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

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 our methodology is promising, confirming that DeepTC learns the spatiotemporal dynamics of the atmosphere by the WRF effectively.

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 use of modern deep-learning techniques, have recently attempted to predict the trajectory as well as detect the center of TC. Studies using RNN [1], GA (genetic algorithm) [2], ANN (Artificial Neural Network) [3] trained with latitude, longitude, wind speed, and pressure, and LSTM with track data [4] with a theoretical toy model-Lorenz 96 [5] have been introduced. However, these studies have a limitation that the results still need to be verified with a real atmospheric model. There also are trials for center detection [6] and intensity estimation [7, 8, 9] with CNN using satellite images. [9] has tried detect center using re-analysis data after TC, but the approach has a drawback 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 WRF simulation dataset, which is one of the high-level, rich, and realistic spatiotemporal data of atmosphere as well as possible data at the time of forecast.

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.

2 Data

WRF is a mesoscale numerical weather prediction model designed for both atmospheric research and
operational forecasting applications \[10 \]. 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, 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 \[11 \]. 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 Agency’s (JMA’s) official best track information, which has a precision of one decimal place.

| Table 1: Descriptions of the experimental variables and their spatial dimension |
|-------------------------------|-----------------|-----------------|-----------------|
| 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                       | SST                           | Skin sea surface temperature |
| QCLD           | Cloud water mixing ratio                       | TSK                           | Surface skin temperature     |
| QRAIN          | Rain water mixing ratio                        | RAINC                         | Accumulated total cumulus precipitation |
| QCIE           | Ice mixing ratio                               | RAINNC                        | Accumulated total grid scale precipitation |
| QSNOW          | Snow mixing ratio                              | GLR                           | TDX 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
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

\[1 \] A subjectively-smoothed representation of a tropical cyclone’s location and intensity over its lifetime. (defined by the National Hurricane Center) The Meteorological Agency of each country is presenting the best track of TC after precise post-analysis after the TC has passed.

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

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 [12], 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 $3 \times 3$ 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 ($24 \times 2$) 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 RMSE 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.

In our experiments, we observed that using too many kernels (e.g., 16 and 32) caused overfitting, and using eight kernels produced stable learning. Then, we checked the performance of the test dataset on the model built with the eight kernels. The result was 3.81 and 2.6 (RMSE, degree) at 150 and 200 epochs, respectively (Table 2). There was a about 49% of error drop compared to models built with two filters on average. For reference, one degree in latitude is approximately 8 km and one degree in longitude is approximately 11 km, and the average diameter of a TC center is known to be approximately 30 km. For further analysis, we measured RMSE at each time (Figure 5) by calculating the error from each output node. We found a tendency that the error increases with time. It seems that WRF simulation errors increased over time and DeepTC learned this simulation data.

<table>
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<th>Model</th>
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Table 2: Prediction error (in degree) with test set with trained model at each condition

4 Conclusion

In the preliminary study, we applied the WRF simulation datasets to ConvLSTM, as we aim to reliably predict the trajectory of TCs. The key contribution of this study is that we have proposed an ensemble model, which utilizes multiple WRF models that are widely used in actual TC path predictions, with a deep learning technique. By utilizing meteorological variables (such as U, V, W, and SST), which are influential on TC path, we have predicted the movement of the TCs. The initial experimental results have demonstrated that our methodology is promising. The main reason for this is the ConvLSTM can easily learn on the spatial and temporal dynamics of the atmosphere simulated by the WRF. In our future endeavors, we will experiment with a dataset by split by TCs. Finally, the authors are working towards synthesizing trajectory prediction results through use of a model trained by satellite images to enhance overall system performance.
References


