# Particle Swarm Optimization and Image Analysis

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## INTRODUCTION

Particle Swarm Optimization (PSO) is a simple but powerful optimization algorithm, introduced by Kennedy and Eberhart (Kennedy 1995). Its search for function optima is inspired by the behavior of flocks of birds looking for food.

Similarly to birds, a set (swarm) of agents (particles) fly over the search space, which is coincident with the function domain, looking for the points where the function value is maximum (or minimum). In doing so, each particle's motion obeys two very simple difference equations which describe the particle's position and velocity update.

A particle's motion has a strong random component (exploration) and is mostly independent from the others'; in fact, the only piece of information which is shared among all members of the swarm, or of a large neighborhood of each particle, is the point where the best value for the function has been found so far. Therefore, the search behavior of the swarm can be defined as emergent, since no particle is specifically programmed to achieve the final collective behavior or to play a specific role within the swarm, but just to perform a much simpler local task.

This chapter introduces the basics of the algorithm and describes the main features which make it particularly efficient in solving a large number of problems, with particular regard to image analysis and to the modifications that must be applied to the basic algorithm, in order to exploit its most attractive features in a domain which is different from function optimization.

## BACKGROUND

One of the most attractive features of PSO, apart from its effectiveness and robustness with respect to local minima, is certainly its simplicity, which makes it trivial to implement in any programming language. It is also very versatile and applicable to a large number of optimization problems, virtually to any problem defined within a space for which a metric can be defined. However, its behavior, which mainly depends on the values of three constants, is still far from being fully understood. Extensive work (Engelbrecht2005, Clerc2006, Poli2007a) has provided very important insights into the properties of the algorithm, in studies where the dynamic properties of the swarm have been studied, even if under some restrictive assumptions.

The model which underlies PSO describes the motion of a swarm of particles within the domain of a function, usually termed *fitness function* as for evolutionary algorithms (Eiben 2004, de Jong 2006), seeking for its optimum. Such a motion is comparable to the random motion of a set of independent non-interacting particles within a force field generated by two attractors, one of which is specific to each cell.

The basic PSO equations for a generic particle P within the swarm are

$$\underline{X}_P(t) = \underline{X}_P(t\text{-}1) + \underline{v}_P(t) \tag{1}$$

$$\underline{v}_P(t) = \omega * \underline{v}_P(t\text{-}1) + C_1 * \text{rand}() * [\underline{X}_{Pbest} - \underline{X}(t\text{-}1)] + C_2 * \text{rand}() * [\underline{X}_{gbest} - \underline{X}(t\text{-}1)] \tag{2}$$

where $\underline{v}_P$ is the velocity of particle P, $C_1$ and $C_2$ are two positive constants, $\omega$ is the so-called inertia weight, $\underline{X}_P$ is the position of particle P, $\underline{X}_{Pbest}$ is the best-fitness point reached by P up to time t-1, $\underline{X}_{gbest}$ is the best-fitness point found by the whole swarm, rand() is a random value taken from a uniform distribution in the interval [0,1].

In its motion, the swarm explores the space effectively, usually converging rapidly to the optimum,

even if its behavior is strongly dependent on the values of ω, $C_1$, and $C_2$, which must be therefore set very accurately.

## PARTICLE SWARM OPTIMIZATION AND IMAGE ANALYSIS

Even if much is still to be learned and discovered about PSO from a theoretical point of view (Kennedy 2007), as regards applications PSO is gaining more and more popularity. As reported in (Poli2007b), a very recent in-depth review of the field, searching the IEEExplore (http://ieeexplore.ieee.org) technical publication database by the keyword PSO returns a list of much more than 1,000 titles, about one third of which deal with theoretical aspects. This means that, to date, an incomplete list of PSO application papers adds up to little less than 1,000. Amazingly, about two thirds of them have been published in the last two years.

Image analysis is one of the fields to which PSO is being applied most frequently. As shown by a large number of papers in the image processing and computer vision literature, image analysis problems can be often reformulated as optimization problems, in which an objective function, directly derived from the physical features of the problem, is either maximized or minimized. In most cases, an optimum set of parameters which define the solution are sought using an optimization method. For most real-world problems, usually severely affected by noise or by the natural variability of the instances of the objects which must be detected, this is often inevitable, since methods in which closed-form solutions are directly applied are not usually robust enough with respect to such features. A large number of examples of applications of both traditional and evolutionary optimization methods including, as such, PSO, are reported in the literature.

In this section we will not consider direct applications of PSO as optimizers for an objective function. We will focus our attention on applications in which PSO is not only a way to 'tune' a more general algorithm by adapting it to the specific features of the problem at hand, but is directly part of the solution.

We will first introduce some general considerations on image analysis problems, which define the requirements imposed by them. This will allow us to reformulate some typical classes of problems encountered in image analysis, such as object detection and tracking or image segmentation, to include PSO, or some adapted version of its basic formulation, into the solution. We will then briefly show two examples of applications of PSO to segmentation and object detection, in which the above mentioned considerations have been taken into account.

## PSO for Object Detection and Segmentation

In considering the application of PSO to image analysis tasks, one could assume the swarm to fly over the image to detect points or regions of interest. Therefore, the domain of the fitness function becomes the image itself. The fitness value to be assigned to each point can then be defined as a local function of image intensity in a neighborhood of that point, returning high values in points where features similar to the ones which are sought are found.

However, more global information must usually be extracted in image analysis tasks. In fact, while the basic PSO algorithm aims at finding a single optimum within the fitness landscape under exploration, in several image analysis applications more than one optimum (multiple objects) are to be found. This situation is typical of object recognition tasks, where the goal is to identify all possible occurrences of an object of interest characterized by a set of specific features. Similarly, in region-based segmentation, several regions with homogeneous features must be accurately located. Such requirements, encountered also in many other application areas, have led to the definition of several variants of PSO, in which particles are subdivided into a predefined number of sub-swarms, based on some clustering technique (Kennedy 2000, Veenhuis 2006, Passaro 2008), or through speciation (Chow 2004, Bird 2006, Leong 2006, Yen 2006), to achieve a dynamical reconfiguration of the swarm and the detection of an arbitrary number of regions of interest within the search space.

The velocity update function must also be modified in order to let the swarm spread as uniformly as possible over a whole area of interest featuring high fitness values. Such modifications may include introducing repulsive forces between particles, to prevent the whole swarm from converging onto the same point, and limiting particles' mobility inside a region of interest, to keep the swarm compact and in a stable configuration.

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