The Prediction Method of Tropical Cyclone Intensity Change Based on Deep Learning

Wenke Wang[1] and Xin Wang[1]

[1]National University of Defense Technology

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Abstract

A prediction algorithm of tropical cyclone (TC) intensity change based on deep learning is proposed by exploring the distribution characteristics of atmospheric and oceanic elements. we adopted three dimensional convolutional neural network (3D-CNN), which is part of a most advanced approach, to learn the implicit correlation between the spatial distribution characteristics of three dimensional environmental variables and TC intensity change. Image processing technology is also used to enhance the data of a small number of TC samples to generate the train set. On the basis of TC instantaneous three dimensional state and the influence of sea surface temperature, we extract the spatial hybrid features from TC image patterns to predict 24 h intensity change. Experimental results show that the Mean Absolute Error (MAE) of TC intensity change prediction and the accuracy of strengthening and weakening classification are both have a significant improvement

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The Prediction Method of Tropical Cyclone Intensity Change Based on Deep Learning

Xin Wang [1], Wenke Wang [2]

[1] College of computer, National University of Defense Technology, Changsha, China.

[2] College of Meteorology & Oceanography, National University of Defense Technology, Changsha, China.

Corresponding author: Wenke Wang (wangwenke@nudt.edu.cn)

Key Points:

- The spatial mixed distribution features of three dimensional environmental variables are proposed to predict TC intensity change.
- The deep learning model is trained with data augmentation and shows a significant improvement in intensity change prediction.
- The scheme based on deep learning algorithm achieves higher classification accuracy of TC enhancement and attenuation.

Abstract

A prediction algorithm of tropical cyclone (TC) intensity change based on deep learning is proposed by exploring the distribution characteristics of atmospheric and oceanic elements. we adopted three dimensional convolutional neural network (3D-CNN), which is part of a most advanced approach, to learn the implicit correlation between the spatial distribution characteristics of three dimensional environmental variables and TC intensity change. Image processing technology is also used to enhance the data of a small number of TC samples to generate the train set. On the basis of TC instantaneous three dimensional state and the influence of sea surface temperature, we extract the spatial hybrid features from TC image patterns to predict 24 h intensity change. Experimental results show that the Mean Absolute Error (MAE) of TC intensity change prediction and the accuracy of strengthening and weakening classification are both have a significant improvement.

Plain Language Summary

TC motion makes important influence to human beings and infrastructure. Predicting TC intensity is crucial, especially in the 24 h warning time. TC intensity change prediction can be regarded as both regression and classification problems. In this study, an algorithm based on deep learning is proposed to improve TC intensity change predictions, which combines the distribution features and interaction of atmospheric and oceanic variables.

1 Introduction

Tropical cyclone (TC) is a warm-core atmospheric vortex system that occurs and develops on the warm ocean surface (Gao et al., 2018). The disaster is mainly caused by strong wind, heavy rain and storm surge, which is one of the most destructive nature disasters (Q. Zhang et al., 2009). TC intensity prediction and rapid intensification prediction, especially in the warning time frame within 24-48 h, remains a major challenge(Gao et al., 2016). TC intensity change is affected by complex physical processes. The difficulty in predicting TC intensity is mainly due to our limited understanding of complex processes and various factors related to TC enhancement and attenuation (W. Zhang, Gao, et al., 2013). Existing studies have summarized three main factors leading to TC intensity change: ocean characteristics such as sea surface temperature (SST) and latent heat flux (Ito et al., 2015; M. Zhang et al., 2016); internal structural characteristics such as eyewall and structural asymmetry (Sitkowski et al., 2011); environmental impact such as vertical wind shear and humidity (Xuyang et al., 2013). It is generally believed that the change depends on the combination of these factors (Chen P, 2011; Wang & Wu, 2004).

At present, TC intensity prediction methods can be divided into three categories: statistical prediction method, numerical prediction method and deep learning method. The traditional statistical method to study the change of TC intensity needs to consider the selection of multiple predictors, such as maximum potential intensity and relative vorticity (Gao & Chiu, 2012; Gao et al., 2016; Jinjie et al., 2011; Lee et al., 2019; Su et al., 2010). However, the predictability of predictors is uneven and inconclusive. Previous studies used decision trees to classify 24 h intensity change, but could only qualitatively evaluate TC change (Gao et al., 2016; W. Zhang, Gao, et al., 2013). The numerical prediction method based on the thermodynamic equation adopts different parameterization schemes and obtains obvious and unique results in performance and characteristics, nevertheless, it is quite sensitive to the initial field and boundary conditions (R. Chen et al., 2019). With the development of artificial intelligence, scholars have also tried to use deep learning to solve TC problems, and this approach continues to attract attention (B.-F. Chen et al., 2019; Jiang et al., 2018). Chen et al. used three dimensional convolutional neural network and long short-term memory (LSTM) network to predict 24 h intensity. However, the number of time series samples were insufficient for the demand of deep learning. In addition, the feature information of the reanalysis text data is limited by the variable values and the number of grids (R. Chen et al., 2019).

As is known to all, TCs have strong vertical movement in the process of development. In the three dimensional state, the dynamic and thermal characteristics of TCs can be better represented. The influence of water vapor and heat cannot be ignored (Sitkowski et al., 2011; Xuyang et al., 2013). Previous studies have shown that relative humidity and water vapor flux are effective potential predictors of TC intensification stage (Cocks & Gray, 2002; Xuyang et al., 2013). Moreover, large numbers of studies have shown that SST also plays an important role in TC generation and development (Gao et al., 2016; Ito et al., 2015; Jiang et al., 2018; M. Zhang et al., 2016).TC in different life stages distributes with distinct flow field features (Ge & Colle, 2019). For each TC, at each moment in its evolution, there exists a set of eigenvectors containing numbers of potential TC intensity, precipitation, movement and lifespan features, which relates to the relevant attributes of TCs (Ge & Colle, 2019). Each set of eigenvectors represents a single TC sample. TC is a quasi-circular symmetrical closed low pressure system with great gradient. The peripheral environment influence appears asymmetric (Kerns & Chen, 2013). In the upper-air weather map, when the isotherm falls behind the contours, the high-altitude trough will tend to deepen; otherwise, when the isotherm is ahead, the trough will weaken (Fischer et al., 2019). The distribution features and interaction of atmospheric and oceanic variables imply a series of potential changes (Guo & Tan, 2018; Kerns & Chen, 2013; Maloney Eric & Hartmann Dennis, 2000; Russell et al., 2013).

Aiming to improve on the previous methods, we combine a simple TC model with deep learning techniques to predict TC intensity change and classify. The proposed method can represent the instantaneous three dimensional characteristics of TCs comprehensively without the selection and complex calculation of various predictors. The quality of the method’s outcomes is assessed by comparing them with other methods. Experimental results show that our method, to a certain extent, simplified the process of problem solving and obtained great effect, which has improved the prediction skills of TC intensity.

2 Data and Methodology

2.1 Reanalysis Data and Best Track Data

In this study, the environmental variables including space atmosphere and sea surface are from European Centre for Medium-Range Weather Forecasts (ECMWF) reanalysis datasets. The spatial resolution is 0.125°×0.125° with a temporal resolution of 6 h. The best track data set of TCs is released by the Shanghai typhoon research institute, China Meteorological Administration (M. Ying et al., 2014), including latitude, longitude and maximum sustained wind speed (MSW) recorded every 6 hours. The data of the western North Pacific for 22 years (1997-2018) was selected in this study. We excluded the samples in the narrow sea area, only kept the samples at a certain distance from land, so as to avoid the disturbance of land on TCs (W. Zhang, Leung, et al., 2013).

2.2 Methodology

To cover the entire height and region of TCs as well as reduce the computational complexity, we select atmospheric levels at 100, 200, 300, 500, 700, 850, 1000Hpa (R. Chen et al., 2019; Kerns & Chen, 2013). The three dimensional space atmosphere variables and two dimensional sea surface variables of TC center ranges in 10°×10° are from the reanalysis data of European Centre for Medium-Range Weather Forecasts. Then we visualized the multiple variables under different isobaric levels (Figure 1) and stacked the images by space order to represent the characteristics of three dimensional space structure of TCs. The sea surface variables were regarded as the lower boundary conditions on TC space. On the basis of TC instantaneous flow field distribution in the process of development, we established the implicit pattern between the environmental field and TC intensity change by extracting the spatial hybrid features. The interaction between tropical cyclones and basic variables leads to various changes in TC intensity, from rapid intensification to rapid weakening (Fischer et al., 2019). Through the circulation and interaction of the high and low space, we hope the deep learning method can capture related patterns by extracting similar features and judge the changes in a certain period of time.

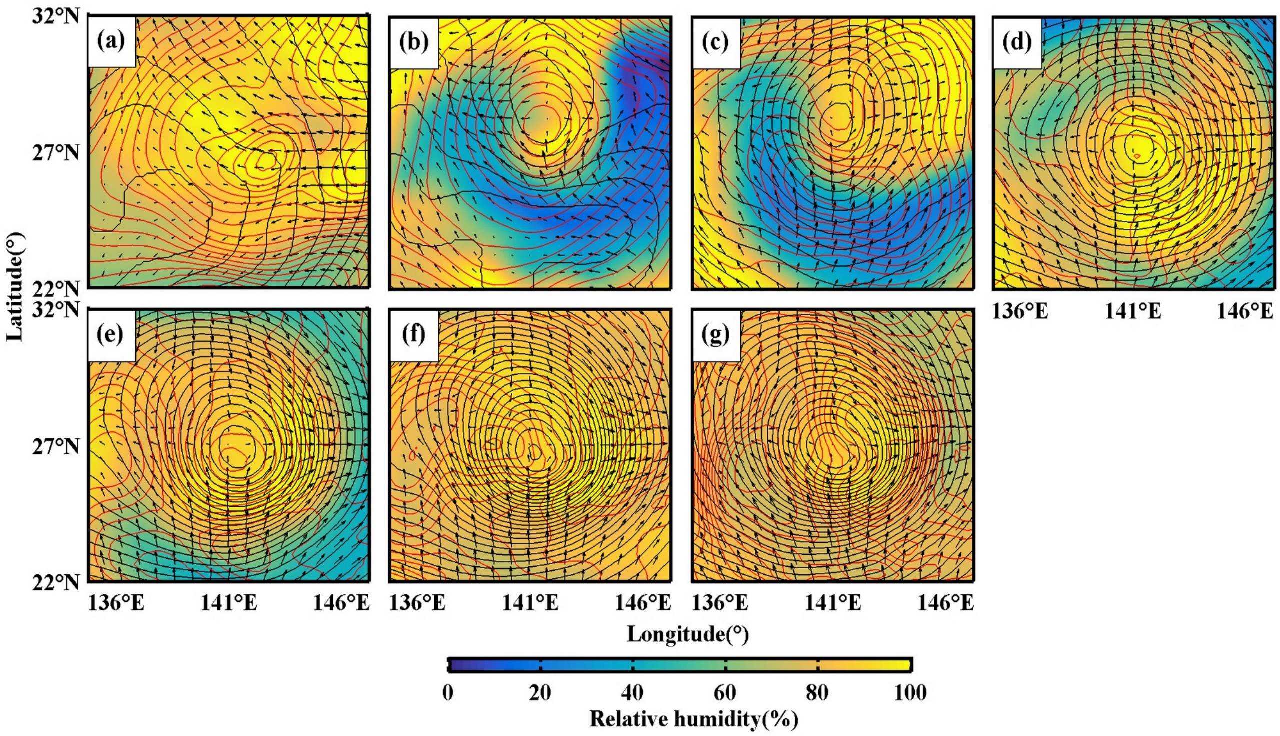

Figure 1. Flow field distribution images of atmospheric elements under each isobaric surface. (a): 100Hpa, (b): 200Hpa, (c): 300Hpa, (d): 500Hpa, (e): 700Hpa, (f): 850Hpa, (g) 1000Hpa. In each image, vector arrows represent wind (length represents size [m/s], arrow represents direction), color represents relative humidity [%], red contours represent temperature [°C], and black contours represent geopotential height [gpm].

2.3 Data Augmentation

In order to meet the demand of deep learning algorithms that need a large number of samples for training, data augmentation technology can help carry out the next research, so we chose some samples for expansion. We added Gaussian noise to each original image in the samples with nonlinear distribution of a mean value $\mu = 0$ and a variance of $\sigma = 0.0096$. Based on the actual noise situation of the complex environment samples, the method of calculating the variance is designed as shown in formula (1):

$$\sigma = \frac{x^2}{m^2} \tag{1}$$

Where m is the maximum value of the image pixel and x is the noise effect that we added in the original image. In this study, we collected a total of 3433 original samples. Each of these samples was made up of 8 images with a pixel resolution of 226 × 226, totaling 27464 images. Among them, 1000 samples were randomly selected and saved as test set. The rest 2433 original samples were extended through data augmentation for model training and validation process. Data augmentation reduces the time to obtain samples manually as well as the probability of network over-fitting under the condition of insufficient training samples.

3 Network design and training

A CNN network consists of several processing layers to extract continuously abstract features of input data, and match these features with the target studied as regression tasks or classification tasks (B.-F. Chen et al., 2019). Each layer is composed of numerous neurons, which calculates the weighted linear combination of inputs and trains the model on the dataset to optimize the model parameters through the nonlinear action of activation function. This paper used ReLUs (Nair & Hinton, 2010) as the nonlinear activation function among layers to study the relationship between the input and output variables, which is very important to effectively reduce the gradient disappear problems of training neural network and is beneficial to gradient descent and error back propagation. The last output layer used tanh as activation function. The effect growing when the features differ significantly in loops. Its output is zero mean distribution and values range from -1 to 1, the relevant formulas are as follows:

$$f(x) = \mathrm{Re}LU(x) = \begin{cases} x & x > 0 \\ 0 & x \le 0 \end{cases} \tag{2}$$

$$f(z) = \tanh(z) = \frac{e^{z} - e^{-z}}{e^{z} + e^{-z}} \tag{3}$$

As shown in Figure 3, our TC-3DCNN model is mainly composed of convolution layers and fully connected (FC) layers. The 3D convolution kernels extract the information of tropical cyclones from a pixel neighborhood of cube space center (Han et al., 2019; L. Ying et al., 2017). Generally, in CNN networks, pooling layers through a certain method filter redundant data to achieve the purpose of reducing computational complexity (Shuiwang et al., 2013; Tran et al., 2014). However, the image characteristics of TCs lead us not to use pooling layer because it degrades the resolution of the detected features and may miss important characteristic of tropical cyclones (B.-F. Chen et al., 2019), such as the contour information. In TC-3DCNN network, we added a dropout layer after the last convolution layer, which is a regularization technique (Srivastava et al., 2014). During the training process, a certain proportion of neurons were randomly selected to be disconnected, and only the information transmitted by the remaining neurons was retained to prevent over-fitting of the model and improve the performance of the model.

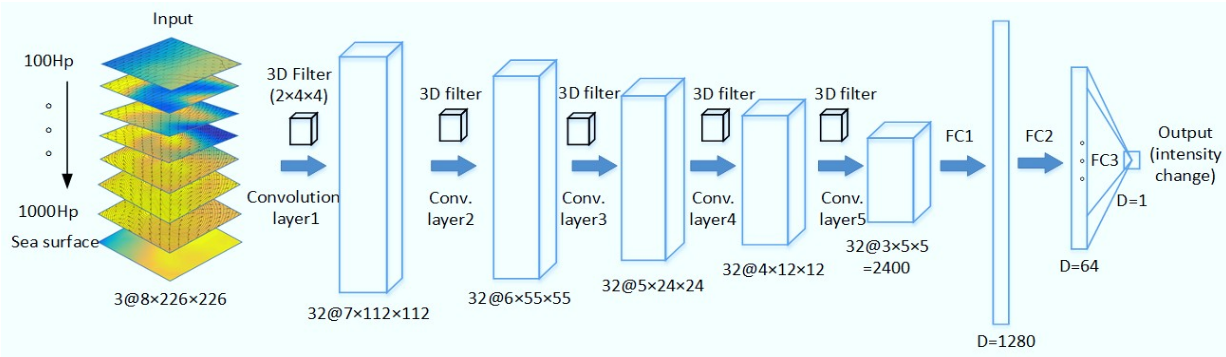

Figure 2. The flow chart and architecture of TC-3DCNN neural network.

In our model, the training starts with the initialization of the weight of the nodes between the layers, and then updates the parameters through gradient descent. By iterating the samples in the training set and minimizing the loss function, the optimal solution is fitted to achieve the optimal performance. After preprocessing, the model had 3 × 8 × 226 × 226 = 1225824 (Figure 2) input values. After five convolution layers, these features are compressed into 2400 core features. Finally, three fully connected layers were applied to convert 2400 features into one predicted TC intensity change. At the end of the learning process, the model calculated the loss function and updated the weight through continuous iteration. For the predicted value, we used the Mean Square Error (MSE) as the loss function and the Mean Absolute Error (MAE) as the evaluation standard.

The optimization function in the model is used to update and calculate the network parameters that affect the model training and model output to approximately reach the optimal value, so as to minimize the loss function. Adam (Adaptive moment estimation) is a commonly used optimization function (Kingma & Ba, 2014), it dynamically adjusts each parameter by using the first-order moment estimation and second-order moment estimation of the gradient, and updates different parameters through migration correction, as described below:

$$m_t = \beta_1 m_{t-1} + (1 - \beta_1)\nabla L \tag{4}$$

$$V_t = \beta_2 V_{t-1} + (1 - \beta_2)\nabla^2 L \tag{5}$$

$$\hat{m}_t = m_t / (1 - \beta_1^t) \tag{6}$$

$$\hat{V}_t = V_t / (1 - \beta_2^t) \tag{7}$$

$$\theta_{t+1} = \theta_t - lr \cdot \hat{m}_t / (\sqrt{\hat{V}_t} + \varepsilon) \tag{8}$$

in the formula, β_1 and β_2 is the exponential decay rate of the estimated moment value, m_t and V_t is the first-order moment and second-order moment variables of time t, and lr is the learning rate. It is assumed that under time t, the first derivative of the objective function of the parameters is ∇L, and equations (4) and (5) are updates to the first order offset moment estimation and second order offset moment estimation of the gradient. The offset term is corrected by formula (6) and (7) according to the gradient, and the parameter update is completed by formula (8). θ_t is the parameter variable of three dimensional convolutional neural network at time t, including the weight and offset.

4 Results

4.1 TC Intensity Change Prediction

Our model was trained on two Titan Xp GPUs of 12 GB memory under Ubuntu 16.04 systems. The latest official released tensorflow-gpu2.0 was adopted as the deep learning framework at the backend of keras to build the 3D convolutional neural network. This framework supported CUDA 10.0 and Opencv 4.3 versions. The entire training process of our model took about 18 minutes, and the test process cost about 5 seconds. Our initial training by setting different batch-size to adjust the number of model iterations under each epoch. Because the 3D data consumes huge memory, the batch-size cannot be too large. However, the loss curves of the model will constantly fluctuate if batch-size is too small, which is difficult to converge. Eventually, we set batch-size to 16, making the model get stable training effect. When learning rate equals 0.0004, our model achieved the best test result 6.5 kt, which is the average value of multiple runs. We ran the program 10 times, each time randomly taking 1000 samples from all the original samples as test set, the remaining samples were extended through data augmentation to retrain the model. The result was also currently the most robust, demonstrating the excellent performance of our model under the parameter conditions.

We compared the result with other methods, these methods included traditional statistical models and the widely used numerical models as well as deep learning models (R. Chen et al., 2019). The averaged intensity errors in past 5 years from China Meteorological Administration (CMA) and National Hurricane center (NHC) reports are used for the comparison. An improved statistical-dynamical method for TC intensity change prediction, which combined statistical methodology with numerical weather prediction system, has also been compared to our model (Lee et al., 2019). The results are shown in Table 1, suggesting that the MAE of our model is better compared with existing models. The MAE of our model is 6.5 kt while the lowest MAE of statistical and numerical models are 10.9 kt and 12.9 kt. Meanwhile, compared with the deep learning model as well as the NGR method, our model got a better MAE value and simplified the experimental process. We achieved good experimental result by considering only the current time of tropical cyclones. The fact proved that our deep learning method successfully captured the implicit pattern between the distribution features of environment variables and TC variation.

Table 1

The MAE values of TC intensity change prediction compared with existing models

Category	Method	MAE1(kt)	MAE2(kt)
Statistical method	PLS	11.5	
	WIPS	10.9	
Numerical method	GFS	12.9	
	GRAPES-TCM	13.7	
Statistical-dynamical method	NGR		11.3
Deep learning method	CNN-LSTM	7.4	
	TC-3DCNN (ours)	6.5	6.3

Note. PLS = Partial Least Square Regression Scheme; WIPS = Western North Pacific Topical Cyclone Intensity Prediction Scheme; GRAPES-TCM = Tropical Cyclone Model based on Global Regional Assimilation Prediction System; GFS = Global Forecast System; NGR = Net

Energy Gain Rate (Lee et al., 2019); CNN-LSTM (R. Chen et al., 2019). MAE1 is calculated by all TCs while MAE2 is only for TCs that had a wind speed at or above 34 kt.

4.2 TC Intensity Change Classification

There would be three categories of samples on the label: positive (indicating intensity increased), negative (indicating intensity decreased) and zero (indicating intensity unchanged). Our model can quickly predict the three categories of samples. The predicted results for the three categories were statistically analyzed, respectively. For the category of prediction, we used Accuracy as evaluation indicator. The formula is as follows:

$$Accuracy = (TP + TN) / (TP + FP + TN + FN) \tag{9}$$

In the formula, TP represents the samples that are actually positive and predicted to be positive, FP represents the samples that are actually negative but predicted to be positive, FN represents the samples that are actually positive and predicted to be negative, and TN represents the samples that are actually negative and predicted to be negative. The classification results are shown in Table 2. For intensity increased ($\Delta V \quad 10$ kt/24 h) and decreased ($\Delta V \leq -10$ kt/24 h), the accuracy predicted is 96.1%. For the criterion of intensifying ($\Delta V \quad 5$ kt/24 h) and weakening ($\Delta V \leq -5$ kt/24 h), the prediction accuracy is 92.0%. For the criterion of intensifying ($\Delta V > 0$ kt/24 h) and nonintensifying ($\Delta V \leq 0$ kt/24 h), the prediction accuracy is 83.1%. Compared with the reference based on the method of decision trees (W. Zhang, Gao, et al., 2013), the results suggest that our deep learning method and the prediction accuracy are better and have more stable performance under different criteria of intensity change classification. It is also shown that our method can effectively extract the change features of TCs in different life stages and improve the classification skills of intensity change.

Table 2

Comparison of accuracy under different classification criterion

Classification criterion	Decision tree	TC-3DCNN (ours)
$\Delta V \quad 10kt / 24\ h$ and $\Delta V \leq -10kt / 24\ h$	90.2%	96.1%
$\Delta V \quad 5kt / 24\ h$ and $\Delta V \leq -5kt / 24\ h$	81.5%	92.0%
$\Delta V > 0kt / 24\ h$ and $\Delta V \leq 0kt / 24\ h$	77.4%	83.1%

4.3 Performance evaluation of data augmentation

In addition to the above results, we also explored the impact of data augmentation on our network performance. Under the condition of the same model architecture and configuration parameters, we randomly selected 1000 original samples as the test set, respectively. The training samples was set to three cases: the original samples for no data augmentation, half of the original samples for data augmentation and all of the samples for data augmentation. The test results of the three cases are shown in Table 3.

Table 3

Performance evaluation with different ratios of data augmentation.

Ratio	MAE(kt)	Accuracy1	Accuracy2	Accuracy3

0.0	7.3	94.1%	89.2%	82.0%
0.5	6.9	95.0%	90.2%	82.4%
1.0	6.5	96.1%	92.0%	83.1%

Note. The accuracy adopts the three classification criterion in table 3.

It can be intuitively seen from the comparison in Table 4 that the network trained by the sample set after data augmentation obtains lower prediction errors and higher classification accuracy, which directly demonstrates the effectiveness and necessity of data augmentation for our model. At the same time, the convergence speed of the model is accelerated and the performance has been improved. The data augmentation technique can be successfully applied to our prediction of TC intensity change.

5 Conclusions and Prospect

In this study we propose that the flow field distribution characteristics and spatial interactions of atmospheric and oceanic elements are valuable prediction indicators of TCs and are correlated with TC intensity change. To explore this idea, we take advantage of the 22 years of environmental variables made available by ECMWF and train deep learning model to predict and classify TC intensity change. The prediction method is solely based on the image patterns of TC environmental variables and does not require any calculation of TC parameters. Compared with the existing methods, our model gets a better MAE value and higher classification accuracy.

We only used the data in the current moment of TCs and simulate TC instantaneous three dimensional state to better represent the spatial mixed features. The implicit patterns between the features and TC intensity change were successfully captured and learned by our model. The other innovation of the proposed method lies in data augmentation based on a small number of TC accurate samples, which enabled us to solve the problem of insufficient deep learning samples. Meanwhile, it better optimizes our model and improves the training efficiency.

The proposed method can be further improved. For example, the fine features associated with TC intensity change and the influence degree of these features are unknown. Besides, the range and height of these features are still worth studying. We believe that addressing these issues will enhance the forecast accuracy. In the future, we can continue to study the issues and extract more fusion features to predict longer time limit and other TC attributes of concern, such as life span. Furthermore, we can apply this method to the study of different sea areas and landfall tropical cyclones, which will be much interesting and significant.

Acknowledgments, Samples, and Data

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References

Chen, B.-F., Chen, B., Lin, H.-T., & Elsberry, R. L. (2019), Estimating Tropical Cyclone Intensity by Satellite Imagery Utilizing Convolutional Neural Networks. *Weather & Forecasting, 34*, 447-465. doi:10.1175/WAF-D-18-0136.1

Chen P, Y. H., Chan JCL. (2011), A Western North Pacific Tropical Cyclone Intensity Prediction Scheme. *Acta Meteorologica Sinica*(5), 611.

Chen, R., Wang, X., Zhang, W., Zhu, X., Li, A., & Yang, C. (2019), A hybrid CNN-LSTM model for typhoon formation forecasting. *GeoInformatica*(3), 375. doi:10.1007/s10707-019-00355-0

Cocks, S. B., & Gray, W. M. (2002), Variability of the Outer Wind Profiles of Western North Pacific Typhoons: Classifications and Techniques for Analysis and Forecasting. *Monthly Weather Review, 130*(8), 1989. doi:10.1175/1520-0493(2002)130<1989:VOTOWP>2.0.CO;2

Fischer, M. S., Tang, B. H., & Corbosiero, K. L. (2019), A Climatological Analysis of Tropical Cyclone Rapid Intensification in Environments of Upper-Tropospheric Troughs. *Monthly Weather Review, 147*(10), 3693-3719. doi:10.1175/MWR-D-19-0013.1

Gao, S., & Chiu, L. S. (2012), Development of Statistical Typhoon Intensity Prediction: Application to Satellite-Observed Surface Evaporation and Rain Rate (STIPER). *Weather & Forecasting, 27*(1), 240-250. doi:10.1175/WAF-D-11-00034.1

Gao, S., Wang, D., Hong, H., Wu, N., & Li, T. (2018), Evaluation of Warm-Core Structure in Reanalysis and Satellite Data Sets Using HS3 Dropsonde Observations: A Case Study of Hurricane Edouard (2014). *JOURNAL OF GEOPHYSICAL RESEARCH-ATMOSPHERES, 123*, 6713-6731. doi:10.1029/2017JD028263

Gao, S., Zhang, W., Liu, J., Lin, I. I., Chiu, L. S., & Cao, K. (2016), Improvements in Typhoon Intensity Change Classification by Incorporating an Ocean Coupling Potential Intensity Index into Decision Trees*,+. *Weather & Forecasting, 31*(1), 95-106. doi:10.1175/WAF-D-15-0062.1

Ge, K., & Colle, B. A. (2019), Multidecadal Historical Trends in Tropical Cyclone Intensity and Evolution Characteristics for Two North Atlantic Subbasins. *JOURNAL OF GEOPHYSICAL RESEARCH-ATMOSPHERES*. doi:10.1029/2019JD030710

Guo, Y.-P., & Tan, Z.-M. (2018), Impacts of the Boreal Spring Indo-Pacific Warm Pool Hadley Circulation on Tropical Cyclone Activity over the Western North Pacific. *Journal of Climate, 31*, 1361-1375. doi:10.1175/JCLI-D-17-0422.1

Han, Y., Gao, Y., Zhang, Y., Wang, J., & Yang, S. (2019), Hyperspectral Sea Ice Image Classification Based on the Spectral-Spatial-Joint Feature with Deep Learning. *Remote Sensing, 11*. doi:10.3390/rs11182170

Ito, K., Kuroda, T., Saito, K., & Wada, A. (2015), Forecasting a Large Number of Tropical Cyclone Intensities around Japan Using a High-Resolution Atmosphere-Ocean Coupled Model. *Weather & Forecasting, 30*(3), 793-808. doi:10.1175/WAF-D-14-00034.1

Jiang, G.-Q., Xu, J., & Wei, J. (2018), A Deep Learning Algorithm of Neural Network for the Parameterization of Typhoon-Ocean Feedback in Typhoon Forecast Models. *Geophysical Research Letters, 45*, 3706-3716. doi:10.1002/2018GL077004

Jinjie, S., Yuan, W., Peiyan, C., & Lianshou, C. (2011), A statistical prediction scheme of tropical cyclone intensity over the western North Pacific based on the partial least square regression. *Acta Meteorologica Sinica*(5), 745.

Kerns, B. W., & Chen, S. S. (2013), Cloud Clusters and Tropical Cyclogenesis: Developing and Nondeveloping Systems and Their Large-Scale Environment. *Monthly Weather Review, 141*(1), 192-210. doi:10.1175/MWR-D-11-00239.1

Kingma, D. P., & Ba, J. (2014), Adam: A Method for Stochastic Optimization. *the 3rd International Conference for Learning Representations*.

Lee, W., Kim, S.-H., Chu, P.-S., Moon, I.-J., & Soloviev, A. V. (2019), An Index to Better Estimate Tropical Cyclone Intensity Change in the Western North Pacific. *Geophysical Research Letters, 46*, 8960-8968. doi:10.1029/2019GL083273

Maloney Eric, D., & Hartmann Dennis, L. (2000), Modulation of Eastern North Pacific Hurricanes by the Madden–Julian Oscillation. *Journal of Climate, 13*(9), 1451.

Nair, V., & Hinton, G. E. (2010). *Rectified linear units improve Restricted Boltzmann machines.* Paper presented at the 27th International Conference on Machine Learning, ICML 2010, June 21, 2010 - June 25, 2010, Haifa, Israel.

Russell, L. E., Lianshou, C., Jim, D., Robert, R., Yuqing, W., & Liguang, W. (2013), Advances in Understanding and Forecasting Rapidly Changing Phenomena in Tropical Cyclones. *Tropical Cyclone Research and Review*(1), 13. doi:10.6057/2013TCRR01.02

Shuiwang, J., Wei, X., Ming, Y., & Kai, Y. (2013), 3D Convolutional Neural Networks for Human Action Recognition. *IEEE Transactions on Pattern Analysis and Machine Intelligence, Pattern Analysis and*

Machine Intelligence, IEEE Transactions on, IEEE Trans. Pattern Anal. Mach. Intell., 35(1), 221-231. doi:10.1109/TPAMI.2012.59

Sitkowski, M., Kossin, J. P., & Rozoff, C. M. (2011), Intensity and Structure Changes during Hurricane Eyewall Replacement Cycles. *Monthly Weather Review, 139*(12), 3829-3847. doi:10.1175/MWR-D-11-00034.1

Srivastava, N., Hinton, G., Krizhevsky, A., Sutskever, I., & Salakhutdinov, R. (2014), Dropout: A Simple Way to Prevent Neural Networks from Overfitting. *Journal of Machine Learning Research, 15*, 1929-1958.

Su, Y., Chelluboina, S., Hahsler, M., & Dunham, M. H. (2010). *A new data mining model for hurricane intensity prediction.* Paper presented at the Proceedings - 10th IEEE International Conference on Data Mining Workshops, ICDMW 2010.

Tran, D., Bourdev, L., Fergus, R., Torresani, L., & Paluri, M. (2014), Learning Spatiotemporal Features with 3D Convolutional Networks. *In Proceedings of the 2015 IEEE International Conference on Computer Vision*.

Wang, Y., & Wu, C. C. (2004), Current understanding of tropical cyclone structure and intensity changes - a review. *Meteorology and Atmospheric Physics, 87*, 257-278. doi:10.1007/s00703-003-0055-6

Xuyang, G., Li, T., & Peng, M. (2013), Effects of vertical shears and midlevel dry air on tropical cyclone developments. *Journal of the Atmospheric Sciences*(12), 3859.

Ying, L., Haokui, Z., & Qiang, S. (2017), Spectral-Spatial Classification of Hyperspectral Imagery with 3D Convolutional Neural Network. *Remote Sensing, 9*(1), 67. doi:10.3390/rs9010067

Ying, M., Zhang, W., Yu, H., Lu, X., Feng, J., Fan, Y., et al. (2014), An Overview of the China Meteorological Administration Tropical Cyclone Database. *Journal of Atmospheric & Oceanic Technology, 31*(2), 287-301. doi:10.1175/JTECH-D-12-00119.1

Zhang, M., Zhou, L., Chen, D., & Wang, C. (2016), A genesis potential index for Western North Pacific tropical cyclones by using oceanic parameters. *Journal of Geophysical Reseach-Oceans, 121*, 7176-7191. doi:10.1002/2016JC011851

Zhang, Q., Wu, L., & Liu, Q. (2009), TROPICAL CYCLONE DAMAGES IN CHINA : 1983–2006. *Bulletin of the American Meteorological Society, 90*(4), 489.

Zhang, W., Gao, S., Chen, B., & Cao, K. (2013), The application of decision tree to intensity change classification of tropical cyclones in western North Pacific. *Geophysical Research Letters, 40*, 1883-1887. doi:10.1002/grl.50280

Zhang, W., Leung, Y., & Wang, Y. (2013), Cluster analysis of post-landfall tracks of landfalling tropical cyclones over China. *Climate Dynamics*(5-6), 1237. doi:10.1007/s00382-012-1519-5