multi-objective optimization problems. Moore and Chapman proposed it in 1999 to extend it to multi-objective optimization [2], more than thirty proposals of different Multi-Objective Optimization PSOs (MOPSOs)have been known now a days.

PSO have been widely used in the last decade because of its good performance and simplicity. In the field of multiobjective optimization, many variants of multi-objective PSO algorithms have been proposed In this paper we proposed the so-called Speed-constrained Multi-objective PSO algorithm, or SMPSO [3], which has shown a remarkable performance in terms of different assessment criteria: quality of results, accuracy, time consuming ,convergence towards the optimum solutions [4], and scalability with the problem size[5].

The remaining of the paper is structured as follows. Section II describes the PSO algorithm. The next section (Section 3) describes the SMPSO algorithm. In Section IV, describe the enhancement in SMPSO from PSO. Finally, Section V presents the conclusions and acknowledgement..

2. Algorithms

2.1 Clustering

Clustering is partitioning a collection of objects into non overlapping groups, or clusters of objects where objects in a cluster are more similar to one another than to objects in other clusters.

2.2 Particle swarm optimization

PSO is a population based metaheuristic algorithm. It is inspired in the social behavior of birds within a flock. Each potential solution to the problem is called particle and the population of solutions is called swarm. The way in which PSO updates the particle xi at the generation t is through the formula:

$$x_i(t) = x_i(t-1) + v_i(t)$$
(1)

where the factor vi(t) is velocity and it is given by

$$v_i(t) = w * v_i(t - 1) + C1 * r1 * (xpbest_i - x_i) + C2 * r2 * (xgbest_i - x_i)$$
 (2)

In this formula, *xpbest_i* is the best solution that x_i has stored, xgbest_i is the best particle (also known as the leader) that the entire swarm has viewed, w is the inertia weight of the

Algorithm 1 Pseudo code of a general PSO algorithm [7].

particle and controls the effect of global and local experience, r1 and r2 are two random numbers and having range [0, 1], and C1 and C2 are specific parameters which control the effect of the personal and global best particles. Algorithm 1 describes the pseudo-code of a general singleobjective PSO. The algorithm starts by initializing the swarm (Line 1), which includes both the positions and velocities of the particles. The pbest of each particle is initialized, as well as the leader (Line 2). Then, during a maximum number of iterations, each particle move through the search space and update its position (Line 6), it is evaluated (Line 7), and its pbest is also calculated (Lines 6-8). At the end of each iteration, the leader is updated. As commented before, the leader can be the gbest particle in the swarm. However, it can be a different particle depending on the social structure of the swarm (i.e., the topology of the neighbourhood of each particle) [6].

3.1 Speed-constrained Multi-objective PSO(SMPSO)

SMPSO (Speed constrained Multi-objective PSO) is a metaheuristic based on the OMOPSO algorithm that was designed to cope with difficulties of OMOPSO when solving multi-objective problems. The SMPSO approach is to apply a constraint velocity to control the so-called swarm explosion

Algorithm 2 Pseudo code of SMPSO [8]

1: initializeSwarm() 2: initializeLeadersArchive()

- 3.
- generation = 0 4: while generation < maxGenerations do
- 5 computeSpeed() // Eqs. 2 - 7
- 6: 7: updatePosition() // Eq. 1
- mutation() // Turbulence
- 8: evaluation()
- updateLeadersArchive() 9: 10: updateParticlesMemory()
- generation ++ 11:
- 12: end while
- 13: returnLeadersArchive()

Algorithm 2 describe the pseudo code of SMPSO. First, initialize the swarm (Line 1). This phase have position, velocity, and p (individual best) of the particles. In Line 2 the leaders archive is also initialized with the non-dominated solutions in the swarm . Then, the main loop is executed with maximum number of iterations. First, the velocities and positions of the particles are computed (Lines 5 and 6) and then a mutation operator is applied with a probability that is already given (Line 7). The resulting particles are evaluated (Line 8) and both the particle's memory and the leaders archive are updated (Lines 9 and 10). The algorithm returns the leaders archive as the approximation set found (Line 13).

3. Enhancement of SMPSO over PSO

We analyze this issue of PSO and proposed SMPSO, which incorporates a velocity constraint mechanism. We find that SMPSO shows a promising behaviour on those problems where the other algorithms fail. There are some following enhancement in SMPSO from PSO

• Velocity constriction

By applying velocity constriction, erratic movements of the velocity have vanished, so the particle is taking values inside the bounds of the variable and thus it is moving along different regions the search space[7]. of The velocity constriction equation [8] is:

$$v_{i,j}(t) = \begin{cases} delta_j & \text{if } v_{i,j}(t) > delta_j \\ -delta_j & \text{if } v_{i,j}(t) \le -delta_j \\ v_{i,j}(t) & \text{otherwise} \end{cases}$$
(1)

where

$$delta_j = \frac{(upper_limit_j - lower_limit_j)}{2}$$
(2)

Summarizing, in SMPSO the velocity of the particles is calculated then the resulting velocity is then multiplied by the constriction factor and the resulting value is constrained by using Eq. 1.

• Multi Objective

SMPSO (Speed constrained Multi-objective PSO) is a metaheuristic based on the OMOPSO algorithm that was designed to cope with difficulties of OMOPSO when solving multi-objective problems.

Constriction coefficient

SMPSO we adopted a constriction coefficient (Eq. 3) obtained from the constriction factor χ originally developed by Clerc and Kennedy in [9].

$$\chi = \frac{2}{2 - \varphi - \sqrt{\varphi^2 - 4\varphi}}$$

where

$$delta_j = \frac{(upper_limit_j - lower_limit_j)}{2}$$

Polynomial-based mutation

OMOPSO applies a combination of uniform and nonuniform mutation to the particle swarm (uniform mutation to the first 30% of the swarm, non-uniform to the next 30%, and no mutation to the rest of particles). polynomial mutation [10] is applied to the 15% of the particles in SMPSO [8].

• External archive

External archive is used to retain the non-dominated solutions found during the search. SMPSO is a multiobjective optimization, where more than one conflicting functions must be optimized simultaneously. The reason is related to the non-dominance concept, that applies to two solutions when none of them improves the other in all the objectives; if yes, then one dominates the other. By adopting non-dominance the outcome is a partialorder relationship, so defining the concept of "best solution" is not so clear as in single-objective optimization [11].

4. Conclusion

In this paper we have given review on the PSO and SMPSO for optimization of gene expression microarray data. SMPSO is adopted to overcome the limitation of PSO for huge microarray data. It provides improvements over PSO both in terms of accuracy and time.

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