Journal of Engineering and Applied Sciences 12 (Special Issue 9): 8689-8694, 2017
ISSN: 1816-949X

High Order Robotics Arm Modelling Based on ANFIS Technique

[1]Wesam M. Jasim and [2]Esam T. Yassen
[1]College of Computer Science and Information Technology,
[2]Information Technology Center, University of Anbar, Ramadi, Iraq

Abstract: Finding the reliable and precise solution for inverse kinematics is considered as one of the most challenging problems in robotics manipulator. This is because the geometry of robot and the equations of nonlinear trigonometric that characterize the relationship between the cartesian space and the joint space. Thus, it has been a fertile area of research which has drawn researching efforts from various communities such as operation research and artificial intelligence. Additionally, solving this problem is necessary in real-time control. In this study, we investigate the performance of a new hybrid technique in solving the problem of the industrial manipulators inverse kinematics solution. The proposed hybrid technique combines an Artificial Neural Network (ANN) with fuzzy logic system (ANFIS). In order to evaluate the performance of the proposed model, the simulation to identify the joints of 3 and 6-DOF robots are utilized. The simulation results have showed the effectiveness of the hybrid model in solving the problem of the inverse kinematics. This demonstrates that the integration of the ANN and the fuzzy logic can fit the actual manipulator joints with an acceptable error.

Key words: Robotics manipulator, inverse kinematics, artificial neural network, fuzzy logic, simulation, utilized

INTRODUCTION

The robot kinematics describes the motion behaviour of the robot joints regardless the effects of the forces and moments. Forward and inverse kinematics are the two possible solutions for the robotics manipulator. Forward kinematics solution is to find the end-effector pose based on the robotics joint parameters. In contrast, inverse kinematics solution is to find the joint angles and displacement based on the pose of the arm end-effector. However, the inverse kinematics solution is more complex than the forward kinematics solution. In this research, the inverse kinematics modelling of the robotic manipulators is considered.

There are several solutions of inverse kinematics were distinguished such as iterative, algebraic, geometric and analytic methods. An iterative method was presented by Kostic *et al*. (2004) to calculate the inverse kinematics of a RRR robotic manipulator. Barragan *et al*. (2014) an interactive Bayesian identification method was introduced to model the robotic manipulator mechanism type without need to find the individual joints. The common problem of infeasibility in the inverse kinematics solution was solved by Suleiman *et al*. (2015). The presented algorithm achieves good results when it was tested on the Baxter research robot with the end-effector and joints speed limitation was considered.

Latterly, researchers have made the artificial intelligent based approaches a focus attention for inverse kinematics solution. Considerable studies were achieved to model the robotic manipulators inverse kinematics in terms of artificial intelligent methods. An Artificial Neural Network (ANN) approach was implemented to solve the 6-DOF Denso VP6242 robotic arm inverse kinematics by Almusawi *et al*. (2016) and it was also applied to find the inverse kinematics solution of two or higher DOF robotics manipulator by Daya *et al*. (2010). Duka (2014) a feed forward ANN was proposed to identify the inverse kinematics solution of a 3-DOF manipulator to be used in the manipulator control phase.

Several artificial intelligent algorithms were tested in simulation to identify the inverse kinematics of the 7-DOF whole arm manipulator and 6-DOF Titan II Teleoperation system by Barragan *et al*. (2014). These algorithms showed a good performance in terms of low root mean square error. Genetic algorithm is proposed to identify the inverse kinematics solution of 4-DOF robotic system with the help of fuzzy logic model by Bang *et al*. (2009). The results showed the effectiveness of combining the genetic with the fuzzy logic techniques in optimizing the angles and displacements of the robotic arm. The Genetic algorithm was presented by Kouml (2011) combined with a neural network to model the inverse kinematics solution of robotic arms. The identification errors were reduced to micrometer level. Kenwright (2014) Genetic algorithms were proposed to model the inverse kinematics solution to be used in control of the manipulators motion.

Corresponding Author: Wesam M. Jasim, College of Computer Science and Information Technology, University of Anbar, Ramadi, Iraq

In this study, the combination of the ANN and fuzzy logic system was proposed to solve the problem of the industrial manipulators inverse kinematics solution. The proposed algorithm was tested in simulation to identify the joints of 3 and 6-DOF robots.

MATERIALS AND METHODS

The robots mathematical model: Two spaces were employed in kinematics mathematical modelling of robotic manipulators; Cartesian and quaternion spaces. It has been shown, the rotations of any rigid body can be derived using different approaches to combine it is translational and rotational dynamics such as, Euler angles, quaternion and Tait-Bryan. Newton-Euler based Euler angles approach was widely used in this status but it has three important drawbacks. Firstly, the Euler angles representation of the attitude suffers from the singularity problem which called “gimbal lock”. Singularity problem occurs by losing one degree of freedom of the attitude when dividing the pitch angles $\theta = \pm 90$ by zero. Secondly, it is very slow in computation because it has sine and cosine terms. Thirdly, the Jacobian cost function of the system states requires long time in computation because its matrices almost have at least sine or cosine in each element which may lead to crush the system (Jasim and Gu, 2014; Alothman *et al*., 2015). In this research, Euler angles will be used to perform the rigid body rotation in Cartesian space.

According to the above representations, homogenous transformation based on orthogonal real matrices of $R^{4\times4}$ has been widely used in robotics representation. It was confirmed by Denavit and Hartenberg (DH) that only four parameters were desired for the transformation between any two robotic joints. These DH four parameters the link length a_{i-1}, the link twist α_{i-1}, the link offset d_i and the joint angle θ_i have introduced to be the standard way to represent the robotic manipulators. In the following, two robotic manipulators will be described to be identified based on ANFIS.

RRR robotic arm: The first robotic manipulator to be modelled is a 3-Revolute DOF RRR. It is wire frame kinematic model is shown in Fig. 1 and it is DH parameters are listed in Table 1. The robot tip cartesian positions x, y and z are Kostic *et al*. (2004):

$$x = \cos\theta_1\left(a_3\cos\left(\theta_2+\theta_3\right)+a_2\cos\theta_2\right)+\left(d_2+d_3\right)\sin\theta_1 \tag{1}$$

Table 1: RRR manipulator DH parameters

i	α_i (rad.)	a_i (m)	θ_i	d_i (m)
1	$\pi/2$	0.000	θ_1	0.560
2	0	0.200	θ_2	0.169
3	0	0.415	θ_3	0.090

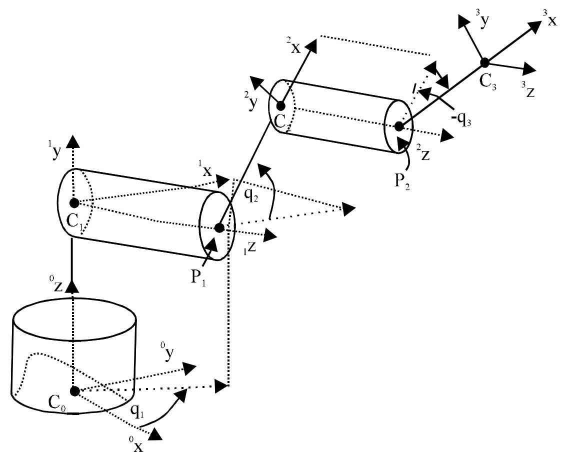

Fig. 1: The RRR manipulator kinematic model

$$y = \sin\theta_1\left(a_3\cos\left(\theta_2+\theta_3\right)+a_2\cos\theta_2\right)-\left(d_2+d_3\right)\cos\theta_1 \tag{2}$$

$$z = a_3\sin\left(\theta_2+\theta_3\right)+a_2\sin\theta_2 + d_1 \tag{3}$$

And the inverse kinematics equations can be calculated from Eq. 1-3 as:

$$\theta_1 = \frac{\operatorname{asin}\left(x\left(d_2+d_3\right)+y\sqrt{x^2+y^2-\left(d_2+d_3\right)^2}\right)}{x^2+y^2} \tag{4}$$

$$\theta_3 = \frac{\operatorname{atan}\left(\pm\sqrt{\frac{1-\left(p_h^2+p_v^2-a_2^2-a_3^2\right)^2}{\left(2a_2a_3\right)^2}}\right)}{\frac{p_h^2+p_v^2-a_2^2-a_3^2}{2a_2a_3}} \tag{5}$$

$$\theta_2 = \operatorname{atan}\frac{\left(\left(a_2+a_3\cos\theta_3\right)p_v-a_3\sin\theta_3\,p_h\right)}{\left(a_2+a_3\cos\theta_3\right)p_h+a_3\sin\theta_3\,p_v} \tag{6}$$

$$p_h = \sqrt{\left(x-\left(d_2+d_3\right)\sin\theta_1\right)^2+\left(y+\left(d_2+d_3\right)\cos\theta_1\right)^2} \tag{7}$$

$$p_v = z-d_1 \tag{8}$$

Six-DOF industrial planar: The second robotic manipulator to be modelled is a 6-DOF industrial planar

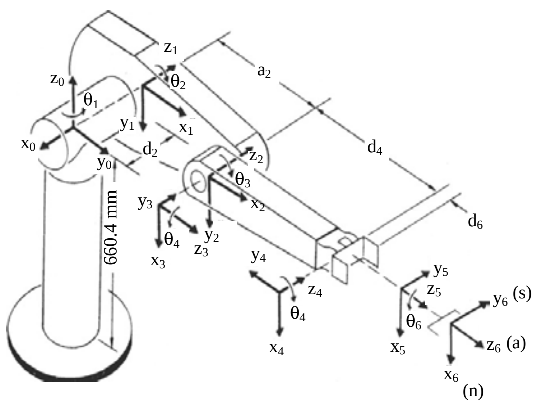

Fig. 2: 6-DOF robotic manipulator kinematics

Table 2: 6-DOF manipulator DH parameters

i	α_i(rad.)	a_i(m)	θ_i	d_i(m)
1	0	0.0000	θ_1	0.000
2	$-\pi/2$	0.4318	θ_2	0.000
3	0	0.0190	θ_3	0.125
4	$-\pi/2$	0.0000	θ_4	0.432
5	$\pi/2$	0.0000	θ_5	0.000
6	$-\pi/2$	0.0000	θ_6	0.000

shown in Fig. 2. The DH parameters are shown in Table 2. The end-effector Cartesian coordinates are Kucuk and Bingul (2006):

$$x = \cos\theta_1\left(a_2\cos\theta_2 + a_3\cos\theta_{23} - d_4\sin\theta_{23}\right) - d_3\sin\theta_1 \quad (9)$$

$$y = \sin\theta_1\left(a_2\cos\theta_2 + a_3\cos\theta_{23} - d_4\sin\theta_{23}\right) + d_3\cos\theta_1 \quad (10)$$

$$z = a_2\sin\theta_2 - a_3\sin\theta_{23} - d_4\sin\theta_{23} \quad (11)$$

And the inverse kinematic equations solved from Eq. 9-11 are:

$$\theta_1 = \operatorname{atan2}(x, y) - \operatorname{atan2}\left(d_3, \sqrt{x^2 - y^2 - d_3^2}\right) \quad (12)$$

$$k = \frac{x^2 + y^2 + z^2 - a_2^2 - a_3^2 - d_3^2 - d_4^2}{2a_2} \quad (13)$$

$$\theta_3 = \operatorname{atan2}(a_3, d_4) - \operatorname{atan2}\left(k, \sqrt{a_3^2 + d_4^2 - k^2}\right) \quad (14)$$

$$\theta_{23} = \operatorname{atan2}\begin{pmatrix} z(-a_3 - a_2\cos\theta_3) - (x\cos\theta_1 + y\sin\theta_1) \\ (d_4 - a_2\sin\theta_3),\ z(a_2\sin\theta_3 - d_4) - \\ (a_3 + a_2\cos\theta_3)(x\cos\theta_1 - y\sin\theta_1) \end{pmatrix} \quad (15)$$

$$\theta_2 = \theta_{23} - \theta_3 \quad (16)$$

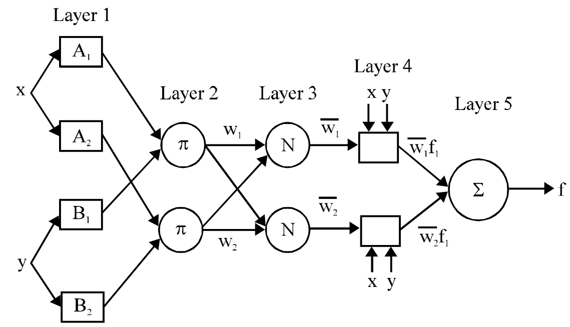

Fig. 3: ANFIS structure

$$\theta_5 = \operatorname{atan2}\left(\sqrt{r_{12}^2 + r_{22}^2}, r_{23}\right) \quad (17)$$

$$\theta_4 = \operatorname{atan2}\left(\frac{r_{33}}{\sin\theta_5}, \frac{-r_{13}}{\sin\theta_5}\right) \quad (18)$$

$$\theta_6 = \operatorname{atan2}\left(\frac{-r_{22}}{\sin\theta_5}, \frac{r_{12}}{\sin\theta_5}\right) \quad (19)$$

The ANFIS algorithm: This study, explains the adaptive neuro-fuzzy inference system algorithm detail. ANFIS is an integration of the ANN and the fuzzy logic. It is a supervised learning algorithm has five layers shown in Fig. 3. The second, third and fifth layers have fixed nodes and the adaptive nodes are in the first and fourth layers only. The fuzzy inference system is a sugeno type in which the membership function parameters are calculated based on backpropagation gradient descent technique. The sugeno type of the fuzzy system rules are of the form:

- If x is A_1 and y is B_1, then $f_1 = c_{11}x + c_{12}y + c_{10}$
- If x is A_2 and y is B_2, then $f_2 = c_{21}x + c_{22}y + c_{20}$

where, A_1, A_2, B_1 and B_2 are the fuzzy sets, c_{11}, c_{12}, c_{10}, c_{21}, c_{22} and c_{20} are the designed parameters which are calculated during the training process. The ANFIS layers output calculations are:

Layer 1: The node function is the membership grade of the fuzzy set:

$$O_i^1 = \beta A_i(x), \text{for } i = 1, 2$$

Or:

$$O_i^1 = \beta B_{i-2}(y), \text{for } i = 3, 4$$

Where:

i = The node number

β = The membership function

Layer 2: The node output is the firing strength of the rule:

$$O_i^2 \quad w_i \quad A_i(x) \; B_i(y), \text{ for } i \quad 1, 2$$

Layer 3: The node output is the ith rule's firing strength divided by the rule's firing strengths summation which is called normalized firing strengths:

$$O_i^3 = \overline{w_1} = \frac{w_i}{w_1 + w_2}, i = 1, 2$$

Layer 4: The node function is:

$$O_i^4 = \overline{w_1} f_i = \overline{w_i} \left(c_{i1} x + c_{i2} y + c_{i0} \right)$$

Layer 5: The node output is the overall network output; it is the summation of all the signals:

$$_i^5 \quad \overline{\sum_i \quad _1 \; _i} \quad \frac{\sum_i w_i f_i}{\sum_i w_i}$$

RESULTS AND DISCUSSION

Simulations: The ANFIS scheme given in Fig. 3 was implemented in MATLAB for the robotic manipulators modelling purpose. In order to validate our proposed technique, two different manipulators were trained and tested in for inverse kinematics modelling. One ANFIS was designed for each manipulator joint, it consists of three membership functions in the input layer and 27 rules in the next layer. Each network was trained for 100 epochs with 400 sample input-output data and then it was tested on 100 sample input data.

The simulation results of modelling the first manipulator -3-DOF RRR arm- were illustrated in Fig. 4-7. The training errors of the three joint angles are shown in Fig. 4 while the tested joint angles θ_1-θ_3 are illustrated in Fig. 5-7, respectively. Figure 8-14 show the simulation results of training and testing the second robotic manipulator -6-DOF robotic arm. The parameters were chosen to be $r_{12} = r_{13} = r_{21} = r_{22} = r_{33} = 1$ and r_{23}. Figure 8 describes the training RMSE of the six joint parameters and the remaining figures show the tested joint and end-effector angles compared with that of the actual ones.

Figure 1-8 shows the neuro-fuzzy technique can trained the data of the robotic arm inverse kinematic parameters with very small RMS error with an acceptable

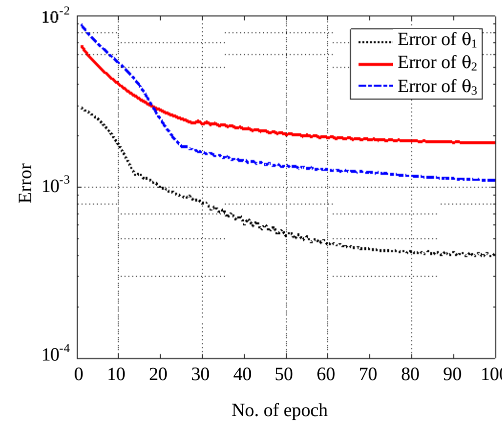

Fig. 4: RMSE of the three joint angles in first arm

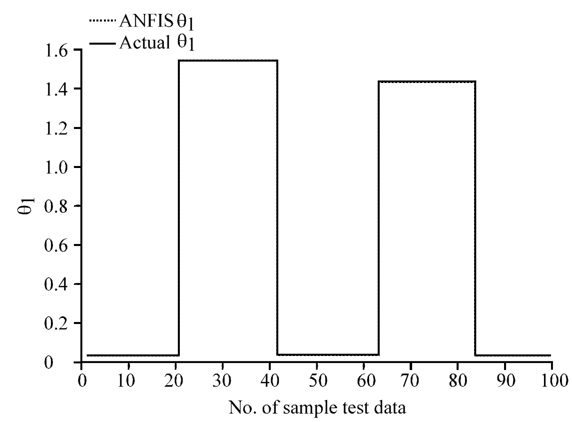

Fig. 5: θ_1 ANFIS test output in first arm

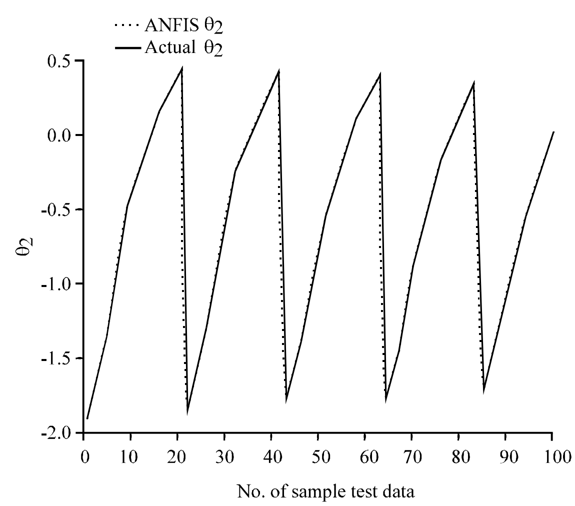

Fig. 6: θ_2 ANFIS test output in first arm

number of epochs 100. The testing figure show that, the ANFIS networks of the manipulator joints can fit the actual ones with an acceptable error when they were compared.

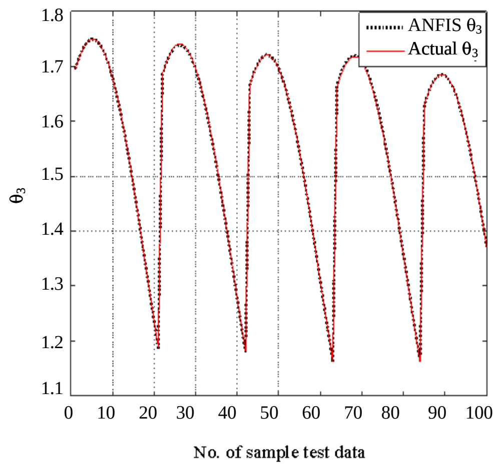

Fig. 7: θ_3 ANFIS test output in first arm

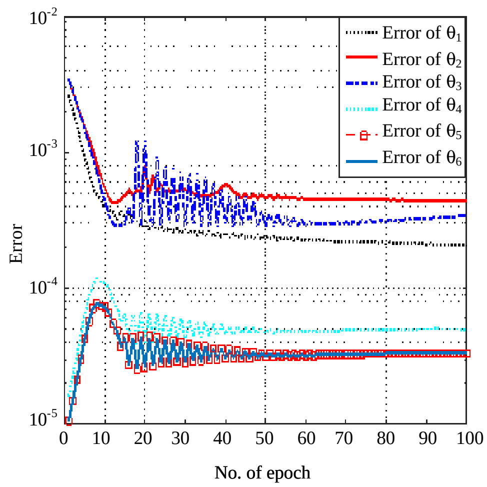

Fig. 8: RMSE for the six joint angles in second arm

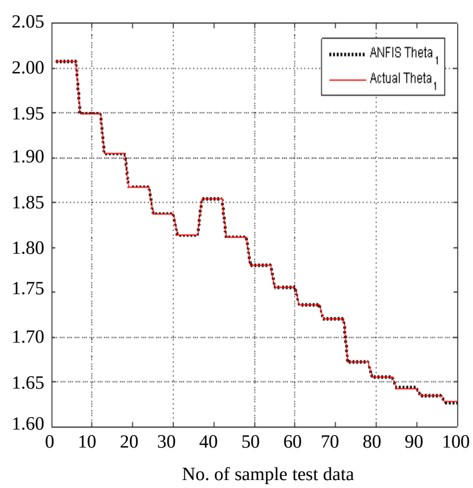

Fig. 9: θ_1 ANFIS test output in second arm

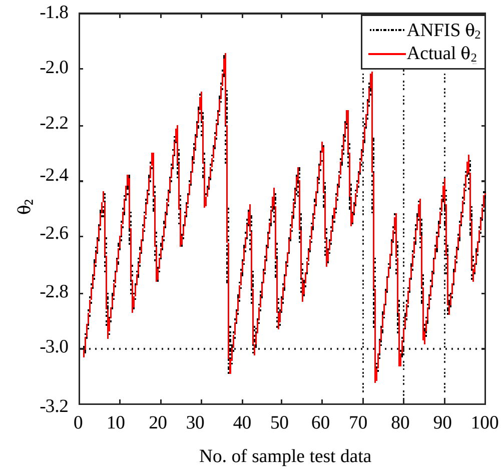

Fig. 10: θ_2 ANFIS test in second arm

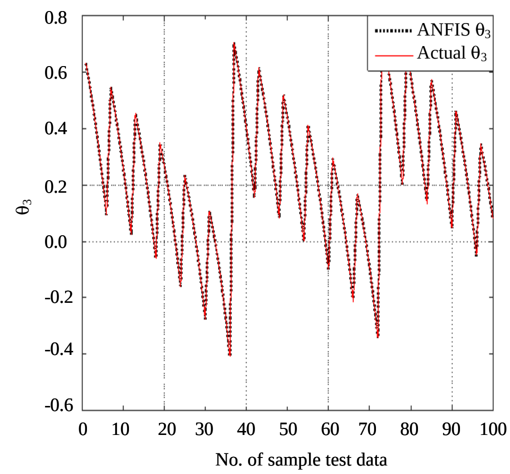

Fig. 11: θ_3 NFIS test in second arm

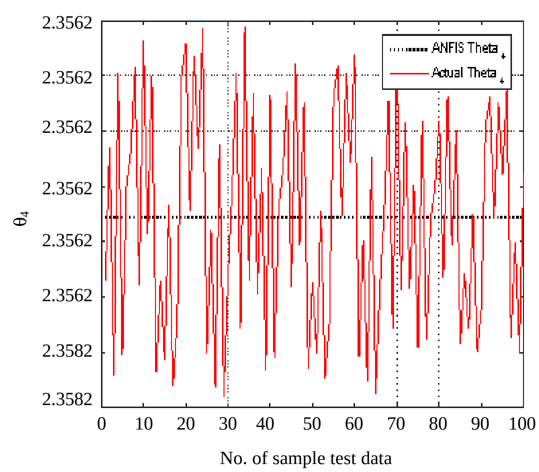

Fig. 12: θ_4 ANFIS test in second arm

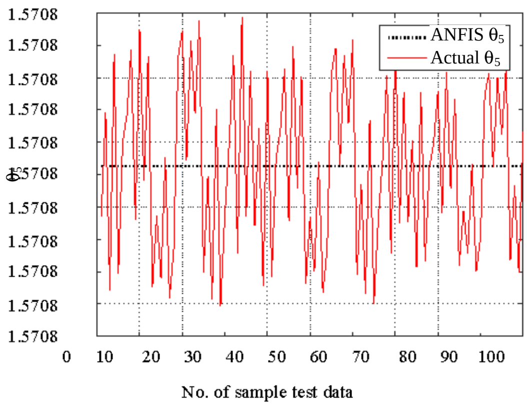

Fig. 13: θ_5 ANFIS test in second arm

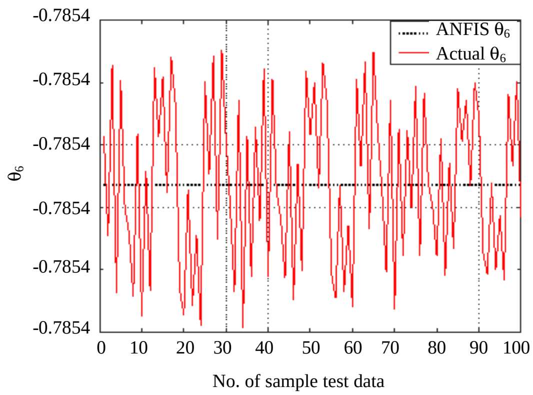

Fig. 14: θ_6 ANFIS test in second arm

CONCLUSION

In order to find the reliable and precise solution for inverse kinematics, this study proposed a new hybrid technique based on an artificial intelligence. In this technique an Artificial Neural Network (ANN) was combined with fuzzy logic system and resulted in a new technique denoted as (ANFIS). The performance of ANFIS is evaluated based on the simulation to identify the joints of 3 and 6-DOF robots. The experimental results have showed the effectiveness of the ANFIS in solving the problem of the industrial manipulators inverse kinematics solution as it achieved the precise control and decrease the computing time.

REFERENCES

Almusawi, A.R., L.C. Dulger and S. Kapucu, 2016. A new artificial neural network approach in solving inverse kinematics of robotic arm (Denso VP6242). Comput. Intell. Neurosci., 2016: 1-10.

Alothman, Y., W. Jasim and D. Gu, 2015. Quad-rotor lifting-transporting cable-suspended payloads control. Proceedings of the 21st International Conference on Automation and Computing (ICAC), September 11-12, 2015, IEEE, Glasgow, England, UK., ISBN:978-0-9926-8011-4, pp: 1-6.

Bang, V., R. Kumar and Y. Singh, 2009. Fuzzy-genetic optimal control for four degree of freedom robotic arm movement. World Acad. Sci. Eng. Technol., 60: 489-492.

Barragan, P.R., L.P. Kaelbling and T.L. Perez, 2014. Interactive bayesian identification of kinematic mechanisms. Proceedings of the IEEE International Conference on Robotics and Automation (ICRA), May 31-June 7, 2014, IEEE, Hong Kong, China, ISBN:978-1-4799-3686-1, pp: 2013-2020.

Daya, B., S. Khawandi and M. Akoum, 2010. Applying neural network architecture for inverse kinematics problem in robotics. J. Software Eng. Appl., 3: 230-239.

Duka, A.V., 2014. Neural network based inverse kinematics solution for trajectory tracking of a robotic arm. Procedia Technol., 12: 20-27.

Jasim, W. and D. Gu, 2014. H8 control for quadrotor attitude stabilization. Proceedings of the International Conference on Control (CONTROL), July 9-11, 2014, IEEE, Loughborough, England, UK., ISBN: 978-1-4799- 5011-9, pp: 19-24.

Kenwright, B., 2014. Epigenetics and Genetic algorithms for inverse kinematics. Exp. Algorithms, 9: 39-51.

Kostic, D., B.D. Jager, M. Steinbuch and R. Hensen, 2004. Modeling and identification for high-performance robot control: An RRR-robotic arm case study. IEEE. Trans. Control Syst. Technol., 12: 904-919.s

Kouml, R., 2011. A neuro-genetic approach to the inverse kinematics solution of robotic manipulators. Sci. Res. Essays, 6: 2784-2794.

Kucuk, S. and Z. Bingul, 2006. Robot Kinematics: Forward and Inverse Kinematics. In: Industrial Robotics: Theory, Modelling and Control, Cubero, S. (Ed.). In Tech, Germany, ISBN:3-86611-285-8, pp: 117-148.

Suleiman, W., F. Kanehiro and E. Yoshida, 2015. Infeasibility-free inverse kinematics method. Proceedings of the IEEE/SICE International Symposium on System Integration (SII), December 11-13, 2015, IEEE, Nagoya, Japan, ISBN:978-1-4673-7242-8, pp: 307-312.