An Automatic Framework of Region-of-Interest Detection and Classification for Networked X-Band Weather Radar System

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Abstract Nowadays, S-band weather radars are designed to observe weather conditions within large area. However, S-band radars suffer from large blind zone at low elevation and fixed scan strategy so that they are not efficient for surveillance of convective weathers such as tornado. Networked X-band weather radars are thereby proposed to overcome this issue. One key problem of networked radar is to automatically determine the type and the precise position of convective cells that are worthwhile to detect. In this paper, a tailor-made framework is proposed to automatically find the convective cells and retrieve information of them from refectionivity product of networked X-band weather radars. The framework consists of three substeps: convection pixel retrieval by Back Propagation Neural Network (BPNN), convection cell construction by Density-Based Spatial Clustering of Applications with Noise (DBSCAN), and convection cell classification by Convolutional Neural Network (CNN). Evaluation results show that the proposed algorithm is capable to identify isolated single-cell and multicell convective storms from the reflectivity image accurately. Therefore, the proposed framework is capable to provide information for networked X-band weather radars so that they can track harmful convective weathers. The proposed framework has been embedded in the meteorological command and control (MCC) center of networked X-band radar system in Chengdu.

Plain Language Summary Weather radar is significant in modern meteorological observation system. Recently, networked X-band weather radars are attractive because it provides an efficient way to detect and track harmful convective weather such as tornadoes. One of the most difficult tasks of networked X-band weather radars is to automatically determine clouds that are possible to endanger our regular live. It is not an easy mission because clouds are notoriously changeable, and the time resolution of our weather radars is relative low. In this paper, we propose an algorithm to challenge this problem by utilizing machine learning methods. According to the evaluation results, our algorithm is accurate and computational efficient, and it has been embedded into the networked X-band radar system in Chengdu.

1. Introduction

Convective weather is one of the major types of weather events causing meteorological disasters. It can produce (or contribute to) atmospheric and hydrological hazards, such as damaging winds, tornadoes, and flash flooding (Fritsch & Forbes, 2001). Detection and early warning of dangerous weather processes are difficult for the widely used S-band weather radars because they are designed to cover large area by fixed scanning strategy. On the other hand, networked X-band radar system is a good solution for this issue. Typical networked X-band radars consist of several X-band radars, which located tens of kilometers away from each other, and an automatic control center is designed to send meteorological commands to the radars and analyze radar data. The first testbed of networked X-band radars was established by The National Science Foundation Center for Collaborative Adapting Sensing of the Atmosphere (CASA) (Wang & Chandrasekar, 2010). Similar testbed was introduced in Nanjing, China since 2013 (Li et al., 2016). Various scanning strategies were designed for different types of clouds so that the networked radars could retrieve sufficient information for rapidly changing convective weather system (Mclaughlin et al., 2009). Nevertheless, one key issue for the networked X-band radars to detect dangerous convective weather is an automatic algorithm to determine which cloud is more likely to cause meteorological disasters in the near
future; hence, it is worthwhile to monitor this region by nearby radars by a specific scanning strategy. It is not an easy task because clouds are notoriously changeable, and the time resolution of our weather radars is relatively low. In the testbeds mentioned above, a simple thresholding method is applied to determine the region of interest (e.g., the region whose reflectivity is larger than 35 dBZ (Li et al., 2016, Wang & Chandrasekar, 2010)). Apparently, this thresholding method is not capable to clearly describe the shape, position, and type of the clouds that are potential to cause meteorological disasters. Lack of these information may result in wrong detection and tracking lost of the harmful convective clouds. Therefore, it is significant to research on a real-time, accurate algorithm to determine the regions-of-interest and extract information for the regions.

There have been a number of researches on automatic cloud classification. In the early stage of human-free cloud classification, various classification and recognition algorithms based on radar horizontal and vertical echo characteristics of weather targets have been developed (Awaka et al., 1997; Biggerstaff & Listemaa, 2000; Churchill & Houze, 1984; Houze, 1973; Steiner et al., 1993; Steiner & Houze, 1993). For example, two-dimensional background-exceeding technique was used to divided precipitation clouds into convective and stratiform (Churchill & Houze, 1984). Subsequently, Steiner et al. developed a new algorithm called SHY95 (Steiner et al., 1995), and Biggerstaff and Listemaa proposed a new classification algorithm abbreviated as BL to improve the accuracy of classification on the basis of SHY95 (Biggerstaff & Listemaa, 2000). However, extra information called the height of freezing level (0 °C) is needed for BL algorithm to calculate the bright band fraction. Identification method based on the estimated drop size distribution (DSD) was proposed in Bringi et al., 2009, in which a new precipitation category called “mixed” area was introduced.

Since the development of machine learning algorithms, precipitation cloud classification based on supervised machine learning has been published in the literature. These algorithms introduced hand-made meteorological features into supervised machine learning methods such as fuzzy logic (Wang et al., 2012; Yang et al., 2013), decision tree (Gagne et al., 2009), neutral network (Lei et al., 2019; Xu et al., 2017), and others (Baldwin et al., 2005; McGovern et al., 2017). Performance of these algorithms is generally better than traditional algorithms like SHY95 and BL.

Deep learning has achieved great improvement on image recognition and image classification in the past decade. Deep convolutional neural networks (CNN) were also applied for cloud image classification (Zhang et al., 2018). CNN-based ice crystals classification was proposed in Xiao et al. (2019). Ozone profile shapes were characterized by using neural networks (Xu et al., 2017). Okamura et al. studied multipixel retrieval of optical thickness and droplet effective radius of inhomogeneous clouds (Okamura et al., 2017). However, to the best of the authors’ knowledge, CNN has not been proposed to identify types of cloud from radar reflectivity.

Convective storms could be further identified according to the distribution of convective cells. For example, convective storms were classified as single-cell storms, multicell storms, and line storms (Browning, 1978), while Marwitz proposed to divide them into multicell storms, supercell storms, severe shear storms, and line storms (Chisholm, 1973; Marwitz, 1972). It is worth noting that the identification is not unique. For example, multicell storms and line storms may contain several cells that are supercells (Yu, 2011).

Despite the automatic algorithms mentioned above, this work is the first to propose a complete framework of determining the region-of-interest and extracting information of the regions for the meteorological command and control (MCC) center of a networked X-band radar system. Our framework consists of three parts: cloud pixel classification, cloud pixel clustering, and convection cell identification. The contribution of this work is highlighted as follows.

1. A complete framework of region-of-interest detection is proposed. The framework acts as a significant part in the MCC center of a networked X-band weather radar.
2. The input of the proposed framework is the real-time reflectivity data from the networked X-band radars. No extra information is needed.
3. The framework is computational efficient so that real-time controlling is supported.
4. The framework is evaluated in networked X-band radar system located in Chengdu, China. Subjective and objective results are illustrated and discussed.
The rest of the paper is structured as follows. Equipment and data that are used in this work are given in section 2. Section 3 describes the details of the proposed framework. Evaluation results and discussion are shown in section 4. A summary is provided in section 5.

2. Equipment and Data

The data used in this paper are the observed weather data from three networked X-band Doppler radars located in Chengdu, China. The localization and cover area of the three weather radars are shown in Figure 1. The two radars in Chengdu locate approximate 30 kilometers away from each other, and the radar in Ziyang locates around 50 kilometers from the other two. There are a triangular overlapped coverage regions among them in which clouds could be well monitored by the three networked radars. The networked radars are controlled by an automatic meteorological command and control (MCC) center, and the scanning tasks of the radars are determined in real time by the proposed framework in MCC.

The observed weather data were collected from 16 August 2017 to 3 October 2019. The whole data set consists of composed radar reflectivity of 615 observations from 38 days in the rainy seasons of the 2 years. In the data set, 2519040 rain pixels are identified as convective pixels by our algorithm (every reflectivity pixel covers 200 m × 200 m area). The convective pixels are hereafter clustered into 615 unique convective cells, each of which is described as a reflectivity image. After normalization, 515 objects are randomly selected as the training set of the proposed convolutional neural network (CNN), and the rest 100 cases are listed in the testing set.

3. Framework Description

The proposed framework consists of three blocks: cloud pixel classification, cloud pixel clustering, and convection cell identification. Real-time reflectivity data are introduced into the first block. In the first block, a back propagation neural network (BPNN) based classification algorithm (Lei et al., 2019) is applied to divide the precipitation cloud into convective rainfall and stratiform rainfall pixel by pixel. In the second block, density-based spatial clustering algorithm (DBSCAN) is used to cluster the convective pixels into several convective cells. These cells are considered as potential risky storms, and MCC center is about to arrange...
scanning tasks to corresponding radar so that the stormy regions are carefully monitored by specific scanning strategy such as radar height indicator (RHI) and fast volume scan (FVS). These regions are also called region-of-interest (ROI) of the MCC. In the final block, the convective regions are inputted into a deep convolutional neural network (CNN) to further identify the type of the convective cells so that their future position could be better estimated. The working flowchart of the proposed framework is shown in Figure 2.

### 3.1. Cloud Pixel Classification

In our previous study (Lei et al., 2019), six distinguished features are extracted from radar product, and a back propagation neural network (BPNN) model is carefully trained to identify convective pixels from the reflectivity image. This model is modified to realize cloud pixel classification in this block. Different from the original idea, all the horizontal features, including mean background reflectivity, horizontal gradient
of reflectivity, and area of region whose reflectivity is higher than 35 dBZ (shorted as F2, F4 and F5 in Lei et al., 2019), are calculated from the composed reflectivity of the radars, rather than the 3-km constant altitude plan position indicator puzzle (CAPPIPZ). The modified features consist of cloud information at all the altitudes; hence, they are expected to better describe the horizontal structure of the target. For more details about BPNN, the reader is referred to Lei et al. (2019).

In the end of this block, the radar reflectivity is separated pixel by pixel into convective pixels and stratiform pixels. Apparently, the convective regions are more dangerous and worthwhile to be monitored. The output of this block is shown in Figure 3 in which the convective pixels are colorized in red.

### 3.2. Cloud Pixel Clustering

Even though the convective pixels are identified from the reflectivity image in the first block, they have not been aggregated into independent weather system cells. It is critical to know whether convective pixels belong to one weather system or different systems, because pixels in different weather systems are expected to move to isolated directions.

Generally, pixels that belong to the same weather system are more likely to be spatially adjacent to each other. Therefore, it is reasonable to partition weather systems according to the spatial distribution of the convective pixels. A well-known density-based spatial clustering algorithm called DBSCAN is applied to cluster the cloud pixels (Ester et al., 1996). The steps of our cloud pixel clustering are briefly described as follows.

**Step 1:** For all the convective pixels in a reflectivity image, a pixel \((x_0, y_0)\) is selected as core point if it satisfies the following criteria.

\[
Z(x_0, y_0) \geq 45 \text{dBZ}, \quad Z(x_0, y_0) = \max(Z(x, y)) \text{, for } \|(x, y) - (x_0, y_0)\| \leq D_{\text{eps}},
\]

where \(Z(x, y)\) is the reflectivity of pixel \((x, y)\), \(\max(.)\) symbolizes the maximum operator, and \(\|\|\) states the Euclidean distance of two pixels. \(D_{\text{eps}}\) is set to 6 empirically in this work.

**Step 2:** Select a core point arbitrarily. A cluster \(C_k\) containing this core point is generated.
Step 3: Scan all the pixels in the reflectivity image and classify all the pixels into cluster $C_k$ if they satisfy

$$\text{dist}(p, C_k) \leq D_{\text{eps}},$$

(2)

where $\text{dist}(\cdot)$ calculates the minimum Euclidean distance between pixel $p$ and pixels inside cluster $C_k$. The step stops until no more pixels could be identified into cluster $C_k$.

Step 4: Remove pixels in cluster $C_k$ from the reflectivity image.

Step 5: Repeat steps 2–4 to generate more clusters until all the core points are visited. Clusters in which the number of member pixels is less than 40 are considered as noise and are removed from the final result.

Examples of successful clusters are shown in Figure 4.

### 3.3. Convection Cell Identification

Once the convective pixels are clustered into cells, they are further studied and classified by a well-trained convolutional neural network (CNN). Since the success of AlexNet in ILSVRC 2012, CNN has been widely applied in image recognition and classification (Deng et al., 2009; Krizhevsky et al., 2012). In our work, a simple CNN is proposed to identify the convection cells as isolated single-cell systems and multicell systems. We did not introduce the category of linear storms because we can seldom observe large-scale weather systems in an inland basin city. Nevertheless, our model could be easily extended to identify more categories of weather systems once there are sufficient observation data.

The structure of proposed CNN is shown in Figure 5, and the detailed information of the layers is given in Table 1. Note that although a deeper network is helpful for accurate classification, our network is computational efficient so that it is suitable for real-time application in MCC.

Normalized reflectivity images of 515 convective systems in our training set are applied to train our CNN model. They were manually labeled as isolated single-cell storms and multicell storms. The training set consists of 106 isolated single-cell and 309 multicell storms, while the testing set is composed of 48 isolated single-cell and 52 multicell storms.

Accuracy is a basic statistical value to evaluate the quality of a CNN model. In this paper, accuracy is defined as the ratio of the number of samples, which are correctly classified by the model to the total number of convective storms for a given training or testing data set. Accuracy is formulated as follows:
where $N$ is the total number of convective storms in the data set, $\hat{y}_i$ states the predicted value of the $i$-th convective storms, and $y_i$ stands for the corresponding label value. The isolated single-cell is defined as $(1,0)$, and the multicell is defined as $(0,1)$. $I(.)$ is the indicator function. If all the kinds of convective storm of predictive labels are consistent to the ground truth, the accuracy is 1.0.

The softmax entropy loss is used in the training scheme. The cross-entropy loss characterizes the distance between the true distribution and the predicted distribution. It is defined as

$$loss = -\frac{1}{N} \sum_{i=0}^{N} \sum_{k=0}^{N} n_{jk} \log \left( \hat{n}_{jk} \right),$$

where $n_{jk}$ is the value of the $k$-th element in the $j$-th sample convective storm, and $\hat{n}_{jk}$ symbolizes the corresponding value of the prediction value. The smaller the value of the entropy loss is, the closer the two probability distributions. Number of the epochs is set to 40, the learning rate is set to 0.009, and the minibatch is set to 10. The decrease of entropy loss during the training iterations is shown in Figure 6.

According to the learning curve, the model is stable after around 25 epochs. The accuracy in the training set reaches 98% after training.

### 4. Experimental Results and Analysis

In the beginning of this section, the performance of the proposed CNN is evaluated both subjectively and objectively. Figure 7 shows some classification results by the proposed CNN, where the upper four (Figures 7a–7d) are identified as isolated single-cell storms, and the lower four samples (Figures 7e–7h) are classified as multicell storms. The eight samples are randomly selected from the result of test data. One can notice that the identification is reasonable, because the storms in Figures 7a–7d are independent, where the samples in Figures 7e–7h contains multiple convection regions that are tightly connected together.

Moreover, the objective matrices are calculated to evaluate the performance of the proposed CNN in the testing set. The contingency scores are the probability of detection (POD), cumulative success index (CSI), and false rate (FAR) defined as follows:
where $n_{\text{success}}$, $n_{\text{false alarm}}$, and $n_{\text{total}}$ are the number of successes, false alarms, and total of prediction, respectively. Success is defined when the classified category of the pixel is the same to the label, and false alarm is defined when the pixel is classified opposite to reference.

Table 2 shows the statistical score for the classification result in the testing set. The POD values for both categories are relatively high while the FAR values are small. The overall performance of the CNN model is satisfactory. The average accuracy in the testing set is 83%.

Figure 8 shows the result of the whole framework. A radar composed reflectivity image, captured from three networked X-band radar in Chengdu at 0718 UTC in 28 July 2019, is shown in Figure 8a. The image is hereby inputted into the proposed framework, and the final result is shown in Figure 8c. Twelve convective cells are identified, and their corresponding types and probability are shown in the Figure 8c. For comparison, Figure 8b illustrates the classification result of region-of-interest by thresholding method in the testbed of CASA (Wang & Chandrasekar, 2010) and Nanjing (Li et al., 2016).

One can notice that the identification of ROI from two approaches is roughly similar. However, our framework could separate different convective regions and identify the types of the convective cells. It provides useful information for MCC to determine the regions to be monitored. On the other hand, thresholding result contains a number of tiny regions, which could be considered as noise of the radar product. Moreover, the convective regions in Figure 8b could not be further divided into different storm cells; therefore, it is difficult to determine the position of ROI, which is needed to be scanned.

Figure 6. The decrease of entropy loss during training.

Figure 7. Identification results of the proposed CNN. (a–d) isolated single-cell systems; (e–h) multicell systems.
Our framework has been applied in the MCC center of the networked X-band radar system in Chengdu, China. Figure 9 shows a particular case of heavy rain captured at 1700UTC on 12 September 2019. The proposed framework identified the middle region as multicell storm; hence, the MCC center arranged RHI scanning tasks to the three radars for detection of vertical cross-sections of the storm region. As a multicell storm, the MCC center carried out RHI scanning immediately at three different positions that located at the head, body, and the tail of the storm, as shown in Figures 9a–9c. Figure 9 shows evidence of the advantage of the proposed framework that it can automatically provide the types of storms to MCC so that MCC may arrange appropriate scanning strategy to particular types of storms. The methods of radar task arrangement and scanning strategies are out of the scope of this paper.

Finally, the computational complexity of the proposed framework is evaluated. The framework is implemented by MATLAB program in a laptop with an Intel CPU 2.0GHz. The average running time of the whole framework is around 6 second, indicating that our framework is potential to be applied in real-time control in MCC (the scanning period of our networked radar system is 2 minutes). The most time-consuming block is

| Algorithm | Convection type | POD | FAR | CSI |
|-----------|----------------|-----|-----|-----|
| CNN       | Single-cell    | 0.75| 0.12| 0.67|
|           | Multicell      | 0.90| 0.20| 0.73|

**Table 2**

*Statistical Score for Isolated Single-Cell and Multicell Classification in the Testing Set*

**Figure 8.** (a) The radar combined reflectivity at 0718 on 28 July 2019. (b) Classification result of region-of-interest by thresholding method. (c) The recognition map of the proposed framework (”S” means isolated single-cell, and “M” means multicell. The confidence of the classification is also provided).
cloud pixel clustering because it is an iterative algorithm. Note that our program is not fully optimized for efficiency.

5. Conclusion

In this work, a novel framework is proposed to automatically identify convective cells and retrieve type of them from composed reflectivity of networked X-band weather radars. The framework consists of multiple machine learning algorithms to achieve fast and accurate classification of weather system by single input of reflectivity data. The identification results are hereby utilized by MCC to decide which regions need to be carefully monitored. The training data and testing data were captured from networked X-band weather radar in Chengdu, China, during 16 August 2017 to 3 October 2019. Evaluation results show the recognition accuracy on the training set reaches 98%, and the accuracy on the testing set is 83%. The proposed algorithm has been applied in our MCC center and is potential to be generalized in every real-time networked weather radar systems given that the CNN model is transfer trained according to their local meteorological data.

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