A Spatial-Temporal Hybrid Model for Airspace Complexity Prediction

Wenbo Du, *Member, IEEE*, Biyue Li, Jun Chen, Yisheng Lv, *Senior Member, IEEE*, Yumeng Li

***Abstract*—Airspace complexity is a key indicator that reflects the safety of airspace operations in air traffic management systems. Furthermore, to achieve efficient air traffic control, it is necessary to accurately predict the airspace complexity. In this article, we propose a novel spatial-temporal hybrid deep learning model for airspace complexity prediction to efficiently capture spatial correlations as well as temporal dependencies pertaining to the airspace complexity data. Specifically, we apply convolutional networks to discover the short-term temporal patterns and skip long short-term memory networks to model the long-term temporal patterns of airspace complexity data. Furthermore, it is observed that the graph attention network in our proposed model, which emphasizes capturing the spatial correlations of the airspace sectors, can significantly improve the prediction accuracy. Extensive experiments are conducted on the real data of six airspace sectors in Southwest China. Experimental results show that our spatial-temporal deep learning approach is superior to state-of-the-art methods.**

***Index Terms*— Airspace Complexity, Deep Learning, Graph Attention Network**

I. Introduction

AIRSPACE complexity is often an objective and critical indicator for evaluating the operational safety of given airspace. Air traffic management (ATM) is an aviation term encompassing all systems that assist aircraft to depart from an airport, transit airspace, and land at a destination airport [1]. For ATM systems, it is a worldwide applied standard that the airspace is partitioned into sectors as the basic control unit [2], [3]. Air traffic controllers (ATCos) manage each sector through effective strategic and tactical decisions, such as traffic flow modification, staff planning, and sector redesign, to achieve efficient and orderly airspace operation situations.

Excessive airspace complexity brings great difficulties in decision-making to ATCos, resulting in lower control efficiency and higher airspace operation risks. In contrast, operating airspace sectors at lower airspace complexity will lead to inefficiently used airspace resources. Therefore, reliable prediction of airspace complexity is essential to achieve the required air traffic control performance.

NASA Ames Research Center first defined a comprehensive metric to describe airspace complexity, called dynamic density, which is calculated as a linearly weighted sum of 9 complexity factors [4]. With the advent of machine learning, scholars have further explored the dependencies among more complexity factors. A pioneering work by Chatterji used artificial neural networks to establish a nonlinear mapping between complexity factors and airspace complexity [5]. Subsequently, a series of works have been applied to calculate the real-world airspace complexity through supervised learning [6], unsupervised learning [7], transfer learning [8], etc. However, the above methods are insufficient to model the temporal dependencies implicit in the variation of airspace complexity.

The deep learning techniques have been successfully applied in the field of air traffic management, including air control safety monitoring [9], air traffic flow forecasting [10], and estimated time-of-arrival prediction [11]. Among the extensive deep learning methods, long short-term memory (LSTM), convolutional neural networks (CNNs) [12], and graph neural networks (GNNs) [13] are widely used for time series analysis in intelligent transportation systems [14]. However, it is difficult to employ these methods seamlessly for predicting airspace complexity due to its inherent characteristics: 1) a mixture of short-term and long-term repetitive temporal patterns; 2) spatial correlations dominated by the topology of airspace sectors.

Given these concerns, we propose a spatial-temporal hybrid model for airspace complexity prediction. The contribution of this article is threefold.

- We design a tailored ***G**raph learning-based **S**patial-temporal **C**omplexity prediction model* (GSC), to efficiently capture both the spatial and temporal features pertaining to the airspace complexity data. To the best of our knowledge, this is the first time that a spatial-temporal deep learning approach is applied to predict airspace complexity.
- The proposed GSC model incorporates convolutional layers and skip long short-term memory (Skip-LSTM)

This work was supported in part by the National Key Research and Development Program of China under Grant 2019YFF0301400; in part by the National Natural Science Foundation of China (NSFC) under Grant 61961146005; and in part by the Engineering and Physical Sciences Research Council (EPSRC) under Grant EP/N029496/2. *(Corresponding author: Yumeng Li.)*

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layers to mine short- and long-term repetitive temporal patterns in airspace complexity data, respectively. The graph attention layers in GSC model can exploit the spatial topology of sectors to extract spatial correlations.

- We conduct a series of comparison experiments on real airspace complexity datasets. The experimental results also demonstrate the superiority of the proposed model.

The rest of this article is organized as follows. Section II provides the problem description and describes the GSC model in detail. Section III presents an experimental investigation. Finally, we conclude this study and provide further discussion in Section IV.

II. METHODOLOGY

In this section, we introduce the problem formulation of airspace complexity prediction. Then, we provide an overview of the proposed spatial-temporal deep learning model followed by specific discussions of each component.

A. Problem Formulation

Airspace complexity can be defined as a comprehensive index determined by synthesizing multiple complexity factors. The representative list of 28 complexity factors, such as aircraft density, variability in aircraft speed, and geometric volume of sectors can be referred to [6]. The detailed descriptions of these complexity factors can also be found in our previous work [7]. Furthermore, the airspace complexity is discretized into three levels: high, normal, and low. In this context, the airspace complexity prediction problem can be formulated as a classification task, in which the objective is to find the optimal mapping from a series of historical observations to future complexity levels.

As shown in Fig. 1, since the proposed model consists of a temporal module and a spatial module, the input of our model consists of two parts. Firstly, the input of the temporal module is comprised of a series of historical observations on the target sector with a time window length of 30 minutes. Hence, the first part of the input can be denoted as $X_{\text{temporal}} \in \mathbb{R}^{30\times29}$, where the row represents the time step, and the first 28 columns represent complexity factors while the last column indicates the complexity level. Secondly, the input of the spatial module consists of an adjacency matrix and a node feature matrix, where the adjacency matrix $A \in \mathbb{R}^{6\times6}$ is used to describe the geographical adjacency relationship between six sectors, and the node feature matrix $X_{\text{spatial}} \in \mathbb{R}^{6\times29}$ includes 29 features (i.e., 28 features for complexity factors and 1 feature for complexity level) of both the target sector and its neighboring sectors at the current moment. Finally, the output of the GSC model is the predicted airspace complexity level in the next time step, which is represented as a one-hot vector $Y \in \mathbb{R}^{1\times3}$.

B. Overview of the GSC model

Fig. 1 shows the framework of the proposed GSC, which is mainly composed of two modules, namely, the spatial module and the temporal module. First, the spatial module aims to model the spatial-temporal dependencies of the target airspace sector with its geographically neighboring airspace sectors. To distinguish the impacts among different sectors, the attention mechanism is applied. Second, the temporal module consisting of CNN and Skip-LSTM, extracts the mixture of long-term and short-term temporal patterns hidden in the airspace complexity series. To alleviate the gradient vanishing issue, skipping links are added between the LSTM units. Finally, the spatial-temporal hybrid features are combined and simultaneously leveraged to predict the airspace complexity level in the fusion layers. We utilize the SoftMax activation function to get the discrete output of the GSC model, which is the predicted complexity level consisting of high, normal, and low.

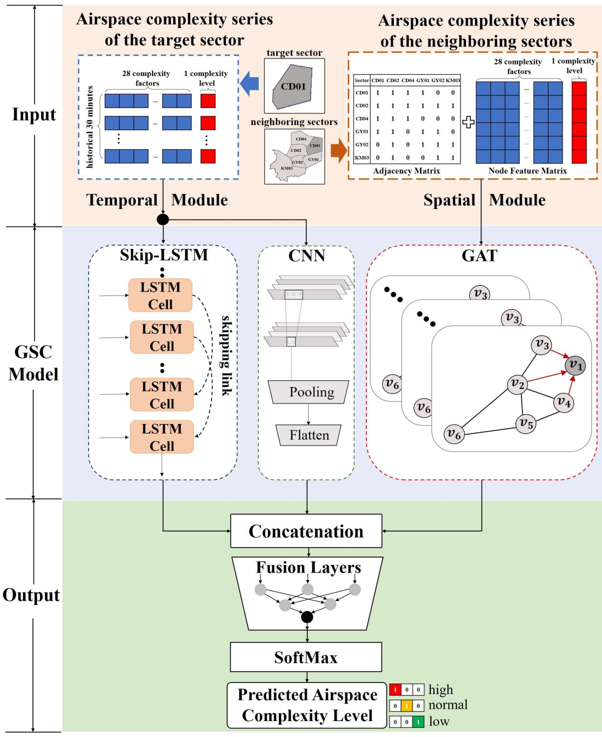

Fig. 1. The framework of the graph learning-based spatial-temporal complexity prediction model (GSC).

C. The Spatial Module

The input of the spatial module is a series of spatiotemporal graph signals constructed from the sector network and airspace complexity features at each time step. The sector network is built based on the geographical adjacency of the target sector with its neighboring sectors, where a node represents a sector. As shown in Fig. 1, for example, "CD01" is the target sector, represented as v_1, and its adjacent sectors are "CD02", "CD04", and "GY01", denoted as v_2, v_3, and v_4, respectively. The sector network is formulated by the adjacency matrix. If two nodes are adjacent, there is an undirected edge between them, and the value in the adjacency matrix is "1". Otherwise, the edge connecting nodes i and j does not exist, and the corresponding entry A_{ij} is "0". Moreover, the features in dimension 29 of each node are composed of the airspace complexity factors and the related complexity level.

To reveal the importance of the two sectors, the self-attention mechanism is applied. The importance of sector i to j is denoted as α_{ij}, where α_{ij} can be computed as

$$\alpha_{ij} = \frac{\exp\left(a^T[W_G v_i || W_G v_j]\right)}{\sum_{k\in N_i} \exp\left(a^T[W_G v_i || W_G v_j]\right)} \tag{1}$$

where a^T is the attention kernel and W_G are the trainable weights. v_i denotes the features of sector i . $||$ is the concatenation operation. N_i is the number of neighbors of node i.

Finally, the weighted averaging aggregate function is used to get the features of neighboring sectors into fusion. The feature fusion in the spatial domain is represented as

$$h_{G,i} = \sigma\left(\sum_{j\in N_i} \alpha_{ij} W_G v_j\right) \tag{2}$$

where α_{ij} is the learned attention value, and σ represents the non-linear activation function.

D. The Temporal Module

The input to the temporal module is a series of historical observations of the target sector, including complexity factors and complexity levels. First, to capture the short-term temporal patterns, a one-dimensional convolution is firstly performed on the input sequence, which is a slice of historical observations. The convolution kernels roll along the time axis and produce the outputs of the convolutional layers. Second, the Skip-LSTM extracts long-term temporal patterns. Canonical LSTM usually fails to capture long-term correlations due to gradient vanishing. Motivated by the residual links, skip connections are added in LSTM to memorize the relative long-term dependencies in airspace complexity sequences. The Skip-LSTM allows direct backpropagation from the current recurrent unit to farther recurrent units, reducing the effect of gradient vanishing. Specifically, the t-th hidden state in the Skip-LSTM layers is computed as

$$r_t = \sigma(x_t W_{xr} + h_{t-p} W_{hr} + b_r) \tag{3}$$

$$u_t = \sigma(x_t W_{xu} + h_{t-p} W_{hu} + b_u) \tag{4}$$

$$c_t = RELU(x_t W_{xc} + r_t \odot (h_{t-p} W_{hc}) + b_c) \tag{5}$$

$$h_t = (1 - u_t) \odot h_{t-p} + u_t \odot c_t \tag{6}$$

where x_t is the input sequence and h_t is the output features at timestamp t. p is the number of skipped hidden recurrent units. $\odot$ presents the Hadamard product of two tensors, and σ represents the sigmoid function. $W_{xr}, W_{hr}, W_{xu}, W_{hu}, W_{xc}, W_{hc}$ and b_r, b_u, b_c are the weights and bias.

Finally, fully connected layers are utilized to combine the outputs of the Skip-LSTM layers. The inputs of the dense layers include p outputs of the Skip-LSTM layers from timestamp $(t-p+1)$ to t denoted by $h_{t-p+1}, h_{t-p+2}, \dots, h_t$:

$$h_{S,i} = \sum_{k=0}^{p-1} W_k h_{t-k} + b_s \tag{7}$$

where W_k and b_s represent the weights and bias of the dense layers. $h_{S,i}$ is the output of the i-th Skip-LSTM layers.

III. Experiments

A. Dataset

The airspace complexity data used in this article is collected from six airspace sectors located in southwestern China, including "Chengdu01" (CD01), "Chengdu02" (CD02), "Chengdu04" (CD04), "Guiyang01" (GY01), "Guiyang02" (GY02) and "Kunming03" (KM03). The geographical characteristics of these airspace sectors are shown as the input of the spatial module in Fig. 1. More detailed descriptions of the airspace sectors can also be found in our previous work [7]. The study period is from 8:00 to 24:00 on July 28, 2010. Each sample corresponds to a one-minute air traffic scenario for one sector, and all samples are arranged in chronological order. The dimension of each sample is 29, in which the first 28 features are complexity factors and the last one is the complexity level (Low/Normal/High) assigned by ATM experts.

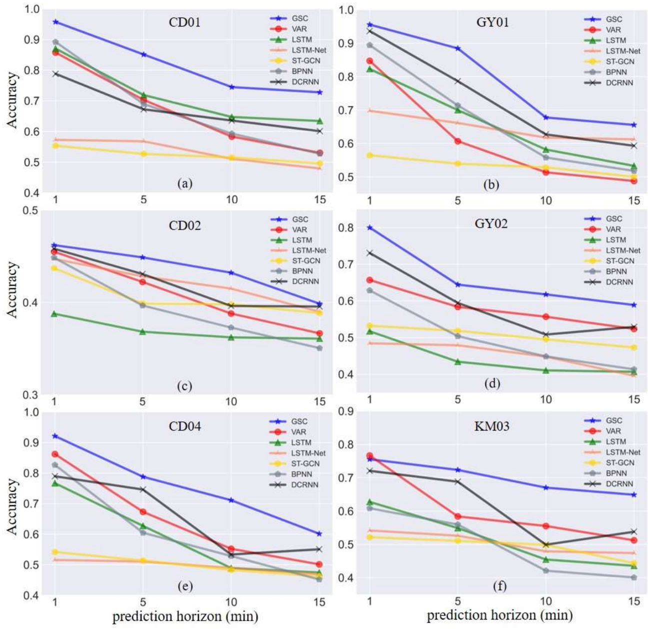

Fig. 2. Performance comparison with existing methods.

B. Baselines and Implementation

To illustrate the advantages of our model, we compare the proposed GSC model with the vector autoregressive model (VAR), LSTM, LSTM-Net [15], spatial-temporal graph convolutional networks (ST-GCN) [16], BPNN [6], diffusion convolutional recurrent neural network (DCRNN) [17].

The parameter settings of all these baselines are determined through the grid search over all tunable hyperparameters. For all methods, 70% of the data is used as training samples. 10% and 20% of the data is used as validation and testing samples, respectively. In this work, the time window length is set to 30 minutes, based on the practical application [18] and a previous representative related study [19]. The prediction horizons are set to 1/5/10/15 minutes.

C. Results and Analysis

We carry out 100 seeded runs and use the average accuracy to evaluate the performance of all baseline methods. The accuracy is defined as $\frac{N_{\text{correct}}}{N_{\text{all}}}$, where N_{correct} denotes the number of testing samples which are correctly predicted and N_{all} represents the total number of testing samples.

1) Model Comparison: Fig. 2 summarizes the prediction results of the 7 methods on 6 target sectors. The larger the time

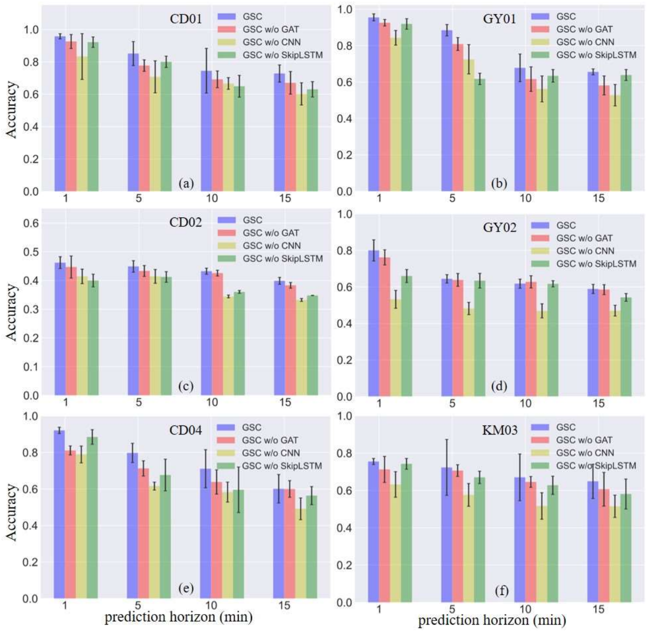

Fig. 3. Ablation experiments on six airspace sectors.

length is, the more difficult the prediction tasks are. It can be seen from the results that the proposed GSC model almost outperforms all baseline methods on all datasets.

Among all compared baselines, VAR, LSTM, and BPNN perform similarly for short prediction horizons, while LSTM-Net, ST-GCN, and DCRNN fail to model temporal correlations within airspace datasets. It can also be seen that the superiority of GSC to VAR, LSTM and BPNN is more significant if the prediction horizon becomes longer. This is mainly contributed to the Skip-LSTM layers of GSC, which help capture the long-term temporal dependencies in the airspace complexity data. In addition, the graph attention layers in GSC mine the spatial information of the airspace sectors, which further improves the prediction accuracy.

It is worth pointing out that all methods perform much worse on CD02. An intuitive explanation is the geographical location of CD02, which is adjacent to the other five sectors. The spatial topological relationship of CD02 is more complicated.

2) Variant Comparison: An ablation study is conducted to further demonstrate the efficiency of each component in the GSC. Specifically, GSC w/o GAT means the GSC without the graph attention layers. GSC w/o CNN and GSC w/o Skip-LSTM represent GSC without convolutional layers and GSC without Skip-LSTM layers, respectively.

Fig. 3 shows the error box including the accuracy and variance over 100 runs on each airspace sector. Without the convolutional layers, the accuracy of the short-term (i.e., 1 min and 5 min) prediction will significantly decrease. Other significant layers in our proposed GSC are the Skip-LSTM layers. Without the Skip-LSTM layers, the accuracy of the long-term (i.e., 10 min and 15 min) complexity prediction will decrease more than that of the short-term prediction accuracy in some sectors. The Skip-LSTM layers extract the long-term repetitive temporal patterns of the data through the skip connections that connect the current recurrent unit with a much farther recurrent unit. The effectiveness of graph attention layers in extracting spatial-temporal dependencies can also be demonstrated.

IV. Conclusion

In this article, we propose a novel airspace complexity prediction method GSC that incorporates graph attention layers, Skip-LSTM layers and convolutional layers. The proposed GSC model can capture the spatial correlations, long-term and short-term temporal dependencies of the airspace complexity data. When evaluated on real-world sector datasets, the GSC achieves better results than the state-of-the-art baselines. However, the current graph attention layers of our model are not effective enough, indicating that the spatial correlations are not well captured. In future work, the dynamic spatial topology of airspace sectors will be considered to further improve the prediction model.

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