

# Stochastic Stability Analysis of the Linear Continuous and Discrete PSO Models

Juan Luis Fernández-Martínez and Esperanza García-Gonzalo, University of Oviedo  
IEEE TRANSACTIONS on Evolutionary Computation, june2011 (july2009)JCR4.589

## Análisis estadístico de la atracción central estocástica

1. The Particle Swarm Optimization (PSO) Revised
2. Stochastic Analysis of the Linear PSO Continuous Model
  - Particular Cases
  - Second Order Moments and the Lyapunov Equation
3. Oscillation Center Dynamics
4. Stochastic Analysis of the Linear Generalized PSO
  - Linear GPSO Difference Equation
  - Stochastic Center of Attraction
  - PSO Second Order Trajectories and the PSO Parameter Tuning

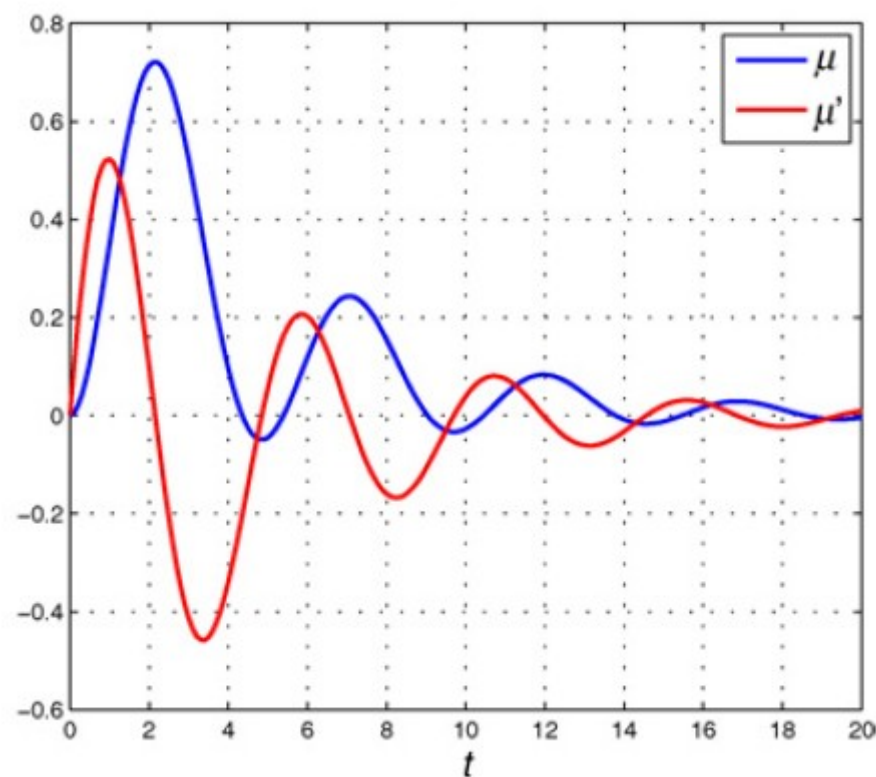
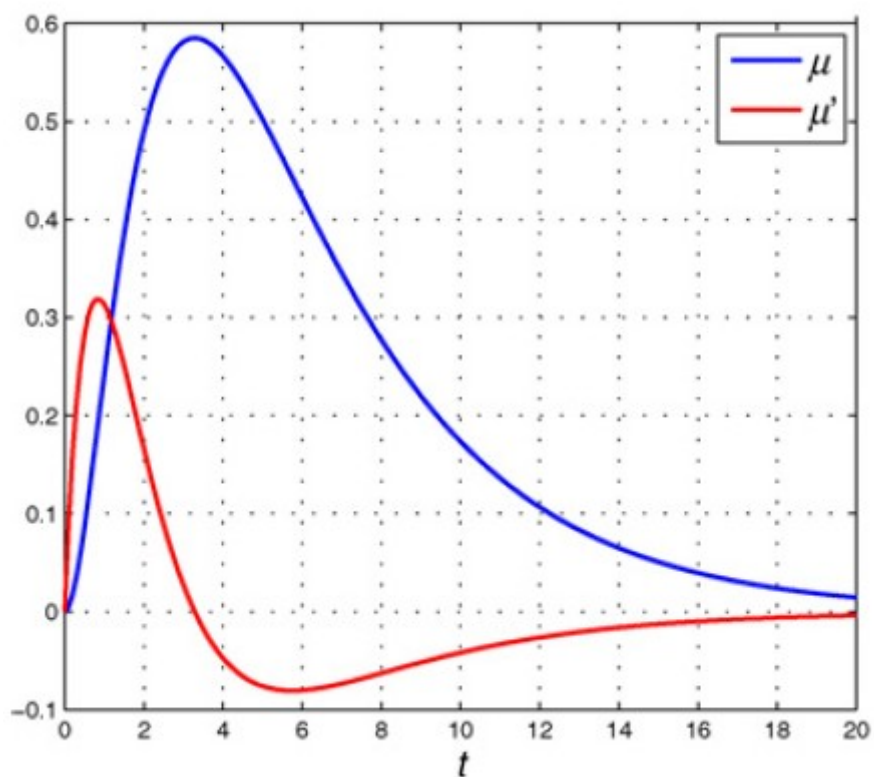
## 5. Comparison Between the Linear Continuous PSO and GPSO Models and Real Simulations

- Homogeneous Trajectories
- Transient Trajectories and Final Discussion

## 6. Conclusion

# Particle Swarm Optimization

- Este artículo trata de encontrar un análisis estocástico lineal de una curva atraída por un centro de atracción estocástico.



El eje x representa el tiempo, el eje y representa la posición

# PSO Basics

La formulación es sencilla, se tiene una velocidad, con la cual se obtiene la posición. Se evalúa la posición de cada individuo con una función de coste  $c(\mathbf{x}_i)$ .

$$\mathbf{v}_i^{k+1} = \omega \mathbf{v}_i^k + \phi_1 (\mathbf{g}^k - \mathbf{x}_i^k) + \phi_2 (\mathbf{l}_i^k - \mathbf{x}_i^k)$$

$$\mathbf{x}_i^{k+1} = \mathbf{x}_i^k + \mathbf{v}_i^{k+1}$$

Con  $\phi_1 = r_1 a_g$   $\phi_2 = r_2 a_l$   $r_1, r_2 \rightarrow U(0, 1)$   $\omega, a_l, a_g \in \mathbb{R}$ .

Una region de estabilidad de primer orden puede ser:

$$S_D = \{ (\omega, \bar{\phi}) : |\omega| < 1, 0 < \bar{\phi} < 2(\omega + 1) \}$$



Punto Negro

La siguiente diferencia vectorial involucra a cada uno de los individuos del Swarm

$$\begin{cases} \mathbf{x}_i^{k+1} + (\phi - \omega - 1)\mathbf{x}_i^k + \omega\mathbf{x}_i^{k-1} = \phi\mathbf{o}_i^k = \phi_1\mathbf{g}^k + \phi_2\mathbf{l}_i^k \\ \mathbf{x}_i^0 = \mathbf{x}_{i0} \\ \mathbf{x}_i^1 = \varphi(\mathbf{x}_i^0, \mathbf{v}_{i0}) \end{cases}$$

Las trayectorias se estabilizan en torno a :

$$\mathbf{o}_i^k = \frac{a_g\mathbf{g}^k + a_l\mathbf{l}_i^k}{a_g + a_l}$$

a centered discretization in acceleration

$$\mathbf{x}_i''(\mathbf{t}) \simeq \frac{\mathbf{x}_i(t + \Delta t) - 2\mathbf{x}_i(t) + \mathbf{x}_i(t - \Delta t)}{\Delta t^2}$$

and a regressive schema in velocity

$$\mathbf{x}_i'(t) \simeq \frac{\mathbf{x}_i(t) - \mathbf{x}_i(t - \Delta t)}{\Delta t}$$

Difference equation (4) can be considered the result of a centered discretization in acceleration

$$\mathbf{x}_i''(\mathbf{t}) \simeq \frac{\mathbf{x}_i(t + \Delta t) - 2\mathbf{x}_i(t) + \mathbf{x}_i(t - \Delta t)}{\Delta t^2} \quad (5)$$

and a regressive schema in velocity

$$\mathbf{x}_i'(t) \simeq \frac{\mathbf{x}_i(t) - \mathbf{x}_i(t - \Delta t)}{\Delta t} \quad (6)$$

in time  $t = k \in \mathbb{N}$ , applied to the following system of stochastic differential equations:

$$\begin{cases} \mathbf{x}_i''(t) + (1 - \omega) \mathbf{x}_i'(t) + \phi \mathbf{x}_i(t) = \phi_1 \mathbf{g}(t) + \phi_2 \mathbf{l}_i(t) & t \in \mathbb{R} \\ \mathbf{x}_i(\mathbf{0}) = \mathbf{x}_{i0} \\ \mathbf{x}_i'(\mathbf{0}) = \mathbf{v}_{i0} \end{cases}$$

$$\begin{aligned} \mathbf{v}_i(t + \Delta t) &= (1 - (1 - \omega) \Delta t) \mathbf{v}_i(t) + \phi_1 \Delta t (\mathbf{g}(t) - \mathbf{x}_i(t)) \\ &+ \phi_2 \Delta t (\mathbf{l}_i(t) - \mathbf{x}_i(t)), \mathbf{x}_i(t + \Delta t) = \mathbf{x}_i(t) + \Delta t \cdot \mathbf{v}_i(t + \Delta t) \\ t, \Delta t &\in \mathbb{R} \end{aligned}$$

$$\mathbf{x}_i(0) = \mathbf{x}_{i0} \quad \mathbf{v}_i(0) = \mathbf{v}_{i0}.$$

# Stochastic analysis

$$\frac{d\mathbf{Y}(t)}{dt} = A\mathbf{Y}(t) + \mathbf{b}(t) \quad (9)$$

$$\mathbf{Y}(0) = \begin{pmatrix} x(0) \\ x'(0) \end{pmatrix}$$

where

$$\mathbf{Y}(t) = \begin{pmatrix} x(t) \\ x'(t) \end{pmatrix} \quad A = \begin{pmatrix} 0 & 1 \\ -\phi & \omega - 1 \end{pmatrix}$$

$$\mathbf{b}(t) = \begin{pmatrix} 0 \\ \phi_1 g(t) + \phi_2 l(t) \end{pmatrix}.$$

Interpreted in the mean square sense<sup>1</sup> [19], the mean of the stochastic process  $x(t)$ ,  $\mu(t) = E(x(t))$ , fulfills the following ordinary differential equation:

$$\begin{aligned} & \mu''(t) + (1 - \omega) \mu'(t) + \bar{\phi} \mu(t) \\ & = E(\phi o(t)) = \frac{a_g E(g(t)) + a_l E(l(t))}{2} \quad t \in \mathbb{R} \quad (10) \\ & \mu(0) = E(x(0)) \\ & \mu'(0) = E(x'(0)). \end{aligned}$$



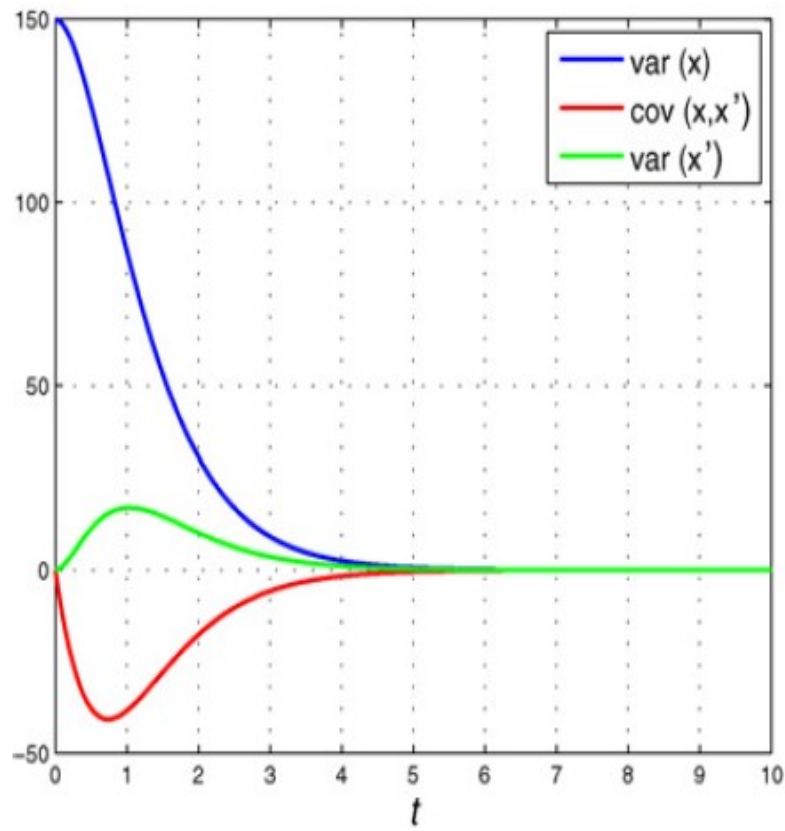
$$\mu(t) = \mu_h(t) + \mu_p(t) \quad (11)$$

where  $\mu_h(t)$  is the general solution of the corresponding homogeneous differential equation, and

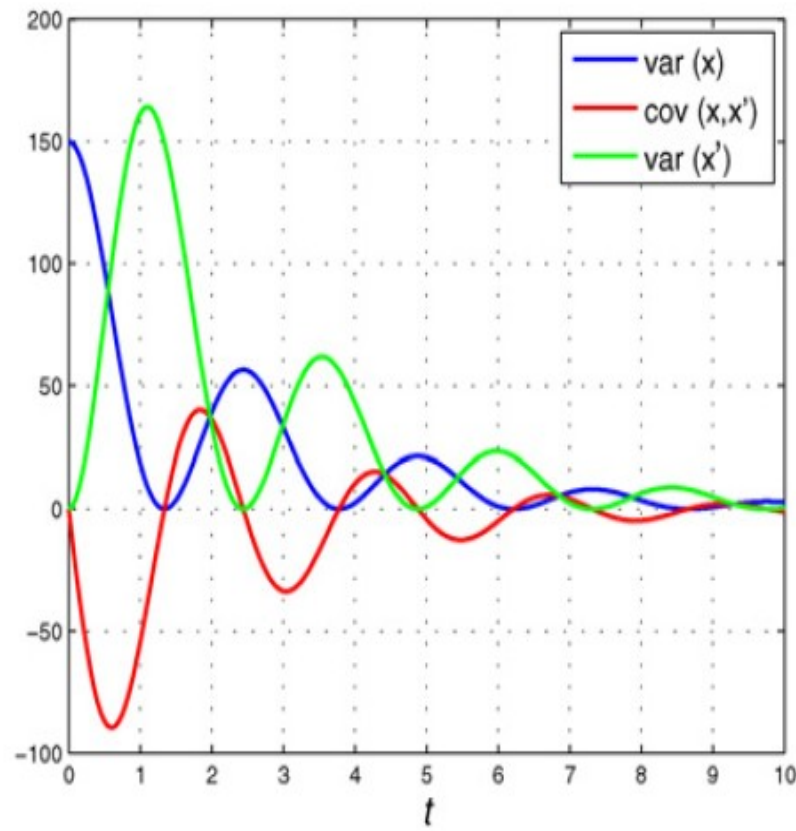
$$\mu_p(t) = \frac{a_g E(g(t)) + a_l E(l(t))}{a_g + a_l}.$$

This last expression for  $\mu_p(t)$  turns out to be  $E(o(t))$ , where

$$o(t) = \frac{a_g g(t) + a_l l(t)}{a_g + a_l}.$$



(a)



(b)

Fig. 2. Homogeneous solution of the covariance equation for the same  $(\omega, \bar{\phi})$  points as in Fig. 1, which located on the complex and real zones of the second order stability region. (a) Real zone. (b) Complex zone.