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ROBOT MANIPULATOR JOINT CONTROL WITH NEURO-FUZZY FRICTION COMPENSATION

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Abstract. *The main objective of this paper is to propose a new friction compensation mechanism applied to robotic actuators. Friction is a phenomenon that changes with time and with actuator's operational conditions. To deal with these parameters variations, it is proposed a neuro-fuzzy algorithm for friction identification and compensation. A Neural Network (NN) was trained off line. The NN output (compensation friction torque) is multiplied by a gain, obtained with a Fuzzy inference algorithm, to deal with friction parameters variations and to adjust the compensation torque. Simulation results showed good performance, indicating that the actuator becomes approximately linear.*
Keywords: *Friction, compensation, neural networks, fuzzy systems, robotic actuators.*

1. Introduction

At present, there are many applications of neural networks (NN) in the science domain (Jung and Hsia (1998), Kaynak, O. and Ertugru, M. (1997)). This subject has been object of great attention of the scientific community. In Miller *et al.* (1995), for instance, there is an important description of the history of the so-called neural networks.

This paper investigates the identification of the friction torque of a geared motor drive joint robotic actuator using neural networks. The main motivation is the difficulty in obtaining a very realistic drive joint dynamic model mainly due to the internal non-linear friction characteristics of the actuators (Armstrong (1988)). In spite of NN application in robotic been relatively old (approximately fifteen years ago), NN applications to drive joint non-linear friction estimation are more recent. Dapper *et al.* (1999), proposed an hybrid force-position control to the 6 DOF manipulator robot. Using a neural network, they estimated the dry friction of the actuators, and showed with simulations improvements in the efficiency of the hybrid control for slow movements of the end-effector. Selmic and Lewis (2000) tested, with simulations, the possibility of a NN to learn the friction torque given by a representative friction model. In the present work, it is verified that a NN shows good results. However, the NN compensation performance decays with time, due to the friction parameters variations. Because of this, it is proposed a fuzzy inference system to deal with this problem. Experimental results showed good performance, as it will be seen in the next sections.

Neuro-Fuzzy systems have been developed to many science and technological applications, mainly from the last twenty years (Jung and Hsia (1998)). It has been seen that the evolution of a determined intelligent systems is neuro-fuzzy computing: NN recognizes patterns and fuzzy inference systems incorporates human concepts. The present work shows an effort, using a neuro-fuzzy system, to eliminate non-linear friction torque acting into a harmonic-drive robotic actuator.

2. The drive joint robotic actuator

A geared motor drive joint robotic actuator can be visualized as a motion transmitter element containing an internal elasticity of constant K, as represented in Fig. 1. The motor torque T_m is applied to the rotor with inertia I_r. Non-linear frictions are always present in this kind of dynamics, making no integral transmission of the motor torque to the load inertia I_s coupled at the gear output axis. The Eq.(1) describes the dynamic of this system (Gomes and Chrétien (1992)). T_{at} is the non-linear friction torque (Gomes and Rosa, (2003)), θ_r and θ_s are respectively the rotor and load angular positions, and n is the gear ratio.

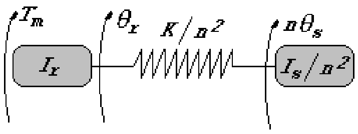


Fig. 1. Representation of a geared motor drive joint robotic actuator.

$$
\begin{aligned}
& I_r\,\ddot{\theta}_r + \frac{K}{n^2}\left(\theta_r - n\theta_s\right) = T_m - T_{at} \\
& I_s\,\ddot{\theta}_s - K\left(\frac{\theta_r}{n} - \theta_s\right) = 0
\end{aligned}
\tag{1}
$$

To train NN it is necessary to create training patterns. As it will be seen later, these patterns can be generated by experimental identification of the friction torque using different motor torques in open and closed loops. However, the model given by the Eq.(1) is not convenient for friction identification because of the internal elasticity. Since the elastic constant for the geared motor drive joint is usually high, a rigid approximation is acceptable for experimental friction torque identification purposes. The model for friction torque identification is simplified to the form:

$$\left(I_r + \frac{I_s}{n^2} \right) \ddot{\theta} = T_m - T_{at} \tag{2}$$

In order to identify experimentally the non-linear friction torque (T_{at}), it is necessary to know the rotor and load inertias, the gear ratio, the angular rotor acceleration and the motor torque. It is important to point out that the experimental friction torque identified using Eq. (2) is not the most realistic one, since the internal elasticity was neglected. As it was shown by Taghirad and Bélanger (1996), the harmonic drives are sources of non-linear friction and compliance. Effectively, compliance appears mainly with locked load experiments. Experimental results in this situation show that there is an hysteretic behavior, related to the internal elasticity and friction. However, for free motion of the actuator output axis, the model approximation given in Eq. (2) may be assumed for friction identification.

3. The friction model

The friction model used in this work was proposed by Gomes and Rosa (2003). Several constant electromagnetic torques were applied to the rotor of an harmonic-drive, with a rigid load coupled at the output axis. The rotor velocity was measured to each motor torque level. Since there are no others external torques, for each stationary velocity, the friction torque is equal to the applied motor torque. A set of rotor velocities and friction torque points were then obtained experimentally and they were fitted by two polynomial equations, each one for a specified rotation sense (Fig. 2). These polynomial equations are:

$$T_{at} = f_i + f_{vi}\dot{\theta} + c_i\dot{\theta}^2 \tag{3}$$

i may be p or n for positive or negative rotor velocity. The identified parameters are the following:

$f_p = 0.177649 Nm$; $f_n = -0.173692 Nm$;

$f_{vp} = 0.256339 Nm/rd/s$; $f_{vn} = 0.236330 Nm/rd/s$;

$c_p = -0.059613 Nm/rd^2/s^2$; $c_n = 0.047777 Nm/rd^2/s^2$

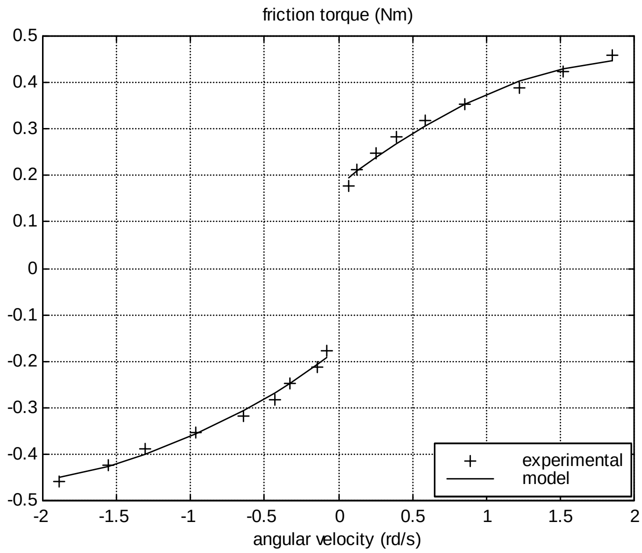


Fig. 2 Friction torque: experimental and model.

The friction model used in this work has mainly two objectives: to write the friction torque in the differential equation as an internal dynamic effect, instead of as an external torque; to reproduce the stick-slip modes by friction's trajectories conception in the stiction region (velocity near zero).

The friction torque is written, as an internal dynamic effect, in the form:

$$T_{at} = f_v^* \dot{\theta} \tag{4}$$

f_v^* is the variable viscous friction coefficient. In order to T_{at} represents the friction's trajectories, the value of f_v^* has to be obtained in the form indicated by the algorithm (7). To use this algorithm, it is important to assure that the rotor velocity will be inside the interval of positive and negative velocities limits that generated Fig. 2. T_{res} is the resulting torque through the drive joint, that can be evaluated from the equation:

$$T_{res} = T_m - T_l = T_m - K\left(\frac{\theta_r}{\eta} - \theta_s\right) \tag{5}$$

where T_l is the load torque. If there is no load contact or load torque (gravitational, for example) and the drive joint is approximately rigid, T_{res} is equal to T_m. $\dot{\theta}_{\lim}$ is the smallest possible stationary rotor velocity in open loop, measured as 0.07 *rd/s*. $f_s^* = 0.93(f_p - f_n)/2$ (93% of the averaged dry friction) and $f_{\lim}$ is the largest value that can be assumed by the variable viscous friction coefficient (final stick trajectory before the zero velocity), given by the equation:

$$f_{\lim} = \left|\frac{f_i + c_i\dot{\theta}_{st}^2}{\dot{\theta}_{st}}\right| + f_{vi}\,, \tag{6}$$

where $\dot{\theta}_{st} = \gamma\dot{\theta}_{\lim}$. It was used $\gamma = 0.025$ meaning that $\dot{\theta}_{st}$ was considered 2.5% of the smallest possible stationary rotor velocity in open loop. Physically, $\dot{\theta}_{st}$ is the smallest rotor velocity and below this value, there is only micro elastic displacements between materials at a microscopic level (presliding displacement).

if $\left|\dot{\theta}\right| \geq \dot{\theta}_{\lim}$ then

$f_v^* = \dfrac{f_i + c_i\dot{\theta}^2}{\dot{\theta}} + f_{vi}$; {outside of stick-slip}

else

<u>if</u> $\left|T_{res}\right| > f_s^*$ then

$f_v^* = \dfrac{f_i + f_{vi}\dot{\theta}_{\lim} sign(\dot{\theta}) + c_i\dot{\theta}_{\lim}^2}{\dot{\theta}_{\lim} sign(\dot{\theta})}$;{slip trajectory}

else

if $\dot{\theta} = 0$ then

$\dot{\theta} = eps$; {1e-10, for example} (7)

endif;

$f_v^* = \dfrac{f_i + c_i\dot{\theta}^2}{\dot{\theta}} + f_{vi}$; {stick trajectory}

if $f_v^* > f_{\lim}$ then

$f_v^* = f_{\lim}$; {final stick trajectory}

endif;

endif;

endif;

The model presented here was obtained for a motor drive joint with harmonic drive and gear ratio $n = 100$, but the used modeling process can be applied to any motor drive joint of robots. Physical reasons and more details are given in Gomes and Rosa (2003).

4. NN architeture

The NN architecture proposed to learn the friction torque is a multi-layer fully connected feed-forward network (Gervini *et al.* (2003), Beale and Jackson, (1991)) using back propagation with momentum (Fausett (1994)) as training rule. The input layer is composed with two neurons (motor torque and rotor velocity) and the output layer is composed by one neuron (friction torque).

After testing several feed-forward network configurations to identify a configuration able to learn and to reproduce the training patterns with minimum neurons, it was verified that a neural network with only one intermediate layer and with only four neurons in this layer is sufficient to reproduce the training patterns. Fig. 3 shows the architecture of the proposed NN.

The neuron architecture is showed in Fig. 4, where it was used a sigmoidal activation function (tanh). After training, the NN reproduced the training patterns with 98% of accuracy.

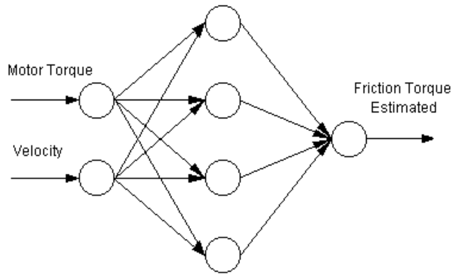


Fig. 3. NN architecture.

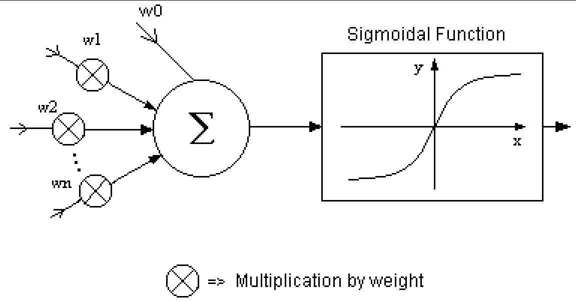


Fig. 4. Neuron architecture.

5. NN training pattrerns

Many simulations were performed and in all of them the friction torque was obtained through the model given in (2). These simulations were made in open and closed loops and the obtained friction torque data were used as patterns for the NN training process, as can be seen in Fig. 5. The friction torque obtained through the model simulation (red in Fig. 5) is used as training patterns. Fig 5 shows also the friction torque recognized by the NN. It can be seen that the accuracy is really high. It is interesting to note that the experiments were accomplished with a great variety of motor torques, in open and closed loops. The diversification of the proposed training patterns was important to the NN generalization. Only four neurons, in just one hidden layer, showed good generalization into the envelope of training patterns limited by the actuator maximum torque. Outside this envelope effectively there is no generalization.

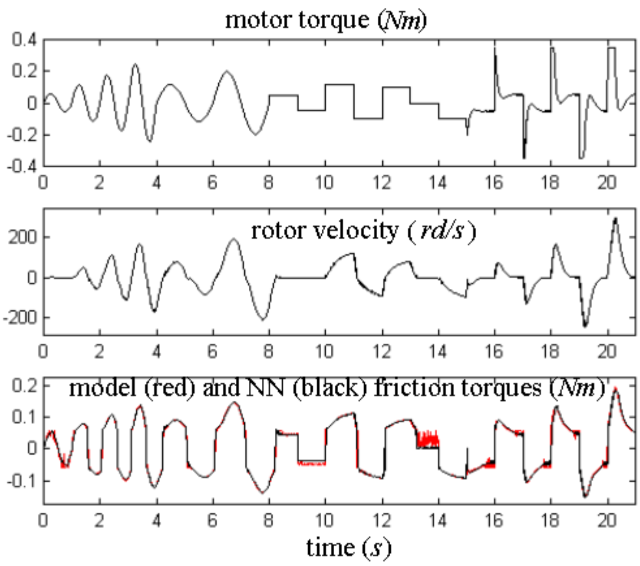


Fig. 5. Motor torque, rotor velocity and friction torque.

6. Fuzzy inference system

In the tribology domain, it is a consensus to admit friction parameters variation. The main causes are associated with material and operating conditions of the actuators. There is also a dependence related to the gear output axis angular position and changes in the load inertia. These parameters variations may decrease the performance of the NN friction compensation. However, it was verified that it is not necessary to train the NN again to guarantee a good performance, but just to multiply its output signal by a gain (*g*). For smoothly reference position trajectory (showed in Fig. 9), the final stationary error is due to a bad friction compensation. This error becomes input in the fuzzy system and returns the gain *g* as output. Fig. 6 shows a synthesis of the fuzzy system, which uses the linguistic variables showed in Table I.

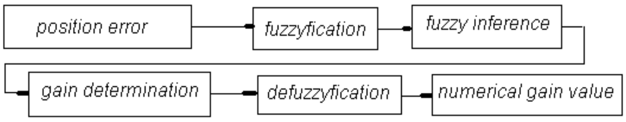


Fig. 6. Fuzzy logic system.

TABLE I. Linguistic variables.

abs(error) (fuzzy input)	gain (fuzzy output)
VH => Very High	VH => Very High
H => High	H => High
M => Medium	M => Medium
S => Short	S => Short
Z => Zero	N => Nominal

Triangular membership functions were used, as showed in Fig. 7, where *N* corresponds to the nominal gain. After many simulations, the limit values of the membership function that produce stable responses and good performance were identified, as showed in Table II.

TABLE II Membership functions limit values.

e_1	0.05°	w_1	1.05
e_2	0.3°	w_2	1.1
e_3	0.5°	w_3	1.15
e_4	0.7°	w_4	1.2
e_5	1°	w_5	1.25

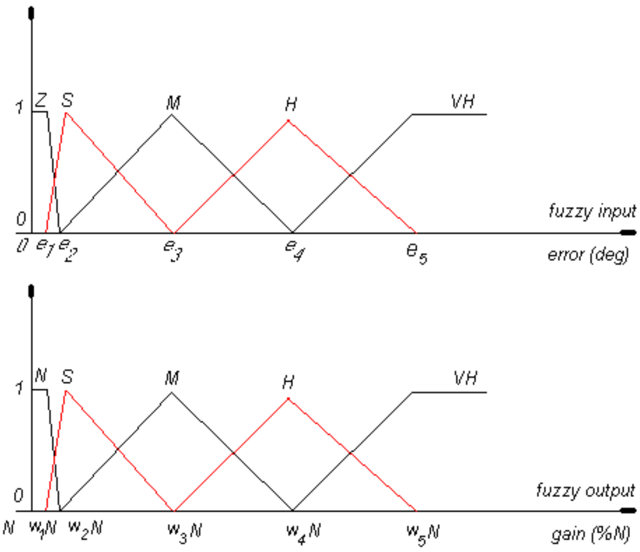


Fig. 7. Input and output membership functions.

Considering the steady state trajectory track error as the difference between reference and gear output axis angular position,

$$e = \theta_{ref} - \theta \tag{8}$$

the following algorithm composes the if then rules, which is applied after each track position:

$$if\ \ f\left(e, q_{ini}, q_{fin}\right) < 0,\ w_i = 2 - w_i;\ end, \tag{9}$$
$$i = 1,2,\ldots,5\ .$$

$$
\begin{aligned}
& if\ |e| = Z, g = N; \\
& \quad elseif\ \ |e| = S, g = S; \\
& \quad\quad elseif\ |e| = M, g = M; \\
& \quad\quad\quad elseif\ |e| = H, g = H; \\
& \quad\quad\quad\quad else \\
& \quad\quad\quad\quad g = VH; \\
& \quad\quad\quad end, \\
& \quad\quad end, \\
& \quad end, \\
& end,
\end{aligned} \tag{10}
$$

$$N = g; \tag{11}$$

To start fuzzy process requires an initial knowledge of the nominal gain *N*, which may be equal to 1 (just NN output is considered initially). Equation (9) is required to prevent over compensation and to guarantee the convergence process. $f\left(e, q_{ini}, q_{fin}\right)$ is a function of the error and initial and final reference positions, that identifies if the angular position exceeded the reference one (over compensation situation) at the steady state. It is important to note that after each gain evaluation (algorithm (10)), the nominal gain variable is brought up to date with (11). Another important point is that it is considered a different gain (*g*) to each actuator rotation sense.

7. Compensation mechanism and simulations

The proposed friction compensation mechanism is very efficient, in spite of being simple. It consists of a direct rejection of the friction estimated by NN multiplied by the estimated fuzzy gain (g). The motor torque in k+1 instant has the form:

$$T_m\left(k+1\right) = T_c\left(k\right) + g\hat{T}_{at}\left(k\right) \tag{12}$$

$T_c\left(k\right)$ is the control torque, i.e., the effectively desired torque to be applied at *k* instant, assuming an actuator without friction. $\hat{T}_{at}\left(k\right)$ is the estimated non-linear friction (NN output), with the rotor velocity $\dot{\theta}_r\left(k\right)$ and motor torque $T_m\left(k\right)$ as NN input. If there is load torque (gravitational or contact torques, for example), NN input torque may be the applied resulting torque in the actuactor.

It was used a proportional and derivative control meaning that in (12), $T_c\left(k\right)$ is a simple PD control.

Fig. 8 shows simulations with and without friction compensation. It is evident the good performance obtained with the NN friction compensation, avoiding the great steady-state error. To test the fuzzy algorithm, a variation in the static friction on the order of twenty percent was imposed. This means that the plant was considered as having the friction torque 20% greater than that one of the nominal model. At first, it was considered *N*=*g*=1 in the fuzzy algorithm (Fig. 9) and a significant steady-state error remains. For each repetition of the track position trajectory, a new fuzzy gain is calculated and the steady-state error becomes less significant. After six trajectories, there is no more fuzzy gain variation and the friction compensation performance is reestablished, as can be seen in the last graphic of the Fig. 9. The fuzzy gain grows up from 1 to 1.1991, in order to compensate the imposed friction parameter variation.

8. Conclusions

This work proposes a new strategy to implement friction compensation with application to robotic actuators. The main motivation to this new proposition started from the results obtained with only a neural network (NN) friction compensation. In reason of time variations of the friction parameters, the performance of the NN compensation decreases. For instance, if the actuator remains off during one week, the performance may be not the same in relation to that one previously obtained. However, it was verified that the performance is reached again adjusting a gain that multiplies de NN output. It can be concluded that the NN actually learned the behavior of the friction phenomenon and only the torque dead zone changed significantly with time. Therefore, it was projected a fuzzy inference system only to identify this gain and to deal with time variations of the friction parameters. Others conclusions are summarized below related to the proposed neuro-fuzzy friction compensation mechanism:

- there is a large NN generalization (into the learn enveloppe limited by the actuator maximum motor torque) due to the training strategy and to the chosen net structure;
- simplicity of the proposed net structure, which means a great economy in terms of processing time in real implementations;
- the proposed mechanism turns the actuator approximately linear;
- the structure fuzzy is very simple and appears to be an excellent approach to deal with time variation of the friction parameters.

The continuation of the research initiated at the present work will deal with the experimental validation in an harmonic-drive actuator and a posterior implementation, in real time, of the neuro-fuzzy friction compensation mechanism in a 6 dof rigid robot manipulator.

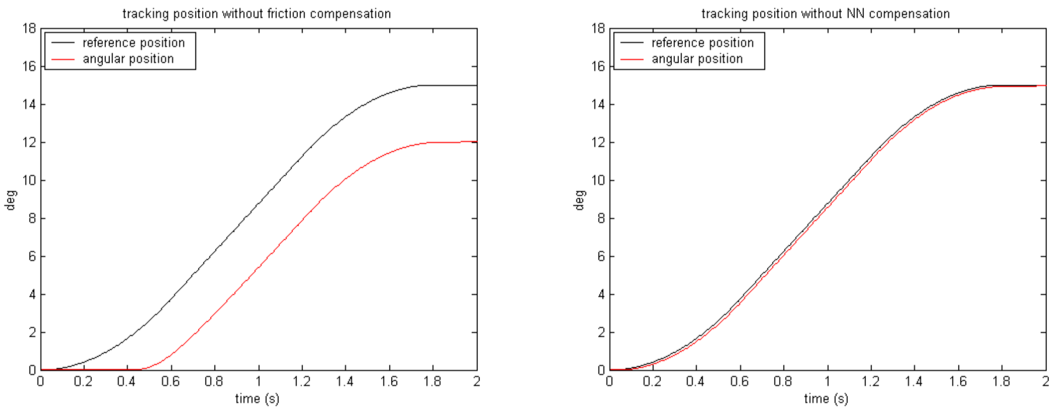


Figure 8. Tracking position control without friction compensation and with NN friction compensation.

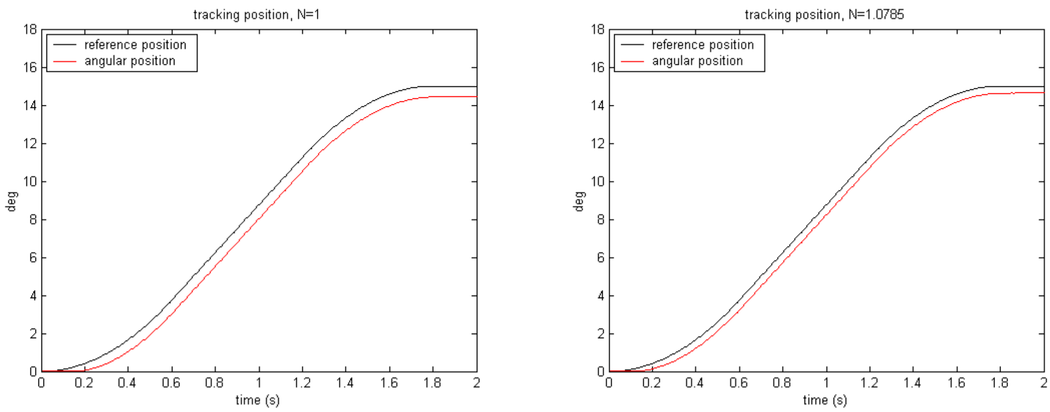
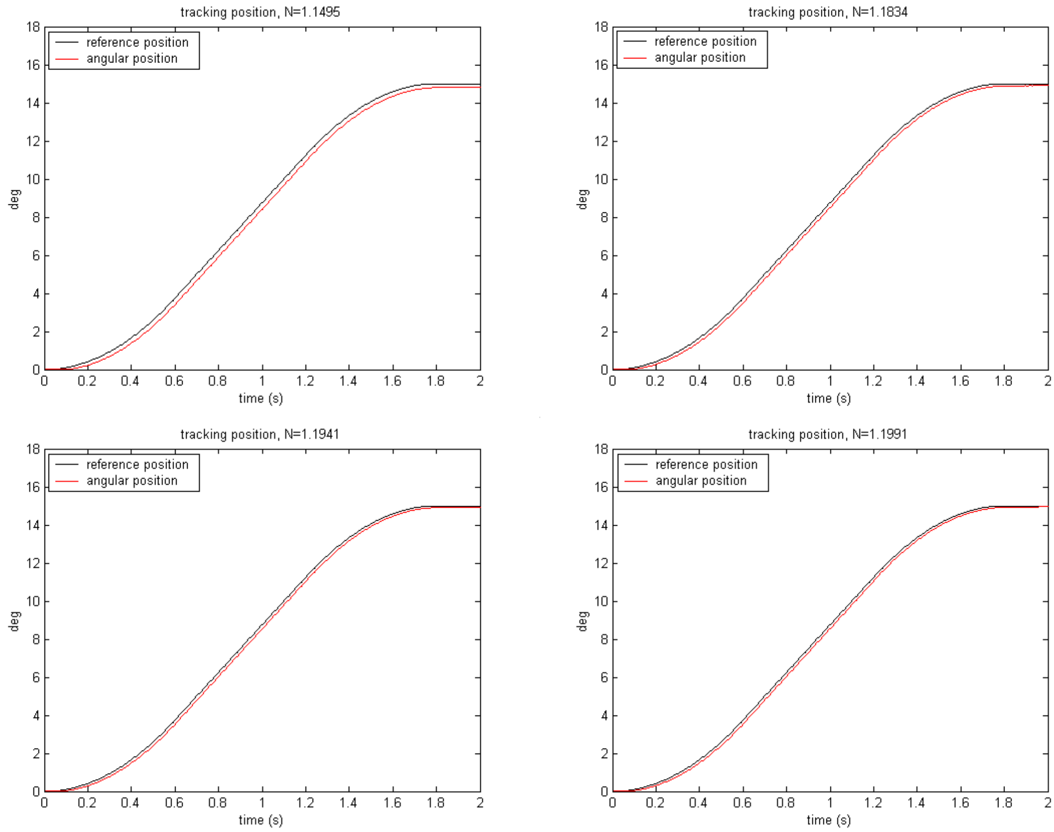


Figure 9. Application of the fuzzy algorithm to compensate friction parameter variation.



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