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Radial Velocity and Bernouli Maximization Restricted Boltzmann Feedback Controller for Accurate Trajectory Tracking

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Abstract: - Accurate target tracking for rotary wing Unmanned Aerial Vehicle (UAV) is a fascinating application and a very demanding and complex field of research owing to the composite fluctuations and the diversified speed of moving target with respect to time. For this reason, several control algorithms have been evolved to track a target for rotary wing UAV. In this work a method called, Radial Velocity and Bernouli Maximization Restricted Boltzmann Feedback Controller (RV-BMRBFC) is introduced with the objective of suitable controller identification for accurate trajectory tracking in UAV. The RV-BMRBFC method is split into three sections, namely, data processing, controller identification and feedback controller for accurate trajectory tracking. First, the raw data obtained from Drone Dataset (UAV) is subjected to Partial Derivative Lagrangian-based Drone data processing for generating computationally efficient drone data for efficient controller identification. Second with the processed drone data as input Radial Velocity and Visual Axis Waypoint is applied for significant controller identification. The objective function in our work is formulated based on the response time, peak overshoot and settling time. By taking into consideration these objective function results, fitness is measured for all the processed controller identified results. Finally, Expected Bernoulli Maximization Restricted Boltzmann Machine-based Feedback Controller is applied with the identified controller positions for accurate trajectory tracking. With the obtained controller positions, target position data is said to be identified with which accurate trajectories are tracked in UAV. Experimental assessment is performed with diversified quantitative metrics like trajectory tracking accuracy, trajectory tracking time, trajectory tracking error rate and trajectory tracking overhead. The analyzed results demonstrate the superior performance of our proposed RV-BMRBFC method when compared with the two state-of-the-art methods.

Keywords: Target Tracking, Unmanned Aerial Vehicle, Partial Derivative, Lagrangian, Radial Velocity, Visual Axis, Waypoint, Expected Bernoulli Maximization, Restricted Boltzmann Machine

I. INTRODUCTION

Unmanned Aerial Vehicles (UAVs) are extensively employed in different fields such as military, healthcare and agriculture, where UAVs are deployed for target tracking, delivery of medicine and precise aerobiological sampling autonomously under the supervision of an operator. A novel intelligent controller employing adaptive neural network with a non linear control model using Lyapunov function was designed in [1] with the purpose of focusing on the frictional forces and external disturbances. Moreover the application of a fused error signal as single input in neural network importantly minimized the computational complexity and ensured accurate tracking of trajectory in an intelligent fashion. As a result target tracking was ensured with reduction in tracking error. A complicated dynamic method though can ensure accuracy however may not be pertinent in computational aspects. Thus to address on this issue, a data driven method was designed in [2] with the purpose of enhancing autonomous tracking. Here, the nonlinearities present between lateral and longitudinal vehicle dynamics were captured with reduced computational cost. In [3], an overview of contemporary control-related research from the angle of multibody dynamics was investigated. Tracking trajectory for autonomous vehicles (AVs) is specifically addressed by means of control law design that in turn ensures fixed realistic trajectories on the basis of the trajectory error. However, vehicle dynamics exhibits complicated nonlinearities and crucial variability. With the purpose of solving nonlinearity, trajectory tracking control employing nonlinear was proposed in [4]. Here, steady state error was reduced considerably. Yet another method employing extreme machine learning was applied in [5] to focus on the velocity errors. Here the control algorithms were learnt via parameter adjusting that in turn minimized velocity errors. In [6], deep neural networks were employed for designing real time tracking and control framework that with the aid of motion planning element ensured accurate tracking. Over the recent few years, AV driving has become the centric point of evolution in the area of

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UAV. Several methods have been researched over the recent few years for ensuring reliable trajectory tracking controller. In [7], deep deterministic policy gradient algorithm of the double critic network was applied that in turn sent the control commands to the vehicle for making wise decisions via Markov decision process. As a result accuracy was ensured. Yet another neural networks learning based on both online and offline strategy was proposed in [8].

I.1 Contributions of the paper

A novel Radial Velocity and Bernouli Maximization Restricted Boltzmann Feedback Controller (RV-BMRBFC) is introduced with the following novel contributions,

- To improve the trajectory tracking accuracy, the RV-BMRBFC method is designed based on three major processes namely data processing, controller identification and feedback controller design.
- First, Partial Derivative Lagrangian-based Drone data processing is proposed in the RV-BMRBFC method for finding the computationally efficient drone data required for further processing from the raw dataset. The Partial Derivative Lagrangian mechanics is applied for minimizing the tracking time and finally selects the significant features.
- To reduce tracking error, RV-BMRBFC method uses Radial Velocity and Visual Axis Waypoint-based controller identification.
- To improve tracking accuracy and reduce overhead, the proposed machine learning classifier uses the Expected Bernoulli Maximization function for analyzing the testing and tainting features. Then the Restricted Boltzmann Machine with the aid of sigmoid activation function returns the trajectory tracking outcomes by minimizing the transition error.
- Finally, comprehensive experimental assessment is carried out with different types of performance metrics to illustrate the proposed RV-BMRBFC method over conventional methods.

I.2 Organization of the work

The rest of the paper is arranged into different sections as follows. Section 2 reviews the related works in the domain of controller identification for trajectory tracking. An elaborate description of the proposed RV-BMRBFC method with the aid of pseudo code and figurative is given in Section 3. Section 4 describes the experimentation settings with detailed discussion on the performance results of the proposed and conventional methods with different metrics. At last, Section 5 concludes the paper.

II. RELATED WORKS

Of late, as the evolution of robotic technology, the intelligent robots have been extensively utilized both in military and civilian areas, to name a few being, target tracking, missions involving strategy for detecting attack and ensuring rescue missions, home serices and so on. In [9] a trajectory tracking control mechanism employing fuzzy adaptive neurons was presented. Here, with the aid of integrative derivative controllers based on the self-tuning proportional mechanism accurate and precise trajectory tracking was ensured. Yet another fuzzy neural network approximator was presented in [10] for ensuring accurate trajectory tracking control. Learning space for implementing general motions is large and also the dynamics are found to be huge, non linear in nature, differing in time and complexity also. In [11] fuzzy neural network supervised training method was applied to reduce the position tracking error. Also a fuzzy inference system in an adaptive fashion was proposed by fine tuning parameters and weight coefficients. As a result accuracy was also improved. The design of controller has occupied a large space in several domains. In [12], a proportional integral derivative employing cascaded model for trajectory tracking was proposed. Also by controlling the position and angular velocity resulted in the accuracy and robustness. To recognize the chief evolution estimation of object detection and tracking pipeline rigorously, in [13] a survey of prevailing deep learning network based materials and methods for both detecting of objects and tracking of the same via distinct controllers were designed in detail. Yet another adaptive controller employing extended state observer via robust integral was applied in [14] with the objective of minimizing the average tracking error. The extremely achievable trajectory planning of UAV is very significant in certain tasks but has not yet received much attention. This is because of the reason that most of the prevailing studies employed rationalized UAV model with certain restriction to design trajectory. However, tracking features of UAV were not taken into consideration fully. In [15], a novel UVA model based on control oriented design for trajectory planning method was proposed. Here by employing trajectory mapping network not only ensured computation speed but also improved prediction accuracy. A convolutional neural network for UAV was employed in [16] for avoiding involved in controller design. Here, the UAV was controlled with the purpose to follow a hypothesized trail while retaining its position adjacent to the trail center.

However, the trajectory error aspect was not focused. To concentrate on this issue, Lyapunov function was applied in [17] via adaptive neural network system that with the aid of motion trajectory not only improved the control accuracy but also reduced the trajectory error significantly. Yet another deep DNN was designed in [18] for designing state estimation and controller. A feedback controller employing dynamic neural network (DNN) was proposed in [19] with the objective of addressing scenarios involving uncertain nonlinear systems. Generalized regression neural network was applied in [20] for focusing on the tracking errors.

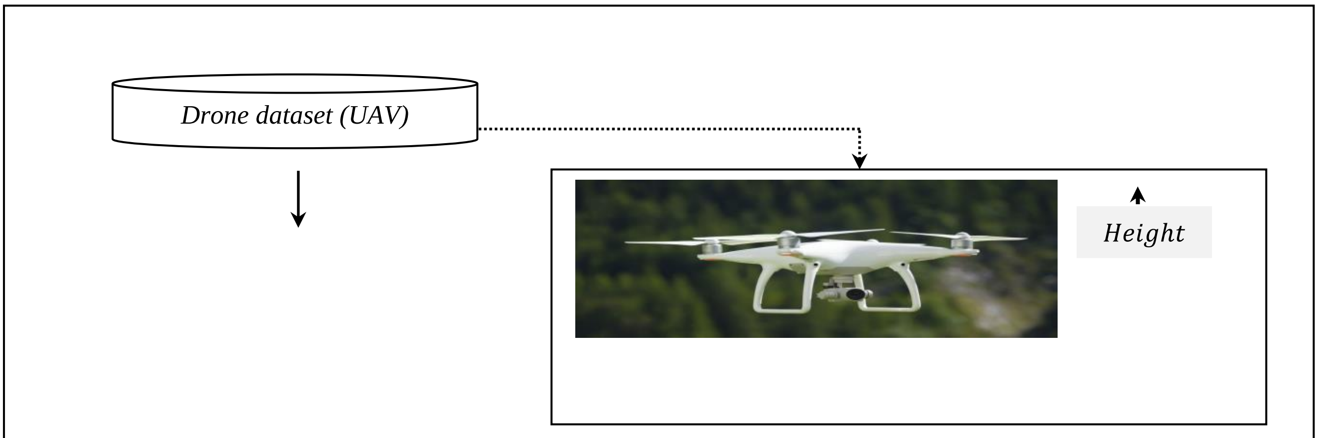
III. Radial Velocity and Bernouli Maximization Restricted Boltzmann Feedback Controller (RV-BMRBFC)

Trajectory tracking problem for UAVs has inspired crucial awareness from the robotics research section over the past few years. This is predominantly owing to the prospective applications where perfect and accuracy trajectory tracking are necessitated. Traditionally several controller based algorithms has been developed for trajectory tracking in UAV, however with minimum focus on steady state error. With this intend, optimization based control algorithms are designed to choose optimal controller parameter value for minimizing the time consumption or response time. Also to track the trajectories, optimization controllers are incorporated using artificial intelligence techniques by and track the trajectory with lesser computational complexity using RV-BMRBFC. The proposed RV-BMRBFC method consists of three parts, data processing, controller identification and feedback controller for accurate trajectory tracking in UAV. The elaborate description of RV-BMRBFC method is provided in the following sections.

III.1 Partial Derivative Lagrangian-based Drone data processing

Unmanned Aerial Vehicles (UAVs) has observed a mushroom growth over the past few years due to the technological advancement and increased accessibility. Nevertheless, UAV positioning remains a demanding issue, specifically in confined locations. Positioning the aircraft proportional to another object or designing a suitable controller for accurate trajectory tracking is a frequent task that is laborious and cumbersome to accomplish. Here, an autonomous data processing model employing Partial Derivative Lagrangian mechanics is presented that is able to design suitable controller and maintain appropriate relative position to a drone object. Correspondingly, the UAV is depicted to operate for rotary wing UAVs, providing increased effectiveness and autonomy and safety. Figure 1 shows the structure of Partial Derivative Lagrangian-based Drone data processing model.

As illustrated in the above figure, with the drone dataset Unmanned Aerial Vehicle (Rotary Wing Unmanned Aerial Vehicles) obtained from https://www.kaggle.com/datasets/dasmehdixtr/drone-dataset-uav consists of 2718 files both including JPG (i.e., 1359) and txt file (i.e., 1359) respectively. Each txt file includes five features '$F = \{f_1, f_2, f_3, f_4, f_5\}$' namely, class_id, x_initial_pos or x width ('x_w'), y_initial_pos or y width ('y_w'), x_final_pos or x height ('x_h') and y_final_pos or y height ('y_h') respectively.



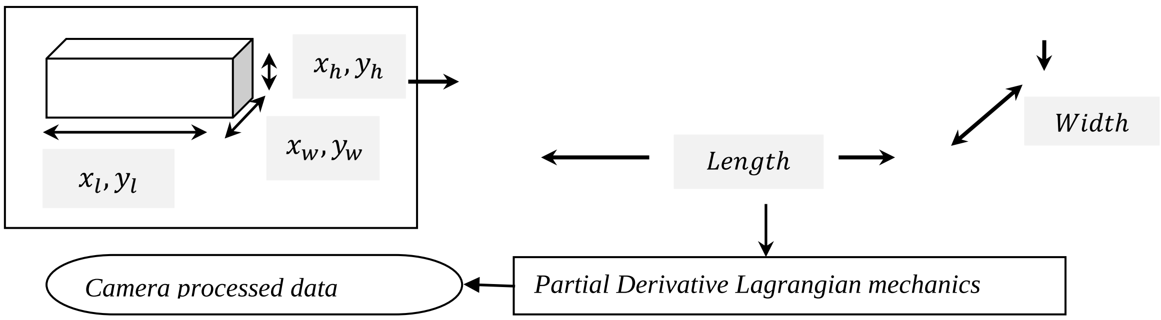


Figure 1 Structure of Partial Derivative Lagrangian-based Drone data processing

$$IM = [SI_1F_1\ SI_1F_2\ \dots\ SI_1F_n\ SI_2F_1\ SI_2F_2\ \dots\ SI_2F_n\ \dots\ \dots\ \dots\ \dots\ SI_mF_1\ SI_mF_2\ \dots\ SI_mF_n\ ] \tag{1}$$

With the above formulated input matrix 'IM' as given in equation (1), the width and height of each sample images are obtained from the dataset. Following which initially the length is formulated as given below.

$$x_l = x_w * x_h;\ y_l = y_w * y_h\ where\ (x, y) \in IM \tag{2}$$

According to the Partial Derivative Lagrangian mechanics, the arbitrary model of the Rotary Wing Unmanned Aerial Vehicles is derived in the form of Lagrangian equation as given below.

$$PR = \frac{d}{dt}\left[\frac{\partial T}{\partial c_i'}\right] - \frac{\partial T}{\partial c_i} = C_i \tag{3}$$

From the above equation (3), 'T' refers to the Rotary Wing UAVs kinetic energy, 'c_i', 'c_i'' and 'C_i' denotes the abstract coordinates, abstract velocity and abstract force, 'C_1', 'C_2' and 'C_3' represent the length of the sample image, the width of the sample image and the height of the sample image respectively. The pseudo code representation of Partial Derivative Lagrangian-based Drone data processing is given below.

Input: Dataset 'DS', Sample images '$SI = \{SI_i, \dots, SI_m\}$' Features '$F = \{F_1, .., F_n\}$'

Output: computationally efficient drone data processing 'PR'

1: **Initialize** '$m = 2718$', '$n = 5$'

2: **Initialize** 'x_w', 'y_w', 'x_h', 'y_h'

3: **Begin**

4: **For** each Dataset 'DS' with Sample images 'SI', Features 'F'

5: Formulate input matrix as given in equation (1)

6: Evaluate length of Sample images 'SI' as given in equation (2)

7: Obtain arbitrary model of the Rotary Wing Unmanned Aerial Vehicles as given in equation (3)

8: **Return** processed results 'PR'

9: **End for**

10: **End**

Algorithm 1 Partial Derivative Lagrangian-based Drone data processing

As given in the above algorithm, with the objective of reducing the tracking time involved during the design of controller, first the data from drone dataset (UAV) are subjected to formulation of input matrix split into distinct features and sample images. Following which with the width and height of each drone obtained from the raw dataset, length of each drone is evaluated to obtain its positioning. Following which Partial Derivative Lagrangian mechanics is applied that being a function of objects or samples position, velocity and force is designed in such a way that the action is defined as the integral of Lagrangian over time is minimized, therefore minimizing the tracking time involved in controller design.

III.2 RADIAL VELOCITY AND VISUAL AXIS WAYPOINT-BASED CONTROLLER IDENTIFICATION

The fundamental process for a UAV to perform trajectory tracking is to generate a set of waypoints with which the controller can be designed. Then, the UAV successively advances in connection with the waypoint and acts in accordance with the planned controller identification. Also, the objective of controller training remains in retaining the error within the permissible extent.

In our work, Radial Velocity-based Visual Axis Waypoint Behavior analysis model is designed based on the geometric association between the UAVs, the preceding waypoint and the succeeding waypoint respectively. Following which the new visual axis parameters are arranged to fine tune the waypoint behavior of rotary ring UAVs. In this manner, using Radial Velocity-based Visual Axis not only introduces intelligent computing but also maintains the reliability of conventional object tracking controller as far as possible. Figure 2 shows the structure of Radial Velocity and Visual Axis Waypoint-based controller identification. As shown in the below figure with the drone sample images and processed results 'PR' obtained as input, initially, with the dual waypoints by taking into considerations the preceding and succeeding waypoints lead distance and damper distance are measured. Following which, according to the visual axis the Radial Velocity is applied to measure waypoint behavior for controller identification. To start with the angular motion formulated by the dual waypoints is mathematically represented as given below.

$$\alpha = tan^{-1}\left[PR\left(x_{j+1} - x_j, y_{j+1} - y_j\right)\right] \tag{4}$$

From the above equation (4), the geometric association between the vehicle (i.e., processed results) 'PR' is obtained by taking into considerations the preceding waypoint 'x_j, y_j' and the succeeding waypoint '$x_{j+1}y_{j+1}$,' respectively. Following which the, lead distance 'Dis_L' and lead damper '$Damp_L$' are obtained from angular motion 'α' and the length of the drone or sample 'x_l, y_l' in action as given below.

$$PR_m = Dis_L = \left(x_l - x_j\right) cos\, cos\, (\alpha) + \left(y_l - y_j\right) sin\, sin\, (\alpha) \tag{5}$$

$$PR_n = Damp_L = -\left(x_l - x_j\right) sin\, sin\, (\alpha) + \left(y_l - y_j\right) cos\, cos\, (\alpha) \tag{6}$$

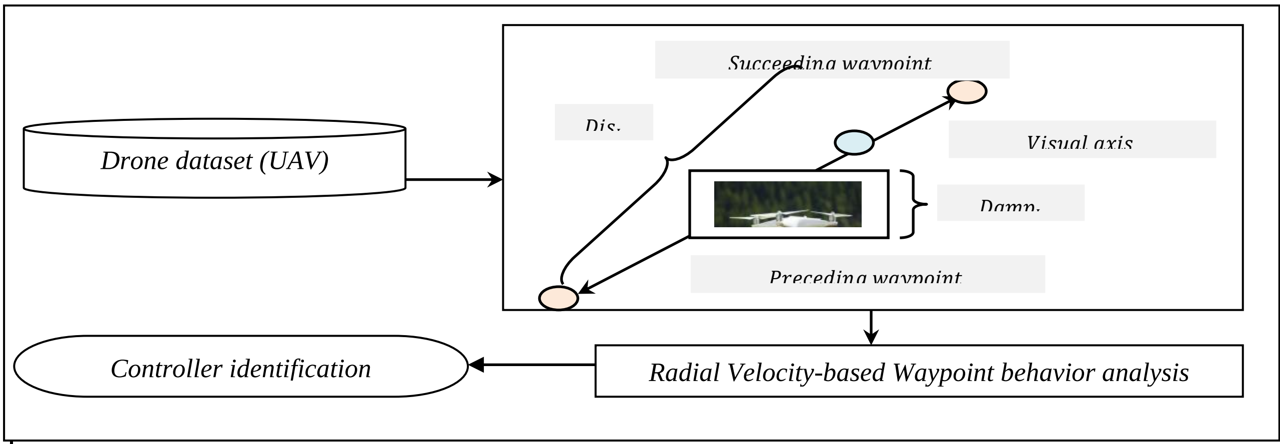
From the above equations (5) and (6), 'PR_m (Dis_L)' represent the instantaneous position of a target with respect to the observer and '$PR_n(Damp_L)$' denotes the instantaneous velocity with respect to the observer. Following which the Radial Velocity to analyze waypoint behavior for planned controller identification is formulated as given below.

$$\frac{dPR}{dt} = \frac{d<PR_m, PR_n>^{1/2}}{dt} \tag{7}$$

$$\frac{dPR}{dt} = \frac{1}{2}\frac{<PR_m, PR_n>}{dt}\frac{1}{PR} \tag{8}$$

$$CI = \frac{dPR}{dt} = \frac{1}{2}\frac{<\frac{dPR_m}{dt}, PR_m> + <PR_n, \frac{dPR_n}{dt}>}{PR_m, PR_n} = \frac{PR_m, PR_n}{PR} \tag{9}$$

From the above equations (7), (8) and (9), by fine tuning the 'PR_m' and 'PR_n' on the basis of the instantaneous position and instantaneous velocity, the controller identification (i.e., their corresponding positions) is made in an efficient manner wherein the track error nearing zero are reduced in a significant manner. This in turn minimizes the tracking error in an efficient manner. The pseudo code representation of Radial Velocity and Visual Axis Waypoint-based controller identification is given below.



Input: Dataset 'DS', Sample images '$SI = \{SI_i, \ldots, SI_m\}$' Features '$F = \{F_1, .., F_n\}$'

Output: Error minimized controller identification 'CI'

1: Initialize '$m = 2718$', '$n = 5$', processed results 'PR'

2: Begin

3: For each Dataset 'DS' with Sample images 'SI', Features 'F' and processed results 'PR'

4: Evaluate the angular motion formulated by the dual waypoints as given in equation (4)

5: Evaluate lead distance and lead damper as given in equations (5) and (6)

6: Formulate Radial Velocity to analyze waypoint behavior for planned controller identification as given in equations (7), (8) and (9)

7: Return controller identified results 'CI'

8: End for

9: End

Algorithm 2 Radial Velocity and Visual Axis Waypoint-based controller identification

As given in the above algorithm, with the objective of reducing the tracking error involved in controller identification and therefore to promote tracking performance, Radial Velocity and Visual Axis Waypoint-based controller identification is designed. Finally, Radial Velocity is applied to analyze waypoint behavior for planned controller identification with minimum error.

III.3 Expected Bernoulli Maximization Restricted Boltzmann Machine-based Feedback Controller for accurate trajectory tracking

Finally, in this work, the objective function is computed for all planned controller identification values taking into consideration the response time, peak overshoot, and settling time with which suitable feedback controller for accurate trajectory tracking is made. On the basis of this objective function, Expected Bernoulli Maximization is obtained for all the parameter values, wherein the optimal best solution is obtained via Restricted Boltzmann Machine, therefore improving the accuracy with minimum overhead. Here Expected Bernoulli Maximization Restricted Boltzmann Machine is utilized to evaluate the feedback control parameters in a flexible manner. Figure shows the structure of Expected Bernoulli Maximization Restricted Boltzmann Machine-based Feedback Controller for accurate trajectory tracking.

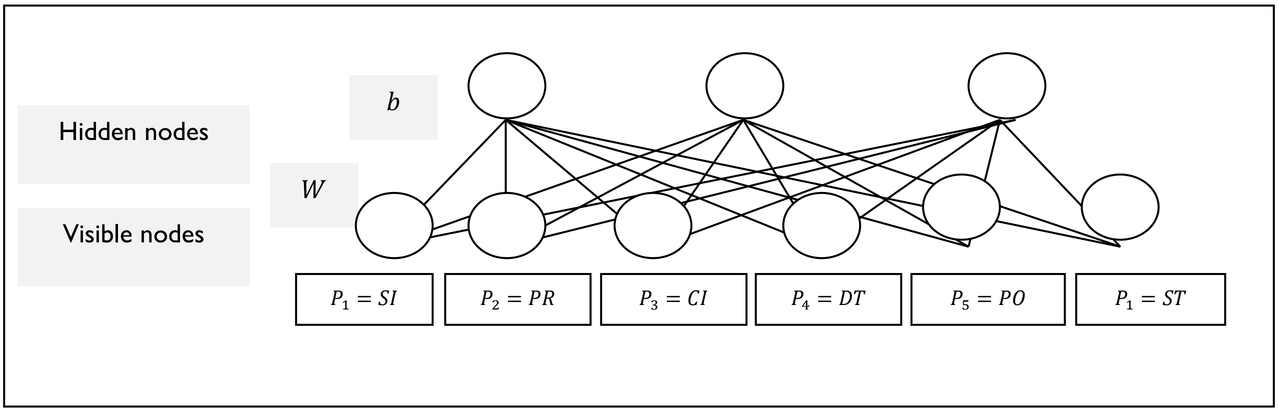


Figure 3 Structure of Expected Bernoulli Maximization Restricted Boltzmann Machine-based Feedback Controller

As shown in the above figure, Initially, three objective functions are measured. First, delay time or response time is defined as the time required for response to reach 50% of final value in the first time itself. Peak overshoot 'PO' or peak percent overshoot is defined as the difference between peak of 1st time and steady output.

$$PO = e^{-\frac{\pi * 0.5}{\sqrt{1-(0.5)^2}} * 100} \tag{10}$$

Finally, settling time 'ST' is defined as the time that is consumed the response to reach and stay within the specified range (i.e., between 2% to 5%) of its final value.

$$ST = \frac{4}{\xi \omega_n} \tag{11}$$

The Expected Bernoulli Maximization Restricted Boltzmann Machine is a neural network designed on the basis of energy. The integrated energy functions of both visible and hidden variables are formulated as given below.

$$E(CI(P), h) = -h^T W \frac{CI(P)}{\sigma} - \frac{\left(CI(P) - C^T\right)^2}{2\sigma^2} - b^T h \tag{12}$$

From the above equation (12), the initial formulation is designed based on the visible layer arbitrary vector '$P = [P_1, P_2, \dots., P_6]^T$' (i.e., P_1 =sample images, P_2 =processed results, P_3 =controller identified results, P_4 =delay time, P_5 =peak overshoot, P_6 =settling time) and the hidden layer arbitrary vector '$H = [H_1, H_2, \dots., H_6]^T$', the weight matrix '$W \in R^{6*6}$', bias '$C \in R^6$', '$b \in R^6$' and '$\sigma$' representing the standard deviation associated with Expected Bernoulli Maximization visible vector 'P' respectively. Then, the Expected Bernoulli Maximization for each controller identified 'CI' visible vector 'P' is mathematically stated as given below.

$$q^{i+1} = argmax\ E\{ln\ ln\ Prob(CI(P), \varepsilon; q) | SI: q^i \} \tag{13}$$

From the above equation (13), 'i' represents the Expected Bernoulli Maximization iteration and '$argmax\ E$' denotes the expectation subjected on the observations 'SI' under parameter hypothesis 'q^i'. In the coding process, given the features or controller identified samples '$CI(P)$' in the visible layer, then the probability that a neuron in the hidden layer gets activated is given by sigmoid function as given below.

$$Prob\left(h_j = 1 | CI(P)\right) = sigmoid\ \left(W_j * \frac{CI(P)}{\sigma^2} + b_j\right) \tag{14}$$

The above arbitrator generates a number between 0 and 1, if the number is less than the measured 'h_j', then the result of hidden layer node is 1 otherwise it is 0. In a similar manner, in the decoding process, given the current state of all neurons (i.e., the processed results and the objective function) in the hidden layer, then the probability that a neuron in the visible layer is activated is then formulated as given below.

$$Prob(CI(P)_k = 1|h) = N(C_k W_k + CI(P), \sigma^2) \quad (15)$$

From the above equation (15), '$N(\mu, \sigma^2)$' represent Gaussian probability density function with mean '$\mu = C_k W_k + CI(P)$' and standard deviation 'σ^2' respectively. Then, the arbitrator generates a number between 0 and 1, if the number is less than the measured '$CI(P)_k$', then the visible layer node is '$CI(P)_k$' and on contrary it will take the arbitrary number.

Finally, by alternately performing coding and decoding, the transition error being minimal infers that the Expected Bernoulli Maximization Restricted Boltzmann Machine inclines to be in equilibrium state, therefore corroborating the objective with maximal accuracy and minimal overhead. The pseudo representation of Expected Bernoulli Maximization Restricted Boltzmann Machine-based Feedback Controller for accurate trajectory tracking is given below.

Input: Dataset 'DS', Sample images '$SI = \{SI_i, \dots, SI_m\}$' Features '$F = \{F_1, \dots, F_n\}$'
Output:
1: Initialize '$m = 2718$', '$n = 5$', processed results 'PR', controller identified results 'CI', '$\xi = 0.5$', '$\omega_n = 6\ rad/sec$' 2: Begin 3: For each Dataset 'DS' with Sample images 'SI', Features 'F', processed results 'PR' and controller identified results 'CI' 4: Evaluate peak overshoot as given in equation (10) 5: Evaluate settling time as given in equation (11) 6: Obtain integrated energy functions of both visible and hidden variables as given in equation (12) 7: Obtain Expected Bernoulli Maximization for each controller identified 'CI' visible vector 'P' as given in equation (13) 8: Trigger coding process as given in equation (14) 9: If '$Prob\left(h_j = 1|CI(P)\right) \leq val(h_j)$' 10: Then result of hidden layer is 1 11: Else result of hidden layer is 0 12: End if 13: Trigger decoding process as given in equation (15) 14: If '$Prob(CI(P)_k = 1|h) \leq CI(P)_k$' 15: Then visible layer node is '$CI(P)_k$' 16: Else assign arbitrary value to $CI(P)_k$ 17: End if 18: End for 19: End

Algorithm 3 Expected Bernoulli Maximization Restricted Boltzmann Machine-based Feedback Controller for accurate trajectory tracking

As given in the above algorithm, with the objective of improving the accuracy and reducing the overhead, first, three objective functions are formulated, i.e., the response time, peak overshoot and settling time. Finally, following by coding and decoding processes separately based on the transition error provides the results of trajectory tracking of UAV.

IV. EXPERIMENTAL SETUP

In this section, the proposed Radial Velocity and Bernouli Maximization Restricted Boltzmann Feedback Controller (RV-BMRBFC) method and existing intelligent controller [1] and data driven method [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 controller identification for accurate trajectory tracking using the proposed and existing two methods are discussed based on certain parameters such as trajectory tracking accuracy, trajectory tracking time, trajectory tracking overhead and trajectory tracking error rate with respect to a number of sample images. The performances of the proposed and existing methods are discussed with the aid of tabulation and graphical illustrations.

IV.1 Performance analysis of trajectory tracking time

In this section first the paramount performance metrics used to analyze controller for accurate trajectory tracking called, the trajectory tracking time is measured. The trajectory tracking time refers to the time consumed in tracking the corresponding trajectory via controller.

$$TT_{time} = \sum_{i=1}^{m} SI_i * Time\ (TT) \quad (16)$$

From the above equation (16), trajectory tracking time 'TT_{time}' is measured by taking into consideration the sample images 'SI_i' and the actual time consumed in tracking the corresponding trajectory '$Time\ (TT)$' via controller. It is measured in terms of milliseconds (ms).

Table 1 Tabulation for trajectory tracking time using RV-BMRBFC, Intelligent controller [1] and Data driven method [2]

Sample images	Trajectory tracking time (ms)		
	RV-BMRBFC	Intelligent controller	Data driven method
120	4.2	5.04	5.76
240	5.35	6.75	7.85
360	5.85	8	8.85
480	7	9.15	10
600	7.55	9.95	12.55
720	8.25	11.35	13.15
840	9	12.15	14.35
960	10.35	14	15.35
1080	10.85	14.35	17
1200	11.35	15	18.35

The performance evaluation of trajectory tracking time .From the overall results it is inferred that the trajectory tracking time of RV-BMRBFC method is significantly minimized by 24% and 34% when compared to existing methods.

IV.2 Performance analysis of trajectory tracking error

Second most paramount metrics in identifying the controller for accurate trajectory tracking is the trajectory tracking error. This is due to the reason that lesser the error more efficient the method is said to be and vice versa. The trajectory tracking error is measured as given below.

$$TT_{error} = \sum_{i=1}^{m} \frac{SI_{TIA}}{SI_i} \tag{17}$$

From the above equation (17), the trajectory tracking error 'TT_{error}' is measured by employing the sample images 'SI_i' and the sample images that were not tracked accurately 'SI_{TIA}'. It is measured in terms of percentage (%).

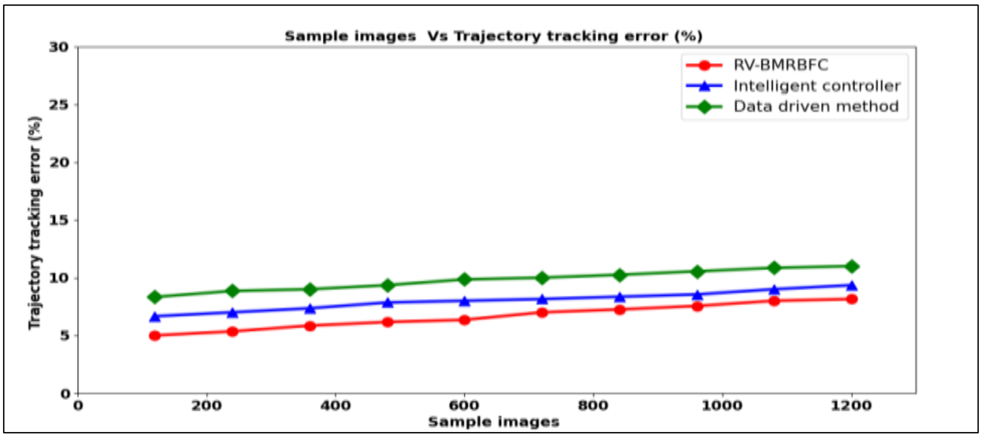


Figure 4 Trajectory tracking error versus sample images

Figure 4 given above shows the graphical representation of trajectory tracking error. Finally, waypoint behavior for planned controller identification was obtained via Radial Velocity that in turn reduced the target tracking error using RV-BMRBFC method by 17% and 32% than the [1],[2].

IV.3 Performance analysis of trajectory tracking accuracy

Suitable controller identification based trajectory tracking accuracy is measured. The trajectory tracking accuracy is measured as the ratio between accurate trajectory samples to total number of sample images and is measured as below.

$$TT_{acc} = \sum_{i=1}^{m} \frac{SI_{TA}}{SI_i} \tag{18}$$

From the above equation (18), the trajectory tracking accuracy 'TT_{acc}' is measured by taking into considerations the sample images 'SI_i' and the sample images accurately tracked 'SI_{TA}'. It is measured in terms of percentage (%).

Table 2 Tabulation for trajectory tracking accuracy using RV-BMRBFC, Intelligent controller [1] and Data driven method [2]

Sample images	Trajectory tracking accuracy (%)		
	RV-BMRBFC	Intelligent controller	Data driven method
120	95.83	90.83	87.5
240	95	RV-BMRBFC 90.35	86.66
360	94.35	90.15	86.35
480	94	90	86
600	93.85	89.15	85.45
720	93.55	89	85
840	93	88.15	84.35

960	92.85	88	84
1080	92	87.35	83.25
1200	91.45	87	83

Table 2 given above lists the performance of trajectory tracking accuracy .The average of 10 simulation runs indicates that the proposed RV-BMRBFC method enhances the trajectory tracking accuracy by 5% and 10% upon comparison with [1] and [2] respectively.

IV.4 Performance analysis of trajectory tracking overhead

Finally, in this section the overhead incurred in trajectory tracking via suitable controller is measured as given below.

$$TT_{OH} = \sum_{i=1}^{m} SI_i * Mem\ (TT) \tag{19}$$

From the above equation (19), the trajectory tracking overhead 'TT_{OH}' is measured using sample images 'SI_i' and the memory consumed '$Mem\ (TT)$' in performing the overall process. It is measured in terms of kilobytes (KB).

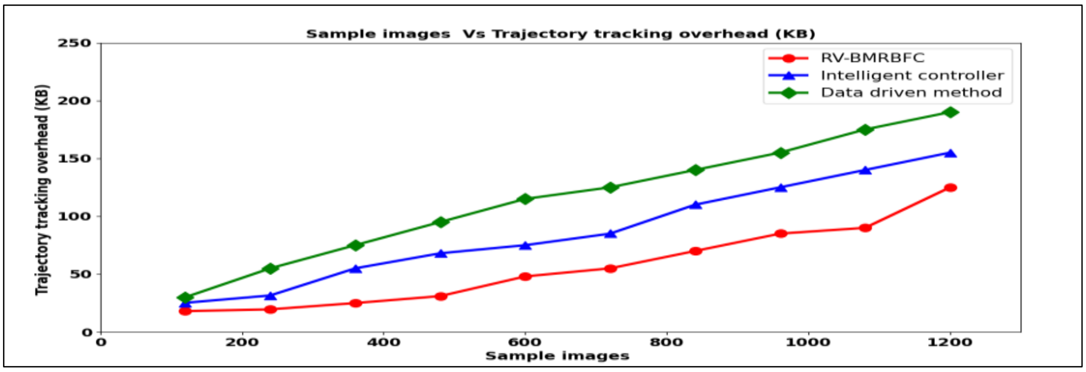


Figure 5 Trajectory tracking overhead versus sample images

Finally, figure 5show graphical representation of trajectory tracking overhead. Therefore by eliminating the irrelevant arbitrary vector parameters and retaining the essential arbitrary vector parameters in the visible layer in turn improved the trajectory tracking overhead using RV-BMRBFC by 37% compared to [1] and 53% compared to [2].

V. CONCLUSION

Moving target tracking is a smart application and hence considered as a complicated field of research due to the complicated dynamics and the varying speed of the moving target with time. UAV can have complicated dynamics and kinematics that governs flight of such multirotor devices. Recently, many control algorithms have been developed to track a moving target using a camera. In this work a suitable Radial Velocity and Bernouli Maximization Restricted Boltzmann Feedback Controller (RV-BMRBFC) for accurate target tracking is developed to further improve the identification performance. First, the drone data is used for obtaining both the textual and image information with the purpose of identifying controller for target tracking. Here, processing of drone data is performed using Partial Derivative Lagrangian function to obtain its positioning for further processing. Then Radial Velocity and Visual Axis Waypoint are employed in RV-BMRBFC method for identifying controller with minimal error. Finally, using Expected Bernoulli Maximization Restricted Boltzmann Machine-based Feedback Controller accurate target tracking is said to be ensured. A comprehensive experimental evaluation is performed using diversified performance metrics like trajectory tracking accuracy, trajectory tracking time, trajectory tracking overhead and trajectory tracking error rate with respect to the number of samples. The overall performance results illustrate that the presented RV-BMRBFC method achieves higher accuracy with minimum time than the conventional methods.

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