Multi-Dimensional Particle Swarm Optimization

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***Abstract*— the behavior of a single organism in a swarm is often insignificant but their collective and social behavior is of paramount importance. The particle swarm optimization (PSO) was introduced by Kennedy and Eberhart in 1995 as a population based stochastic search and optimization process. It is originated from the computer simulation of the individuals (particles or living organisms) in a bird flock or fish school, which basically show a natural behavior when they search for some target (e.g. food). In the basic PSO algorithm, the particles are initially distributed randomly over the search space with a random velocity and the goal is to converge to the global optimum of a function or a system. Each particle keeps track of its position in the search space and its best solution so far achieved. This is the personal best value (the so-called *pbest*) and the PSO process also keeps track of the global best solution so far achieved by the swarm with its particle index (the so called *gbest*). So during their journey with discrete time iterations, the velocity of each agent in the next iteration is computed by the best position of the swarm (position of the particle *gbest* as the *social* component), the best personal position of the particle (*pbest* as the *cognitive* component), and its current velocity (the *memory* term). Both *social* and *cognitive* components contribute randomly to the position of the agent in the next iteration. In principle, PSO follows the same path of the other evolutionary algorithms (EAs) such as Genetic Algorithm (GA), Genetic Programming (GP), Evolutionary Strategies (ES) and Evolutionary Programming (EP). The common point of all is that EAs are in population based nature and thus they can avoid being trapped in a local optimum. Thus they can find the optimum solutions; however, this is never guaranteed. In this study, we propose a novel optimization technique, the so-called Multi-Dimensional Particle Swarm Optimization (MD PSO), which re-forms the native structure of swarm particles in such a way that they can make inter-dimensional passes with a dedicated dimensional PSO process. Therefore, in a multidimensional search space where the optimum dimension is unknown, swarm particles can seek for both positional and dimensional optima. This eventually negates the necessity of setting a fixed dimension *a priori*, which is a common drawback for the family of swarm optimizers. Therefore, instead of operating at a fixed dimension *N*, the MD PSO algorithm is designed to seek both positional and dimensional optima within a dimension range, ($D_{\min} \le N \le D_{\max}$). In order to accomplish this, each particle has two sets of components, each of which has been subjected to two independent and consecutive processes. The first one is a regular positional PSO, i.e. the traditional velocity updates and due positional shifts in *N* dimensional search (solution) space. The second one is a dimensional PSO, which allows the particle to navigate through dimensions. Accordingly, each particle keeps track of its last position, velocity and personal best position (*pbest*) in a particular dimension so that when it re-visits that the same dimension at a later time, it can perform its regular "positional" fly using this information. The dimensional PSO process of each particle may then move the particle to another dimension where it will remember its positional status and keep "flying" within the positional PSO process in this dimension, and so on. The swarm, on the other hand, keeps track of the *gbest* particles in all dimensions, each of which respectively indicates the best (global) position so far achieved and can thus be used in the regular velocity update equation for that dimension. Similarly the dimensional PSO process of each particle uses its personal best dimension in which the personal best fitness score has so far been achieved. Finally, the swarm keeps track of the global best dimension, *dbest,* among all the personal best dimensions. The *gbest* particle in *dbest* dimension represents the optimum solution and dimension, respectively. We investigated the application of the proposed method over two well-known domains, nonlinear function minimization and data clustering. An extensive set of experiments show that in both application domains, MD PSO can converge to the global optimum at the true (optimum) dimension as long as the basic PSO can on a fixed dimension.**