DENAVIT HARTENBERG NEWTON OPTIMIZED ITERATIVE DEMING REGRESSION BASED OPTIMAL TRAJECTORY TRACKING

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ABSTRACT:
Unmanned Aerial Vehicles (UAVs) also referred to as drones are competent of performing mission related operations in an autonomous fashion. For the purpose of more accurately tracking designated trajectories with minimal response time and convergence speed, numerous trajectory tracking in UAV have been proposed. Progresses in computer and electronic technologies have smoothened evolution in automation control and intelligent algorithms and also certain significant contributions have been made into action on the trajectory tracking in UAV. In this work a method called, Denavit Hartenberg and Newton Optimized Iterative Deming Regression (DH-NOIDR) trajectory tracking in UAV with the objective of minimizing the response time and convergence speed is proposed. The DH-NOIDR method is divided into two parts, namely path planning and trajectory tracking. UAV path planning enables UAVs to key away from impediments and tracks the target in an efficient manner. To produce optimal paths without impediments collision for UAVs, a novel path planning algorithm based on 3D position information and frames of reference using Denavit Hartenberg parameters are initially proposed. With this type of design employing Denavit Hartenberg parameters results in the optimal path planning therefore reducing response time, and improving accuracy. Second, with the path planning results, a combination of TDoA and machine learning technique employing Deming Regression function is proposed that with the aid of three distinct characteristics, fine tuning the positioning of the drone, enhancing the iteration to ensure optimal search and setting the termination condition by reducing the sum of square residuals (SoSR) convergence-efficient trajectory tracking results are said to be obtained. The testing results have revealed that the DH-NOIDR method surpassed the state-of-the-art on the drone dataset in terms of response time, accuracy, error and convergence speed. In particular, the response time and convergence speed were reduced by 38% and 36% in comparison to earlier work respectively.

1.Introduction

Not long ago the trajectory tracking applications of UAVs have been extensively utilized in innumerable real world applications where human functioning is restricted. With the shooting up of data volume and accuracy prerequisites for specific applications, the reliable operations of UAV, i.e. minimizing the response time has been identified as one of the most essential factors. Efficient trajectory tracking algorithms enable optimal and smooth trajectory with minimum response time.

A joint optimization method considering delay and energy into factor called, Deep Deterministic Policy Gradient (DDPG) was introduced in [1]. Initially, the unconstrained dynamics with input saturation were included in Deep Reinforcement Learning (DRL) based model with the purpose of significantly offloading tasks and efficiently managing allocation of resources in a cost efficient manner. Based on the computational cost being a standardized function of time delay and energy, UAV put forwards its solutions to End User Devices in such a manner so as to combine trajectory and cost optimization. However, the response time involved in 3D trajectory dynamics were not focused. An improved Salp Swarm Algorithm (LASSA) with Rapidly-exploring Random Trees (RRT) (LASSA-RRT) considering patrol effectiveness of UAV, cost involved in trajectory and its corresponding cost involving power consumption was proposed in [2]. In addition the predation process of the salps group was embodies into the random sampling that in turn minimized the arbitrary point invalid sampling and conversed the search mechanism with the purpose of enhancing global search with minimal sampling time and length. While UAV will be pivotal in arriving at the objectives of future 6G networks, numerous proceedings must be addressed in order to make the most of its prospective advantages. Such advantages consist of computational load, response time and accuracy. A deep reinforcement learning (DRL) based UAV method was designed in [3] that by optimizing the joint action therefore optimizing the trajectory tracking efficiency in a significant manner. However under the presence of numerous uncertainties along with external impediments time delay were said to be identified. To address on this issue, a Linear Quadratic Tracker with Integrator model was presented in [4]. With this design model and employing linear and angular velocity component, the delay time involved in tracking was found to be improved. Yet another method to address uncertainty was handled in [5] employing fuzzy adaptive tracking controller method. By employing this controller method the constraints were provided in the form of linear matrix inequality that in turn not only reduced the prediction error but also ensured high accuracy.Trajectory tracking for real time application has long been a demanding issue but crucial element as far as robotics are concerned. Owing to the pervasiveness of nonlinear dynamics, and high dimensionality, it is frequently found to be both laborious and cumbersome in optimizing the trajectories. A bi-level optimization method employing parametric nonlinear programming was proposed in [6] that with the aid of analytical gradients ensured computation speed and accuracy to a greater extent. Yet another collaborative target tracking method employing alternating direction penalty method was designed in [7]. Through the use of this collaborative mechanism ensured optimal performance with regard to time and accuracy. Over the past several years, UAVs have manifested assurance for an extensive span of real time applications, to name a few being disaster rescue, protection of wildlife and remote surveillance. In most of the application to make certain the accomplishment of numerous tasks, UAV must traverse in a safe manner between numerous locations to accomplish numerous tasks. An optimization method employing proximal policy was presented in [8]. By using this proximal policy and generalized deep reinforcement learning in a distributed manner ensured tracking accuracy in a significant manner. Despite ensuring accuracy both the method did not concentrate on the execution time. To address on this issue, hybrid method employing modified ant colony optimization and memory efficient algorithm was proposed in [9]. By using this hybrid method by means of first identifying efficient path and then tracking the trajectory resulted in the improvement of both accuracy and response time to a greater extent. A refined deep reinforcement learning approach focusing on the convergence was introduced in [10]. Here a specialized loss function was presented that with the aid of stack ensured accuracy and convergence speed to a greater extent. Yet another method focusing on the convergence speed employing novel DRL-based end to end controller was proposed in [11]. By employing this controller the convergence speed was improved to a greater extent. A trajectory planning method towards tracking was designed in [12]. Here, with the aid of trajectory mapping network computation speed and accuracy was ensured.

In this study, we introduce a method, called, Denavit Hartenberg and Newton Optimized Iterative Deming Regression (DH-NOIDR) trajectory tracking in UAV. The primary goal of this work is to reduce the response time in addition to convergence speed by designing an optimal method for trajectory tracking in UAV. Many studies have been introduced focusing on optimization and machine learning techniques. In contrast, the DH-NOIDR method combines the path planning and trajectory tracking in UAV. First drone data is collected using the drone dataset and stored in the form of input vector. Next, with the obtained traffic data, DenavitHartenberg UAV path planning is designed to focus on the response time and accuracy. Following which, Optimized Iterative Deming Regression algorithm is applied to the obtained optimal path for tracking the trajectory with minimal convergence and error.

1.1 Contributing remarks

- To design an optimal method for minimizing response time during trajectory tracking in UAV, Denavit Hartenberg and Newton Optimized Iterative Deming Regression (DH-NOIDR) method is introduced on the basis of two distinct processes namely, path planning and trajectory tracking.
- To select optimal path, Denavit Hartenberg UAV path planning is applied to the collected drone data and finally the interpolated results are arrived at towards efficient path planning with minimal response time and maximum trajectory tracking accuracy.
- Newton Optimized Iterative Deming Regression-based optimal trajectory tracking is then applied for arriving at the accurate trajectory tracking with minimal error.
- Immense experiments are organized to measure the performance of the DH-NOIDR method and state-of-the-art methods. The results achieved shows that our proposed, DH-NOIDR method provides enhanced performance regarding response time, trajectory tracking accuracy, convergence rate, efficiency and trajectory tracking error.

1. Related works

Autonomous drones are progressively used to accumulating pertinent technical data about the Earth. In recent decades, swift technological evolutions have unfastened their prospective as a pliable, cost efficient tool ensuring smooth tracking.

A combination of an adaptive neuro fuzzy logic and particle swarm optimization was introduced in [13] to minimize tracking error. The applications of trajectory tracking have been extended from medical to healthcare and agriculture. In [14] variable resolution images were obtained using coarse grid search for accurate agriculture monitoring. A review of multi-agent trajectory tracking employing optimization methods were investigated in [15]. In recent decades there are at present big challenges as far as urban environments are concerned. Moreover novelty is materials and methods have been approaching owing to the increase in traffic and space utilization. However, electrically powered UAVs are an environmentally and time-efficient substitute even in remote locations. With the objective of optimizing flight trajectories tailored a star algorithm was introduced in [16] to minimizing the energy required for UAV in city environments. Autonomous drone detection and tracking employing multi frame deep learning technique was introduced in [17]. In [18] focus was made on ensuring good adaptability, speed and significant tracking performance employing double critic network and deterministic probabilistic gradient model. Yet another energy efficient mechanism using first order taylor series expansion was designed in [19]. However, issues were not addressed as far as complex scenarios were concerned. To focus on this issue, piecewise potential field was designed in [20] that with the aid of lead plane wingman structure ensured accuracy even in the context of complicated scenarios.

Inspired through the aforementioned articles, though some trajectory tracking mechanism in UAV ensures accuracy but failed to concentrate on the response time factor. Conversely, despite improvement observed regarding overhead incurred in trajectory tracking, two major trajectory tracking aspects, like convergence speed and error rate were not focused. To concentrate on all the above said four performance metrics, in this work, an optimal method for trajectory tracking in UAV focusing on the response time called, DenavitHartenberg and Newton Optimized Iterative

Deming Regression (DH-NOIDR) is designed. The elaborate description of the DH-NOIDR method is provided in the following sections.

2. DenavitHartenberg and Newton Optimized Iterative Deming Regression (DH-NOIDR) trajectory tracking in UAV

UAVs have become very admired amidst researchers in recent years, owing to their potentialities of several applications including meteorological surveillance, monitoring disaster, military surveillance and so on. To minimize response time and convergence speed , numerous investigations have been carried out for UAVs. Nevertheless, due to nonlinearity traditional method may perform poorly under uncertainty. In this work a method called Denavit Hartenberg and Newton Optimized Iterative Deming Regression (DH-NOIDR) trajectory tracking in UAV is proposed. The DH-NOIDR method is divided into two parts, and a summary is provided below.

2.1 Denavit Hartenberg UAV path planning

The first and foremost objective in the design of trajectory tracking in UAV is to minimizes the response time in an optimal manner. To achieve this objective, path planning remains the major issues to be handled so that the target can be tracked in an efficient manner. Also, the main purpose of path planning remains in minimizing response time and maximizing accuracy involved in trajectory tracking in UAV. With this objective in this section a Denavit Hartenberg UAV path planning model is designed. Figure 1 shows the structure of Denavit Hartenberg UAV path planni

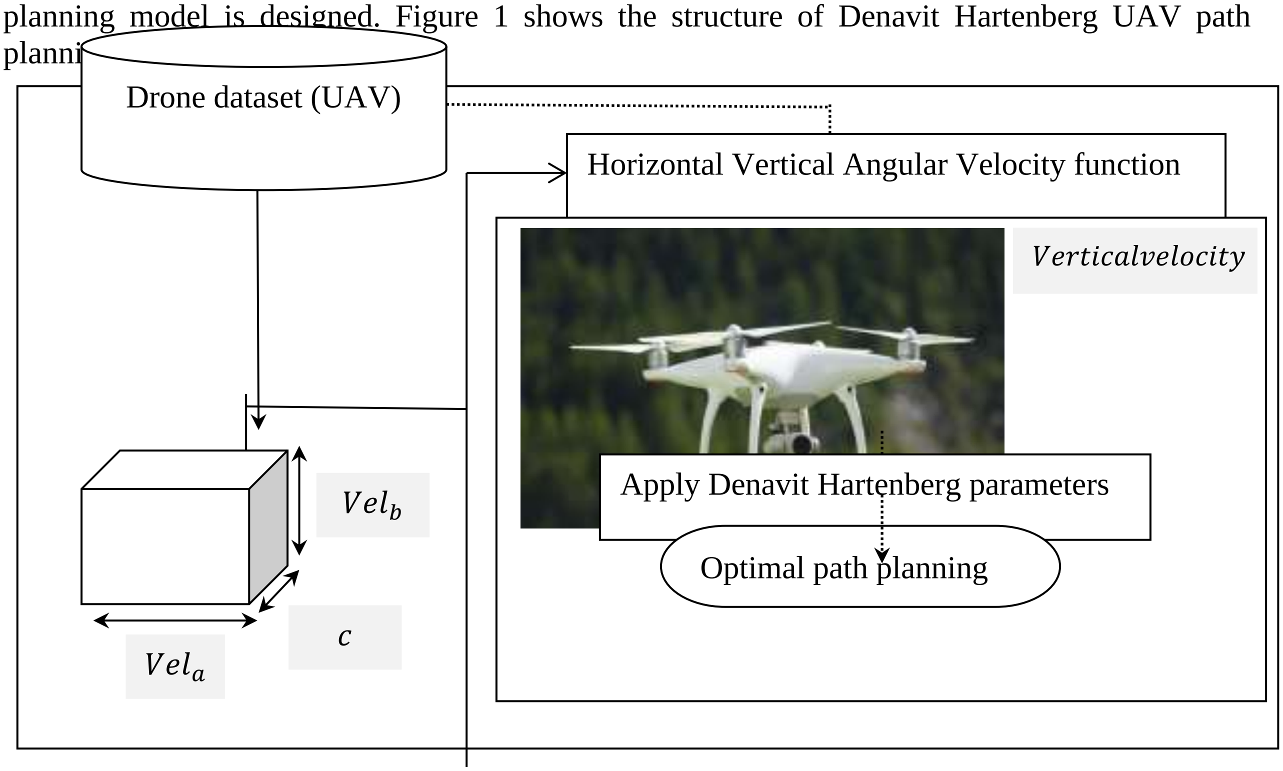

Figure 1 Structure of DenavitHartenberg UAV path planning model

Taking 3D position information and frames of reference of UAV as objective function, the path planning model is improved to minimize computational cost and time for optimal trajectory tracking in UAV. As illustrated in the above figure, initially, 3D position information is achieved through the Horizontal Vertical Angular Velocity function. By obtaining this 3D position information, the i.e., the horizontal, vertical and angular velocity into consideration the response time will gets faster or earlier. Following which Denavit Hartenberg parameters like origin, scale and orientation is considered to model optimal path planning. By employing the Denavit Hartenberg parameters accuracy is also said to be maintained.

In this work to perform trajectory tracking in UAV in order to minimize the response time and maximize the accuracy as said before, a raw drone dataset Unmanned Aerial Vehicle

(Rotary Wing Unmanned Aerial Vehicles) obtained from https://www.kaggle.com/datasets/dasmehdixtr/drone-dataset-uav is considered as input. The drone dataset comprises of 2718 files. Here the overall files in the form of JPG and txt files are split into 1359 each to perform trajectory tracking with minimal response time. Also in the text file five features '$F = \{F_1, F_2, F_3, F_4, F_5\}$' (i.e., x width ('$x_w$'), y width ('$y_w$'), x height ('$x_h$') and y height ('$y_h$') respectively are present. The input matrix for performing the corresponding task of trajectory tracking in UAV is mathematically stated as given below.

$$IM = [SI_1F_1SI_1F_2 \ \dots \ SI_1F_nSI_2F_1SI_2F_2 \ \dots \ SI_2F_n \ \dots \ \dots \ \dots \ \dots \ SI_mF_1SI_mF_2 \ \dots \ SI_mF_n] \quad (1)$$

From the above equation (1) provided with the input matrix 'IM' the width and height of each sample drone images are obtained for further processing. Let us further consider the drone (UAV) in a 3-dimensional (3D) environment. The vector '$p(t)$', '$q(t)$' and '$r(t)$' provides with the present 3D location or position of the UAV in action and is mathematically formulated as given below.

$$p(t) = b(t)cos\big(\mu(t)\big), whereb(t) \in [0, z_1] \quad (2)$$

$$q(t) = b(t)sin\big(\mu(t)\big) \quad (3)$$

$$\mu(t) = c(t), wherec(t) \in [-z_2, z_2] \quad (4)$$

$$r(t) = a(t), wherea(t) \in [-z_3, z_3] \quad (5)$$

From the above equations (2), (3), (4) and (5) the 3D location or position information $p(t)$', '$q(t)$' and '$r(t)$' are obtained based on the cosine and sine angle of the horizontal plane '$\mu(t)$', horizontal velocity '$b(t)$', angular velocity '$c(t)$' and vertical velocity '$a(t)$' respectively. These functional values are said to be varying according to the control inputs '$[z_1, z_2, z_3]$' (i.e., class_ID, width and height of each drone sample). Moreover to ensure optimal path planning, Denavit Hartenberg parameters are employed wherein with the application of frames of reference (i.e., origin, scale and orientation) as set by a reference points. Here, the reference points are regarded as a two-dimensional coordinates that not only retains dynamic system characteristics but also decreases the amount of input (i.e., coordinates). The coordinate transformations along a serial UAV consisting of 'l' links form the kinematics equations of the UAV is then represented as given below.

$$[T] = [b_1][a_1][b_2][a_2] \dots\dots [b_l][a_l] \quad (6)$$

With the above coordinate transformations (6) as illustrated in figure, 'Vel_a' and 'Vel_b' represent the UAV horizontal and vertical velocities, 'c' representing the UAV angular velocity and 'θ_t' denoting the heading angle of UAV respectively. Then, the UAV position increment alongside the coordinate transformations 'Δt' is mathematically stated as given below.

$$\Delta a = Vel_a \Delta t Cos\theta_t - Vel_b \Delta t Sin\theta_t \quad (7)$$

$$\Delta b = Vel_a \Delta t Sin\theta_t - Vel_b \Delta t Cos\theta_t \quad (8)$$

$$\Delta t = c\Delta t \quad (9)$$

From the above equations (7), (8) and (9), the transformation '$[T]$', the joints connecting the links 'b_i' and 'a_i' are mathematically stated as given below.

$$[b_i] = [Cos\theta_i - Sin\theta_i 00 Sin\theta_i Cos\theta_i 0000100001] \quad (10)$$

$$[a_i] = \big[10000 Cos\alpha_{i,i+1} - Sin\alpha_{i,i+1} 00 Sin\alpha_{i,i+1} Cos\alpha_{i,i+1} 00001\big] \quad (11)$$

From the above formulates (10) and (11), 'θ_i' refers to the rotation around 'b_i' axis whereas '$\alpha_{i,i+1}$' refers to the angle measured around 'a_i' axis. Finally, by considering the 3D position information and frames of reference of UAV into action, optimal path planning towards target tracking is said to be achieved.

Input: Dataset 'DS', Sample images '$SI = \{SI_i, \ldots, SI_m\}$' Features '$F = \{F_1, .., F_n\}$'
Output: Optimal path planning results '$([b_i][a_i])$
Step 1: **Initialize** 'm', 'n' Step 2: **Begin** Step 3: **For** each Dataset 'DS' with Sample images 'SI' and Features 'F' Step 4: Formulate input matrix as given in equation (1) Step 5: Formulate 3D location or position of the UAV in action as given in equations (2), (3), (4) and (5) Step 6: Evaluate coordinate transformations along a serial UAV as given in equation (6) Step 7: Evaluate UAV position increment alongside the coordinate transformations as given in equations (7), (8) and (9) for 'l' links Step 8: Obtain the joints connecting the links 'b_i' and 'a_i' as given in equations (10) and (11) to model path planning Step 9: Return optimal path planning results '$([b_i][a_i])$' Step 10: **End for** Step 11: **End**

Algorithm 1 DenavitHartenberg UAV path planning algorithm

In algorithm 1, with the raw drone dataset obtained as input, initially, the path planning mission is modeled in detail by formulating the input matrix for performing the corresponding task of trajectory tracking in UAV. Then, the optimal path vector is proposed to optimize UAV trajectory through the use of 3D location or position information. As per the target position information, with the aid of Denavit Hartenberg parameters ensuring optimal observation in the vertical plane, as well as converge to the standoff distance in the horizontal plane, therefore corroborating the objective of maximizing the accuracy and minimizing the response time.

2.2 Newton Optimized Iterative Deming Regression-based optimal trajectory tracking in UAV

With the sophisticated drone technology shifting towards real time, traditional trajectory tracking cannot be applied to UAV owing to constrained computational resources and the unstable movements of UAVs in dynamic environments, therefore resulting in error and enhancing the overhead incurred with a greater number of iterations. To address on this issue, in our work, Newton Optimized Iterative Deming Regression-based optimal trajectory tracking in UAV is designed that with the aid of three different functionalities achieve the objective. Figure 2 shows the structure of Newton Optimized Iterative Deming Regression-based optimal trajectory tracking in UAV.

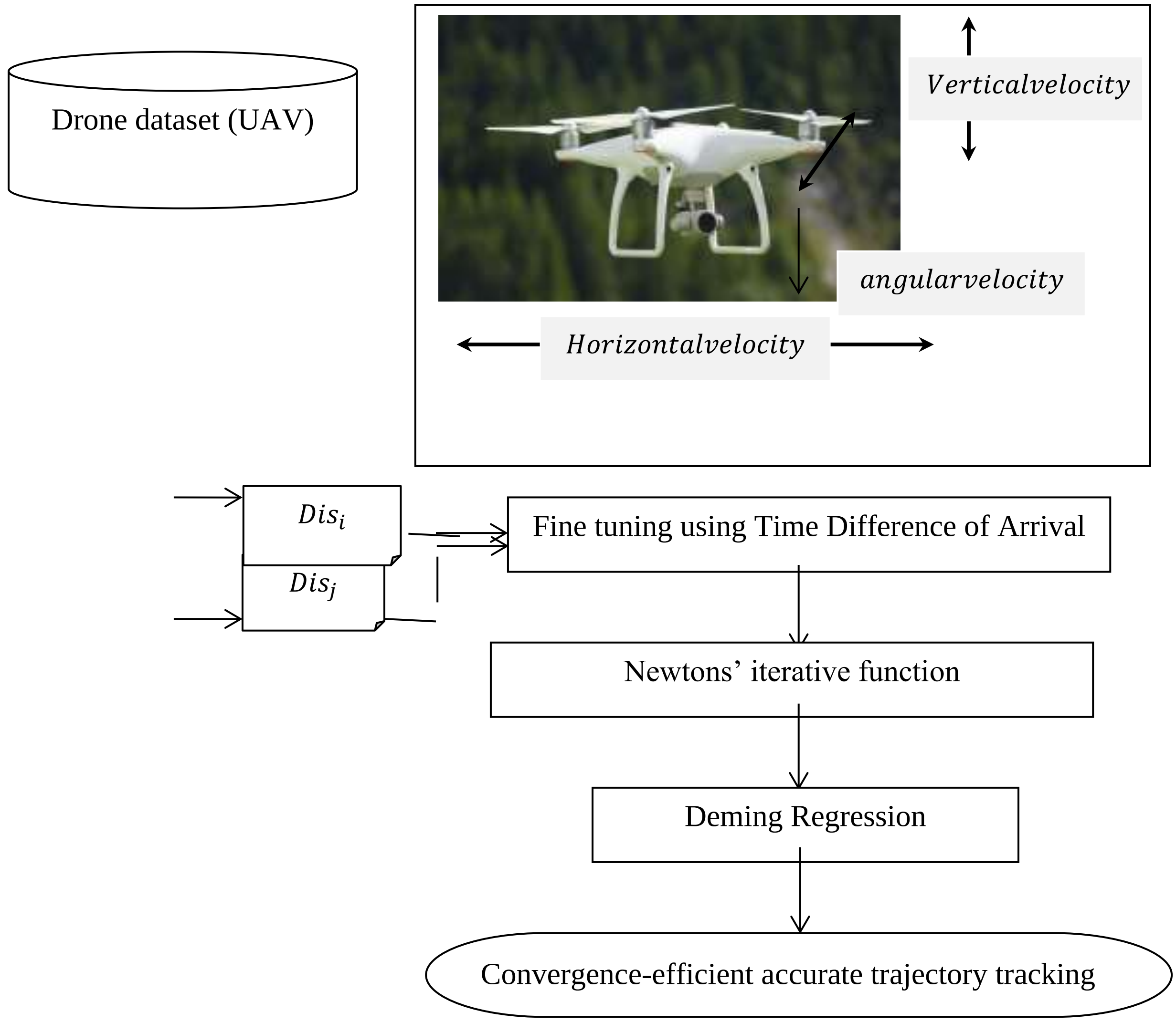

Figure 2 Structure of Newton Optimized Iterative Deming Regression-based optimal trajectory tracking

As illustrated in the above figure, to start with fine tuning of particles (i.e., drones) for optimization at the next moment are performed in such a manner wherein the initial conditions and optimization functions at adjoining time instances are proportionately homogenous. The fine tuned optimal solution has a high likelihood of emerging near the optimal solution. Let us consider that the location of the '$i-th$' UAV at time 't' is '$Pos_i(t) = [a_i(t), b_i(t), c_i(t)]$'. Moreover, Time Difference of Arrival (TDoA) factor is employed in our work to calculate the tracked trajectory entities in a precise and accurate manner. TDoA is among the mechanisms employed in tracking the trajectory by determining the difference between the time-of- arrival 'ToA' of radio signals of the corresponding sample drones.

In order to ensure that the optimal trajectory tracking is made TDoA optimization is required. Then, let '$Sol_{opt} = Sol_{i,j,k}(t+1) = \left[Sol_i(t+1), Sol_j(t+1), Sol_k(t+1)\right]$' represents the optimal solution. At this time, as long as the '$i-th$', '$j-th$' and '$k-th$' UAV move to the optimized position, the optimal positioning of the target is said to be achieved. The TDoA positioning is initially formulated according to the primary location and secondary location. Then, the gap separating the trajectory to be tracked and the primary location is represented as

'Dis_i' and in a similar manner, the distance between the trajectory to be tracked and the secondary location is denoted as 'Dis_j' and is mathematically stated as given below.

$$Dis_i = \sqrt{(a-a_i)^2 + (b-b_i)^2 + (c-c_i)^2} \tag{12}$$

$$Dis_j = \sqrt{\left(a-a_j\right)^2 + \left(b-b_j\right)^2 + \left(c-c_j\right)^2} \tag{13}$$

Taking into considerations the above distance factors (12) and (13) into account the optimization process in our work does not require to distribute spatial positions of the initialized value in an arbitrary manner within the feasible space so as to ensure acceptable convergence rate. Then, the TDoA with respect to each established mode of target positioning is converted into Newton's function for optimization, therefore ensuring faster search for the target trajectory. This is mathematically stated as given below.

$$f_i(a,b,c) = \sqrt{(a-a_i)^2 + (b-b_i)^2 + (c-c_i)^2} - \sqrt{\left(a-a_j\right)^2 + \left(b-b_j\right)^2 + \left(c-c_j\right)^2} \tag{14}$$

The speed update in the above formulate (14) only takes into consideration the local optimal and global optimal of this search. At the preliminary stages of the search, both the local optimal and the global optimal were found to be relatively poor, however, by employing the Newtons function by employing gradient of a function iteratively solve the optimizations issues in an accurate manner, therefore minimizing the error to a greater extent. The gradient of a function to iteratively solve the optimization issues using Newtons function via Jacobian matrix is mathematically stated as given below.

$$f'(a,b,c) = \left[\frac{\partial f_1}{\partial a}\frac{\partial f_1}{\partial b}\frac{\partial f_1}{\partial c}\frac{\partial f_2}{\partial a}\frac{\partial f_2}{\partial b}\frac{\partial f_2}{\partial c}\frac{\partial f_3}{\partial a}\frac{\partial f_3}{\partial b}\frac{\partial f_3}{\partial c}\right] \tag{15}$$

With the above target position evaluated using equation (15), line of best fit for two dimensional (i.e., coordinate) axis is formulated using Deming Regression with the objective of reducing the error factor to a greater extent. Let us assume that the available trajectory position be '(b_i, a_i)' be the measured observations of the true trajectory positional values '(b_i', a_i')' that lie on the regression line as given below.

$$b_i = b_i' + \varepsilon_i \tag{16}$$

$$a_i = a_i' + \eta_i \tag{17}$$

From the above equations (16) and (17), the errors 'ε_i' and 'η_i' are set to be in such a manner that '$\delta = \frac{\sigma_\epsilon^2}{\sigma_\eta^2} = 1$'. Finally, to minimize the overall response time, the total number of iterations has to be made as shorter as possible. Hence, a termination condition employing Sum of Squared Residuals (SoSR) is employed in our work that stops the tracking process when the trajectory converges, keeping away from succeeding incoherent operations.

$$SoSR = \sum_{i=1}^{n} \left(\frac{\epsilon_i^2}{\sigma_\epsilon^2} + \frac{\eta_i^2}{\sigma_\eta^2}\right) = \frac{1}{\sigma_\eta^2}\sum_{i=1}^{n} \left([b_i - \beta_0 + \beta_1 a_i']^2 + \delta[a_i - a_i']^2\right) = (SoSR) \tag{18}$$

In this manner, by improving the above three aspects (i.e., fine tuning via TDoA, faster search via Newton's function and enhancing convergence speed by means of deming regression) the efficiency of the trajectory tracking in UAV can be improved (i.e., minimizing number of iterations required for trajectory tracking).

Input: Dataset 'DS', Sample images '$SI = \{SI_i, \dots, SI_m\}$' Features '$F = \{F_1, \dots, F_n\}$'
Output: Convergence-minimized optimal and accurate trajectory track results
Step 1: **Initialize** optimal path planning results '$([b_i][a_i])$' Step 2: **Begin** Step 3: **For** each Dataset 'DS' with Sample images 'SI', Features 'F' and optimal path planning results '$([b_i][a_i])$' Step 4: Evaluate TDoA positioning derived from the primary location and secondary location as provided in equations (12) and (13) Step 5: Evaluate TDoA with respect to each established node of target positioning as given in equation (14) Step 6: Measure gradient of a function using Jacobian matrix as stated in equation (15) Step 7: Measure measured observations of the true trajectory positional values using Deming Regression function as given in equations (16) and (17) Step 8: Evaluate Sum of Squared Residuals (SoSR) to obtain accurate and optimal iterations as given in equation (18) Step 9: Return trajectory tracked results Step 10: **End for** Step 11: **End**

Algorithm Newton Optimized Iterative Deming Regression-based optimal trajectory tracking

As stated in the above algorithm with the purpose of tracking the trajectory with minimum numbers of iterations (i.e., convergence-efficient manner) and error, first, the optimal path planning results are subjected to TDoA positioning on the basis of primary and secondary location so as to optimize the drones for detection to be homogenous is vogue. Second, to ensure faster search and minimize error with respect to each target positioning trajectory Jacobian matrix via Newton function is formulated. Finally, to obtain accurate and optimal iterations Sum of Squared Residuals are formulated with which the trajectory tracking results are obtained with minimum number of iterations.

3. Experimental setup

Proposed DH-NOIDR trajectory tracking in UAV and existing Deep Deterministic Policy Gradient (DDPG) [1] and (An improved Salp Swarm Algorithm (LASSA) with Rapidly-exploring Random Trees (RRT) (LASSA-RRT) [2] are implemented in Python using the drone dataset taken from https://www.kaggle.com/datasets/dasmehdixtr/drone-dataset-uav?select=dataset_xml_format. The optimal method to minimize the response time during trajectory tracking in UAV using the proposed and the two current methods are examined by taking into considerations four parameters, namely response time, trajectory tracking accuracy, convergence speed and trajectory tracking error in relation to a number of sample images.

4. Performance results

Performance results of proposed DH-NOIDR method and existing DDPG [1] and LASSA-RRT [2] are discussed based on certain parameters like, response time, trajectory tracking accuracy, trajectory tracking error and convergence speed with respect to distinct numbers of sample images.

4.1 Performance analysis of response time

Response time refers to the amount of time consumed for a server to respond to a client's request. Measured in milliseconds, the timer begins as soon as theclient submits a request for tracking a trajectory and it concludes when the server sends its initial response. Trajectory tracking time is different from the response time in a way where the response time takes into consideration tracking the corresponding trajectory and sending the response to the to the requested client whereas on the other hand, trajectory tracking time only takes into consideration tracking the corresponding trajectory and not the response into action. This is mathematically formulated as given below.

$$Res_{time} = \sum_{i=1}^{m} SI_i * Time(TT) * Time(Res(TT)) \quad (19)$$

From the above equation (19), the response time 'Res_{time}' is quantified by taking into considerations the number of sample images 'SI_i', time for trajectory tracking '$Time(TT)$' and the time taken in providing the response '$Time(Res(TT)$'. It is measured in terms of milliseconds (ms). Table 1 reports the performance of response time with respect to distinct numbers of sample images ranging between 120 and 1200. An average of 10 simulation runs were performed which indicates that the proposed DH-NOIDR method reduces the response time by 33% and 43% when compared to [1] and [2].

Table 1 Tabulation of response time using DH-NOIDR, DDPG [1] and LASSA-RRT [2]

Sample images	Response time (ms)		
	DH-NOIDR	DDPG	LASSA-RRT
120	3.6	5.22	7.56
240	3.85	6	8
360	4.25	7.25	8.45
480	5.5	8	9
600	6	8.85	10.35
720	6.55	9.35	11
840	6	9	10
960	5.55	8.35	9.25
1080	5.25	8.15	8.85
1200	6	8.55	9

4.2 Performance analysis of trajectory tracking accuracy

Second, in this section, the trajectory tracking accuracy is measured. The trajectory tracking accuracy refers to the accurate tracking of the trajectory being made by the method in analysis. This is represented mathematically formulated as shown below.

$$TT_{acc} = \sum_{i=1}^{m} \frac{SI_{TA}}{SI_i} \quad (20)$$

From equation (20), target tracking accuracy 'TT_{acc}' is measured by taking into considerations sample images 'SI_i' and the sample images tracked accurately 'SI_{TA}'. It is measured in percentage (%).

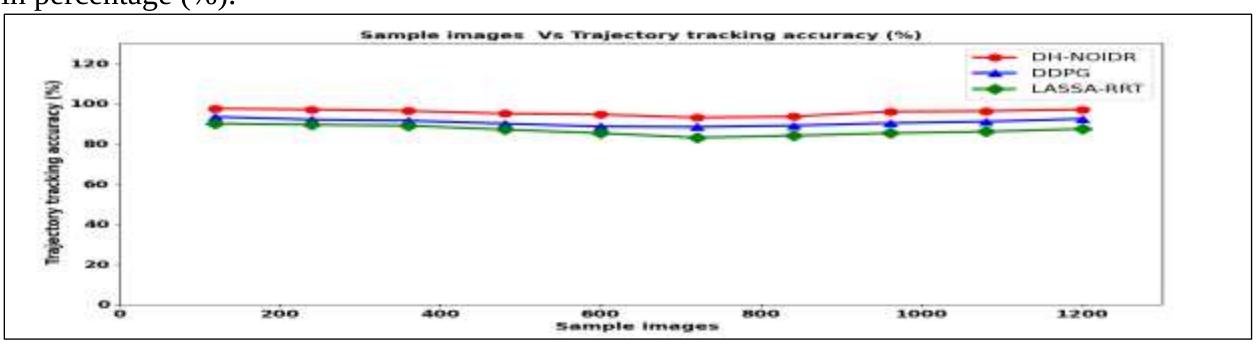

Figure 3 Graphical representation of trajectory tracking accuracy

Figure 3 given above illustrates the accuracy involved in the trajectory tracking process in UAV.The simulation outcomes presented here demonstrates that the proposed DH-NOIDR method improved the accuracy by 6% compared to [1] and 10% compared to [2]. Though a downward trend was noted for the first set of 720 samples then saw a steep increase for the other remaining set of 480 sample images. Also simulation results indicate better performance with use ofDH-NOIDR upon comparison to [1] and [2]. The trajectory tracking accuracy improvement using DH-NOIDR method was owing to the application of Denavit Hartenberg UAV path planning algorithm. By using this algorithm both optimal observation in the vertical plane, as well as converge to standoff distance in the horizontal plane were ensured, therefore improving the trajectory tracking accuracy to a greater extent. Also by employing Denavit Hartenberg parameters two-dimensional coordinates is employed that not only retains dynamic system characteristics but also reduces the coordinates input to a greater extent.

4.3 Performance analysis of trajectory tracking error

Third in this section the trajectory tracking error is measured and validated. While performing trajectory tracking certain amount of wrong tracking are made and therefore resulting in erroneous information. This is known as trajectory tracking error. This is represented mathematically as shown below.

$$TT_{error} = \sum_{i=1}^{m} \frac{SI_{TIA}}{SI_i} \quad (21)$$

From equation (21), the trajectory tracking error 'TT_{error}' is measured taking into considerations the sample images 'SI_i' and sample images tracked inaccurately 'SI_{TIA}'. It is measured in percentage (%).Table 2 lists performance of target tracking error using three methods. The simulation findings presented here suggest thatproposed DH-NOIDR method reduced tracking error by 32% and 50% than the [1], [2].

Table 2 Tabulation of trajectory tracking error

Sample images	**Trajectory tracking error (%)**		
	DH-NOIDR	DDPG	LASSA-RRT
120	3.33	5	6.66
240	3.55	5.25	7
360	3.85	5.85	7.35
480	4	6	8
600	4.15	6.75	8.75
720	5	7	9
840	4.35	6.35	8.25
960	4.15	6.16	8
1080	3.55	5.25	7.55
1200	3	4	7

4.4 Performance analysis of convergence speed

Finally, convergence speed or the number of iterations required to perform the actual trajectory tracking process is detailed. Table 4 lists the performance of convergence speed using the three methods.

Table 3 Tabulation of convergence speed

Methods	**Convergence speed (with optimization technique) – number of iterations**	**Convergence speed (without optimization technique) – number of iterations**
DH-NOIDR	3	5
DDPG	6	9
LASSA-RRT	8	12

Table 3 given above lists the convergence speed or the quantity of iterations required to track the trajectory in UAV. Measurements were made both the application of optimization technique and without the application of optimization technique. First, using optimization technique the convergence speed or the number of iterations using DH-NOIDR method was determined to be reduced upon comparison to [1] and [2]. Also simulation results performed with 1200 sample images also the convergence speed using DH-NOIDR method was better than [1] and [2]. The reason was including three aspects like fine tuning via Time Difference of Arrival (TDoA) determined the difference between time-of- arrival of the corresponding sample drones. In addition, faster search was ensured using Newton's function via Jacobian matrix and finally, to enhance the convergence speed deming regression was applied that in turn ensured overall convergence speed upon comparison to [1] and [2] respectively.

5. Conclusion

The conventional format of the trajectory tracking in UAV comprises of several latitude and longitude data that is irrelevant to optimal path planning and hence these may be neglected. For this reason, an optimization model employing Denavit Hartenberg parameters has been used to handle this circumstance. For achieving this goal, the 3D location or position information ensuring optimal observation in the vertical plane via Denavit Hartenberg parameters. In the initial phase, the proposed DH-NOIDR method obtains the drone information from drone dataset and finally interpolates them to model computationally efficient optimal path planning for further processing, therefore minimizing the response time. In the next phase, trajectory tracking is focused by employing Newton Optimized Iterative Deming Regression algorithm. In addition, to focus on the trajectory tracking error and convergence speed, Demings regression function is applied to analyze dynamic updates and obtain feasible solution and reducing the convergence speed in a significant manner. Simulations are performed to validate the proposed DH-NOIDR method and the state-of-the-art methods in terms of response time, trajectory tracking accuracy, trajectory tracking error and convergence speed. Moreover, the simulation results exhibit that the proposed DH-NOIDR method outperforms the conventional state-of-the-art methods in terms of numerous performance matrices, therefore providing optimal trajectory tracking with minimal response time. From the analysis and validation, the proposed DH-NOIDR method seems promising results and outperforms its convention counterpart.

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