Recognition of Similar Weather Scenarios in Terminal Area Based on Contrastive Learning

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Abstract: In order to improve the recognition accuracy of similar weather scenarios (SWSs) in terminal area, a recognition model for SWS based on contrastive learning (SWS-CL) is proposed. Firstly, a data augmentation method is designed to improve the number and quality of weather scenarios samples according to the characteristics of convective weather images. Secondly, in the pre-trained recognition model of SWS-CL, a loss function is formulated to minimize the distance between the anchor and positive samples, and maximize the distance between the anchor and the negative samples in the latent space. Finally, the pre-trained SWS-CL model is fine-tuned with labeled samples to improve the recognition accuracy of SWS. The comparative experiments on the weather images of Guangzhou terminal area show that the proposed data augmentation method can effectively improve the quality of weather image dataset, and the proposed SWS-CL model can achieve satisfactory recognition accuracy. It is also verified that the fine-tuned SWS-CL model has obvious advantages in datasets with sparse labels.

Key words: air traffic control; terminal area; similar weather scenarios(SWSs); image recognition; contrastive learning

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0 Introduction

In recent years, with the rapid development of the domestic air transport industry, the limited airspace resources and traffic surges in the airspace have made the air traffic control more complicated. Weather is the main factor affecting the air traffic and different weather will have different degrees of influence on the traffic control in terminal area. With long-term experience, some rules for formulating or selecting control strategies can be discovered and summarized. For experienced controllers, they usually can release operation strategies quickly based on their experience. However, for most controllers, due to the lack of experience in dealing with some weather scenarios, it is difficult for them to make appropriate control strategies. Therefore, it is important to recognize the similar weather scenarios (SWSs) in terminal area so as to help the controllers clearly understand the real-time status and make strategies according to the historical similar scenarios and strategies.

To recognize the similar scenarios in air traffic, in recent years, scholars have carried out a lot of researches and achieved some results[1-4]. The existing recognition methods of similar traffic scenarios are mostly based on numerical weather data, rather than the existing weather images. Therefore, the recognition accuracies of these methods are mainly dependent on the features of the numerical weather data extracted from weather radar monitoring data. With the development of deep learning technology

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and its great success in image recognition, it provides us a new idea for the recognition of similar weather scenarios in terminal area with the abundance of weather images. Considering the weather images have no labels, in this paper, we attempt to take advantage of the contrastive learning in learning feature representation and semantic embedding, and propose a recognition model for similar weather scenario based on contrastive learning (SWS-CL). In this method, the unlabeled convective weather images are the input, and a data augmentation method is designed to improve the number and quality of the images. Then, the pre-trained SWS-CL model is obtained by calculating the loss function, which is designed to minimize the distance between the anchor and positive samples, and maximize the distance between the anchor and the negative samples at the same time in the latent space. After that, the pre-trained SWS-CL model is fine-tuned with a few labeled samples to improve the recognition accuracy. Finally, the performance of the proposed SWS-CL method is validated on the real convective weather image dataset. The contributions of this paper can be summarized as follows:

(1) A data augmentation is designed for convective weather images and its effectiveness is verified.

(2) SWS-CL is proposed to improve the recognition accuracy of similar weather scenarios in terminal area.

(3) The proposed SWS-CL model is verified to achieve a better recognition accuracy on the real weather image dataset and has good performance on low-labeled images.

1 Related Works

In recent years, scholars have carried out a lot of researches on similar traffic scenarios and obtained some meaningful results. Liu et al.[1] used a semi-supervised learning algorithm to measure the similarity of each weather variable in the airport weather data based on some similarity relationships given in advance, analyzed airport runway acceptance rates and runway configuration results under similar weather conditions, and then made control decision for a given date according to the decisions made on the similar historic days. Chen et al.[2] performed cluster analysis on the traffic scenarios under convective weather, and analyzed the similarity of the airport arrival rates, departure rates and control strategies with unbalanced capacity and flow under different weather. Xie et al.[3] measured the similarity of the air traffic data and selected similar spatial-temporal data to search the similar scenarios. Schelling et al.[4] used the dynamic time warping algorithm to calculate 13 similarity matrices, completed the division of flight trajectories under the different weather conditions, and then gave the route selection strategies under similar weather. Hu et al.[5] used Euclidean distance and DTW to measure the similarity of the discrete features and time series features of busy sector, and input it to the spectral clustering model to identify the similar operation scenes. Chen et al.[6] proposed an active support vector machine metric learning algorithm to measure and identify the similar traffic scenes, in which a semi-supervised method can be used in cases without sample labels.

The above methods are all applied to the numerical weather data converted from the original convective weather images with large information loss, so the accuracies of these methods are limited. So far, research on the recognition of similar traffic scenarios directly based on convective weather images is rare. Deep learning technology can get deep feature extraction on images and has made great success in the field of computer vision, which inspires us to solve the recognition of SWSs with the images directly. However, the success of deep learning algorithms is very dependent on the labels of images, which is scarce in our convective weather image dataset. To avoid the requirement for labels, a common practice is to use data augmentation methods, such as rotation, cropping, etc., to obtain augmented samples of anchors as positive samples. In the same batch of training data, other samples are regard as negative samples. Contrastive learning is proposed to minimize the distance between the anchor and positive samples, and maximize the distance between the anchor and the negative samples in the latent space by its loss function. By this way, contrastive learning can implement some machine learning tasks by using the characteristics of the images without label information.

A simple framework for contrastive learning of visual representations (SimCLRS)[7] was proposed in 2020 and then widely used in computer vision. SimCLR learns visual representations by maximizing the agreement between differently augmented views of the same example via a contrastive loss in the latent space. It proves that data augmentation plays a critical role in prediction task and learnable nonlinear transformations can improve the quality of samples. Later, Cai et al.[8] used SimCLR to create an multi-modality fusion framework for glaucoma grading. She et al. [9] applied SimCLR to create a multi-taskself-supervised framework to extract semantic information from synthetic data and make visual representations. Ayush et al.[10] provided a self-supervised learning framework based on SimCLR for remote sensing data, which can shorten the gap between self-supervised and supervised learning on image classification, object detection and semantic segmentation. Agastya et al.[11] applied SimCLR to optical remote sensing data and proved that the detection precision was nine times better than the traditional supervised learning methods. Vu et al.[12] introduced SimCLR to classify diseases based on X-ray images.

Inspired by existing works, in this paper, we try to build a SWS recognition model based on the contrastive learning framework SimCLR to make full use of the unlabeled data and improve the recognition accuracy.

2 Method

The recognition of SWS is essentially a classification task based on convective weather images. Fig.1 illustrates the framework of SWS-CL. We first design a data augmentation method for the convective weather image. Then, the augmented convective weather images are used as the input of the contrastive learning process to extract high-quality feature representations to complete the pre-training SWS recognition model. Finally, a few labeled convective weather images are used to supervise the fine-tuning of the obtained pre-training model to improve the accuracy of SWS recognition.

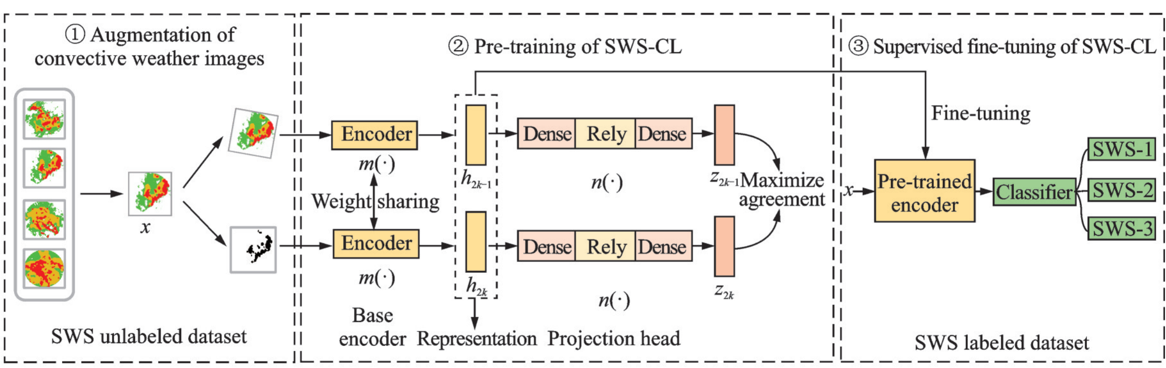

Fig.1 Framework of SWS-CL

2.1 Augmentation of convective weather images

The weather images are collected in real time by authoritative weather center with a certain frequency. Each image accurately depicts the intensity and distribution of convective weather in a certain airspace, and different convective weather affects the traffic flow in the terminal area at different degrees. Usually, severe convective weather will have a lethal effect on traffic flow which is the scenario needs to be focused. However, since severe convective weather only occurs occasionally, there are not enough typical images in the samples and most samples are of no convective weather or mild convective weather. Therefore, it is necessary to design a suitable data augmentation method to expand the training dataset artificially by generating more equivalent samples from the limited samples. Furthermore, since the core idea of contrastive learning is to shorten the distance between positive samples and anchor samples, and reduce the distance between negative samples and anchor samples in the embedding space, the quality of the selected positive and negative samples directly determines the performance of the whole model. However, the samples have no labels, and it is difficult to build positive and negative sample pairs with unlabeled samples.

Common image transformations including color distortion, cropping and resizing, vertical flipping and horizontal flipping[13], as shown in Fig.2.

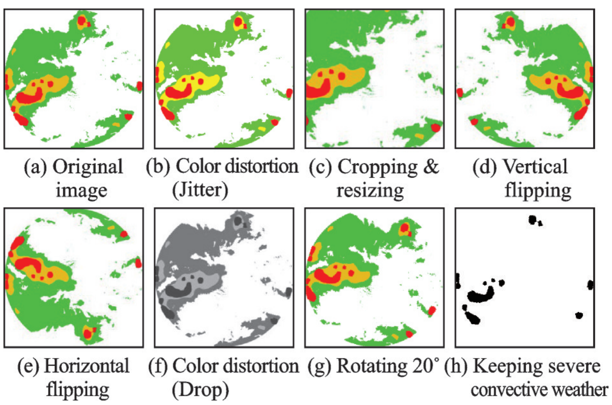

Fig.2 Weather image transformations

In the original image (Fig.2(a)), red, yellow and green represent severe, moderate and mild convective weather correspondingly. Color distortion (Jitter) (Fig.2(b)) may change the contrast and brightness of the images, which is meaningless for similar weather recognition. Cropping and resizing (Fig.2(c)) may cut off a part of the severe convective weather which may significantly affect the recognition result. Flip operations (Figs.2(d,e)) will change the direction of convective weather, which is also important for air traffic control. Color distortion (Fig.2(f)) coverts the color image to grayscale, which may weaken the weather information.

After several trials, we find that the image we get after rotating the original image with a slight random angle between 1° and 20° is similar to the original image, which is helpful for SWS recognition. Since only severe convective weather will affect air traffic, we can only keep the red areas in the image and convert it to Hue saturation value (HSV) format with Hue=[0—10]∪[156—180], Saturation=[43—255], Value=[46—255], which can enable the model to learn more patterns of severe convective weather. Thus, we design a data augmentation method based on random rotation and keep severe convective weather for our recognition task, as shown in Fig.3.

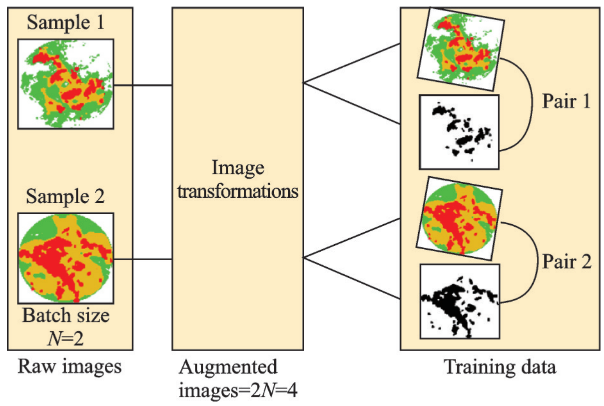

Fig.3 Augmentation of weather images

From Fig.3 we can see that the batch size of an augmentation is 2, and for each image in a batch, a pair of augmented images are generated by the two transformations. One is a rotation of the original image with a random angle from 1° to 20°, and the other is keeping the red parts of the original image and converting it to some HSV values. Specifically, since we consider each sample in a batch belongs to an unknown class, for the original Sample 1, the two samples generated from itself in Pair 1 are its positive sample pairs and the two samples generated from Sample 2 in Pair 2 is its negative sample pairs. So as to original Sample 2. By this way, we cannot only double the sample size in a batch, but also get the positive sample pairs and negative sample pairs for each original sample. It should be noted that for the two samples in Pair 1, if one is set as the anchor point, the other is its positive sample, and the two samples in Pair 2 are its negative samples. Therefore, data augmentation prepares the dataset for comparative learning.

2.2 Definition of contrastive loss

SWS-CL attempts to learn a mapping function, $f: x \rightarrow z \in \mathbb{R}^d$, in an unsupervised way. Then the augmented weather images $\tilde{x}_i$ and $\tilde{x}_j$ can get their semantic representation $\boldsymbol{z}_i = \mathrm{Net}(x_i)$ and $\boldsymbol{z}_j = \mathrm{Net}(x_j)$ through the neural network. Here, $\tilde{x}_i$ is the anchor sample and $\tilde{x}_j$ is the positive sample. In multi-classification problem, $\boldsymbol{z}_i$ and $\boldsymbol{z}_j$ are both one-hot vectors and the cosine similarity is used to measure their distance as

$$\mathrm{sim}\left(\boldsymbol{z}_i, \boldsymbol{z}_j\right) = \frac{\boldsymbol{z}_i^{\mathrm{T}} \boldsymbol{z}_j}{\|\boldsymbol{z}_i\| \|\boldsymbol{z}_j\|} \tag{1}$$

It can be concluded that the closer $\boldsymbol{z}_i$ is to $\boldsymbol{z}_j$ are, the closer $\mathrm{sim}\left(\boldsymbol{z}_i, \boldsymbol{z}_j\right)$ is to 1. For a given sample, the contrastive loss function is defined as

$$L(\tilde{x}_i, \tilde{x}_j) = -\lg \frac{\exp\left(\mathrm{sim}\left(\boldsymbol{z}_i, \boldsymbol{z}_j\right)/\tau\right)}{\sum_{k=1}^{2N} \exp\left(\mathrm{sim}\left(\boldsymbol{z}_i, \boldsymbol{z}_k\right)/\tau\right)} \tag{2}$$

where $\mathrm{sim}\left(\boldsymbol{z}_i, \boldsymbol{z}_j\right)$ is the similarity of positive sample pair and $\mathrm{sim}\left(\boldsymbol{z}_i, \boldsymbol{z}_j\right)$ the similarity of negative sample pair. Specifically, we require that the similarity $\mathrm{sim}(\boldsymbol{z}_i, \boldsymbol{z}_j)$ of positive samples should be as large as possible, and the similarity $\mathrm{sim}(\boldsymbol{z}_i, \boldsymbol{z}_k)$ of negative samples should be as small as possible. The temperature coefficient τ is defined to control the penalty strength on hard negative samples. Specifically, contrastive loss with small temperature coefficient tends to penalize much more on the hardest negative samples so that the local structure of each sample tends to be more separated, and the embedding distribution is likely to be more uniform. By calculating the contrastive loss for all pairs of positive samples including $(\tilde{x}_i, \tilde{x}_j)$ and $(\tilde{x}_j, \tilde{x}_i)$ in a batch, key features with discriminative representation capability are extracted from the images with the aim to minimize the distance between the anchor $\tilde{x}_i$ and positive sample $\tilde{x}_j$, and maximize the distance between the anchor and the negative samples $\tilde{x}_k$ in the latent space.

The total loss for a batch is defined as

$$l = \frac{1}{2N} \sum_{k=1}^{N} \left[l(x_{2k-1}, x_{2k}) + l(x_{2k}, x_{2k-1}) \right] \tag{3}$$

where N is the batch size. By calculating the loss in each batch, the pre-trained SWS-CL model can be obtained on the unlabeled image dataset.

2.3 Pre-training of SWS-CL

The main process of the pre-training of SWS-CL model is described as in Algorithm 1.

Algorithm 1 Pre-training of SWS-CL

Input: Dataset X; Batch size N; Constant τ

Output: Encoder network $m(\cdot)$

(1) While SWS-CL is not converged do

(2) Sample a minibatch $\{x_k\}_{k=1}^{N}$ from X

(3) Get $\tilde{x}_{2k-1}$ and $\tilde{x}_{2k}$ with image transformations

(4) Extract representation with Base encoder $m(\cdot)$

(5) Get z_{2k-1}, z_{2k} with Projection head $n(\cdot)$

(6) For all $i \in \{1, \cdots, 2N\}$ and $j \in \{1, \cdots, 2N\}$

Calculate $l(\tilde{x}_i, \tilde{x}_j)$ based on Eq.(1)

Calculate L based on Eq.(2)

Update networks $m(\cdot)$ and $n(\cdot)$

(7) End while

2.4 Supervised fine-tuning of SWS-CL

In this section, the pre-trained SWS-CL model is fine-tuned by using a few labeled convective weather images to re-train the model. As shown in Fig.4, in the supervised fine-tuning step, we transfer parameters from the pre-trained model and add an output layer to realize the network structure and parameter sharing between unlabeled data and labeled data. The pre-trained SWS-CL model can automatically extract deep features, but the weights of the output layer of SWS-CL model are randomly initialized. If these random values are allowed to be backpropagated to the entire network through gradient updates, this may destroy previously trained weights. To avoid this problem, we freeze all layers of the main body of the network and only train the output layer on the labeled dataset. The training data is forward propagated to the network as before, but the backpropagation stops in the output layer. It can significantly reduce the risk of overfitting in downstream model training stage, reduce the workload of parameter tuning and obtain recognition results more quickly.

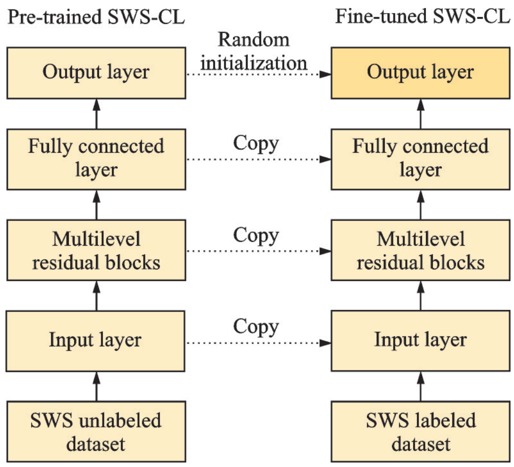

Fig.4 Fine-tuning process

3 Experiments and Discussion

In this section, the performance of SWS-CL method is verified by the comparative experiments. We introduce the image dataset and experiments setting in detail at first. The experiments have two parts. The first part mainly discovers the impact of the proposed data augmentation method on the model. In the second part, the impacts of the hyperparameters of SWS-CL are studied.

3.1 Dataset

The dataset we use in our experiments is the weather avoidance field (WAF) data of the Guangzhou Baiyun International Airport terminal area collected from 2018 to 2019 with 10 min interval. There are 80 000 unlabeled and 4 000 labeled convective weather images of the terminal area. 80 000 unlabeled and 2 000 labeled images are used for training. 2 000 labeled images are used for testing. The size of the image is 1 250×1 250. There are three types of labels, SWS-1, SWS-2, SWS-3, which are evaluated by the experts of air traffic control, as shown in Fig. 5. It can be seen that label SWS-1, SWS-2 and SWS-3 represent the mild, moderately and severe convective weather scenarios correspondingly.

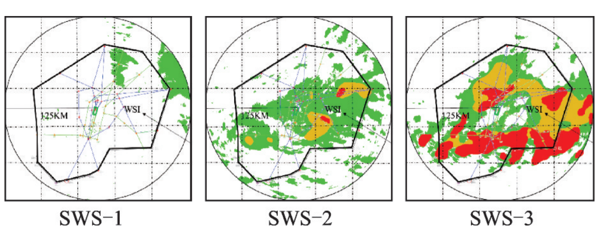

Fig.5 Labels of convective weather images

3.2 Setting of experiments

Five experiments are carried out to verify effectiveness of the proposed data augmentation method and SWS-CL model. In all the experiments, ResNet-50[14] is used as the embedding network for contrastive learning.

ResNet-50[14]: Training ResNet-50 on the original labeled images to get a recognition accuracy as the baseline.

ResNet-50+our augmentation: Training ResNet-50 on the labeled images augmented by our augmentation method.

Pre-trained SWS-CL+ common augmentations: Training the pre-trained SWS-CL model (ResNet-50+CL) on the unlabeled images augmented by common augmentation methods.

Pre-trained SWS-CL+ our augmentation: Training the pre-trained SWS-CL model on the unlabeled images augmented by our augmentation method.

Fine-tuned SWS-CL+ our augmentation: Retraining the pre-trained SWS-CL model on a few labeled images augmented by our augmentation method.

The experiments are performed on Python and TensorFlow 2.0 framework. The batch size of the model is 525, the epoch is 300, and the temperature coefficient is 0.05. The Adam optimizer is used and the size of the input image is 224×224.

3.3 Experimental results and discussion

3.3.1 Performance comparison

The recognition accuracies of all five experiments are shown in Table 1.

Table 1 Results of comparative experiments

Experiment	Accuracy/%
ResNet-50 (Baseline)	71.45
ResNet-50+our augmentation	75.56
Pre-trained SWS-CL+ common augmentation	57.69
Pre-trained SWS-CL+ our augmentation	66.44
Fine-tuned SWS-CL+ our augmentation	**83.76**

It can be seen that the accuracy of ResNet-50 is 71.45%, and the accuracy of ResNet-50+our augmentation is increased by 4.11%, which proves that our proposed data augmentation method has a positive effect on the model. In addition, pre-trained SWS-CL+ our augmentation improves the performance by 7.74% compared with the common augmentation, which also shows that our augmentation method still has better performance in pre-trained SWS-CL. Fine-tuned SWS-CL + our augmentation improves the performance of ResNet-50 by 12.31%. Compared with pre-trained SWS-CL + our augmentation, the supervised fine-tuning of SWS-CL with a few labeled images improves the accuracy by 18.33%, which verifies that our method has obvious advantages on the dataset has few labels.

3.3.2 Impacts of parameters

There are three key hyperparameters, epoch, batch size and temperature coefficient, in the proposed SWS-CL model. In this section, we will study their impacts on the performance of pre-trained SWS-CL with all the settings the same as those in Section 3.2, except the focused hyperparameter.

3.3.3 Epoch

Epoch means the iteration times of training a deep learning algorithm. Fig.6 and Fig.7 show the effect of different epoch on the performance of the pre-trained SWS-CL model. From Fig.6, we can find that the accuracy of pretrained SWS-CL model increases with the epoch size. In Fig.7, as the epoch increases, the loss becomes lower. More epochs mean more negative samples can be used to improve model performance. If there are 20 consecutive increases in the loss value, the training can be stopped.

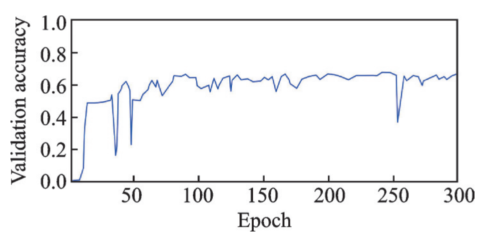

Fig.6 Impact of epoch size on accuracy

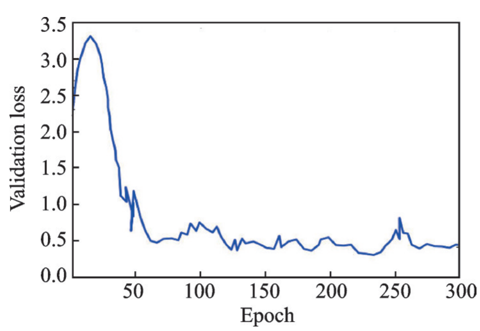

Fig.7 Impact of epoch size on loss

3.3.4 Batch size

Batch size means the number of images used in each iteration of training. It can be seen from Fig.8 that the larger the batch size, the higher the model accuracy. When the batch size is 525, the accuracy reaches the highest 66.44%. A larger batch size means that more negative samples can be used to accelerate the convergence and improve the model performance. At a given batch size, when the accuracy no longer improves after 20 consecutive iterations, it can be considered that the highest accuracy has been reached, and the training at this batch size can be stopped.

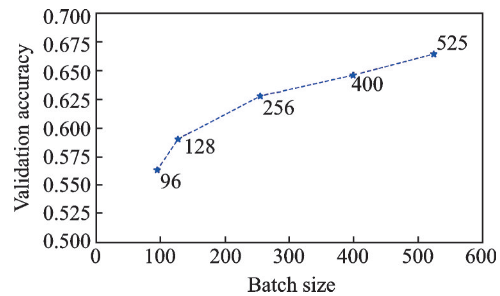

Fig.8 Impact of batch size on accuracy

3.3.5 Temperature coefficient

The temperature coefficient means how much the contrastive loss penalizes the hard negative samples. The larger the temperature coefficient, the smaller the penalty for hard negative samples. The smaller the temperature coefficient, the larger gradient the hard negative samples will get to separate them from the positive samples. The impact of temperature coefficient on pre-trained SWS-CL model is shown in Table 2. It can be found that the best temperature coefficient is 0.05.

Table 2 Impact of temperature coefficient on accuracy

Temperature coefficient	Accuracy / %
0.01	59.83
0.05	**66.44**
0.08	63.93
0.10	61.96

4 Conclusions

The contrastive learning technology is applied for the recognition of SWS in terminal area. A data augmentation method for convective weather images is designed to generate more useful images to be used as the input of the following learning. A contrastive loss is defined to extract high-quality features to train the pre-trained SWS-CL model on the augmented and unlabeled weather images. Finally, the pre-trained SWS-CL model is supervised fine-tuned with a few labeled images to improve the recognition accuracy of SWS. The results of five comparative experiments demonstrate that the proposed convective weather image augmentation method can effectively improve the quality of the dataset, and the proposed supervised fine-tuned SWS-CL model can achieve satisfactory recognition accuracy of SWS with few labeled samples. Based on our proposed SWS-CL model, more similar meteorological scenarios can be classified, and then control strategies under similar scenarios can be extracted to help controllers quickly make control decisions for the current scenario.

References

[1] LIU Y, SEELHORST M, POZDNUKHOV A, et al. Assessing terminal weather forecast similarity for strategic air traffic management[C]//Proceedings of the 6th International Conference on Research in Air Transportation. Turkey: [s.n.], 2014: 26-30.

[2] CHEN J T, KICINGER R, SCHELLING S, et al. Using weather translation and machine learning to identify similar weather impact day[C]//Proceedings of AIAA Guidance, Navigation, and Control Conference. [S.l.]: AIAA, 2017: 1727.

[3] XIE J, REDDY KOTHAPALLY A, WAN Y, et al. Similarity search of spatiotemporal scenario data for strategic air traffic management[J]. Journal of Aerospace Information Systems, 2019, 16(5): 187-202.

[4] SCHELLING S, KROZEL J A. Machine learning approach for finding similar weather-impacted situations in En route airspace[C]//Proceedings of AIAA Guidance, Navigation, and Control Conference. [S.l.]: AIAA, 2017: 1920.

[5] HU M H, ZHANG X, YUAN L G, et al. Identifying similar operation scenes for busy area sector dynamic management[J]. Transactions of Nanjing University of Aeronautics and Astronautics, 2020, 37(4): 615-629.

[6] CHEN H Y, HOU X Y, YUAN L G, et al. Identification of similar air traffic scenes with active metric learning[J]. Transactions of Nanjing University of Aeronautics and Astronautics, 2021, 38(4): 625-633.

[7] CHEN T, KORNBLITH S, NOROUZI M, et al. A simple framework for contrastive learning of visual representations[C]//Proceedings of the 37th International Conference on Machine Learning. Vienna, Austria: PMLR, 2020.

[8] CAI Z, LIN L, HE H, et al. Corolla: An efficient multi-modality fusion framework with supervised contrastive learning for glaucoma grading[C]//Proceedings of the 2022 IEEE 19th International Symposium on Biomedical Imaging (ISBI). [S.l.]: IEEE, 2022.

[9] SHE D Y, XU K. Contrastive self-supervised representation learning using synthetic data[J]. International Journal of Automation and Computing, 2021, 18(4): 556-567.

[10] AYUSH K, UZKENT B, MENG C, et al. Geography-aware self-supervised learning[C]//Proceedings of the IEEE/CVF International Conference on Computer Vision. [S.l.]: IEEE, 2021.

[11] AGASTYA C, GHEBREMUSSE S, ANDERSON I, et al. Self-supervised contrastive learning for irrigation detection in satellite imagery[C]//Proceedings of the International Conference on Machine Learning. [S.l.]: [s.n.], 2021.

[12] VU Y N T, WANG R, BALACHANDAR N, et al. Medaug: Contrastive learning leveraging patient metadata improves representations for chest X-ray interpretation[C]//Proceedings of Machine Learning for Healthcare Conference. [S.l.]: PMLR, 2021.

[13] DVORNIK N, MAIRAL J, SCHMID C. On theimportance of visual context for data augmentation in scene understanding[J]. IEEE Transactions on Pattern Analysis and Machine Intelligence, 2019, 43(6): 2014-2028.

[14] HE K, ZHANG X, REN S, et al. Deep residual learning for image recognition[C]//Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition. [S.l.]: IEEE, 2016.

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Author contributions Dr. CHEN Haiyan designed the study, analyzed the result and revised the manuscript. Mr. LIU Zhenya designed the method, implemented the model and wrote the manuscript. Dr. ZHOU Yi contributed to the discussion and revision of the study. Prof. YUAN Ligang contributed to the discussion and background of the study. All authors commented on the manuscript draft and approved the submission.

Competing interests The authors declare no competing interests

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基于对比学习的终端区相似气象场景识别

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摘要：为了提高终端区相似气象场景（Similar weather scenarios，SWSs）的识别准确率，提出一种基于对比学习的SWS（SWS based on contrastive learning，SWS-CL）识别模型。首先，针对对流天气图像特点，设计了一种数据增强方法来增加天气图像样本的数量和质量。接着，设计了一种对比损失函数使向量表征空间中的正样本与锚点样本之间的距离更近，而负样本与锚点样本之间的距离更远，进而基于对比学习技术在无标记样本集上训练得到相似气象场景分类预训练模型。最后，利用少量标记样本对预训练SWS-CL模型进行监督微调，进一步提高SWS-CL模型的性能。在广州终端区气象图像集上的对比实验表明，所提出的数据增强方法能有效提高气象图像集的质量，所提出的SWS-CL模型能取得令人满意的识别精度，且在标签稀少的数据集上具有明显的优势。

关键词：空中交通管制；终端区；相似气象场景；图像识别；对比学习