

Prediction of Tropical Storms Using Self-organizing Incremental Neural Networks and Error Evaluation

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Abstract. In this paper, we propose a route prediction method that uses a self-organizing incremental neural network (SOINN). For the training and testing of the neural network, only the latitude and longitude of the tropical storm and atmospheric information around East Asia are required. Our proposed method can predict the movement of a tropical storm with only a short calculation time, and the prediction accuracy is close to the accuracy of the Japan Meteorological Agency. This paper describes the algorithm used for the neural network training, the process for handling the data sets and the method used to predict the storm trajectory. Additionally, experimental results that indicate the performance of our method are presented in the results section.

Keywords: Self-organizing incremental neural network · Meteorology · Natural disaster · Tropical storm

1 Introduction

Currently, natural disasters are being researched in a variety of ways. For example, there have been several investigations into the political [1], economic [2], and statistical aspects of natural disasters [3]. Since natural disasters have a large impact on society, many researchers have made substantial efforts to mitigate the damage that can arise from them. There are many phenomena that are classified as natural disasters such as floods, droughts, and earthquakes. In this paper, we only focus on tropical storms, particularly typhoons.

As technology has developed over the years, tropical storms have been analyzed in many ways including satellite imaging and weather radar [4]. Additionally, the prediction of the movement of tropical storms has also been previously considered [5, 6]. Since analyzing weather information is a big data problem, modern methods of weather prediction or simulation take a significant amount of time even if the calculations are done by a super computer.

To address this issue, we propose a novel method that uses a self-organizing incremental neural network (SOINN) that is trained on big data (i.e., the meteorological information). Since SOINN demonstrates good performance with respect to calculation times, the predicted route of a tropical storm can be calculated quickly. Moreover,

accuracy is very important to evaluate the target; therefore, we will also calculate the accuracy of the predicted route. Finally, simulated tropical storms will be presented. Throughout this paper, we use an Intel® Core™ i7 CPU 870 2.93 GHz with 16.0 GB RAM, and the results are calculated using MATLAB.

2 Training Procedure

2.1 Self-organizing Incremental Neural Network

A SOINN, which was originally proposed by Shen and Hasegawa [7], can be trained without initializing the number of nodes and locations. SOINNs have also previously been reported to display robust performances when handling noisy datasets. Figure 1 depicts the SOINN algorithm [8] that is used in this paper. By applying SOINN, it becomes possible to handle the problem even if there is only few data for training. We have a limitation of data, than, SOINN was decided to adapting for prediction model.

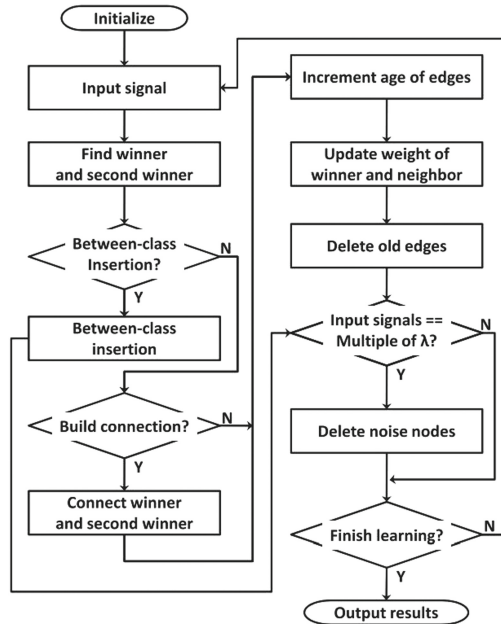


Fig. 1. Algorithm of SOINN

In this paper, we set $\lambda = 1000$, $age_{max} = 5000$. In SOINN, the nodes deleted if it doesn't updated until age_{max} . It was reported that if λ is low, SOINN becomes strong at noise and hard to make cluster, and if λ is high, it becomes weak at noise and easy to make cluster. We hope that data don't disappear by age_{max} and become easier to make cluster, the value of λ and age_{max} are considered.

2.2 Tropical Storms

Several names can be used to describe tropical storms, such as typhoons, cyclones, and hurricanes. The name that is applied to a tropical storm in question is selected based on where the storm is occurring. For example, if the storm occurs in the Atlantic or Northeast Pacific, the term “hurricane” is used. If the storm occurs in the Northwest Pacific, it is called a “typhoon”. Lastly, the term “cyclone” is used if the storm occurs in the South Pacific or the Indian Ocean [9].

In this paper, we only consider data from typhoons, and the data for these typhoons are presented in Table 1. The location of the typhoon, starting from when it was born and ending when it disappeared and measured in 3-hour intervals, was acquired from the Japan Meteorological Agency (JMA) [10].

Table 1. Classification of typhoon used in learning (T1511 means 11th typhoon which came in 2015)

Classification	Numbering of typhoon
Landing to Japan	T1511, T1512, T1515, T1518, T1607, T1609, T1610, T1611, T1612, T1616
Approach to Japan	T1506, T1507, T1509, T1513, T1514, T1516, T1517, T1520, T1521, T1526, T1601, T1606, T1613
No affect to Japan	T1519, T1523, T1524, T1525, T1527, T1602, T1603, T1604, T1605, T1608, T1614, T1615

2.3 Atmosphere

Atmospheric conditions are also considered when training the SOINN on typhoon data. For atmospheric analysis, we set the longitude to the x-axis and the latitude to y-axis. We only considered the longitudinal range of 115–155 and the latitudinal range of 20–50 in this paper. We divided the longitude into 4 parts and the latitude into 3 parts, which divides the data area into 12 parts. We then evaluated each area’s atmosphere based on the following scheme:

- (1) If high pressure dominates in that area, the area is given a value of 1.
- (2) If low pressure dominates in that area, the area is given a value of 0.
- (3) If neither high nor low pressure is dominant in that area, the area is given a value of 0.5.

In this study, digitalizing process divided the study area in 12 parts. It ignores specific distribution, then, the error derived by this ignorance would be appeared. It is needed to consider the division which helps to reinforce the performance.

The atmospheric data was acquired from the Japan Weather Association [11] (Fig. 2).

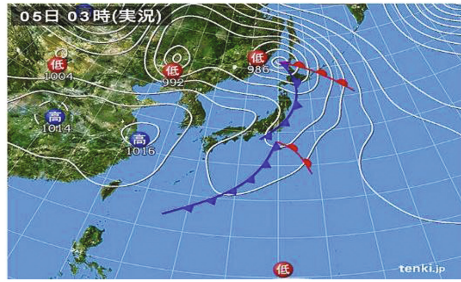


Fig. 2. Atmosphere map in 2015/05/05 3:00 Am, East Asia.

0	0.5	0	0.5
1	0.5	0.5	0.5
0.5	0.5	0.5	0.5

Fig. 3. Example of evaluating Fig. 2.

3 Experiment

To verify the effectiveness of the proposed route prediction method, we used the 5 typhoons listed in Table 2. We used all of the landing typhoons that occurred in 2015 and 2016 to train the SOINN. Thus, we selected typhoons T1408 and T1419, which occurred in the desired time interval. For the approaching typhoons, T1617 was selected because it is the most recent data point for the approaching category. Although T1618 is technically the most recent approaching typhoon, its route is similar to those of T1408 and T1419, and therefore we elected to use T1617 and not T1618. Most of the typhoons that fall into the “no effect” category disappeared very quickly. However, T1504 and T1626 occurred in the desired time interval and existed for more than one week. Therefore, they were selected for analysis.

Table 2. Classification of typhoon used for test. (T1408 means 8th typhoon which came in 2014)

Classification	Numbering of typhoon
Landing to Japan	T1408, T1419
Approach to Japan	T1617
No affect to Japan	T1504, T1626

When we use the typhoon’s location data for learning and testing, the following normalization is applied. $T_{Latitude}$ denotes the latitude value of typhoon and

MAX (T_{La_all}) denotes the maximum value in all $T_{Latitude}$. $T_{Longitude}$ denotes the longitude value of typhoon and MIN(T_{Lo_all}) denotes the minimum value in all $T_{Longitude}$.

$$T_{NormalizedLatitude} = (T_{Latitude} - MIN(T_{La_all})) / (MAX(T_{La_all}) - MIN(T_{La_all})) \quad (1)$$

$$T_{NormalizedLongitude} = (T_{Longitude} - MIN(T_{Lo_all})) / (MAX(T_{Lo_all}) - MIN(T_{Lo_all})) \quad (2)$$

3.1 Prediction Method

To predict the route of the typhoon, the following algorithm is used.

Algorithm 1. Method of predicting route

- (1) **Parameters** : \vec{x}_n : vector of location in time n, \vec{x}_m^* : vector of predicted location in time m, N : set of neurons.
- (2) In time t, combine four vectors $\vec{x}_t, \vec{x}_{t+1}, \vec{x}_{t+2}, \vec{x}_{t+3}$ in one vector \vec{X}_T
- (3) For every typhoons, in whole time T, create data set \vec{X}_T
- (4) Get N from SOINN learned by \vec{X}_T
- (5) In time c, Find the min Euclid-distance between $(\vec{x}_c, \vec{x}_{c+1}, \vec{x}_{c+2})$ and N.
- (6) Define the nearest neuron between $(\vec{x}_c, \vec{x}_{c+1}, \vec{x}_{c+2})$ and N is \vec{N}_c
- (7) Assuming that $\vec{x}_{c+3}^* = \vec{N}_{c+3} - \vec{N}_{c+2} + \vec{x}_{c+2}$.
- (8) Includes \vec{x}_{c+3}^* to \vec{X}_T
- (9) Get N from SOINN learned by new \vec{X}_T

By repeating Algorithm 1 N times, we can predict the location of the typhoon after 3 N hours.

3.2 Location Adjustment

Because only 35 typhoons are used for training the algorithm, the amount of data is not enough. Therefore, we applied the Algorithm 2 after the Algorithm 1 before repeating.

Algorithm 2. Location adjustment

- (1) **Parameters** : \vec{x}_n : vector of location in time n, \vec{x}_m^* : vector of predicted location in time m, N : set of neurons, \vec{N}_c : the nearest neuron between $(\vec{x}_c, \vec{x}_{c+1}, \vec{x}_{c+2})$ and N, r1 : coefficient of long-side, r2 : coefficient of short side.
- (2) if $|\vec{N}_{n+3} - \vec{N}_{n+2}| > r1 \times \text{average}(|\vec{x}_{n+2} - \vec{x}_{n+1}| + |\vec{x}_{n+1} - \vec{x}_n|)$ then
- (3) $\vec{x}_{n+3}^* = (\vec{x}_{n+2} - \vec{x}_n) / 2 + \vec{x}_{n+2}$
- (4) else
- (5) if $|\vec{N}_{n+3} - \vec{N}_{n+2}| < r2 \times \text{average}(|\vec{x}_{n+2} - \vec{x}_{n+1}| + |\vec{x}_{n+1} - \vec{x}_n|)$ then
- (6) $\vec{x}_{n+3}^* = (\vec{x}_{n+2} - \vec{x}_n) / 2 + \vec{x}_{n+2}$
- (7) end if

If the predicted location is evaluated too far by step (2) in Algorithm 2, $\overrightarrow{x_{n+3}^*}$ will be changed to follow their original movement. A similar thing happens when predicted location is evaluated too close. In this report, we set $r1 = 1.5$ and $r2 = 0.8$.

3.3 Result

By using Algorithms 1 and 2, we predicted the route of 5 typhoons for testing the performance. From the JMA homepage, we can check the average error for predicting 24 and 48 h ahead [12]. We also estimated the error for the 24- and 48-hour predictions from our algorithm. During this time, we predicted the movement of the storm until it changed to an extratropical low. The following table presents the average distance between the real storm location and the predicted location. According to Table 3, the error of prediction in landing typhoon is bigger than other error. One of the main reason is shortage of data in landing type. We expect that result might be improved with more data.

Table 3. Average error of location of proposed method

Typhoon number	24 h prediction	48 h prediction
T1408	163.5 km	383.0 km
T1419	120.8 km	257.9 km
T1504	55.9 km	89.0 km
T1617	85.3 km	221.2 km
T1626	102.1 km	278.7 km
Total average	105.5 km	250.0 km

We also present the average error for different years from the JMA. The JMA uses two super computers-a FUJITSU PRIMEHPC FX100 and a FUJITSU PRIMERGY CX2550M1-and professional datasets that are not available to the public for calculations [13] (Table 4).

The total average error of our predictions is 105.5 km for 24 h and 250.0 km for 48 h. The SOINN takes only 0.663 s to be trained on the dataset. The specific calculation times are shown in Table 5.

Figures 4, 5, 6, 7, 8, 9, 10 and 11 present the actual and predicted movement of the storm. The cross points in Figs. 7, 8, 9, 10 and 11 indicate the real location of the typhoon. The lines that originate from each cross point indicate the predicted route at that point. Due to space limitations, we only present the actual and predicted routes for T1408 at full size. The remaining figures are presented in a smaller size.

Table 4. Average error of location by Japan Meteorological Agency

Year	24 h prediction	48 h prediction
2016	79 km	142 km
2015	72 km	119 km
2014	101 km	177 km

Table 5. Calculation time for prediction

	Used time
Learning from original data set	0.663 s
T1408	15.190 s
T1419	15.510 s
T1504	12.591 s
T1617	10.945 s
T1626	10.991 s

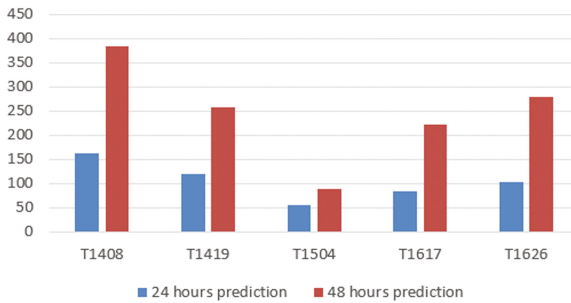


Fig. 4. Average error of location by our method

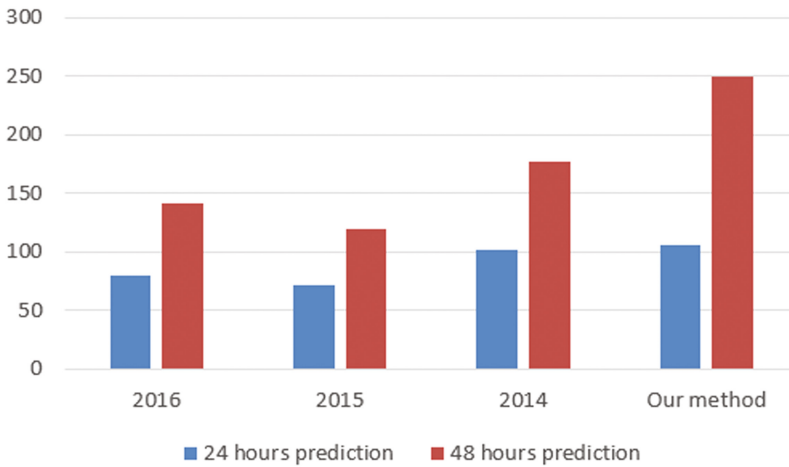


Fig. 5. Comparing error of ours with error of Japan Meteorological Agency

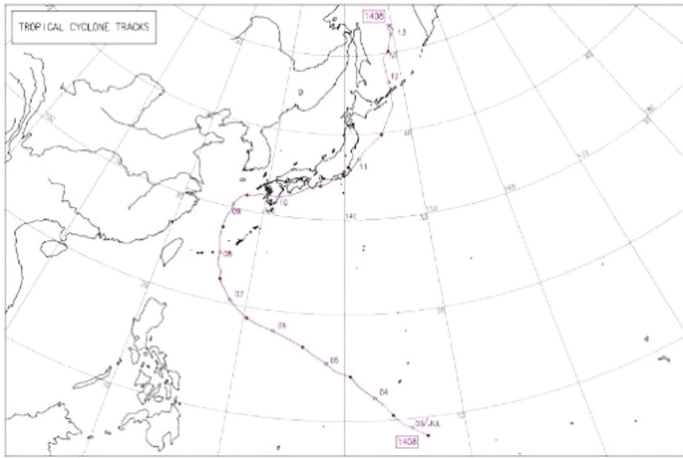


Fig. 6. Route of T1408

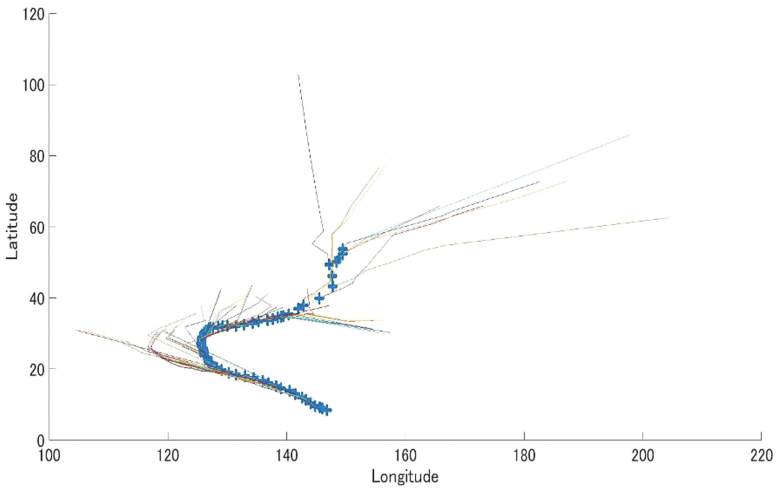


Fig. 7. Predicted route of T1408

In Figs. 7, 8, 9, 10 and 11, lines indicate the predicted movement four days into the future from each point. However, we did not calculate the error in the distance prediction two days into the future.

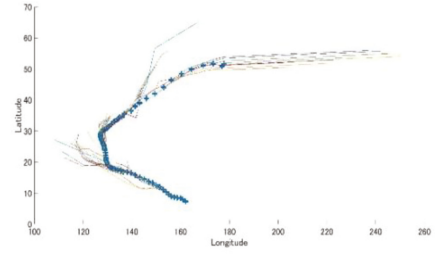
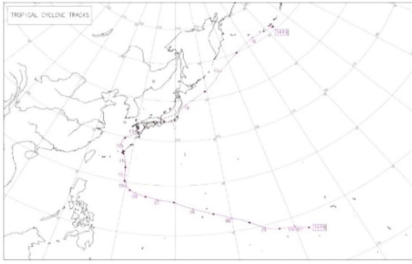


Fig. 8. Route of T1419 in left and predicted route of T1419 in right

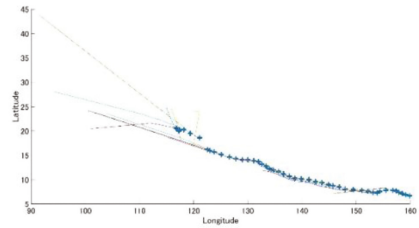
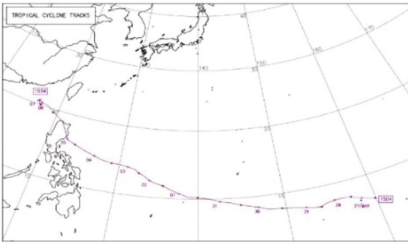


Fig. 9. Route of T1504 in left and predicted route of T1504 in right

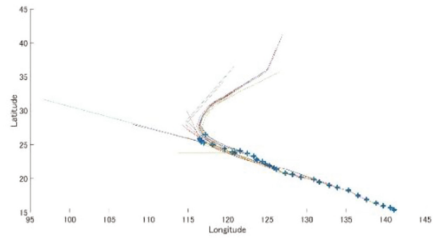
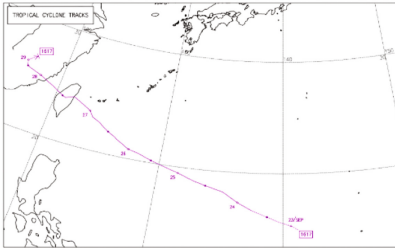


Fig. 10. Route of T1617 in left and predicted route of T1617 in right

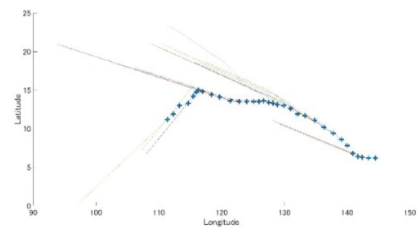


Fig. 11. Route of T1626 in left and predicted route of T1626 in right

4 Conclusion

In this paper, we used SOINN to predict the routes of tropical storms. Our proposed method shows a close accuracy to the JMA predictions, even though our method takes only a few seconds for the calculations. Furthermore, we only used open tropical storm data from 2015 and 2016. Though we used only open data that we refined slightly, our method indicates a high accuracy and fast calculation speed. This results based on one of the characteristic of SOINN: online learning. There is substantial potential for improvement if larger, more specific meteorological datasets are used. We, therefore, conclude that our method is effective and performs well in predicting the routes of tropical storms.

References

1. Fair, C.C., Kuhn, P.M., Malhotra, N., Shapiro, J.N.: Natural disasters and political engagement: evidence from the 2010-11 Pakistani Floods. *Q. J. Political Sci.* **12**(1), 99–141 (2017)
2. Toya, H., Skidmore, M.: Economic development and the impacts of natural disasters. *Econ. Lett.* **94**(1), 20–25 (2007)
3. Guha-Sapir, D., Vos, F., Below, R., Ponserre, S.: Annual disaster statistical review 2011: the number and trends. Centre for Research on the Epidemiology of Disasters (CREED) (2012)
4. Jochen, Z., Andreas, N.: *Early Warning Systems for Natural Disaster Reduction*, 1st edn. Springer, Heidelberg (2003)
5. Lin, T.C., Hamburg, S.P., Lin, K.C., Wang, L.J., Chang, C.T., Hsia, Y.J., Vadeboncoeur, M. A., McMullen, C.M., Liu, C.-P.: Typhoon disturbance and forest dynamics: lessons from a northwest Pacific subtropical forest. *Ecosystems* **14**(1), 127–143 (2011)
6. Bellingham, P.J., Takashi, K., Shin-ichiro, A.: The effects of a typhoon on Japanese warm temperate rainforests. *Ecol. Res.* **11**(3), 229–247 (1996)
7. Shen, F., Hasegawa, O.: An incremental network for on-line unsupervised classification and topology learning. *Neural Netw.* **19**(1), 90–106 (2006)
8. Yamasaki, K., Makibuchi, N., Shen, F., Hasegawa, O.: Self-organizing incremental neural Network-SOINN- and its usage. *Brain Neural Netw.* **17**(4), 187–196 (2010)
9. National Ocean Service Homepage. <http://oceanservice.noaa.gov/facts/cyclone.html>
10. Japan Meteorological Agency Homepage. http://www.data.jma.go.jp/fcd/yoho/typhoon/route_map/index.html
11. Japan Weather Association's information Homepage. <http://www.tenki.jp/guide/chart/>
12. Japan Meteorological Agency Homepage, Average error of the year. http://www.data.jma.go.jp/fcd/yoho/typ_kensho/table.html
13. Japan Meteorological Agency Homepage, Facility introduction. <http://www.mri-jma.go.jp/Facility/supercomputer.html>