Automatic detection of hock echo by using deep learning

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SUMMARY:
The tornadoes frequently occur in Japan as well as United States. Many tornadoes in Japan are generated in the sea, then landfall and caused severe damages to houses, plants and even peoples. For the mitigation of such disaster, we need early information system with weather radar. Parent clouds of tornadoes are usually detected as the vortex signal, i.e., the couplet of maximum and minimum peaks of Doppler velocity in Doppler radar observations. Doppler velocity data, are however largely biased by environmental wind velocity and complex pre-processing is needed. The present study aims to examine the automatic detection of parent clouds of tornadoes based on the hock echo pattern in reflectivity data. We employed SSD as deep learning algorithm. The results show that the hock echo patterns are almost accurately detected at less than 0.6 sec except low resolution full observation range data. The recall and precision are about 0.8 and 0.9, respectively.

Keywords: tornado, Doppler radar, hock echo, deep learning

1. INTRODUCTION

The tornado disasters are relatively frequent events in Japan. Especially, the mid shoreline of Tosa Bay is hot spot of tornadoes. The frequency is 32 per year per 10000 km^2, which is one order larger than the value for the Tornado alley in United States (Sassa et al. 2011). Then, we constructed the radar network composed of 6 X-band polarimetric radars around Tosa Bay and made PPI observation at 5 elevation angles every 1 minute. We observed 26 parent convective systems of tornado for 8 years from 2014 (Fujii and Sassa 2022). Most of them were born in Tosa Bay and approach inland and caused tornado damage. If the early information of tornado approaching is issued based on radar data, we can mitigate tornado disaster. For this purpose, we need automatic detection system for tornado vortices. Usually, the vortex in cloud is found based on the couplet signal of maximum and minimum Doppler velocities. The Doppler velocity signal is however biased by the environmental wind velocity. Especially, the bias is very large when the parent convective system moves fast. This fact means that the couplet signal varied largely depending on the environmental wind velocity even for the vortex having same rotating velocity. This is serious problem for the deep learning algorithm detecting distinctive pattern form figures.

Figure 1 shows typical figure of radar reflectivity and Doppler velocity. The couplet of Doppler velocity added the velocity of approaching to the radar is clearly observed as shown in red circle. The colour showing the vortex changes with the location from the radar. We need additional pre-processing which eliminates the bias data due to environmental wind, in order to detect the couplet signal. On the other hand, the reflectivity keeps almost same level regardless the movement of the parent cloud. The hock echo pattern is also clearly observed in the reflectivity in Fig. 1, though the system is small isolated non-supercell thunderstorm. It does not have mesocyclone. The hock echo shows the rotating motion around the tornado vortex. Such hock echo patterns frequently appear even in the non-supercell. The present study aims to examine the possibility of detection of tornadoes by using deep learning with reflectivity data. The preprocessing of figure is not needed for the reflectivity data.

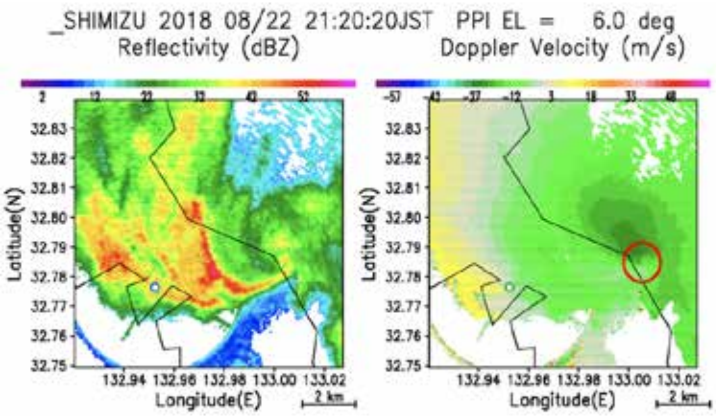

Figure 1. Example of radar reflectivity and Doppler velocity data of parent thunderstorm of tornado. Red circle denotes the couplet of maximum and minimum Doppler velocity.

2. DETECTION METHOD AND ANALYZED DATA

We employed SSD (Single Shot multibox Detector) developed by Wei et al. (2016) as deep learning algorithm. SSD is one of the object detector using CNN (Convolutional Neural Network). Its strong point is that its tunning is easy. SSD was run on the open source library, Pytorch, in the PC with GPGPU. The reflectivity data listed in Table 1 observed at lowest elevation angle every one minute are used for learning. The rotated figures at 45 deg. to 315 deg. at interval of 45 deg. are added to increase data and totally 2336 figures are used for learning. The learning of 2000 in times spent 65 hours. The events for detection were listed in Table 2. All events are same with those for learning, but the data at different elevation angle or different time were used. Figure 2 shows the example of annotation data. Original reflectivity is the lefthand side figure. In this figure, the lines showing shoreline and no echo region are recognized as strong noise. Then, white area and lines are converted to weak echo level and the hock echo pattern was intensified as shown in the right figure.

Table 1. The events for learning

date	Parent convective system
December 22, 2016	Isolated thunderstorm
July 3, 2018	Isolated thunderstorm
July 22, 2018	Isolated thunderstorm
August 16, 2018	Squall line
September 30, 2018	Super cell

Table 2. The events for detection

date	Parent convective system
December 22, 2016	Isolated thunderstorm
July 3, 2018	Isolated thunderstorm
July 22, 2018	Isolated thunderstorm
September 30, 2018	Super cell

3. RESULTS AND DISCUSSION

The detection time is only 0.6 sec. The fact shows that the detection can be made in quasi-real time. The typical result is shown in Fig. 3. In this case, the system type is supercell and the hock echo shows that the existence of mesocyclone. But the detection is failed in some case. Such example is shown in Fig. 4. In this case, rounded echo pattern outside of hock echo is also detected.

Then, we evaluated recall and precision shown as following equations,

$$\text{Recall}=TP/(TP+FN), \qquad \text{Precision}=TP/(TP+FP)$$

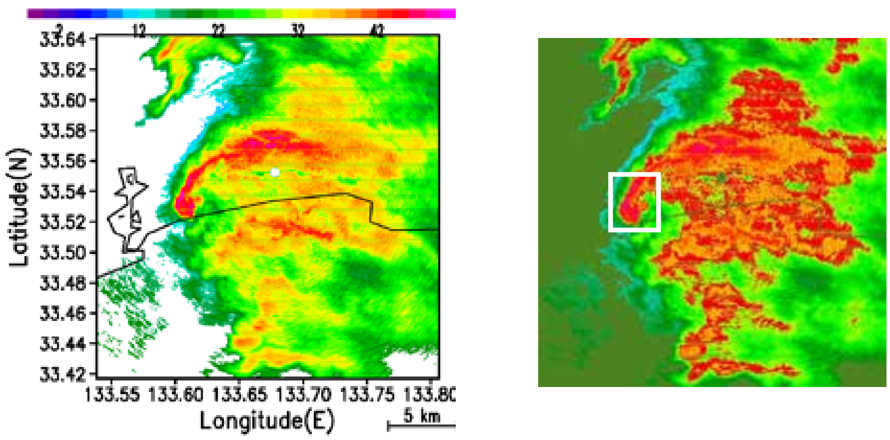

Figure 2. Pre-processed annotation data, the left: original reflectivity data, the right: filtered figure. The white rectangle shows the annotation area including hock echo pattern.

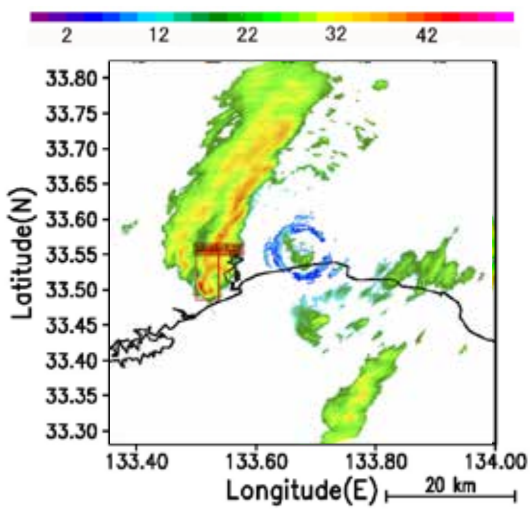

Figure 3. Example of successfully detected hock echo pattern

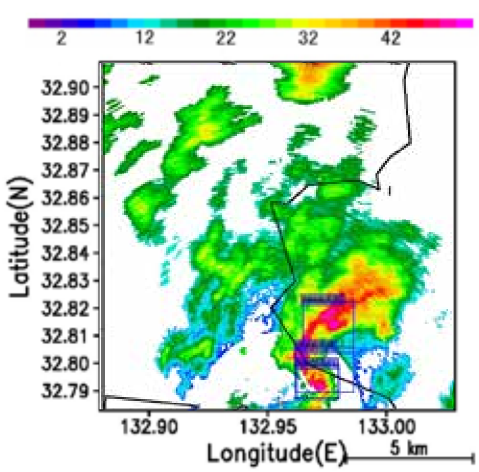

Figure 4. Example of failed detection

where, TP, FN, FP are the numbers of accurately detected hock echo, of actual hock echo and of false detected echo, respectively. The results are shown in Fig. 5. In this figure, threshold shows the matching rate with the target object and annotation data. For the closeup figure of convective system, recall and precision show good performance of more than 0.8 and 0.9, respectively. On the other hand, the detection becomes difficult in the full range observation data. This is caused by low resolution of the hock echo relative to the total observation range.

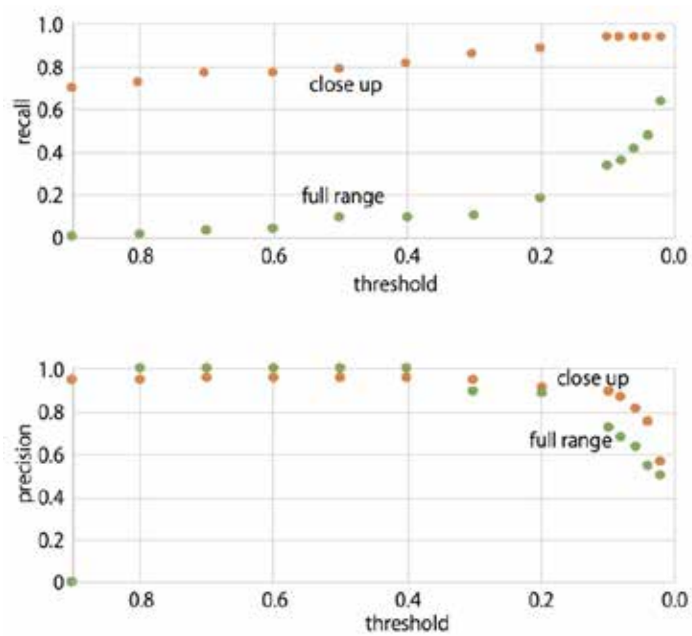

Figure 5. Recall and precision at various threshold.

4. CONCLUSIONS

The automatic detection scheme with reflectivity data of weather radar is found to work well except for some error mainly due to pure resolution of radar data. The detection can be carried on quasi-real time. Of course, the present detection system will not work for the convective system without hock echo. Our future work is to make the detection system with Doppler velocity. We believe that the combined system with reflectivity and Doppler velocity has best performance.

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