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Airspace Capacity Overload Identification Using Collision Risk Patterns

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Abstract—The ever increasing demand for air travel may induce en-route airspace capacity overload which endangers flight safety and elicit air traffic congestion. Knowledge of airspace capacity overload is important for air traffic flow management and flight planning to mitigate air traffic congestion without compromising airspace safety level. Since the primary task of air traffic controllers is to manage traffic flow within the constraints imposed by safety requirements, i.e., to warrant the collision risk at a low level, in this paper, we use the aircraft mid-air collision risk for a given airspace as the indicator of airspace capacity overload. With given air traffic data and airspace configurations, the collision risk distributions inside an airspace is determined through collision risk modelling. Based on the density and intensity of collision risk, the collision risk distributions are converted into heatmaps and collision risk patterns are further recognized from the heatmaps using image processing technique. Three major states of airspace workload can be identified from these patterns: normal state, transition state and overload state. For new traffic data during a given time period, by matching its collision risk distribution to the closest collision risk pattern, we are able to identify whether the airspace is overloaded or not. The experimental study in an en-route sector of the Singapore airspace has manifested the ability of the proposed method in collision risk pattern recognition and capacity overload identification.

I. INTRODUCTION

Knowledge of capacity of an airspace is pertinent to long-term strategic planning. In most air traffic control systems the airspace capacity is quantified as the maximum number of flights that may enter an airspace per hour averaged over a sustainable period of time and is used to manage a safe, orderly and efficient traffic flow [1]. Due to the increasing demand of air traffic, the airspace capacity could be overloaded. It is of great significance to identify if the capacity of an airspace is overloaded or not as such an initiative could facilitate air traffic delay mitigation as well as conflict resolution.

During the past decades, a myriad of methods have been developed concerning the analytical description of airspace capacity. A large set of these methods are based on regression models of controller workload generated by complexity factors for different air traffic situations. In Monitor Alert Parameter (MAP) model, the mean sector transit time (the average time required for aircraft to fly through the sector) is used as the sole complexity factor for determining the controller workload and the sector capacity [2]. While the full workload model

[3] accounts for all task types (transit, recurring, conflict, background) constituting controller workload. With a preset workload intensity threshold, the sector capacity can be described as a function of the threshold and the set of complexity factors that contribute to the workload intensity. The assessment of the workload intensity induced by complexity factors has mainly been done by asking the subjective personal opinion of controllers [4], by observing controllers at work and measuring the time they spend on various actions [5] or by measuring their physiological parameters [6]. Finally, regression techniques, which can be simple linear [1] or logistic regression [7] as well as more developed methods, such as neural networks [8], are used to find the function that best fits the correspondence between the sector capacity and the complexity factors. Once this function is defined, it can be applied to calculate the sector capacity under targeted traffic situations subject to the workload intensity threshold. These analytical models can result precise enough estimations in a certain airspace. However, the biggest disadvantage of these analytical models derives from their overly elaborated way of describing complexity factors. The resulted mathematical formula to calculate the capacity is static which makes it hard to capture the intrinsic mechanism lies behind the complexity factors as well as changes and evolution of the sector.

These shortcomings of analytical models lead to the emergence of other models which are more applicable. One way is to develop models that simply focus on representing air traffic complexity with a few metrics instead of trying to define the relationship between traffic situations and the workload they generate. In [9], the authors built metrics of the intrinsic complexity of the traffic in the airspace based on the structure and the geometry of the traffic, which synthesized a traffic complexity indicator to better quantify the congestion in an airspace sector. Their methods can reflect the traffic complexity inside a sector but has not developed a distinct connection between the traffic complexity and the sector capacity. In other words, we are not able to judge if a sector is overloaded with the complexity values calculated using this method.

The models introduced so far all contextualize air traffic as a set of single aircraft. It is however also possible to model air traffic as a structure of air traffic flows. In [10], for the representation of the correspondence between the characteristics

of air traffic flows and traffic pattern they use self-organizing maps. For each traffic pattern, they use the average flight distance inside the sector under this pattern as an indicator to identify a sector capacity, which is realized by observing a phase transition in the average flight distance when the number of aircraft increases. Then for a given traffic situation, the capacity can be determined through pattern recognition. This work sheds light on the dynamic capacity estimation using data-driven method instead of analytical model based on controller workload. The shortcoming of this method comes from the Self Organizing Map (SOM) which they have adopted to build the traffic patterns, since SOM is an unsupervised learning method whose result is hard to be explained and validated objectively. Only three traffic patterns have been extracted from the dataset using SOM which limits the precision and diversity of capacity estimation and prediction. Moreover, the validation of the usage of average flight distance inside a sector as a capacity indicator is not manifested.

In the above researches, aircraft count is the only measurement of airspace capacity which can vary with traffic complexity and other factors. However, the representation of airspace capacity using aircraft count has obvious limitations, because the capacity of a sector is not determined simply by the number of aircraft handled by the controller in scope as it is influenced by many other factors like the disposition of aircraft in the airspace, relative aircraft velocity and heading, aircraft types, size and shape of the sector, weather, availability and quality of ATC equipment etc. Sometimes the controller in charge of an operational sector can accept more aircraft than the actual capacity and in some occasions will refuse some flights even though the capacity has not been reached. Thus, the feeling of the controller about the capacity overload can not be simply summarized by the number of aircraft, though they are correlated.

In recent years, researchers have started to use new capacity measurements, such as “sector operations”, i.e., the merge and split of sectors, which reflects whether the traffic situation in a sector can be safely handled by controllers [11], [12], and “Domino Effect Parameter”, i.e., whether the conflicts in a sector can be solved without causing conflict chain reactions [13]. These representations are more comprehensive and integrated to reflect the capacity of a sector. Sector operations is a comprehensive and integrated measure to identify capacity overload. However, this approach is only limited on sector overload instead of any airspace. The “Domino Effect Parameter” are calculated through fast time simulations which can be affected by the conflict resolution algorithm adopted and may not apply to real traffic situations. Therefore it is necessary to seek for new metrics, which are integrated, comprehensive and capable of reflecting air traffic controller workload, to predict sector capacity overload.

Current air traffic control operations are highly structured to help air traffic controllers manage traffic flow within the constraints imposed by safety requirements [14]. Air Traffic Control procedures are designed to facilitate the safe and efficient flow of aircraft through the airspace [15]. Under Instrument

Flight Rules (IFR), responsibilities for safety and efficiency are shared between the pilots and air traffic controllers. In general, the pilots follows an IFR flight plan (filed prior to the flight) that defines the horizontal and vertical components of the route to be flown. The pilot has the responsibility to fly along the route within certain limits of accuracy. These limits assure that each aircraft remains in its assigned airspace and is procedurally separated from other aircraft flying different routes. Air traffic controllers are responsible for assuring that aircraft under their supervision remain separated to avoid the risk of collision. The aircraft mid-air collision risk inside an airspace is the primary issue to be avoided by air traffic controllers. Therefore it can be a indicator of whether an airspace is overloaded or not.

Therefore in this research, we use the collision risk as a measure to identify airspace overload. When two aircraft cross each other, there will be a risk of collision at this crossing point. The distribution of the crossing points along with the risk value associated characterizes the collision risk inside an airspace, which contributes to the controller workload. To identify airspace capacity overload using collision risk, we first compute the collision risk distributions inside an airspace through collision risk modelling [16]. Then a set of heatmaps are generated to represent the collision risk distributions, while the heat of an area on the heatmap is characterized by the density of crossing points in this area as well as their collision risk values. Eventually, twelve collision risk patterns are recognized from the generated heatmaps by using image processing techniques. From the discovered patterns, we have identified three major stages of workload: normal state, transition state and overload state. We have applied this proposed method to one month flight data of a sector in Singapore airspace and the three states have been clearly observed. Upon identifying the three collision risk stages, for a given traffic situation, we can identify whether the sector capacity is overloaded by pattern matching. If it is matched onto the overload state, that means the sector has reached the capacity limit and the collision risk will increase dramatically if more flights are accepted in this sector.

The remainder of the paper is organized as follows. Section II delineates in detail the proposed generic method for identifying capacity overload for a given airspace. Section III demonstrates the experimental study in an en-route sector in Singapore airspace and discusses the results. Section IV concludes the paper.

II. METHODOLOGY

A. Methodology Overview

This paper presents a method for airspace capacity overload identification based upon collision risk patterns. Fig. 1 presents a concept diagram of the proposed method. It can be seen from Fig. 1 that the proposed approach encompasses three key steps: collision risk modelling, collision risk heatmap generation and collision risk pattern recognition.

To better comprehend how the three components interact with each other, in Fig. 1 we illustrate the proposed method

Figure 1. The conceptual diagram of the proposed method for airspace capacity overload identification.

using a concept diagram. Given the air traffic data and the airspace configuration, a collision risk model is introduced to identify the distribution of crossing points as well as their associated collision risk values. The outcome of the collision risk modelling step, i.e., collision risk distribution, is then converted into heatmaps in the heatmap generation step based on the collision risk densities and intensities. In the third step, the pattern recognition technique, more specifically, the image clustering technique, is applied to the generated heatmaps to uncover the latent collision patterns. The recognized patterns are further categorised into 3 classes, viz, low, medium and high collision risk, which respectively correspond to the normal state, transition state and overload state of the capacity. Eventually, for a new traffic scenario we can identify the corresponding airspace capacity overload state by matching its heatmap with the discovered patterns. In what follows, we delineate in detail how each step works.

B. Collision Risk Modelling

Collision Risk is defined by ICAO as “the expected number of mid-air aircraft accidents in a prescribed volume of airspace for a specific number of flight hours due to loss of planned separation” [17]. Vertical collision risk accounts for two basic factors, namely the likelihood of the loss of vertical separation and the exposure to the loss of vertical separation. This exposure occurs when two aircraft at adjacent flight levels cross each other. Depending on traffic geometry, the crossing of aircraft may be broadly subdivided into same direction traffic (zero intersection angle), opposite direction traffic (180° intersection angle) and crossing traffic (remaining intersection angles) [18]. Slightly different models exist for the different traffic geometries. Flight data are the essential data source in estimating the exposure to the risk due to the loss of vertical

separation. The likelihood of the loss of vertical separation due to typical aircraft height deviations depends on the probability distributions of Altimetry System Error (ASE) and Flight Technical Error (FTE).

1) *Data Preparation*: Before computing collision risk, it is necessary to prepare the air traffic data required, which includes flight data and airspace configuration data. The flight data comprises aircraft type, departure/destination airport, entry/exit points, entry/exit level, entry/exit time, and flying duration in the airspace. The required airspace configuration data is the intermediate waypoints of the airways in the target airspace [19]. With the information of intermediate way points, the route of a given flight can be best represented instead of a straight segment connecting the entry/exit points.

2) *Counting Crossings*: As mentioned previously, two aircraft are exposed to the risk of vertical collision when they are fly at adjacent flight levels and are crossing each other. In order to determine the crossing between flights, we adopt the nominal projection method proposed in [20] to estimate the positions of the aircraft based on their current status. By doing so, for each pair of flights, we can identify the closest point of approach (CPA) between them based on their predictable routes. If the CPA is within 1000 feet vertically and 5 nm horizontally, then the crossing is counted.

With the crossing points being prepared, it can be fed forward to the collision risk calculation. Further, for those potential crossings, the CPA positions (lat, long, alt) together with the time taken of the two aircraft flying to CPA are recorded for later use in generating collision risk heatmaps.

3) *Collision Risk Computation*: We adopt the collision risk calculation model in [16], [21] to compute the collision risk of the crossing points. Collision risk can be acquired using the air traffic data prepared in section II-B1 while taking

into consideration of multiple factors: the navigation accuracy, lateral/vertical deviations, airway network structures, tracks of two crossing aircraft, aircraft number and size, and the flight duration within the airspace. The collision risk is required to be no more than the Target Level of Safety (TLS) of the fatal accident per flight hour to ensure the flight safety in the airspace.

The vertical collision risk of two aircraft on adjacent flight levels along the same route can be described as:

$$N_{az} = 2P_z(S_z)P_y(0)n_z(equiv) \left(1 + \frac{|\bar{y}|}{2\bar{V}} + \frac{\lambda_{xy}|\bar{z}|}{\lambda_z 2\bar{V}}\right) \quad (1)$$

where N_{az} represents the estimated number of fatal aircraft accidents per flight hour due to the loss of vertical separation. The factor $\left(1 + \frac{|\bar{y}|}{2\bar{V}} + \frac{\lambda_{xy}|\bar{z}|}{\lambda_z 2\bar{V}}\right)$ is a function of relative aircraft speed and aircraft dimension. $\bar{V}$ is the average ground speed of aircraft. $|\bar{y}|$ is the average relative crossing speed between two aircraft at adjacent flight levels. $|\bar{z}|$ is the average relative vertical crossing speed between two aircraft that have lost the vertical separation of S_z feet. A typical aircraft can be characterized by two parameters when computing the technical vertical risk, namely the average diameter (λ_{xy}) and the average height (λ_z) of a standing cylinder representing the aircraft.

$P_z(S_z)$ is the vertical overlap probability for aircraft at adjacent flight levels with the vertical separation 1000ft (S_z). This suggests that two aircraft still have the potential of vertical overlap while properly flying at adjacent flight levels. $P_y(0)$ represents the lateral overlap probability of aircraft following the same route. It can be calculated through the time proportion α of an aircraft flying in the airspace with satellite navigation (GNSS) versus radio navigation (VOR/DME):

$$P_y(0) = 2\lambda_y \left(\frac{(1-\alpha)^2}{2\sigma_{VOR/DME}\sqrt{\pi}} + \frac{2\alpha(1-\alpha)}{\sqrt{\sigma_{VOR/DME}^2 + \sigma_{GNSS}^2}\sqrt{2\pi}} + \frac{\alpha^2}{2\sigma_{GNSS}\sqrt{\pi}} \right) \quad (2)$$

where $\sigma_{VOR/DME}$ and σ_{GNSS} stand for the standard deviation for VOR/DME navigation and GNSS navigation respectively. $V_{rel}(\theta)$ is the average relative horizontal speed between aircraft at adjacent flight levels following two routes that intersect at an angle θ . $V_{rel}(\theta)$ can be formulated as:

$$V_{rel}(\theta) = \bar{V}\sqrt{2(1 - \cos\theta)} \quad (3)$$

$P_z(S_z)$, $P_y(0)$ and $\left(1 + \frac{|\bar{y}|}{2\bar{V}} + \frac{\lambda_{xy}|\bar{z}|}{\lambda_z 2\bar{V}}\right)$ are calculated for the entire airspace, so they remain constant for all crossing points. The subscript z are used to label aircraft flying at adjacent flight levels.

The only term remained is $n_z(equiv)$, which is calculated taking into consideration of the contribution of all crossing points. One crossing point will contribute 1 count $n_z(opp)$,

$n_z(same)$ and $n_z(\theta)$, which denote the frequencies of opposite direction crossing, same direction crossing and angled crossing respectively. $n_z(equiv)$ is formulated as:

$$\begin{aligned} n_z(equiv) &= n_z(opp) + n_z(same) \frac{\left(\frac{|\bar{y}|}{|\Delta V|} + \frac{\lambda_{xy}|\bar{z}|}{\lambda_z |\Delta V|}\right)}{\left(1 + \frac{|\bar{y}|}{2\bar{V}} + \frac{\lambda_{xy}|\bar{z}|}{\lambda_z 2\bar{V}}\right)} + \\ &\quad \frac{1}{P_y(0)\left(1 + \frac{|\bar{y}|}{2\bar{V}} + \frac{\lambda_{xy}|\bar{z}|}{\lambda_z 2\bar{V}}\right)} \sum_{i=1}^n n_z(\theta_i) \left(1 + \frac{\frac{\pi}{2}\lambda_{xy}|\bar{z}|}{V_{rel}(\theta_i)2\lambda_z}\right) \\ &= n_z(opp) + An_z(same) + \sum_{i=1}^n B_i n_z(\theta_i) \end{aligned} \quad (4)$$

where

$$\begin{aligned} A &= \left(\frac{|\bar{y}|}{|\Delta V|} + \frac{\lambda_{xy}|\bar{z}|}{\lambda_z |\Delta V|}\right) / \left(1 + \frac{|\bar{y}|}{2\bar{V}} + \frac{\lambda_{xy}|\bar{z}|}{\lambda_z 2\bar{V}}\right) \\ B_i &= \frac{1}{P_y(0)\left(1 + \frac{|\bar{y}|}{2\bar{V}} + \frac{\lambda_{xy}|\bar{z}|}{\lambda_z 2\bar{V}}\right)\left(1 + \frac{\frac{\pi}{2}\lambda_{xy}|\bar{z}|}{V_{rel}(\theta_i)2\lambda_z}\right)} \end{aligned} \quad (5)$$

in which $|\Delta V|$ represents the relative longitudinal speed between two aircraft. $n_z(\theta_i)$ denotes frequencies of crossings with angle θ_i , $i = 1, \dots, n$. By rearranging the terms, Eq. 4 can be reorganized as a sum of the collision risk contribution of all types of individual crossing points. The reorganized $n_z(equiv)$ can be rewritten as:

$$n_z(equiv) = \sum_{i=1}^{n_z(opp)} 1 + A \sum_{j=1}^{n_z(same)} 1 + \sum_{k=1}^{n_z(\theta)} B_k \quad (6)$$

If we represent the kinematics factor $\left(1 + \frac{|\bar{y}|}{2\bar{V}} + \frac{\lambda_{xy}|\bar{z}|}{\lambda_z 2\bar{V}}\right)$ as C , it can be seen from Eqs. 6 and 1 that the collision risk at a same direction, opposite direction and angled direction crossing point is $2P_z(S_z)P_y(0)AC$, $2P_z(S_z)P_y(0)C$ and $2P_z(S_z)P_y(0)BC$.

C. Collision Risk Heatmap Generation

With the required flight data prepared for a particular airspace during a certain time period, together with the equations in Section II-B, we will be able to discover when and where the crossing of two aircraft occurs, what type the crossing is, what the collision risk of the crossing is and the distribution of the crossing points. In other words, the distribution of crossing points as well as their associated collision risk can be determined for air traffic during any interested time slot. This distribution and the collision risk values can be delineated by a heatmap. The heat value of a point on the map reflects the density of the crossing points nearby and their collision risk values.

Assume that during a time slot, there are a number of n crossing points. For each crossing point c_i , $i = 1, 2, 3, \dots, n$, the position is denoted by (x_i, y_i) with x_i and y_i being its longitude and latitude respectively. The collision risk value of c_i is denoted by w_i . In a heatmap, the heat influence of a crossing point c_i in its proximity shall be stronger when the distance to it is smaller and the collision risk of it is larger,

which can be described using a two dimensional Gaussian function centered at (x_i, y_i) and weighted by its collision risk value w_i :

$$f(x, y) = w_i e^{-\frac{(x-x_i)^2 + (y-y_i)^2}{\sigma^2}} \quad (7)$$

in which σ defines the range of the influence from (x_i, y_i) . Therefore the overall heat value at a point (x, y) can be described as the sum of influences of all crossing points over it:

$$H(x, y) = \sum_{i=1}^n w_i e^{-\frac{(x-x_i)^2 + (y-y_i)^2}{\sigma^2}} \quad (8)$$

By computing the heat values of all points in the area and reflecting the heat values to certain colors, a heatmap can be generated to represent the distribution and risk values of crossing points in the 2D plane (latitude-longitude) of the airspace. Fig. 2 shows an example of heatmap generated for a sector of the Singapore airspace for collision risk during 20 minutes. The area in "red" is subject to high density of crossing points and high collision risk values, while the area in "blue" is subject to low density and low values. In the "white" area, there is no crossing points thus the collision risk is zero.

Figure 2. The heatmap generated in an airspace sector with air traffic data during 20 minutes.

D. Collision Risk Pattern Recognition

The above subsection presents the way to generate collision risk heatmaps for traffic data during given time periods. These heatmaps reflect the collision risk distribution inside an airspace, which have the potential to indicate the sector capacity overload. In this section we aim to recognize patterns from the collision risk heatmaps. To do so, image processing techniques which involve feature selection and clustering are adopted.

1) *Image Feature Selection*: Each heatmap is handled as an image which has a fixed size of $m \times n$. For a heatmap, the most important features are the colors and positions of the colors. Therefore, for each heatmap we directly extract its RGB features which further have been reshaped into a row vector with $m \times n \times 3$ elements.

2) *Image Clustering*: Clustering is to organize a set of observations, such as data items or feature vectors, into classified patterns [22]. Clustering has been widely used in many research fields. However, it still remains a difficult problem since it requires proper assumptions, research context and expert knowledge. In air traffic management domain, clustering is also a very popular technique which have been widely applied on pattern analysis of air traffic [23], [24]. Such as identifying spatial traffic patterns from flight track data for monitoring, anomaly detection and airspace redesign purposes [25], [26]. Gariel et al. [25] developed a framework for airspace monitoring based on the use of density-based clustering to learn typical patterns of operation and assess the conformance of flight trajectories. Similarly, Rehm [27] and Enriquez [26] relied on hierarchical and spectral clustering respectively to identify nominal and abnormal spatial traffic patterns to/from a specific airport. In [28] clustering methods were applied to analyse route patterns to reduce the number of paths between two airports.

In this paper, we apply the well-known k-means++ clustering method developed in [29] to discover the collision risk patterns from the heatmaps. The k-means++ algorithm improved the traditional k-means algorithm [30] by spreading out the k initial cluster center: the first cluster center is chosen uniformly at random from the data points that are being clustered, after which each subsequent cluster center is chosen from the remaining data points with probability proportional to its squared distance from the point's closest existing cluster center.

Although k-means++ is simple, quick and satisfactory when clustering 2D data, its main drawback is that it requires the prescription of k , i.e., the number of clusters. To determine the best value of k , Ref. [31] suggested a 'knee' point method which runs the clustering method with respect to different k that ranges from k_{min} to k_{max} and the Sum-Square-Error (SSE) which is the sum of squared distances of all samples to their cluster centers is utilized as the validity index to measure the clustering results. When one visualizes the values of SSE with respect to k , then the optimal number of clusters k_{best} is determined as the knee point on the curve.

Assume that we have n_h heatmaps. Let $V = \{v_1, v_2, v_3, \dots, v_{n_h}\}$ be the set of representative vectors of heatmaps and $C = \{c_1, c_2, c_3, \dots, c_{k_c}\}$ be the set of k_c non-overlapping clusters. The clustering algorithm tries to find the optimal number of clusters k_c^* and the optimal partition $P^{k_c^*} = \{p_1, p_2, p_3, \dots, p_{k_c^*}\}$ of the vectors. Then the clustering algorithm for the heatmaps is developed as follows:

Let k_{min} and k_{max} be the minimum and maximum number of clusters, and r be the number of repeat. To determine the optimal number of clusters k_c^* , for each number of clusters $k_c \in [k_{min}, k_{max}]$, k-means++ algorithm is run repeatedly for r times and the 'best' validity index q_{k_c} , i.e., minimum SSE, as well as the corresponding partition $P^{k_c} = \{p_1, p_2, p_3, \dots, p_{k_c}\}$ is recorded. q_k is then plotted against k and the k at the 'knee' point of the plot is determined as the optimal number of clusters k_c^* . Correspondingly, the optimal partition will

Algorithm 1 Heatmap clustering algorithm

Input: n_h Heatmaps

- 1) Convert n_h heatmaps into n_h representing vectors $V = \{v_1, v_2, v_3, \dots, v_{n_h}\}$.
- 2) for $k_c = k_{min}$ to k_{max} :
 for $i = 1$ to r :
 Run k-means++ of i clusters for the n_h vectors;
 Compute $q_{k_c}^i$, i.e., SSE.
 end
 $q_{k_c} = \min\{q_{k_c}^1, \dots, q_{k_c}^r\}$;
 Record the corresponding partition P^{k_c} ;
end
Plot q_{k_c} against k_c and identify the "Knee" point;

Output: Optimal k_c^* and the corresponding partition $P^{k_c^*}$.

be $P^{k_c^*} = \{p_1, p_2, p_3, \dots, p_{k_c^*}\}$. The clustering algorithm is presented in Algorithm 1.

3) *Collision Risk Pattern Matching*: By applying the clustering algorithm to the generated heatmaps, k_c^* clusters of heatmaps will be formed. Each of these clusters suggests one collision risk pattern and each pattern is related to a certain phase of sector workload situations: normal state, transition state or overload state. Therefore for a given traffic scenario, by matching it to its best-fit collision risk pattern, we are able to identify if the sector is operating below capacity, going through a transition phase or capacity overloaded.

III. EXPERIMENT

The above section describes the proposed method for capacity overload identification for a given airspace with given air traffic data. To verify the efficacy of the proposed method, in this Section we carry out the experimental study on an en-route sector in Singapore airspace using one month air traffic data. Note that most of time, the sector is operating below the capacity and it is difficult to collect enough high workload data. Therefore to identify the capacity overload theoretically, we have intensified the one month flight data three times as the original data.

A. Collision Risk Computation

First, the airspace data, i.e., the entire set of airways and corresponding intermediate way points, for the target sector is determined. Then the one month en-route flight data between FL290 and FL410 in this sector are selected and, for each flight, the entry/exit time, entry/exit waypoint, entry/exit level, departure/destination airport and aircraft type are identified. The airspace data together with the flight data are fed into a collision risk simulator with the built-in collision risk computation model. Upon the completion of the simulation, the crossing points associated with their time of occurrence, position of occurrence and collision risk value can be obtained for further processing.

B. Heatmap Generation

With the collision risk distribution obtained in last step, the heatmaps are generated at a granularity of per minute. Since the average flight time in the target sector is around 20 minutes, a flight flying across the sector can possibly be affected by the collision risk occurred in last 20 minutes. Therefore, for the collision risk heatmap generated at each minute, we consider the collision risks that have happened within a 20 minute time window before it. In other words, each heatmap represents the collision risk occurred in last 20 minutes. For one month flight data, 16342 heatmaps are generated. Note that the proposed method is a generic method that can be applied onto any airspace and any air traffic data. To show the experimental results more clearly and for the convenience of data processing, we randomly sampled 2000 heatmaps from the original set for collision risk pattern recognition.

C. Collision Risk Pattern Recognition

To prepare the 2000 heatmaps for clustering, image processing is first applied. Each heatmap is meshed into 365×278 pixels and each pixel is described by its RGB features. Thus each heatmaps is represented by a $365 \times 278 \times 3$ 3D matrix which is further reshaped into a vector containing $365 \times 278 \times 3$ elements. The vectors can then be fed to the clustering algorithm in Section II-D to divide the heatmaps into different clusters, i.e., different collision risk patterns.

Figure 3. The determination of number of clusters: average SSE and minimum SSE are plotted versus the number of clusters.

D. Cluster Parameter Setting for Experiment

To determine the appropriate number of clusters, k-means++ clustering algorithm is run 10 times for different k that ranges from 3 (k_{min}) to 22 (k_{max}). The average SSE and minimum SSE of the 10 runs for each k are recorded and the results are

Figure 4. The recognized twelve collision risk patterns (p1-p12).

Figure 5. Collision risk versus aircraft count under different patterns.

shown in Fig. 3. It can be seen from Fig. 3 that the decrease in average SSE and minimum SSE have distinctly slowed down at $k = 12$, which is regarded as the "knee" point. Therefore the number of clusters is set as 12.

E. Results

Organizing the heatmaps into 12 clusters, the resulted 12 patterns are shown in Fig. 4. Each cluster is regarded as a collision risk pattern. It can be observed from Fig. 4 that, in patterns p4, p1, p6 and p12, the "heat" is low and distributed in a sparse manner. While in patterns p5, p7, p10 and p8, the "heat" starts to increase and turning into a higher density. In patterns p3, p11, p2 and p9, the "heat" becomes very high and dense.

Fig. 5 shows the collision risk versus aircraft count under different patterns. Each data point in Fig. 5 represents one collision risk heatmap generated for a 20 minutes time period. Its vertical coordinate, i.e., the collision risk value, is the total collision risk of all crossing points that have appeared during the 20 minutes, while the horizontal coordinate, i.e., the aircraft count, is the number of flights entered the sector during the 20 minutes. The red curve delineates the average collision risk of the data points in accordance with the aircraft count. It can be seen that as more aircraft entering the sector, the collision risk increases quadratically, although showing some fluctuations which are likely caused by different traffic complexities and weathers. This also manifests the efficacy of using collision risk as an indicator of airspace capacity overload. We can also observe that the collision risk values under the "low-heat" patterns, i.e., pattern p4, p1, p6 and p12 as show in Fig. 6a, is low, while 94.71% of them are below

Figure 6. Collision risk versus aircraft count under low, medium and high collision risk patterns. Pattern p1, p4, p6 and p12 refer to the low collision risk area in the left panel. Pattern p5, p7, p8 and p10 refer to the medium collision risk area in the middle panel. Pattern p2, p3, p9 and p11 refer to the high collision risk area in the right panel.

0.8×10^{-13} and slightly increase (almost insensitive) with aircraft count. As for the "medium-heat" patterns, p5, p7, p10 and p8 as show in Fig. 6b, 74.01% of the collision risk values fall between 0.8×10^{-13} to 2×10^{-13} and increase with a higher speed than under "low-heat" patterns. This percentage is relatively lower because the "medium-heat" patterns are transition phases from low collision risk to high collision risk, therefore the range of these patterns covers part of the low collision risk area as well as part of high collision risk area. Under the "high-heat" patterns p3, p11, p2 and p9 as show in Fig. 6c, 90.52% of the collision risk values are above 2×10^{-13} and increase quadratically with the aircraft count.

In fact, this indicates that under "low-heat" patterns, the sector is operating normally and has enough workload/safety margin to accommodate more aircraft without causing evident increase in collision risk. Under "medium-heat" patterns, the workload is also acceptable but we can observe distinct increase in collision risk. While under "high-heat" patterns, the collision risk increase dramatically and it is becoming impossible to handle more aircraft. Therefore, the three sets of patterns can be regarded as normal state, transition state and capacity overload state respectively. Once a new traffic scenario is given, by generating a heatmap and matching it to the closest pattern, we are able to identify whether this sector is overloaded.

IV. CONCLUSION

In this paper, we proposed a data driven method for identification of airspace capacity overload. To achieve this goal, we first developed a generic method to recognize different collision risk patterns in a given sector with given flight data. The proposed method comprises three components: collision risk computation, collision risk heatmap generation and collision risk pattern recognition. We then carried out an experimental study over an en-route sector in Singapore airspace using one month ADS-B flight data using the proposed method. The results show that there are 12 patterns of collision risk in

the sector, which can be further organized into three classes: normal state, transition state and capacity overload state. Then for a given traffic scenario, the sector capacity overload can be identified by matching the given traffic scenario collision patterns to its closest matched pattern. The results highlight the efficacy of using collision risk as an effective indicator of airspace capacity. In future work, we will extend the model to predict the airspace capacity overload and also identify the factors that may lead to the phase transition from low to medium to high.

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