Lyapunov Function Based Neural Networks for Adaptive Tracking of Robotic Arm

Muhammad Saleheen Aftab and Muhammad Shafiq

***Abstract*—In this paper, we aim to present an adaptive position controller for multiple degree of freedom robotic manipulators. A decentralized approach is presented that utilizes Lyapunov function based artificial neural networks as inverse controllers of the robot's nonlinear coupled dynamics. The proposed scheme is successfully implemented on the real time control of the TQ MA3000 robotic manipulator. Promising experimental results show the effectiveness of the proposed algorithm in the sense of fast convergence of adaptive tracking error and stability of the closed loop.**

***Index Terms*—Lyapunov function, neural networks, adaptive tracking, robotic arm.**

I. Introduction

Robotics plays an integral part in industrial automation and mechanization. Consequently, significant research has been conducted on the dynamic control of robotic systems. Robotic manipulator mimics the functionality of a human arm, which has highly complex and coupled nonlinear dynamics [1]. Initial successful implementations of robotic control include various centralized adaptive and robust control architectures [2]-[4]. But these centralized techniques are complex and computationally intensive [5], [6]. On the other hand, computationally simple control methodologies have been proposed for complex nonlinear systems [7]-[9]. Many decentralized control architectures based on artificial neural networks and fuzzy logic systems have been proposed to identify and control the nonlinear coupled dynamics of robotic manipulators [10], [11]. A tracking controller is designed in [12] by combining fuzzy logic with sliding mode control. In [13], a decentralized neural network control is developed for uncertain robot manipulators. However, in these techniques, mathematical formulation of error convergence and closed loop stability conditions is not provided. These techniques generally rely upon computer simulations and experimental results for convergence and stability proofs. Moreover, their performance has not been analyzed for more than 2-DOF robotic systems.

In this paper, we present a decentralized adaptive controller for position tracking of multiple DOF robotic manipulators. The proposed control architecture employs the Lyapunov function based artificial neural networks for the online identification and control. In this technique, the error convergence and closed loop stability are guaranteed with the Lyapunov stability theory. The real time implementation of the decentralized controller is performed on the TQ MA3000 robotic manipulator. For the major axes joints, smooth and stable position tracking is achieved with the proposed adaptive decentralized control scheme.

Manuscript received July 31, 2015; revised October 26, 2015.

The authors are with the Department of Electrical and Computer Engineering, Sultan Qaboos University, Muscat, Sultanate of Oman (e-mail: saleheen.aftab@live.com, mshafiq@squ.edu.om).

II. Preliminaries and Problem Formulation

A. System Description

TQ MA3000 is a 5-DOF robotic manipulator manufactured by TecQuipment Limited for industrial applications. Fig. 1 shows the sketch of the robotic system. The system has three major joint axes: waist, shoulder and elbow; and two minor joint axes: wrist pitch and wrist roll. The major and minor joint movement is limited to 270°. To carry payload, a pneumatic gripper is attached with the wrist. In MA3000, brush type PWM servo amplifier, by Advanced Motion Controls, is used to drive the DC gear motors and the joint position is sensed with potentiometers. The system can be interfaced with computer to perform controlled operation.

B. PC Interface and Calibration

In this study, the controller performance for position tracking of the major joints of TQ MA3000 robot is evaluated. For real time computation, a standard IBM PC with Intel Pentium IV processor and 3GB RAM is used. The controller is programmed in Simulink real time target environment and data acquisition is performed through Humusoft MF624 PCI interface card. The operating voltage range for input and output channels of the data acquisition card is limited between ±10V. We have recorded the output voltages and the corresponding joint positions for various input voltages. The joint position exhibits a linear relationship with the output voltage as follows: the waist position varies at 40°/V, the shoulder position varies at 20°/V and the elbow position varies at 30°/V. These calibration values are used to convert the system response from volts to degrees.

C. Problem Statement

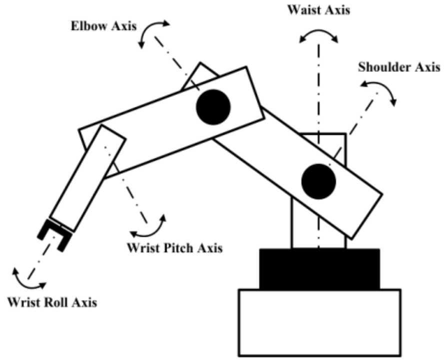

Fig. 1. TQ MA3000 5 DOF robotic manipulator.

doi: 10.18178/ijmmm.2017.5.1.285

In this study, our objective is to design a decentralized control architecture for position control of the TQ MA3000 robotic manipulator (Fig. 1). We will consider the nonlinear and strongly coupled dynamics of the robotic system as black box for controller development. The proposed controller should accomplish the following requirements: smooth and stable tracking in the presence of coupling effects between the movement of the manipulator joints, and convergence of closed loop steady state error to zero in finite time.

III. Proposed Decentralized Adaptive Controller

In this section, we present an adaptive inverse control algorithm for position tracking of each major joint of the TQ MA3000 robotic manipulator. Fig. 2 depicts the proposed decentralized control scheme that employs three separate adaptive inverse controllers. The definitions of various symbols used in Fig. 2 are presented in Table I. Internally, the elbow, shoulder and waist controllers are based on the Lyapunov function neural networks tracking (LNT) control architecture. The LNT architecture uses two artificial neural networks as controller (NNC) and estimator (NNE) in a unified framework, as shown in Fig. 2. The NNC acts as direct adaptive inverse controller that minimizes the controller closed loop error. On the other hand, NNE computes the desired control effort for NNC. In this scheme, the elbow, shoulder and waist LNT controllers learn the inverse dynamics of the robotic system and produce an appropriate control command $u_{EL}(k)$, $u_{SH}(k)$ and $u_{WS}(k)$ such that the position tracking errors $e_{EL}(k)$, $e_{SH}(k)$ and $e_{WS}(k)$ are minimized.

The controller and estimator in the LNT architecture are typical three layered artificial neural networks with four hidden neurons, as shown in Fig. 3. In this figure, $x(k)$ is the excitation signal, q^{-1} is the time shift operator, $u(k)$ is the network output, $w_{ij}^{(1)}(k)$ and $w_{1j}^{(2)}(k)$ are the network interconnection weights, $e(k)$ and $d(k)$ are the error to be minimized and network's desired response respectively. $\delta(k)=h(e(k),d(k))$ is used to update the weights $w_{ij}^{(1)}(k)$ and $w_{1j}^{(2)}(k)$. The output $u(k)$ of the neural network is given by (1):

$$u(k)=\sum_{j=1}^{n} w_{1j}^{(2)}(k)S_j(k) \tag{1}$$

$S_{\mathrm{j}}(k)$ is the output of the hidden neurons, as given by (2):

$$S_j(k)=\varphi\left(\sum_{i=1}^{n} w_{ij}^{(2)}(k)x(k-i+1)\right) \tag{2}$$

where $\varphi(\bullet)=\tanh(\bullet)$ is the nonlinear activation function, $i=j=1,2,\ldots,n,$ and $n=4$ is the number of hidden neurons. If the weights $w_{ij}^{(1)}(k)$ and $w_{1j}^{(2)}(k)$ are updated with:

$$w_{1j}^{(2)}(k)=\frac{\delta(k)}{nS_j(k-1)} \tag{3}$$

$$w_{ij}^{(1)}(k)=\frac{1}{nx(k-i+1)}\varphi^{-1}\left(\frac{\delta(k)}{nw_{1j}^{(2)}(k)}\right) \tag{4}$$

where $\delta(k)=h(e(k),d(k))=\sqrt{\beta}e(k-1)+d(k),$ and β is the network training rate, then the closed loop system stability can be guaranteed by Lyapunov stability theory, provided the plant to be controlled is bounded input bounded output (BIBO) stable. The Lyapunov function is constructed from the error dynamics of the artificial neural networks, which has the following form:

$$V(k)=e^2(k) \tag{5}$$

After simple manipulations, it can be obtained that $\Delta V(k)=e^2(k)-e^2(k-1)=-(1-\beta)e^2(k-1).$ Stability is guaranteed by keeping $0<\beta<1$. Further, the relationship between the learning errors of the NNC and NNE is given by the following:

$$e_C(k)=-\gamma e_E(k) \tag{6}$$

where, $\gamma=\sqrt{\beta_E/\beta_C}$.

Since the joint positions of the robotic manipulator are only locally stable, the system is stabilized via feedback gains K_{EL}, K_{SH} and K_{WS} as shown in Fig. 2. The discrete time (DT) closed loop inputs to the robotic system $\Delta_{EL}(k)=u_{EL}(k)-\theta_{EL}(k)$, $\Delta_{SH}(k)=u_{SH}(k)-\theta_{SH}(k)$, and $\Delta_{WS}(k)=u_{WS}(k)-\theta_{WS}(k)$ are converted into continuous time (CT) signals $\Delta_{EL}(t)$, $\Delta_{SH}(t)$ and $\Delta_{WS}(t)$ by digital-to-analog converter on the data acquisition card. The robotic system produces position outputs as CT signals $\theta_{EL}(t)$, $\theta_{SH}(t)$ and $\theta_{WS}(t)$ which are converted into DT signals $\theta_{EL}(k)$, $\theta_{SH}(k)$ and $\theta_{WS}(k)$ by analog-to-digital converter for feedback.

IV. Experiment Results

In this section, the tracking performance of the proposed decentralized control architecture has been discussed. For experiments, we have selected following values of learning parameters: For elbow LNT controller, $\beta_C=0.75$ and $\beta_E=0.35$; for shoulder LNT controller, $\beta_C=0.3$ and $\beta_E=0.1$; and for waist LNT controller, $\beta_C=0.225$ and $\beta_E=0.1$. Moreover, for feedback stabilization, $K_{EL}=K_{SH}=K_{WS}=10$ and for controller excitation inputs, $x_{EL}=x_{SH}=x_{WS}=0.25$ have been selected. The desired signals for joints position tracking are given in (7):

$$\begin{aligned} r_{EL}(k)&=60\sin\left(\frac{2\pi k}{50}\right),\\ r_{\mathrm{SH}}(k)&=30\sin\left(\frac{2\pi k}{50}+180°\right),\\ r_{WS}(k)&=80\sin\left(\frac{2\pi k}{50}\right)\end{aligned} \tag{7}$$

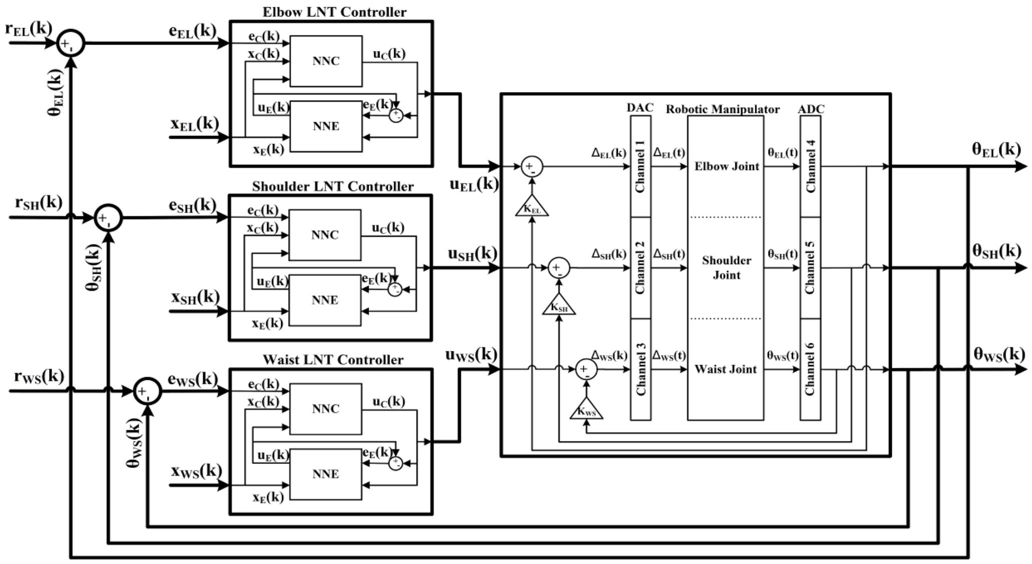

Fig. 2. Proposed adaptive inverse control architecture based on Lyapunov function neural network tracking controller.

TABLE I: DEFINITION OF SYMBOLS USED IN PROPOSED DECENTRALIZED ADAPTIVE CONTROL ARCHITECTURE

Symbol	Definition
$r_{EL}(k)$, $r_{SH}(k)$, $r_{WS}(k)$	Desired position of elbow, shoulder and waist joints
$\theta_{EL}(k)$, $\theta_{SH}(k)$, $\theta_{WS}(k)$	Actual position of elbow, shoulder and waist joints
$x_{EL}(k)$, $x_{SH}(k)$, $x_{WS}(k)$	Excitation input for elbow, shoulder and waist controllers
$e_{EL}(k)$, $e_{SH}(k)$, $e_{WS}(k)$	Tracking error in elbow, shoulder and waist joints
$u_{EL}(k)$, $u_{SH}(k)$, $u_{WS}(k)$	Control command for elbow, shoulder and waist position tracking
K_{EL}, K_{SH}, K_{WS}	Feedback stabilization gains for elbow, shoulder and waist joints
$\Delta_{EL}(k)$, $\Delta_{SH}(k)$, $\Delta_{WS}(k)$	Control input to elbow, shoulder and waist joints after stabilization
$e_C(k)$, $e_E(k)$	Learning error for NNC and NNE
$x_C(k)$, $x_E(k)$	Excitation input for NNC and NNE
$u_C(k)$, $u_E(k)$	Control signal output from NNC and NNE

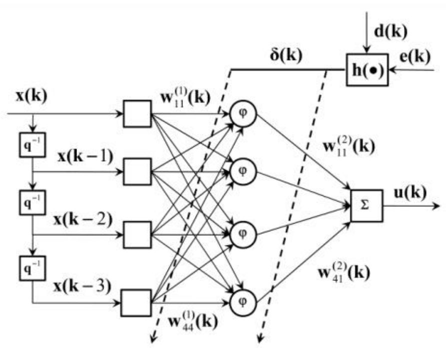

Fig. 3. Three layered Lypunov function neural network with four hidden neurons.

Fig. 4 shows the experiment results for tracking of the major joint positions of the TQ MA3000 robotic manipulator. It is evident that smooth and stable tracking is achieved as the actual position closely follows the desired position profiles. Initially, a few ocsillations are observed but the response improves as the time progresses and the controllers learn the inverse dynamics. Moreover, the potential effects of joint couplings have been effectively neutralized by the proposed decentralized control scheme. The LNT controllers produce stable and bounded control effort as shown in Fig. 5. Fig. 6 validates the relationship between $e_C(k)$ and $e_E(k)$ experimentally in (6). Note that $\gamma_{EL} = 0.683$, $\gamma_{SH} = 0.577$ and $\gamma_{WS} = 0.444$ for the chosen values of the LNT learning parameters. It can be inferred that the closed loop error $e_C(k)$ is indeed equivalent to the amplified estimator error $e_E(k)$.

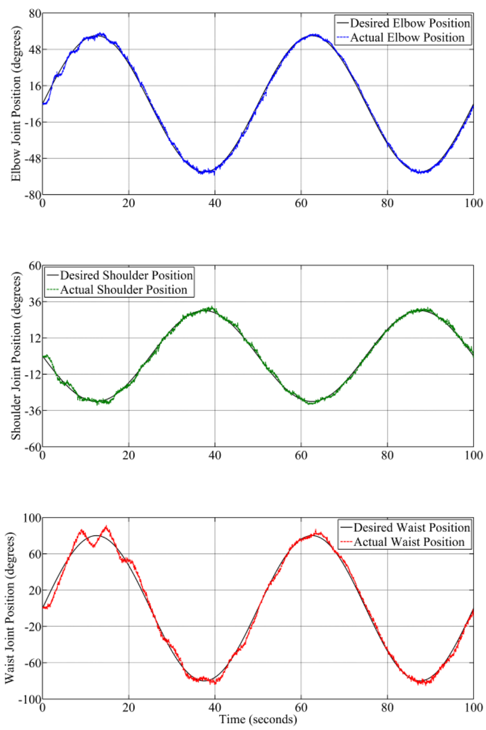

Fig. 4. Major joint positions tracking response.

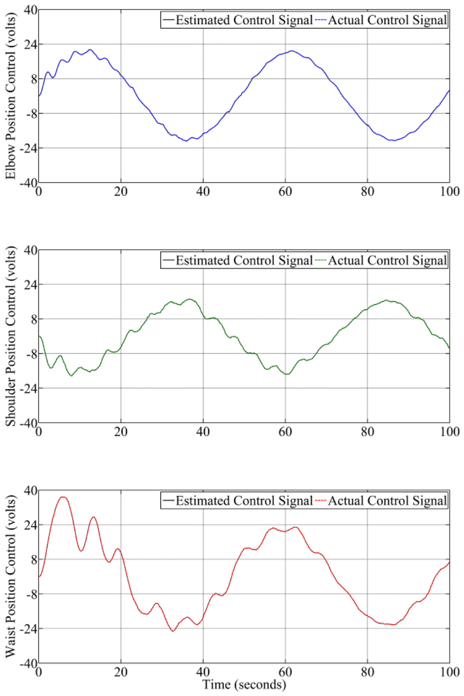

Fig. 5 Estimated & actual control signals.

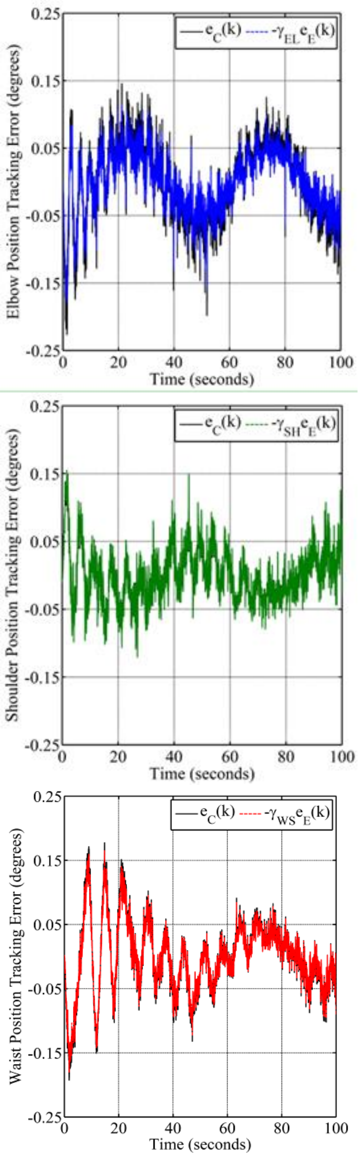

Fig. 6. LNT controller & estimator error signals for elbow, shoulder and waist positions tracking.

V. Conclusion

In this article, we have presented a decentralized adaptive controller for position tracking of TQ MA3000 robotic manipulator. The proposed control architecture does not require plant description. Instead, it uses the universal approximation capability of artificial neural networks for controller development. In this scheme, Lyapunov function neural networks are trained as adaptive inverse controllers to approximate the inverse robot dynamics. With this technique, the real time control of 3-DOF robotic manipulator has achieved fast error convergence and closed loop system stability. The promising experimental performance has successfully validated the theoretical implications of the proposed decentralized adaptive controller.

Acknowledgment

The authors appreciate the support provided by Sultan Qaboos University in this research work.

References

[1] A. Babiarz, R. Bieda, K. Jaskot, and J. Klamka, "The dynamics of the human arm with an observer for the capture of body motion parameters," *Bulletin of the Polish Academy of Sciences: Technical Sciences*, vol. 61, pp. 955-971, 2013.

[2] M. W. Spong, J. S. Thorp, and J. M. Kleinmark, "Robust microprocessor control of robot manipulators," *Automatica*, vol. 23, pp. 373-379, 1987.

[3] C. Abdallah, D. Dawson, P. Dorato, and M. Jamshidi, "Survey of robust control for rigid robots," *IEEE Control Systems Magazine*, pp. 24-30, 1991.

[4] F. L. Lewis, C. T. Abdallah, and D. M. Dawson, *Control of Robot Manipulators*, New York: Macmillan, 1993.

[5] M. Liu, "Decentralized control of robot manipulators: Nonlinear and adaptive approaches," *IEEE Trans. on Automatic Control*, vol. 44, pp. 357-363, 1999.

[6] R. G. Hernandez, E. N. Sanchez, V. Santibaez, M. A. Llama, and E. B. Corrochano, "Real-time decentralized neural block controller for a robot manipulator," in *Proc. IEEE/RSJ International Conference on Intelligent Robots and Systems*, 2009, pp. 906-911.

[7] Z. Jiang, "Decentralized and adaptive nonlinear tracking of large-scale systems via output feedback," *IEEE Trans. on Automatic Control*, vol. 45, pp. 2122-2128, 2000.

[8] Q. Zhou, P. Shi, H. Liu, and S. Xu, "Neural-network-based decentralized output-feedback control for large scale stochastic nonlinear systems," *IEEE Trans. on Systems, Man, and Cybernetics, Part B: Cybernetics*, vol. 42, pp. 1608-1619, 2012.

[9] M. Shafiq and N. R. Butt, "Utilizing higher-order neural networks in U-model based controllers for stable nonlinear plants," *International Journal of Control, Automation and Systems*, vol. 9, pp. 489-496, 2011.

[10] P. M. Mary and N. S. Marimuthu, "Self-organizing decentralized intelligent position controller for robot manipulator," in *Proc. India International Conference on Power Electronics*, 2006, pp. 161-166.

[11] N. Sadati and E. Elhamifar, "Adaptive fuzzy decentralized control of robot manipulators," in *Proc. International Conference on Industrial Electronics and Control Applications*, 2005, p. 6.

[12] H. Ho, Y. Wong and A. Rad, "Robust fuzzy tracking control for robotic manipulators," *Simulation Modelling Practice and Theory*, vol. 15, pp. 801-816, 2007.

[13] K. Tan, S. Huang, and T. Lee, "Decentralized adaptive controller design of large-scale uncertain robotic systems," *Automatica*, vol. 45, pp. 161-166, 2009.

Muhammad Saleheen Aftab completed B.E. in electronics engineering from NED University of Engineering and Technology, Karachi, Pakistan in 2009. He has also completed MSc in Electrical Engineering with specialization in electronic instrumentation & control systems from Sultan Qaboos University, Muscat, Oman in 2015. His research interests include modelling and control of nonlinear systems with computationally intelligent

techniques, robotics and power systems control.

He has served electrical power production company in Pakistan for troubleshooting and maintenance at the Instrumentation and Control Department. He has also played an active role in the design and development of the electrical payload system of indigenous remote sensing satellite of Pakistan. Currently, he is working as a research assistant in the Department of Electrical and Computer Engineering, Sultan Qaboos University, Oman. He has co-authored more than ten research publications in various international and local conferences as well as peer-reviewed journals.

Mr. Aftab is an active member of the prestigious IEEE communities including the control systems, industrial electronics and power systems societies.

Muhammad Shafiq received his B.E. degree in electronic engineering from NED University of Engineering and Technology, Karachi, Pakistan in 1989. He completed his PhD studies in information and computer engineering at Chiba University, Chiba, Japan in 1997. His research interests include applied nonlinear control, adaptive control and soft computing techniques applied to control systems.

He has worked as technical manager at Thalus, Saudi Arabia. He served King Fahd University of Petroleum and Minerals as a faculty member. He worked as a professor under higher education commission at GIKI and IIUI, Pakistan. Presently, he is working as a faculty member in ECE, SQU, Oman. He is among the authors of more than eighty journal and conference papers.

Dr. Shafiq has worked with Pakistan Engineering Council as a member of accreditation teams formed for accrediting several electrical, electronic and mechatronics engineering programs in Pakistan. He was a member of the national curriculum development committee for communication systems under HEC, Pakistan. He has supervised several M.S. and PhD thesis.