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Short-Term Trajectory Prediction Using Generative Machine Learning Methods

Thanh-Ha Le*, Phu N. Tran*, Duc-Thinh Pham*, Michael Schultz†, Sameer Alam*
*Air Traffic Management Research Institute, Nanyang Technological University, Singapore
{ha.le, phutran, dtpham, sameeralam}@ntu.edu.sg
†Institute of Logistics and Aviation, Dresden University of Technology, Germany
michael.schultz@tu-dresden.de

***Abstract*—Aircraft trajectory prediction is at the heart of the air traffic control (ATC) system. An accurate prediction of aircraft's future locations is essential for the air traffic controllers (ATCOs) to maintain the situational awareness of the traffic and to have proper strategies of congest management and separation assurance, which in turn contribute to a safe and efficient operation of the airspace. In this work, we propose a machine learning method for short-term aircraft trajectory prediction on a sector-based basis. Historical trajectories (from ADS-B data) are divided into clusters based on their spatial behaviors in the sector. Then, for each of the trajectory clusters, a predictive model is trained for future location prediction of the aircraft following the corresponding pattern. In the prediction phase, given the information of an aircraft when it is approaching the sector, our model first predicts the general pattern of the aircraft's trajectory in the sector, and based on the predicted pattern, the most appropriate predictive model is chosen to predict the aircraft's future locations. The whole future trajectory of the aircraft within the sector can also be generated. The evaluation shows that our model can achieve an average trajectory-wise error as low as 1.06 NM at 5-minute look-ahead time and 1.69 NM at 10-minute prediction horizon. The mean absolute error of the total travel time in the sector ranges from 9.8 seconds to 26.5 seconds depending on the trajectory pattern.**

***Index Terms*—short-term trajectory prediction, aircraft trajectory, random forests, regression.**

I. Introduction

In a complex, stochastic, and safety-critical system like the air traffic management (ATM) system, the predictability of the system becomes essential in maintaining a safe and efficient operation. A key functionality of the ATM system is air traffic control, in which air traffic controllers (ATCOs) perform aircraft separation assurance and traffic congestion management. Of these two, separation assurance is more tactical, and usually the ATCOs have a limited amount of time for decision making in the event of potential loss of separation between aircraft. At this tactical level, short-term aircraft trajectory prediction is necessary for the ATCOs to foresee any potential conflict between aircraft, so that they can issue deconfliction advisories to the pilots in a timely manner. Furthermore, an accurate prediction of the aircraft trajectories would allow the ATCOs to confidently reduce the safety buffer in their resolution advisories, and this could potentially contribute to the improvement of the airspace capacity.

As trajectory prediction plays an essential role in the ATC system, much effort has been put into the development of algorithms for aircraft trajectory prediction. Especially, we observed in the literature within the last decade a very noticeable emphasis on the applications of machine learning methods for trajectory prediction [1], [2]. The shift towards machine learning methods is, in fact, well expected given the immense advancements in predictive models using machine learning and the broader availability of aviation surveillance data (e.g. Automatic Dependent Surveillance – Broadcast or ADS-B data).

Various machine learning techniques and different types of historical data have been employed to predict aircraft trajectories in many different contexts. In particular, Ayhan et al. [3] considered that different realizations of the aircraft trajectory for a given origin-destination airports are resulted from the changes in the weather parameters. They modeled this relation by the Hidden-Markov Model (HMM) and used the Viterbi algorithm to train the model's parameters. Their model achieved horizontal accuracy of 12.601 kilometers (cross-track error), given that high resolution of weather data were available. Leege et al. [4] discussed the application of Generalized Linear Models (GLMs) to the trajectory prediction problem for aircraft sequencing and merging, in which the authors used both aircraft historical positional data and meteorological data. The model predicted arrival time of the descending aircraft at fixed points. It achieved a mean absolute error of 7 seconds for 15 NM prediction horizon, and 24 seconds for 45 NM prediction horizon. Hybrid approach that learns dynamic parameters from historical data were proposed by Lin et al. [5], in which the authors built a hybrid statistical model with double stochastic process involving HMM and Gaussian Mixture Models (GMMs) to predict the future location of the aircraft with a prediction error as low as 206.35 m (mean) and 90.70 m (standard deviation). Various deep learning techniques have been also employed for the trajectory prediction, such as Recurrent Neural Networks [6], Long Short-Term Memory (LSTM) [7], Deep Generative Convolutional Recurrent Neural Networks [8], and Multi-cell Neural Networks (M-CNN) [9].

In this paper, we propose a machine learning method for short-term trajectory prediction, on the sector-based basis, using only historical ADS-B data. We aim to build models that can predict the trajectory of an aircraft in a given sector when the aircraft is about to enter the sector. In our approach, we first detect clusters in the historical trajectories such that trajectories in each cluster share similar spatial behaviors. Then, predictive model is built for each cluster using the Random Forests (RF) algorithm. After that, the model is used to generate the trajectory of the aircraft through the sector. We evaluate the performance of the models using different sets of input feature and target of prediction, at different look-ahead times (i.e. 5 minutes and 10 minutes). In this work, we assume that the altitude and the lateral position of the aircraft can be decoupled and treated separately, and we focus on the prediction of lateral location of the aircraft. Although additional altitude prediction model, which is not in the scope of this study, is required to produce 4D trajectory prediction, such separation helps to reduce the complexity of individual model and improve the model's interpretability.

II. Methodology

A. Data preparation

We collect a dataset that includes ADS-B records from March 1st to March 15th, 2019 over sector 2E which is an en-route area within Singapore Flight Information Region (FIR), managed by Singapore Area Control Center (ACC), for providing air traffic service from flight level FL120 to flight level FL360 inclusive. We have chosen Sector 2E in Singapore FIR as this is the main feeder sector into the Singapore TMA, having interface with three FIR boundaries Ho Chi Minh FIR, Bangkok FIR and Kuala Lumpur FIR. This sector has high degree of flight vectoring and tactical trajectory management making it a natural choice for demonstration of trajectory prediction problem. Figure 1 depicts the spatial characteristics of the selected sector. Due to the limitation of the ADS-B data receiver, some trajectories have missing parts and noise, we have to filter it out. To solve it, we eliminate trajectories with less than 6 points because of lacking information. All the trajectories are re-sampling with the same time stamp 30 seconds.

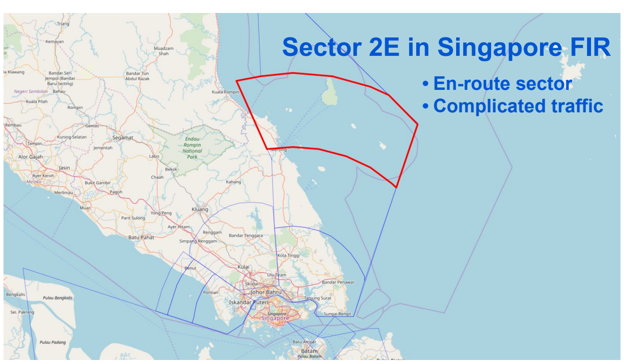

Fig. 1. Sector 2E in Singapore FIR.

Holding trajectories are not considered in our study so we eliminate them from our dataset. The final dataset has 3309 trajectories with 40190 data points. The statistics of the dataset is described in detail in Table I.

TABLE I
Statistics of the dataset

Attributes	Count
Flight ID	3309
Origin Airport	69
Destination Airport	62
Position (long, lat, al)	40190
Aircraft type	25
Tail number	704
ICAO Callsign	522
UTC Time	2 weeks

B. General approach to models training and prediction

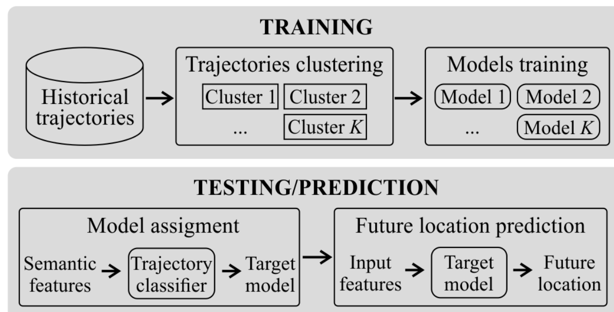

Fig. 2. General approach to the training and the prediction phases. The training phase consists of trajectories clustering and model training for each cluster. The testing/prediction phase begins with model assignment, followed by future location prediction using the assigned model.

To improve the prediction performance, we shall detect clusters in historical trajectories such that in each cluster, the shape-wise variance of the trajectories is relatively small. From there, a future location predictive model will be trained for each group of trajectories. Thus, the training phase, as shown in Figure 2, has two major steps: (1) clustering the historical trajectory into K groups, and (2) training K models (one for each cluster) for future location prediction. Here, K is a parameter to be determined. In the testing/prediction phase, given the information of the aircraft when it is approaching the sector (i.e. semantic features in Figure 2), we first predict the trajectory group (among K clusters) that aircraft's trajectory most likely belong to. In other words, we predict the general shape of the aircraft's future trajectory and the most appropriate model for future location prediction (see Model assignment in Figure 2). A trajectory classifier will be trained to perform this task. Next, recent information about the aircraft's behavior (i.e. input features in Figure 2) is fed into the assigned model to perform future location prediction.

C. Trajectories clustering

We perform trajectories clustering to detect underlying patterns in shape of the historical trajectories. It is understandable that the shape of a trajectory is influenced by the locations at which the aircraft enters and exits the sector. From our

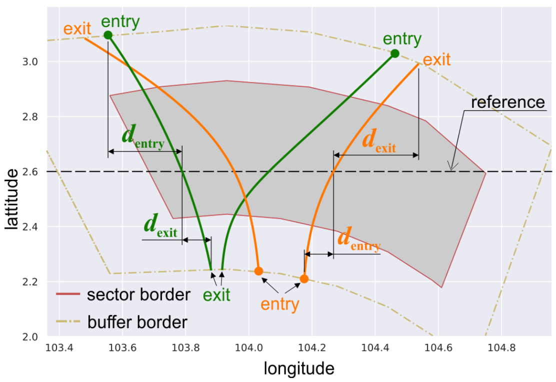

Fig. 3. Illustration of features being used for trajectories clustering, in which each of the historical trajectories is represented by the aircraft's entry and exit locations and the two distances d_{entry} and d_{exit}.

observations, the spatial behavior of the trajectory can be modeled by some distances from the trajectory to a fixed reference geometry. For the selected sector, we define as the reference a horizontal line that is latitudinally positioned at $lat_{\text{ref}} = 2.6°\text{N}$ (Figure 3). Such value of lat_{ref} was obtained by empirical experiments. Then, the feature d_{entry} is defined as the longitudinal distance from the aircraft's entry location to the intersection of the trajectory and the reference line, and d_{exit} as longitudinal distance from the aircraft's exit location to the same intersection (Figure 3). Here, d_{entry} and d_{exit} may take either positive or negative values; their signs and magnitudes co-influence the trajectory's shape. The features used for trajectories clustering are summarized in Table II. Each trajectory is represented by this 6-dimensional feature vector, and all the trajectories' feature vectors are fed into the K-means clustering algorithm. We tries different values of K (from one to ten clusters), and $K = 8$ results in the most acceptable shape-wise variance in each group.

TABLE II
FEATURES USED FOR TRAJECTORIES CLUSTERING

Features	Dimension
Entry location (long, lat)	2
Exit location (long, lat)	2
Distances d_{entry} and d_{exit}	2
Total	**6**

Figure 4 depicts the eight groups of historical trajectories, in which the first four groups are trajectories of aircraft entering the sector from the north and the last four groups from the south. This shows that the selection of clustering features (see Table II) not only allows the algorithm to detect patterns in shape of the trajectories, but also enables it to discriminate the moving directions of aircraft along those paths. This is important because along any trajectory rather than a straight line, the aircraft's behavior is dependent on its moving direction. For convenience, we shall refer to the first four groups as southbound traffic and the last four groups northbound.

The trajectories in each group can be represented by the group's mean trajectory, which is demonstrated in Figure 4 by a black curve. The mean trajectory is constructed by the average longitudes and latitudes calculated at synchronized timestamps over all trajectories in the same group.

Histograms of travel time of clusters are demonstrated in Figure 5. The average travel time of Group 1 is longest and Group 8 is shortest. It is consistent to see Group 1 has longest travel distance and Group 8 has shortest one in the histogram of travel distance of each clusters in Figure 6. The average travel time and average travel distance of each cluster are described in Table III.

TABLE III
AVERAGE TRAVEL TIME AND AVERAGE TRAVEL DISTANCE OF EACH CLUSTER

	Average travel time (s)	Average travel distance (NM)
Group 1	542.52	62.63
Group 2	470.12	52.73
Group 3	411.69	46.55
Group 4	488.96	55.81
Group 5	383.79	47.66
Group 6	387.06	47.57
Group 7	396.47	49.13
Group 8	368.68	45.95
Average	**431.16**	**51.00**

D. Model assignment

Building model assignment is the first task of testing part. From the entry point's information of the aircraft, we try to predict which group or which trajectory pattern the aircraft will follow when it fly through the sector. To robust our classifiers, we build two classifiers for two directions: southbound and northbound. Thus, each classifier is trained on 4 groups of each direction.

Feature extraction: We do some feature engineering for categorical features: Callsign, Origin airport and Destination airport.

For Callsign, instead of using a distinct number to represent each Callsign, we calculate 4D vector with each component is conditional probability that an aircraft will belong to a particular group given its Callsign.

$$Callsign \rightarrow \begin{bmatrix} p(cluster1|Callsign) \\ p(cluster2|Callsign) \\ p(cluster3|Callsign) \\ p(cluster4|Callsign) \end{bmatrix}$$

We apply the same method for Origin airport and Destination airport. A list of features is described in Table IV

Traning model: Using the features, we experiment on different machine learning models: Random Forrest, one-versus-all Support Vector Machine and Multi-layer Percepton.

E. Future location prediction

We train the location predictive models for each group of trajectories which we have obtained from clustering step in training phase.

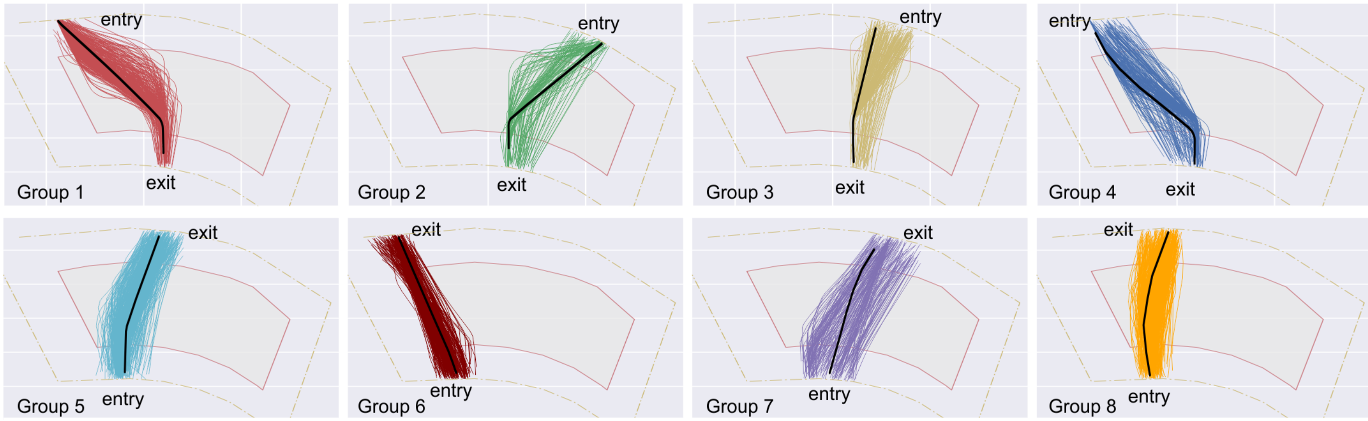

Fig. 4. Eight groups of historical trajectories as the result of trajectories clustering. The first four groups (on the first row of the figure) are southbound traffic, and the last four groups are northbound traffic. The black curve in each group is the representation of all the trajectories belonging to the same group.

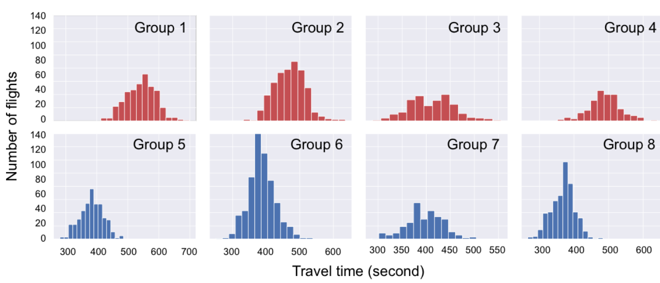

Fig. 5. Distribution of the travel time (in seconds) in the sector, computed for each of the trajectory clusters. The first four groups (red) are southbound traffic and the last four groups (blue) are northbound.

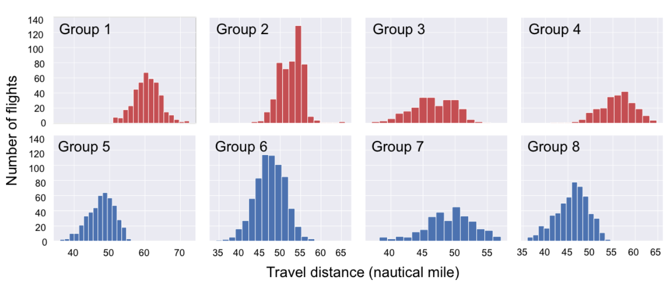

Fig. 6. Distribution of the travel distance (in nautical miles) in the sector, computed for each of the trajectory clusters. The first four groups (red) are southbound traffic and the last four groups (blue) are northbound.

TABLE IV
SEMANTIC FEATURES FOR MODEL ASSIGNMENT

Features	Dimension
first point (long, lat, al)	3
ground speed	1
aircraft type	1
hour in day	1
callsign	4
origin airport	4
destination airport	4
Total	**18**

Feature extraction: to predict position of the aircraft in the next timestamp, we extract following features of the aircraft: longitude, latitude, time, current heading, Δ_{long} and Δ_{lat}.

- *time* feature is normalized by minus to time of the entry point. The entry point of the trajectory has *time* 0.
- Δ_{long} and Δ_{lat} are respectively longitudinal and latitudinal distance to the reference point. Each cluster has an own reference point. The reference point of each group is determined by the last point of the mean trajectory of this group. While the *current heading* feature brings the information about the next position of the aircraft in a few seconds, Δ_{long} and Δ_{lat} measure the heading follows the representative pattern which was found in clustering step.

Target learning: Due to divergence of the data, predicting directly the value of the next longitude and latitude does not bring effective learning. We attempt to predict different information that can be used to re-calculate the next position of the aircraft: δ_{long}, δ_{lat}, $\delta_{heading}$ and $|\overrightarrow{v}|$.

- δ_{long} and δ_{lat} are the longitudinal and latitudinal change of the the aircraft in a time interval.
- $\delta_{heading}$ is the change of heading of the aircraft in a time interval.
- $|\overrightarrow{v}|$ is the norm of velocity vector of the aircraft.

Training model: In this step, we fit different combinations of features and targets to find best models. We consider two machine learning models: Multi-dimensional Regression with Neural Network, Random Forrest Regression (RF). However, after an initial experiment, we figure out that only RF models are suitable for our dataset while Neural Network faces some difficulties in convergences. Thus, at the end, only RF is selected to build our predictive model.

Generative model: To generate the whole trajectory of the aircraft through the sector, we iterate the prediction using the future location prediction model that the output of current step will be the input of next step.

III. EXPERIMENT

We split the dataset into 3 subsets: training set, validation set and testing set with ratio 70% for training, 10% for validation and 20% for testing . Table VI describes the dataset in detail.

TABLE V
FEATURES AND TARGET LEARNING

Model	**Features**	**Target learning**	**Algorithm**
Model 1 (M1)	long, lat, time	δ_{long}, δ_{lat}	RF
Model 2 (M2)	long, lat, time, current heading	$\delta_{heading}$, $\lvert\overrightarrow{v}\rvert$	RF
Model 3 (M3)	long, lat, time, current heading, Δ_{long}, Δ_{lat}	$\delta_{heading}$, $\lvert\overrightarrow{v}\rvert$	RF

TABLE VI
NUMBER OF FLIGHTS IN TRAINING, VALIDATION AND TESTING SET

Direction	Training set	Validation set	Testing set	Total
Southbound	1006	112	279	1397
Northbound	1397	150	374	1921
Total	2403	262	653	3309

The given trajectories data is used to train and evaluate our Model Assignment using three multi-label machine learn classifiers: Random Forrest, Multilayer Perceptron (MLP) and one-versus-all Support Vector Machine. The evaluating metric is accuracy (Acc):

$$Acc = \frac{|\hat{Y} \cap Y|}{|Y|}$$

With $\hat{Y}$ is the predicted label and Y is the true label.
Based on the results from the Model Assignment, we use the corresponding generative model of the cluster to generate the short-term trajectory for the aircraft. To compare the performance of different combinations of features and targets, we experiment with 3 models which were described in Table V then report average results on Southbound and Northbound direction. The final system produces a list of time and location of the aircraft. We measure the results in two aspects: error in located prediction and error in time of traveling prediction.

To evaluate the located prediction, we calculate the trajectory-wise average error (TWAE) follows formula below:

$$TWAE = \frac{1}{n}\sum_{i=1}^{n} E_i$$

n is number of position (longitude, latitude) in the trajectory of the aircraft. E_i is the Euclidean distance (in nautical mile) between every predicted point's 2D coordinate (latitude and longitude) and the ground truth.

The travel time of each aircraft is calculated from the entry point until it exits the sector. We use Mean Absolute Error (MAE) to measure the error of traveling time.

$$MAE = \frac{1}{n}\sum_{i=1}^{n} |\hat{y}_i - y_i|$$

To avoid overfitting and select the parameters, we do 3-fold cross validation on a grid search of parameters for each model.

IV. Result and Discussion

A. Result of the model assignment

After using grid search to optimize the parameters for both RF, SVM and MLP, we found that RF gives lightly better prediction accuracy than SVM and MLP. Thus, we report only the 3-fold cross validation result of the Random Forrest Classifier in Table VII in both Southbound classifier and Northbound classifier.

From the result in Table VII, we can conclude that we do not encounter with overfitting. The average accuracy in testing set of both Southbound and Northbound direction are approximate 90%. Finally, the Southbound model is trained with maximum depth of the tree is 9 and number of estimators is 30. For Northbound model, they are 14 and 20 respectively.

TABLE VII
RESULT OF MODEL ASSIGNMENT

		Southbound	**Northbound**
Fold 1	Training	0.9237	0.9140
	Testing	0.8839	0.9053
Fold 2	Training	0.9172	0.9092
	Testing	0.9140	0.8926
Fold 3	Training	0.9043	0.9141
	Testing	0.9161	0.8842
Average	Training	0.9229	0.9125
	Testing	0.9047	0.8940

B. Result of the generative model

TABLE VIII
TRAJECTORIES-WISE AVERAGE ERROR IN NAUTICAL MILES AND MEAN ABSOLUTE ERROR IN SECOND

Direction	Model	TWAE in n.mile			MAE in second	
		5m	**10m**	**Optimal**	Mean	STD
Southbound	M1	1.76	2.4	2.07	28.53	21.95
	M2	1.22	1.95	1.59	25.83	18.96
	M3	**1.06**	**1.69**	**1.39**	**23.32**	19.06
Northbound	M1	1.68	2.16	2.09	15.28	13.31
	M2	1.16	1.65	1.56	14.47	12.62
	M3	**1.11**	**1.60**	**1.5**	**13.68**	13.12

In Table VIII, we also report the trajectory-wise average error in different look-ahead time: 5 minutes, 10 minutes and Optimal is the time each aircraft exits the sector.

In location prediction, the best results in both Southbound and Northbound directions were offered by Model 3. We can achieve TWAE = 1.06NM for 5-minute look-ahead time, and TWAE = 1.69NM for 10-minute look-ahead time. The result for optimal setting (TWAE = 1.39NM) reflects the predicted error over the selected sector. Model 1 does not perform well because of lacking the information about the heading and the trajectory pattern of the group. Similarly, Model 3 performs better than Model 2.

As discussed, using the output of current step as input of the next step to generate the trajectory of the aircraft makes the TWAE cumulative. For all models in both Southbound and Northbound, the 10 minutes trajectory prediction approximately doubles the TWAE over 5 minutes. From experiment, we observe that, 80% the error increase in first 6 minutes and only 20% increase from 6 to 10 minutes. The look-ahead time error of all models are illustrated in Figure 7.

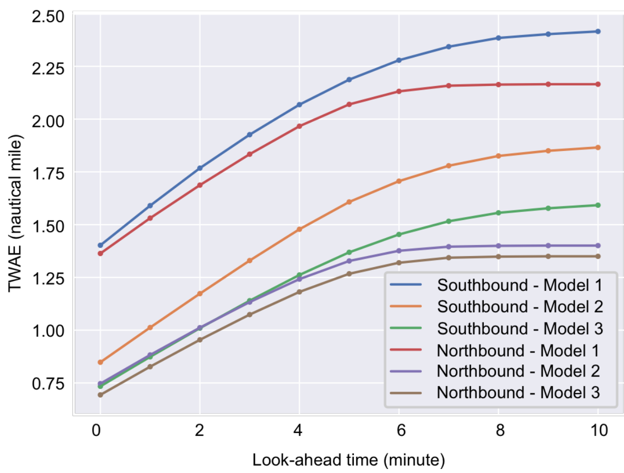

Fig. 7. Trajectory-wise absolute errors (TWAE) of different models performed on two traffic directions (i.e. southbound and northbound). It is noticeable that the TWAE are most stable when the look-ahead ranges from 6 to 10 minutes.

In the travel time prediction, the best results in both Southbound and Northbound directions were obtained by Model 3 which is consistent to the location prediction. The MAE for Southbound and Northbound models are 23.32s and 13.68s, respectively while the average travel time of all the trajectories are 8 and 6.5 minutes respectively. All the errors are less than 5% of the average travel time. Due to the cumulative error, the MAE of travel time in Southbound Models is bigger than Northbound Models.

Finally, after comparing all the combinations of features and models, using the best model, we generate all trajectories of each cluster from the entry point to exit point and calculate the error. The final results are illustrated in Table IX.

Figure 8 illustrates an example a full short-term trajectory generated by our model. Based on the location of the entry point, the model assignment predicts the future trajectory of the aircraft is most similar to trajectory pattern of group 4. Thus, we use the associated generative model of group 4 to generate locations of the aircraft after every 30 seconds in the sector (blue points in the figure). The full trajectory has 16 points and total travel time is around 8 minutes. The predicted trajectory (blue curve) is very close to the actual flown path of the aircraft.

TABLE IX
FINAL RESULTS

Cluster	TWAE (n.mile)	MAE (s)	Std. MAE
Group 1	1.99	26.5	19.71
Group 2	1.20	22	20.3
Group 3	0.60	16.85	13.16
Group 4	1.70	26.32	18.26
Group 5	1.93	14.82	14.04
Group 6	1.12	14.52	13.18
Group 7	1.76	16.86	15.99
Group 8	1.19	9.80	9.40

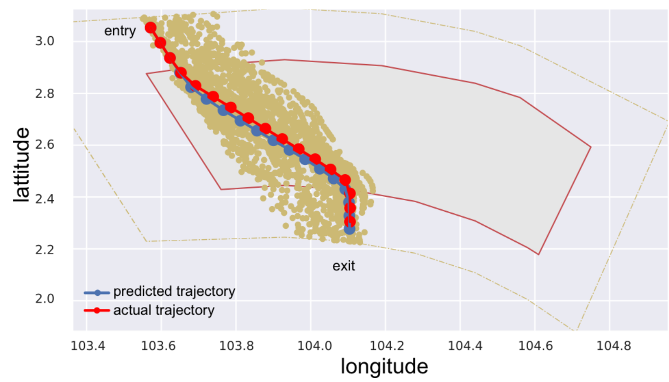

Fig. 8. An example of the predicted trajectory generated by our model (for group 4). The red curve is the actual flown trajectory and the blue curve is our prediction.

V. Conclusion

In this paper, a novel short-term trajectory prediction approach using machine learning with different sets of features and targets is proposed. The proposed model contains clustering-based processing and generative machine learning model to generate next positions of the aircraft. First, a list of features to cluster trajectories that have similar shape are proposed then traffic patterns of the sector can be extracted from the clusters. The data of each cluster is used to train its associated generative model. Given the entry point information, we build classifier models to predict which traffic pattern the aircraft will follow then generate the whole trajectory of the aircraft over the sector. All the training and testing are built on real data over sector 2E in Singapore FIR. The results are evaluated in both future location prediction (TWAE) and travel time (MAE).

In this study, we have assumed that the lateral position and the altitude of the aircraft can be decoupled, and solely focused on the prediction of lateral location. Future extension of this research includes the development of of predictive model for aircraft altitude such that the two can be combined to produce full 4D trajectory prediction. Also, it is important to consider the generalization of the approach such that it can work for any sector with minimal alteration to the model.

Acknowledgment

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