Intelligent Multiobjective Particle Swarm Optimization Based on AER Model

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Abstract. How to find a sufficient number of uniformly distributed and representative Pareto optimal solutions is very important for Multiobjective Optimization (MO) problems. An Intelligent Particle Swarm Optimization (IPSO) for MO problems is proposed based on AER (Agent-Environment-Rules) model, in which competition and clonal selection operator are designed to provide an appropriate selection pressure to propel the swarm population towards the Pareto-optimal Front. An improved measure for uniformity is carried out to the approximation of the Pareto-optimal set. Simulations and comparison with NSGA-II and MOPSO indicate that IPSO is highly competitive.

1 Introduction

Particle Swarm Optimization (PSO) is a relatively recent heuristic algorithm inspired by the choreography of a bird flock developed by Eberhart and Kennedy [1, 2]. It has been found to be successful in a wide variety of single optimization task. Recently, there have been several recent proposals to extend PSO to deal with multi-objective problem [3-8]. Coello[3,4] uses a secondary repository of particles that is later used by other particles to guide their own flight. Hu[5] uses lexicographic ordering to optimize one objective at a time. Moore [6] emphasizes the importance of performing both an individual and a group search, but the author did not adopt any scheme to maintain diversity. Parsopoulos [7] adopts dynamic weights to build up search ability of the algorithm. Ray [8] uses crowding to maintain diversity and a multi-level sieve to handle constraints. In this paper, a new model for PSO is provided, and an Intelligent Particle Swarm Optimization (IPSO) for MO problems is proposed based on AER (Agent-Environment-Rules) model to provide an appropriate selection pressure to propel the swarm population towards the Pareto-optimal Front. Simulations and comparison with MOPSO [4] and NSGA-II [9] show the proposed algorithm can achieve a good convergence and diversity of solutions.

A general minimization MO problem includes n decision variables, l objective functions and m constraints. Objective functions and constraints are functions of the decision variables. The optimization goal is to

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$$\begin{aligned} &\min_{x \in R^n} y = F(x) = (f_1(x), \cdots, f_l(x)) \\ &s.t.\ g = g(x) = (g_1(x), \cdots, g_m(x)) \le 0 \end{aligned} \tag{1}$$

$X = \{x \mid x \in R^n, g_i(x) \le 0, i = 1, \cdots, m.\}$ is called feasible solution space. Very often, the objective functions can not be optimized simultaneously, and the decision maker has to accept a compromise solution.

Let $U = (u_1, \cdots, u_l)$, $V = (v_1, \cdots, v_l)$ be two vectors, then U dominates V denoted as $U \preceq V$ if and only if $u_i \le v_i (i = 1, \cdots, l)$ and $u_i < v_i$ for at least one component. This property is known as Pareto Dominance. Thus, a solution x of the MO problem is said to be Pareto Optimal if and only if there does not exist another solution y such that $F(y)$ dominates $F(x)$ .The set of all Pareto Optimal solutions of MO problem is called Pareto Optimal Set and we denote it with P^* and the set $PF^* = \{F(x) \mid x \in P^*\}$ is called Pareto Front. $Pareto(I) = \{x \mid x \in I, \nexists y \in I, F(y) \prec F(x)\}$ is defined as the Pareto filter of set $I \subset X$.

2 A Modified Particle Swarm Optimization

It is well-known that the update of particle in the standard PSO is very monotone and invariable, that is to say a new particle is generated only based on the velocity v , the best position *pbest* which the current particle has visited so far and the best position *gbest* which the entire population has found so far. In addition, there exists no sharing of information with other particles in the population, except that the particle can access the global best or *gbest* is replaced by local best particle, but in the first case information sharing is difficult and seldom, and easily gets trapped in local optima; in the second case the velocity of approximation will be reduced. While for MO problem, sharing of information among the individuals or particles in a population or swarm is crucial in order to introduce the necessary selection pressure to propel the population moving towards the true Pareto-optimal Front. Hence, a modified model for PSO is given based on the local perception of each particle in the following.

$$\begin{cases} v = v + c_1 r_1 (pbest - x) + c_2 r_2 (nbest - x) + c_3 r_3 (gbest - x) \\ x = x + wv \end{cases} \tag{2}$$

In this new model, each particle can not only remember its best position *pbest* of the current particle found so far and the best positions *gbest* of the swarm found so far, but also the local best position *nbest* of the current particle's neighbors found. It needs to be pointed out here that *gbest* is used to speed up convergence and the *nbest* is used to escape the local optima. The Constriction factor w depends on the energy of each particle or its distance to the optimal solution *gbest*.