CIKM AnalytiCup 2017: Short-Term Precipitation Forecasting Based on Radar Reflectivity Images

Yichen Yao
Department of Engineering Mechanics
Tsinghua University
Qinghuayuan Road 1, Beijing
China
yaoyichen@aliyun.com

Zhongjie Li
Department of Thermal Engineering
Tsinghua University
Qinghuayuan Road 1, Beijing
China
lizhongjie1989@163.com

ABSTRACT

This article describes the final solution of Team Marmot, who finished in 1st place in the CIKM AnalytiCup 2017 – "Short-Term Quantitative Precipitation Forecasting Challenge" sponsored by Shenzhen Meteorological Bureau and Alibaba Group. In this paper, we provide an approach to reasonably predict the short-term precipitation at the target site in the future 1-2 hours based on historical radar reflectivity images. Our solution regards cloud trajectory method based on velocity vector obtained by the SIFT (Scale-invariant feature transform) algorithm which matches descriptors in the adjacent time frames. Convolutional neural network is adopted with features including pinpoint local radar images, spatial-temporal descriptions of the cloud movement, and the global description of the cloud pattern.

KEYWORDS

Radar reflectivity image, precipitation forecast, SIFT, convolutional neural network

1 INTRODUCTION

High-intensity rainfall within a short period of time causes severe damage in populated areas. An accurate weather prediction service can support casual usage such as outdoor activity and provide early warnings of floods. Weather radar, with its advantage of short-term predictive capability and high-spatiotemporal resolution, has been applied for precipitation forecast. In the CIKM AnalytiCup 2017 challenge, contestants are provided with radar maps within 1.5 hours. Each radar map covers the radar reflectivity of the surrounding 101 km × 101 km areas of the target site. Radar maps are measured at different time spans, specifically 15 time spans with an interval of 6 minutes, and in 4 different heights from 0.5km to 3.5km with an interval of 1km. Therefore, 60 historical radar images are provided for one sample to predict the total precipitation amount on the ground in the future 1-2 hours for each target site. Figure 1 illustrates the data format of the current competition, and Figure 2 presents a typical example of the 60 historical radar images. The dataset have been collected and desensitized by the Shenzhen Meteorological Bureau, during a total time span of 3 years, in which the first two years data are used for training and the third year for testing. Our task here is to predict the exact precipitation amount with the objective to minimize the prediction error. The root mean square error (RMSE) is used to evaluate the predicting performance in the contest.

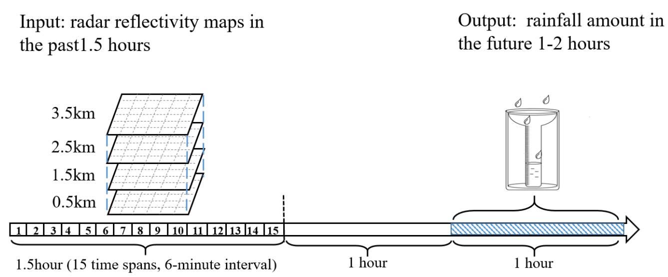

Figure 1: Illustration of the data format.

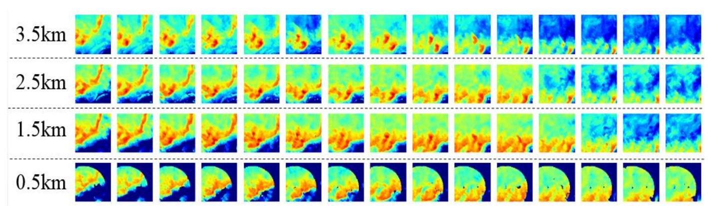

Figure 2: Visualization of historical radar images of 15 time spans in 4 different heights.

2 SOLUTION

2.1 Framework

The framework of the current solution is shown in Figure 3. In the pre-processing stage, sub-regional images are connected by template matching and formed into large domain panorama. Key points are detected and described by the SIFT algorithm, rendering local descriptions of the cloud structures. The SIFT descriptors are pair-matched between two adjacent time frames to acquire the relative displacement in the time interval. Then the velocity field could be derived from the relative displacement at each of key point. Resorting to Taylor frozen hypothesis [1], the trajectory that

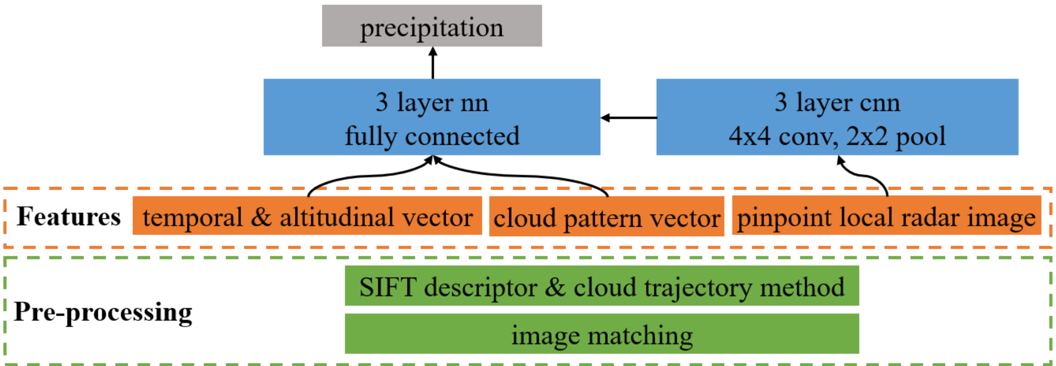

Figure 3: **Flowchart of the current solution**

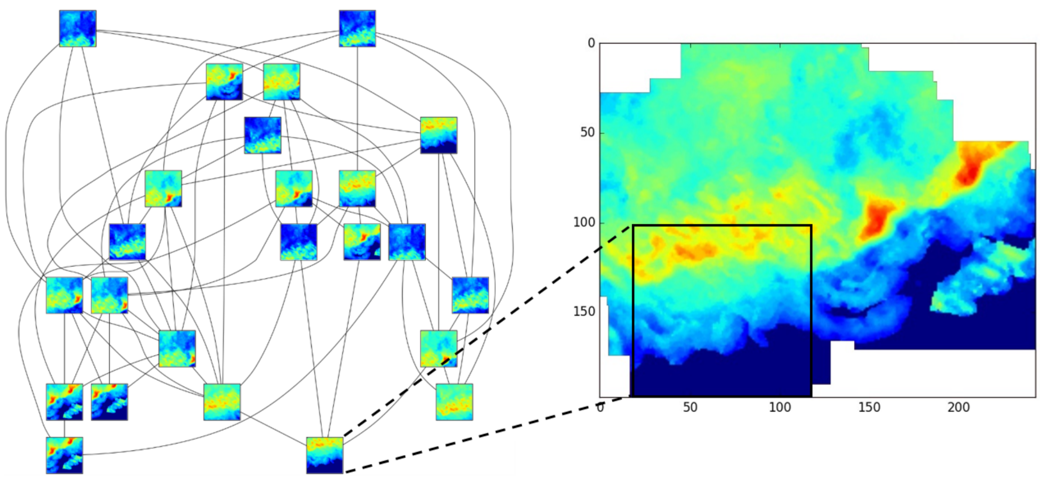

Figure 4: **An example of sub-image matching.**

passes through the target site can be extrapolated. The features are generally classified into three categories. The local radar images (41 × 41 km) along the extrapolated trace can provide direct association between radar reflection and precipitation. The temporal and altitudinal vectors describe the evolution of radar reflective statistics along different time frames and radar observation heights. The cloud pattern vector depicts the cloud type in the whole image area (101 × 101 km), which is embedded as the histogram of reflective intensity and SIFT descriptor classes. Convolution neural network model is adopted and the architecture is shown in the Figure. Local images are fed into a 3-layer convolution neural net and each layer includes a 4 × 4 convolution kernel and a 2 × 2 max pooling kernel. Then the output images are flattened and concatenated with other two types of features, and passed to a 3-layer fully connected neural net with the precipitation required to be predicted at the output layer.

2.2 Sub-image Matching

In both the training and testing sets, the sample images are not mutually independent in space, but the neighborhood sub-region of the target site. Template matching of the small sub-region is adopted to build the spatial connections among samples images and the relative coordinates of all the target sites. A typical example of the image matching process is illustrated in Figure 4 and presents the linkages between images and the corresponding panorama of radar maps after image matching. After this process, a global prospect of the cloud structure could be obtained. Meanwhile, the availability of larger surrounding areas of the target site could provide larger candidate area for the trace tracking of the rain cloud discussed in the next section.

2.3 Local Descriptor and Trace Tracking

The accurate prediction of precipitation at a specific target site requires precise tracking on the trajectory of the cloud movement. Taylor frozen hypothesis is a theory that constructs the spatial-temporal relation of fluid driven by the advection flow, and is widely applied in meteorology and fluid dynamics. In this assumption, the advection contributed by turbulent circulations themselves is small and therefore the advection of a flow field of turbulence passing a fixed point can be taken to be entirely due to the mean flow. In other words, the temporal variations at a fixed location can be partially deduced from the spatial variations.

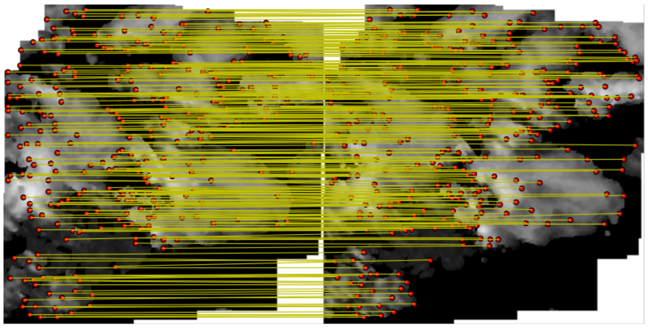

Figure 5: **An example of matching SIFT descriptor vectors of two radar images at two adjacent timestamps.**

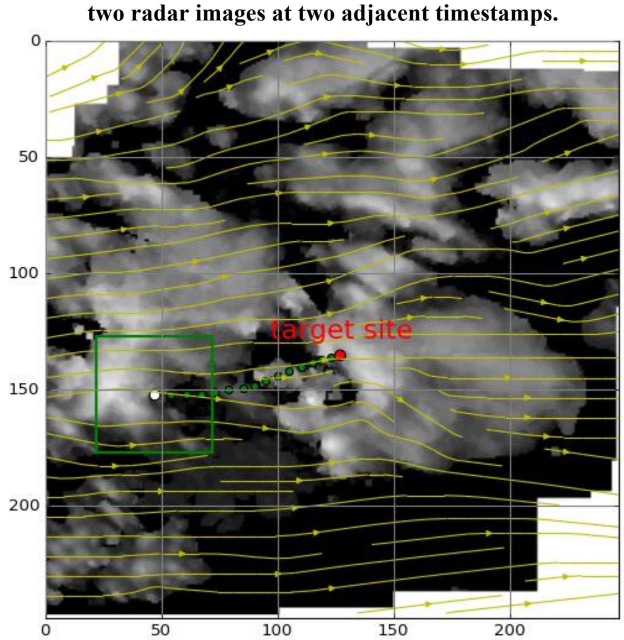

Figure 6: **Illustration of the trajectory lines**

To obtain the velocity field, the relative displacement of key points at two adjacent timestamp images should be calculated, and the displacement of the timespan is obtained by coordinate differences between the matched key points. Key points are detected according to the FAST algorithm [2], and the description of the key points are calculated by SIFT descriptor [3], which takes sub-region areas and computes the gradient orientation histogram. The distance function that constructs the connections between adjacent images is the normalized cross correlation. Typical example of the matched SIFT descriptor are illustrated in Figure 5. Key points detected from FAST algorithm are marked as red dots, and the matched SIFT descriptor are connected by yellow lines. Figure 6 presents the trajectory lines that would move to the target site in the future 1.5 hours. Red dot is the target site. Green dots are the trace positions with 6-minute interval. Yellow streamlines are the convoluted trajectory lines along the spatial velocity vector. The green box are the pinpoint surrounding area which would appear at the target site, and is chosen as image features in the convolutional neutral network.

2.4 Feature Representation

Three major types of feature representations are included in the current net. In the horizontal plane, both large area and global description of cloud pattern and small regions around the precise pinpoint position are included. In the altitudinal and temporal direction, the spatial and temporal subtle change among different image frames are compared and described.

2.4.1 Pinpoint radar reflectively image. Based on Taylor frozen hypothesis and pair-matched SIFT descriptor discussed in section 2.3, the trajectory that passes through the target site could be extrapolated. The local radar images (41 km × 41 km) along the extrapolated trace are selected as input features of the convolutional neural network to provide direct association between radar reflection and precipitation.

2.4.2 Temporal - altitudinal description. 60 time frames of the historical radar images are available with 15 frames along the temporal direction and 4 along the altitudinal direction. Reflective statistics are calculated in each time frame, including maximum value, mean value, standard deviation and cloud coverage. The temporal and spatial vectors describe the evolution of radar reflectivity along the rainfall process.

2.4.3 Global description of cloud pattern. The cloud pattern vector depicts the cloud type in the whole image area, which distinguishes the rainfall difference under various large-area cloud formation:

- Histogram of typical SIFT descriptors. The typical descriptors are obtained by k-means clustering of all the local SIFT descriptors in the training set, and the histogram of descriptor belong to each cluster is obtained as the vector representation of the cloud type.
- Histogram of radar reflectivity intensity.
- Cloud velocity, direction, acceleration, trace curvature. The velocity vector is described in the Section 2.3.
- Statistics of radar reflectivity, the differences compared with the neighbour measurement sites.

3 CONCLUSIONS

In the present study, feasible solution method for the short-term precipitation forecasting mission is provided. In the pre-process stage, cloud trajectory lines are tracked based on velocity vector, which is obtained by matching SIFT descriptors in two adjacent time frames. Afterwards, convolutional neural network is adopted, with features including pinpoint local radar images, altitudinal-temporal descriptions of the cloud movement, and the global descriptions of the cloud pattern. Good accuracy is achieved by the current method, with the mean square error of precipitation around 11.0 mm. Our results win the first place in the final evaluation of the CIKM Analytical Cup Challenge.

ACKNOWLEDGMENTS

The current research focused on the CIKM AnalytiCup 2017, supported by Shenzhen Meteorological Bureau, Alibaba Group and CIKM 2017.

APPENDIX

Source Code：the source code of our solution is made public on GitHub. Visit https://github.com/yaoyichen/CIKM-Cup-2017 for the implementation details of our models.

REFERENCES

[1] Taylor G. I. 1938. *Production and dissipation of vorticity in a turbulent fluid*. Proceedings of the Royal Society of London. Series A, Mathematical and Physical Sciences, 15-23.
[2] Rosten, E., & Drummond, T. 2006. Machine learning for high-speed corner detection. *Computer Vision–ECCV 2006*, 430-443.
[3] Lowe, D. G. (2004). Distinctive image features from scale-invariant key points. *International journal of computer vision*, 60(2), 91-110.