Supplementary Material

The supplementary material is constituted of the details of our hyperparameters setting, the details of the data that we used, the extended experiments, and more visualizations of our prediction results.

1 The Setting of hyperparameters

The main hyperparameters in this work include the number of sampling l and the number of generators K. The hyperparameter l is set as 6 so that the MGTCF could give six tendencies as a prediction. It is the same with the prediction of meteorological agencies, which usually provide six possible tendencies of TC when it makes a TC forecast. The K is set as 6. Through the statistics of historical TC data in CMA, we find that there are 6 possible directions of the future trajectory. Besides, the number of possible future trajectory tendencies is more than that of future intensity tendencies. So, we set K as 6 and want these generators can predict suitable tendencies to cover all possibilities.

2 The Details of Data

The main data we used are about three parts: inherent attributes data of TC ($Data_{1d}$), meteorological grid data ($Data_{2d}$), and environment data. We will also upload a representative subset of our data in the **Code & Data Appendix**.

2.1 Inherent Attributes Data of TC

$Data_{1d}$ we used is from the CMA-BST. It covers tropical cyclones that develop over the western North Pacific. We select the data of longitude, latitude, pressure, and wind at the TC's center as the training data to describe the TC. We download CMA-BST at CMA Tropical Cyclone Data Center (CMA 2019). The examples of $Data_{1d}$ are shown in Table 1:

ID	useless	LONG	LAT	PRES	WND	YYYYMMDDHH	Name
0.0	1.0	-0.30	-3.40	0.76	-1.00	1958102006	Kathy
1.0	1.0	-0.60	-3.40	0.70	-0.80	1958102012	Kathy
2.0	1.0	-0.88	-3.48	0.70	-0.80	1958102018	Kathy
3.0	1.0	-1.16	-3.60	0.70	-0.60	1958102100	Kathy
4.0	1.0	-1.44	-3.68	0.44	-0.40	1958102106	Kathy
5.0	1.0	-1.60	-3.56	0.50	-0.40	1958102112	Kathy

Table 1: Examples of $Data_{1d}$. **ID** means the point time of TC, **useless** is not used in our method, **LONG** means the Longitude (0.1°E) of TC, **LAT** means the latitude (0.1°N) of TC, **PRES** denotes the minimum pressure (hPa) near the TC center, and **WND** means the two-minute mean maximum sustained wind (MSW; m/s) near the TC center. **YYYYMMDDHH** is the date and time in UTC of TC, **Name** is the name of the TC

The data in $Data_{1d}$ was normalized by some rules. In column **ID**, 0.0 means that this record was the first record of this TC and the time between 0.0 and 1.0 is 6 h. In column **LONG**, these data are normalized longitude of the TC. The rule of longitude normalization is:

$$LONG_{normalized} = \frac{LONG - 1300}{50} \quad (1)$$

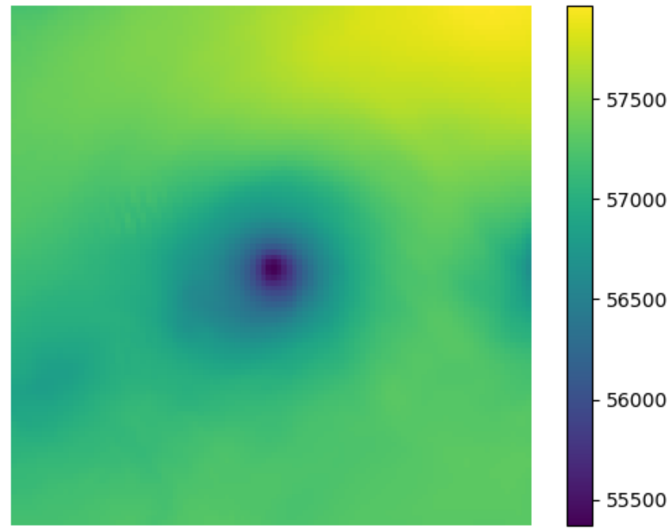

Figure 1: The example of GPH. Generally, the lower the value (geopotential metre(gpm)), the lower the pressure.

LONG is the original Longitude data (0.1°E).

In column **LAT**, these data are normalized latitude of the TC. The rule of latitude normalization is:

$$LAT_{normalized} = \frac{LAT - 300}{50} \quad (2)$$

LAT is the original latitude data (0.1°E).

In column **PRES**, these data are normalized pressure of the TC. The rule of pressure normalization is:

$$PRES_{normalized} = \frac{PRES - 960}{50} \quad (3)$$

PRES is the original pressure data (hPa).

In column **WND**, these data are normalized wind of the TC. The rule of wind normalization is:

$$WND_{normalized} = \frac{WND - 40}{25} \quad (4)$$

WND is the original wind data (m/s).

2.2 Meteorological Grid Data

There are many meteorological grid data of TC, including satellite images, meteorological fields. The $Data_{2d}$ we used is Geopotential Height (GPH). We choose the 500 hPa geopotential height data to describe the pressure structure of TC. The region ($25° \times 25°$) nears the TC center of the GPH is chosen as the training data. The example of GPH is shown in Figure 1.

2.3 Environment Data

To our knowledge, there is no open environment dataset of TC. Thus, we mine some important environment data in the diverse $Data_{1d}$ and $Data_{2d}$ with some meteorologists. The example of environment data is shown in Table 2. As demonstrated in Table 2, the Moving Velocity is a crucial attribute for trajectory prediction. It can help MGTCF

Key	Value
Moving Velocity	0.2003
Month	000000001000
Location Longitude	000010000000
Location Latitude	000100
History Direction (24 h)	00000010
History Intensity Change (24 h)	0010
Subtropical High	GPH

Table 2: The environment data of TC LINGLING at the date 2019/09/06 18:00.

to estimate how far the TC will move in the future. The value of Moving Velocity **0.2003** is a normalized number. The Month contains the season information of TC, and the TC developed over the western North Pacific has different rules of development in different seasons. Thus, Month is also important environment data. The value of the Month is a one-hot code with a length of 12. We divide the 12 months into 12 categories. The **000000001000** means that the month of TC is September because the ninth position of the Month one-hot code is 1. In addition, the tendencies of TC over land or sea also are different. The location of TC is a critical attribute as it can tell us whether a typhoon is over sea or land. The values of Location Longitude and Location Latitude are also one-hot codes. We divide the area ($0°N - 60°N, 80°E - 160°W$) into a 6×10 grid. The Location Latitude **000100** and Location Longitude **000010000000** mean that TC is over the region from $30°N - 40°N$ and $120°E - 130°E$. The history data of TC also contain useful information. We divide the directions of trajectory into 8 categories, including east, southeast, south, southwest, west, northwest, north, and northeast. What is more, the change tendencies of intensity are divided into 4 categories, including strengthening, strengthening and then weakening, weakening, and keeping the same. The values of the history data are one-hot codes. The History Direction (24 h) **00000010** means the direction of moving during the last 24 h is north and the History Intensity Change (24 h) **0010** means the intensity of TC during the last 24 h is weakening. Otherwise, we also extract more environment information from $Data_{2d}$. The TC developed in the western North Pacific usually moves along the edge of subtropical high. GPH contains the location and scope information of subtropical high. Thus, we add GPH to our environment data. Although these data cannot fully represent the environment factors of TC, it is still an interesting attempt to build an environment factors dataset of TC. We will also continue to refine this dataset and collect more useful data.

3 Extended Experiments

3.1 Comparison Experiment in 2014-2017

Combining deep learning and TC prediction is a novel and potential interdiscipline. There are a few open-source projects for TC prediction. We cannot find many suitable methods to make a comparison. Recently, we find a very suitable comparison method DBF-Net (Liu et al. 2022), a method experimented on the same data CMA-BST with us. It also uses the data of the CMA-BST and GPH to make a prediction and obtains great results. However, DBF-Net is experimented from the year 2014 to 2017 while our method MGTCF is experimented from the year 2017 to 2019. Thus, we cannot directly compare the results of MGTCF with that of DBF-Net. We want to get the results of DBF-Net from the year 2017 to 2019, but the code is not open momentarily. It takes time to reproduce the DBF-Net and we do not have enough time. So, we train and verify MGTCF on the data from the year 1950 to 2013 and obtain the test results from the year 2014 to 2017. The comparison experiment is shown in Table 3. We will open our code.

Methods	Distance (km)			
	6 h	12 h	18 h	24 h
extrapolation	33.78	79.20	135.48	201.28
CLIPER-BP	37.53	73.31	115.13	162.62
FFN	32.90	-	-	136.10
BiGRU-att	-	-	-	147.38
DBF-Net	31.30	58.94	87.60	119.05
MGTCF	**23.55**	**43.16**	**64.43**	**90.79**

Table 3: Comparisons of average absolute error of TC trajectory prediction of different methods from the year 2014 to 2017.

As shown in Table 3, we only compare MGTCF with DBF-Net in trajectory prediction as DBF-Net only takes the trajectory prediction of TC. MGTCF outperforms DBF-Net, because of the design for receiving heterogeneous meteorological data, the Multi-Generators with GC-Net, and the Env-Net. Our method also gets better results than the methods listed in the paper of DBF-Net. Otherwise, compared with the results from the year 2017 to 2019, MGTCF also gets good results from the year 2014 to 2017. It means MGTCF can adapt to different environment in different years.

4 More Visualizations

To show the performance of MGTCF intuitively, we visualize more examples in Figure 2 and upload the video version in the **Multimedia Appendix**.

References

CMA. 2019. CMA Tropical Cyclone Best Track Dataset. https://tcdata.typhoon.org.cn/en/zjljsjj_sm.html. Accessed: 2012.

ECMWF. 2022. the Fifth-Generation Atmospheric Reanalysis of the Global Climate (ERA5). https://tcdata.typhoon.org.cn/en/zjljsjj_sm.html.

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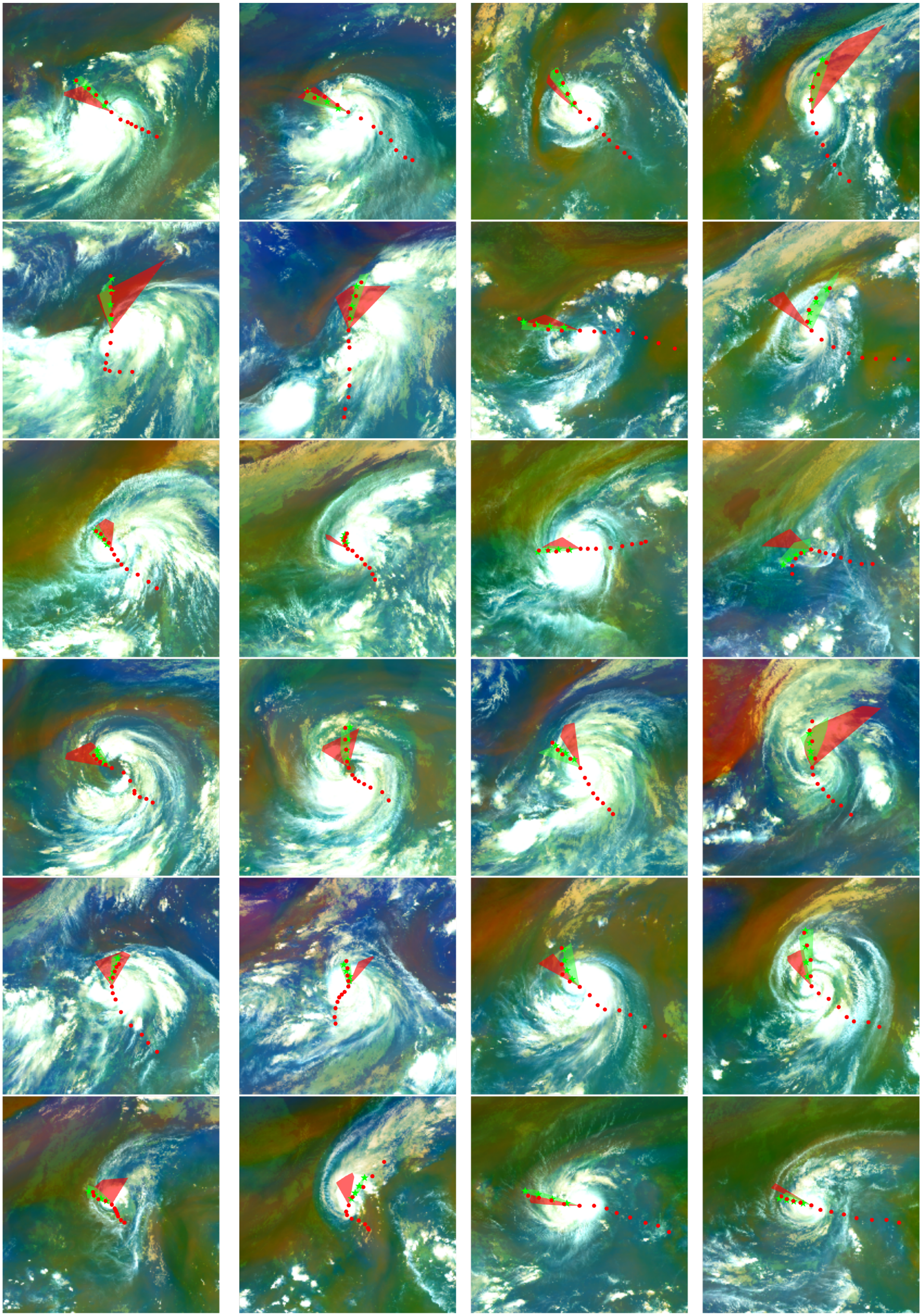

Figure 2: Examples of trajectory predictions from 6 h to 24 h and the comparison between our method and MMSTN on the potential region predictions.