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Optimization of DH Parameters of 6R Robotic Manipulator Using JAYA Approach

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ABSTRACT

Manipulation of robots is carried out by the operators through a sequence of commands. However, the accuracy of the manipulation is still hindered due to parameter uncertainty. This results in less accurate robotic operations and hence affects the job performance. Due to measurement errors and sensor faults, the operation of robots malfunctions. Generally, errors are reduced with the use of high precision sensors and correcting hardware faults. However, corrections can also be made on a software platform to handle the correction process. Presently, the Denavit–Hartenberg (DH) parameters of a robotic manipulator are optimized for forward kinematics problems. The optimization is carried out using the JAYA approach. The 6R MTAB Aristo XT robot is selected as a case study for the experimental validation of the proposed approach. Experimental results reveal that the optimization of DH parameters improves accuracy for forward kinematic estimation problems. The proposed JAYA approach can further be extended to other robotic manipulators for parameter optimization problems.

KEYWORDS

6-DOF Robot, Forward Kinematics, JAYA Algorithm, Mean Square Error (MSE), MTAB, PSO, Trajectory Path

INTRODUCTION

Because the structures of robotic manipulators vary, they have distinct kinematic models. As a result, these models are linked to a variety of mathematical functions to determine the relationship between joint angles and their positions. In most cases, the joints are connected in series and are controlled by actuators such as motors. The gripper is commonly used at the end of a series of connected links. The position of the robotic arm in the three-dimensional coordinate system is defined by this. The estimated problem for robotic models is divided into two categories: 1) forward kinematics and 2) inverse kinematics. Forward kinematics (Saha, 2014) is derived from equations that derive relationships between the location of the gripper and the joints. Inverse kinematics is the process of estimating joint angles from end position information.

The transformation matrices are utilized to establish the relationship between this angle position data. The rotational and translational relations defined by the transformation matrices cannot be generalized a priori for all sorts of robots. Because each robot has its own joint spaces and limitations, a mathematical model must be developed to determine the relationship between joint angles and position. Although fuzzy-based tactics have been shown to be effective for such estimates (Jamwal et al., 2010), they cannot be applied to all robots. Machine Learning (ML) models can be used to discover such correlations, which may overcome the hampered generalization problem (Craig, 2009). Several

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machine learning algorithms addressing the generalization of robotic manipulators to anticipate robot position have been suggested in the last decade. The Fuzzy Logic methodology is used to study the path planning of a 6R robot, and it has been proven that the Gaussian membership function produces superior results than other membership functions (Sahu & Choudhury, 2018).

Various optimization approaches are compared for the inverse kinematics problem of a serial robot manipulator (Ayyıldız & Çetinkaya, 2016). An optimized approach for a redundant serial robotic manipulator is presented (Kivela et al., 2017). The optimization approaches are also found helpful in estimating the position information for 2-DOF using genetic programming (Arellano & Rivera, 2019). The hybrid algorithm comprising fuzzy system, genetic algorithm and immune algorithm has been proposed for solving the forward kinematics problem of the stewart platform (Sheng et al., 2006). Also, joint space and orientation representations for the forward kinematics estimation is presented (Grassmann & Burgner-Kahrs, 2019). Optimum design parameters of the robotic gripper have been obtained by using various meta-heuristics techniques like ABC, FA, TLBO, ACO, and PSO algorithm (Mahanta et al., 2019). In this article, a two-step methodology such as geometric modeling followed by the formulation of objective functions is adopted to solve the problem.

The Particle Swarm Optimization (PSO) approach used for various forward and inverse kinematic estimation can be found in (Jahandideh & Namvar, 2012) (Durmus et al., 2011) (Huang et al., 2012) (Li et al., 2007) (Zhang & Gao, 2012). For inverse kinematics, a new quantum-behavioured particle swarm algorithm has been proposed recently (Dereli & Köker, 2020). A Meta-Heuristic Paradigm for solving the Forward Kinematics of 6-6 General Parallel Manipulator (Chandra et al., 2009). Also, inverse kinematics problems have been solved using the Firefly Algorithm (Rokbani et al., 2015). A series of meta-heuristic approaches applicable to robotics can be found in (Erdogmus & Toz, 2012). Other than PSO, the forward kinematics of parallel manipulators have been solved with the Genetic Algorithm (Boudreau & Turkkan, 1996). The inverse kinematics for arm movements of robots is presented in the article (Cavdar et al., 2013). Various meta-heuristic methods like ACO, PSO, FA, FOA, FWA and ABC swarm intelligent optimization algorithms are employed to optimize the global and local path planning of mobile robots (Lei et al., 2019).

However, in spite of all the generalization models, the uncertainty exists in the robots creating difficulty in the estimation process. An optimization technique for identifying robot manipulator parameters under uncertainty is presented in (Li et al., 2016). Based on the problem stated in the paper (Li et al., 2016), the present paper focuses on the DH parameter optimization. Although the PSO, genetic algorithm, and firefly algorithms are widely applied for the kinematic estimation, the JAYA (Rao, 2016) approach is unexploited so far. Hence, presently the JAYA approach is applied for optimization of Denavit–Hartenberg (DH) parameters for the 6-DOF forward kinematic estimation under uncertainty.

Forward Kinematics Modeling

The position and orientation of end-effector relies on multiple (for each joint) homogeneous transformation matrices. So, the forward kinematics problem can be well-established with information on joint position and rotational constraints. Figure 1 shows the experimental setup of the MTAB Aristo-XT robot. An Aristo robot is a six-axis articulated robot with all rotary joints.

Figure 1. Aristo XT 6-DOF Robot in home position

The transformation matrix between end-effector and base frame, for a 6-R robot, can be represented as follows.

$$T_6 = A_1 * A_2 * A_3 * A_4 * A_5 * A_6 \quad (1)$$

Where, the transformation matrix T_6 can be described as a product of six homogeneous transformation matrices represented as A_i (each $i = 1,2,3...6$ .represents a joint). And each 4×4 transformation matrix A_i can be represented as:

$$A_i = \begin{bmatrix} \cos(\theta_i) & -\cos(\alpha_i)\sin(\theta_i) & \sin(\alpha_i)\sin(\theta_i) & a_i\cos(\theta_i) \\ \sin(\theta_i) & \cos(\alpha_i)\cos(\theta_i) & -\sin(\alpha_i)\cos(\theta_i) & a_i\sin(\theta_i) \\ 0 & \sin(\alpha_i) & \cos(\alpha_i) & d_i \\ 0 & 0 & 0 & 1 \end{bmatrix}. \quad (2)$$

$$T = \begin{bmatrix} n_x & o_x & a_x & p_x \\ n_y & o_y & a_y & p_y \\ n_z & o_z & a_z & p_z \\ 0 & 0 & 0 & 0 \end{bmatrix} \quad (3)$$

Where, with reference to the base frame, the position of the end-effector is represented as vector p, and the orientations are represented as n, o, and a vectors. The a represents the approach vector, o represents the orientation vector, and n is normal to both a and o vectors.

Robotic DH Parameters Under Uncertainty

A robot is generally characterized by the ideal DH parameters. The DH parameters of the experimented ARISTO XT 6-DOF robot are presented in Table 1.

Table 1. *Joint-link parameters for the 6r Mtab Aristo-XT Robot*

$\mathbf{Joint}_{\mathrm{i}}$	$\alpha_i(\mathrm{deg})$	$\alpha_{\mathrm{i}}\left(\mathbf{mm}\right)$	$\mathbf{d}_{\mathrm{i}}\left(\mathbf{mm}\right)$
1	90	0	158
2	0	300	0
3	90	0	0
4	90	0	-378.5
5	90	0	0

Let a robot, specified as a function $f\left(.\right)$ of its DH parameters a,d,α and six joint angles as θ. So, robotic operation can be represented as in Eq 4.

$$f\left(a,\ d,\ \alpha,\ \theta\right) = P \tag{4}$$

Where, a represents the ideal link length, d represents the ideal link offset; α represents the ideal twist angle and P represents the ideal $X,Y\, and\, Z$ position information of the end effector.

However, due to uncertainty, the forward kinematic estimation redirects to a different position information introducing error. So, the DH parameters generally differ from its ideal values and introduce the position error. Hence, for modeling the uncertainty the Eq. 4 can be rewritten as Eq. 5.

$$f\left(\Delta a,\ d,\ \Delta\alpha,\ \theta\right) = \Delta P \tag{5}$$

Where, Δa represents the real link length, Δd represents the real link offset; $\Delta\alpha$ represents the real twist angle and ΔP represents the real $X,Y\, and\, Z$ position information of the end effector. The errors in the DH parameters can be represented as .$\Delta \mathrm{a} = \mathrm{a} + \delta \mathrm{a}$., $\Delta \mathrm{d} = \mathrm{d} + \delta \mathrm{d}$, and $\Delta \mathrm{a} = \mathrm{a} + \delta \mathrm{a}$ for link length, link offset, and twist angle, respectively. This will result in the ideal DH parameter to its uncertainty as in Table 2.

In order to obtain the uncertainty DH parameters, the link length $\delta \mathrm{a}$, link offset $\delta \mathrm{d}$ and twist angle $\delta \mathrm{a}$ should be optimized in such a way that the position estimation will be accurate. Presently, the JAYA optimization is adopted for finding such uncertainty DH parameters for forward kinematic estimation problems.

Table 2. *Joint-link parameters for the 6R MTAB Aristo-XT robot with uncertainty.*

$\mathbf{Joint_i}$	$\alpha_i\,(\mathbf{deg})$	$\mathbf{a_i}\,(\mathbf{mm})$	$\mathbf{d_i}\,(\mathbf{mm})$
1	$90 + \delta\alpha_1$	$0 + \delta a_1$	$158 + \delta d_1$
2	$0 + \delta\alpha_2$	$300 + \delta a_2$	$0 + \delta d_2$
3	$90 + \delta\alpha_3$	$0 + \delta a_3$	$0 + \delta d_3$
4	$90 + \delta\alpha_4$	$0 + \delta a_4$	$-378.5 + \delta d_4$
5	$90 + \delta\alpha_5$	$0 + \delta a_5$	$0 + \delta d_5$

JAYA Optimization Approach

Rao (Rao, 2016) proposed the Jaya algorithm, which is gaining popularity because of its simplicity and durability. The current solution in this method always seeks to advance towards the best solution without using any additional algorithmic hyper-parameters like others do.

Let, $f(x)$ be the goal function that has to be minimized or maximized. Assume that there are m design variables and n possible solutions (i.e. population size $k = 1, 2, \ldots, n$) in each iteration i. Let's say the best candidates for $f(x)$ are represented as $f(x)_b$ while the worst candidates in the complete candidate solution are represented as $f(x)_w$. If $X_{j,k,i}$ represents the value of the j^{th} variable for the k^{th} candidate during the i^{th} iteration, then the equation used to update $X_{j,k,i}$. to $X'_{j,k,i}$.is expressed as in Eq. 6.7.

$$X'_{j,k,i} = X_{j,k,i} + \Delta X \tag{6}$$

$$\Delta X = r^1_{j,i}\left(X_{j,b,i} - |X_{j,k,i}|\right) - r_{j,i}^{\,2}\left(X_{j,w,i} - |X_{j,k,i}|\right) \tag{7}$$

where, $r^1_{j,i}$ and $\mathrm{r}^2_{\mathrm{j,i}}$ are the two uniformly distributed random numbers for the j^{th} variable during the i^{th} iteration in the range (0 to 1).

The tendency of the solution to move closer to the best solution is indicated by the term $+r^1_{j,i}(X_{j,b,i} - X_{j,k,i})$ whereas the tendency of the solution to avoid the worst solution is indicated by the term $-r^2_{j,i}(X_{j,w,i} - X_{j,k,i})$. So, the algorithm always tries to get closer to success (i.e. reaching towards the best solution) and tries to avoid failure (i.e. moving away from the worst solution). The algorithm is named as Jaya (a *Sanskrit* word meaning *victory* or *triumph*) because it always strives towards the best solution.

Algorithm 1 is the pseudocode for the proposed DH parameter estimation. (Rao, 2016) also has a full description of the Jaya optimization algorithm. In this study, the same optimization algorithm is employed to optimize the DH parameters. The subsection below provides a description of Jaya for DH parameter optimization.

Modeling the Objective

The objective is defined as the Mean Square Error of the position estimate and is presented as in Eq. 8.

$$C = \sqrt{\frac{(p_x - p'_x)^2 + (p_y - p'_y)^2 + (p_z - p'_z)^2}{3}} \tag{8}$$

Constraints are defined as 1), 2), and 3) where, the, and are represented as the upper and lower bounds for the link length, link offset, and twist angle, respectively.

Experimental Setup

The Aristo XT MTAB robot is selected as a case study to perform forward kinematics analysis. The joint-link parameters for the 6R MTAB Aristo-XT robot are presented in Table 3. The experimental setup consists of a 6R Aristo-XT robot in which the robot position is determined by the first three degrees of freedom and is located in the arm. The following three degrees of freedom provide orientation and are located in the end effectors. The six joint angles (A_1 to A_6 . within the given specified limits are known as input variables, whereas the position of the end-effector (world coordinates $X, Y\ and\ Z$. are expressed as outputs. The Aristo Version 1.4 software is used for the simulation of the robot and is presented in Fig-2. Various applications like palletizing, loading/ unloading, gluing, spray painting, polishing, segregation of objects using vision systems, etc. can be performed by the Aristo-XT robot.

The experimental variation of the six angles is presented in Figure 3 and the trajectory of the experimental variation is presented in Figure 4. The collected dataset consists of 800 samples. The performances are evaluated in terms of MSE using tables and graphical representations, for each $X, Y\ and\ Z$ location; and also using three-dimensional representations.

Simulation for the proposal is carried out using MATLAB18-b software, installed on a PC of Intel i-5, 12 GB RAM.

Figure 2. Coordinates of robots using aristo simulation

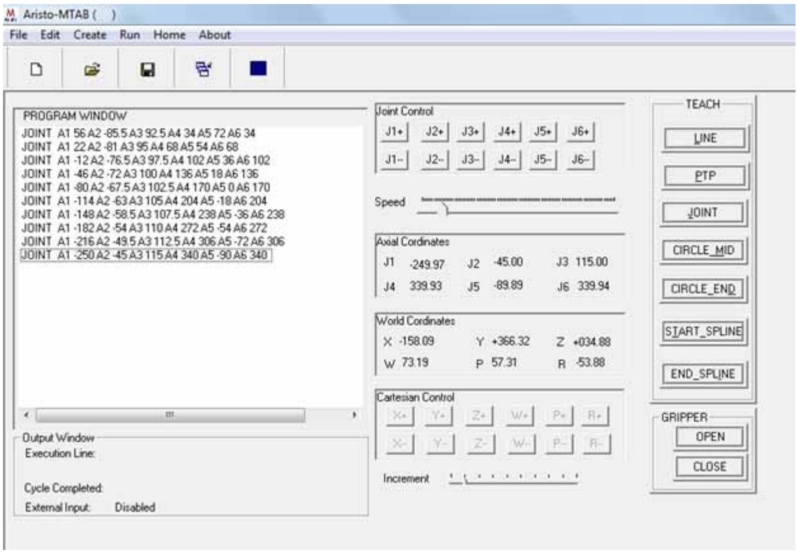


Table 3. Joint-link parameters for the 6R MTAB Aristo-XT robot

$\mathbf{Joint}_i$	$\theta_i(\text{deg})$	$\alpha_i(\mathbf{deg})$	$\alpha_i(\mathbf{mm})$	$\boldsymbol{d}_1(mm)$	θ_i^{min}	θ_i^{max}
1	0	90	0	158	-150	+150
2	90	0	300	0	+60	+120
3	160	90	0	0	+130	+190
4	-180	90	0	-378.5	-210	-150
5	0	90	0	0	-90	+90
6	0	0	0	64	-165	+165

Algorithm 1 Jaya for optimal DH parameter estimation
1: Procedure JAYA
Initialize: Ub,Lb,DH
Initialize: particles DH ~ U [Ub,Lb]
Pbest=min (f (DH)) Psolbest=DH (argmin (f (DH)))
Psolworst=DH(argmax (f (DH)))
Gbest=Pbest
Gsol=Psolbest

$$G_{sol} = P_{sol}^{best}$$

2: while termination criteria not met do

3: $DH = DH + r1\left(P_{sol}^{best} - DH\right) - r2\left(P_{sol}^{worst} - DH\right)$.

4: $DH = DH\left(Ub,\ Lb\right)$

5: $P_{best} = \min\left(f\left(DH\right)\right)$.

6: $P_{sol}^{best} = B\left(\text{argmin}\left(f\left(DH\right)\right)\right)$

$P_{sol}^{worst} = B\left(\operatorname{argmax}\left(f\left(DH\right)\right)\right)$.
If $P_{best} < G_{best}$ *then*
$G_{best} = P_{best}$
$G_{sol} = P_{sol}^{best}$
end if
end while
Final G_{sol} .is the optimal band sequence DH_{opt}
end procedure

Results and Discussion

Both the JAYA and PSO approach are applied to optimize the robot DH parameters. The convergence curve of the JAYA optimization approach is presented in Figure 5. The aim of the JAYA approach is to minimize error using the cost function in Eq. 8. Figure 5 presents the Mean Square Error curve as an objective cost function over 50 iterations. It shows both the global best cost and local mean cost over 50 iterations. The decreasing trend in Figure 5 clearly shows the significance of the proposed JAYA approach for optimization of the DH parameters under uncertainty.

Figure 3. Experimental variation of angles for six rotary joints

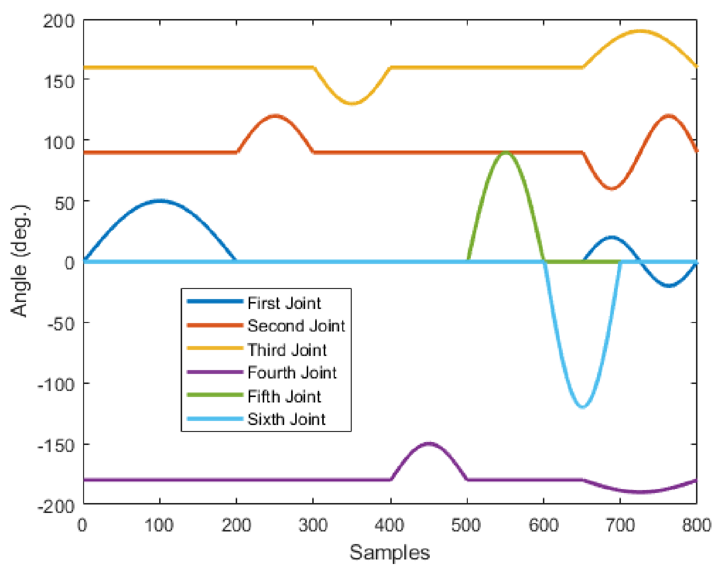


Figure 4. Trajectory path for the experimental variation of angles for six rotary joints

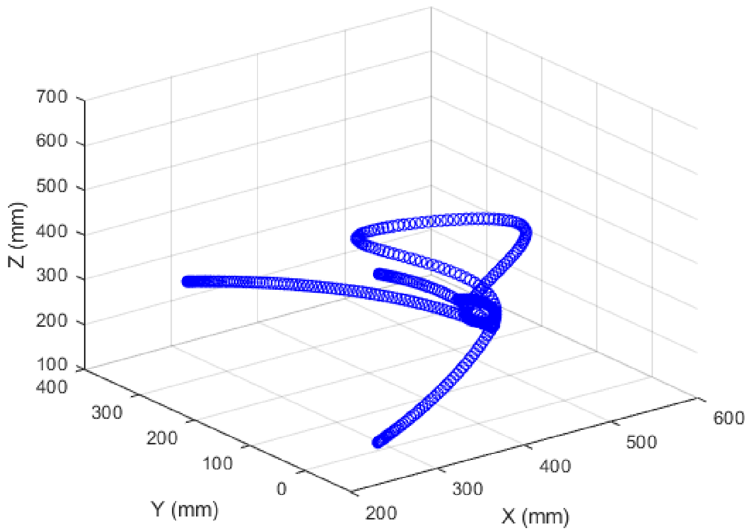


Table 4. PSO optimized DH parameters with uncertainties

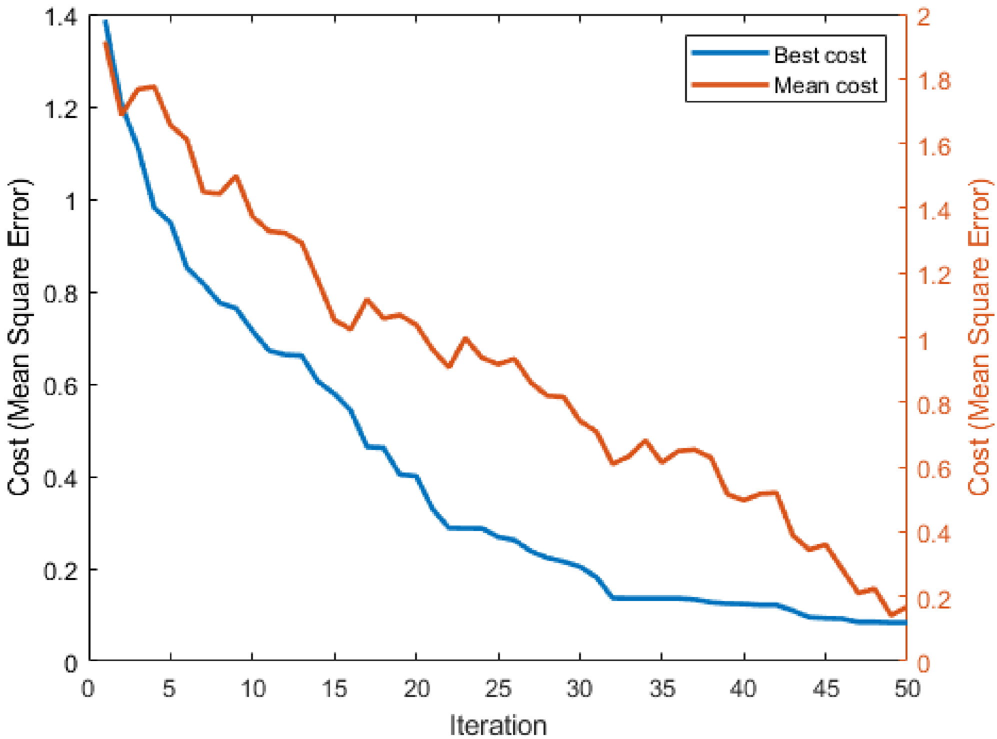
Joint_i	$\alpha_i\,(\text{deg})$	$\alpha_i\,(\text{mm})$	$d_i\,(\text{mm})$
1	90 + 0.791	0 + 08	158 + 05
2	0 + 0.219	300 + 12	0 + 09
3	90 + 5.213	0 + 13	0 + 11
4	90 + 1.993	0 + 33	–378.5 + 31
5	90 + 2.982	0 + 08	0 + 02
6	0 + 1.016	0 + 07	64 + 11

Table 5. JAYA optimized DH parameters with uncertainties

Joint_i	$\alpha_i\,(\text{deg})$	$\alpha_i\,(\text{mm})$	$d_i\,(\text{mm})$
1	90 +2.181	0 + 12	158 + 07
2	0 + 1.324	300 + 17	0 +12
3	90 + 1.573	0 + 17	0 + 09
4	90 + 2.749	0 + 27	–378.5 + 17
5	90 + 3.014	0 + 09	0 + 03
6	0 + 0.348	0 + 07	64 + 02

The obtained optimized DH parameters for PSO and proposed JAYA are presented in Table 4 and Table 5 respectively. From Table 5 it is clear that the JAYA approach resulted in the δa, δd, and $\delta \alpha$ DH parameters which represent the estimated optimized values for six joints of link length, link offset and twist angle parameters, which are different from the PSO parameters in Table 4.

Figure 5. *Convergence curve of Jaya optimization approach*

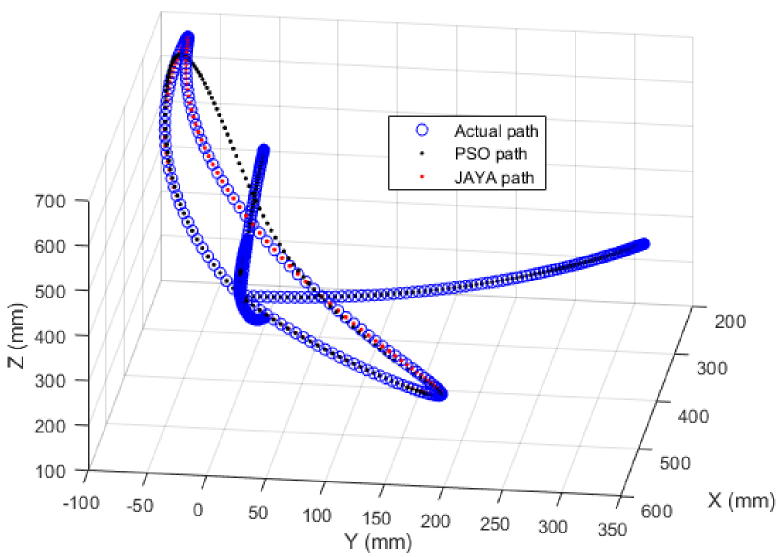


Based on the optimized DH parameters, robotic forward kinematic estimation using mathematical models is performed using Eq. 1. Based on the experimental variation of six rotary joint angles in Fig. 3, the end effector position estimation is performed for both with and without optimization of DH parameters. The Mean Square error of $X, Y \; and \; Z$ position estimation for PSO and JAYA approach are presented in Table 6. From the table it is observed that the MSE for each axis is as $X, Y \; and \; Z$. and the mean MSE of the proposed JAYA approach is less than PSO approach. The significant decrease in mean MSE from 4.25 to 0.47 represents the traditional PSO and the proposed JAYA approach, respectively. The trajectory curves for both conditions are presented in Figure 6. From Figure 6 it can be observed that the PSO path does not follow the actual path, while, when DH parameters are optimized using JAYA, the trajectory is almost identical to the ideal path. This signifies the proposed JAYA approach for DH parameter optimization under uncertainty for forward kinematics estimation problems.

Table 6. Mean Square Error for $X, Y \ and \ Z$ .locations with mean of MSE comparison for PSO and JAYA approach

Joint$_i$	$X - MSE$	$Y - MSE$	$Z - MSE$	$MEAN - MSE$
PSO	3.81	4.84	4.12	4.25
JAYA	0.71	0.32	0.37	0.47

Figure 6. Trajectory comparison for PSO and Jaya optimization approach



CONCLUSION

Due to widespread application of robotic automation, estimation of position from their joint angles is necessary and the relevant approaches are widely available in the literature. Due to uncertainty in the robotic manipulators, calibration is required in the tools or in the measurement process. Such a calibration can also be carried out using the optimization of DH parameters. This can lower manual intervention, hardware corrections, and also the time to solve the uncertainty problem. Presently, the JAYA approach is adopted for optimization of the DH parameters under uncertainty. The convergence curve shows the efficiency of the JAYA algorithm. The obtained DH uncertainties are reported in Table 5 and further forward kinematics estimation using mathematical models is performed. The obtained results of the trajectory path in Figure 6 clearly show the significance of the proposed approach. From Table 6 it is clearly observed that the mean MSE of the proposed JAYA approach is 0.47, which is much smaller than the MSE of 4.25 of the state-of-art PSO approach. However, further experiments can be carried out on other robotic configurations for global validation of the proposed approach.

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