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A Machine Learning-Based Framework for Aircraft Maneuver Detection and Classification

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***Abstract*—The increasing availability of historical air traffic data (e.g., Automatic Dependent Surveillance-Broadcast (ADS-B) data) has enabled more advanced post-analysis of traffic scenarios, which leads to a better understanding of decision-making in air traffic control. Such kind of analysis is often complex and requires a careful design of analysis tools. Advanced machine learning techniques are shown to be very effective in dealing with the complexity of air traffic data analysis. This paper presents a machine learning-based framework to detect aircraft maneuvers in past traffic data and classify the maneuver into three key air traffic maneuvers. Aircraft maneuvers are identified in the ADS-B data using Isolation Forest algorithm, followed by maneuver clustering using K-means algorithm. Three time-dependent contextual features are proposed for dynamic traffic scenario representation and shown to be effective for maneuver clustering. Each maneuver cluster is associated with a label provided by Air Traffic Controllers (ATCOs), indicating the reason for such maneuver which took place in the past. Experiments were conducted on the framework using a dataset of 2793 arrival trajectories over 30 days in two Singapore Flight Information Region sectors. The results show that the framework efficiently allows post-analysis of air traffic scenarios, by which one can gain better insights into the decision-making patterns of ATCOs in response to various air traffic scenarios.**

***Keywords*—air traffic management; machine learning; time-series analysis**

I. Introduction

The rapidly increasing number of passengers and air traffic demand in the Asia Pacific, which shares around thirty percent of total global air traffic, requires adequate Air Traffic Management System (ATM) [9]. In the post Top of Descent phase of flight, tactical decisions of Air Traffic Controllers (ATCOs) are often influenced by several factors such as weather conditions, the workload in terminal maneuvering area (TMA), aircraft separation and sequencing, as well as other unexpected events. A careful analysis of past traffic scenarios may provide insights into the flight maneuver made by ATCOs, which may lead to a better understanding of ATCOs' decision patterns, and potentially their decision-making process under complex scenarios. In this paper, the authors propose a framework for such analysis by clustering and classifying past traffic scenarios using machine learning techniques. In particular, the framework detects aircraft maneuvers in past scenarios and classifies the maneuvers based on their contexts i.e., the circumstances leading to the maneuvers.

Advances of machine learning-based techniques for clustering and classification techniques have been benefiting air traffic data analysis in several aspects such as anomaly detection, traffic density and complexity, operational conformance, etc. For air traffic clustering, Gariel [7] used Density-based spatial clustering of applications with noise (DBSCAN) and K-means to identify the anomaly trajectories for evaluating airspace operational procedures. Murca [11] also used DBSCAN for clustering and identifying trajectory patterns in the airspace and applied Random Forest (RF) for evaluating flight conformance and usage of airspace resources. Basora [3] used two methods of Euclidean Distance-based clustering and Symmetrized Segment-Path Distance-based clustering to identify trajectory flows to support the flow-centric operation of SESAR. Andrienko [2] use various clustering techniques on spatial condition of activating and non-activated segments of trajectories on three case studies to demonstrate the ability of the clustering method to detect route selection, to explore landing scheme, and to reconstruct the air traffic network. The result shows a high level of generalization and recognition in detecting patterns and behaviors of air traffic scenarios. Olive [14] showed that clustering trajectories near the airports by Density-Based Spatial Clustering of Applications with Noise (DBSCAN) reflected the Standard Arrival Routes (STARs) in real-world operations. The clustering combines with trajectories' segment analysis result in labeling and insight about standard practices of ATCO at Toulouse airport.

The accomplishment of clustering methods facilitates further research on the classification of ATCO actions and on anomaly detection. Bosson [4] used seven supervised non-neutral network and neural network methods on a data set of the final ten minutes of flight of 20,822 arrivals spanning 30 days at Dallas Fort Worth airport. The result, including sensitivity and feature importance analysis, shows a high accuracy rate with the short requirement in training time for non-neutral net methods. Malakis [10] used a decision tree on classical and non-classical metrics to classify the air traffic scenarios in the simulation environment. The result shows a high level of accuracy and interpretable conditions for different classes of traffic scenarios. Later on, Olive combined the previous work of clustering air traffic with Autoencoder to detect controller's actions near the airport [12] and to detect

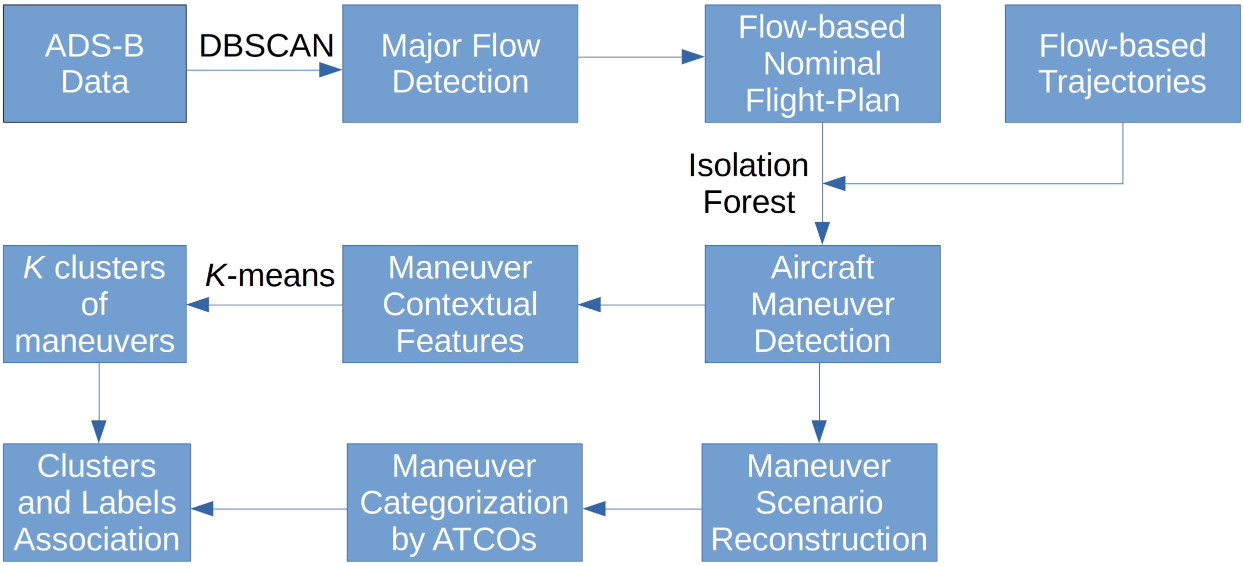

Figure 1: An overview of the proposed approach for aircraft maneuver detection and classification.

anomaly trajectories in en-route phase [13]. The result of anomaly trajectories is validated with the weather, runway information, and operational procedures.

The applications of machine learning techniques for flight trajectories analysis are shown to be effective. However, most previous works focused on the analysis on the flight trajectory level and did not perform the analysis at the scenario level i.e., considering the context of the trajectory being analyzed. Furthermore, the use of operational data provided by subject-matter experts were limited in the previous works. Aiming to address these limitations, this paper focuses on the development of a machine learning-based framework for aircraft maneuver detection and classification that makes use of feedback from ATCOs. Given past traffic data (e.g., ADS-B data) in a sector, the framework first detects the major traffic flows using the DBSCAN algorithm and constructs for each flow a nominal flight trajectory. Next, an aircraft maneuver is determined by detecting any flight trajectories that were significantly deviated from the nominal flight-plan, using Isolation Forest (IF) algorithm [17]. Then, the framework constructs the contextual features for each of the detected maneuvers using ADS-B data. Contextual features refers to the time-dependent features that describe the evolution of the traffic scenario from the time the maneuvering aircraft entered the sector till the time it exited the sector. These contextual features are then used for clustering the maneuvers using K-means algorithm. Finally, the clustering results are validated by a limited set of labels given by subject-matter experts (ATCOs). Here, the validation refers to the association of a maneuver cluster with a maneuver label independently suggested by the ATCOs. The analysis using the proposed framework can provide insights into the decision-making patterns in sector control. By discovering those patterns from past traffic scenarios, this approach serves as a significant complement to other approaches where controllers' decision are acquired directly from human-in-the-loop experiments [16, 8, 18].

The rest of this paper is organized as follows. The proposed framework is described in Section II. Details of the methodology are presented in Section III, which includes an overview of the framework and descriptions of algorithms used. The results are discussed in Section IV and Section V describes early conclusions drawn from the results.

II. Proposed Framework

The overview of the proposed framework is summarized in Figure 1, which consists of the following steps:

1) The framework learns to detect major traffic flows in a sector using DBSCAN algorithm [6] on past ADS-B data.
2) From flown tracks data within each major flow, a nominal flight-plan is reconstructed. In this paper authors are not using flight-plan data from Airlines or from Air Traffic Services Provider (ANSP), the reconstruction of flight-plan is required to serve the aircraft maneuver detection. The authors of this paper assume that, within a major flow, any flight trajectory that is significantly deviated from the flow's nominal flight-plan is considered as a maneuver.
3) Using the nominal flight-plan of each flow, the framework detects aircraft maneuvers from all trajectories within the flow by the IF algorithm.
4) The algorithm constructs, for each of the detected maneuvers, the contextual features in the form of time series. These time series capture the dynamic evolution of the traffic scenario that includes the maneuvering aircraft over time.
5) The contextual features of the detected maneuvers are used for clustering those maneuvers using K-means algorithm.
6) The resultant clusters from Step 5 are associated with the labels provided by subject-matter experts (ATCOs)

to establish the reason/purpose of each maneuver cluster. To facilitate this, authors reconstructed all the past scenarios (that have aircraft maneuvers) and requested ACTOs' label provision on each of them. Each label given by the ATCOs also indicates the rationale of the aircraft maneuvers.

The ADS-B data used in this paper were collected from 15-April-2019 to 15-May-2019 within Singapore Flight Information Region (FIR), the map of sectors show in Figure 2. The dataset includes 2793 flight trajectories.

III. METHODOLOGY

A. Major Flows Detection and Flight-Plan Reconstruction

The authors of this paper adopt the DBSCAN algorithm to cluster the traffic in a sector into major flows. DBSCAN is a density-based clustering algorithm that works by grouping a sets with minimum n points within a threshold distance ϵ. This method is able to cluster data points into high-density groups, and to separate outlier points that cannot be regrouped or are in low-density clusters.

In this context, a major flow refers to a group of flights within which all flights follow a common nominal flight-plan. The nominal flight-plan of a major flow is reconstructed from the ADS-B data. To facilitate DBSCAN algorithm, each flight trajectory in a sector is represented by a 5-dimensional vector (i.e., a data point), whose elements include

- longitude of entry point (i.e., where the aircraft entered the sector)
- latitude of entry point
- longitude of exit point (i.e., where the aircraft exited the sector)
- latitude of exit point
- total length of the trajectory in the sector (total traveled distance)

All the geometry information are projected in Universal Transverse Mercator coordinate system. The shortest pairwise distance between each data point and the others is calculated and sorted. The parameters of the DBSCAN algorithm include ϵ, which is calibrated based on the pairwise distance associated with the highest gradient value, and bounded maximum value from empirical experiment.

For each major flow identified in the previous step, a nominal flight-plan is constructed, assuming that all flights within the flow are to follow this flight-plan unless there were ATC interventions. The nominal flight-plan is constructed considering information of all waypoints and fixes found within the geographical region associated with the flow.

B. Aircraft Maneuver Detection

For aircraft maneuver detection, the authors of this paper assume that, within a major flow, any flight trajectory that is significantly deviated from the nominal flight-plan is due to aircraft maneuver. Thus, the maneuver detection can be considered by detecting the outliers of trajectories within a major flow. Isolation Forest (IF) algorithm is adopted for such outlier detection.

The algorithm identify anomalies by creating decision trees over random features. The path travel through random partitioning are recorded, and later be used to calculate the anomaly score, hence, the outliers are likely to be separated with shorter path. The anomaly score is calculated as:

$$c(m) = \begin{cases} 2H(m-1) - \frac{2(m-1)}{n} & \text{for } m > 2 \\ 1 & \text{for } m = 2 \\ 0 & \text{otherwise} \end{cases} \quad (1)$$

where n is the testing data size, m is the size of the sample set and H is the harmonic number and be estimated as:

$$H(i) = ln(i) + \gamma \quad (2)$$

with $\gamma = 0.5772156649$ is Euler-Mascheroni constant. The normalized anomaly score for anomalies is close to 1, and below 0.5 for normal.

Isolation Forest (IF) is an ensemble-based anomaly detection method working as a discriminator without having to generalize the data patterns in advance. It finds the anomaly by calculating an anomaly-score for each data point, and based on contamination rate to classify whether a given data point is outlier or not. IF could detect the anomaly trajectories within a set of trajectories that share the same nominal flight-plan, and helps to overcome the problems of insufficient true labels and rare event of maneuvers.

C. Contextual Features Engineering and Maneuver Clustering

For each of the detected aircraft maneuvers, the framework computes the contextual features that describe the time evolution of the traffic circumstances in which the maneuver took place. Each contextual feature is a time series spanning over a time window from the moment the maneuvering aircraft entered the sector till it exited the sector. Three contextual features that best represent a maneuvering scenario have been identified as follows (see Figure 3 for an illustration).

- *Cross-track distance.* This feature observes the cross-track distance between the trajectory of the maneuvering aircraft and the nominal flight-plan during the scenario's time window.
- *Heading change.* This feature monitors the changes in the heading of the maneuvering aircraft during the scenario's time window.
- *Traffic density at merging point.* This feature computes the approximated time-dependent traffic density (i.e., the number of aircraft) within 50 nautical miles from the merging point of the sector. The employment of this feature implies that aircraft maneuvers are usually required to maintain safe separation at the merging point or to provide spacing between aircraft (sequencing).

These three time series are then concatenated to form a 1-dimensional feature vector that carries the dynamic contextual information of a maneuver. Feature vectors of all detected maneuvers are then clustered using K-means clustering algorithm. Here, the value of K is determined by the number of total possible maneuver classes suggested by the ATCOs. The distance metrics used with K-means algorithm is the Dynamic Time Warping, and the centroid of each cluster

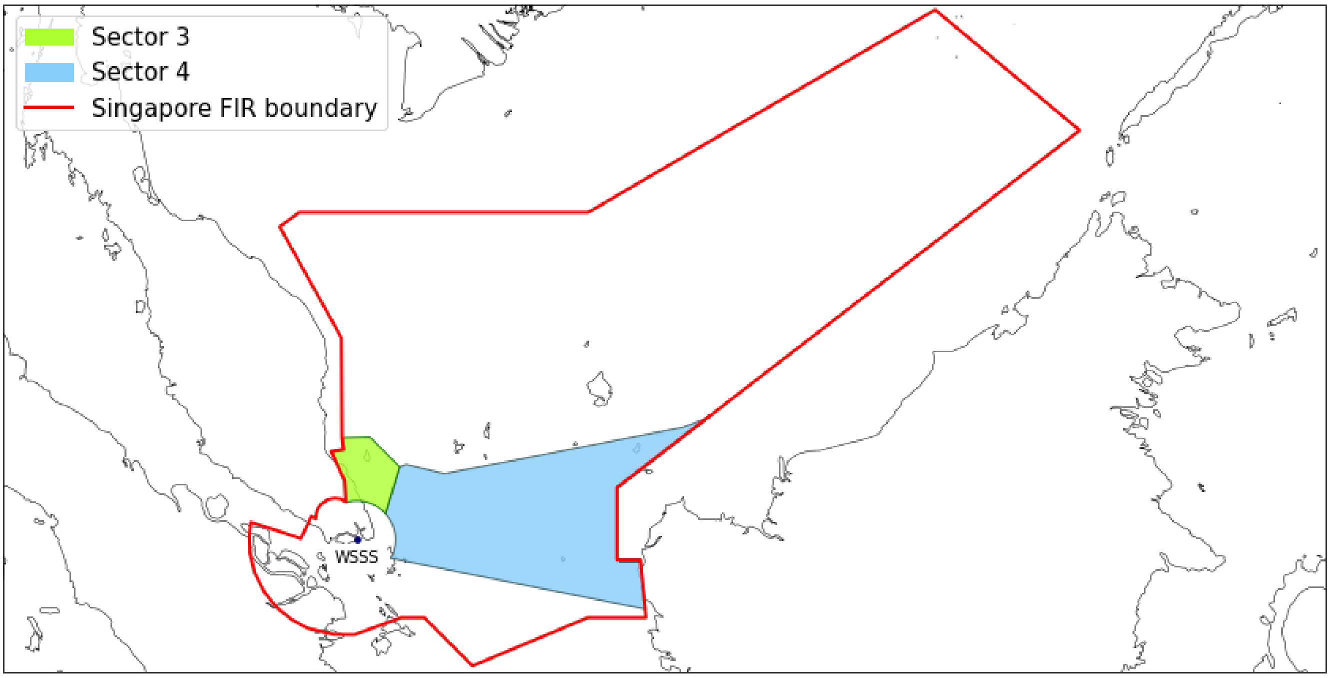

Figure 2: Illustration of Singapore FIR with Sector 3 and Sector 4 highlighted and location of Singapore Changi Airport (WSSS) identified.

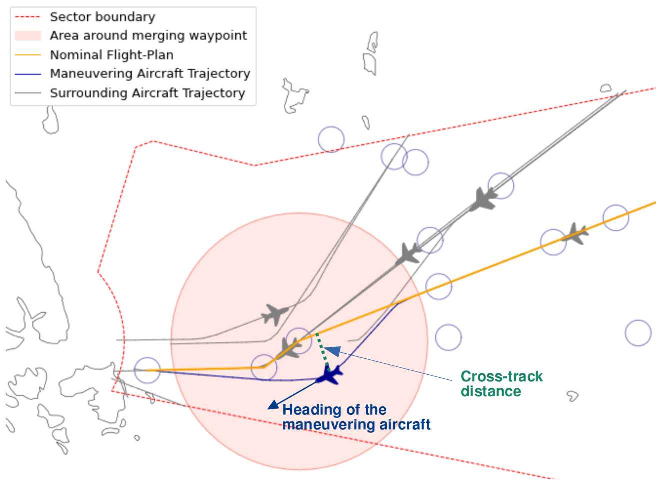

Figure 3: Illustration of the three proposed contextual features. Cross-track distance is measured between the maneuvering aircraft and the nominal flight-plan. Changes in the heading of the maneuvering aircraft is observed over time. Traffic density at merging waypoint is the number of aircraft within 50 nautical miles from the merging waypoint (the orange circle).

is calculated using the Dynamic Time Warping Barycenter Average (DBA) distance [15]. DBA calculates a represented sequence that minimize the sum squared distance to all other sequences in the set by repeatedly refining the initial average sequence.

IV. Results and Discussion

The authors of this paper performed aircraft maneuver detection using the ADS-B data collected within Sector 3 and Sector 4 of Singapore FIR in one month time from 15-April-2019 to 15-May-2019. The experiments were limited to Sector 3 and Sector 4 because these are the two sectors that have the most maneuver labels suggested by the subject-matter experts (see Section IV-C for details).

A. Major Flow Detection and Nominal Flight-Plan Reconstruction

Figure 5 demonstrates the results of major flows detection and nominal flight-plan reconstruction for Sector 3 and Sector 4 in Singapore FIR. One can observe that 34% of the trajectories cannot be associated with any major flow and those trajectories were discarded. In the experiments conducted, the authors only keep trajectories of arriving flights as most of the ATC interventions were to prepare the flights for a safe and orderly arriving at the TMA.

The daily clustering result is analyzed to construct nominal flight-plans for significant flows in the selected sector of Singapore FIR. With geometric information of significant waypoints in Singapore FIR, the final result has two significant flows in the selected sector with a share segment before entering the TMA area. This finding plays an essential role in the next step of maneuver detection due to conditions for sequencing and spacing around the merging point.

B. Results of Aircraft Maneuver Detection

The maneuver detector using the IF algorithm focuses on the identification of maneuver which has a high average deviation from the nominal flight-plan. The detector works

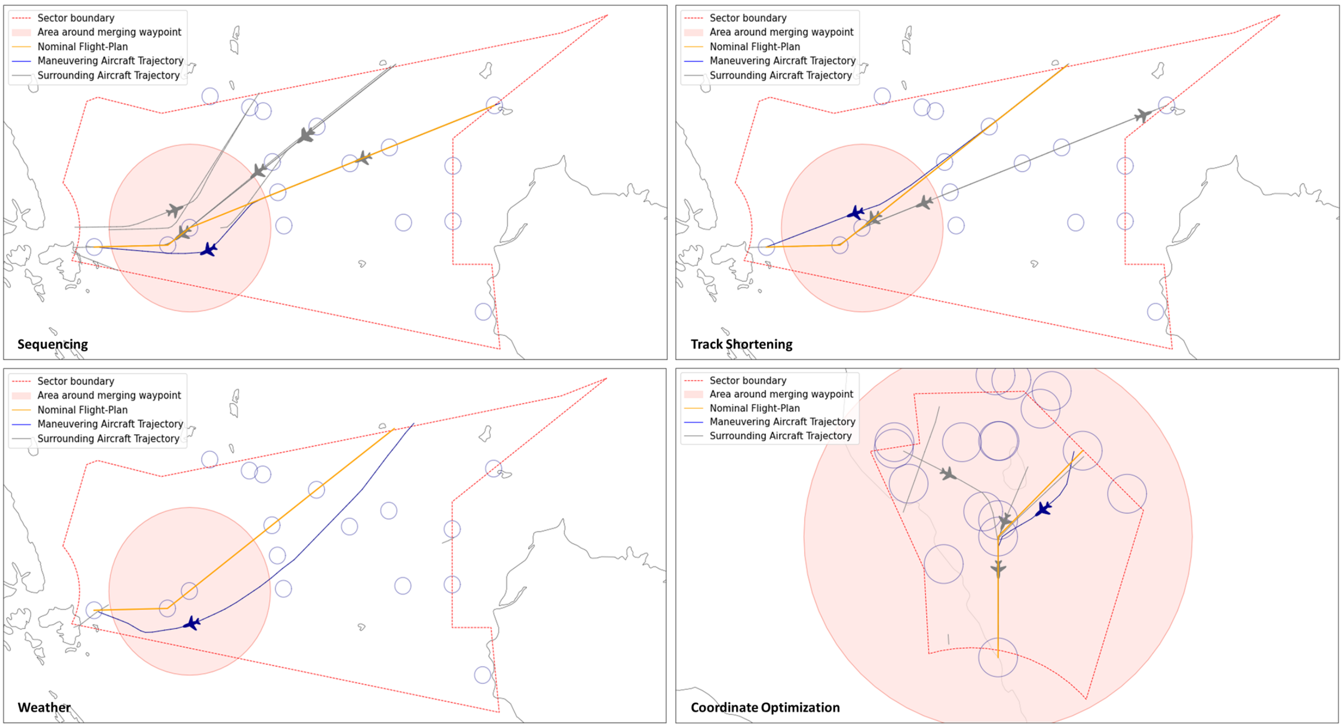

Figure 4: Examples of maneuver categories provided by the ATCOs. Refer to [1] for the complete set of scenario animations communicated to the ATCOs.

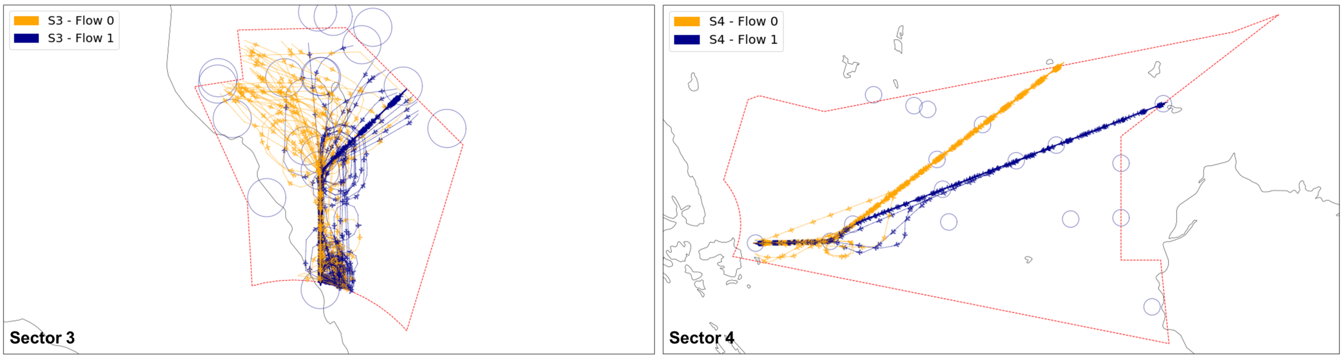

Figure 5: Major flows detection in Sector 3 and Sector 4 of Singapore FIR.

well with the traffic scenarios in which most aircraft obey the nominal flight-plan. However, it is sensitive with traffic flow in which there exist trajectories with extreme deviations. This is because those extremely deviated trajectories, from the nominal flight-plan, cause the model to ignore those maneuvers with less significant deviations.

As mentioned in Section III, the performance of the IF algorithm is influenced by the contamination rate, which is determined by empirical experiments and validated by visual analysis. The parameters of the IF algorithm must be specific to individual traffic patterns in different sectors in order to achieve good performance. For example, the high-variance traffic pattern in Sector 3 requires a larger contamination rate to avoid insignificant changes in flight trajectories being detected as maneuvers. Here, it is worth highlighting that all the expected abnormal in flight trajectories, such as holding activities, are filtered out before maneuver detection being performed.

The maneuver detection was performed on the basis of daily data because traffic flows within a sector can be different and this requires different contamination rate for the IF algorithm to perform well [17, 5].

Figure 6 illustrated the detected aircraft maneuvers in Sector 3 and Sector 4, with traffic in each sector being separated into two major flows. In 2793 trajectories in one-month ADS-B data, 532 trajectories are identified to have aircraft maneuvers.

C. Collection of Aircraft Maneuver Labels from ATCOs

A subset of detected maneuvers is communicated to ATCOs for feedback on the categorization of the maneuvers. Each of the scenarios communicated to the ATCOs consists of an animation that replicates the radar screen during the time window when the maneuver were happening. The ATCOs

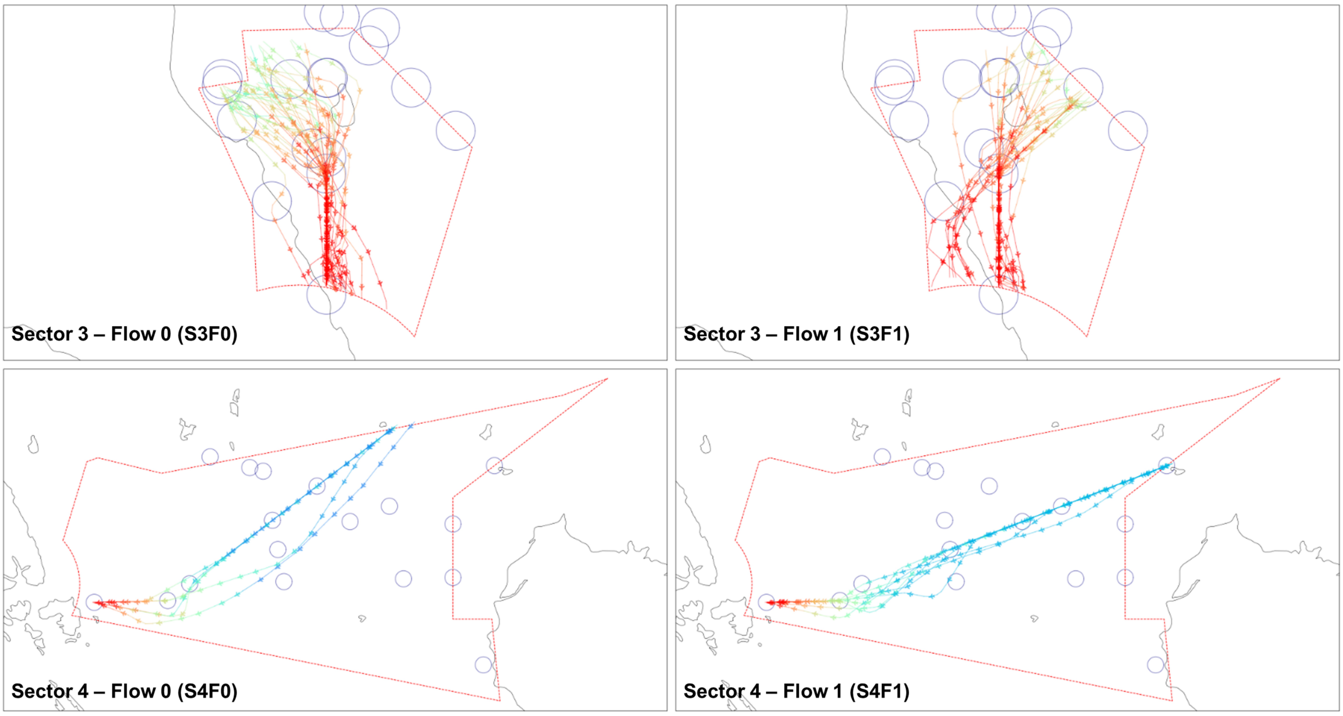

Figure 6: Illustration of detected aircraft maneuvers having ATCOs' label in Sector 3 and Sector 4 of the Singapore FIR. The color gradient indicates aircraft's altitude (lower altitude toward red color).

involved in this exercise are from the Civil Aviation Authority of Singapore (CAAS) and highly experienced and familiar with the air traffic control operation in the chosen sectors. A summary of aircraft maneuver categorization from the ATCOs is provided in Table I. From the ATCOs' feedback, the highest frequent category is Sequencing for maintaining the minimum separation, resolving conflicts or scheduling the traffic. Two others category is Track Shortening or Coordinate Optimization mainly focus utilizing available resources of sector's space or runway capacity. The Weather category is hard to be recorded due to the lacking of weather information in historical traffic data.

TABLE I. Summary of Maneuver Labels by ATCOs

ATCOs' labels \ Sectors	1	3	4	6	7	Total
Sequencing	3	46	12	5	4	70
Track Shortening	1	21	3	-	4	29
Weather	2	3	6	-	-	11
Coordinate Optimization	3	23	-	-	14	39

Due to various constraints, the set of labels acquired from the ATCOs is fairly limited. For a reasonable association between maneuver clusters and labels given by ATCOs, only Sector 3 and Sector 4 were included in our experiments.

D. Maneuver Clustering Results

As summarized above, there are maximum four categories of aircraft maneuver suggested by the ATCOs, depending on the chosen sector. In this work $K = 3$ and $K = 4$ were chosen as input to the K-means algorithm. Further, maneuver clustering was performed at two levels. On the first level, flow-based maneuvers were clustered for each sector. On the second level, all maneuvers from Sector 3 and Sector 4 were combine and run the clustering once.

Figure 7 shows the flow-based maneuver clusters for Sector 3 and Sector 4, separately, with $K = 3$. In Figure 7, *S3F0* refers to Sector 3 Flow 0, and the same annotation applies to S3F1, S4F0 and S4F1. The three rows of the figure represent three clusters. In each cluster plot, each curve in black color is a 1D feature vector that represents a maneuver and was resulted from the concatenation of the three contextual time series, as described in Section III. The concatenation was performed in the order: traffic density at merging point, cross-track distance, heading change. The red curve in each cluster represents the centroid of the cluster.

Figure 8 shows the maneuver clusters in each flow of Sector 3 and Sector 4 when $K = 4$. The maneuver clustering results for the combined traffic of all flows in Sector 3 and Sector 4 are presented in Figure 9 and Figure 10 for $K = 3$ and $K = 4$ respectively.

The maneuver clustering results shown in Figure 7 to Figure 10 demonstrate that the centroids the maneuver clusters are highly distinguishable. This implies the chosen contextual features are very effective in the characterization of unique behaviors of the maneuvers.

E. Maneuver Clusters and ATCOs' Labels Association

This subsection discusses how well the maneuver clustering results match with the labels provided by the subject-matter experts (ATCOs). This step attempts to add operational interpretation to the maneuver clusters discovered by the

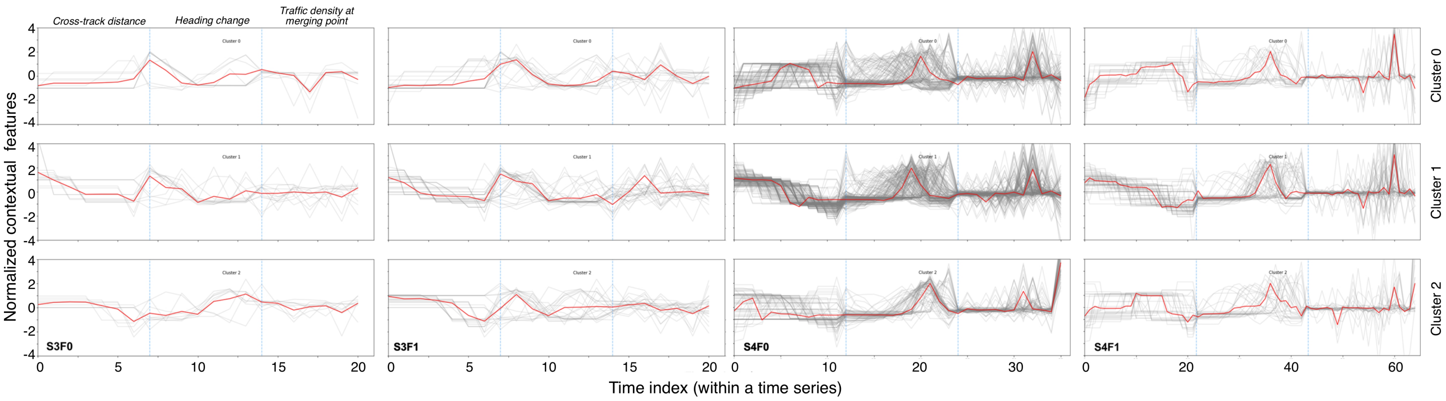

Figure 7: Maneuver clusters in each flow Sector 3 and Sector 4 with $K = 3$

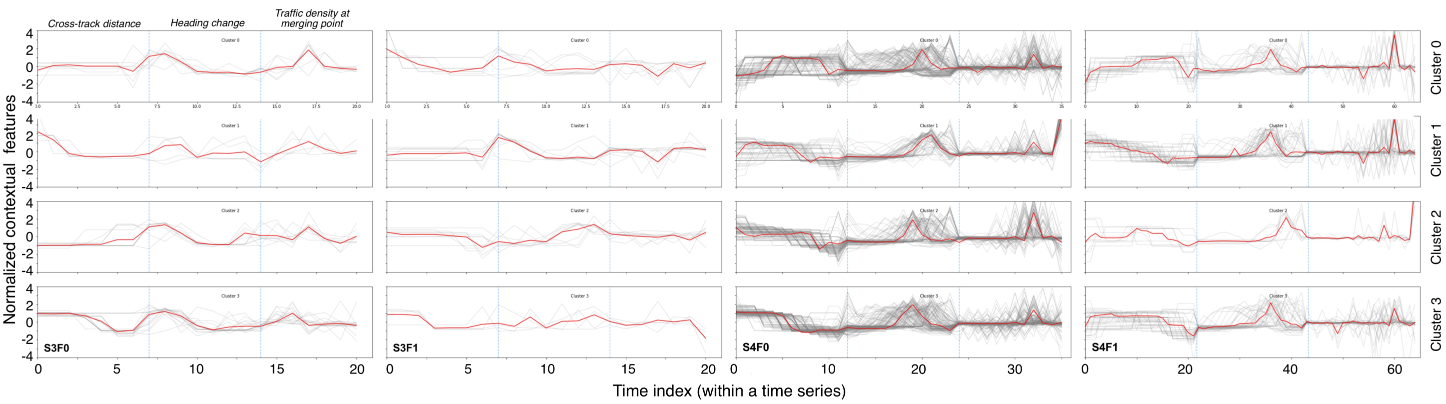

Figure 8: Maneuver clusters in each flow of Sector 3 and Sector 4 with $K = 4$

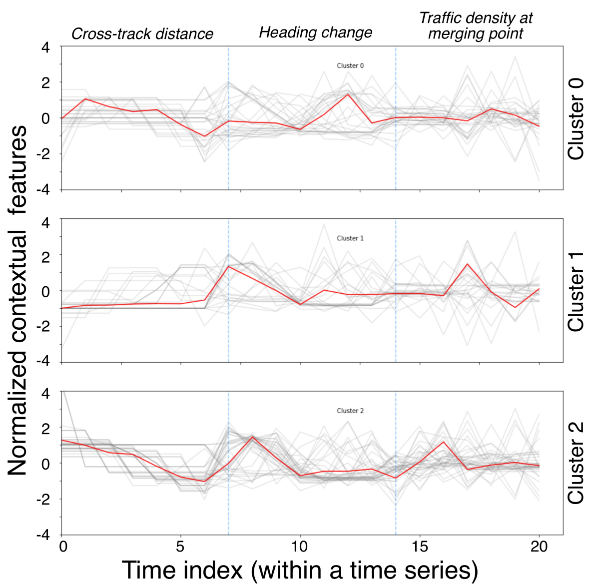

Figure 9: Maneuver clusters of combined traffic (Sector 3 and 4) with $K = 3$

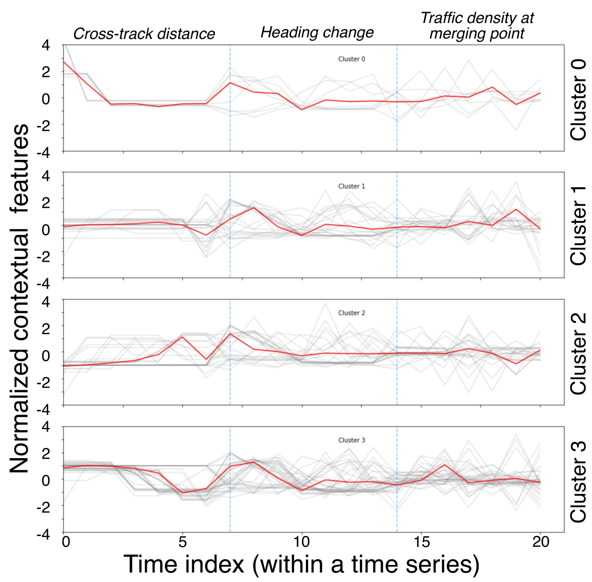

Figure 10: Maneuver clusters of combined traffic (Sector 3 and 4) with $K = 4$

algorithms. The results are reported in Table II to Table VII with details as follows.

- **Table II**: 2 separated flows in Sector 3 with $K = 3$.
- **Table III**: 2 separated flows in Sector 3 with $K = 4$.
- **Table IV**: 2 separated flows in Sector 4 with $K = 3$.
- **Table IV**: 2 separated flows in Sector 4 with $K = 4$.
- **Table VI**: Combined traffic in Sector 3 and Sector 4 with $K = 3$.
- **Table VII**: Combined traffic in Sector 3 and Sector 4

TABLE II. Clustering results for Sector 3 with $K = 3$

Flow	ATCOs' label	# maneuvers	Cluster	Ratio
0	Sequencing	5	0	0.18
		18	**1**	**0.64**
		5	2	0.18
	Track Shortening	1	0	0.17
		2	1	0.33
		3	2	0.50
	Coordinate Optimization	1	0	0.25
		1	1	0.25
		2	2	0.50
	Weather	1	1	1
1	Sequencing	4	0	0.27
		8	1	0.53
		3	2	0.20
	Track Shortening	2	0	0.40
		3	1	0.60
	Coordinate Optimization	3	0	0.27
		2	1	0.18
		6	2	0.55

TABLE III. Clustering results for Sector 3 with $K = 4$

Flow	ATCOs' label	# maneuvers	Cluster	Ratio
0	Sequencing	6	0	0.21
		3	1	0.10
		4	2	0.14
		15	**3**	**0.54**
	Track Shortening	1	0	0.17
		3	2	0.50
		2	3	0.33
	Coordinate Optimization	1	0	0.25
		1	1	0.50
		2	2	0.25
	Weather	1	1	1
1	Sequencing	4	0	0.27
		6	1	0.40
		3	2	0.20
		2	3	0.13
	Track Shortening	2	0	0.40
		3	1	0.60
	Coordinate Optimization	2	0	0.18
		1	1	0.09
		6	2	0.55
		2	3	0.18

with $K = 4$.

Each table mentioned above reports the number of maneuvers that belong to a label suggested by ATCOs and how they are associated with one or more maneuver clusters. The Ratio column indicates the ratio of maneuvers that share the same label being grouped in a cluster. Ideally, maneuvers that share the same ATCOs' label should fall into the same cluster and those with different ATCOs' labels must be in different clusters. However, when training data is insufficient, imperfect results may happen and maneuvers of the same label can be grouped in more than one clusters.

One can observe that the number of clusters K has significant influence on the matching between ATCOs' labels and the clusters. Also, the results in Table II to Table V are unstable because in flow-based approach, the number of labels in each maneuver category is very limited. Thus, the authors of this paper attempt to combine traffic from all flows of the two sectors, despite the fact that dynamic behaviors of these flows are very unique.

TABLE IV. Clustering results for sector 4 with $K = 3$

Flow	ATCOs' label	# maneuvers	Cluster	Ratio
0	Sequencing	4	0	1.00
	Track Shortening	**4**	**0**	**0.80**
		1	2	0.20
	Weather	1	0	0.50
		1	1	0.50
1	Sequencing	1	0	0.17
		4	1	0.67
		1	2	0.17
	Weather	1	1	0.50
		1	2	0.50

TABLE V. Clustering results for sector 4 with $K = 4$

Flow	ATCOs' label	# maneuvers	Cluster	Ratio
0	Sequencing	4	0	1.00
	Track Shortening	2	0	0.40
		1	1	0.20
		2	2	0.40
	Weather	1	0	0.50
		1	3	0.50
1	Sequencing	2	0	0.33
		2	1	0.33
		2	3	0.33
	Weather	2	3	1.00

Tables VI and VII show the results for combined traffic at $K = 3$ and $K = 4$. One can see that in both cases, the labels and clusters matching for Track Shortening and Weather are insignificant. This is because the amount of data in these two categories are very limited comparing with that

TABLE VI. Clustering results for all the maneuvers with K=3

ATCOs' label	# maneuvers	Cluster	Ratio
Coordinate Optimization	**10**	**0**	**0.67**
	3	1	0.20
	2	2	0.13
Sequencing	11	0	0.20
	15	1	0.27
	29	**2**	**0.53**
Track Shortening	5	0	0.31
	5	1	0.31
	6	2	0.38
Weather	2	0	0.40
	1	1	0.20
	2	2	0.40

TABLE VII. Clustering results for all the maneuvers with $K = 4$

ATCOs' label	# maneuvers	Cluster	Ratio
Coordinate Optimization	1	0	0.07
	7	**1**	**0.47**
	3	2	0.20
	4	3	0.27
Sequencing	5	0	0.09
	10	1	0.18
	16	2	0.29
	24	**3**	**0.44**
Track Shortening	1	0	0.06
	4	1	0.25
	4	2	0.25
	7	3	0.44
Weather	1	0	0.20
	1	1	0.20
	1	2	0.20
	2	3	0.40

in the other two (Coordinate Optimization and Sequencing). For Coordination Optimization and Sequencing, the results at $K = 3$ are more promising given higher ratios of matched maneuvers: for Coordination Optimization, 0.67 at $K = 3$ compared with 0.47 at $K = 4$; for Sequencing, 0.53 at $K = 3$ compared with 0.44 at $K = 4$. Here, an important implication is that at both values of K, highest ratios of Coordination Optimization and Sequencing happen at two different clusters. This suggests that the proposed approach and contextual features are capable of discriminating different classes of aircraft maneuver by just using unsupervised learning.

Although the dataset [1] used in this research is limited to the tedious and time consuming labeling tasks by human, the proposed framework demonstrated promising preliminary results in past maneuver classification. In the case where past scenarios and the corresponding labels are more sufficiently provided, the framework would have more significant contribution to expert knowledge mining and modeling for decision-making in ATC. Such insight into how ATCOs responded to a specific traffic scenario in the past would be an important part of a broader artificial intelligent (AI) system for supporting ATCOs. Knowledge being extracted from past ATCOs' decisions is a valuable resource for training future AI-based traffic advisory tools in a manner that is more conformant with the ATCOs.

V. Conclusion

In this paper, a machine learning-based framework for aircraft maneuver detection and classification is proposed. This framework first identifies major traffic flows using the DBSCAN algorithm, then detects aircraft maneuvers by the Isolation Forest algorithm, and finds maneuver clusters using the unsupervised K-means algorithm. The maneuver clusters can be validated by a small set of ground truth labels provided by subject-matter experts, i.e., Air Traffic Controllers. Results demonstrates that the proposed contextual features are helpful in characterizing time-dependent traffic scenarios and beneficial to the maneuvers classification and reasoning. The framework can work well with limited number of true labels. Authors believe that the proposed framework is efficient in post-analysis of air traffic scenarios, by which one could associate traffic scenarios' characteristics with the rationales behind air traffic control interventions. Thus, the results from this framework can be used to gain deeper understanding of tactical decision-making in sector control.

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