Robot Manipulator 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, and to confirm it through experimental results. 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. Experimental results showed good performance, indicating that the actuator becomes approximately linear.

Resumo. O principal objetivo do presente artigo é propor um novo mecanismo de compensação de atrito aplicado a atuadores robóticos e ainda, testa-lo a partir de resultados experimentais. O atrito é um fenômeno que varia com o tempo e com as condições operacionais do atuador. Para lidar com tais variações, está sendo proposto um algoritmo neuro-fuzzy para a identificação e a compensação do atrito. Uma rede neural artificial (RNA) foi treinada off line. A saída da RNA (torque de compensação do atrito) é multiplicada por um ganho, obtido a partir de um algoritmo fuzzy, a fim de lidar variações nos parâmetros do atrito e ajustar o torque de compensação. Resultados experimentais mostraram um bom desempenho, indicando que o atuador tornou-se aproximadamente linear.

1. Introdução

At present, there are many applications of neural networks (NN) in the science domain (Jung and Hsia (1998), Kaynak, O. and Erçok, 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, confirmed by experimental results.

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 equation (1) describes the dynamic of this system (Gomes and Chrétien (1992)). $T_m$ is the non-linear friction torque (Gomes and Rosa, (2003)), $\theta_r$ and $\theta_s$ are respectively the rotor and load angular positions, and $n$ is the gear ratio.

\[
I_r \ddot{\theta}_r + \frac{K}{n^2} (\theta_r - n \theta_s) + F_r = T_m \\
I_s \ddot{\theta}_s + K \left( \frac{\theta_r}{n} - \theta_s \right) + F_s = 0
\]  

(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 equation (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:

\[
\left( I_r + \frac{I_L}{n^2} \right) \ddot{\theta} = T_m - T_{at}
\]  

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 equation (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 hysteresis behavior, related to the internal elasticity and friction. However, for free motion of the actuator output axis, the model approximation given in equation (2) may be assumed for friction identification.

3. NN architecture

It was used the NN structure proposed in (Gervini et al., 2003). 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 capable to learn and to reproduce the training patterns with a minimum neurons, it was verified that a neural network with only one intermediate layer and with only four neurons in this layer were sufficient to reproduce the training patterns. Fig. 2 shows the architecture of the proposed NN. Many experiments were performed, and in all of them the experimental friction torque was obtained through the model described by the equation (2). These experiments were made in open and closed loops and the obtained friction torque data were used as patterns for the NN training process.

An initial difficulty was to measure the experimental acceleration. The angular acceleration was found as follows. At first, the rotor velocity was obtained through online time position (encoder) derivative, generating a rotor velocity with a certain noise. This signal was then filtered by a least square sixth order polynomial in segments, i.e. each part of the velocity signal different from zero was considered as one segment. It was filtered independently and after joined together to form the entire velocity signal. The rotor acceleration was obtained from the analytical time derivative of the smoothing polynomial velocity. The obtained acceleration was then used in the experimental determination of the friction torque to generate NN training patterns.

It was used a hyperbolic tangent as activation function (tanh). After training, the NN reproduced the training patterns with 98% of accuracy.

Fig. 3 shows the experimental friction torque (used as training patterns) and 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. 2. NN architecture.](image)

![Fig. 3. Experimental and NN estimated friction.](image)

4. 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. 6), 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. 4 shows a synthesis of the fuzzy system, which uses the linguistic variables showed in Table 1.
Table 1. Linguistic variables.

<table>
<thead>
<tr>
<th>abs(error) (fuzzy input)</th>
<th>gain (fuzzy output)</th>
</tr>
</thead>
<tbody>
<tr>
<td>VH =&gt; Very High</td>
<td>VH =&gt; Very High</td>
</tr>
<tr>
<td>H =&gt; High</td>
<td>H =&gt; High</td>
</tr>
<tr>
<td>M =&gt; Medium</td>
<td>M =&gt; Medium</td>
</tr>
<tr>
<td>S =&gt; Short</td>
<td>S =&gt; Short</td>
</tr>
<tr>
<td>Z =&gt; Zero</td>
<td>N =&gt; Nominal</td>
</tr>
</tbody>
</table>

Triangular membership functions were used, as showed in Fig. 5, where $N$ corresponds to the nominal gain. After many experiments, the limit values of the membership function that produce stable responses and good performance were identified, as showed in Table 2.

Table 2. Membership functions limit values.

<table>
<thead>
<tr>
<th>$e_i$</th>
<th>$\theta$</th>
<th>$w_i$</th>
<th>$\omega$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$e_1$</td>
<td>0.05°</td>
<td>$w_1$</td>
<td>1.05</td>
</tr>
<tr>
<td>$e_2$</td>
<td>0.3°</td>
<td>$w_2$</td>
<td>1.1</td>
</tr>
<tr>
<td>$e_3$</td>
<td>0.5°</td>
<td>$w_3$</td>
<td>1.15</td>
</tr>
<tr>
<td>$e_4$</td>
<td>0.7°</td>
<td>$w_4$</td>
<td>1.2</td>
</tr>
<tr>
<td>$e_5$</td>
<td>1°</td>
<td>$w_5$</td>
<td>1.25</td>
</tr>
</tbody>
</table>

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

$$ e = \theta_{ref} - \theta $$  \hspace{1cm} (3)

the following algorithm composes the if then rules, which is applied after each track position:
\begin{equation}
\text{if } f(e, q_{ini}, q_{fin}) < 0, \quad w_i = 2 - w_i; \quad \text{end}, \quad i = 1, 2, ..., 5
\end{equation} \hspace{1cm} (4)

\begin{align*}
\text{if } |e| = Z, \quad g = N; \\
\text{elseif } |e| = S, \quad g = S; \\
\text{elseif } |e| = M, \quad g = M; \\
\text{elseif } |e| = H, \quad g = H; \\
\text{else} \\
\quad g = VH; \\
\text{end}, \\
\text{end}, \\
\text{end}, \\
\text{end}, \\
\text{end}, \\
\end{align*} \hspace{1cm} (5)

\begin{equation}
N = g; \hspace{1cm} (6)
\end{equation}

\begin{figure}[h]
\centering
\includegraphics[width=\textwidth]{membership_functions}
\caption{Input and output membership functions.}
\end{figure}

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 (4) is required to prevent over compensation and to guarantee the convergence process. \(f(e, q_{ini}, q_{fin})\) 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 (5)), the nominal
gain variable is brought up to date with equation 6. Another important point is that it is considered a different gain \( g \) to each actuator rotation sense.

6. Compensation mechanism and experiments

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:

\[
T_m(k+1) = T_c(k) + g \hat{T}_w(k)
\]

(7)

\( T_c(k) \) is the control torque, i.e., the effectively desired torque to be applied at \( k \) instant, assuming an actuator without friction. \( \hat{T}_w(k) \) is the estimated non-linear friction (NN output), with the rotor velocity \( \hat{\theta}_r(k) \) and motor torque \( T_m(k) \) 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 actuator.

It was used a proportional and derivative control meaning that in (7), \( T_c(k) \) is a simple PD control.

Fig. 6 shows experimental results with and without neuro-fuzzy (N-F) friction compensation. The reference position is the red curb on the left graphic and the equivalent motor torque is showed on the right graphic. The experimental result with N-F compensation is the final trajectory of the Fig. 8. It is evident the good performance obtained with N-F compensation, avoiding the great steady-state error.

A sequency of six tracking position control are showed in Fig. 8. The reference positions are the blue curbs on the left graphics and the equivalents motor torques are showed on the right graphics. It can be seen that the error decreased from the trajectory 1 to the trajectory 6 with the successive application of the neuro-fuzzy (N-F) compensation. The final steady state error of the trajectories are showed in Fig 7. The error decrease slowly from one to another trajectory because it was not imposed a great variation in the limit values of the membership function, but the experimental control with N-F compensation becomes more stable with this limit values.

7. Conclusões

This work proposes a new strategy to implement friction compensation with application to robotic actuators, confirmed by experimental results. The experimental results were obtained with the second actuator of a six dof scara robot manipulator. 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. 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 really on
line fuzzy correction, in each discrete time of the control and also, to apply the neuro-
 fuzzy friction compensation to the flexible structures control problem.
Fig. 8 A sequence of tracking position control with neuro-fuzzy friction compensation.
References


