Research on Typhoon Identification of FY-4A Satellite Based on CNN-LSTM Model

Wenqing Feng[1], Xinyu Pi[1], Lifu He[1], Jing Luo[1], Ouyang Yi[1], Qiming Cao[1], Zihang Li[2], and Zhao Zhen[2](✉)

[1] State Key Laboratory of Disaster Prevention and Reduction for Power Grid Transmission and Distribution Equipment, State Grid Hunan Electric Company Limited Disaster Prevention and Reduction Center, Changsha, China
wq_feng@whu.edu.cn
[2] Department of Electrical Engineering, North China Electric Power University, Baoding, China
georgiazhz@foxmail.com

Abstract. Typhoons are one of the most serious natural disasters, which are extremely destructive and pose a great threat to the safe operation of power grids. To improve the risk warning and pre-control capability of power grid operation under typhoon weather, this paper proposes a typhoon cloud system identification method based on a two-dimensional convolutional neural network (CNN) and long short-term memory (LSTM) network. First, the spectral features are selected according to the physical characteristics of clouds, combined with the square field of point clouds as the spatial information of point clouds to construct a sample library of typhoon cloud blocks; then, the spatial features are automatically extracted by the convolutional neural network; Finally, the LSTM network extracts the spatial local difference features and the time series features of continuous changes of a typhoon cloud system to provide multi-angle features for satellite cloud map to identify typhoon cloud system. Combined with the multi-channel scanning imaging radiometer AGRI (Advanced Geostationary Radiation Imager) data in the geostationary Fengyun-4 meteorological satellite (FY-4A), the monitoring and research of typhoon weather in Guangdong Province, China, is taken as an example. The experimental results show that compared with the Faster-RCNN method of abstracting typhoon features for identification, the CNN-LSTM model-based typhoon identification method can achieve a more detailed division between typhoon and non-typhoon regions based on the multidimensional features of the cloud system in typhoon regions, and achieve better identification results.

Keywords: Typhoon Cloud System Identification · CNN-LSTM Hybrid Model · Feature Extraction · FY-4A Satellite

1 Introduction

Under the strategic background of “peak carbon dioxide emissions” and “carbon neutrality,” the scale of new energy installed capacity has continued to increase, and the

H. Yang et al. (Eds.): SmartGIFT 2022, LNICST 483, pp. 117–129, 2023.
https://doi.org/10.1007/978-3-031-31733-0_11

operating characteristics of large power grids have undergone profound changes. At the same time, the impact of natural disasters such as typhoons, lightning, freezing, and mountain fires on the power grid has become increasingly prominent [1, 2]. Among them, the summer typhoon has threatened the safe and stable power grid operation in my country's southeastern coastal areas [3, 4]. Effectively improving typhoon forecasting [5–7] and real-time monitoring capabilities can enhance the ability of large power grids to resist the impact of extreme weather such as typhoons. Therefore, the development of practical typhoon identification methods is of great significance to the safe operation of power grids.

Currently, there are few conventional statistical and observation data, and it is difficult to identify typhoons' locations accurately. However, satellite remote sensing data has high spatial and temporal coverage and resolution and is an essential means of observing and studying typhoons [8, 9]. It not only makes up for the low observation height of the ground meteorological observatory, but also makes up for the limited observation range. In the research of typhoon monitoring based on satellite cloud images, the edge contour features or gray image threshold are mostly used to identify and locate the typhoon. The traditional conventional methods include the threshold method, mathematical morphology method, rotation coefficient method and least square fitting method. In 2003, Liu et al. [10] proposed a method for locating the center of a typhoon with an eye on a satellite cloud image based on the mathematical morphology method. The typhoon cloud system was extracted by using erosion and expansion edge extraction techniques, and the center and radius of the maximum inscribed circle were obtained. In 2012, Li et al. [11] extracted typhoon cloud features based on image threshold segmentation technology based on entropy, obtained typhoon eye contour based on morphology and seed filling method, and applied gravity calculation method to locate the typhoon center. Experiments show that the positioning deviation is small and the positioning algorithm is feasible. Qiao et al. [12] used gray prediction and Chan-Vese model to obtain the positioning center based on infrared sequence images. The gray prediction is to obtain the initial position of the typhoon at the next predicted time point. After the Chan-Vese model calculates the eyewall near the typhoon center, a circle is fitted to obtain the typhoon center. This method is mainly used for the position of eyeless typhoons. The positioning accuracy of typhoons in the weakening period is relatively low, which needs further improvement. Liu et al. [13] automatically identified tropical cyclone cloud systems based on Canny edge detection and contour extraction. Although there may be some errors in obtaining the image centroid, this method can automatically track tropical cyclones. In 2014, Geng et al. [14] determined the segmentation threshold of the target cloud system based on satellite images and the maximum inter-class variance method, combined with the characteristics of cloud system area and brightness temperature distribution, and used the rotation coefficient to identify tropical cyclone cloud systems automatically.

However, the traditional method has some limitations in practical application, such as the mathematical morphology method is complicated to implement and takes much time; in the process of least squares fitting circle, the texture characteristics of the cloud system are ignored. At present, machine learning is widely used in the field of image recognition.

Some scholars have also begun to apply machine learning methods to typhoon recognition. Based on cloud texture features in satellite cloud images, deep convolutional neural networks extract and learn cloud features to realize typhoon recognition. The positioning of the boundary position is more time-saving and efficient than traditional identification methods. Zhou et al. [15] proposed a GCN-LSTM model framework, which uses satellite cloud images to classify and predict t1000phoons at different levels. The experimental results show that the algorithm of the model can effectively improve classification accuracy. Shi et al. [16] conducted a study on cloud type classification. Considering the unique characteristics of clouds, it is believed that local rich texture information may be more important than global layout information, so it is recommended to use convolution-based activation-based features for terrestrial cloud classification. Some scholars [17] have converted the typhoon identification problem into a target identification problem and realized how to locate the whole typhoon cloud system on the cloud map. This method achieves identification by abstracting the features of the typhoon region's satellite cloud map without analyzing the cloud system's characteristics.

At present, there are few practical applications related to typhoon cloud system monitoring using deep learning methods, so for the traditional mathematical morphology method to achieve a complex process, it is difficult to apply to the actual typhoon cloud system monitoring as well as the current deep learning-based practices mostly abstract typhoon features on a large range of cloud maps to achieve the localization of typhoon identification, without deep excavation of typhoon cloud system features, however, based on deep learning methods to extract Typhoon cloud system features to identify typhoon cloud system is rarely studied, this paper analyzes and integrates for typhoon cloud system features, and proposes a typhoon cloud system identification method based on two-dimensional convolutional neural network (CNN) and long short-term memory (LSTM) network. The contributions of this paper are summarized as follows:

1. To improve the recognition of typhoon cloud systems, this paper constructs a sample library with square neighborhood cloud blocks based on the data of fourteen channels of the FY-4A satellite and the brightness temperature difference of cloud tops and effectively fuses the typhoon spatial-spectral information.
2. In this paper, we propose a typhoon cloud system identification method based on CNN-LSTM networks to analyze the multidimensional features of typhoon cloud systems and automatically extract spectral and spatial features from cloud maps using hybrid models, avoiding relying on human experience to manually design and extract mathematical morphological features.
3. This paper uses AGRI (Advanced Geostationary Radiation Imager) data from (FY-4A) as the data source for the study of Guangdong Province, China. The experimental results show that the proposed CNN-LSTM model-based typhoon cloud system identification method can better distinguish typhoon areas from non-typhoon areas and achieve better identification results.

2 Methodology

2.1 Convolutional Neural Network

In recent years, CNN has been widely used in the field of image processing. The network model uses the gradient descent method to minimize the loss function to reversely adjust the weight parameters in the network layer by layer and improves the accuracy of the network through frequent iterative training [18, 19]. The basic structure of CNN consists of an input layer, a convolution layer, a pooling layer, a fully connected layer, and an output layer. Generally, several convolution layers and pooling layers are used, and the convolution layers and pooling layers are alternately set. The CNN structure is shown in Fig. 1.

Convolutional layer: The convolutional layer contains many feature maps. The function of the convolutional layer is to use the convolution kernel to perform the convolution operation on each convolutional image, and then use the activation function to perform nonlinear processing on the convolution result. The formula for the convolutional layer is as follows:

$$x_j^l = f\left(\sum\nolimits_{i \in M_j} x_j^{l-1} w_{ij}^l + b_j^l\right) \tag{1}$$

where l represents the number of layers; w represents the convolution kernel; b represents the bias value; M_j represents the feature map of the middle layer; f represents the activation function.

Pooling layer: After the initial feature extraction of the convolution layer, the output feature map size may be too large, which will result in too many features in the output result. After inputting to the classifier, it may lead to over-fitting. After the convolutional layer, the pooling layer is connected to reduce the features through dimensionality reduction, retain the main features, increase the receptive field of the convolution kernel, and enhance the fitting ability.

Fully connected layer: As the last layer in the hidden layer of CNN, its output will be passed to the output layer. The main function is to integrate the highly abstracted features after multiple convolutions, and then normalize them. Both output a probability, and the subsequent classifiers are classified according to the probability obtained by the full connection.

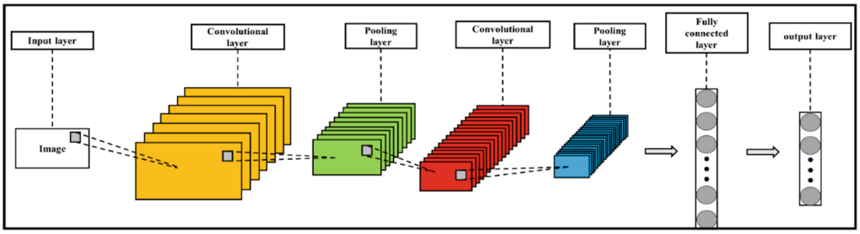


Fig. 1. Structure of the CNN (Color figure online)

2.2 Long Short Term Memory

LSTM network is an improved recurrent neural network (RNN), which can effectively overcome the gradient disappearance problem in RNN and can accurately model with short-term or long-term data [20, 21]. LSTM implements a more refined internal processing unit and adopts three gates to achieve efficient storage and update of contextual information. There are three types of gates in LSTM cells: input gates, forget gates, and output gates. The network basic unit is shown in Fig. 2. The feature information extracted by CNN is transmitted to the cell unit of LSTM, where the input x_t in the forget gate, the state memory unit $C_{t\text{-}1}$, and the intermediate output ht−1 jointly determine the forgetting part of the state memory unit. The x_t in the input gate is changed by the sigmoid and tanh functions to jointly determine the update information of the state memory unit. The intermediate output h_t is determined by the updated C_t and the output o_t. The calculation formula is as follows:

$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f) \tag{2}$$

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \tag{3}$$

$$g_t = tanh(W_g \cdot [h_{t-1}, x_t] + b_g) \tag{4}$$

$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o) \tag{5}$$

$$C_t = g_t \odot i_t + C_{t-1} \odot f_t \tag{6}$$

$$h_t = o_t \cdot \tanh(C_t) \tag{7}$$

where f_t, i_t, g_t, o_t, h_t and C_t are the states of the forget gate, input gate, input node, output gate, intermediate output and state unit, respectively; W_f, W_i, W_g, W_o are the matrix weights of the corresponding gates; $b_f, b_i,$ b_g, b_o are the bias terms of the corresponding gate and memory unit respectively; $\odot$ represents the bitwise multiplication of elements in the vector; σ represents the change of the sigmoid function; tanh is the activation function.

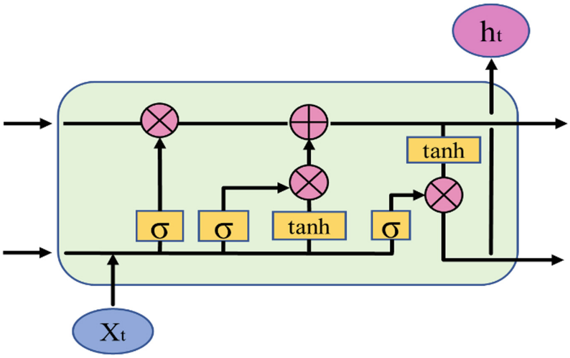


Fig. 2. LSTM cell

2.3 CNN-LSTM Combined Model

The C-LSTM (Convolutional-LSTM) combination model has been used in many fields such as text sentiment analysis [22]. Experiments have shown that CNN-LSTM performs better than CNN or LSTM alone. The overall process of the model is mainly divided into five steps: 1. Input the standardized data picture into the CNN convolution layer, and use the wide convolution kernel to extract image features adaptively. 2. The extracted features are subjected to the pooling operation of the maximum pooling layer to reduce the data dimension and retain the main feature information. 3. The standardized data images are serialized, and the time-dimensional information is extracted from the static images using long and short-term memory networks. 4. The ADD layer combines the described depth image features and spatial sequence features. 5. Use the Softmax activation function to classify Integration image features to complete image recognition. The network structure of the combined model is shown in Fig. 3 below. The detailed process is as follows:

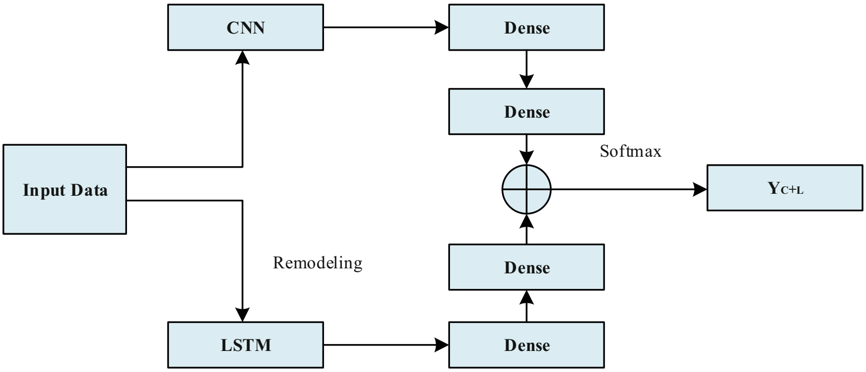


Fig. 3. CNN-LSTM combined model

3 Data Preprocessing

In December 2016, the first three-axis stable geostationary meteorological satellite, Fengyun-4 (FY-4A), independently developed by my country, was launched. FY-4A is the second-generation synchronous orbit meteorological satellite after Fengyun-2 (FY-2). It is equipped with a total of three instruments, including a multi-channel scanning radiation imager (Advanced Geostationary Radiation Imager), a lightning imager (Lighting Mapping Imager, LMI), and the Geostationary Interferometric Infrared Sounder (GIIRS), among which, AGRI is currently among the world's leading geostationary imagers, and can replace the FY2's Visible and Infrared Spin Radiometer (Visible and Infrared Spin Scan Radiometer, VISSR). The multi-channel scanning imaging radiometer AGRI on the FY-4A used in this paper can generate a full disk image observation every 15 min, with a total of 14 channels, including two visible light channels (red and blue light) and near-infrared and thermal infrared channels, etc., the wavelength range is from visible light to long-wave infrared (0.45–13.8 μm), and the spatial resolution of AGRI is 4 km, which meets the time resolution requirements of real-time dynamic monitoring of sand and dust. The data used are 4 km resolution China regional data and GEO calibration data with 14 channels in AGRI.

3.1 Cloud Feature Selection

By changing the HDF data format of FY-4 into a grayscale image format, the identification of typhoon cloud systems can usually be carried out according to the characteristics of cloud range size, shape, pixel distribution, spectral, and texture [23, 24].

The grayscale image representation information, the luminance ratio between different bands, and the color representation information in the satellite cloud image constitute the spectral characteristics of the cloud image [25, 26]. It has corresponding pixels corresponding to it in the image. Specifically, on the image of the converted infrared channel of FY-4A, since it reflects the temperature information, it essentially shows the temperature in the cloud image. Since the surface, ocean, and various cloud systems have different temperatures on the one hand, and on the other hand, and their vertical heights are also different, the absorbed light is also different. Furthermore, the emissivity of different light is also different in different objects, so the grayscale information fed back by the ocean, the surface and various cloud systems is not the same, so the spectral characteristics can be used as the main feature to distinguish the typhoon cloud system from the surface and ocean.

However, it is impossible to accurately distinguish typhoon cloud systems from other cloud systems by simply relying on spectral features. Therefore, texture and geometric features need to be introduced in the process of cloud feature selection. The texture in the satellite cloud image is composed of many indistinguishable particles in the smallest unit of the imaging resolution system, and many different cloud systems can be identified according to this feature of texture. Due to the differences in the intracloud circulation, atmospheric circulation, and water vapor content of various cloud systems, they usually have their texture structures. Visually, the texture features of cloud systems can be roughly divided into regular and irregular, smooth and rough, smooth and undulating, etc. Typhoon cloud systems have relatively smooth texture features and have a significant rotation coefficient. A rotating body, so texture features can be used as the main feature to distinguish other cloud systems. In addition, different cloud systems have different pixel distributions on satellite cloud maps. Typhoon cloud systems are expressed in the form of a very concentrated pixel distribution on meteorological satellite cloud maps.

This paper uses the 14 single spectral channel features in the FY-4A satellite cloud image data, and also selects 2 comprehensive channel spectral features Brightness Temperature Difference (BTD). BTD not only helps to improve the impact of geographical changes on cloud system identification, but also It can weaken the influence of the sun's altitude angle on the identification of cloud systems, so as to distinguish different cloud phases, thereby reducing the identification error of a single channel. Finally, the single pixel data in the channel data is converted into pixel block data that can contain texture features.

3.2 The Establishment of Sample Library

Combined with the satellite images obtained by the National Meteorological Satellite Meteorological Center in Guangdong and the early warning information of typhoon weather from the China Meteorological Administration information platform, four typical typhoon processes from 2020 to 2022 were determined, namely CHABA, Cempaka, Higos,and Nuri, of which FY-4A satellite data imaging time is 16:00 on July 2, 2022 (Beijing time), 14:00 on July 20, 2021, 8:00 on August 19, 2021, and 11:00 on June 14, 2020. In addition, referring to the classification of satellite cloud images by meteorological experts, texture features with a coverage range of 32 km * 32 km are generally selected. The coverage of a single pixel in the data used in this paper is 4 km * 4 km. To match it, an 8 * 8 square neighborhood sample (coverage range of 32 km * 32 km) is selected. Then, 16 spectral features are selected for each pixel point, the size of the cloud block sample data is 16 * 8 * 8, and finally, the sample data size is processed to 32 * 32. The flow chart of cloud block sample establishment is shown in Fig. 4 below.

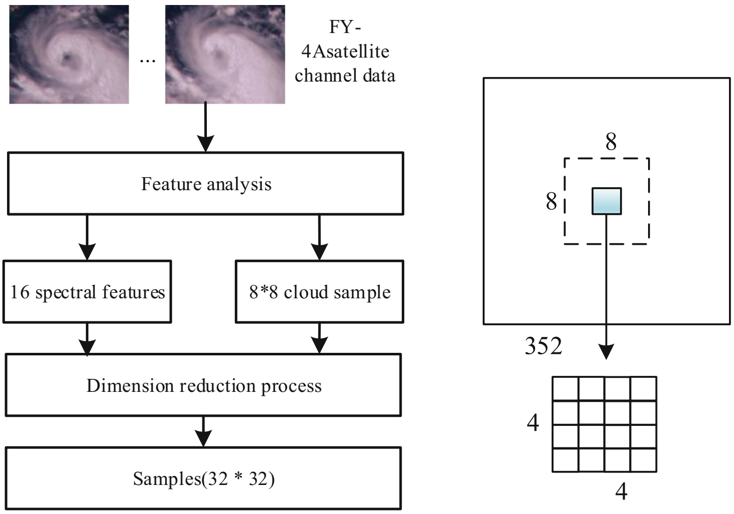


Fig. 4. The flow chart of cloud block samples

The construction of the sample library is mainly divided into three steps. The flow chart of the sample library establishment is shown in Fig. 5 below. The detailed steps are as follows:

(1) Cut out the study area and select areas with large typhoon frequency and typhoon range based on satellite images of the National Meteorological Satellite Meteorological Center and typhoon weather warning information on the China Meteorological Administration information platform, including Guangdong and adjacent sea areas.
(2) Mark the typhoon area, use the data of the first three channels of the multi-channel scanning imaging radiometer AGRI in the FY-4A to synthesize RGB images and

find the RGB images when the typhoon occurred by comparing the geographical and time information of the historical typhoon occurrence area. The satellite cloud map is split into typhoon area and non-typhoon area.

(3) Construct a data set. Using 16 satellite remote sensing data of typhoon region and non-typhoon region are integrated into multiple square neighborhood samples to obtain cloud block sample data of typhoon region and non-typhoon region and construct datasets of typhoon cloud block type and non-typhoon cloud block type for model training.

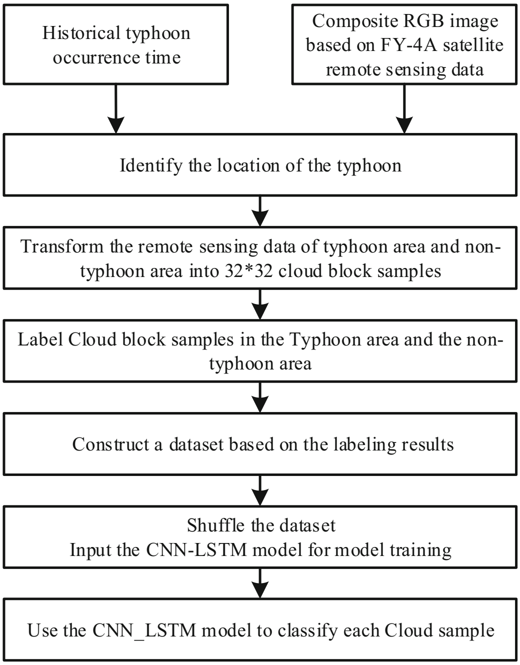


Fig. 5. Flow chart of cloud sample library

4 Analysis of Results

4.1 Experimental Data and Model Adjustment

The number of network layers, the number of filters, and the size of the filter in the CNN network require repeated experiments. The optimal hyperparameter settings of the network are selected according to the classification accuracy. By fixing the number of network layers and filters and changing the filter size step by step, the optimal filter size with the highest classification accuracy is obtained. The same fixed parameter debugging method is used to obtain other optimal hyperparameter settings. In the CNN-LSTM network model, the number of convolutional layer filters is 30, 40. The filter size is 3 * 3, the number of LSTM units is 128 parameters, the optimizer is set to Adam, the input image size is 32 * 32, the initial learning rate is 0.001, the decay rate is 0.1, the batch size is set to 64. The maximum epoch parameter is set to 200.

4.2 Comparative Experiment Analysis

To verify the recognition effect of the CNN-LSTM network model, the typhoon "Hagupit", which occurred on August 3, 2020, is selected as the test sample, and a satellite cloud image with the size of 352 * 352 containing typhoon cloud systems and other cloud systems is selected for testing. The network training results are obtained using the same experimental data in the same practical environment.

The results of typhoon identification based on the Faster-RCNN model are shown in Fig. 6. This method treats the typhoon identification problem as a target detection problem. The red box represents the identification frame in the cloud map to identify the localized typhoon cloud systems. However, the identification results are insufficient to distinguish typhoon cloud systems and non-typhoon cloud systems within the localization range.

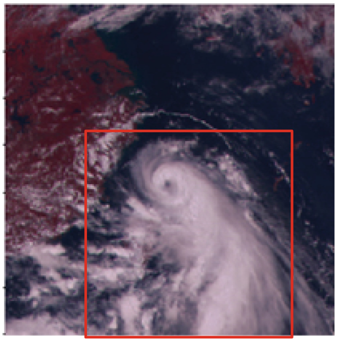


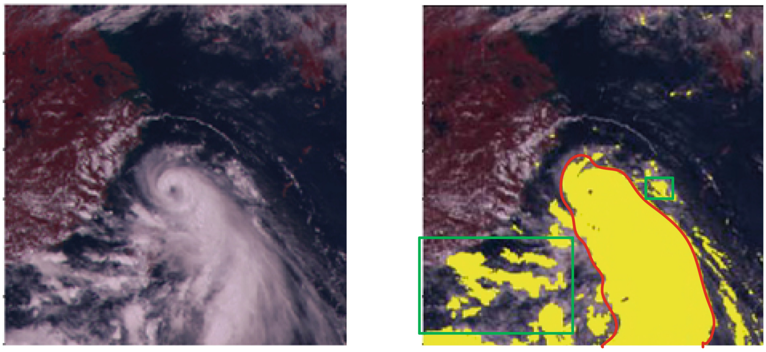
Fig. 6. Identification results of typhoon based on Faster-RCNN model (Color figure online)

The proposed method identifies typhoon cloud systems based on their spectral, textural, and pixel features, as well as the connectivity of the cloud system.

Firstly, the method of identifying typhoon cloud systems based on spectral features is used as a comparison method, using fourteen channels of FY-4A data and two integrated channels of spectral features bright temperature difference (BTD) as input data. This method identifies typhoon cloud systems and non-typhoon cloud systems based on the feature that typhoon cloud systems usually have large optical thickness and reflectivity of the cloud body and uses pixel points as the basic unit to identify typhoon cloud systems and non-typhoon cloud systems. The experimental results are shown in Fig. 1. The yellow pixel dots in the red box line are typhoon cloud systems, while the yellow pixel dots in the green box line are other cloud systems. It can be found that typhoon cloud systems can be effectively identified by using spectral features, but there is a large area of misidentified area, and the location of typhoon cloud systems cannot be accurately judged based on the characteristics of typhoon cloud system connectivity.

The proposed method introduces texture features based on spectral features and recognizes pixel blocks based on the CNN-LSTM model of the typhoon recognition method. The results are shown in Fig. 8. Compared with the method that introduces spectral information alone, the method can solve the problem of false recognition in small area regions, such as the green boxed area in the upper right corner of Fig. 7(b). It can effectively reduce the false recognition rate, such as the boxed area in the lower left corner of Fig. 7(b).

As shown in Fig. 8(a) and (b), the typhoon cloud system identification results of the CNN-LSTM network are compared with the CNN model identification results. The typhoon cloud system is determined based on RGB synthetic images, and pixel-by-pixel statistics analyze the typhoon cloud system monitored by both models. The results show that about 13% of the pixel blocks in the CNN model-based typhoon cloud system identification method are incorrectly identified. In comparison, about 9.5% of the pixel blocks in the CNN-LSTM model-based typhoon cloud system identification method are incorrectly identified. This shows that the CNN-LSTM model can better utilize the cloud system features and can effectively improve the recognition accuracy of the typhoon cloud system.



(a) (b)

Fig. 7. RGB composite image (a), Typhoon identification method based on spectral features (b)

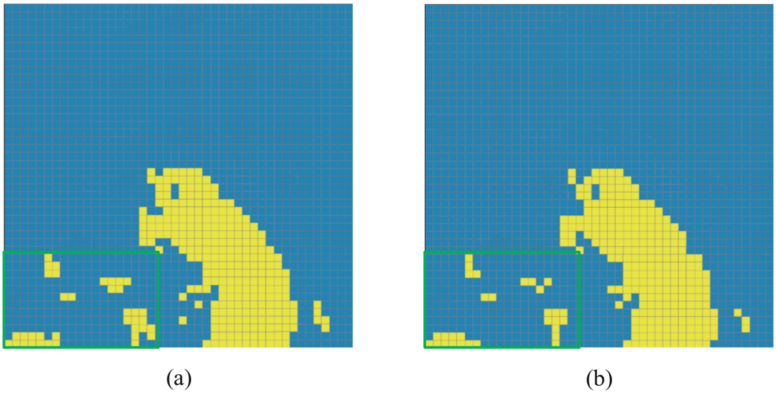

(a) (b)

Fig. 8. Typhoon identification method based on spatial and spectral fusion features. CNN model (a), CNN-LSTM model (b)

5 Conclusion

To fully use the space-spectral information, this paper proposes a typhoon identification method for the FY-4A satellite based on the CNN-LSTM network. In terms of combining spatial-spectral information, the effective spectral features are selected according to the physical characteristics of the typhoon cloud system, and the spatial information of the square neighborhood is combined to form the characteristics of the typhoon cloud system. Based on the data of 14 bands in AGRI obtained by Fengyun-4 (FY-4A), a typhoon cloud block sample was constructed, and the CNN-LSTM network model was used to identify the typhoon cloud system in Guangdong Province, China. The experimental results show that compared with the Faster-RCNN method of abstracting typhoon features for identification, this paper mines the multidimensional features of cloud systems in typhoon regions and proposes a method of identifying typhoon cloud systems based on CNN-LSTM model, which can better distinguish typhoon regions from non-typhoon regions and achieve better identification results.

References

1. Ye, J., Lin, G., Zhang, M., Gao, L.: Hazard analysis of typhoon disaster-causing factors based on different landing paths: a case study of Fujian Province China. Nat. Hazards **100**(2), 811–828 (2020)
2. Guo, Y., Hou, Y., Liu, Z., Du, M.: Risk prediction of coastal hazards induced by Typhoon: a case study in the coastal region of Shenzhen, China. Remote Sens. **12**(11) (2020)
3. Wang, L., et al.: Special field measurement results of an onshore wind farm connected to power grid of Taiwan power system subject to Typhoon Matmo. IEEE Trans. Ind. **55**(1), 158–166 (2019)
4. Yuan, S., Quiring, S.M., Zhu, L., Huang, Y., Wang, J.: Development of a typhoon power outage model in Guangdong, China. Int. J. Electr. Power Energy Syst. **117** (2020)
5. Kossin, J.P., Olander, T.L., Knapp, K.R.: Trend analysis with a new global record of tropical cyclone intensity. J. Clim. **26**(24), 9960–9976 (2013)

6. Ruttgers, M., Jeon, S., Lee, S., You, D.: Prediction of typhoon track and intensity using a generative adversarial network with observational and meteorological data. IEEE Access **10**, 48434–48446 (2022)
7. Zhou, G., Xu, J., Qian, Q., Xu, Y.: Discriminating technique of typhoon rapid intensification trend based on artificial intelligence. Atmosphere (Basel) **13**(3) (2022)
8. Mei, W., Lien, C.C., Lin, I.I., Xie, S.P.: Tropical cyclone-induced ocean response: a comparative study of the South China Sea and tropical Northwest Pacific. J. Clim. **28**(15), 5952–5968 (2015)
9. Xingfa, G., Xudong, T.: Overview of China earth observation satellite programs. IEEE Geosci. Remote Sens. Mag. (2015)
10. Liu, Z., Zhou, L., Wu, B.: The center location of eyed typhoon in satellite cloud image. PR AI **16**(3), 334–337 (2003)
11. Li, H., Huang, X.Y., Qin, D.Y.: Research the artificial intelligent algorithm for positioning of eyed typhoon with high resolution satellite image. In: Proceedings of the 2012 5th International Joint Conference on Computational Sciences and Optimization, CSO 2012, pp. 889–891 (2012)
12. Qiao, W., Li, Y., Xu, Y., Hu, Q.: Typhoon center locating based on gray model and Chan-Vese model. Laser Infrared **42**(4), 443–447 (2012)
13. Liu, Y., Shao, L., Yang, W.: Automatic recognition tropical cyclone method based on satellite images. Mar. Forecast. **29**(1), 13–17 (2012)
14. Geng, X., Li, Z., Yang, X.: Tropical cyclone auto-recognition from stationary satellite imagery. J. Image Graph. **19**(6), 964–970 (2014)
15. Zhou, J., Xiang, J., Huang, S.: Classification and prediction of typhoon levels by satellite cloud pictures through GC–LSTM deep learning model. Sensors (Switzerland) **20**(18), 1–17 (2020)
16. Shi, C., Wang, C., Wang, Y., Xiao, B.: Deep convolutional activations-based features for ground-based cloud classification. IEEE Geosci. Remote Sens. Lett. **14**(6), 816–820 (2017)
17. Lu, X., Qian, Q., Wang, D., Zhou, G., Xu, J.: Intelligent technique of typhoon vortex detection based on object detection with deep learning of satellite. J. Trop. Meteorol. **38**(4), 492–501 (2022)
18. Yan, J., et al.: Frequency-domain decomposition and deep learning based solar PV power ultra-short-term forecasting model. IEEE Trans. Ind. Appl. **57**(4), 3282–3295 (2021)
19. Wang, F., Yu, Y., Zhang, Z., Li, J., Zhen, Z., Li, K.: Wavelet decomposition and convolutional LSTM networks based improved deep learning model for solar irradiance forecasting. Appl. Sci. **8**(8), 1–29 (2018)
20. Wang, F., Xuan, Z., Zhen, Z., Li, K., Wang, T., Shi, M.: A day-ahead PV power forecasting method based on LSTM-RNN model and time correlation modification under partial daily pattern prediction framework. Energy Convers. Manag. **212** (2020)
21. Zhen, Z., et al.: Ultra-short-term irradiance forecasting model based on ground-based cloud image and deep learning algorithm. IET Renew. Power Gener. 1–13 (2021)
22. Naqvi, U., Majid, A., Abbas, S.A.: UTSA: Urdu text sentiment analysis using deep learning methods. IEEE Access **9**, 114085–114094 (2021)
23. Liu, J., Wang, F., Zhen, Z.: Deep learning based visualized speed matrix forecasting model for wind power forecasting. In: 2020 IEEE Student Conference on Electric Machines and Systems, pp. 9–25 (2019)
24. Wang, F., et al.: A satellite image data based ultra-short-term solar PV power forecasting method considering cloud information from neighboring plant. Energy **238** (2021)
25. Si, Z., Yang, M., Yu, Y., Ding, T.: Photovoltaic power forecast based on satellite images considering effects of solar position. Appl. Energy. **302** (2021)
26. Zhao, X., Wei, H., Wang, H., Zhu, T., Zhang, K.: 3D-CNN-based feature extraction of ground-based cloud images for direct normal irradiance prediction. Sol. Energy **181**, 510–518 (2019)