Air Traffic Operation Complexity Analysis Based on Metrics System

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Abstract: In order to quantitatively analyze air traffic operation complexity, multidimensional metrics were selected based on the operational characteristics of traffic flow. The kernel principal component analysis method was utilized to reduce the dimensionality of metrics, therefore to extract crucial information in the metrics. The hierarchical clustering method was used to analyze the complexity of different airspace. Fourteen sectors of Guangzhou Area Control Center were taken as samples. The operation complexity of traffic situation in each sector was calculated based on real flight radar data. Clustering analysis verified the feasibility and rationality of the method, and provided a reference for airspace operation and management.

Key words: operation complexity; traffic metrics; kernel primary component analysis; hierarchical clustering

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0 Introduction

Advanced technologies and new operational concepts have been applied to air transport system, leading to a great leap forward in safety, capacity, and efficiency in the last decades. However, the complexity of the system has increased as well, which has drawn many researchers and operation managers' attention to the underlying mechanisms of the system. Nonlinear approaches, including complexity, chaos and fractal analyses, have provided strong tools to delve into the air traffic control system. For instance, the complexity of air traffic has become a hot topic over the past few years and great achievements have been obtained. The number of aircraft is taken as the most relevant indicator to complexity, and has been widely used in Europe, U. S. and other developed countries. This approach is to contrast the number of aircraft and the capacity of airspace to determine the opening and merging of sectors[1-2]. Refs. [3-5] proposed a dynamic density model and established a relationship between traffic complexity and controller's workload. An intrinsic complexity model was proposed to measure the complexity of multiple coupled aircraft by means of the aircraft pair convergence/non-convergence situation based on the aircraft pair's relative speed and relative positions[6-8]. Refs. [9-10] developed a traffic flow perturbation analysis model to analyze the degree of change when the aircraft dealt with perturbation under different traffic situations. They also designed a complexity map to show the perturbation effect within the controlled range.

Obviously, many factors contribute to air traffic operation complexity. Researchers have proposed different complexity models. However, each model only considers partial influencing factors. In order to comprehensively reflect the operation complexity of air traffic, multidimensional factors should be considered in one metrics system[11-12]. Therefore, we proposed an analysis method based on metrics system. We selected quantitative metrics to construct the metrics sys-

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tem, and facilitated the kernel principal component analysis method to extract information from traffic flow metrics system. Last, we employed hierarchical clustering method to cluster sectors into different categories. The results showed that the proposed method was capable of representing air traffic operation complexity.

1 Complexity Metrics System

The air traffic operation complexity mainly relates to traffic distribution, dynamic operation of aircraft, and coupling effect of traffic flow[12-13]. Therefore, the metrics system is constructed based on the three aspects.

First of all, aircraft are the basic components of traffic flow, and their spatial and temporal distributions are important for the analysis of operation complexity. Secondly, aircraft exhibit dynamic features within 3D space. Climbing, cruising and descending compose a flight process. Finally, there are coupling relationships between different aircraft. Any change of an aircraft state may trigger a complex chain of reactions. The airspace perturbation analysis and the study of intrinsic complexity of traffic have illustrated this attribute. Thus, an aircraft pair (i. e. a pair of aircraft), instead of a single aircraft, is the fundamental object for the analysis. In summary, the operational characteristic metrics of air traffic should include: (1) Number of aircraft; (2) Average flight distance of aircraft; (3) Average flying time of aircraft; (4) Total flying distance of aircraft; (5) Total flying time of aircraft; (6) Number of aircraft climbing; (7) Number of aircraft descending; (8) Number of aircraft in level flight; (9) Average speed of aircraft; (10) Standard deviation of speed of aircraft; (11) Average heading of aircraft; (12) Standard deviation of heading of aircraft; (13) Minimum horizontal separation of aircraft pair on the same flight level within airspace; (14) Minimum vertical separation of aircraft pair on the same flight level within airspace; (15) Critical exponent of separation, which is based on how close the separation between the two aircraft will be in relation to the separation minima; (16) Number of aircraft pairs with relative distance between 0—5 nautical miles; (17) Number of aircraft pairs with relative distance between 5—10 nautical miles. The detailed definitions and calculation models of the metrics are given in Ref. [12].

2 Kernel Primary Component Analysis

Primary component analysis (PCA) is a linear dimensionality reduction method, which is commonly used in multi-metrics comprehensive evaluation[14]. However, PCA cannot solve nonlinear problems in normal operation situation, because it may result in scattered contribution rate of each metric. In recent years, with the development of support vector machine, a surge of research on kernel method has emerged. Kernel principal component analysis (KPCA), involving kernel method, is the extension of PCA for nonlinear problems, which maps the sample data through the nonlinear function into the high dimensional linear characteristic space, where the principal component is calculated[15]. Compared with PCA, KPCA is not only suitable for handling nonlinearly problems, but also able to retain more information[15]. Since the complexity metrics are largely nonlinear interacted, we chose KPCA to extract information of principal components.

The detailed steps of KPCA are given as follows.

(1) M airspace samples at the same time as well as N metrics are selected. The matrix of the data of original samples is defined as $\boldsymbol{x}=(\boldsymbol{x}_{mn})_{M\times N}$, where $\boldsymbol{x}_{mn}$ represents the data of the nth metrics of the mth sample.

(2) According to standardized metrics data, $X_{mn}=\dfrac{x_{mn}-\bar{x}_n}{\sqrt{\mathrm{var}(x_n)}}$, the standardized matrix $\boldsymbol{X}=(X_{mn})_{M\times N}$ is obtained, where $\bar{x}_n=\dfrac{1}{M}\sum_{m=1}^{M}x_{mn}$, $\sqrt{\mathrm{var}(x_n)}=\sqrt{\dfrac{1}{M-1}\sum_{m=1}^{M}(x_{mn}-\bar{x}_n)^2}$, where var represents variance.

(3) The appropriate kernel function is de-

fined to calculate the kernel matrix. In this paper, the radial basis function (RBF) is used as

$$k(x,y)=\exp\left(\frac{-\|x-y\|^2}{2a^2}\right) \tag{1}$$

where $a = 1\ 000$ [15].

(4) The kernel matrix $\boldsymbol{K}$ is updated, and $\overline{\boldsymbol{K}}$ is obtained.

(5) The calculated eigenvalues and eigenvectors of $\overline{\boldsymbol{K}}$ are $\lambda_1, \lambda_2, \cdots, \lambda_n$ and $v_1, v_2, \cdots, v_n$, respectively.

(6) The eigenvalues are sorted in the descending order, and the corresponding eigenvectors are adjusted. Gram-Schmidt orthogonal method is used to standardize the eigenvectors, and $\varepsilon_1, \varepsilon_2, \cdots, \varepsilon_n$ are calculated.

(7) Define contribution rate δ_n as the ratio of the eigenvalue λ_n to the sum of all eigenvalues. The cumulative contribution rate is $\delta_1+\delta_2+\cdots+\delta_n$. If $\delta_1+\delta_2+\cdots+\delta_t \geqslant P$ (P is the threshold of accumulated contribution rate which is set based on experience), t principal components are extracted as $\varepsilon_1, \varepsilon_2, \cdots, \varepsilon_t$. Since there are too many metrics selected in this paper, P is set as 95%[14-15].

(8) Based on the modified kernel matrix $\overline{\boldsymbol{K}}$, its projection on the standard eigenvector is calculated as: $\boldsymbol{T}=\overline{\boldsymbol{K}}\cdot\varepsilon, \varepsilon=(\varepsilon_1, \cdots, \varepsilon_t)$. And the projection is the data of the original sample after the dimensionality reduction and extraction using KPCA.

(9) According to the projection, the composite score[14] of the samples in terms of principal component is calculated with the same method as PCA, so that the comprehensive complexity value of the airspace samples is obtained when considering multiple factors of the complexity. The composite score of sample m is calculated as $F_m = \delta_1 f_m(\varepsilon_1) + \delta_2 f_m(\varepsilon_2) + \cdots + \delta_t f_m(\varepsilon_t)$, where $f_m(\varepsilon_t)$ indicates the score of sample m based on primary component ε_t, $f_m(\varepsilon_t) = x_m \cdot \varepsilon_t$.

3 Hierarchical Clustering Method

Hierarchical clustering method is one of the most widely used clustering methods[16-17]. The basic principle is: Given M samples with each sample initially as a class, the distances between samples and between classes are predetermined. First, the distances between samples are calculated. The classes with the shortest distance are combined into a new one. Then the distances between the new classes and other classes are calculated, and again the classes with the shortest distance are combined into a new class. A class is removed each time until M samples are combined into one class. Finally, the above clustering process is drawn in a pedigree chart. The number of classes is determined according to a given principle. The distances between classes can be defined by multiple methods. The square sum of deviations is also known as the Ward method. Its basic principle stems from the analysis of variance, which can give optimal clustering and at the same time ensure the minimum square sum of deviations between the same classes of samples as well as the maximum square sum of deviations between different classes. The hierarchical clustering method based on square sum of deviations is used in this paper.

In order to quantitatively determine the optimal clustering results, the cluster quality discrimination function is developed. The closeness indicates the degree of similarity between different objects in the same cluster. The greater the degree of similarity, the greater the closeness and the better the clustering effect. The separability suggests the degree of separation between the objects in different clusters. The greater the degree of separation, the greater the separability and the better the clustering effect. The closeness and the separability together determine the cluster quality function.

Given that there are M objects and each object has N attributes, the matrix of the object attribute is $\boldsymbol{X}=(x_{mn})_{M\times N}$, where x_{mn} represents the data of the nth metric of the mth sample. The vector of mth sample is $\boldsymbol{X}_m = x_{m1}, x_{m2}, \cdots, x_{mN}$, $m=1,2,\cdots,M$, and the distance of any two objects X_i and X_j is $D(X_i, X_j)=\sqrt{\sum_{k=1}^{N}(x_{ik}-x_{jk})^2}$.

M objects are clustered into L classes, and each sample could only belong to one class, $C=\{C_1, C_2, \cdots, C_l, \cdots, C_L\}, 1<L\leqslant M$. The closeness of the cluster subset is expressed as

$$\operatorname{com}(C_l)=\begin{cases}\dfrac{\left(\sum\limits_{X_i\in C_l}\sum\limits_{X_j\in C_l, X_j\neq X_i}(D(X_i,X_j))^2\right)^{\frac{1}{2}}}{C^2_{|C_l|}} & |C_l|\neq 1\\ \dfrac{\sum\limits_{X_j\in C, X_j\neq X_i}D(X_i,X_j), X_i\in C_l}{|C|-1} & |C_l|=1\end{cases} \tag{2}$$

where $C^2_{|C_l|}$ represents the number of non-repeated object compositions contained in the cluster subset, $|\cdot|$ the number of elements in the subset. The closeness of C containing L clusters is shown as

$$\operatorname{com}(C)=\sum_{l=1}^{L}\operatorname{com}(C_l)\cdot|C| \tag{3}$$

The separability of any two cluster subsets is expressed as

$$\operatorname{sep}(C_l,C_k)=\frac{\left(\sum\limits_{X_i\in C_l}\sum\limits_{X_j\in C_k}(D(X_i,X_j))^2\right)^{\frac{1}{2}}}{|C_l|\cdot|C_k|}\qquad L\neq 1 \tag{4}$$

The separability $\operatorname{sep}(C)$ of C containing L clusters is calculated as

$$\operatorname{sep}(C)=\begin{cases}\dfrac{\sum\limits_{C_l,C_k\in C\quad l\neq k}\operatorname{sep}(C_l,C_k)}{C^2_{|C|}} & L\neq 1\\ \dfrac{\sum\limits_{X_i\in C_l}\left(\sum\limits_{X_j\in C_l}D(X_i,X_j)^2\right)^{\frac{1}{2}}}{(|C_l|-1)\cdot|C_l|} & L=1\end{cases} \tag{5}$$

The cluster quality function can be obtained from the closeness and separability of the clusters, which is expressed as

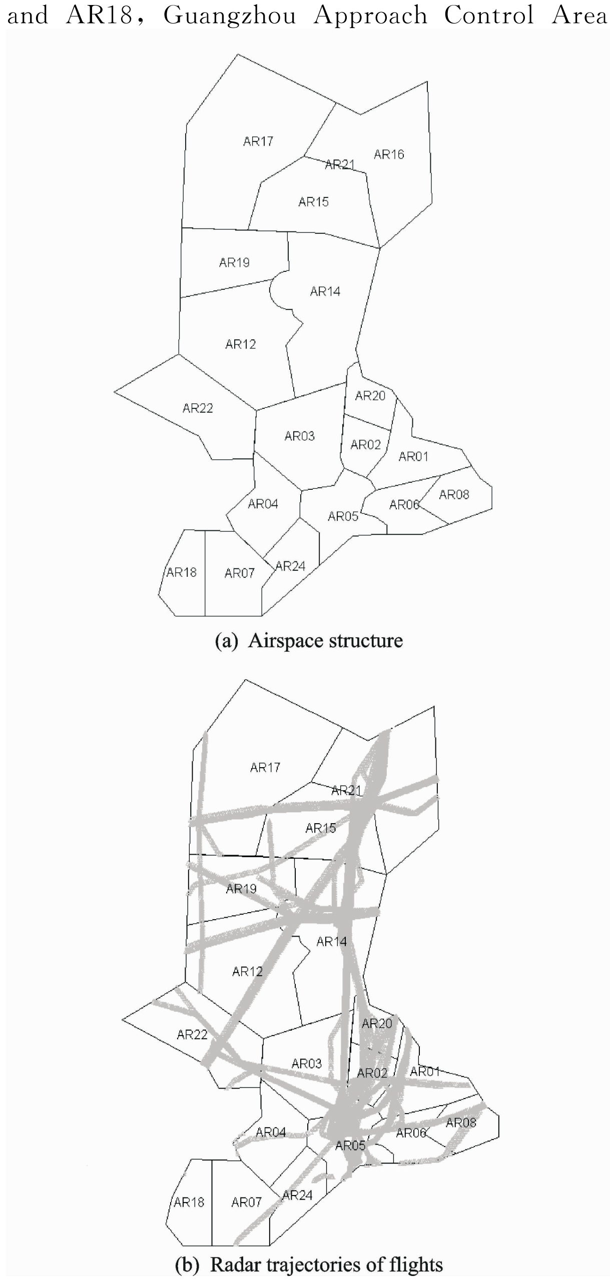
$$\operatorname{cqt}(C)=\operatorname{sep}(C)/\operatorname{com}(C) \tag{6}$$

Thus, the cluster quality can be determined according to the cluster quality function. The larger the function value, the better the clustering effect. As a result, the optimal number of clusters is determined.

4 Case Study

The proposed method was implemented based on the data from Guangzhou Area Control Center. The airspace structure is shown in Fig. 1(a). Fig. 1(b) shows the radar trajectories of flights between 9:00—10:00, Sep 13, 2012, providing intuitively understanding of the airspace structure and traffic distribution in Guangzhou region.

Most sectors are high-altitude sectors, while the remains are medium and low-altitude sectors. There are 21 high-altitude sectors above 7 800 m, including AR01-08, AR11-22 and AR24. Wuhan Approach Control Area is under AR15 and AR16, Zhanjiang Approach Control Area is under AR07 and AR18, Guangzhou Approach Control Area



(a) Airspace structure

(b) Radar trajectories of flights

Fig. 1 Airspace structure and radar trajectories in Guangzhou Area and Zhuhai Approach Control Area are under AR05 and AR02, and Changsha Approach Control Area is under AR13. Due to the lack of height information in the flight radar data obtained from the operation backup system, when there is an approach control sector under a high-altitude sector, the flight radar data that belongs to the approach control sector will be misclassified into the high-altitude sector, leading to excessive data of the high-altitude sector. This will influence the analysis result. Therefore, the above influenced high-altitude sectors were excluded from this study. The remaining 14 sectors were taken as airspace samples, which were represented by Sectors 1—14 in order to simplify the expression. The 17 metrics were represented by MT1—17 in the order listed above.

Operation complexity metrics were calculated at 18:57:29 of one day. Part results are shown in Table 1. When the cumulative contribution rate of principal components of metrics reached 95%, a total of seven principal components were extracted. The cumulative contribution rate is up to 95.97%, as shown in Table 2.

Table 1 Results of operation complexity metrics

Sector	MT1	MT2/km	MT3/min	MT4/km	MT5/min	…	MT17/pair
1	8	174.5	7.2	1 395.8	57.4	…	1
2	8	176.0	7.1	1 407.7	56.9	…	3
3	4	173.0	5.8	691.7	23	…	0
4	2	123.2	5.3	246.3	10.5	…	0
5	4	91.2	4.7	364.8	18.8	…	1
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
11	3	60.7	3.9	182.0	11.8	…	0
12	6	130.8	9.5	784.6	57.0	…	0
13	7	118.7	28.5	831.0	199.5	…	1
14	5	71.2	3.0	356.2	14.8	…	1

Based on the principal components extracted by KPCA, the composite scores of sector samples were calculated, as shown in Table 3. Then the clustering analysis was carried out. Fig. 2 is the obtained cluster pedigree chart.

Table 2 KPCA results of operation complexity metrics

Principal component	1	2	3	4	5	6	7
Eigenvalue	0.007 63	0.004 53	0.004 12	0.001 90	0.001 54	0.000 79	0.000 67
Eigenvector	0.326 76	0.147 42	0.090 74	−0.108 54	0.020 74	0.213 67	−0.178 62
	−0.169 71	0.047 23	−0.510 03	0.019 95	0.090 79	−0.026 85	0.345 05
	0.059 15	−0.370 59	−0.126 96	0.149 92	0.081 54	−0.072 96	0.283 28
	0.188 00	0.024 11	−0.321 08	−0.043 07	−0.198 94	0.121 66	−0.246 80
	0.176 67	−0.307 93	−0.006 23	0.154 06	0.019 97	−0.036 04	0.049 67
	0.126 32	0.3138 45	0.000 20	0.042 90	−0.638 16	0.274 94	0.232 14
	−0.351 75	0.079 73	0.449 81	0.471 99	0.037 66	0.320 10	−0.148 32
	0.267 31	0.027 24	0.016 53	−0.305 86	0.466 75	0.094 44	−0.315 95
	−0.205 46	0.502 21	−0.230 82	0.325 55	0.377 30	−0.010 19	−0.130 66
	0.125 74	−0.262 95	0.186 46	0.372 90	0.056 44	−0.211 02	0.206 43
	−0.299 87	−0.297 60	0.295 27	−0.416 46	0.120 80	0.350 11	0.149 14
	0.251 36	0.049 40	0.148 89	0.053 54	0.025 25	−0.484 95	−0.052 33
	−0.380 59	−0.149 99	−0.333 70	−0.195 36	−0.015 67	0.052 24	−0.020 46
	−0.422 69	0.092 58	0.173 38	−0.257 34	−0.280 76	−0.573 28	−0.253 20
	0.132 99	−0.254 52	−0.084 92	0.042 51	−0.262 07	0.069 55	−0.394 00
	0.175 75	0.359 84	0.252 48	−0.306 66	0.098 35	−0.081 40	0.474 63
Contribution rate	0.345 7	0.205 2	0.186 6	0.086 0	0.069 7	0.036 0	0.030 5
Cumulative contribution rate/%	34.57	55.09	73.75	82.35	89.32	92.92	95.97

TabLle 3 Composite scores of sector samples

Sector sample	1	2	3	4	5	6	7
Composite score	0.086 54	0.141 55	−0.041 14	−0.180 59	−0.000 44	−0.152 66	0.097 98
Sector sample	8	9	10	11	12	13	14
Composite score	0.096 50	0.004 50	−0.088 39	−0.077 41	0.031 93	0.076 71	0.004 92

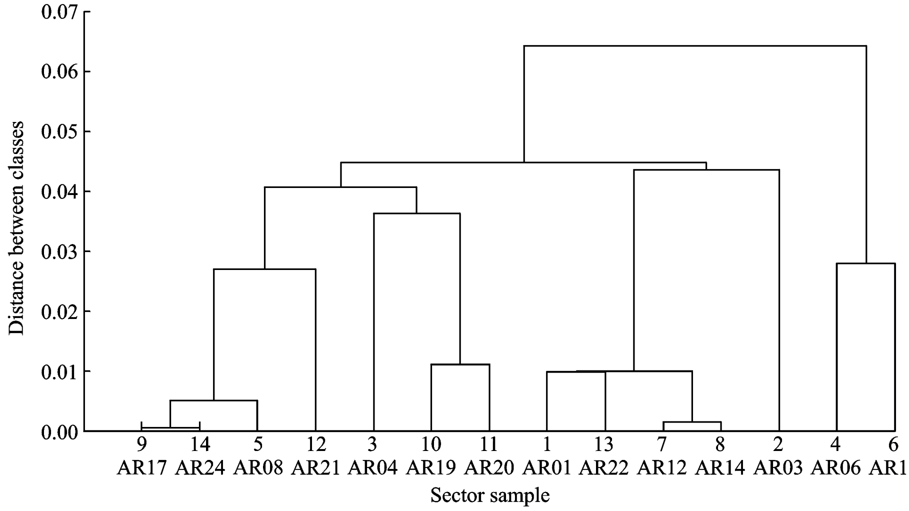


Fig. 2 Cluster graph

According to the cluster quality function and the operation complexity, sector samples were clustered into three categories. AR03, AR01, AR22, AR12 and AR14 were clustered into the first category. AR21, AR24, AR17, AR08, AR04, AR19 and AR20 were clustered into the second category, and AR06 and AR11 were clustered into the third category. These three categories have different characteristics: (1) The common characteristics of the first category represented by AR03 showed that there were a larger number of aircraft. Although there were some aircraft in the climbing state, most flights were in level flight. The speed distribution had a large fluctuation range (large standard deviation), while the minimum horizontal separation was between 6—10 nautical miles, and the minimum vertical separation distribution was between 300—600 meters. Due to the wide distribution of the traffic flow, the flights exhibited obvious dynamic feature. There was a strong coupling relationship between flights, and the intrinsic attribute was prominent. Therefore the operational situations of these sectors were most complex. (2) The main characteristics of the second category represented by AR21 were that the number of aircraft was at the intermediate level, with flights basically in level flight. The average speed was between 600—800 km/h, and the fluctuation range was small. The distribution ranges of minimum horizontal and vertical separations were enlarged, with only a few sectors had a pair of aircraft within 5—10 nautical miles. Compared with the first category, the traffic density of the second one was smaller. The aircraft's dynamic state began to stabilize, and the speed distribution was consistent. The coupling effects between aircraft became weak, so the overall operation complexity dropped off. (3) The operation situations in the third category of AR06 and AR11 were relatively simple. Due to the small number of aircraft, the distributions of most metrics decreased, and the minimum horizontal and vertical separations were large. The dynamic characteristics were not obvious, and the interaction between aircraft was not significant. So the operational characteristic was the simplest one.

In summary, the distribution of traffic flow, dynamic states and the coupling relations are important factors that contribute to operation complexity of air traffic situation. Although the number of aircraft is not equivalent to the complexity (for example, AR03 and AR01 had the same number of aircraft, but the scores of the complexity were not equal), it plays an important role in analyzing the complexity. Based on the method of study operation complexity, managers can assess the operation complexity of airspace units in real time and control flights to reduce the complexity. They can also identify operational problems through the analysis of historical radar data.

5 Conclusions

We chose some related quantitative metrics to describe the multi-dimensional operational characteristics, therefore to study the operation complexity of air traffic. Then we utilized KPCA to reduce dimensionality and refine the high-dimensional metrics system, which helped to extract composite score to analyze the complexity of sector sample. The hierarchical clustering method was used to analyze the complexity level of multiple sectors, indicating the feasibility of the proposed method. Finally, we took Guangzhou Area Control Center as an example to verify effectiveness of the method. The results also provided a reference for the airspace management.

In the future, we will focus on integrating more operational factors into the metrics system, and try to involve more time slots in dynamic clustering analysis to explore fluctuations of operation complexity of multiple sectors.

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