

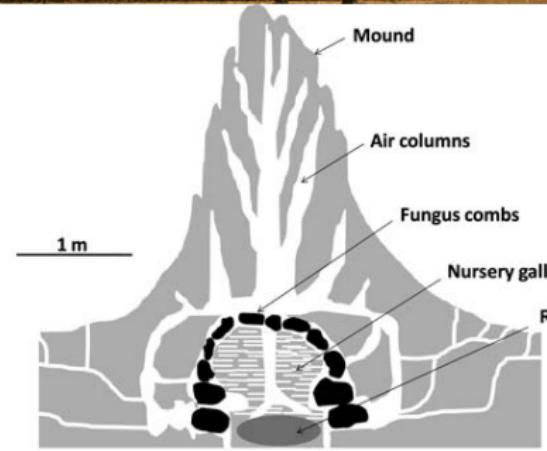
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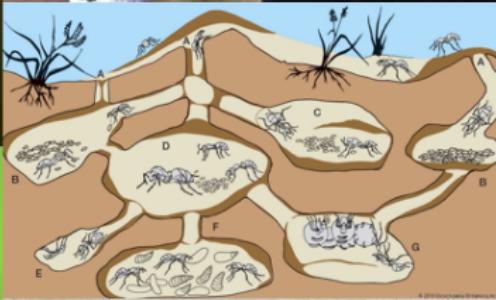
INTELIGENCIA COLECTIVA

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INTRODUCCIÓN





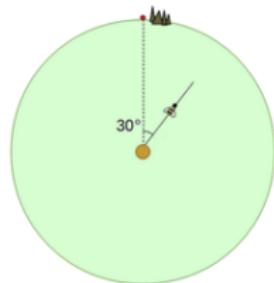
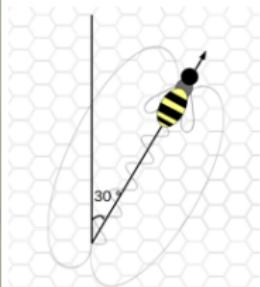
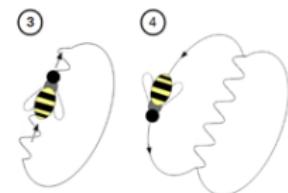
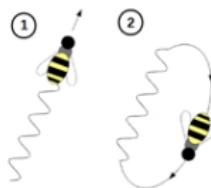
Karl von Frisch

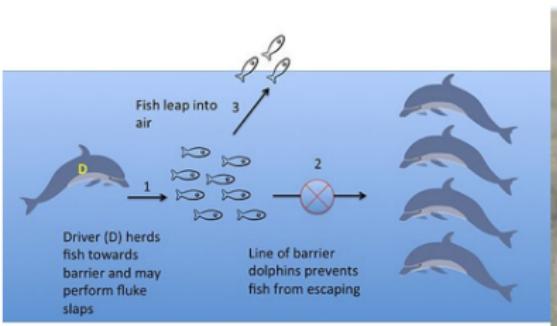


round dance



waggle dance

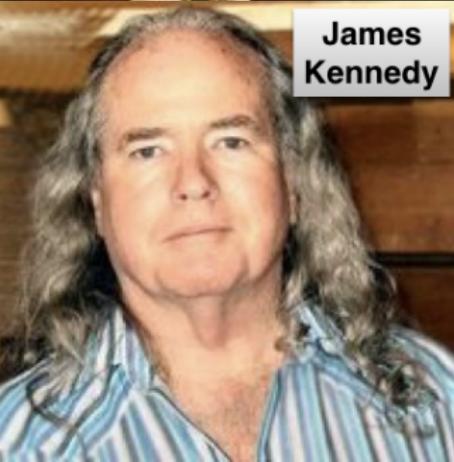




Es modelar el comportamiento simple de individuos, y las interacciones locales con el ambiente y sus vecinos para obtener comportamientos más complejos que pueden ser usados para resolver problemas principalmente de optimización.

PSO

Russell
Eberhart





Particle Swarm Optimization

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ABSTRACT

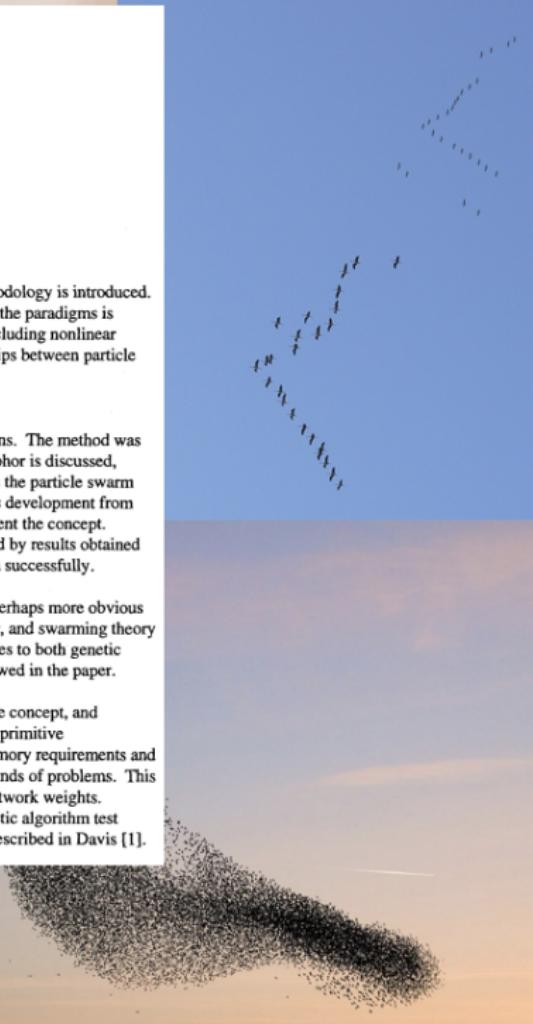
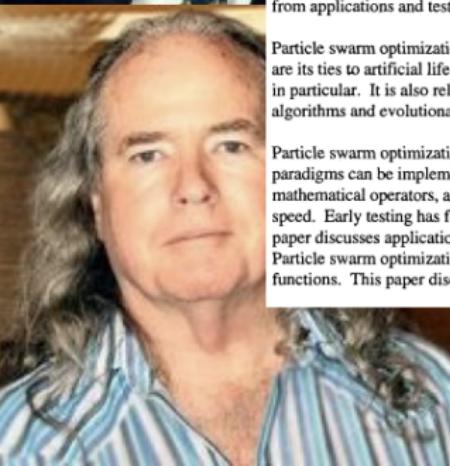
A concept for the optimization of nonlinear functions using particle swarm methodology is introduced. The evolution of several paradigms is outlined, and an implementation of one of the paradigms is discussed. Benchmark testing of the paradigm is described, and applications, including nonlinear function optimization and neural network training, are proposed. The relationships between particle swarm optimization and both artificial life and genetic algorithms are described.

1 INTRODUCTION

This paper introduces a method for optimization of continuous nonlinear functions. The method was discovered through simulation of a simplified social model; thus the social metaphor is discussed, though the algorithm stands without metaphorical support. This paper describes the particle swarm optimization concept in terms of its precursors, briefly reviewing the stages of its development from social simulation to optimizer. Discussed next are a few paradigms that implement the concept. Finally, the implementation of one paradigm is discussed in more detail, followed by results obtained from applications and tests upon which the paradigm has been shown to perform successfully.

Particle swarm optimization has roots in two main component methodologies. Perhaps more obvious are its ties to artificial life (A-life) in general, and to bird flocking, fish schooling, and swarming theory in particular. It is also related, however, to evolutionary computation, and has ties to both genetic algorithms and evolutionary programming. These relationships are briefly reviewed in the paper.

Particle swarm optimization as developed by the authors comprises a very simple concept, and paradigms can be implemented in a few lines of computer code. It requires only primitive mathematical operators, and is computationally inexpensive in terms of both memory requirements and speed. Early testing has found the implementation to be effective with several kinds of problems. This paper discusses application of the algorithm to the training of artificial neural network weights. Particle swarm optimization has also been demonstrated to perform well on genetic algorithm test functions. This paper discusses the performance on Schaffer's f6 function, as described in Davis [1].



Particle Swarm Optimization

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▼ J. Kennedy ; R. Eberhart

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Abstract:

A concept for the optimization of nonlinear functions using particle swarm methodology is introduced. The evolution of several paradigms is outlined, and an implementation of one of the paradigms is discussed. Benchmark testing of the paradigm is described, and applications, including nonlinear function optimization and neural network training, are proposed. The relationships between particle swarm optimization and both artificial life and genetic algorithms are described.

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Publisher: IEEE

$$v_i^j(t+1) = W v_i^j(t) + C_1 r_1(t)(y_i^j(t) - x_i^j(t)) + C_2 r_2(t)(\hat{y}_i^j(t) - x_i^j(t))$$

$x_i^j(t)$ y $v_i^j(t)$ denotan respectivamente, la posición y velocidad de la partícula i , en su dimensión j , en el tiempo t . W es el peso de inercia, C_1 y C_2 son los coeficientes de los componentes cognitivo y social, respectivamente, y r_1, r_2 son números aleatorios en $[0, 1]$.

Además, y_i es la mejor posición encontrada por la partícula i y \hat{y} es la mejor posición del vecindario de la partícula i (componente social).

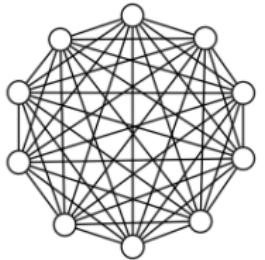
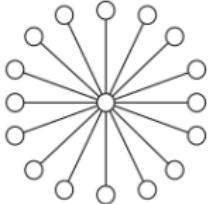
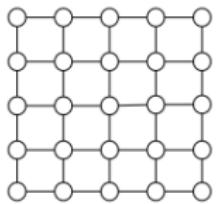


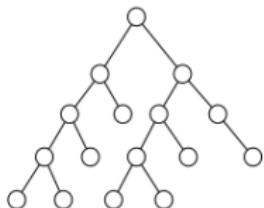
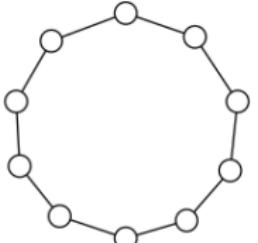
Figura 2.1: Topología completamente conectada.



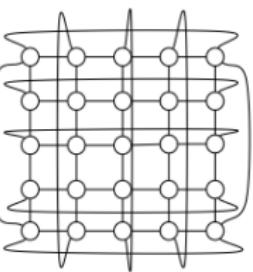
(a) Estrella



(b) Malla

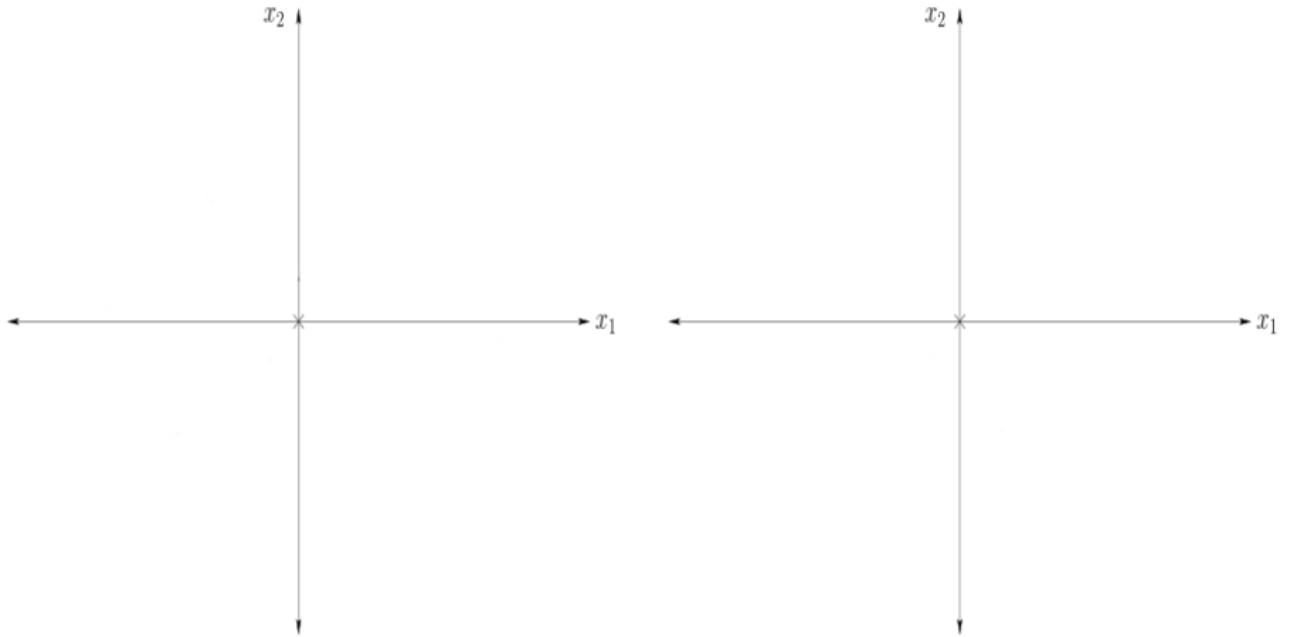


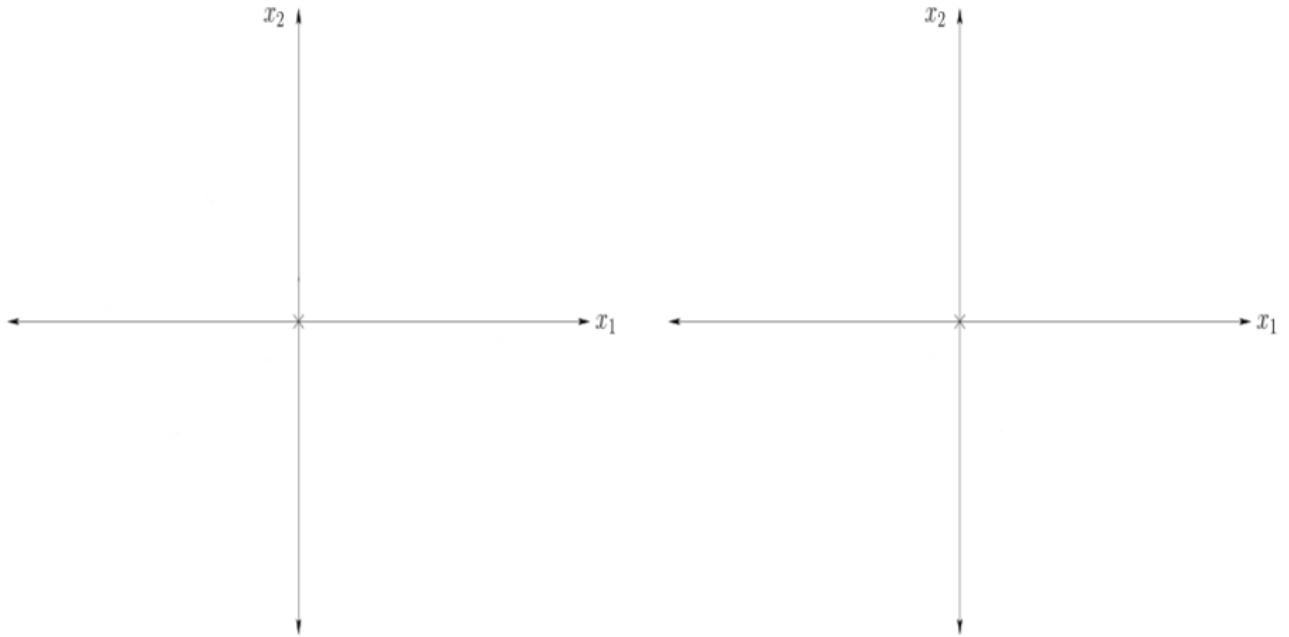
(c) Árbol

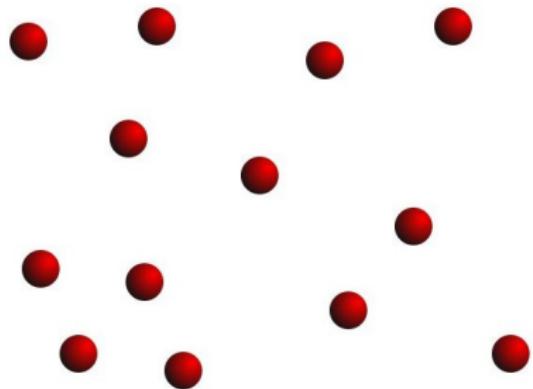


(d) Toroidal

Figura 2.2: Topología en anillo.







Begin

For each particle do

1. Initialize x and v randomly
2. Evaluate fitness function: $f(x)$
3. Initialize $y \leftarrow x$

EndFor

4. Select Gbest

Do

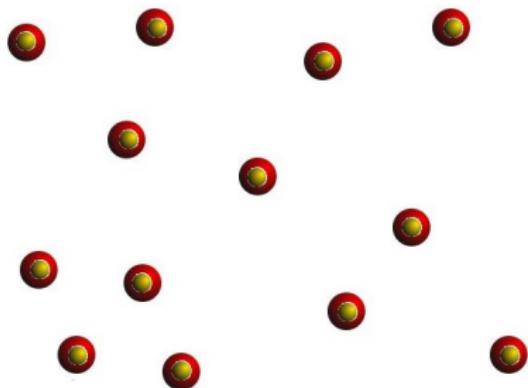
For each particle x do

5. Compute its speed using:
 $v \leftarrow Wv + C_1 r(0, 1)(y - x) + C_2 r(0, 1)(\hat{y} - x)$
6. $x \leftarrow x + v$ on each dimension
7. Evaluate the new position: $f(x)$
8. If $f(x) \leq f(y)$ then $y \leftarrow x$
9. If $f(x) \leq f(\hat{y})$ then $\hat{y} \leftarrow x$

EndFor

While max. number of iterations is not reached

End.



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3. Initialize $y \leftarrow x$

EndFor

4. Select Gbest

Do

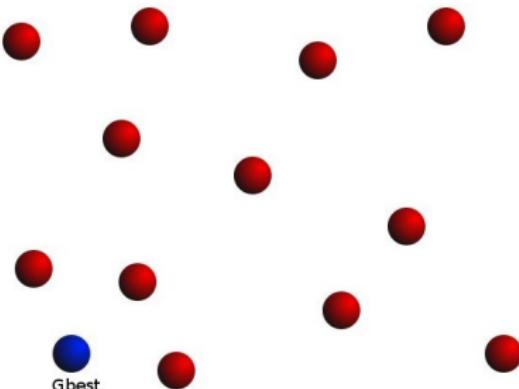
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EndFor

While max. number of iterations is not reached

End.



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EndFor

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Do

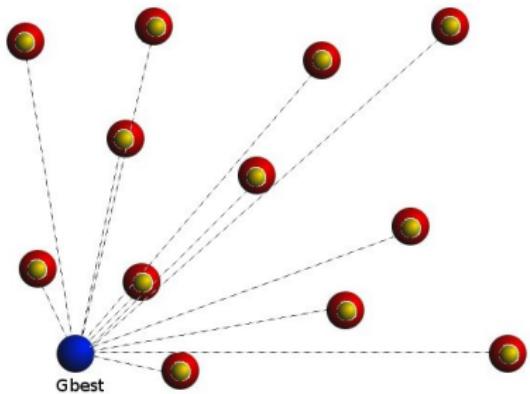
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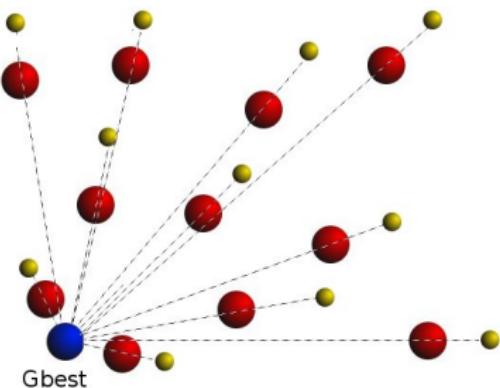
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For each particle x do

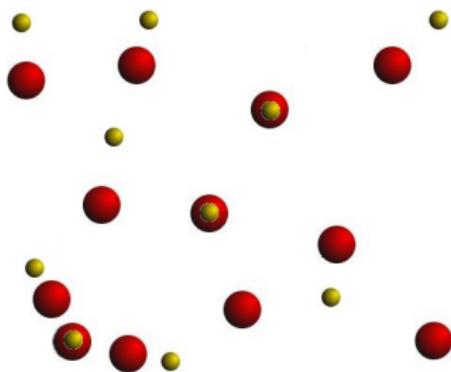
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EndFor

While max. number of iterations is not reached

End.

Algoritmo del PSO



Begin

For each particle do

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3. Initialize $y \leftarrow x$

EndFor

4. Select Gbest

Do

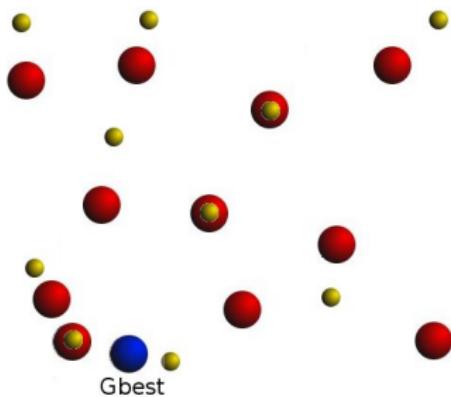
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EndFor

While max. number of iterations is not reached

End.



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Do

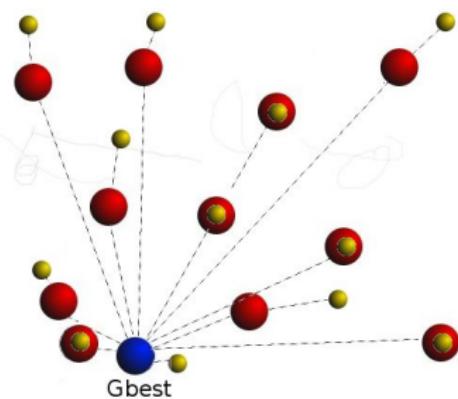
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EndFor

While max. number of iterations is not reached

End.



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EndFor

While max. number of iterations is not reached

End.

$$f(x) = \sum_{i=1}^n x_i^2$$

$$\begin{aligned}f(x, y) = & -20 \exp \left(-0.2 \sqrt{0.5 (x^2 + y^2)} \right) \\& - \exp \left(0.5 (\cos(2\pi x) + \cos(2\pi y)) \right) + e + 20 \\x, y \in & [-32.768, 32.768]\end{aligned}$$

https://en.wikipedia.org/wiki/Test_functions_for_optimization

<http://doi.org/10.1109/ICNN.1995.488968>

¿Preguntas?, ¿comentarios?:

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