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Adaptive control with composite learning for tubular linear motors with micro-metric tolerances

D. Naso, F. Cupertino, B. Turchiano, *Senior Member*

Abstract— **This paper examines an adaptive control scheme for tubular linear motors with micro-metric positioning tolerances. Uncertainties such as friction and other electro-magnetic phenomena are approximated with a radial basis function network, which is trained online using a learning law based on Lyapunov design. Differently from related literature, the approximator is trained using a composite adaptation law combining the tracking error and the model prediction error. Stability analysis and bounds for both errors are established, and a report on an extensive experimental investigation is provided to illustrate the practical advantages of the proposed scheme.**

I. Introduction

Direct-drive tubular linear synchronous motors (TLSM) are increasingly widespread in miniaturized robotics and automation applications, because the absence of mechanical reduction and transmission devices (gears, lead screws, etc.) permits to obtain higher precision, higher acceleration/deceleration, and reduced dimensions with respect to rotary actuators. However, the lack of reduction gears emphasizes the influence of other uncertainties such as friction, cogging forces and load disturbances. In particular, the compensation of these uncertainties indispensable in ultra-precise positioning systems, in which the TLSM must be able to track a position reference with micro-metric (dynamic and steady state) precision.

Existing literature can be broadly classified in two main topics, namely off-line identification and adaptive compensation. Off-line identification consists of obtaining an accurate parametric model of the phenomena of interest (friction, backlash, hysteresis, etc.) which is later incorporated in a compensation mechanism. For instance, state of art methods for friction compensation employ dynamic models such as the LuGre [3], the Leuven [16] and the Generalized Maxwell-Slip [1] models. These methods show a remarkable accuracy, but on the other hand they are often computational demanding, both in the identification [17] and in the compensation stage (since they feature one or several unmeasurable states, discretized nonlinear observers with adequate sampling times have to be implemented in the control law [3], [19]).

Moreover, there are many practical applications in which obtaining a model with the accuracy required for effective cancellation is not possible [5], since the characteristics of the phenomena of interest may vary with time, temperature, and other uncertain factors. These cases need adaptive approaches in which the uncertain phenomena are identified and simultaneously compensated online. Generally, domain-specific models (e.g., dead-zones [9], LuGre [7], [19] continuously differentiable models [11]) are adopted when exact knowledge of the remaining dynamics is available. To compensate for further residual uncertainties, literature proposes either robust-control techniques (e.g. backstepping [20]) or adaptive approaches based on universal approximators. More specifically, nonlinear approximators such as neural networks [14] or fuzzy systems [5] are considered when the system features other uncertainties as unknown payload, load forces, etc., which can be effectively captured by a joint model of all unmodeled phenomena, as for the case of the TLSM application considered in this paper.

Adaptive compensation with universal approximators relies on feedback linearization and Lyapunov design arguments, which permit to obtain robust learning algorithms [4, Section 4.6] driving tracking and parameter errors to exponentially decrease outside a compact set C. This set practically represents a theoretical lower bound for tracking performance, and reducing its size remains an open problem, not only for micrometric positioning systems. The size of C depends on a number of fundamental factors, such as the minimum functional approximation error (MFAE) guaranteed by the selected approximator, the knowledge about bounds for the uncertain terms (also necessary for stability proof), the characteristics of the parameter adaptation law, and the influence of noise and other stochastic phenomena.

Literature has investigated a number of possible strategies to refine the asymptotical behavior, each with its own merits and limitations. These include truncated Taylor series expansion to achieve adaptation of the nonlinear parameters of the approximator (e.g., [18]) or formulations in which the size of C is made inversely proportional to the learning rate [7], [14]. Unfortunately, it is difficult to exploit these strategies in micro-metric positioning systems. In fact, schemes based on Taylor expansion need to define conservative bounds for the higher order terms of the series. These bounds increase the controller gain, and consequently cause a nervous control action (the current fed to the linear drive), inducing overheating, mechanical resonances and other undesirable effects. The same considerations apply to

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The authors are with Dipartimento di Elettrotecnica ed Elettronica, Politecnico di Bari, Bari, Italy, Fax:-+39 080 5963 410 (e-mail: naso@poliba.it).

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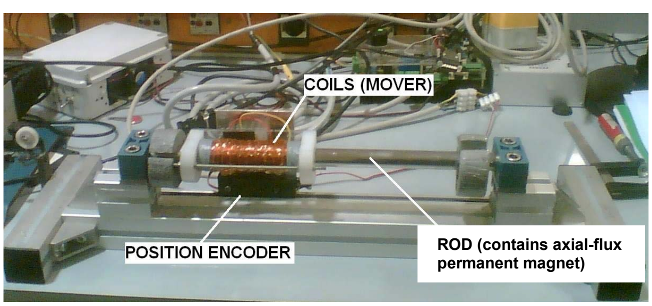
schemes requiring high learning rates. After some threshold, further increases of this parameter tends to worsen the closed loop performance or even cause instability [5].

This paper suggests a different way to overcome these problems and obtain further improvements of the tracking performance based on *composite learning laws* [15]. In contrast to adaptive compensation schemes proposed in the mentioned literature (which use learning laws only based on the tracking error), composite adaptation employs both tracking error and prediction error to guide the learning of approximator parameters. Composite adaptation should contribute to obtain faster adaptation processes which, in turn, should lead to a further reduction of the tracking error. This type of hybrid learning method has been sparsely considered in recent literature [2], [12], [13] but, to author's best knowledge, its application to nonlinearity compensation in micrometric tracking has not been explored.

The reminder of this paper is organized as follows. Section II introduces the problem and related assumptions. Section III discusses the main peculiarities arising from composite adaptation. Finally, Section IV and V summarize the experimental investigation, and the conclusive remarks, respectively.

II. Problem and Assumptions

The TLSM is a three-phase linear motor composed of a mover containing the three phase windings and a tubular rod containing the permanent magnets, as depicted in Fig.1. The permanent magnets are cylindrically shaped, axially magnetized and uniformly distributed in sequence of permanent magnets and spacers. The three-phase windings are wrapped around the rod and the mover does not contain magnetic material, so cogging forces are avoided. The motor is driven by a PWM voltage source inverter, and the i_d and i_q control loops are controlled by two identical PI controllers that make the current transients negligible with respect to the mechanical dynamics (i.e. $i_d^* = i_d = 0$ and $i_q^* = i_q = u(t)$ where asterisks denote reference signals and u indicates controller output).



Fig, 1. A prototype of tubular linear synchronous motor illustrating the main components.

The mechanical dynamics of the TLSM can be described as follows:

$$m\ddot{x} + f^*(\dot{x},t) + d^*(x,t) = k^* u(t) \quad (1)$$

where m is the overall mass of the moving equipment (sum of masses of mover and payload) $f^*(\dot{x},t)$ is the friction force, $d^*(x,t)$ is a bounded disturbance modeling nonlinear elastic forces generated by coupling and protective covers, measurement noise and other uncertainties, and k^* is the control gain (the force constant). For convenience of notation (1) can be normalized as follows:

$$\ddot{x} + f(\dot{x},t) + d(x,t) = ku(t) \quad (2)$$

where $f(\dot{x},t) = f^*(\dot{x},t)/m$, $d(x,t) = d^*(x,t)/m$ and $k = k^*/m$. We assume that k is known precisely, but the proposed adaptive scheme could be easily extended to cases in which k is unknown (e.g., due to payload changes). Finally, dropping the dependence from t and grouping the uncertain terms in a vectorial function

$$h(\underline{x}) = f(\dot{x},t) + d(x,t) \quad (3)$$

with

$$\underline{x} = \begin{bmatrix} x & \dot{x} \end{bmatrix}^T \quad (4)$$

we can rewrite (2) as

$$\ddot{x} = -h(\underline{x}) + ku \quad (5)$$

The control system must be designed so that the mover position accurately follows a smooth, differentiable reference x_d with first and second derivatives smooth and bounded. The control action must also ensure that the state and adapted parameters remain bounded. Moreover, an additional design goal is to obtain controllers with limited bandwidth because high-frequency oscillations of the current may generate excessive overheating under stressed operating conditions.

A. General assumption

Let us define the tracking error

$$e = x_d - x \quad (6)$$

and the filtered tracking error

$$e_F = \dot{e} + c_1 e + c_2 \int_0^t e(\tau)d\tau \quad (7)$$

where c_1 and c_2 are two design parameters.

Derivating (7) and using (5)-(6), we obtain

$$\dot{e}_F = \ddot{x}_d + c_1\dot{e} + c_2 e + h(\underline{x}) - ku \quad (8)$$

Since $h(\underline{x})$ is unknown, we introduce the following parametrized approximator

$$\hat{h}(\underline{x}) = \hat{\theta}^T \phi(\underline{x},\hat{\sigma}) \; . \quad (9)$$

In (9), vector $\hat{\sigma}$ indicates the parameters having a nonlinear influence on the output while $\hat{\theta}$ indicates the parameters with linear influence on the output. In this paper, we consider a radial basis function neural network (RBNN) as a function approximator, although the method could be easily implemented with any other linear-in-the-parameter approximator (see [4] for a comprehensive discussion). The RBNN is also augmented with an extra node containing a finite jump function as proposed in [5] or [14]) to better describe the typical discontinuity of the friction force around zero velocity, Similarly to most of the mentioned literature, the vector $\hat{\sigma}$ will be fixed a priori, while $\hat{\theta}$ will be subject to online learning.

For a given specified vector of parameters $\hat{\sigma}$, let us consider the *ideal parameter vector* θ^* for which a suitable norm of the residual error of approximation $\varepsilon_h = \varepsilon_h(\underline{x};\theta^*)$ of the unknown function $h(\underline{x})$ is minimum [4], and write

$$h(\underline{x}) = \theta^{*T}\phi(\underline{x}) + \varepsilon_h \tag{10}$$

Let us define the following control action:

$$u(t) = \frac{1}{k}\left(\lambda e_F + \ddot{x}_d + c_1\dot{e} + c_2 e + \hat{h}(\underline{x}) + v(t)\right) \tag{11}$$

where λ is a design parameter *v(t)* is an auxiliary control action that will be specified later on. Substituting (10)-(11) into (8) and after straightforward manipulations, we obtain the filtered error dynamics

$$\dot{e}_F + \lambda e_F = \tilde{\theta}^T\phi(\underline{x}) + \varepsilon_h - v(t) \tag{12}$$

where $\tilde{\theta} = \theta^* - \hat{\theta}$.

B. Nonlinear predictor and filtered prediction error

The prediction error is a complementary form of information that can be exploited to improve the approximation of $h(\underline{x})$. Since the acceleration is not directly available for measurement (it has to be obtained by applying twice direct differentiation of position), it is convenient to adopt a filtered prediction scheme [2], [4]. Let us define the *predicted acceleration* as the output of the following filtered estimator

$$\dot{\hat{\dot{x}}} = -\alpha\hat{\dot{x}} - \alpha\dot{x} - \hat{h}(\underline{x}) + ku(t) \tag{13}$$

in which $\hat{\dot{x}}$ is the predicted velocity, and α is a positive user defined constant. Moreover, let us introduce the *filtered prediction error*

$$e_P = \hat{\dot{x}} - \dot{x}\,. \tag{14}$$

in which $\dot{x}$ is the measured speed. It has to be noted that also the measured speed is obtained from direct differentiation of the position, so the filtered estimator is mainly introduced to avoid the need of performing this operation twice. Finally, differentiating (14), and using (5) and (13) we obtain

$$\dot{e}_P + \alpha e_P = \tilde{\theta}^T\phi(\underline{x}) + \varepsilon_h \tag{15}$$

in which the similarity with (12) can be easily observed.

C. Learning Laws

The parameter adaptation laws are based on Lyapunov design arguments. The main result is summarized in the following theorem.

Theorem 1. *Consider the system (1) with the control given by (11), the parameter update rule*

$$\dot{\hat{\theta}} = \gamma\phi(\underline{x})e_A - \nu\hat{\theta}\,, \tag{16}$$

and the auxiliary control term

$$v(t) = \rho e_P\,, \tag{17}$$

where $e_A = e_F + \rho e_P$ *is the augmented error,* γ, ν *and* $\rho < 2\alpha$ *are three positive design constants.*
Then, the tracking error e, the filtered errors e_F *and* e_P *and the approximator parameters* θ^* *are Uniformly Ultimately Bounded (UUB).*

The proof is in the appendix.

III. Discussion of Design Issues

The proposed adaptive scheme has some peculiarities with respect to other approximation-based compensators described in literature [7], [8], [14]. First, it can be noted that the filtered error (7) includes an integral term, which makes the control action in (11) interpretable as a PID control augmented with further compensation terms. The use of an integral action in positioning systems subject to friction has been frequently discussed. Some papers [7],[8] consider the integral action counterproductive in micro-metric positioning systems due to the risks of limit cycles (the so-called *hunting effect*). On the contrary, recent studies [6] have confirmed that under proper tuning the integral term does not induce limit cycles, and is useful to guarantee a zero steady state error also under the effects of disturbances. For this reason, it has been introduced in (7).

Clearly, the integral action makes the filtered error e_F nonzero (and consequently may force the approximator parameters to change) even when both tracking and prediction errors are zero. Therefore, in order to prevent an excessive parameter drift, an adequate joint tuning of the gains ν and γ in adaptive law (16) (also known as *sigma-modification* [4]) is necessary in our scheme (see Fig.5).

Another important issue regards the inclusion of the prediction error in the adaptation law. It can be noted that the stability proof in the appendix leads to exponential bounds for the tracking and prediction error that are not decreasing for higher learning rates (in contrast to what is obtained in [7] and [14]). In other words, since the term d_2 in (25)-(27) contains the factor $\gamma\varepsilon_h^2/2$, we cannot claim that higher learning rates determine better asymptotical performance. However, also this aspect should not be considered a shortcoming, because various studies (see next section or [5]) confirm that the learning rate cannot be set arbitrarily large in practical implementations. For this reason, even if it would be possible to make the asymptotical bounds of our approach inversely dependent from the learning rate (e.g., the adaptive bounding scheme in [7]), we do not consider their application useful to further enhance the precision of our control scheme.

It can be also noted that our approach uses the direct differentiation of the position as the velocity signal. This issue has also been frequently discussed in literature on precision motion control, and various types of observers have been proposed to obtain smoother velocity measures. It has to be mentioned that an experimental investigation has shown that a velocity observer does not improve the quality of the tracking of the TLSM. On the contrary, an empirical comparison showed that the inherent limited noisiness of the signal obtained by direct differentiation may be even beneficial, as it acts as a form of additional dithering [21] contrasting the effects of static friction.

IV. Experimental Results

The experimental tests are performed on single degree of freedom linear positioning system with a TLSM having the following rated specifications: rated isq current 4A, R=4.9Ω, L=1.15mH, mass of the mover 2.75kg. In all the experiments reported in this paper, the maximum q-axis current has been limited to the rated current. The adaptive control algorithms are executed on a dSPACE 1104 board based on a 250 MHz Motorola Power PC microprocessor, which discretizes the continuous-time control laws with Euler method and a sampling time T_s=250 μs. The output provided by the control board is a voltage signal acting as reference for the current control loop. The position of the linear drive is measured with an encoder having a resolution of 1.25μm.

The reference trajectories (see Fig.2) are obtained by filtering a repeating sequence of variable amplitude steps with a nonlinear filter that shapes its output so as to keep the maximum speed and acceleration within the selected limits [10]. In our experiments, the maximum acceleration is 4m/s^2 and the maximum speed is 0.5m/s. The approximator is a RBNN with 20 neurons. Inputs are normalized with respect to their maximum values and the radial basis functions are uniformly spread in the square [-1,1]×[-1,1]. The remaining configuration parameters are empirically chosen as follows: λ=100, γ=0.2, ρ=0.2, α=20.

The left-hand side of Fig. 3 shows the typical performances of a well-tuned linear PID controller. Without nonlinear compensation, the tracking precision is generally below 50 μm (with the error peak occurring during the longest moves), and the steady state error during constant references is not eliminated. The feedforward compensation contributes to obtain a smoother tracking performance, but the amplitude of errors remains almost unvaried. The performance of a standard adaptive compensation scheme (with a RBNN approximator and a learning law based only on the tracking error) is shown in the right-hand side of Fig.3. The tracking performance is significantly improved with respect to PID controllers, with a position error peak below 25μm and a zero steady state error. Increasing the learning rate does not produce further enhancements of the tracking performance, but generates nervous, oscillatory responses.

Fig.4 shows the position and speed tracking achieved with composite adaptation. The peak of tracking error is nearly 50% lower than the case of learning based on filtered tracking only. Fig.5 shows that in spite of the integral term in the filtered error, the parameters reach a trend with constant average once learning is completed. Finally, the response to sinusoidal references is used to evaluate the characteristics of the control action. Fig.6 shows the RMS of the control action (applied current) during tracking of sinusoidal waves of increasing frequencies, obtained with standard and composite adaptation laws. For each law, we used the learning rate corresponding to the best tracking performance. It can be easily noted that composite adaptation has also a generally lower RMS current effort, and thus a higher overall efficiency.

V. Conclusions

This paper proposed an adaptive compensation scheme for linear actuators with micro-metric positioning tolerances. The uncertainties are approximated with a radial basis function network, which is trained online by a learning law combining the tracking error and the model prediction error. The injection of the filtered prediction in the adaptation signal leads to an improvement of about 50% in terms of reduction of error peak for a single DOF axis. The extension of the method to MIMO and multi-DOF systems, the adoption of self-organizing approximators with adaptive and problem-specific structures, and a deeper investigation of the sensitivity of performances with respect to the design parameters are among the subjects of ongoing research.

Appendix

Proof of Theorem 1.

Let us consider the following Lyapunov candidate function

$$V(e_F, e_P, \tilde{\theta}) = \frac{\gamma}{2} e_F^2 + \frac{\gamma\rho}{2} e_P^2 + \frac{1}{2} \tilde{\theta}^T \tilde{\theta} \quad (18)$$

The derivative of V is:

$$\dot{V}(e_F, e_P, \tilde{\theta}) = \gamma e_F \dot{e}_F + \gamma\rho e_P \dot{e}_P + \tilde{\theta}^T \dot{\tilde{\theta}} =$$
$$= \gamma e_F \left(-\lambda e_F + \tilde{\theta}^T \phi(\underline{x}) + \varepsilon_h - v(t) \right)$$
$$+ \gamma\rho e_P \left(-\alpha e_P + \tilde{\theta}^T \phi(\underline{x}) + \varepsilon_h \right) + \tilde{\theta}^T \dot{\tilde{\theta}} =$$
$$= -\gamma\lambda e_F^2 + \gamma\tilde{\theta}^T \phi(\underline{x}) e_F + \gamma e_F \varepsilon_h - \gamma e_F v(t) - \gamma\alpha\rho e_P^2 \quad (19)$$
$$+ \gamma\tilde{\theta}^T \phi(\underline{x}) \rho e_P + \gamma\rho e_P \varepsilon_h + \tilde{\theta}^T \dot{\tilde{\theta}} =$$
$$= -\gamma\lambda e_F^2 - \gamma\rho\alpha e_P^2 + \tilde{\theta}^T \left(\gamma\phi(\underline{x}) e_A + \dot{\tilde{\theta}} \right)$$
$$+ \gamma e_A \varepsilon_h - \gamma e_F v(t)$$

Using (16) and since $\dot{\tilde{\theta}} = -\dot{\hat{\theta}}$ we obtain

$$\dot{V}(e_F, e_P, \tilde{\theta}) = -\gamma\lambda e_F^2 - \gamma\alpha\rho e_P^2 + \nu\tilde{\theta}^T \hat{\theta} + \gamma e_A \varepsilon_h - \gamma e_F^8 v(t) \quad (20)$$

Using the following inequality

$$\tilde{\theta}^T \hat{\theta} \le -\frac{1}{2} \tilde{\theta}^T \tilde{\theta} + \frac{1}{2} \theta^{*T} \theta^* \quad (21)$$

we obtain

$$\dot{V}(e_F, e_P, \tilde{\theta}) \le -\gamma\lambda e_F^2 - \gamma\alpha\rho e_P^2 - \frac{1}{2} \nu\tilde{\theta}^T \tilde{\theta}$$
$$+ \frac{1}{2} \nu\, \theta^{*T} \theta^* + \gamma e_A \varepsilon_h - \gamma v(t) e_F$$
$$\le -\gamma\lambda e_F^2 - \gamma\alpha\rho e_P^2 - \frac{1}{2} \nu\tilde{\theta}^T \tilde{\theta} + \frac{1}{2} \nu\, \theta^{*T} \theta^*$$
$$+ \frac{\gamma}{2} \varepsilon_h^2 + \frac{\gamma}{2} e_A^2 - \gamma v(t) e_F \quad (22)$$
$$= -\gamma\lambda e_F^2 - \gamma\alpha\rho e_P^2 - \frac{1}{2} \nu\tilde{\theta}^T \tilde{\theta} + \frac{1}{2} \nu\, \theta^{*T} \theta^*$$
$$+ \frac{\gamma}{2} \varepsilon_h^2 + \frac{\gamma}{2} e_F^2 + \frac{\gamma}{2} \rho^2 e_P^2 + \gamma\rho e_F e_P - \gamma v(t) e_F.$$

Using (17) we obtain

$$\dot{V}(e_F, e_P, \tilde{\theta}) \le -\gamma(\lambda - \tfrac{1}{2}) e_F^2 - \gamma\rho(\alpha - \frac{\rho}{2}) e_P^2 - \frac{1}{2} \nu\tilde{\theta}^T \tilde{\theta}$$
$$+ \frac{1}{2} \nu\, \theta^{*T} \theta^* + \frac{\gamma}{2} \varepsilon_h^2 + \gamma\rho e_F e_P - \gamma v(t) e_F \quad (23)$$
$$= -\gamma(\lambda - \tfrac{1}{2}) e_F^2 - \gamma\rho(\alpha - \frac{\rho}{2}) e_P^2 - \frac{1}{2} \nu\tilde{\theta}^T \tilde{\theta}$$
$$+ \frac{1}{2} \nu\, \theta^{*T} \theta^* + \frac{\gamma}{2} \varepsilon_h^2.$$

Finally, introducing

$$d_1 = \min\left\{ 2\lambda - 1, 2\alpha - \rho, \nu \right\} \quad (24)$$

$$d_2 = \frac{1}{2} \nu\, \theta^{*T} \theta^* + \frac{1}{2} \gamma \varepsilon_h^2 \quad (25)$$

we obtain $\dot{V} \le -d_1 V + d_2$. Therefore, using standard arguments [4, Appendix A] we obtain

$$V(t) \le \left(V(0) - \frac{d_2}{d_1} \right) e^{-d_1 t} + \frac{d_2}{d_1} \quad (26)$$

Thus, for every $\mu > \frac{d_2}{d_1}$ there exists a time T_μ such that for all $t \ge T_\mu$ we have $V(t) \le \mu$.

Moreover, since $V \ge \frac{\gamma}{2} e_F^2$, we obtain

$$| e_F | \le \sqrt{ \frac{2}{\gamma} \left(V(0) - \frac{d_2}{d_1} \right) e^{-d_1 t} + \frac{2}{\gamma} \frac{d_2}{d_1} }. \quad (27)$$

Similar bounds can be found for e_P and $\tilde{\theta}$ with an analogous procedure.

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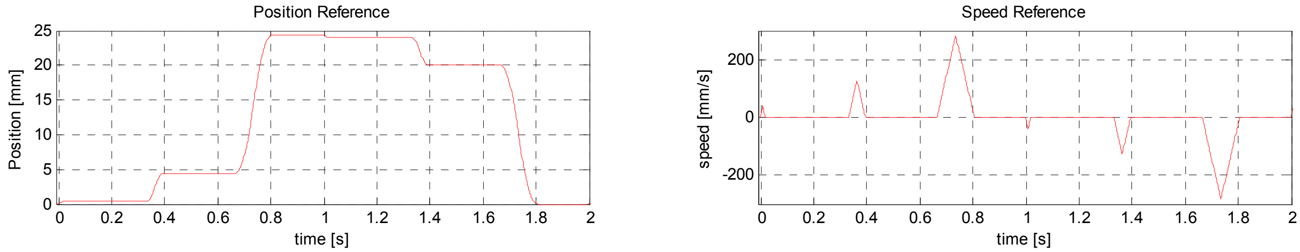

Fig. 2. The first period of position and speed references, obtained with the filter described in [10]

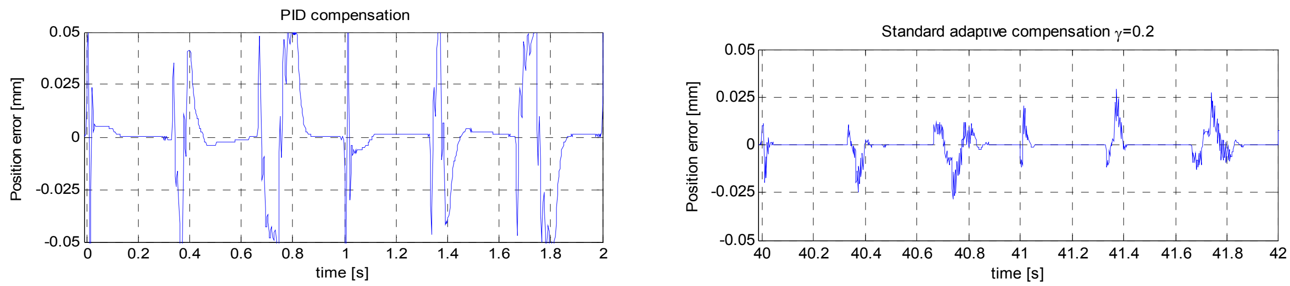

Fig.3. Position tracking performance of a well-tuned PID, and of a standard adaptive compensation.

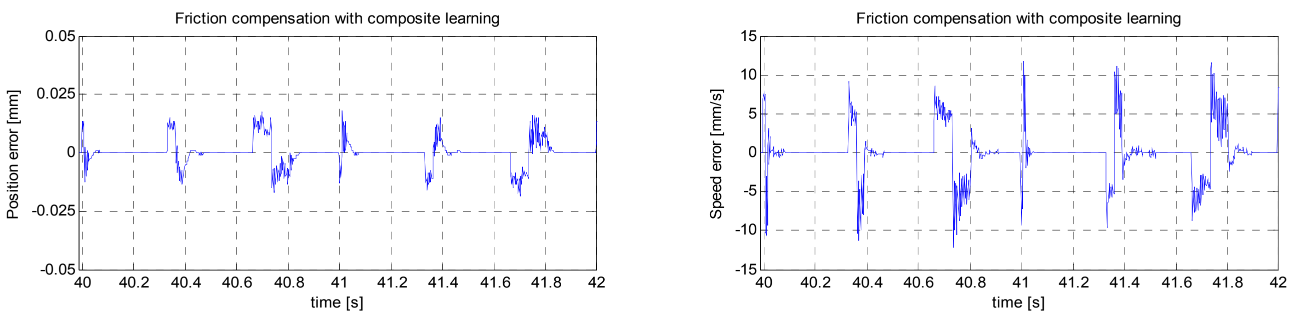

Fig. 4. Position and speed tracking error with composite learning laws. The peaks of the tracking error is nearly 50% smaller than in the case of tracking-error based learning.

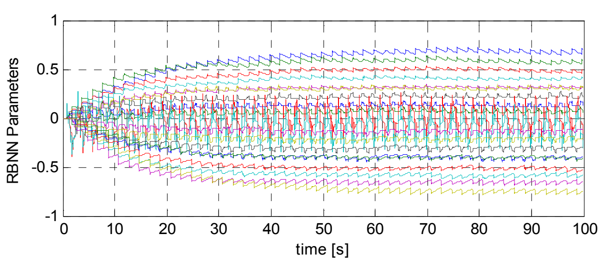

Fig. 5. Evolution of the adapted parameters of RBNN.

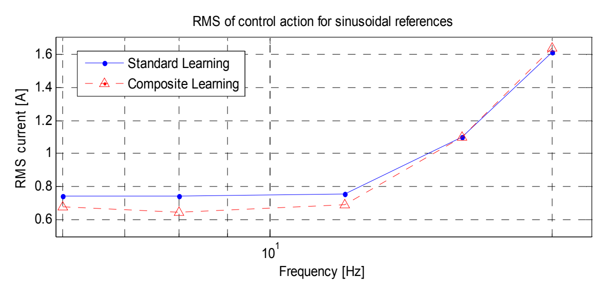

Fig. 6. RMS of control action for sinusoidal references Fig. 7..

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