A Deep Learning Approach for Rainfall Estimation from Dual-Polarization Radar and Gauges Measurements for Landfall Typhoon in South China

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Abstract

At present, the raindrop size distribution (DSD) fitting method and traditional neural network method are the main quantitative precipitation estimation (QPE) algorithms. The former is not enough to express the spatiotemporal variability of the DSDs using generalized *Z-R* parameter relationship, and the latter is limited by the number of network layers, network structure and computing power. Their performance cannot both meet actual needs. In this research, we propose an alternative approach to dual-polarization radar (DPR) QPE. In particular, a radar-gauges dataset (RGD) is constructed for QPE based deep learning using radar raw data and gauges measurements for landfall typhoon in South China, and a deep learning model is designed and trained using this dataset. The model is applied to radar data to produce rainfall estimates. Preliminary results show the promising performance of this novel method compared to traditional QPE estimators.

1. Introduction

The heavy rainfall of landfall typhoons is one of the main natural disasters that cause life and economic losses in South China [1, 2]. The QPE algorithms for typhoon precipitation are different from the other precipitation, because of the differences in the DSD [3, 4]. In principle, the functional relation between rain rate on the ground and radar observations aloft can be obtained from measurements [5]. However, it is difficult to present this functional relation in a simple form duo to the complex spatiotemporal variability in precipitation microphysics [6, 7]. QPE algorithms have been studied in last two decades using dual-polarization radar measurements. The two mainstream methods of QPE are the DSD fitting [8-15] and traditional neural network [16-20]. The former is not enough to express the spatiotemporal variability of the DSDs using generalized *Z-R* parameter relationship [21, 22], and the latter is limited by the number of network layers, network structure and computing power [23, 24].

Prior research has shown that deep leaning can be used to estimate surface rainfall from radar measurements [17, 18, 25, 26]. This deep neural networks approach can fit the complex functional relation from high dimension input space (i.e., radar data) to the target space (i.e., rain gauge measurements) [5]. However, the utilization of deep learning in QPE is subject to many factors such as the representativeness and sufficiency of the training dataset and the ability of computing power and the generalization capability of the trained model to new data [19, 27].

In addition, most of the previous studies focused on single polarization radar and the Constant Altitude Plan Position Indicator of DRP (i.e., reflectivity) [5] and simulated DRP data (i.e., DSD) [28, 29]. Similar application of DPR raw data is yet to be explored for landfall typhoon in South China. Based deep neural networks, this study aims to quest DPR QPE using radar raw data and rain gauge measurements, and evaluate the QPR QPE performance in landfall typhoon precipitation even.

2. Data Set

The research objects are 11 typhoon rainfall events in South China, during 2017-2019.

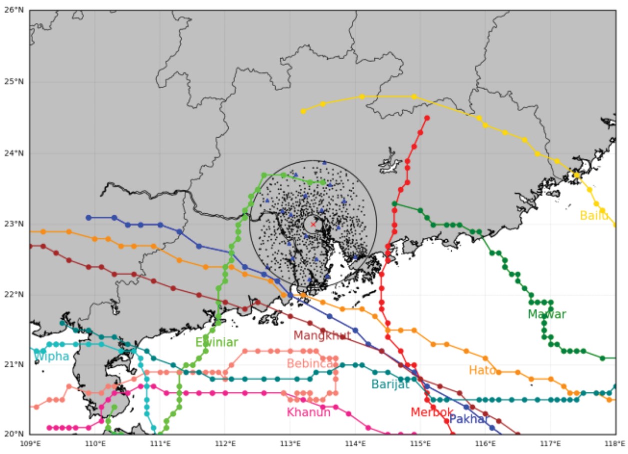

Figure 1. Locations of Guangzhou radar (red fork) and gauges (black dots), and typhoon paths.

Figure 1 shows the locations of radar and gauges used in building RGD, and 11 typhoon paths related.

Table 1 illustrates the sample information of constructed RGD, using Guangzhou radar raw data and gauges measurements of 11 typhoon rainfall events.

Table 1. The sample information of RDG.

#	Tc Name (No.)	Num. of samples in Dataset
1	Merbok (1702)	4502
2	Hato (1713)	19188
3	Pakhar (1714)	30401
4	Mawar (1716)	8992
5	Khanun (1720)	11880
6	Ewiniar (1804)	115737
7	Bebinca (1816)	63874
8	Mangkhut (1822)	47220
9	Barijat (1823)	1412
10	Wipha (1907)	32099
11	Bailu (1911)	39935
	Total	**375240**

3. Methodology

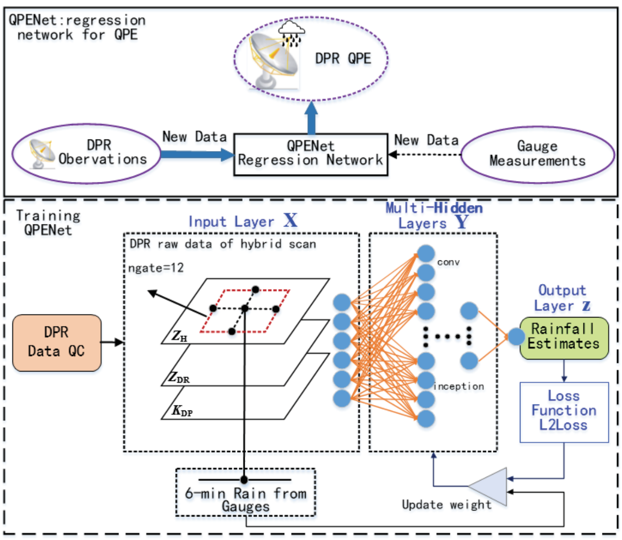

Figure 2. Flow chart for the training of the QPENet model (Lower) based on deep learning and its use to estimate precipitation rate (Upper).

Figure 2 illustrates the process of training the deep learning-based QPE network (QPENet) and its application system. The key component is a machine learning model trained using DPR raw moments and corresponding rain measurement from rain gauges. The QPENet model equation can be expressed in a general from as [5]:

$$\boldsymbol{y}_1 = f(\mathbf{w}_1 \mathbf{X} + \mathbf{b}_1) \tag{1a}$$

$$\vdots$$

$$\boldsymbol{y}_n = f(\mathbf{w}_n \boldsymbol{y}_{n-1} + \mathbf{b}_n) \tag{1b}$$

$$\mathbf{Z} = f(\mathbf{w}_{n+1} \boldsymbol{y}_n + \mathbf{b}_{n+1}) \tag{1c}$$

where $\mathbf{x}$ is the input $13 \times 13 \times 3$ matrix consisting of DPR $Z_\mathrm{h}, Z_\mathrm{dr}, K_\mathrm{dp}$ observables; $\boldsymbol{y}_1 \cdots \boldsymbol{y}_n$ are the outputs of hidden layers from left to right, $\mathbf{w}_1$ is the weight vector for the input matrix, and $\mathbf{w}_2 \cdots \mathbf{w}_{n+1}$ are the weights of the n hidden layer outputs, respectively; $\mathbf{b}_1 \cdots \mathbf{b}_{n+1}$ are the bias terms associated with the input, hidden and output layers; $\mathbf{Z}$ is the output (i.e., DPR precipitation estimates) that will be compared with the target labels (i.e., gauge measured rainfall).

In this paper, the Guangzhou radar moments and corresponding gauge measurements are used for training the QPENet model. From the eleven typhoon events, randomly select one event as the test set, and other events as the training set.

4. Preliminary Results

Table 2. Evaluated scores for 2 kinds QPE algorithms of all hourly rainfall of the Merbok (1702) event.

QPE algorithm	CC	RMSE	NB (%)	NE (%)	Bias
QPENet	**0.94**	**1.41**	**7.55**	**36.07**	**1.08**
$\mathrm{QPE}_{\mathrm{DSD}}$ [30]	0.93	3.14	-15.51	43.63	0.84

In order to demonstrate the performance of the designed QPENet model, we compare the deep learning-based model with the traditional DSD fitting method [30, 31]. In [30], Zhang and Liu have proposed a QPE algorithm for landfall typhoon in South China and showed the promising performance using local DSD data. Table 2 shows the QPENet based on deep learning has better performance than the traditional DSD fitting method.

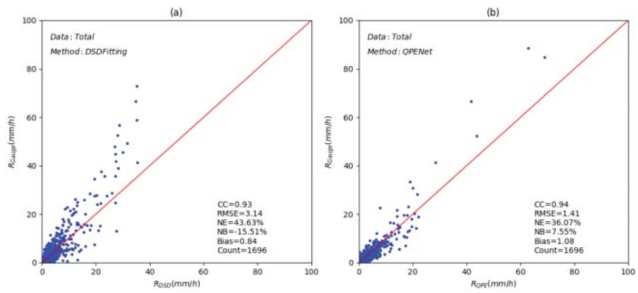

Figure 3. (a) and (b) are scattergrams of rainfall rates estimated using the traditional DSD fitting model in [30] and using the QPENet model based on deep learning from Guangzhou radar versus hourly rainfall measurements from rain gauges during Merbok event, respectively.

Figure 3 illustrates scatter plots of rainfall estimates from both traditional DSD fitting method and deep learning based approach. In particular, Figure 3(a) shows the rain rate estimates from the traditional DSD fitting model in [30] versus hourly rainfall measurements from during Merbok event. Figure 3(b) shows the rain rate estimates from the trained QPENet model versus hourly rainfall measurements from during Merbok event. Compared to traditional DSD fitting method, the deep learning model can greatly reduce the parameterization errors associated with the empirical non-linear regress [29], demonstrating promising performance of the proposed algorithm.

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