ROBUST CONTROL FOR AN ARTIFICIAL MUSCLES ROBOT ARM

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Keywords: Neural Network, Reinforcement Learning, Variable Structure System, Pneumatic Artificial Muscle, Manipulator Robot Arm.

Abstract: We are concerned with the control of a 3-DOF robot arm actuated by pneumatic rubber muscles. The system is highly non-linear and somehow difficult to model therefore resorting to robust control is required.The work in this paper addresses this problem by presenting two types of robust control. One uses neural network control, which has powerful learning capability, adaptation and tackles nonlinearities; in our work the learning performed on-line is based on a binary reinforcement signal without knowing the nonlinearities appearing in the system and no preliminary off-line learning phase is required. The other control law is a Classical variable structure which is robust against parameters variations and external disturbances. Experimental results together with a comparative study are presented and discussed.

1 INTRODUCTION

For most robotic applications, the common actuator technology is electric with very limited use of hydraulics or pneumatics but electrical systems suffer from relatively low power/weight ratio, especially in the case of human-friendly robot or human coexisting and collaborative systems, such as in medical and welfare fields. Therefore, sharing the robot working space with its environment is problematic. Conversely, the human arm is not very accurate, but its lightness and joint flexibility due to the human musculature give it a natural capability for working in contact. A novel pneumatic artificial muscle (PAM) actuator (Caldwell et al., 1993; Bowler et al.), which has achieved increased popularity to provide these advantages, has been regarded during the recent decades as an interesting alternative to hydraulic and electric actuators and applied to construct a therapy robot where high level of safety for humans is required. However, the complex nonlinear dynamics of the PAM manipulator makes it a challenging and appealing system for modeling and control design. As a result, a considerable amount of research has been devoted to the development of various position control systems for the PAM manipulator. The fine control performance could be obtained by using some control strategies such as sliding mode control (Cai and Yamaura, 1997; Carbonell et al., 2001; Tondu and Lopex, 2000; Hamerlain, 1995), adaptive control and so on. However, these systems were based on the assumption that the process to be controlled should be linear and past of the research results are just considered with step reference input. Furthermore, intelligent control techniques have emerged to overcome some deficiencies in conventional control methods in dealing with complex real-world systems in more recent years. Fuzzy controllers (Balasubramanian and Rattan, 2003) have been successfully implemented for many linear and nonlinear processes. However, there were obviously steady-state error, and it also was very hard to implement in practice because of the difficulty in constructing the control rule's bases. In addition, neural network control has been successfully used in many commercial and industrial applications in recent years. An adaptive controller based on the neural network was applied to the artificial hand, which was composed of the PAM (Folgheraiter et al., 2003). Nonlinear PID control to improve the control performance of 2 axes pneumatic artificial muscle manipulator using neural network (NN) has been proposed by Tu Diep (Thanh and Kwan, 2006).

The work in this paper addresses this problem by showing the ability of the NN to learn unmodeled nonlinear dynamics through reinforcement learning.

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In this paper, we will explore a new type of reinforcement learning algorithm (Kim and Lewis, 1997), in which the learning signal is merely a binary "+1" or "-1", from a critic rather than an instructive correction signal. Compared with existing NN learning methods, where learning is performed in a trial-and-error manner, the NN weights in our scheme are tuned on-line, with no off-line learning phase required, in such a fashion that closed-loop performance is guaranteed. The experiments were carried out in practical 3 axes PAM manipulator and the effectiveness of the proposed control algorithm was demonstrated and compared with sliding mode control, which suggests its superior performance and disturbance rejection.

2 ACTUATOR AND MECHANICAL STRUCTURE

The three degrees of freedom (DOF) of the robot manipulator prototype illustrated in figure 1 are considered. It consists of a base joint, a shoulder joint and an elbow joint, all of which are revolute.

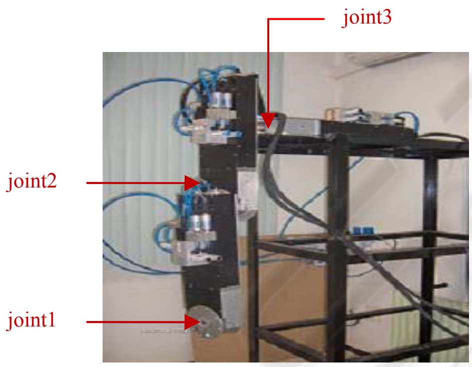

Figure 1: Experimental robot arm.

Since the pneumatic artificial rubber muscles (PAM) are contractile devices, in order to have a bidirectionally actuated revolute joint, two PAM have to be used in what is generally called an antagonistic setup. This is illustrated in figure 2.

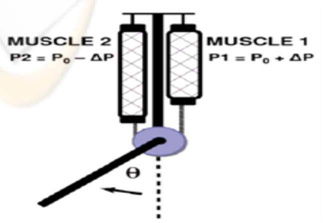

Figure 2: Working principle of a joint.

The muscles in this application were designed to function as biceps. As the internal air pressure increases, the actuator expands in its radial direction and contracts its length. The (PAM) selected as the actuator for this robot arm is the MAS-40 fluidic muscle manufactured by FESTO (Pomiers, 2003).

3 DIRECT REINFORCEMENT ADAPTIVE LEARNING NEURAL NETWORK CONTROL

3.1 Neural Networks

Here we employ a simple “two-layer” feedforward neural network (NN) to approximate a general smooth non linear function on a compact set R^n (Sadegh, 1993). According to the NN approximation property:

$$f(x) = W^T \sigma\left(V^T x\right) + \varepsilon(x) \quad (1)$$

where $x = [1\ x1\ x2\ \dots\ xn]$ is the input to NN, σ( ) is an active function, W and V are defined as the collection of respectively, NN weights for output and hidden layer and $\varepsilon(x)$ is the NN approximation error.

The NN in the remainder of the paper is considered with the first layer weight V fixed. This makes the NN linear in the parameters. Selecting a constant V result in the NN output $y = W^T \sigma(\chi)$.

There exist constant weights W so that the nonlinear function to be approximated can be represented as:

$$f(x) = W^T \sigma(\chi) + \varepsilon(x) \quad (2)$$

with $\|\varepsilon(x)\| < \varepsilon_N$; ε_N is a known value.

Then, the functional estimate can be given by $\hat{f}(x) = \hat{W}^T \sigma(\chi)$ Where $\hat{W}$ is provided by a certain tuning algorithm. In particular in Barron’s paper (Barron, 1993) it was shown that neural networks can serve as universal approximators for continuous functions more efficiently than traditional functional approximators, even though there exists a fundamental lower bound on the functional reconstruction error of order $(\frac{1}{N_k})^{\frac{2}{n}}$ where N_k is the number of neurons in the hidden layer.

3.2 Controller Design

In this paper, the detailed system dynamics and the nonlinearities in the controlled system are assumed to be unknown. It is only supposed that the system belongs to a general class having a canonical structure:

$$\begin{aligned} \dot{x}_1 &= x_2 \\ \dot{x}_2 &= x_3 \\ &\vdots \\ \dot{x}_n &= g(x) + d(t) + u(t) \\ y &= x_1 \end{aligned} \qquad (3)$$

with state $X = [x_1\ x_2 \ldots x_n]^T$, $u(t)$ is the control input to the plant, *d(t)* the unknown disturbance with a known upper bound *bd*, *g(x)* an unknown smooth function and output y.

Define the reference signal as $X_d = [x_d\ \dot{x}_d \ldots\ldots \overset{(n-1)}{x_d}]^T$ A standard use in robotics is the filtered tracking error $r(t) = \Lambda^T e(t)$ Where $\Lambda^T = [\lambda_1\ \lambda_2 \ldots \lambda_n]$ is an appropriately chosen coefficient vector such that $s^{n-1} + \lambda_{n-1} s^{n-2} + \cdots + \lambda_1$ is Hurwitz ($e(t) \to 0$ exponentially as $r(t) \to 0$).

The tracking error vector is defined as $e(t) = X_d - X$. The full filtered tracking error $r(t)$ is not allowed to be used for tuning the action generating NN weights. Only a reduced reinforcement signal *R* is allowed.

$$R = \text{sgn}(r); \quad \text{sgn}(x) = \begin{cases} +1 & if\ x \geq 0 \\ -1 & otherwise \end{cases}$$

The time derivative of the measured performance signal can be written as:

$$\dot{r} = g(X, X_d) + u(t) + d(t) \qquad (4)$$

where $g(X, X_d)$ is a fairly complex nonlinear function of X and X_d .The control input $u(t)$ used to control the plant is given by (Kim and Lewis, 1997):

$$u(t) = -K_v r - \hat{g}(X, X_d) + v(t) \qquad (5)$$

where $\hat{g}(X, X_d)$ is provided by the NN. The performance measurement gain matrix is $K_v = K^T{}_v$ and $v(t)$ is a robustifying vector that will be determined later to offset the NN functional reconstruction error $\varepsilon(x)$ and disturbances $d(t)$.

From (4), the time derivative of the performance measure signal $r(t)$ can be rewritten as:

$$\dot{r} = -K_v r + \tilde{g}(X, X_d) + d(t) + v(t) \qquad (6)$$

where $\tilde{g}(X, X_d) = g(X, X_d) - \hat{g}(X, X_d)$

The continuous nonlinear function $g(X, X_d)$ can be represented by a NN with some constant "ideal" weight W and some sufficient number of input basis function $\sigma(\ )$ as:

$$g(X, X_d) = W^T \sigma(\chi) + \varepsilon(x) \qquad (7)$$

with $\|\varepsilon(x)\| < \varepsilon_N$.

We assume that the ideal weight W is bounded by known positive values (Lewis et al., 1995; Kosmatopoulos, 1990) so that $\|W\|_F \leq W_M$ where W_M is a known value.

Let the NN functional estimate for the continuous nonlinear function $g(X, X_d)$ be given by:

$$\hat{g}(X, X_d) = \hat{W}^T \sigma(\chi) \qquad (8)$$

where the current value $\hat{W}$ is provided by the weight tuning algorithm. From (3) and (4) we have the following performance measure:

$$\dot{r} = -K_v r + \tilde{W}\sigma(\chi) + \varepsilon(x) + d(t) + v(t) \qquad (9)$$

with the weight estimation error $\tilde{W} = W - \hat{W}$.

The robustifying term is given by (Kim and Lewis, 1997):

$$v(t) = -K_z \frac{R}{\|R\|} \qquad (10)$$

with $K_z \geq bd$ And reinforcement learning rule for tuning the action generating NN weights is given by (Kim and Lewis, 1997):

$$\dot{\hat{W}} = F\sigma(\chi)R^T - kF\hat{W} \qquad (11)$$

with $F = F^T$ for the learning rate and $k > 0$ for the speed of convergence. Then the errors r and $\tilde{W}$ are Uniformly Ultimately Bounded (UUB) (Kim and Lewis, 1997). Moreover, the performance measure $r(t)$ can be made arbitrarily small by increasing the fixed control gain K_v .

Proof (Kim and Lewis, 1997). Define the Lyapunov function candidate:

$$L = \sum_{i=1}^{m} |r_i| + \frac{1}{2} tr(\tilde{W}^T F^{-1} \tilde{W})$$

Differentiation yields:

$$\dot{L} = \sum_{i=1}^{m} \text{sgn}(r)^T \dot{r} + tr(\tilde{W}^T F^{-1} \dot{\tilde{W}})$$

Substituting now from the error system (9) and using (11) gives:

$$\dot{L} \leq \sum_{i=1}^{m} -R^T K_v r + R^T \varepsilon(x) + tr(\tilde{W}^T \hat{W})$$

Using the inequality:

$$tr(\tilde{W}^T \hat{W}) = tr\left\{\tilde{W}^T (W - \tilde{W})\right\} \leq \|\tilde{W}\|_F (W_M - \|\tilde{W}\|_F)$$

and $\|\text{sgn}(r)^T\| \leq \sqrt{n}$ results in:

$$\dot{L} \leq \sqrt{n}\,\lambda_{\min}(K_v)\|r\| - k(\|\tilde{W}\|_F - \frac{W_M}{2})^2 + k\frac{W_M^{\ 2}}{4} + \sqrt{n}\,\varepsilon_N$$

which is guaranteed negative as long as either:

$$\|r\| \geq \frac{k\frac{W_M^{\ 2}}{4} + \sqrt{n}\,\varepsilon_N}{\sqrt{n}\,\lambda_{\min}(K_v)}$$

Or

$$\|\tilde{W}\|_F \geq \frac{W_M}{2} + \sqrt{\frac{W_M^{\ 2}}{4} + \frac{\sqrt{n}\,\varepsilon_N}{k}}$$

According to a standard Lyapunov theory extension (Lewis et al., 1993; Narendra and Annaswamy, 1987), this demonstrates the *UUB* of both $\|r\|$ and $\|\tilde{W}\|_F$.

4 VARIABLE STRUCTURE CONTROL

Sliding mode control (SMC) is a type of variable structure control where the dynamics of a nonlinear system is changed by switching discontinuously on time on a predetermined sliding surface with a high speed, nonlinear feedback (Young et al., 1999). Actually, sliding mode controller design has two steps: the first step involves obtaining a sliding surface for desired stable dynamics and the second step is about providing the control law to reach this sliding surface. The system trajectories are sensitive to parameter variations and disturbances during the reaching mode whereas they are insensitive in the sliding mode (Hung et al., 1993). Although CVS (Classical Variable Structure) control is robust against modelling errors, it however requires an approximate model. Knowledge of the assumed model parameter variation bounds is also required.

The identification of each joint dynamics is based on the estimation of coefficients of a presumed linear model. This is achieved by fitting the best linear curve to the input-output data using an ARX model (Autoregressive with exogenous input) in MATLAB. Joint dynamic parameters are identified using various step input signals. The measured response for the joint angle variation θ (radians) corresponding to various step of the pressure between the two muscles is shown in (figure 3).

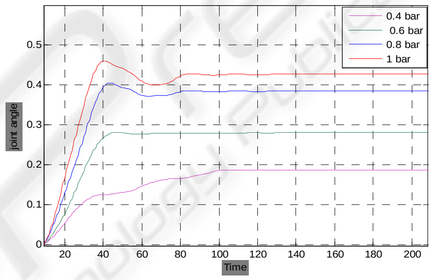

Figure 3: Step response of robot arm (joint 1).

In a linear approximation, the decoupled model for the system dynamics is given in the following form:

$$\ddot{q} + A_1.\dot{q} + A_2.q = B.u \tag{12}$$

Where $q = [q_1, q_2, q_3]^T$ is the displacement vector A_1, A_2 and B are the estimated gain matrices of velocity position and control. These for a decoupled system are:

$$A_1 = diag\ [0.16 \quad 0.17 \quad 1.25]$$
$$A_2 = diag\ [1.19e-2 \quad 0.94e-2 \quad 0.55]$$
$$B = diag\ [0.57e-2 \quad 0.27e-2 \quad 2.23e-3]$$

The sliding mode occurs on a switching surface $S(x) = 0$, which forces the original system to behave as a linear time invariant system, which can be designed to be stable. The switching surfaces are chosen as:

$$S_i(e_i, \dot{e}_i) = \lambda_i e_i + \dot{e}_i \tag{13}$$

$1 \leq i \leq 3$

Where $\lambda_i \succ 0$, $e_i = q_i - q_{id}$ with q_{id} is the desired position. For ideal sliding to occur, the invariance conditions $S_i(e_i,\dot{e}_i)=0 \; and \; \dot{S}_i(e_i,\dot{e}_i)=0$ must be satisfied. This yields the equivalent control:

$$U_{ieq} = b_i^{-1}[(a_{i1}-\lambda_i)\dot{e}_i + a_{i2}e_i + a_{i2}q_{id} + a_{i1}\dot{q}_{id} + \ddot{q}_{id}] \quad (14)$$

Now, due to modelling errors, the estimated equivalent control is given by

$$U^*_{ieq} = b_i^{*-1}[(a^*_{i1}-\lambda_i)\dot{e}_i + a^*_{i2}e_i + a^*_{i2}q_{id} + a^*_{i1}\dot{q}_{id} + \ddot{q}_{id}] \quad (15)$$

where $\overset{*}{b}_i$, $\overset{*}{a}_{ij}$ are estimated mean parameters.

The control U_i is then fixed as $U_i = \overset{*}{U}_{ieq} + \Delta U_i$ while ΔU_i is the high frequency component which ensures the sliding mode and consequently the system insensitivity to parameter variations ,errors modelling and perturbations.

The control U_i is discontinuous across the switching surfaces $S_i(e_i,\dot{e}_i) = 0$

$$U_i = \begin{cases} U_i^+ = U^*_{ieq} + \Delta U_i^+ & \text{if } S_i(e_i,\dot{e}_i) > 0 \\ U_i^- = U^*_{ieq} + \Delta U_i^- & \text{if } S_i(e_i,\dot{e}_i) < 0 \end{cases}$$

The discontinuous component can take several forms in literature the form retained is established by Harashima et al. (Harashima et al., 1986) as:

$$\Delta U_i = (\alpha_i|e_i| + \beta_i|\dot{e}_i| + \gamma_i).\text{sgn}(S_i) \quad (16)$$

5 EXPERIMENTAL RESULTS

Experimental results of both DRAL and CVS control laws applied to a 3-DOF robot arm driven by pneumatic artificial muscles are presented.

5.1 Tracking Trajectory

We present a simultaneous control of all three robot axes for tracking a sinusoidal reference trajectory; joint coupling is significant.

Number of hidden neurons is 20 and activation functions are sigmoid. Experimental parameters are as follows:

$$K_{vi} = \begin{pmatrix} 0.5 \\ 2 \\ 0.5 \end{pmatrix}; \lambda = \begin{pmatrix} 0.02 \\ 0.08 \\ 0.12 \end{pmatrix}; F_i = \begin{pmatrix} 0.2 \\ 0.3 \\ 0.1 \end{pmatrix}; K = \begin{pmatrix} 0.5 \\ 0.5 \\ 0.5 \end{pmatrix}; K_{zi} = \begin{pmatrix} 0.1 \\ 0.1 \\ 0.1 \end{pmatrix}.$$

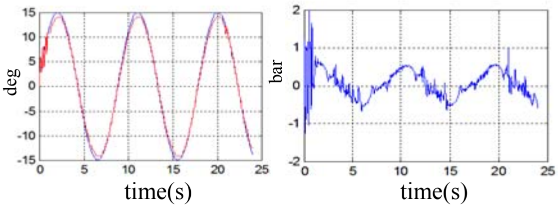

Figure 4: Position and signal of control of joint 1.

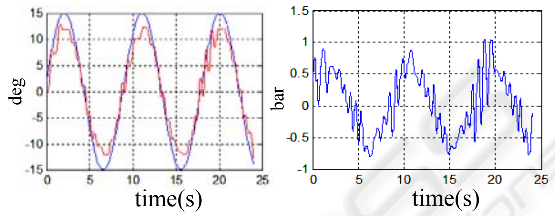

Figure 5: Position and signal of control of joint 2.

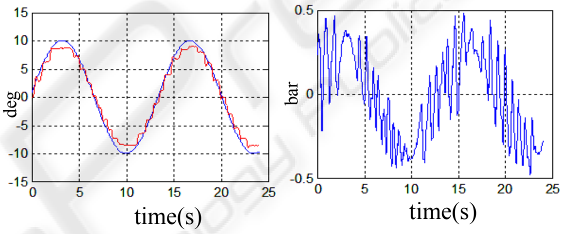

Figure 6: Position and signal of control of joint 3.

The performance of the DRAL controller shows that the trajectory following ability is fairly good. Due to its position in the robot arm the second joint is more difficult to control because of interactions between axes (see Figure 1), moreover, the tracking errors converge to small values as expected from the stability analysis. Though robot non linearity and system dynamics are completely unknown to the DRAL, the algorithm has good properties to cancel the nonlinearities in the robot system, it can also be improved by supplying NN with more input signals (in this work we have considered that NN have to approximate unknown second order dynamics).

5.2 Comparative Study

In order to show the ability of the DRAL to control unknown highly non linear systems our experimental results are compared with those obtained using sliding mode control. Both reference and tracking are considered.

We summarize our concluding remarks in the tables below.

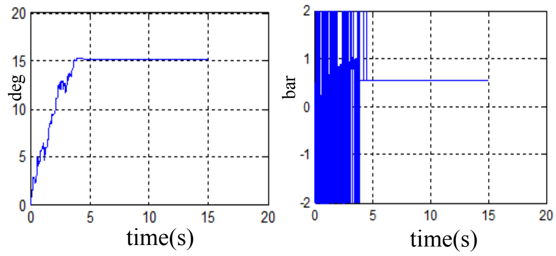

Figure 7: Position and SMC signal control joint 1.

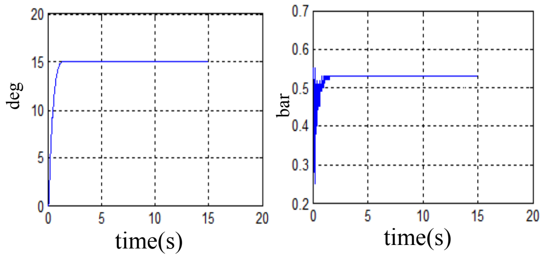

Figure 8: Position and DRAL signal control joint 1.

Table 1.

	DRAL	VSS
Response Time	1.5s	4 s
Chattering	Insignificant	Exist in the transient part
Control	Not energetic Umax=0.53bar	Energetic Umax=2bar
Static error	0.02 degree	0.26 degree

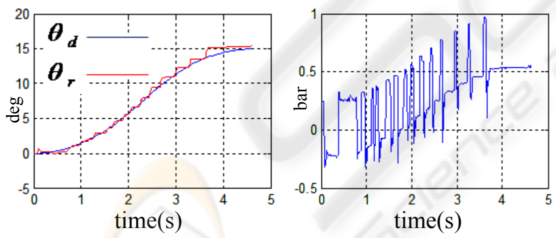

Figure 9: Position and SMC signal control joint 1.

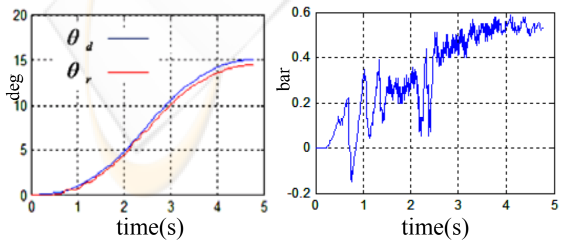

Figure 10: Position and DRAL signal control joint 1.

Table 2.

	Control	Trajectory
DRAL	Umax=0.59bar	Smooth
VSS	Energetic Umax=0.9bar	Incremental

Among the disadvantages of pneumatic artificial muscles we can underline frictions between a rubber tube and the synthetic braid which result on incremental trajectory tracking as shown with VSS control (Fig 9), conversely with DRAL we have attenuated this drawback since the trajectory following is fairly smooth (Fig 10), which proves the ability of neural network to learn unmodeled nonlinear dynamics.

6 CONCLUSIONS

Due to nonlinearities and uncertainties the exact dynamic characteristics of PAM robot manipulator are very difficult to obtain, therefore resorting to robust control is required. Neural network has powerful capability of learning, adaptation and tackling nonlinearity, the proposed neural network controller using reinforcement learning for on line identification of plant dynamics are simple to apply to any control system in order to minimize the position error without knowledge of the plant to be controlled, the algorithm does not require any off-line training or learning phase, the algorithm has proven its performances through experiments and comparative study with sliding mode control. Since the traditional SMC design is a model-based control approach, the partial knowledge of model dynamics deteriorates the control performance; on the other hand we have proven in this work that NN can approximate any unknown complicated nonlinear dynamics consequently, our future investigation will focus on implementation of hybrid control law combining these two methods.

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