SELF-LEARNING OF DELTA ROBOT USING INVERSE KINEMATICS AND ARTIFICIAL NEURAL NETWORKS

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Abstract
As known as Parallel-Link Robot, Delta Robot is a kind of Manipulator Robot that consists of three arms mounted in parallel. Delta Robot has a central joint constructed as an end-effector represented as a gripper. An Analysis of Inverse Kinematic (IK) used to convert the end-effector trajectory (X, Y) into rotations of stepper motors (ZA, ZB and ZC). The proposed method used Artificial Neural Networks (ANNs) to simplify the process of IK solver. The IK solver generated the datasets contain motion data of the Delta robot. There are 11 KB Datasets consist of 200 motion data used to be trained. The proposed method was trained in 58.78 seconds in 5000 iterations. Using a learning rate (α) 0.05 and produced the average accuracy was 97.48%, and the average loss was 0.43%. The proposed method was also tested to transfer motion data over Socket.IO with 115.58B in 6.68ms.

Keywords:
Artificial Neural Network; Delta Robot; Inverse Kinematics; Motion Data; Socket.IO;

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INTRODUCTION
Robots can be classified into two topologies, namely Serial Manipulator and Parallel Manipulator [1]. The parallel manipulator has abilities such as acceleration, stiffness, low inertia, high precision, and faster per-cycle operations. Serial manipulator produced slower movement because of its connected link a chain, and each joint has a mass in which needs to be calculated to achieve the dynamic manipulator. Meanwhile, The Delta Robot joints are mechanically separated to achieves faster movement by using low inertia. Nevertheless, there are still shortcomings in the Delta robot that is a relatively small workspace robot.

Delta Robot consists of three arms that are connected to the base and effector using a universal joint. The key of Delta robot design is using a parallelogram mechanism to maintain the orientation of the end-effector to the base. Since the Delta robot’s Original Patent expired in December 2006 (Europe) and December 2007 (America), the development of research and implementation of the Delta robot has become more widespread [2][3]. The implementation of the Delta robot is used as a type of 3D Printer, Sketcher Robot, Laser Cutting Robot, and Pick and Place robot. So far, the Delta robot has been developed with a focus on a kinematic analysis of the robot’s movement.

Kinematics is a mathematical model that describes the movement of end-effectors through Cartesian coordinates of the active joint position variable or vice versa. However, mathematical calculations of kinematics do not fully reflect perfect results in actual application. There is a position error caused by component manufacturing tolerance, assembly programming, and the dynamic influence of robot mechanics. On the other hand, the translation of forwarding and inverse kinematics on Delta robots is a fairly difficult problem.

The Inverse Kinematics (IK) of a Delta Robot has been derived in several methods. Some methods are numerical algorithm, geometrical method, genetic algorithm (GA),
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Previous work has been done to solve the IK problem using Neural Network (NN). NN can be used to control validations of the IK model. IK model is created based on the robot's geometry and dynamic to solve the forward kinematics problem [4][5].

Other solutions to solve the IK problem of Delta Robot can be by using a hybrid approach are artificial neural network and particle swarm optimization (ANN-PSO) model in the behavior prediction and optimization of channel connectors embedded in normal and high-strength concrete (HSC) [6, 7, 8].

An interesting topic also explained that IK solution could be solved using neural networks combined with a genetic algorithm (GA) [9, 10, 11]. NN-GA is an optimal design method for the parallel robot, which maximizes the volume of the workspace of parallel robots. The neural network learns the motion model of the robot. Then, the genetic algorithm uses this model to generate the optimal parameters of the robot [12].

To overcome this, the proposed method to solve the IK problem is using an Artificial Neural Network (ANN). Our proposed method's loss can be minimised by finding an optimum ANN architecture by constructing the layers, the activation function, and the optimizer. On the other hand, our proposed method is implemented using Socket.IO channels to distribute the pre-model of our IK-ANN data.

**METHOD**

This paper created the Delta robot using the Inverse Kinematics method as an initializing value for the Artificial Neural Network training data. The results of the end-effector position forwarded to the motor motion execution for a displacement of the effector position. Figure 1 shows the process of the proposed method while it trains and tests the ANN Model.

The IK dataset was generated in small rows (200 rows of IK data). The inputs contain any positions of the end-effector on the base frame $R'(O' - x'y'z')$. The outputs contain any directions on $Z-axis (Z_A, Z_B, and Z_C)$. ANN Model (pre-trained) used to train (the dataset) and to test (random inputs) to predict the direction on $Z-axis (Z_A, Z_B, and Z_C)$. Socket.IO implemented as a communication platform in which will broadcast any random input $(x, y)$ from delta robot then tested on ANN trained model to generate a predictive value of $(Z_A, Z_B, and Z_C)$.

**Inverse Kinematics (IK) Analysis**

Inverse Kinematics on this robot is very necessary for the design of robot motion. This function is to find the position of the entire linear actuator or slider towards the end effector. For example, if the end-effector position moves to position $X$ with respect to position $0$, then how much displacement changes (up/down) of the three linear actuators or sliders. In this section, the analysis is based on Stolfi [12].

Delta robot consists of the top platform, bottom platform, and end effector. The reference remains on the $R(0 - xyz)$ frame system located in the middle on the upper platform ($ABC$ triangle). The $Z$-axis is parallel to the end effector, and the $Y$-axis is parallel to $CO$, as shown in Figure 2.
Another reference is the system \( R'(O' - x'y'z') \) located in the middle of the end effector (triangle \( P_1, P_2, P_3 \)). The Z-axis 'is in the direction perpendicular to the end effector, and the Y-axis' is parallel along \( P_3O' \).

As a geometry parameter, where [4]:

\[
OA = OB = OC = R \quad (1)
\]

\[
O'P_1 = O'P_2 = O'P_3 = r \quad (2)
\]

\[
B_1P_1 = B_2P_2 = B_3P_3 = L \quad (3)
\]

The object of inverse kinematics is to determine the position of three linear actuators due to changes in point \( O' \) (middle of the end effector) to the global reference of the \( R \) system.

Point \( O' \) in frame \( R \) can be written as:

\[
[O']^T = (x\ y\ z)^T \quad (4)
\]

The coordinates of the point \( P_i \) in frame \( R' \) can be written as:

\[
[P_i]^T = (rcos(n_i),rsin(n_i),0)^T \quad (5)
\]

Where \( i = 1, 2, 3 \) and:

\[
n(i) = \frac{4i-3}{6}\pi \quad (6)
\]

Adding from two vectors at once will get the position of \( P_i \) with respect to the \( O - xyz \) frame [3].

\[
[P_i]^T = (rcos(n_i) + x,rsin(n_i) + y,z)^T \quad (7)
\]

Meanwhile, to determine the Bi point on frame R:

\[
[B_i]^T = (Rcos(n_i),Rsin(n_i),x_i)^T \quad (8)
\]

Where \( Z_i \) Above is the Z-axis position to be searched as the position of each linear actuator concerning the frame R reference.

As it is known:

\[
L = |[P_i - B_i]| \quad (9)
\]

Then it can be specified as:

\[
(x - x_i)^2 + (y - y_i)^2 + (z - z_i)^2 = L^2 \quad (10)
\]

Where:

\[
x_i = (R - r)cos(n_i) \quad \ldots \quad (11)
\]

\[
y_i = (R - r)sin(n_i) \quad \ldots \quad (12)
\]

By rearranging Equation 10:

\[
z = \pm\sqrt{L^2 - (x - x_i)^2 - (y - y_i)^2} \quad (13)
\]

To find the desired position \( z \) point on each actuator from the Delta robot, only the positive form of (13) is used.
The output layer represents the desired position of \( z \) positions on each actuator described in (13) \((Z_A, Z_B, \text{and } Z_C)\). To calculate the backpropagation process defined as \( f' \) (or called \( \delta_j \) aka “delta”). The derivative of the activation function \( f(x, y) \) and \( y \) as a learning rate. So, the weights will be graded when the gradient descent is calculated by \([18, 19, 20]\),

\[
\delta_j = f'(x, y) \sum_{j=1}^{n} w_{jk} \delta_j
\]  

(16)

**Socket.IO**

Socket.IO is used to distribute the data among the environment by using events called ‘onListening’ and events ‘onEmit.’ Events ‘onListening’ is an event to retrieve incoming data in which distributed through its event. Events ‘onEmit’ is an event to transmit any data into its event \([21\text{]}\)[22].

![Figure 5. Socket.IO Events \([20]\)](image)

Figure 5 represents the Socket.IO events used to distribute data among platforms. The data was trained on the Django server and distribution through socket.IO event onListening ‘x_y_coor’ in which waiting to receive end-effector data \((x, y)\) from the robot delta. then emitting an event ‘z_act_data’, which mean the predictive \( z \) actuator data \((Z_A, Z_B, \text{and } Z_C)\)

**Proposed Design**

Table 1 shows the hyperparameter that might be used to find the optimum ANN architecture to the Sole IK problem as described above.

| Parameters                  | Choices                  | Selected Parameters |
|-----------------------------|--------------------------|---------------------|
| Number of Layers            | [3,4,5,6,7,8]            | 3                   |
| Number of Neurons in Hidden Layers | [2,4,6,...]            | 2, 6, 12            |
| Activation Functions        | ['ReLU', 'Sigmoid', 'TanH', 'Leaky ReLu'] | 'Leaky ReLu'       |
| Optimizer                   | ['SGD', 'ADAM']          | 'ADAM'              |
| Functions Rate \( \gamma \) | [0.01, 0.02, ...]        | 0.05                |

The hyperparameters were selected as the parameter to build ANN architecture in which to find the optimum values of the number of layers, number of hidden layers, activation functions, optimizer, and the learning rate.

**RESULT AND DISCUSSION**

The following is the prototype that was completed as described in Figure 2. As shown in Figure 3, the inverse kinematics inputs taken by the coordinate of the end-effector \((x\text{ and } y)\) to produce the desired \( Z \) position in direction \( A, B \) and \( C \) \((Z_A, Z_B, \text{and } Z_C)\)

![Figure 6. Prototype of Delta Robot](image)

The dataset from robot motion in Figure 6. 200 rows of motion data were collected and stored as a CSV file.

**ANN Training**

The training process was performed using Intel(R) Core© i5-6300HQ CPU@2.30GHz, 16GB RAM, and NVIDIA GeForce GTX 960M 4GB VRAM. The training process followed the hyperparameter shown in Table 1. The training performance was captured in Figure 7.
Figure 7 shows the performance of the ANN Loss and Accuracy. The loss is presented as the red line of the left graph, and the accuracy is presented as the blue line of the left graph. Figure 7(a) shows the loss decreased and the accuracy increased in 1000 iterations. Figure 7(b) shows the loss decreased and the accuracy increased in 2500 iterations. Figure 7(c) shows the loss decreased and the accuracy increased in 5000 iterations. The detailed values of ANN Loss and accuracy were captured in this Table 2.

Table 2 shows the selected hyperparameter was performed in 1000 iterations, 2500 iterations, and 5000 iterations. The loss was decreased by 0.0043 in 5000 iterations, and the accuracy was increased by 0.9748 in 5000 iterations. This iteration step was executed in 58.7826 seconds.

**ANN Testing**

Single point of end-effector coordinated tested as desired coordinated of $x$ and $y$ shown in Figure 7.

The proposed method was tested in single desired coordinated as a set of motion. Figure 8 represents four motions that were tested in Figure 8(a), Figure 8(b), Figure 8(c), and Figure 8(d). By
given any input \( x \) and \( y \), will produce any desired actuators positions in Z-directions \( Z_A, Z_B, \) and \( Z_C \). The detailed values of ANN testing performance were captured in this Table 3.

The proposed method was implemented to perform \( n \) Motions and captured in actuator direction \( Z_A, Z_B, \) and \( Z_C \). Figure 9 shows the algorithm performance to generate 50 motions in the direction \( Z_A \) (Figure 9(a)), \( Z_B \) (Figure 9(b)), \( Z_C \) (Figure 9(c)), and combined (Figure 9(d)).

Table 2. The ANN Loss and Accuracy in (a) 1000 iterations, (b) 2500 iterations, and (c) 5000 iterations

| Executed time (seconds) | 1000 iterations | 2500 iterations | 5000 iterations |
|-------------------------|-----------------|-----------------|-----------------|
| Time                    | 12.5525         | 29.7373         | 58.7826         |
| Num of Epoch            | 1000            | 2500            | 5000            |
| Average Loss            | 0.0787          | 0.0131          | 0.0043          |
| Average Accuracy        | 0.9322          | 0.9528          | 0.9748          |
| Activation Function     | Leaky-ReLu      | Leaky-ReLu      | Leaky-ReLu      |
| Optimizer               | Adam            | Adam            | Adam            |
| Learning Rate (\( \alpha \)) | 0.05          | 0.05            | 0.05            |
| Layers                  | 2 6 12 6 3      | 2 6 12 6 3      | 2 6 12 6 3      |

Figure 9. The Testing Performance of 50 Motions: (a) Motion Data of \( Z_A \), (b) Motion Data of \( Z_B \), (c) Motion Data of \( Z_C \) And (d) Motion Data of \( Z_A, Z_B, \) and \( Z_C \)

Figure 10. The Testing Performance of 100 Motions: (a) Motion Data of \( Z_A \), (b) Motion Data of \( Z_B \), (c) Motion Data of \( Z_C \) And (d) Motion Data of \( Z_A, Z_B, \) and \( Z_C \)
Table 3. The Testing Performance of Single Motion
(a) Motion Set 1, (b) Motion Set 2, (c) Motion Set 3, and Motion Set 4

| Motion Set | 1  | 2  | 3  | 4  |
|------------|----|----|----|----|
| Inputs     |    |    |    |    |
| (meter)    |    |    |    |    |
| X          | 0.7| 0.5| 0.3| −0.4|
| Y          | 0.2| 0.3| 0.6| 0.7 |
| Target     |    |    |    |    |
| (Radian)   |    |    |    |    |
| Z_A        | 0.6086 | 0.5482 | 0.4784 | −0.3098 |
| Z_B        | −1.0696 | −0.5705 | −0.1597 | 0.5508 |
| Z_C        | −0.5474 | −0.5971 | −1.1973 | −1.5789 |
| Predicted  |    |    |    |    |
| (Radian)   |    |    |    |    |
| Z_A        | 0.6256 | 0.5405 | 0.4675 | −0.3031 |
| Z_B        | −1.0751 | −0.5763 | −0.1646 | 0.5553 |
| Z_C        | −0.5255 | −0.6099 | −1.2226 | −1.5499 |

Figure 10 shows the algorithm performance to generate 100 motions in the direction $Z_A$ (Figure 10(a)), $Z_B$ (Figure 10(b)), $Z_C$ (Figure 10(c)), and combined (Figure 10(d)). The desired 50 motions’ $Z$ values are shown in the blue line, which is compared with the actual values represented in the red line.

Table 4 shows the Socket.IO response within a set of motion with 115.6B processed in 6.68 ms, 50 sets of motion with 912.3B processed in 216.35 ms, and 100 sets of motion with 1712.1B processed in 335.56 ms.

| Table 4. Socket.IO Response |
|----------------------------|
| Inputs (motions)           | 1  | 50 | 100 |
| Data Size (Byte)           | 115.6 | 912.3 | 1712.1 |
| Socket.IO Response (ms)    | 6.68  | 216.35 | 335.56 |

CONCLUSION
This study has developed the method to determine the end-effector position using inverse kinematics and substitute by Artificial Neural Network. All the equations are used to determine the position of the slider that will be dataset for ANN. The proposed method used Artificial Neural Networks (ANNs) to simplify the process of IK solver. The IK solver generated the datasets contain motion data of the Delta robot. 11KB Datasets consist of 200 motion data used to be trained. The proposed method was trained in 58.78 seconds in 5000 iterations. Using a learning rate (α) 0.05 produced an average accuracy of 97.48%, and the average loss was 0.43%. The proposed method was also tested to transfer motion data over Socket.IO with 115.58B in 6.68ms.

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REFERENCES
[1] Z. Pandilov, V. Dukovski, “Comparison of The Characteristics Between Serial and Parallel Robots,” Acta Tehnica Corviniensis: Bulletin of Engineering, vol. 1, no. 7, pp. 143-160, 2014
[2] J. Brinker, N. Funk, P. Ingenlath, Y. Takeda, and B. Corves, “Comparative Study of Serial-Parallel Delta Robot with Full Orientation Capabilities,” IEEE Robotics and Automation Letters, vol. 2, no. 2, pp. 920-926, April 2017, doi: 10.1109/LRA.2017.2654551
[3] Z. Iklima, A. Adriansyah, S. Hitimana, “Self-Collision Avoidance of Arm Robot using Generative Adversarial Network and Partial Swarm Optimization (GAN-PSO),” SINERGI, vol. 25, no. 2, pp. 141-152, 2021, doi: 1022441/sinergi.2021.2.005
[4] H. Yuancan and H. Zonglin, “Neural Network Based Dynamic Trajectory Tracking of Delta Parallel Robot,” IEEE International Conference on Mechatronics and Automation (ICMA), Beijing, China, Aug. 2015, pp. 1938-1943, doi: 10.1109/ICMA.2015.7237782
[5] M. Heidari, S.M.R Faritus, S. Shateyi, “Using Artificial Neural Network for Feed Kinematic problem of Under-Constrained Cable Robots,” Journal of Vibroengineering (JVE), vol. 20, no. 1, pp. 385-400, Feb. 2018, ISN: 1392-8716, doi: 10.21595/jve.2017.18633
[6] M. Shariati, et al., “Application of a Hybrid Artificial Neural Network-Particle Swarm Optimization (ANN-PSO) Model in Behavior Prediction of Channel Shear Connectors Embedded in Normal and High-Strength
Z. Iklima, et al., "Self-Learning of Delta Robot Using Inverse Kinematics and Artificial ... Concrete," Applied Sciences, vol. 9, no. 24, pp. 5534, 2019, doi:10.3390/app9245534

[7] P. Srisuk, A. Sento, Y. Kitjaidure, “Inverse Kinematic Solution using Neural Network from Forward Kinematics Equations,” The 9th International Conference on Knowledge and Smart Technology (KST), Thailand, 2017, pp. 61-65, doi: 10.1109/KST.2017.7886084

[8] EG López, W. Yu, X. Li, “Optimal Design of a Parallel Robot Using Neural Network and Genetic Algorithm,” The 10th International Conference on Intelligent Control and Information Processing (ICICIP), Morocco, February 2017, pp. 64-69, doi: 10.1109/ICICIP47338.2019.9012182

[9] K. K. Pavan, M. J. Murali, D. Srikanth, “Generalized solution for inverse kinematics problem of a robot using hybrid genetic algorithms,” International Journal of Engineering & Technology (IJET), vol.7 no. 4.6, pp. 250-256, 2018, p.250-256, doi : 10.14419/ijet.v7i4.6.20486

[10] E. McCormick, W. Yanjun; L. Haoxiang, “Optimization of a 3-RRR Delta Robot for a Desired Workspace with Real-Time Simulation in MATLAB,” The 14th International Conference on Computer Science & Education (ICCSE 2019), Canada, August 2019, pp. 935-941, doi : 10.1109/ICCSE.2019.8845388

[11] A.G.C Premachandra, et al., “Genetic Algorithm Pick and Place Sequence Optimization for a Color and Size Sorting Delta Robot,” The 6th International Conference on Control, Automation and Robotics (ICCAR), Singapore, April 2020, pp. 209-213, doi: 10.1109/ICCAR49639.2020.9108045

[12] F. Tolli, A. Avanzini, B. Welker, and A. Isinhue, "Design Review of Delta Robot," MECE E3430 Engineering Design. pp. 10-19, 2014

[13] A. A. Jaber and R. Bicker, "Industrial Robot Backlash Fault Diagnosis Based on Discrete Wavelet Transform and Artificial Neural Network," American Journal of Mechanical Engineering, vol. 4, no. 1, pp. 21-31, January 2016, doi:10.12691/ajme-4-1-4

[14] R.Y. Putra et al., “Neural Network Implementation for Invers Kinematic Model of Arm Drawing Robot,” International Symposium on Electronics and Smart Devices (ISESD), Bandung, Indonesia, March 2017, pp. 153-157, doi: 10.1109/ISESD.2016.7886710

[15] T. Collins, W. Shen, “PASO: An Integrated, Scalable PSO-based Optimization Framework for Hyper-Redundant Manipulator Path Planning and Inverse Kinematic,” ISI Tech Report, January 2016

[16] H. Su, C. Yang, H. Mdeihly, A. Rizzo, G. Ferrigno and E. De Momi, "Neural Network Enhanced Robot Tool Identification and Calibration for Bilateral Teleoperation," in IEEE Access, vol. 7, pp. 122041-122051, 2019, doi: 10.1109/ACCESS.2019.2936334

[17] B. A. Garro and R. A. Vazquez. “Designing Artificial Neural Networks using Particle Swarm Optimization Algorithms,” Computational Intelligence and Neuroscience, ID: 369298, June 2015, doi: 10.1155/2015/369298

[18] L. F. Carlos et al., “A soft computing approach for inverse kinematics of robot manipulators,” Engineering Applications of Artificial Intelligence, vol. 74, pp. 104–120, September 2018, doi: 10.1016/j.engappai.2018.06.001

[19] S. Mahdi, et al., “Application of a Hybrid Artificial Neural Network- Particle Swarm Optimization (ANN-PSO) Model in Behavior Prediction of Channel Shear Connectors Embedded in Normal and High-Strength Concrete,” Applied Sciences, vol. 9, no. 24, December 2019, doi: 10.3390/app9245534

[20] L. Peiyuan, “Deep Neural Network Based Subspace Learning of Robotic Manipulator Workspace Mapping,” International Conference on Control, Artificial Intelligence, Robotics & Optimization (ICCAIRO), 2018, vol.1, pp. 109-120, doi: 10.1109/ICCAIRO.2018.00027

[21] T. Dewi, C. Anggraini, P. Risma, Y, Oktarina, and M. Muslikhin, "Motion Control Analysis of Two Collaborative Arms Robots in Fruit Packaging System," SINERGI, vol. 25, no. 2, pp. 217-226, 2021, doi: 1022441/sinergi.2021.2.013

[22] Z. Iklima, "Design of Distributed Control Systems in Lighting Installation in 3-Floor Buildings based on LoTaaS (Internet of Things as a Service) using Docker Container", Jurnal Teknologi Elektro, vol.10, no.1, pp. 26-33, 2019, doi: 10.22441/jte.v10i1.004