2022 IEEE 2nd Mysore Sub Section International Conference (MysuruCon)

Clustering of Air Objects based on Path, Missile Path Prediction Using Deep Learning

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2022 IEEE 2nd Mysore Sub Section International Conference (MysuruCon) | 978-1-6654-9790-9/22/$31.00 ©2022 IEEE | DOI: 10.1109/MysuruCon55714.2022.9972383

***Abstract*— For a given instance, the location of the object in air can be demonstrated by quadruples there are latitude, altitude, longitude and velocity. Trajectory is continuous stream time, latitude, altitude and longitude. The proposed work classifies the air objects based on trajectories and group them into meaningful objects such as flying objects, drones, helicopters, fighter, civilian aircraft, unmanned aerial vehicles, missiles, flying bombs, and so on. In this paper, the proposed work estimates the location of air objects by using their trajectory and these provides a guidance to the missiles to shoot the target based on its location where the missile is going to meets the object based on the trajectory. For calculating missile's path, one of the most difficult challenges is applying the missile model to various related simulations is determining the missile path. The traditional way for this task is to use models and numerical methods, that also necessitates a large computational power. The data generated by the traditional system has been used to train the network and test the network, and the defect of the network prediction result is evaluated in this study. Recurrent neural network (RNN) and long short-term memory (LSTM) have been used to perform Clustering of Air Objects based on Path and for Missile Path Prediction. For clustering of air objects, LSTM gave r2 score of 0.997 and for missile path prediction, LSTM with 7 epochs gave an r2 score of 0.791.**

***Keywords*— LSTM, Clustering, RNN, Missile path, Air Objects**

I. INTRODUCTION

The conventional wisdom has been that one state's nuclear acquisition has compelled its adversaries to follow suit throughout the nuclear era. To ensure the safety of its citizens in the face of nuclear war countries have developed various technologies and systems to counter such situations. This proposed work would benefit the Department of Defense by allowing them to predict what air objects are entering the country's airspace and intercept them if they are not authorized to do so [1-2]. Motion data explaining planned and actual flights is used in air traffic management controlled for the planning and monitoring with an aim of growing usage of capacity of the airspace without cargo safety or flight timeliness and compromising passenger [3]. The significant increase in the number of air objects performed in the limited air space complicates planning the task, management the task and monitoring the tasks, these are accessed ever-increasing number of the data and these data must be analyzed [4]. Advanced analytical techniques that are appropriate for data and performing tasks in the aviation field are needed. Tasks that require flight route analysis motivated the proposed work, an analytic process as well as a computational procedure, visual, and interactive approaches, and the central component of density-based clustering of the trajectories which was predicated on similarity routes. Despite its origins, the approaches and techniques are generic this can be applied to the movement of analysis in a variety of fields [5].

Clustering is effective and efficiently used tool for classifying the big number of datasets, difficult datasets and producing the understandable properties and the patterns of the data in dataset. The technique of Clustering trajectories, which is difficult spatiotemporal constructs, necessitates the use of the distance functions to determine the resemblance of trajectories. Neural network model has a good fitting effect on the nonlinear model, so it is used to fit and approximate the nonlinear model of the missile trajectory. On the problem of flight trajectory prediction, traditional methods such as numerical integration method, etc. have the problem of large amount of calculation or low accuracy Therefore, in the latest years, RNN and the LSTM methods have begun to be used to solve flight trajectory prediction problems. A clustering approach for air objects based on their trajectories i.e., provided their velocities and altitudes was done using RNN and missile path prediction based on the latitude, longitude, altitude and velocity using LSTM [6].

II. RELATED WORK

Similarity-based clustering of moving object trajectories is a useful method in movement technique. The Distance functions that are currently available compare the trajectories based on the behavior of trajectory point segments. Thematic attributes, time, and positions may be assigned to the properties. It may be necessary to narrow the scope of the observation to specific parts of the trajectory, such as points and segments with special characteristics. The observer might still only have to cluster the trajectories according to their similarity of required sections, based on the approach. Throughout this procedure, targets the analysis that might shift, and the various sections of the trajectory might be relevant. They recommend an explanatory workflow wherein filtering tools have been used to assign importance flags to trajectories and clustering is conducted using a distance function this function aids in the removal of irrelevant elements, after removal the results of clusters are been summarized for further approaches. There are three different types of case study using the real time data in a field of air traffic, and show how this workflow can be useful for various analyses. This proposed for a general-purpose methods and visualization the different guidelines to aid in the analysis of movement data using relevance-aware trajectory clustering. [1]. One of the most difficult challenges in applying the missile model to various related simulations is determining the missile's flight path. The traditional method for this task is to use models and numerical integration, which necessitates a large amount of computing power. The data has been created from the traditional modules these modules use to the training network and test the network, and the error of the network prediction result is analyzed in this paper. The trained DNN predicts the missile's flight path four times faster than the traditional model, with small error [2].

The proportional navigation (PN) guidance law is introduced to be replaced by the deep neural network-based guidance law. This method employs a supervised learning with a big set to simulated data of the missile system with proportional navigation guidance. By following that, deep neural network guidance law is compared with proportional navigation laws, and its performance has been evaluated using the energy function and hitting rate. Furthermore, the deep neural network-based guidance laws are only on line-of-sight rate input guidance law is introduced and compared to the PN and deep neural network-based guidance laws. Following that, deep neural network laws and the DNNLG laws helps to analyze the character of a place other than the given trained data. [3]. Missile guidance employing PN guidance law have limitations in helping a broad range of applications with differing in the mission and their target variables. The authors propose an Artificial Neural Network to replace the PN guidance laws in order to overcome these limitations. The Artificial Neural Network enables the learning, adaptation, and performs faster. This enhancement may remove the barrier limitations. A Multi-Layer Perceptron was used to implement the Artificial Neural Network method for replacing PN guidance [4].

A new scheme-based guidance is used on the deep reinforcement learning approach on models. The model deep reinforcement learning technique is being used to train deep neural network to make model predictive of guidance dynamics, this guidance dynamic is integrated the model to predictive the different paths with the integral controlled frameworks. In contrast, this model assumes a real place which is same as the deep neural nets trained data, these deep neural nets going to create an impractical in the exercise due to target actuator failures, some of other perturbations, and maneuvering. For solving this type of gap, the proposed employees a meta-learning method that allows deep neural network is a dynamics models with type of modifications in real time. Using this method, the proposed work can mitigate the performance degradation of standard model predictive path integral control has affected by difference in between both the real environment, and training the data [5].

Missile Guidance estimation was done using Kalman Filter Algorithm and PN Guidance Law in python and a Comparitive study was conducted between different types of filters and laws for guidance [6]. A new approach was proposed which was able to estimate the trajectory of an air vehicle using LSTM and good accuracy was achieved [7]. Three different approaches were proposed to predict the trajectory of the vehicle i.e., LSTM, GRU and SAE, results were observed [8]. An algorithm was developed for missile guidance using deep reinforcement learning, DDPG approach is used to train the agent in the RL model and the effectiveness of the approach was validated [9]. A Guidance model was proposed which uses LSTM provided acceleration as a target. An NMPC will be combined with the LSTM, this outperformed all the existing methods [10].

Though there was past work based on missile guidance and on path prediction of missiles, there was no system developed to distinguish air objects based on their speeds and altitude and a missile path prediction system which is capable of remembering previous state's information of where the missile has gone. This paper proposes a novel approach of clustering missile objects based on their trajectories i.e., speed and altitude and also a missile path prediction system using LSTM which will be capable of remembering the past information of the missile.

The paper is organized as follows: Details of some of related works has been discussed in Section II. In section III, the proposed methodology is explained briefly. Results are discussed in sections IV. Conclusion and Future Scope were discussed in the Vth section.

III. PROPOSED METHODOLOGY

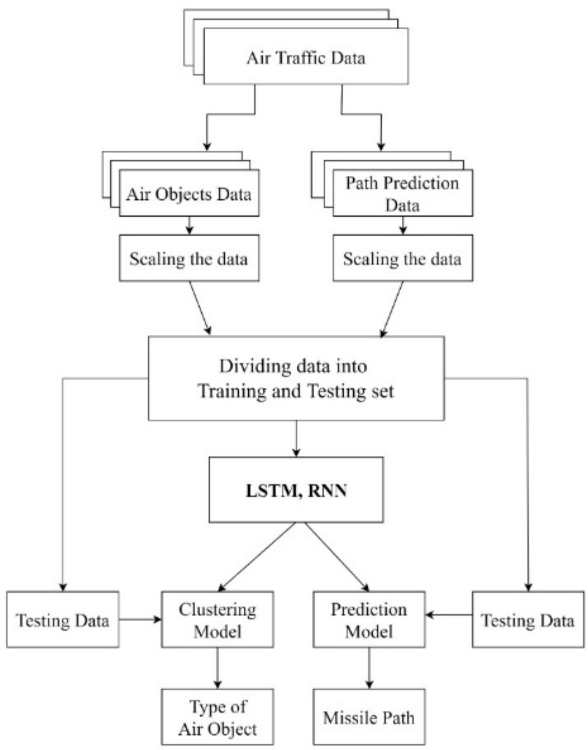

Fig.1. System architecture for clustering of air objects and missile path prediction.

As shown in Fig. 1., the proposed methodology starts with collecting the data from air traffic control websites. There are two datasets i.e., air objects clustering dataset and path prediction dataset. Next the data will be scaled using min max scaling to normalize the data. Clustering is performed based on velocities and altitude, because these factors allow for easy differentiation of all air objects. RNN and LSTM will be utilised as the clustering algorithm. It detects the dense zone by aggregating data points that are physically adjacent to one another. A trajectory is a type of multivariate Time Series data. A time series-specific neural network, such as LSTM, can be used. Sliding windows in LSTM helps in maintaining the continuity and avoids in compromising the dynamic relationships of co-occurring states in long-term cycle, that improves trajectory prediction accuracy.

A. Dataset Description:

Dataset contains trajectories, specifically 5 characteristics such as longitude, latitude, altitude, speed, and time for various air objects such as planes, drones, missiles, flying bombs, etc. This would help the algorithm to gain a fundamental grasp of several alternative trajectories. Data has been grabbed from the trajectories of air traffic websites. Air traffic control monitors aircraft movements and provides advising services. The dataset can also be constructed mathematically by employing various trajectory functions, equations, and simulation.

B. Scaling the data:

After obtaining the training dataset, it will be cleaned, with each parameter pre-processed separately, and then normalised. This is accomplished with min-max scaling. Data is normalised for each trajectory through using first few data points of trajectory. This process will be followed for each subsequent row. This strategy reveals the highs and lows of each row in a unique way. The column method: In few columns, say x, are chosen and the scaling algorithm is fitted to the combined data. The entire dataset may then be simply fit or altered, which would generalise the dataset. Normalization is required before using the data as a training set for an LSTM network. Min-Max normalisation is a linear approach in which data features are scaled in between 0 and 1.

C. Deep learning Algorithms:

- RNN: It is a type of Neural Network. In this network, previous step output was given as input to the present phase. In a typical deep neural net, all the inputs of the network and outputs of the networks are independent to each other; however, when the network is trying to predict the next letter or word of a paragraph in this case, previous words or letters need to remember. Thus, Recurrent neural network was developed due to solve the problem of Hidden Layer. This Hidden layer, helps to remember certain data and it is most precious aspect in Recurrent neural network.
- LSTM: It is a network is a type of RNN modification that was designed to handle instances where RNN has failed. RNN is a variant of network that operates on the present input by taking into account the previous output feedback and temporarily keeping it in memory. The most common uses of this technology are in voice processing, random control, and also in composition of music. Recurrent neural network, however, have some downsides. It is not able to store data for long durations. It is frequently important to rely on data that was preserved for long time ago in estimating current output. Recurrent neural networks, on the other hand, are insufficient to cope with long-term dependencies [14-15].

D. Testing:

The proposed work used freely available open-source flying simulators such as Flight Gear for testing. It has open access to use, change, and share one of the highly real-world resembling flight simulators available. Flight Gear is utilised by desktop flight simulator fans all around the world, as well as for research in organizations and exhibits in museums. It has details of over 400 aircraft, a global view database, a multiple-player environment, extensive sky modelling, a resilient, an aircraft modelling system which is publicly open, a variety of networking options, various display support, a sophisticated programming language, and a publicly open architecture.

IV. RESULTS AND DISCUSSION

Both Clustering of air objects and Missile Path Prediction were implemented in python using TensorFlow library. RNN was run for 30 epochs for clustering the air objects and LSTM was run for 7 and 8 epochs for predicting the missile's path. Different number of epochs were tried out of which these gave the best outputs. The evaluations metrics chosen are coefficient of determination score(r2 score), Explained variance score(EV score), Root mean squared error(RMSE), Mean absolute error(MAE) and Median absolute error(MedAE).

A. Clustering of air objects

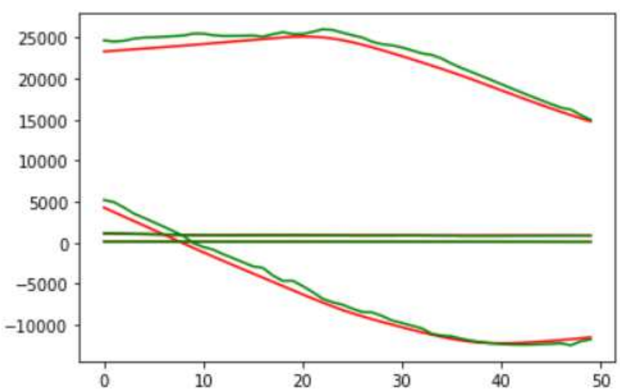

Fig.2(a). Original vs Predicted labels in Clustering of missile objects using RNN

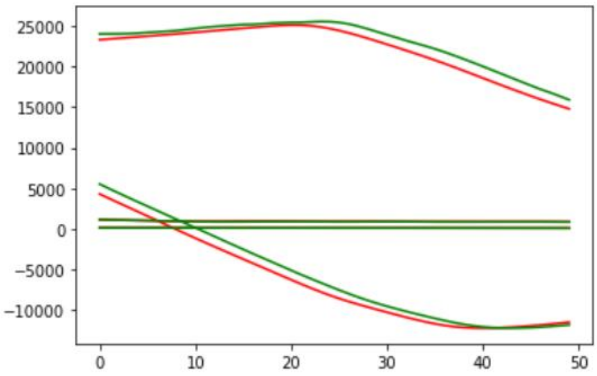

Fig.2(b). Original vs Predicted labels in Clustering of missile objects using LSTM

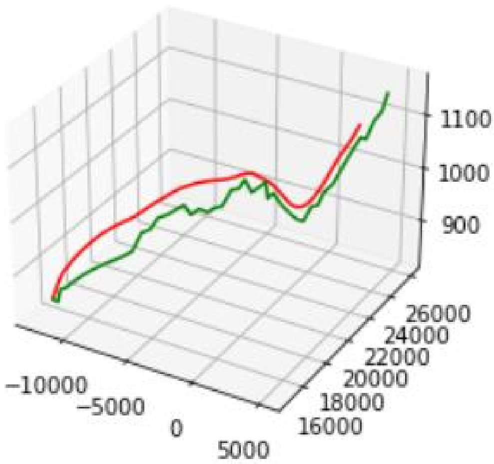

Fig.3(a). 3D plot of original vs Predicted labels in Clustering of missile objects using RNN

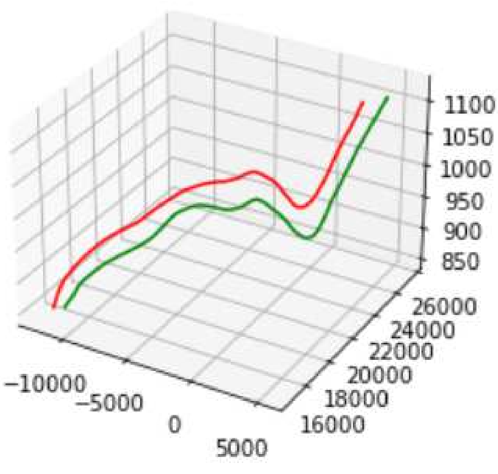

Fig.3(b). 3D plot of original vs Predicted labels in Clustering of missile objects using LSTM

TABLE I. RESULTS OF CLUSTERING OF AIR OBJECTS

Algorithm	**r2 score**	**EV score**	**RMSE**	**MAE**	**MedAE**
RNN	0.9974	0.9974	979.6269	529.5506	443.9003
LSTM	0.9977	0.9977	685.4955	404.3556	353.9672

It can be inferred from Table - I that while both RNN and LSTM are performing equally better in terms of r2 score, EV score, LSTM outperformed RNN in terms of RMSE, MAE, MedAE which shows that LSTM is very efficient in clustering the air objects with correct labels.

In Fig.2(a) and (b), Fig.3(a) and (b), Original labels are shown in red and predicted labels are shown in green.

B. *Missile path Prediction*

It can be inferred from Table – II that LSTM with 7 epochs is clearly outperforming RNN in terms of r2 score, EV score, LSTM, RMSE, MAE, MedAE which shows that LSTM is very efficient in clustering the air objects with correct labels and it works very well on lengthy data such as missile trajectory.

In Fig.4(a) and (b), Fig.5(a) and (b), the missile original path is shown with red and predicted path is shown in blue.

TABLE II. RESULTS OF MISSILE PATH PREDICTION

Model	**r2 Score**	**Explained Variance Score**	**Root Mean Squared Error**	**Mean Absolute Error**	**Median Absolute Error**
RNN - 7 epochs	0.6897	0.9922	290.032	286.3826	280.2883
RNN - 8 epochs	0.5277	0.7030	285.125	248.3148	237.2868
LSTM - 7 epochs	0.7910	0.9264	211.285	182.8557	179.8126
LSTM - 8 epochs	0.7424	0.8691	224.910	194.2097	179.1640

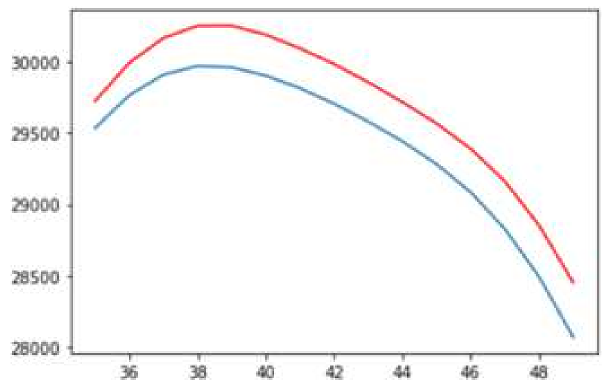

Fig.4(a). Missile path for 7 epochs using RNN

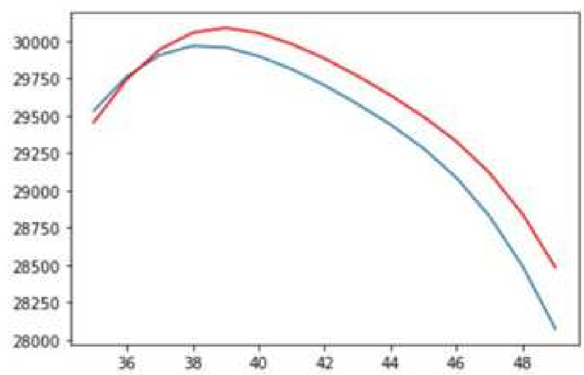

Fig.4(b). Missile path for 7 epochs using LSTM

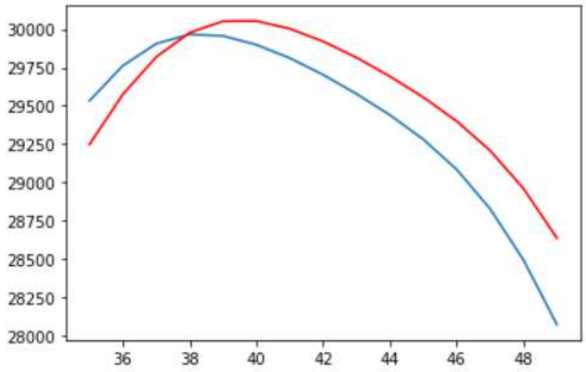

Fig.5(a). Missile path for 8 epochs using RNN

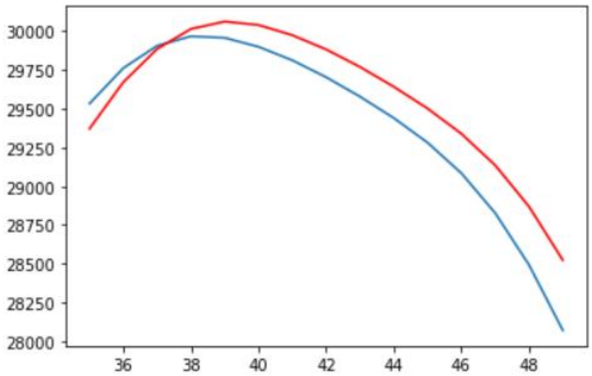

Fig.5(b). Missile path for 8 epochs using LSTM

V. Conclusion and Future Scope

Clustering of air objects was being done using RNN and LSTM, it was shown that LSTM was providing better results. Missile Path was being predicted using RNN and LSTM with 7 & 8 epochs each, it was shown that LSTM with 7 epochs was providing better results. This is very helpful for organizations like DRDO and ISRO, since it can give a clarity about the objects present in air and also can predict the missile's path which can be very effective for ISRO. This work can further be extended by using different deep learning algorithms for clustering the objects and predicting the missile's path and doing a comparative study to find out which algorithm suits the best.

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