DeepTC: ConvLSTM Network for Trajectory Prediction of Tropical Cyclone using Spatiotemporal Atmospheric Simulation Data

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Abstract

Accurate forecasting of tropical cyclone trajectory is important because it can have a great impact on the safety of people and infrastructure. This paper introduces a novel data-driven tropical cyclone path prediction model called *DeepTC*. The proposed model makes use of data generated using the Weather Research and Forecasting model, which simulates spatiotemporal atmospheric conditions. Additionally, the proposed model utilizes convolutional long short-term memory, which is effective when operating on spatial data over time. Experimental results demonstrate that *DeepTC* reduces prediction error significantly, confirming the effectiveness of the proposed model.

1 Introduction

Tropical cyclones (TCs)—known as *hurricanes* in the Atlantic and Northeast Pacific, *cyclones* in the South Pacific and Indian Ocean, and *typhoons* in the Northwest Pacific—are one of the most severe natural disasters. TCs with wind speeds exceeding 31 m/s at their center lead to tens of thousands of people being evacuated and rescued each year. As a result, the precise prediction of the path of an impending storm would help local authorities in their decision making regarding the time and location of evacuation.

Acknowledging the importance of TC prediction as a critical spatiotemporal domain problem, meteorologists rely on numerical weather prediction (NWP) models such as the Weather Research and Forecasting (WRF) model, Model for Prediction Across Scales (MPAS), and Community Atmosphere Model ver 5.0 (CAM5) to predict wind speeds, temperature, air pressure, and other atmospheric indicators, which help to predict the approach path of a TC over its lifetime.

Extant studies, through the use of modern deep-learning techniques, have recently attempted to predict the trajectory of TCs and detect their centers. Studies using recurrent neural networks (RNNs) (1), genetic algorithms (GAs) (2), artificial neural networks (ANNs) (3) trained with latitude, longitude, wind speed, and pressure, and long short-term memory (LSTM) trained with track data (4) and a theoretical toy model-Lorenz 96 (5) have been introduced. However, these studies are limited in that their results still require verification with a real atmospheric model. There have also been trials for center detection(6) and intensity estimation (7; 8) with CNN using satellite images. (9) attempted to detect the center using re-analysis data after a TC, but this approach is limited as a forecaster because re-analysis data is not available when forecasting. To the best of our knowledge, none of the above-mentioned studies employed a WRF simulation dataset, which is high-level, rich, and realistic spatiotemporal data of atmosphere, available at the time of forecast.

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In this study, we propose *DeepTC*, a model capable of predicting the trajectory of TCs using simulation results generated by the WRF numerical model through use of a recently proposed deep learning technique—ConvLSTM network. The key idea is that, by training the proposed model with five different conditioned simulations generated by WRF and the best track[1] for each TC, we exploit *DeepTC* as an ensemble track forecasting model. Through the above exercise, *DeepTC* can learn unique characteristics of differently conditioned simulations, thereby facilitating the generation of more accurate cyclone-trajectory predictions.

In practice, weather forecasters predict the path of a TC by taking into consideration prediction results of multiple WRF models based on present atmospheric conditions, their own experience, and synoptic situations. In this study, we attempt to use DeepTC in the role of the predictor. Further, the use of the ConvLSTM network assists us in the better capturing of spatio-temporal correlations contained within WRF data.

2 Data

WRF is a mesoscale numerical weather prediction model designed for both atmospheric research and operational forecasting applications (Skamarock, 2008). It predicts the future state of atmospheric conditions, starting from initial data—usually operational global atmospheric data. WRF is mainly used for regional models, which require a boundary condition on the global atmospheric data. Although the interval for updating boundary conditions can be changed, in this study, we update the boundary conditions of global data every six hours. WRF as a regional weather prediction model is computationally efficient and represents mesoscale weather phenomena better than global atmospheric models. Therefore, it has been one of the most popular numerical models among atmospheric scientists since the 2000s.

The WRF simulation performed in this study covered the area of the $7 \times 239 \times 279$ grid we set[2], configured at a horizontal resolution of 30 km and adaptive vertical level up to 50 hPa. Originally, WRF generated data for the area $29 \times 239 \times 279$ grid, but we selected 7 levels (5, 7, 9, 12, 14, 16, 19) in the vertical plane, which is meaningful for TCs with our domain knowledge in order to reduce computational cost. At this resolution, each snapshot of the atmospheric states in the WRF output corresponds to a grid. One simulation produces over 100 variables; however, of these, only 25 variables, deemed to be the most significant for cyclone tracking, were used for the training of our model. These selected variables are listed in Table 1, and some are visualized in Figure 1 with VAPOR (10). We used 12 3-Dimensional (in the vertical and horizontal directions) variables, such as x-wind component (U) and y-wind component (V), and 13 2-Dimensional (in the horizontal direction) variables, such as surface pressure and sea surface temperature. The trajectory data was from the Japan Meteorological Agencyś (JMAś) official best track information, which has a precision of one decimal place.

Table 1: Descriptions of the experimental variables and their spatial

3D Variable	Description	Dimension (height,width,length)	2D Variable	Description	Dimension (width,length)
U	x-wind component		Q2	Vapor mixing ratio at 2 m	
V	y-wind component		T2	Temperature at 2 m	
W	z-wind component		TH2	Potential temperature at 2 m	
PH	Perturbation geopotential		PSFC	Surface temperature	
T	Perturbation potential temperature		U10	U at 10 m	
P	Perturbation pressure		V10	V at 10 m	
QVAPOR	Water vapor mixing ratio	(7,239,279)	SST	Skin sea surface temperature	(239,279)
QCLOUD	Cloud water mixing ratio		TSK	Surface skin temperature	
QRAIN	Rain water mixing ratio		RAINC	Accumulated total cumulus precipitation	
QICE	Ice mixing ratio		RAINNC	Accumulated total grid scale precipitation	
QSNOW	Snow mixing ratio		OLR	TOA outgoing long wave	
QGRAUP	Graupel mixing ratio		LH	Latent heat flux at the surface	
			HFX	Upward heat flux at the surface	

In this study, WRF simulation data were generated for 50 TCs that drifted in close proximity to the Korean peninsula, including Rusa, Maemi, Megi, and Ewiniar. Simulations were performed only for the significant period of each TC (i.e., the period for which the TC was most destructive). For

[1] A subjectively-smoothed representation of a tropical cyclone's location and intensity over its lifetime. (defined by the National Hurricane Center)

[2] Left, Bottom (N $-4^\circ 46.825'$, E $107^\circ 77.4'$); Left, Top (N $46^\circ 52.65'$, E $73^\circ 35.24'$); Right, Bottom (N $-4^\circ 46.825'$, E $164^\circ 22.6'$); Right, Top (N $46^\circ 52.65'$, E $-161^\circ 35.2'$)

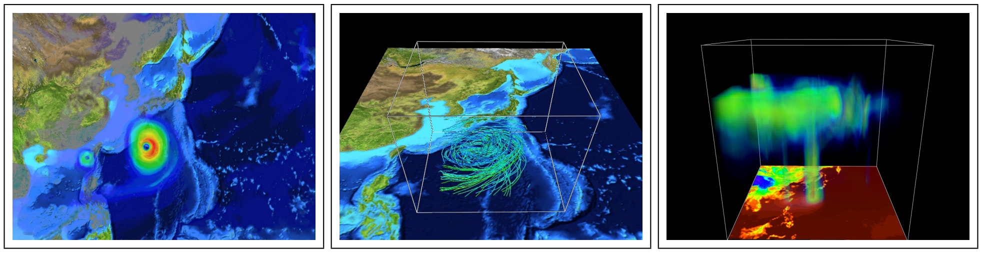

Figure 1: Examples of atmospheric variables by WRF: U,V,W (Wind) (in 2-D), Flow (in 3-D), and Flow+PSFC (in 3-D)

instance, for Rusa, from the total lifetime of the typhoon, simulation data was generated for only 6 days and 6 hours (from 2002.08.26 00:00 h, lat 22.1N long 146.7E to 2002.09.01 00:00 h, lat 38.0N long 128.7E). We started the simulations every six hours, as shown in Figure 2. Specifically, one simulation has five temporal sequences with a six-hour interval between the successive data 24 hours from the start. Subsequently, 25 simulations were performed for Rusa, and the simulations consists of five ensemble runs with five different physics settings for the WRF model (one starts from different initial data, abd the other four follow different physical parameterization schemes), since we intended to build an ensemble-like model that understands the movement of TCs from multiple models. A total of 75 simulations were generated for RUSA, and as a result, 5400 simulations were performed for the 50 TCs. The dataset was then randomly divided into training (60% or approximately 450 GB), validation (20% or approximately 150 GB), and test data (20% or approximately 150 GB).

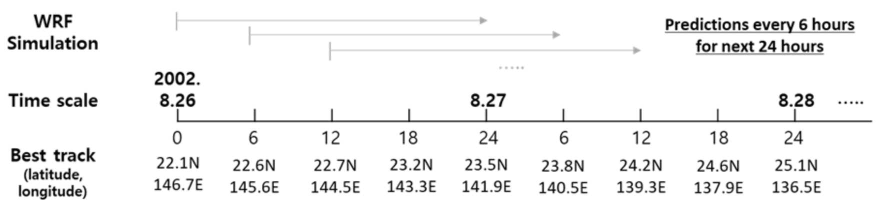

Figure 2: Cyclic simulation for typhoon Rusa

3 Approach & Experiment

The proposed study aims to tackle the problem of reliably predicting the trajectory of a TC using test and training data. To solve this problem, we have used the ConvLSTM network (11), which is known to be effective in operations involving spatial data. It replaces matrix multiplications with convolution operations performed at each gate in the LSTM cell. As a result, it is able to capture underlying spatial features from multi-dimensional data.

The architecture of *DeepTC* utilizing ConvLSTM is presented in Figure 3. The proposed model configuration (many-to-many), thus provides a means of predicting the next sequence of TC positions from the next sequence of simulated atmospheric conditions. The model receives five items of data (X), including 3-D (12 channels) and 2-D (13 channels) variables at regulated time intervals of 6 h. For 3-D data, the Conv3DLSTM cell is invoked to facilitate 3-D convolution, and for 2-D data, the Conv2DLSTM cell is invoked. We used four kernels with 3×3 shape and four kernels with $3 \times 3 \times 3$ shape. Tensors from each cell were flattened, concatenated and fed to a fully-connected (FC) layer. FC layers (24×2) were added to the output of each sequence cell to generate two output values, which represent the expected latitude and longitude. The cost function for the model was set as the root mean squared error (RMSE) of latitude and longitude for each output node.

We trained the model with the Adam optimizer at a learning rate of 0.001. We used random shuffling mini-batches for learning; the mini-batch size was set to 10. The training epoch was 200, and it took approximately 2 h to complete one epoch. The mean absolute error (MAE) was used to measure the prediction accuracy. The testbed environment configuration had dual GPUs (NVIDIA Titan Xp 12 GB) and 128 GB of RAM, and we used TensorFlow 1.8 and Python 3.6.2 for implementation.

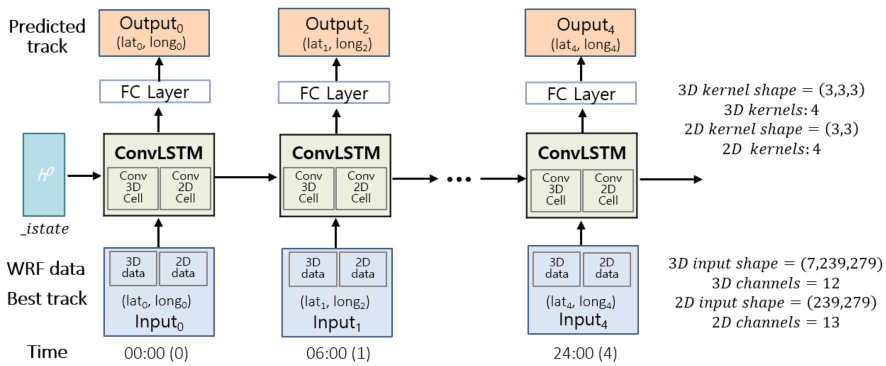

Figure 3: *DeepTC* architecture using ConvLSTM

Figure 3 shows training and validation loss during learning with eight kernels for 200 epochs. In our experiments, we observed that using eight kernels produced stable learning. Therefore, we checked the performance of the test dataset on the model built with the eight kernels. Based on the results(Table 3), MAE of latitude is 1.8 and MAE of longitude is 2.12 with the model built at epoch 200. Average lat and long of all best tracks of our 50 TCs are 25.59 and 130.95. (max lat: 47.9 max long: 174.1, min lat: 10.6, min long: 108.0) At the average point (25.9, 130.95), one degree in lat is 110.78 km and in long is 100.46 km. Thus, the current error around 2 degrees would mean about 200 km (lat 1.8 * 110 km, long 2.12 * 100 km). Furthermore, 6-hour forecast errors are about 176 km in lat and 208 km in long. Note that the center of TC is approximately 30 km and the diameter of middle size TC is around 300∼500 km. Currently, our WRF dataset resolution is 30 km (that means one cell in the data grid is 30 km by 30 km). We expect that the error would decrease if we have a higher resolution of WRF data (e.g., 10 km) with the proposed method. Furthermore, we measured MAE at each time (Figure 3) by calculating the error from each output node. We found that the prediction accuracy decreased with time, as expected.

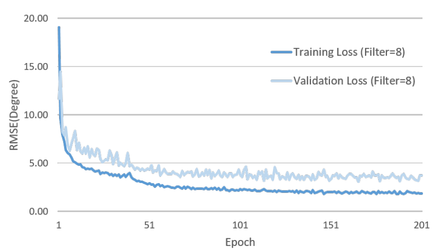

Figure 4: Learning Curve

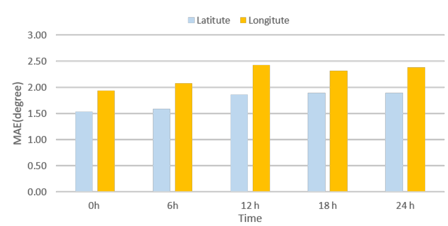

Figure 5: Loss over time with models at each epoch

Table 2: MAE of lat. and long. (in degrees, MAE) with test set and trained model for each condition

Model	Filter	Epoch	Lat.	Long.
DeepTC: ConvLSTM	8	150	2.27	2.52
		200	1.8	2.12

4 Conclusion

In this preliminary study, we applied WRF simulation datasets to ConvLSTM to reliably predict the trajectory of TCs. Experimental results demonstrate that our methodology is promising. The main reason for this is that ConvLSTM can easily learn spatial and temporal representations of the atmosphere simulated by WRF. In future work, we will experiment with a split dataset by TCs instead of dividing the dataset randomly. It is more practical to generate prediction with unseen data from the trained network when we make a forecast with a split dataset. Finally, the authors are working towards synthesizing trajectory prediction results through the use of a model trained by satellite images to enhance overall system performance.

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