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A multi-objective endocrine PSO algorithm and application

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ABSTRACT

A novel multi-objective endocrine particle swarm optimization algorithm (MOEPSO) based on the regulation of endocrine system is proposed. In the method, the releasing hormone (RH) of endocrine system is encoded as particle swarm and supervised by the corresponding stimulating hormone (SH). For multi-objective problem, the new SH is composed by the Pareto optimal solutions which determined by the feedback of RH and SH of current generation. In each generation, RH is divided into different classes according to SH, the best positions of different classes, the best position of current generation and the best positions that the particles have achieved so far are simultaneously used to generate the new RH. The effectiveness of the method is tested by simulation experiments with some unconstrained and constrained benchmark multi-objective Pareto optimal problems. The results indicate that the designed method is efficient for some multi-objective optimization problems.

1. Introduction

Multi-objective optimal problems consist of several objectives that are necessary to be handled simultaneously [1,2], some problems are arose in many applications, where two or more, sometimes competing and/or incommensurable, objective functions have to be minimized concurrently. Most real-world engineering problems, such as investment decision, city programming, program management, university timetable, control system design, are multi-objective optimization problems. The goal of multi-objective optimization methods is to find a set of good trade-off solutions from which the decision maker want to select one. In order to solve multi-objective problem, V. Pareto offers the most common definition of optimum in multi-objective optimization in 1896. Since then, there are lots of mathematical programming techniques are presented to solve multi-objective optimization problems [2,3]. Unfortunately, many of them might not work well when the Pareto front of the task is concave or disconnected [4], because the necessary condition of these methods is that the objective functions are differentiable.

Evolutionary computation techniques are suitable for multi-objective optimizations because they can generate a set of possible solutions simultaneously. During past two decades, evolutionary techniques which using Pareto concept are studied for multi-objective optimization. Most representative multi-objective evolutionary methods, such as NPGA [5], NSGA [6], NSGAII [7], multi-objective GPs [8,9], are utilized to optimize several objectives simultaneously and some efficient results are derived. Especially in recent years, particle swarm optimization (PSO) also plays a very important role in multi-objective optimization because of its convergent speed and simple operator. The preferable reviews of PSO for multi-objective problems are detailed introduced by Parsopoulos and Vrahatis [10] and Sierra and Coello [11]. Among the introduced methods, Pareto-based approaches which related closely to the method of this paper are re-introduced as follow, the specific depiction of other methods for multi-objective problems with PSO are presented in the two references. Ray and Liew [12] introduced a method by using a nearest neighbor density estimator to promote diversity and a multilevel sieve to handle constraints to deal with multi-objective problems. Fieldsend and Singh [13] use an unconstrained elite external archive to store the non-dominated individuals found along the searching process. EA operators (mutation, for example), the niche count and assign a fitness value to the particles with a Pareto ranking approach are utilized to improve the performance of multi-objective algorithm [14]. Clustering techniques are used to improve the performance of multi-objective [15], in the method, sub-swarms are used to probe different regions of the search space. Each sub-swarm has its own group of leaders. These groups are formed from a large set of non-dominated solutions through a clustering technique. Then, each sub-swarm is assigned a group of leaders and the one chosen randomly from those will serve as its guides towards the Pareto front. ε-Dominance method outperforms clustering techniques in computational time, and the convergence and diversity are studied by Mostaghim and Teich [16]. To improve the performance of convergence and distribution with operator in EAs, Sierra and Coello [17] presented a multi-objective PSO algorithm based on crowding distance and ε-domain, the mutation

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operator is introduced to maintain the diversity of swarm. Based on a fully connected topology and incorporates the main mechanisms of the NSGAII [7] to PSO algorithm, an improved multi-objective PSO algorithm in which the next swarm is generated from all the best positions which the particles have achieved so far and all the new positions recently obtained is introduced [18]. Alvarez-Benitez et al. [19] proposed a method based on exclusively on Pareto dominance for selecting leaders from an unconstrained non-dominated archive, and three different selection techniques are presented, the convergent performance of multi-objective PSO algorithm is improved. Raquel and Naval [20] adopts the concept of nearest neighbor density estimator for selecting the global best particle and deleting particles from the external archive of non-dominated solutions, the results show that the method can improve the diversity of the swarm and some good solutions can be derived. Moore and Chapman [21] introduced a multi-objective PSO based on Pareto domain relation, the interaction of different particles is emphasized, but the distribution and the diversity of particles are not maintained well. Hu and Eberhart [22] proposed a dynamic neighborhood PSO which uses an approach similar to lexicographic ordering. Some hybrid approaches are used to improve the performance of multi-objective PSO algorithm [23–26]. Except for theoretic study of PSO in multi-objective optimization, the multi-objective algorithms are also used in practice. Abido [27] introduced a multi-objective particle swarm algorithm for environmental dispatch problem, a redefinition of global best and local best individuals is adopted in the algorithm, and the environmental dispatch problem is successfully solved by it. Parallel PSO and finite difference time-domain (FDTD) algorithm are merged to design multi-band and wide-band patch antenna [28]. In this method, the antenna geometric parameters are extracted by PSO algorithms and the performance of each designed candidate is evaluated by FDTD, the ideal parameters of antenna are derived. Moreover, the applicable domain of PSO for multi-objective optimization has been extended to resource allocation [29], bin packing [30], electromagnetic [31], etc. Though artificial endocrine system and hormonal model of emotions have been studied and used in GA and artificial homeostasis system [32–36], there are few methods of using artificial endocrine system for PSO to improve the performance of multi-objective algorithm in current literatures.

In this paper, a novel multi-objective endocrine particle swarm optimization algorithm (MOEPSO) base on supervising and controlling principles among endocrine system is proposed. According to the principle of modulation between stimulating hormones (SH) and releasing hormones (RH) in endocrine system, the RH is divided into some groups according to the SH, the optimal solution in each class is also used as leader to generate the new RH, and the new SH is composed by the Pareto optimal solutions which determined by the feedback of RH and SH of current generation. The new positions of particles in RH are simultaneously determined by the best positions that they have achieved so far, the global best position of current generation, the best position of the class which they are belonged to. Some unconstrained and constrained multi-objective problems are simulated with different multi-objective optimization methods to evaluate the effectiveness of the presented methods, the results indicate that the given algorithm is a challenging method for multi-objective PSO algorithms.

The remainder of this paper is organized as follows. The description of multi-objective optimization (MOO) is introduced in Section 2. Section 3 describes the simple principle of endocrine system. In Section 4, some main aspects of PSO and multi-objective Endocrine PSO algorithm are introduced. In Section 5, a sketch of MOEPSO Algorithm is presented. Some simulating experiments are shown in Section 6 and some conclusions are given in Section 7.

2. The description of multi-objective optimization (MOO)

In general, three aspects are very important for MOO, the first is that there are two or more objectives should to be optimized simultaneously, the second is that there are constraints imposed on the objectives, the third is that objectives in the problem are usually in conflict with each other.

The mathematical formulation of a minimization problem with M objectives, m inequality constrains, and p equality constrains, the dimension of the variable is n, is given as follows. The goal of the multi-objective optimization is to determine variable vector $\bar{x}_l = (\bar{x}_{l1}, \bar{x}_{l2}, \ldots, \bar{x}_{ln})$ from the domain D, $D \subset R^n$, which optimizes the vector function (1), and satisfies the constrains shown in (2) and (3).

Minimize:

$$F(\bar{x}) = \{f_1(\bar{x}), f_2(\bar{x}), \ldots, f_M(\bar{x})\} \tag{1}$$

$$g_i(\bar{x}) \geq 0, \quad i = 1, 2, \ldots, m \tag{2}$$

$$h_i(\bar{x}) = 0, \quad i = 1, 2, \ldots, p \tag{3}$$

Because there are multiple objectives are involved in MOO, it is not possible to find a single solution which can optimize all objectives. We should find a solution which has trade-off or good compromise among all objectives. So the conventional concept of single objective optimality does not hold, Pareto optimality is usually adopted. Considering a M-objectives minimization problem with searching domain D, some definitions are given as follow [37,38].

Definition 1. (Pareto dominance). The vector $\bar{x}_1 = (\bar{x}_{11}, \bar{x}_{12}, \ldots, \bar{x}_{1k})$ dominates the vector $\bar{x}_2 = (\bar{x}_{21}, \bar{x}_{22}, \ldots, \bar{x}_{2k})$, if and only if the next statement is verified.

$$(\forall i \in \{1, 2, \ldots, k\} : f(\bar{x}_{1i}) \leq f(\bar{x}_{2i})) \wedge (\exists i \in \{1, 2, \ldots, k) : f(\bar{x}_{1i}) < f(\bar{x}_{2i})) \tag{4}$$

Definition 2. (Pareto optimality). $\vec{x^*} \in D$ is a Pareto optimal solution, if and only if the next assertion is verified.

$$\left\{ \vec{x'} \,\middle|\, F(\vec{x'}) \prec F(\vec{x^*}), \vec{x'}, \vec{x^*} \in D \right\} = \Phi \tag{5}$$

Definition 3. (Pareto optimal set). The Pareto optimal set P_s is defined as the set of all Pareto optimal solutions.

$$P_s = \{\vec{x} \in D | \neg \exists \vec{x'} \in D, f(\vec{x'}) \prec f(\vec{x})\} \tag{6}$$

Definition 4. (Pareto optimal front). The Pareto front P_f consists of the values of the objectives corresponding to the solutions in P_s.

$$P_f = \{F(\vec{x}) | \vec{x} \in P_s\} \tag{7}$$

3. A simple introduction of endocrine system

The endocrine system of organisms is composed by endocrine gland, endocrine cell and hormones corresponding to them [35,36], hypothalamus and pituitary are the control centers of different glands, and hormones corresponding to different glands are fed back to them through circle system, this procedure makes a balanceable environment in the inner of biology. The typical structure of endocrine system is shown in Fig. 1 [35]. It is evident that the releasing hormone (RH) is supervised by simulating hormone (SH) of hypothalamus and the SH is determined by the feedback of RH and SH of current generation. Simulating this behavior of hormone in endocrine system, the artificial endocrine PSO can be realized by two swarms, the one is called as SH swarm, the other is called as RH swarm, and the particles in RH swarm are controlled and classed