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Online Identification for Auto-tuning PID based on Wavelet Neural Networks: An Experimental Validation on an AC Motor

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Abstract— **Based on adaptive wavelet neural networks, a PID discrete control scheme for induction motor drives is presented. An auto-tuning wavenet scheme is synthesized for the PID feedback gains by means of gradient-descendent algorithm through online plant identification. The latter uses input and output data for a radial basis neural network (RBNN) with different daughter wavelet activation functions. Infinite impulse response filter in cascade with the output of the RBNN is introduced to prune nodes that contribute poorly for an efficient identification even though gradient-descendent is used. A comparative experimental study under real noisy conditions and no load perturbation shows results for different wavelets (Morlet, RASP1, POLYWOG1 and Shannon); better performance of Morlet and RASP1 wavenet-based tuning are obtained due to its better identification properties.**

keywords– **Wavelet Neural Network, Induction Motor, PID Control, IIR Filter.**

I. Introduction

PID scheme stands for the main controller used in the control process. However, the linear PID algorithm is difficult to regulate processes with nonlinear dynamics or those with large dead time because its stability, let alone, depends largely on a linear state representation over a local domain. Lot of effort has been dedicated to synthesize analytical and experimental techniques to tune the PID feedback gains [1], aiming at regulation with constants gains, based on the linear or linearised representation of the process. Fast, ideally critically damped response for nonlinear plants with PID regulator constitutes an open problem, whose solution remains largely elusive in the literature[1].

State of the art tuning of constant feedback gains of a PID controller for linear plants shows a great limitation: those are synthesized for an assumed state or bounding conditions of the plant in a linear realm. Then, it sounds appealing to explore a time-varying tuning scheme for the actual condition of the plant at each instant, however this intuitive idea leads to assume that a model of the plant is available or measurable. When this is not the case, a network can be used to estimate the plant, then use this knowledge to tune feedback gain, regardless of the linear or nonlinear domain of the plant.

Recently, self-tuning or auto-tuning or adaptive tuning of PID feedback gains have been studied with promising results over the linear model of the process, which is valid under rigorous assumptions on a local domain. For nonlinear plants, PID performance diminishes under a great deal of tuning effort of constant gains to ensure local stability. Then, there remains to explore auto-tuning schemes for the nonlinear plant, which clearly leads to consider some sort of plant estimation. In [4], [5], [6], a wavenet neural networks is studied to identify the nonlinear plant to compute online feedback gains. Recently, [7] and [8] described autotuning that depend on plant parameters, which may dificult due to uncertainties in practice, or subject to noise.

In particular for AC motors, input signals of the flux model cause the conventional speed estimation techniques to fail at very-low-speed operation in a speed-sensorless induction motor drive. Therefore, other techniques have been developed to take into account plant variations online, suggesting in particular neural networks, being among the simplest and most powerful [9], [10], [11], and fuzzy neural networks, [12], [13], [14], [15].

In this paper, an auto-tuning scheme of a discrete PID controller is proposed for regulation of AC motor based on online identification algorithm using wavelet neural networks. Comparative experimental are presented for four different wavelets Morlet, RASP1, POLYWOG1, and Shannon on a real-time experimental platform. Results show better performance those with better identification properties, because tuning depends on the quality of the identification process. Experimental results establishes the validity of the proposed approach.

[1]Although it has been treated widely for robot manipulators in virtue of its noble structural dynamical properties, [2], [3].

II. Wavenet PID Controller

Inspired in [20], a wavenet auto-tuning PID controller scheme is proposed in this section. The rationale of this scheme is to extract knowledge of the plant to tune properly feedback gains according to what the linear or nonlinear plant is at each instant, indeed mimicking conceptually an algorithm to tune constant feedback gains under a given conditions of plant, not at each instant. Then, clearly, this leads to improved performance because it feedback gains code and introduces knowledge of the plant. This allows to get rid of the limiting factor of well-established classical algorithms to tune feedback gains that assume linear or linearized plants. However, this also introduces the necessity to validate it in real-time experiments, which is presented in Section IV.

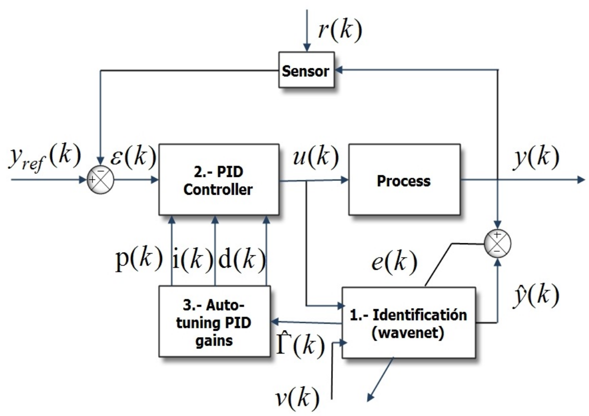

Fig. 1: Block diagram of theproposed auto-tuning wavenet PID controller based on a wavelet neural network for a SISO plant identification, where $r(k)$ stands for white noise with zero mean.

Now, consider the block diagram shown in Fig. 1, which consists of three stages for manipulating the output of a SISO nonlinear system to produce a desired trajectory. The system is composed of: 1.-Identification of the system, 2.- Discrete PID controller, and 3.- Auto-tuning scheme. Notice that the mother wavalet can be in fact other one that guarantees identification of a nonlinear plant. Now, firstly, we show the plant dynamics, then the identification scheme, subsequently we show the controller and finally the auto-tuning procedure.

II-A. Plant Dynamics

Consider a SISO nonlinear dynamic system, it can be represented by the following discrete state equation [16],

$$x(k+1) = f[x(k), u(k), k] \quad (1)$$
$$y(k) = g[x(k), k] \quad (2)$$

where $x(k) \in \mathbf{R}^n$, $u(k), y(k) \in \mathbf{R}$ and $f, g \in \mathbf{C}$ are unknown functions. The input $u(k)$ and the system output $y(k)$ are the only data available. If the linearized system around the equilibrium point is observable, there is an input-output representation given by, [17],

$$y(k+1) = \beta[\mathbf{Y}(k), \mathbf{U}(k)] \quad (3)$$

where

$$\mathbf{Y}(k) = [y(k)\ y(k-1),\ \cdots,\ y(k-n+1)] \quad (4)$$
$$\mathbf{U}(k) = [u(k)\ u(k-1),\ \cdots,\ u(k-n+1)] \quad (5)$$

this is, if there exists a function β that maps the output $y(k)$, input $u(k)$ and theirs $n-1$ past values in $y(k+1)$. An alternative model of an unknown plant that can simplify the algorithm of the control signal is the following

$$y(k+1) = \Phi[\mathbf{Y}(k), \mathbf{U}(k)] + \Gamma[\mathbf{Y}(k), \mathbf{U}(k)] \cdot u(k) \quad (6)$$

if terms Φ and Γ are exactly known, an inverse dynamics control will provide exact linearization for asymptotic stability toward the $y_{ref}(k+1)$ is follows

$$u(k) = \frac{y_{ref}(k+1) - \Phi[\mathbf{Y}(k), \mathbf{U}(k)]}{\Gamma[\mathbf{Y}(k), \mathbf{U}(k)]} \quad (7)$$

However, terms Φ and Γ are unknown and thus (7) cannot be used. To circumvent this, a wavenet neural network is proposed to approximate Φ and Γ purposely to tune feedback gains of a PID regulator, rather than implementing (7).

II-B. System Identification

Let a radial basis neural network identifies a process with activation functions $\psi(\tau)$ based on different daughter wavelet functions $\psi_j(\tau)$ and consider an infinite impulse filter (IIR) in cascade to eliminate those neurons that have negligible contribution in the identification process. The latter to reduce the computational complexity without altering the identification capability of the network by reducing the number of iterations of the learning process, [18], as shown in Fig. 2. The mother

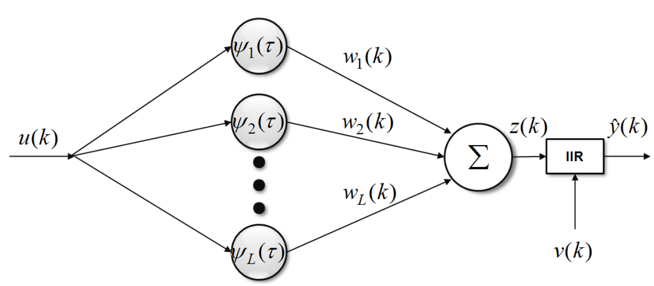

Fig. 2: Diagram of a wavelet neural network with an IIR filter in cascade, where $\psi_j(\tau) = \psi_{a_j b_j}(k) = \frac{k-b_j}{a_j}$ stands for daughter wavelets, for $1 \leq j \leq L$.

wavelet function $\psi(k)$ is generated of different wavelets by its expansion or contraction and translation by the following daughter wavelets, [19],

$$\psi_{a,b}(k) = \frac{1}{\sqrt{a}}\,\psi(\tau) \quad (8)$$
$$\tau = \frac{k-b}{a} \quad (9)$$

TABLE I: Mother wavelets under consideration.

Mother wavelet	$\psi(\tau)$
Morlet	$cos(\omega_0\tau)e^{-0.5\tau^2}$
RASP1	$\frac{\tau}{(\tau^2+1)^2}$
POLYWOG1	$\tau e^{-0.5\tau^2}$
Shannon	$\frac{sin(2\pi\tau)-sin(\pi\tau)}{\pi\tau}$

where $a \neq 0$, $a, b \in \mathbf{R}$ and a a scale variable to expand and contract, and b to translation at instant k. Different wavelets fulfill this, in this paper, it is considered those shown in Table I, [19], whose partial derivative with respect to b are show in Table II. Signal approximation of the wavenet with IIR filter $\hat{y}(k)$ can be calculated as follows, [20],

$$\hat{y}(k) = \sum_{i=0}^{M} c_i z(k-i)u(k) + \sum_{j=1}^{N} d_j \hat{y}(k-j)v(k) \quad (10)$$

$$z(k) = \sum_{l=1}^{L} w_l \psi_l(k) \quad (11)$$

where L stands for the the number of daughter wavelets, w_l are the weights of each neuron in the wavenet, c_i and d_j are the coefficients of forward and backward IIR filter, respectively, for M and N are the number forward and backward IIR filters, respectively. The wavenet parameters are given in vector form by:

$$\mathbf{A}(k) \triangleq [a_1(k),\ a_2(k),\ \cdots,\ a_L(k)]^T \quad (12)$$

$$\mathbf{B}(k) \triangleq [b_1(k),\ b_2(k),\ \cdots,\ b_L(k)]^T \quad (13)$$

$$\mathbf{W}(k) \triangleq [w_1(k),\ w_2(k),\ \cdots,\ w_L(k)]^T \quad (14)$$

and the IIR filter parameters:

$$\mathbf{C}(k) \triangleq [c_0(k),\ c_1(k),\ \cdots,\ c_M(k)]^T \quad (15)$$

$$\mathbf{D}(k) \triangleq [d_1(k),\ d_2(k),\ \cdots,\ d_N(k)]^T \quad (16)$$

All of them are optimized through the well-known least mean squares-based learning algorithm [4] to minimizes a cost function

$$\mathbf{E} = \frac{1}{2}\sum_{k=1}^{T} e^2(k) \quad (17)$$

where the estimation error is

$$e(k) = y(k) - \hat{y}(k) \quad (18)$$

TABLE II: Partial derivative with respect to b, for $\nu_2 = \pi\tau cos(2\pi\tau), \nu_1 = \pi\tau cos(\pi\tau)$.

Mother Wavelet	$\frac{\partial\psi(\tau)}{\partial b}$
Morlet	$\frac{1}{a}[\omega_0 sin(\omega_0\tau)e^{-0.5\tau^2} + \tau h(\tau)]$
RASP1	$\frac{1}{a}\frac{3\tau^2-1}{(\tau^2+1)^3}$
POLYWOG1	$\frac{1}{a}(\tau^2-1)e^{-0.5\tau^2}$
Shannon	$\frac{\pi}{a}\frac{-2\nu_2+\nu_1+sin(2\pi\tau)-sin(\pi\tau)}{(\pi\tau)^2}$

for $\hat{y}(k)$ neural network output and $y(k)$ the real output of the plant. Clearly, to minimization of (17) implies that $e(k) \rightarrow 0 \Rightarrow \hat{y}(k) \rightarrow y(k)$ as $k \rightarrow \infty$. Then, the problem is to tune coefficients of (10) aiming at $e(k) \rightarrow 0$ by increasing the gradient of the cost function along its negative direction times a short steep. This leads to the following update rule for parameter

$$\theta(k+1) = \theta(k) + \Delta\theta(k) \quad (19)$$

$$\Delta\theta(k) = -\mu\frac{\partial\mathbf{E}}{\partial\theta(k)} \quad (20)$$

where $\theta = [\mathbf{A}(k), \mathbf{B}(k), \mathbf{W}(k), \mathbf{C}(k), \mathbf{D}(k)]$, which will eventually minimize (17), for $\mu \in \mathbf{R}$ the learning rate for each of the parameters and

$$\frac{\partial\mathbf{E}}{\partial w_l(k)} = -e(k)\mathbf{C}(k)^T\Psi_l(\tau)u(k) \quad (21)$$

$$\frac{\partial\mathbf{E}}{\partial b_l(k)} = -e(k)\mathbf{C}(k)^T\Psi_{b_l}(\tau)w_l(k)u(k) \quad (22)$$

$$\frac{\partial\mathbf{E}}{\partial a_l(k)} = \tau_l\frac{\partial\mathbf{E}}{\partial b_l(k)} \quad (23)$$

$$\frac{\partial\mathbf{E}}{\partial c_m(k)} = -e(k)z(k-M)u(k) \quad (24)$$

$$\frac{\partial\mathbf{E}}{\partial d_n(k)} = -e(k)\hat{y}(k-N)u(k) \quad (25)$$

for

$$\Psi_l(\tau) = [\psi_l(\tau),\ \psi_l(\tau-1),\ \cdots,\ \psi_l(\tau-M)]^T \quad (26)$$

$$\Psi_{b_l}(\tau) = \left[\ \frac{\partial\psi_l(\tau)}{\partial b_l(k)},\ \frac{\partial\psi_l(\tau-1)}{\partial b_l(k)},\ \cdots,\ \frac{\partial\psi_l(\tau-M)}{\partial b_l(k)}\ \right]^T \quad (27)$$

The problems of local minima, introduced by the gradient descent algorithm, is entertained in Remark 1, at the end of Section III.

II-C. Discrete PID Control Design

Algorithm (19)-(27) guarantees that the output of the wavenet neural network approximates the output of the system, that is

$$\hat{y}(k+1) = \hat{\Phi}[\mathbf{y}(k), \Theta_\Phi] + \hat{\Gamma}[\mathbf{y}(k), \Theta_\Gamma] \cdot u(k) \quad (28)$$

where, using (6) leads to

$$\hat{\Phi}[\mathbf{y}(k), \Theta_\Phi] = \sum_{j=1}^{N} d_j\hat{y}(k-j)v(k) \quad (29)$$

$$\hat{\Gamma}[\mathbf{y}(k), \Theta_\Gamma] = \sum_{i=0}^{M} c_i z(k-i) \quad (30)$$

$$z(k) = \sum_{l=1}^{L} w_l\psi_l(k) \quad (31)$$

Therefore, if both nonlinear functions Φ and Γ are estimated by wavenet functions $\hat{\Phi}$ and $\hat{\Gamma}$ with adjustable parameters Θ_Φ and Θ_Γ, respectively, a PID controller can be designed, [21], [22], [5]. Thus, let

$$u(k+1) = u(k) + p(k)[\varepsilon(k) - \varepsilon(k-1)] + i(k)\varepsilon(k) + d(k)[\varepsilon(k) - 2\varepsilon(k-1) + \varepsilon(k-2)] \quad (32)$$

be the discrete PID regulator, where $p(k)$, $i(k)$ and $d(k)$ are the proportional, integral and derivative gains, for

$$\varepsilon(k) = y(k) - y_{ref}(k) \tag{33}$$

the error at instant k and $y_{ref}(k)$ the constant reference.

II-D. *Auto-tuning of PID Feedback Gains*

Similar to developments to minimize $\mathbf{E}$, auto-tuning of feedback gains $p(k)$, $i(k)$ and $d(k)$ can be computed as follows

$$\begin{aligned} p(k) &= p(k-1) + \mu_P e(k)\hat{\Gamma}(k)[\varepsilon(k) - \varepsilon(k-1)] & (34)\\ i(k) &= i(k-1) + \mu_I e(k)\hat{\Gamma}(k)\varepsilon(k) & (35)\\ d(k) &= d(k-1) + \mu_D e(k)\hat{\Gamma}(k)[\varepsilon(k) - 2\varepsilon(k-1) + \\ &\quad \varepsilon(k-2)] & (36) \end{aligned}$$

where $\hat{\Gamma}(k)$ as described by (30) and the learning rate $\mu = [\mu_P, \mu_I, \mu_D]$ are computed in next Section.

III. Convergence of Wavelet Neural Network (WNN)

We are now in position to state the main result in a theorem, which establishes the stability properties of the closed-loop system based on bounds of the learning rates μ_P, μ_I, μ_D of (34),(35),(36), establishing sufficient condition of the convergence of the WNN.

Theorem 1: Consider a SISO system in closed-loop with the discrete PID controller (32) with auto-tuning feedback gains (34),(35),(36). Then the wavelet neural network (10) with update rule (19) guarantees that regulation error (33) converges locally exponentially if learning rates are chosen as follows

$$0 < \mu < 2/(J_{\hat{y},\theta}^T J_{\hat{y},\theta}) \tag{37}$$

where $J_{\hat{y},\theta} = \frac{\partial \hat{y}(k)}{\partial \theta(k)}$ and

$$\frac{\partial \hat{y}}{\partial \theta} = \left[\frac{\partial \hat{y}}{\partial a_1} \cdots \frac{\partial \hat{y}}{\partial a_L} \frac{\partial \hat{y}}{\partial b_1} \cdots \frac{\partial \hat{y}}{\partial b_L} \frac{\partial \hat{y}}{\partial w_1} \right. \\ \left. \cdots \frac{\partial \hat{y}}{\partial w_L} \frac{\partial \hat{y}}{\partial c_0} \cdots \frac{\partial \hat{y}}{\partial c_M} \frac{\partial \hat{y}}{\partial d_1} \cdots \frac{\partial \hat{y}}{\partial d_N}\right] \tag{38}$$

with convergence of identification error $e(k) = y(k) - \hat{y}(k)$ as $k \to \infty$, with bounded parameter error $\Delta\theta(k)$.

Proof: Let a Lyapunov function candidate be chosen as

$$V(k) = \frac{1}{2}e^2(k) \tag{39}$$

whose increment becomes,

$$\begin{aligned} \Delta V(k) &= V(k+1) - V(k) \\ &= \frac{1}{2}\Delta e(k)\left(e(k) + \Delta e(k) + e(k)\right) \\ &= \frac{1}{2}\Delta e(k)\left(2e(k) + \Delta e(k)\right) & (40) \end{aligned}$$

As it is customary, let the increment of tracking error be computed as follows [23], [24]

$$\Delta e(k) = e(k+1) - e(k) \approx \left[\frac{\partial e(k)}{\partial \theta(k)}\right]^T \Delta\theta(k) \tag{41}$$

which stands for a reasonable approximation of the discrete increment of $e(k)$ for enough small sampling rate k, with respect the bandwidth of the plant. Now, substituting (41) into (40), using (20), one obtains

$$\begin{aligned} \Delta V(k) &= -\mu e(k) J_{e,\theta}^2 \left[e(k) - \frac{1}{2}\mu e(k) J_{e,\theta}^2\right] \\ &= -\frac{1}{2}e^2(k)\mu J_{e,\theta}^2 \left[2 - \mu J_{e,\theta}^2\right] \\ &= -\frac{1}{2}e^2(k)\mu J_{\hat{y},\theta}^T J_{\hat{y},\theta}(2 - \mu J_{\hat{y},\theta}^T J_{\hat{y},\theta}) \\ &= -\frac{1}{2}e^2(k)\mu\nu_1\nu_2 \\ &\leq -\frac{1}{2}e^2(k)\nu_3 \\ &< -\nu_4 V(k) & (42) \end{aligned}$$

where $J_{e,\theta} = \frac{\partial e(k)}{\partial \theta(k)}$, and (37) has been used, for positive constants $\nu_1, \nu_2, \nu_3, \nu_4$. Therefore, (37) drives error $e(k)$ to zero locally exponentially. ■

Remark 1. It is well known that gradient descent and back-propagation algorithms suffer from local minima. In our proposal, this problem occurs but the role of the IIR filter prunes along time any node that does not contribute significantly, then the topology of the network is constantly changing up to reaching a configuration that correspond to $e(k) \to 0$, that is $\hat{y}(k) \to y(k)$ as $k \to \infty$. Certainly, this claim deserves a further insight which is beyond the scope of this paper.

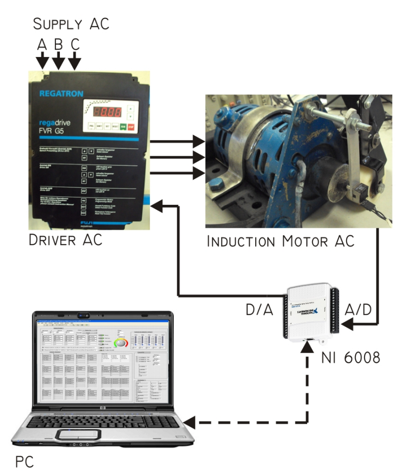

Fig. 3: Test platform.

IV. Experimental Results

The auto-tuning wavenet PID controller (with the following wavelets: Morlet, RASP1, POLYWOG1 and Shannon) was applied experimentally to control the speed of a triphasic AC motor coupled a tachogenerator and the main technical specification are: four poles, 2 HP, which is shown in Fig. 3. The algorithm is implemented on the platform LabVIEW 8.5 and using a data acquisition card NI-USB 6008, both from National Instruments.

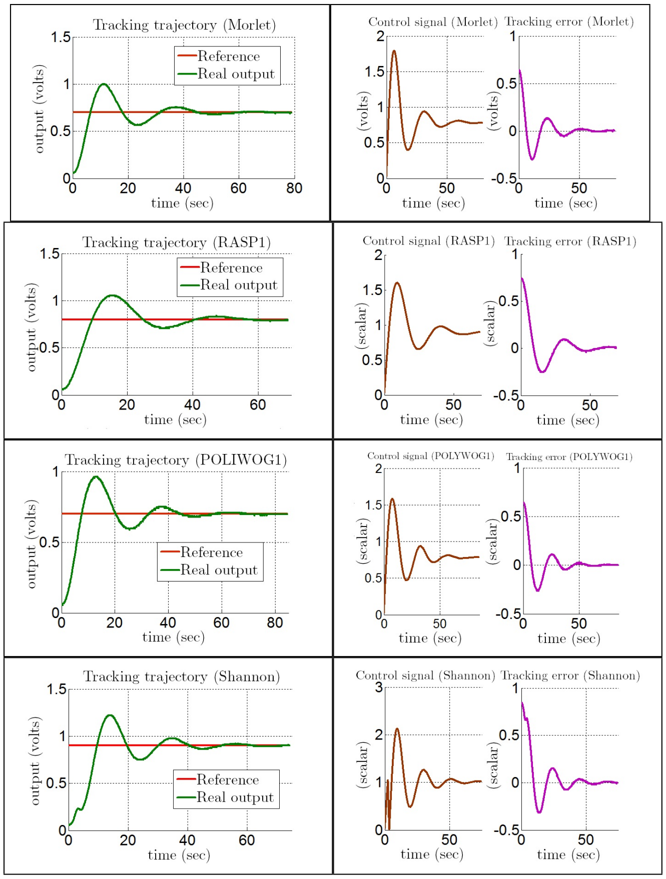

Fig. 4: Tracking trajectory, control signal $u(k)$ and tracking error $\varepsilon(k)$ with Morlet, RASP1, POLYWOG1 and Shannon wavelets.

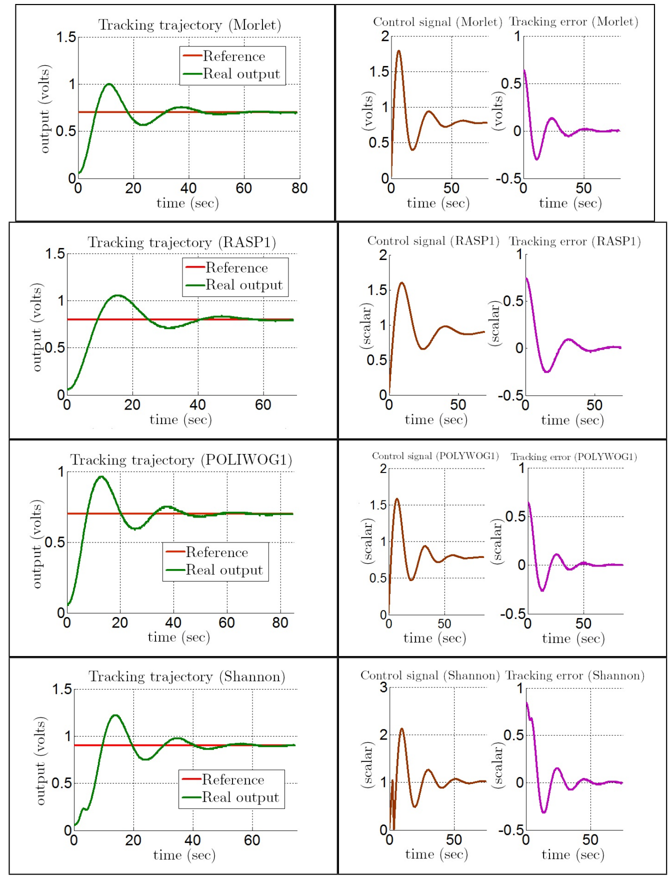

Fig. 5: AC motor identification and estimation error, with Morlet, RASP1, POLYWOG1 and Shannon wavelets.

The parameters for the wavelet neural network are as follows: only 3 neurons are considered for IIR filter coefficients $(\mathbf{C}, \mathbf{D}) = (3, 2)$, in 20 epochs, at $35ms$ of sampling period, and $v = 0.1$ as a persistent signal. Wavenet is initialized as follows: $\mathbf{W} = [3.78, -3.36, -1.99]$, $\mathbf{A} = [-302.6, -55.5, -20]$, $\mathbf{B} = [92.7, 29.4, 107]$. $\mathbf{C} = [-0.4, -0.016, 0.64]$, $\mathbf{D} = [0.34, 1.66]$, and $(p, i, d) = (0.02, 0.02, 0.003)$. Learning rates are $(\mu_w, \mu_a, \mu_b, \mu_c, \mu_d,) = (0.1, 0.1, 0.1, 0.1, 0.1)$, with control feedback gains $(\mu_P, \mu_I, \mu_D) = (0.01, 0.007, 0.009)$.

IV-A. System Identification Results

From Fig. 5 we can see the online results of the identification AC motor and estimation error. The experimental results show that RASP1 and Morlet wavelets have a better identification performance that POLYWOG1 and Shannon wavelets. The RASP1 and Morlet wavelets have the lowest estimation error $e(k)$ during the experiment. With all wavelets the estimation error $e(k)$ is bounded.

IV-B. PID Control Results

Fig. 4 shows the tracking of output $y(k)$ toward $y_{ref}(k)$, with bounded tracking error $\varepsilon(k)$, with control signal as voltage applied to the inverter.

IV-C. Auto-tuning Results

Fig. 6 corresponds to the behavior presented by the PID controller gains during all experiments. In all the cases the $p(k)$, $i(k)$ and $d(k)$ gains are bounded however with the Shannon wavelet occurs oscillations due to oscillations at the identification stage.

Here, all four wavenet PID controls have been compared during a test at the rated rotor flux-linkage at zero-speed. The test has been performed at no-load and at load. Fig. 4 shows the waveforms of the reference, measured, and estimated speed during the time interval of 80 seconds, obtained at no-load with all wavenet PID controls. This figure shows that the best results are achieved by the wavenet PID controls with Morlet wavelet and by wavenet PID controls with RASP1 wavelet, which can work correctly at zero-speed at no-load.

V. CONCLUSIONS

This paper presents a new PID regulator for nonlinear plants that guarantees high-performance. Experimental results are obtained for a induction motor drive where we can conclude that radial basis neural network whith activation functions given by Morlet and RASP1 daughters wavelets provide better identification then better online tuning of the controller than POLYWOG1 and Shannon

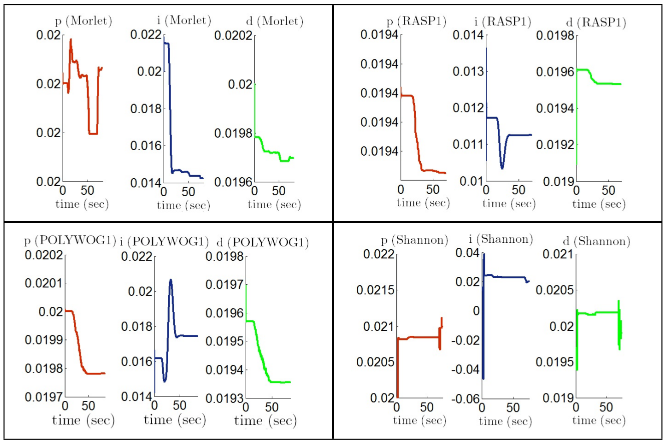

Fig. 6: Behavior of the PID gains $p(k)$, $i(k)$ and $d(k)$ with Morlet, RASP1, POLYWOG1 and Shannon wavelets.

wavelets. Experimental results show the effectiveness of the proposed approach, highlighting that it needs only few wavelets for a fast plant, which suggest that computational complexity i slower in comparison to common wavelet neural networks without IIR filter. The final control architecture exhibits quick estimation, with a smooth control law with small estimation errors both in transient and steady-state operation as well as adequate behavior at zero-speed operation with no load, remarkably without depending on any mathematical model of the induction motor.

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REFERENCES

[1] K. Aström, T. Hägglund, *Advanced PID Control*, ISA, 2006.

[2] S. Kawamura, F. Miyazaki, S. Arimoto, Is a local linear PD feedback control law effective for trajectory tracking of robot motion?, Proceedings., *1988 IEEE Int. Conf. on Robotics and Automation*, 3, pp. 1335-1340.

[3] J.L. Meza, V. Santibanez, R. Soto, M.A. Llama, "Fuzzy self-tuning PID semiglobal regulator for robot manipulators", *IEEE Trans. on Industrial Electr.*, 59(6), pp. 2709-2717, 2011.

[4] M. Sedighizadeh and A. Rezazadeh, "Adaptive PID control of wind energy conversion systems using RASP1 mother wavelet basis function network", in *Proceeding of World Academy of Science, Engineering and Technology*, pp. 269-273, 2008.

[5] K. Ogata, *Discrete-Time Control Systems*, Prentice-Hall, 1995.

[6] J. Cruz, L. Ramos and M. Espejel, "A auto-tuning wavelet PID controller using wavelet networks", in *IEEE CONIELECOMP'10*, pp. 23-31, 2010.

[7] K. Rajashekara, A. Kawamura, and K. Matsuse, *Sensorless Control of AC Motor Drives.* New York: IEEE Press, 1996.

[8] P. Vas, *Sensorless Vector and Direct Torque Control.* Oxford, U.K.: Oxford Science, 1998.

[9] C. Shauder, "Adaptive speed identification for vector control of induction motors without rotational transducers,"*IEEE Trans. Ind. Appl.*, vol. 28, no. 5, pp. 1054-1061, 1992.

[10] H. Tajima and Y. Hori, "Speed sensorless field-orientation of the induction machine,"*IEEE Trans. Ind. Appl.*, vol. 29, no. 1, pp. 175-180, Jan./Feb. 1993.

[11] F. Peng and T. Fukao, "Robust speed identification for speed-sensorless vector control of induction motors,"*IEEE Trans. Ind. Appl.*, vol. 30, no. 5, pp. 1234-1240, Sep./Oct. 1994.

[12] L. Ben-Brahim and R. Kurosawa, "Identification of induction motor speed using neural networks,ïn *Proc. PCC'93*,Yokohama, Japan, 1993, pp. 689-694.

[13] M. Elloumi, L. Ben-Brahim, and M. Al-Hamadi, "Survey of speed sensorless controls for IM drives,ïn *Proc. IEEE IECON'98*, vol. 2, 1998, pp. 1018-1023.

[14] L. Ben-Brahim, S. Tadakuma, and A. Akdag, "Speed control of induc- tion motor without rotational transducers,"*IEEE Trans. Ind. Appl.*, vol. 35, no. 4, pp. 844-850, Jul./Aug. 1999.

[15] T. Chen and T. Sheu, "Model reference neural network controller for induction motor speed control,"*IEEE Trans. Energy Convers.*, vol. 17, no. 2, pp. 157-163, Jun. 2002.

[16] A. Levin and K. Narendra, "Control of nonlinear dynamical systems using neural networks: controllability and stabilization", *IEEE Trans. Neural Netw.*, pp. 192-206, 1993.

[17] A. Levin and K. Narendra, "Control of nonlinear dynamical systems using neural networks - Part II: observability, identification, and control", *IEEE Trans. Neural Netw.*, pp. 30-42, 1996.

[18] S. Haykin, *Kalman Filtering and Neural Networks*, Wiley, 2001.

[19] I. Daubechies, *Ten Lectures on Wavelets*, SIAM, 1992.

[20] S. Parvez and Z. Gao, "Wavelet-based multiresolution PID controller", *IEEE Trans. Ind. Appl.*, pp. 537-543, 2005.

[21] B. Kuo, *Digital Control Systems*, C.E.C.S.A., 1997.

[22] K. Astrom, *Computer-Controlled Systems, Theory and Design*, Pretince-Hall, 1997.

[23] T. Yabuta, T. Yameda, "Learning control uising neural network", Proc. of the *1991 IEEE Int. Conf. on Robotics and Automation*, pp. 740-745.

[24] R.J. Wai, J.M. Chang, "Intelligent control of induction servo motor drive via wavelet neural network", *Electr. Power Syst. Res.*, vol. 61, no.1, pp. 67-76, 2002.