Internal State Identification for Black Box Systems

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Abstract. In digital filter theory, the identification process describes internal dynamic states based on a reference system, commonly known as a black box. The identification process as a function of: a) transition function, b) identified delayed states, c) gain function which depends on convergence correlation error, and d) an innovation process based on the error described by the differences between the output reference system and the identification result. Unfortunately, in the black box concept, the exponential transition function considers the unknown internal parameters. This means that the identification process does not operate correctly because its transition function has no access to the internal dynamic gain. An approximation for solving this problem includes the estimation in the identification technique. This paper presents an estimation for a "single input single output" (SISO) system with stationary properties applied to internal state identification.

Keywords. Digital filter, estimation, functional error, identification, stochastic gradient, reference model.

Estimación de parámetros internos para sistemas tipo caja negra

Resumen. En teoría de filtro digital, el proceso de identificación describe los estados internos del sistema de referencia comúnmente conocido como caja negra. El proceso de identificación está en función de: a) la función de transición, b) los estados identificados retardados, c) la función de ganancia descrita por el error de correlación y, d) por el proceso de innovación basado en el error descrito por las diferencias entre el sistema de referencia de salida y el resultado de la identificación. Desafortunadamente, con respecto a la caja negra, la función de transición considera a un exponencial con los parámetros internos desconocidos. Esto significa que el proceso de identificación no es posible desarrollarlo adecuadamente debido a que su función de transición no tiene acceso a esos parámetros. Una aproximación para resolver este problema es usar una técnica de estimación. En este trabajo se presenta la estimación para un sistema con una sola entrada y una salida (UEUS o en sus siglas en inglés SISO) con propiedades estacionarias, aplicado dentro de un identificador para describir el estado interno del sistema de referencia.

Palabras clave. Filtro digital, estimador, funcional de error, identificación, gradiente estocástico, modelo de referencia.

1 Introduction

A physical system requires validation by mathematical models with respect to different processes. Therefore, the difference between a real system and its mathematical representation tends to be very small in certain sense, usually in the probability form. A specific mathematical model establishes a relationship between its input and output signals, through the transfer function which considers unknown parameters.

A black box system only allows knowing the transfer function without accessing its internal dynamics in a direct form. For this, it is necessary to perform the identification process [1-3], i.e., to describe the internal states according to their inputs and outputs. In turn, the identification technique is dependent from its transition function [4] as the primitive in a differential equation, which also includes its internal gain [5]. The maximum error allowed between the system and the filter signal is the interval [0, 1]. Fig. 1 describes the digital filter action with identification.

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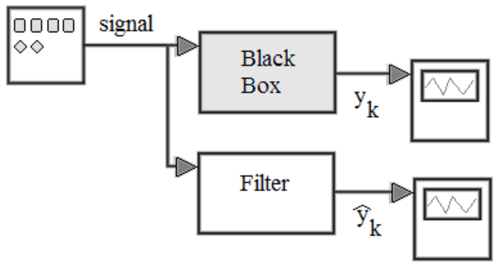

Fig. 1. Digital filter scheme

The simplest identification technique uses the interpolation methods, approximating the function results to the system response [6]. The interpolation has a parameter set playing an important role in the system response convergence [7].

Once obtained, the interpolation function converges in a certain sense to the system response. It is a basic model for black box output tracking.

In control theory, a model is commonly a set of states, when the black box states space depends of the hidden internal parameters and states [8, 9]. The states space form reduces the problem of estimation of a functional that depends on the system output. In a discrete form, they are described as the recursive model [10]. Once the internal states are identified and the parameters are estimated, the model response requires an adaptation algorithm adjusting the parameters at the second step for improving the convergence, and consequently, the model response becomes good enough in a probability sense [11].

In a SISO system, with the input and the output bounded, it is possible to have linear and stationary relationship if the domain conditions are invariant [12] in the probability sense, according to [2, 3]. Conditions are achieved through their stability properties in relation to the proposed transition function, but in its description there also exists an unknown parameter [13, 14]. The traditional identification of this parameter is not feasible, because the system gain applied to the transition function is inside the black box. So, we require the estimation process [15]. The black box identification is a function of the transition function, probability moments and the criterion that affects the dynamical filter, converging to the reference signal [16, 17].

In the identification filter, it is necessary to know the role of the transition and its parameters through the second probability moment. Once the internal parameter has an estimated value, the transition function has sense and the internal identification state has specific results. The estimation based on the gradient of the second probability moment has the parameter evolution. The stationary conditions, which are considered in the estimation technique, allow the identification in recursive form through the estimation. The simulation considers a reference model for estimation, identification and for the interaction between them, as shown in Fig. 2.

2 Experiments

Considering that the estimation is responsible for the description of the internal black box parameters through their output signals and remembering that the transition function is a function of unknown parameters: is it possible to estimate the parameters for finding the transition function that affects the identification filter? Our

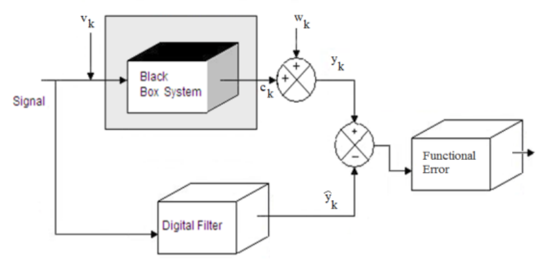

Fig. 2. Digital filter scheme

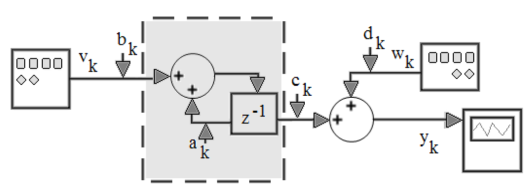

Fig. 3. Black-box system scheme

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answer is yes. We can provide the identification convergence using the functional error. This is generated by the second probability moment between the difference of the actual observable condition and the identification result.

Estimation is a part of the identification process. What can improve the identification response? We consider that the adaptive technique can improve the results. It uses the functional error that affects the estimation results, adjusting the parameter to the goal state.

This paper describes an estimator integrated in an identification technique. The considered system is a first-order stochastic model for invariants' conditions, as shown in Fig. 3.

According to [18], the reference system described by the weapon process in space states [19] has the form $x_{k+1} = a_k x_k + b_k v_k$, with the output $y_k = c_k x_k + d_k w_k$, as shown in Fig. 3, where $\{w(k), k \geq 0\}$ is a discrete stochastic process represented symbolically by $\{w_{k_i}, k_{i=0} = 0, k_{i=1} = 1, k_{i=2} = 2, \ldots\}$, such that for any arbitrary set of points $\{k_i\}$ there is a distribution associated with random variables w_{k_i} for $i = 0, 1, 2, \ldots,$ $n \in Z_+$.

The process is Gaussian, if for any finite set of points $k_{i=0} = 0$, $k_{i=1} = 1$, $k_{i=2} = 2, \ldots$ $k_{i=n} = n$ and their corresponding random variables, there exists mutually exclusive normal distribution for all k_i. It is called Gaussian Stochastic Process expressed as $N(\mu = k_{w_k}, \sigma^2_{w_k} < \infty)$, . In the same way, for $\{v_k, k \geq 0\}$ there also exists a Gaussian Stochastic Process $N(\mu = k_v, \sigma^2_w < \infty)$.

Fig. 3 describes a states space black box system that includes perturbations, which alter both internal (v_k) and external (w_k) values. Inside the dashed line, we describe hypothetically the unknown parameter for a SISO stationary condition.

3 Results

Theorem 1 (Adaptive parameter estimation). Consider that the stochastic model of first order expressed in finite differences describes a system:

$$x_{k+1} = a_k x_k + b_k v_k\,; \quad y_k = c_k x_k + d_k w_k\,. \tag{1}$$

It has a bounded time of evolution $\tau_k < \infty$ according to [20], where $f_{\max_k}$ is the frequency representing the system. It is bounded with $f_{\max_k} < \infty$ [21] with respect to $\{w(k), k \geq 0\}$ and $\{v(k), k \geq 0\}$ like a discrete stochastic processes.

The estimator based on identification state $\hat{y}_k$ has the form

$$\tilde{a}_k = E\{y_{k-1}\hat{y}_k\}\left(E\{y^2_{k-1}\}\right)^{-1}. \tag{2}$$

Proof (Theorem 1). Consider the error function recursively in

$$J_k = \tfrac{1}{k}(E\{e_k^2\} + (k-1)J_{k-1})\,. \tag{3}$$

The error is defined as the difference $e_k := y_k - \hat{y}_k$.

Clearing the state x_k of the system output (1), we obtain

$$x_k = y_k c_k^{-1} - d_k w_k c_k^{-1}\,. \tag{4}$$

Substituting (4) in (1) we have

$$x_{k+1} = a_k(c_k^{-1} y_k - c_k^{-1} d_k w_k) + b_k v_k\,. \tag{5}$$

If the noises $\varepsilon_k := b_k v_k - a_k c_k^{-1} d_k w_k$ and (5) are delayed and then both substituted in (1), we get

$$y_k = \tilde{a} y_{k-1} + \omega_k\,, \tag{6}$$

where $\tilde{a}_k = c_k a_{k-1} c_{k-1}^{-1}$, $\omega_k = c_k \varepsilon_{k-1} + d_k w_k$. After substituting the output in (6), the identification error has the form

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$$e_k = \tilde{a} y_{k-1} + \omega_k - \hat{y}_k \ . \tag{7}$$

Developing the square e_k according to (3), we obtain

$$\begin{aligned} e_k^2 &= \tilde{a}^2 y_{k-1}^2 + \omega_k^2 + \hat{y}_k^2 \\ &+ 2(\tilde{a} y_{k-1}\omega_k - \tilde{a} y_{k-1}\hat{y}_k - \omega_k \hat{y}_k). \end{aligned} \tag{8}$$

Now, using the functional of (3) in (8), we get

$$\begin{aligned} J_k &= \tfrac{1}{k}(\tilde{a}^2 E\{y_{k-1}^2\} + E\{\omega_k^2\} + E\{\hat{y}_k^2\} \\ &+ 2(\tilde{a}\ E\{y_{k-1}\omega_k\} - \tilde{a}\ E\{y_{k-1}\hat{y}_k\} \\ &- E\{\omega_k \hat{y}_k\})) + (k-1)J_{k-1}). \end{aligned} \tag{9}$$

The stochastic gradient in (9) with respect to $\tilde{a}_k$ is described as

$$\begin{aligned} \nabla J_k\big|_{\tilde{a}_k} &= 2\tilde{a}E\{y_{k-1}^2\} \\ &+ 2(E\{y_{k-1}\omega_k\} - E\{y_{k-1}\hat{y}_k\}). \end{aligned} \tag{10}$$

This generates an equilibrium point at the origin equation resulting in

$$\begin{aligned} & 2\tilde{a}_k E\{y_{k-1}^2\} + 2(E\{y_{k-1}\omega_k^2\} \\ & - E\{y_{k-1}\hat{y}_k\}) = 0. \end{aligned} \tag{11}$$

The estimation with disturbance is

$$\tilde{\tilde{a}}_k = \begin{pmatrix} E\{y_{k-1}\hat{y}_k\} \\ -E\{y_{k-1}\omega_k\} \end{pmatrix} \left(E\{y_{k-1}^2\}\right)^{-1}. \tag{12}$$

The description in (12) is based on the identified state $\hat{y}_k$ without noise, as described in (2), where *(*$\tilde{\tilde{a}}_k \equiv \hat{\tilde{a}}_k$*),* i.e., the estimator has the form

$$\tilde{\tilde{a}}_k = E\{y_{k-1}\hat{y}_k\}\left(E\{y_{k-1}^2\}\right)^{-1}. \blacksquare \tag{13}$$

Theorem 2 (recursive estimation). The model (2) with the invariance properties is described recursively in

$$\tilde{\tilde{a}}_k = m_k \tilde{\tilde{a}}_{k-1} + \tilde{S}_k \ , \tag{14}$$

where $\tilde{\tilde{a}}_k$ is in (2).

Proof of Theorem 2. Considering that (2) is a stationary process we obtain

$$\hat{\tilde{a}}_k = \left(\frac{1}{k}\sum_{i=1}^{k} y_{i-1}\hat{y}_i\right)\left(\frac{1}{k}\sum_{i=1}^{k} y_{i-1}^2\right)^{-1}, \tag{15}$$

where the numerator of (15) is described in (16) and denoted as p_k:

$$p_k := \frac{1}{k}\sum_{i=1}^{k} y_{i-1}\hat{y}_i \ . \tag{16}$$

For delayed p_k we get

$$p_{k-1} = \frac{1}{k-1}\sum_{i=1}^{k-1} y_{i-1}\hat{y}_i \ . \tag{17}$$

If we consider (17) in (16), we obtain (18) in the recursive form:

$$p_k = \frac{1}{k}\left(y_{k-1}\hat{y}_k + (k-1)p_{k-1}\right). \tag{18}$$

After substituting (18) in (15), we get

$$\hat{\tilde{a}}_k = \frac{1}{k}\left(y_{i-1}\hat{y}_i + (k-1)p_{k-1}\right)q_k^{-1}. \tag{19}$$

After this, we multiply (19) by the quotient $q_{k-1}(q_{k-1})^{-1}$, where q_k^{-1} is the denominator of (15) considering that $\tilde{\tilde{a}}_{k-1} := p_{k-1}(q_{k-1})^{-1}$. It allows us to get

$$\tilde{\tilde{a}}_k = \frac{1}{k}\left[y_{k-1}\hat{y}_k + (k-1)\tilde{\tilde{a}}_{k-1}q_{k-1}\right]q_k^{-1}. \tag{20}$$

In (21) we present the separation terms considered as

$$\tilde{a}_k = \frac{(k-1)}{k}\left(q_{k-1}q_k^{-1}\right)\tilde{a}_{k-1} + \frac{y_{k-1}\hat{y}_k q_k^{-1}}{k}, \tag{21}$$

whose states have the form

$$\begin{aligned} m_k &:= \frac{(k-1)}{k} q_{k-1} q_k^{-1} \\ \tilde{s}_k &= \frac{1}{k} y_{k-1} \hat{y}_k q_k^{-1}. \end{aligned} \tag{22}$$

Now, considering (22) applied in (21), we have (14). ■

Once we obtained the recursive parameter according to the identification, it is possible to identify the second estimation step.

Theorem 3 (SISO system identification of the internal states). The internal state of the system (x_k) described in (1) has the identifier

$$\hat{x}_{k+1} = \tilde{\hat{a}}_k \hat{x}_k + \tilde{s}_k \hat{w}_k. \tag{23}$$

In optimal form of $\tilde{s}_k$ it has the structure

$$\tilde{s}_k = \hat{a}_k J_k c_k \left(c^2{}_k J_k + R_k\right)^{-1} \in \Re_+^{1,k}; \tag{24}$$

when with the error described in (11), the functional error based on the second probability moment and noise variance are present in

$$\begin{aligned} &J_k := E\left\{e_k^2\right\},\ R_k := E\left\{w_k^2\right\} \\ &a_k,\ c_k, J_k, R_k \in \Re_+^{1,k}. \end{aligned} \tag{25}$$

Proof of Theorem 3. The identifier expressed in (23) is relative with respect to the internal (x_k) and its identifier *($\hat{x}_k$)* is described in (1) having the identification error as

$$e_{k+1} = a_k x_k + b_k v_k - (\tilde{\hat{a}}_k \hat{x}_k + \tilde{s}_k \hat{w}_k). \tag{26}$$

Now, (27) is the innovation process:

$$\hat{w}_k := \hat{y}_k - c_k \hat{x}_k. \tag{27}$$

In (28) we present the result of substituting (27) in (26):

$$e_{k+1} = a_k x_k + b_k v_k - \left(\tilde{\hat{a}}_k \hat{x}_k + \tilde{s}_k \left(\hat{y}_k - c_k \hat{x}_k\right)\right). \tag{28}$$

The error described in (29) considers that the observable signal (y_k) in (27) is substituted by (1) as well as $\lim_{k\to M} \hat{w}_k \underset{c.t.p}{\to} w_k$. Grouping terms, we get the form

$$e_{k+1} = \left(a_k - \tilde{s}_k c_k\right) x_k + b_k v_k - \left(\tilde{\hat{a}}_k - \tilde{s}_k c_k\right)\hat{x}_k - \tilde{s}_k w_k. \tag{29}$$

The eigenvalues $\{\lambda_i(\tilde{\hat{a}}_k)\} \subseteq ([0,1), k)$ satisfy the stable discrete system conditions and whereas $(\tilde{\hat{a}}_k - \tilde{s}_k c_k)$ is a common factor between the internal states of the reference system (x_k) and the identified state ($\hat{x}_k$), i.e., the error has the form

$$e_{k+1} = \left(\tilde{\hat{a}}_{k_k} - \tilde{s}_k c_k\right)\left(x_k - \hat{x}_k\right) + b_k v_k - \tilde{s}_k w_k. \tag{30}$$

Defining the internal state error $e(x_k) := (x_k - x_k)$, which is proportional to the error of the observable states $e(x_k) \cong e_k$ according to (30), we obtain the form

$$e_{k+1} = \left(\tilde{\hat{a}}_k - \tilde{s}_k c_k\right) e_k + b v_k - \tilde{s}_k w_k, \tag{31}$$

when $\tilde{\tilde{a}}_k := (\tilde{\hat{a}}_k - \tilde{s}_k c_k)$. If in the expression (31) the second probability moment is applied, we obtain

$$\begin{aligned} &\tilde{\tilde{a}}_k^2 E\left\{e_k^2\right\} + E\left\{v_k^2\right\} b_k^2 + E\left\{w_k^2\right\} \tilde{s}_k^2 \\ &+ 2(\tilde{\tilde{a}}_k b_k E\left\{e_k v_k\right\} - \tilde{\tilde{a}}_k \tilde{s}_k\, E\left\{e_k w_k\right\} \\ &- b_k \tilde{s}_k\, E\left\{v_k w_k\right\}). \end{aligned} \tag{32}$$

With independent noise in (32), the description is reduced to

$$J_{k+1} = J_k \tilde{\tilde{a}}_k^2 + Q_k b_k^2 + R_k \tilde{s}_k^2. \tag{33}$$

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Replacing in (33) with the formula for ($\tilde{\tilde{a}}_k$) we get

$$J_{k+1} = J_k\left(\tilde{a}_k - \tilde{s}_k c_k\right)^2 + Q_k b_k^2 + R_k \tilde{s}_k^2 \,. \tag{34}$$

Developing (34), the function J_{k+1} is in recursive form described as

$$\begin{aligned} J_{k+1} &= J_k \tilde{a}_k^2 - 2\tilde{s}_k c_k J_k \tilde{a}_k^2 \\ &- \tilde{a}_k^2 J_k c_k \tilde{s}_k^2 + J_k c_k^2 \tilde{s}_k^2 \\ &+ Q_k b_k^2 + R_k \tilde{s}_k^2. \end{aligned} \tag{35}$$

The stochastic gradient ($\nabla J_{k+1|\tilde{s}_k}$) of (35) with the point properties has the minimal description as

$$\nabla J_{k+1|\tilde{s}_k} = -\tilde{a}_k J_k c_k + \tilde{s}_k \left[\, J_k c_k^2 + R_k \right] . \tag{36}$$

From (36) we obtain the optimal gain ($\tilde{K}_k$), summarized in the form:

$$\tilde{S}_k = \tilde{a}_k J_k c_k \left(J_k c_k^2 + R_k\right)^{-1} . \blacksquare \tag{37}$$

According to the model expressed in (1), where finite differences are described, its estimation shown in (3) is presented in Fig. 4.

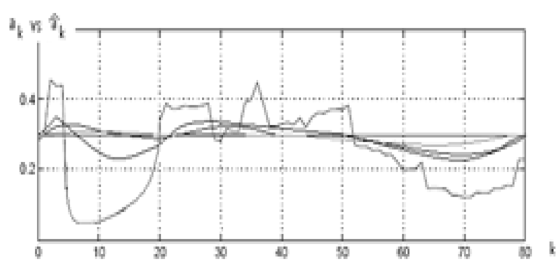

Fig. 4. Optimal parameter estimation evolution

Thus, the estimated parameter is plotted relatively to a standard of 0.4 units. Different amplitudes of noise estimation were performed using the model described in (3), which varied from 0.01 to 0.5. It can be noted that a 0.02 variance estimator has better convergence than the rest of the estimates. Fig. 5 presents the simulation.

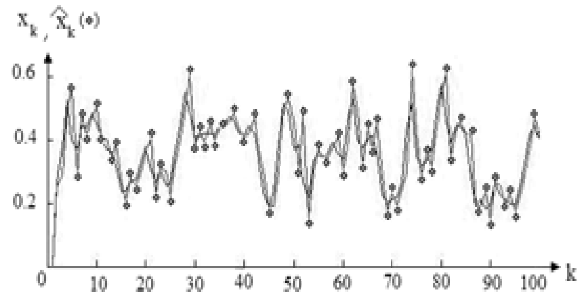

Fig. 5. Internal state identification

4 Conclusion

The digital filtering identification theory allows knowing the internal state dynamics with respect to a reference signal system. Nevertheless, if we consider a black box, this development is impossible. The identifier requires excitation and an output signal system, the transition function, the gain, and the innovation process.

Moreover, within the black box, the parameters are unknown and are used in the transition function and in the identifier, which are required for the estimation technique. This paper constructs the estimation that affects the transition function and consequently the identification. It allows to improve the results dynamically.

References

1. **Rodríguez-Reséndiz, J., Gutiérrez-Villalobos, J.M., Duarte-Correa, D., Mendiola-Santibañez, J.D., & Santillán-Méndez, I.M.** (**2012).** Design and Implementation of an Adjustable Speed Drive for Motion Control Applications. *Journal of Applied Research and Technology*, 10(12), 180–194.

2. **Casco-Sánchez, F.M., Medina-Ramírez, R.C., & López-Guerrero, M. (2011).** A New Variable Step Size NLMS Algorithm and its Performance Evaluation in Echo Cancelling Applications. *Journal of Applied Research and Technology*, 9(3), 302–313.

ISSN 1405-5546
http://dx.doi.org/10.13053/CyS-18-2-2014-039

3. **Bazdresch, M., Cortez, J., Longoria-Gándara, O., & Parra-Michel, R. (2012).** A Family of Hybrid Space-Time Codes for MIMO Wireless Communications. *Journal of Applied Research and Technology*, 10(2), 122–142.

4. **Joham, M., Zoltowski, M.D. (2000).** *Interpretation of the Multi-Stage Nested Wiener Filter in the Krylov Subspace Framework (TR-ECE-00-51).* West Lafayette: Purdue University.

5 **Min-Sung, K., Ho-Lim, C., &Jong-Tae, L. (2012).** Output feedback regulation of a chain of integrators with an unbounded time-varying delay in the input. *IEEE Transactions on Automatic Control,*57(10), 2662–2667.

6 **Zhou, J., Wen, C., & Li,T. (2012).** Adaptive Output Feedback Control of Uncertain in Nonlinear Systems With Hysteresis Nonlinearity. *IEEE Transactions on Automatic Control,* 57(10), 2627–2633.

7 **Herrera, R.S. & Vázquez,J.R. (2012).** Unbalance Sources Identification in Non-Sinusoidal Electric Power Systems.*International Review of Automatic Control*, 5(5), 638–645.

8 **Iskrenovic-Momcilovic, O. (2012).**Discrete-Time Variable Structure Controller Synthesis Using Model in Canonical Subspace. *International Review of Automatic Control*, 5(5), 703–709.

9 **Medel, J.J. & Zagaceta,M.T. (2010).** Estimación–identificación como filtro digital integrado: descripción e implementación recursiva. *Revista Mexicana de Física*, 56(1), 1–8.

10 **Medel, J.J., García, J.C., & Urbieta, R. (2011).** Identificador con comparación entre dos estimadores. *Revista Mexicana de Física,* 57(5), 414–420.

11 **Frizera, A., Ceres, R., & Pons, J.L. (2011).** Filtrado Adaptivo Componentes Involuntarias en Marcha Asistida por Andador para Detección de Intenciones. *Revista Iberoamericana de Automática e Informática Industrial*, 8(2), 71–80.

12 **Gallegos, M.A., Álvarez, R., Moreno, J.A., & Espinosa, G.R. (2010).** Control Vectorial de un Motor de Inducción con Carga Desconocida Basado en un Nuevo Observador no Lineal. *Revista Iberoamericana de Automática e Informática Industrial,* 7(4), 74–82.

13 **Romero, J.A., & Sanchis,R. (2011).**Metodología para la Evaluación de Algoritmos de Auto-ajuste de Controladores PID. *Revista Iberoamericana de Automática e Informática Industrial*, 8(1), 112–117.

14 **Hernández, D.F., Gómez, D., & Thompson, P. (2011).** Implementación de un sistema de control activo para disminuir las vibraciones producidas por personas en una tribuna. *Revista Facultad de Ingeniería Universidad de Antioquia,* 61, 83–92.

15 **Escobar, A., Hernández, C., & Arguello, J. (2011).** Control difuso adaptativo aplicado a un sistema de fermentación de flujo continuo de alcohol. *Revista Facultad de Ingeniería Universidad de* Antioquia, 58, 105–113.

16 **Haykin, S. (1996).** *Adaptive Filter Theory (3rd ed.).* Upper Saddle River, New Jersey: Prentice Hall.

17 **Shiryaev, A.N. (1984)**,*Theory of Probability.* Nauka, Moscow, 22–78.

18 **Wasan, M.T. (1969).** *Stochastic Approximation*. Cambridge, UK: Cambridge University Press.

19 **Bhat, U.N. & Miller, G.K. (2002).** *Elements of Applied Stochastic Processes* (3rd ed.). Hoboken, N.J.: Wiley-Interscience.

20 **Ogatta, K. (1996).** *Sistemas de Control en Tiempo Discreto (*2ª ed.). México: Prentice Hall.

21 **Moreno, F.J., Duitama, J.F., & Ospina, E.C. (2012).** A method for estimating the position and direction of a leader of a set of moving objects. *Revista Facultad de Ingeniería Universidad de Antioquia*, 62, 11–20.

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