An Approach for Radar Quantitative Precipitation Estimation Based on Spatiotemporal Network

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Abstract: Radar quantitative precipitation estimation (QPE) is a key and challenging task for many designs and applications with meteorological purposes. Since the Z-R relation between radar and rain has a number of parameters on different areas, and the rainfall varies with seasons, the traditional methods are incapable of achieving high spatial and temporal resolution and thus difficult to obtain a refined rainfall estimation. This paper proposes a radar quantitative precipitation estimation algorithm based on the spatiotemporal network model (ST-QPE), which designs a convolutional time-series network QPE-Net8 and a multi-scale feature fusion time-series network QPE-Net22 to address these limitations. We report on our investigation into contrast reversal experiments with radar echo and rainfall data collected by the Hunan Meteorological Observatory. Experimental results are verified and analyzed by using statistical and meteorological methods, and show that the ST-QPE model can inverse the rainfall information corresponding to the radar echo at a given moment, which provides practical guidance for accurate short-range precipitation nowcasting to prevent and mitigate disasters efficiently.

Keywords: QPE, Z-R relationship, spatiotemporal network algorithm, radar echo.

1 Introduction

At present, China's rainfall forecast mainly provides a forecast of precipitation for the next few days, but lacks an accurate prediction of short-term rainfall for specific given regions. Traditional methods of meteorology are unable to meet the requirement of high resolution for quantitative precipitation estimation. Water falling gathered by rain gauges tells a rough liquid precipitation, but domestic observation stations are sparsely distributed giving difficulties of obtaining more details of rainfall. Meteorological satellites mainly observe information of the cloud top, which has a low correlation with precipitation. Radar QPE is a measurement based on the empirical formula Z-R

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relationship between radar echo and precipitation to do QPE [Li, Chen, Wang et al. (2020)]. With the advent of the intelligent era, many academic scholars proposed different types of optimization models to reduce the error in radar OPE [Lea, Loris, Marco et al. (2018); Tao, Hsu, Ihler et al. (2018); Song, Chen, Chen et al. (2019)]. Kusiak et al. [Kusiak, Wei, Verma et al. (2013)] verified the effectiveness of multi-layer perceptron, random forest, SVM, classification regression tree and K-nearest neighbor algorithm on QPE, as well as emphasizing the importance of using machine learning for radar data driven problems. Fu et al. [Fu, Xiao, Tan et al. (2015)] improved the function of a radial basis in the neural network model. Compared to the Z-R relationship better accuracy and stability are acquired but only in limited experimental regions. Chen et al. [Chen, Chen, Zhao et al. (2019)] utilized the gradient boost decision tree (GBDT) to study meteorological radar data in South China. Its results are better than the fixed Z-R relationship and the dynamic Z-R relationship, but the issue of inaccurate estimation is not addressed yet. Zhang et al. [Zhang, Yang and Zhang (2019)] considered weighted random forest as well as vertical profile of reflectivity (VPR), and analyzed radar quantitative estimation on rainfall procedure. This work suggested that obtaining precipitation more accurate than traditional Z-R relationship and random forest methods is possible. The previous research is mainly based on traditional machine learning, that suffers from a low effect on the high spatiotemporal resolution of radar.

In recent years, the spatiotemporal networks have been gaining an increasing amount of attention from QPE researchers [Yu, Liu, Wang et al. (2018); Zuo, Yu, Zi et al. (2018); Zhang, Jin, Sun et al. (2018); Chen, Wang, Liu et al. (2019); Wang, Liu, Xu et al. (2019)]. A video fingerprint recognition model based on spatiotemporal deep neural network combined with self-encoding and LSTM (Long Short-Term memory) network is described in Wang et al. [Wang and Li (2018)]. Later, Zhang et al. [Zhang, Bai, Sha et al. (2019)] proposed a mobile network traffic model based on spatiotemporal features, where three-dimensional convolutional network and time convolutional network are employed to extract the spatial characteristics of mobile network traffic, and achieved quality results for short-term traffic prediction. Currently in the meteorological field, there are limited studies on the application of space-time networks to radar QPE. In 2015, Shi et al. [Shi, Chen, Wang et al. (2015)] took advantages of both the convolutional layer and the recursive layer to present Convolutional Long Short-Term Memory (ConvLSTM) for short-term rainfall forecasting, which partially remedied the shortcomings of the optical flow methods by better handling image space and dynamics information. Based on the LSTM network model, Wang et al. [Wang, Long, Wang et al. (2017)] developed radar an echo nowcasting technology by adapting a number of existing works such as spatiotemporal memory unit, hierarchical normalization, deconvolution network, data augmentation. Their results show that the model extrapolates the precipitation is better than other benchmark algorithms.

By studying the spatiotemporal characteristics of radar data and the rapid change of rainfall data, we quantitatively estimated the precipitation of rainfall scanned by the radar for the current 60 minutes. We analyzed the historical radar echo data of Hunan Meteorological Observatory and propose a radar quantitative precipitation estimation algorithm, which is referred to ST-QPE (Spatiotemporal QPE), we also designed a convolutional time-series model QPE-Net8 and a multi-scale feature fusion time-series

model QPE-Net22. We conducted a set of contrast reversal experiments with radar echo data and rainfall data collected by the Hunan Meteorological Observatory, and applied the statistical and meteorological tests on the ST-QPE. The experimental results showed that our method better reflected the rainfall information corresponding to the current radar echo than existing work.

2 Related work

QPE is mainly based on estimated precipitation from weather radar, which works as follows: the meteorological radar emits electromagnetic waves that will get scattered due to intersections with raindrops and snowflakes, then the radar echoes are received by radar antenna and displayed on screens to allow meteorologists to learn the intensity, distribution, movement and evolution of precipitation in the atmosphere according to echo images and thus further to understand the structure and characteristics of the weather system.

2.1 The relationship of radar echo and rainfall intensity

The Z-R relationship reflects the correlation between the radar echo and the rain-fall intensity. Mathematically, the relationship between the radar reflectivity factor Z (unit: mm^6/m^3) and the rainfall intensity R (unit: mm/h) is:

 $Z = aR^b \tag{1}$

where *a* and *b* are empirical constants ($a \approx 200$, *b* [1.5 and 2]), determined by various factors such as time, location and type and nature of precipitation. The *Z*-*R* relationship is the main basis for radar measurement of precipitation, and its measurement accuracy depends on the determination of a and b parameters.

2.2 The analysis of radar and rainfall data

The weather radar collects a radar echo data Z map every 6 minutes, that is to say 240 sheets or time series per day. Each time point contains 12 layers of radar echo data of $m \times n$ latitude and longitude grid points (0.01°, grid point size is 1 km×1 km). Among the 12 layers, layers 1 to 10 are at height of 0.5 km, 1.0 km, 1.5 km, 2.0 km, ..., 5.0 km, the 11th layer is the echo top height, and the 12th layer is the vertical integrated liquid water content.

The rainfall data collects a rainfall intensity R every hour. The rainfall coverage is 5 km×5 km latitude and longitude grid (the lattice distance is 0.05°), as shown in Fig. 1, representing the radar data of 5×5 latitude and longitude grid points.

In general, radar data has time series and spatial characteristics; rainfall data is unstable and strong in spatiotemporal characteristics, due to the rapid change of rainfall process.



Figure 1: Rainfall coverage map

2.3 The description of QPE

According to Eq. (1), the essence of the QPE is the problem of determining parameters a, b based on radar data and rainfall data $\langle Z, R \rangle$. However, because the model described by Eq. (1) is too simple, it cannot reflect the spatiotemporal characteristics of $\langle Z, R \rangle$ well, which makes it difficult to greatly improve the estimation accuracy. This paper attempts to solve this problem by using the deep learning model of spatiotemporal networks.

The precipitation intensity R of a certain location (latitude and longitude) is related to the radar echo factor at the location and its neighboring spatial points (latitude, longitude and altitude). In other words, Z is a 3-dimensional matrix data, and the precipitation intensity R_t at a certain time t. It can be fitted by the following network functions:

$$R_{t} = f^{h}(Z_{t}) = f(f^{(h-1)}(Z_{t})), f(Z_{t}) = w^{*}Z_{t} + b$$
(2)

where f is the convolution function, w is the convolution kernel parameter, b is the offset parameter, and h is the convolution depth.

Now the temporal characteristics of the radar echo data and the rainfall data can be taken into account. According to the radar spatial data $Z_1, Z_2, ..., Z_t$ at the periodic moments of I, 2, ..., T, a more accurate precipitation intensity \hat{R}_t at time t is expressed as:

$$\hat{R}_{t} = g(g(R_{1}, R_{2}, L, R_{t-1}; q), R_{t}; q), t = 1, 2, \dots, T$$
(3)

Therefore, the problem is to find an optimized spatiotemporal network model parameter that makes the hit ratio of the sample data $D = \{ \langle Z_t, R_t \rangle | t = 1, 2, \dots, T \}$ as large as possible.

$$\widehat{\theta} = \arg\max_{\theta} \sum_{t=1}^{T} \log p(|R_t - F(Z_1, Z_2, \cdots, Z_t; \theta)| < \varepsilon)$$
(4)

where F is a spatiotemporal network containing f and g, and θ is the network parameter.

3 Design of spatiotemporal network

For the purpose of investigating the characteristics of spatiotemporal network model in the QPE problem, we propose a deep learning algorithm, which is able to construct a network model not only for the QPE problem but also for more general spatiotemporal sequence problems. Additionally, we introduce the training phase of algorithm and the back-propagation process to evaluate model accuracy. Contributions of this paper relate primarily to this section.

3.1 The strategy of spatiotemporal network

Based on the spatiotemporal characteristics of QPE problem, this paper designs a spatiotemporal deep neural network algorithm model ST-QPE, which extracts the spatial and time characteristics of the radar image respectively to finally find the rainfall amount. The model is divided into two parts, a spatial feature layer and a temporal feature layer. For the layer feature of space, *C* is the convolution operation, σ is the sigmoid activation function, w_i and b_i are the convolution kernel weights and offset parameters, then a formula is defined as Eq. (5).

$$Y_{i+i} = \begin{cases} Z & i=0\\ \sigma(w_i * Y_i + b_i) & otherwise \end{cases}$$
(5)

where *i* denotes the number of convolution layers, and Y_i denotes the input of the i-th layer convolution. *i*=0 indicates that the input of the first-layer convolution is *Z*. When *i*>0, the output of the i-th layer is used as the input into its next layer, and the operation of convolution activation is performed in sequence.

For the layer feature of time, It can be known from Eq. (5) that the feature value Y_{i+1} from the i-th layer in the spatial feature layer is assumed to have a j-layer time series structure, and for each time, by having the state value of the previous time set to h_{t-1} , the operation of the j-th layer timing structure, when j=1:

$$r_{I}^{t} = \sigma(w_{r,I} \times [h_{I}^{t-I}, Y_{i+I}^{t}])$$

$$z_{I}^{t} = \sigma(w_{z,I} \times [h_{I}^{t-I}, y_{i+I}^{t}])$$

$$\tilde{h}_{1}^{t} = tanh(w_{\tilde{h},1} \cdot [r_{t} * h_{1}^{t-1}, y_{i+I}^{t}])$$

$$h_{1}^{t} = (1 - z_{I}^{t}) * h_{1}^{t-1} + z_{I}^{t} * \tilde{h}_{1}^{t}$$

$$y_{1}^{t} = \sigma(w_{o,1} \cdot h_{1}^{t})$$
(6)

When j is otherwise, the j-th layer timing structure is:

$$\begin{aligned} r_{j}^{t} &= \sigma(w_{r,j} \times [h_{j}^{t-1}, h_{j-1}^{t}]) \\ z_{j}^{t} &= \sigma(w_{z,j} \times [h_{j}^{t-1}, h_{j-1}^{t}]) \\ \tilde{h}_{j}^{t} &= tanh(w_{\tilde{h},j} \cdot [r_{j}^{t} * h_{j}^{t-1}, h_{j-1}^{t}]) \\ h_{j}^{t} &= (1 - z_{j}^{t}) * h_{j}^{t-1} + z_{l}^{t} * \tilde{h}_{j}^{t} \\ y_{j}^{t} &= \sigma(w_{o,j} \cdot h_{j}^{t}) \end{aligned}$$
(7)

When t=1, the initial state value $h_j^{r_0}$ of all-time feature layers is 0. In other cases, the timing features are extracted according to Eq. (7). The overall structure of ST-QPE is shown in Fig. 2.



Figure 2: ST-QPE structure

In this paper, two different structures, QPE-Net8 and QPE-Net22, are designed for the connection characteristics of space and time. The difference is that when the time feature extraction layer is carried out, two kinds of operation modes are performed on the spatial features. QPE-Net8's spatial feature operation is a reference structure that uses pure convolution and pooling operations to take the extracted feature values as input into the temporal feature layer and then perform operations involving three timings. Unlike QPE-Net8, QPE-Net22 network uses four sub-sampling operations in the spatial feature extraction layer to accomplish multi-scale feature recognition of images. In each layer of timing operation sampling results of the spatial feature layer are utilized by fusing the multi-scale features, and thoroughly connecting the spatial feature layer and the temporal feature layer through the entire network model.

3.2 QPE-Net8

In QPE-Net8 where an 8-layer network structure is employed, convolution and pooling operations are used to perform feature extraction to ensure a sufficient number of convolutions to extract features, then operations are performed by ConvGRU [Shi, Gao, Lausen et al. (2017)]. QPE-Net8 is implemented alternately by three convolutional layers

and two maximum pooling layers for extracting radar space features, and three layers of ConvGRU cell are used to learn radar timing features. Now the input of the timing layer is the result of the last layer of spatial features, at any given time step:

$$Y_{last+1}^{t} = \sigma \left(C \left(w_{i} * Y_{last}^{t} + b_{i} \right) \right)$$
(8)

For the first cell of the timing layer, the operation of the first-level timing structure becomes: -->

$$r_{1}^{t} = \sigma \left(w_{r,1} \cdot \left[h_{1}^{t-1}, Y_{last+1}^{t} \right] \right)$$

$$z_{1}^{t} = \sigma \left(w_{z,1} \cdot \left[h_{1}^{t-1}, Y_{last+1}^{t} \right] \right)$$

$$\widetilde{h}_{1}^{t} = tanh \left(w_{\tilde{h},1} \cdot \left[r_{1}^{t} * h_{1}^{t-1}, Y_{last+1}^{t} \right] \right)$$
(9)

The timing structure of the second and third layers is identical to Eq. (7).

The structure of QPE-Net8 is shown in Fig. 3. By taking the first six layers of the radar echo data subjected to data preprocessing as channels, inputting the radar data of 10 consecutive moments intermediate eigenvalues are obtained by applying convolution operation to the feature layer. Eigenvalues are then input into each ConvGRU cell unit depending on the timing. Finally, the rainfall data corresponding to the hour is generated. The QPE-Net8 parameter configuration table is shown in Tab. 1.

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out size	Kernel size	Output size	Ζ

 Table 1: OPE-Net8 Network parameter

Input size	Kernel size	Output size	Z
224×224×6	3×3	224×224×64	
224×224×64	3×3	112×112×128	
112×112×128	3×3	56×56×256	



Figure 3: QPE-Net8 network structure

A typical calculation flow of the QPE-Net8 network model is presented in Algorithm 1.

Algorithm1 QPE-Net8			
Input: Training data $D_i = \langle Z_1, Z_2, \cdots, Z_T \rangle, i = 1, 2, \cdots, k$			
Output: The rainfall Y			
1: <i>for t=1, 2,, T</i> :			
2: for $i=1, 2,, n$:			
3: $C_t=Conv_i(Z_t);$			
4: if $i \neq n$ then:			
5: $C_i = Maxpooling_i(C);$			
6: end for			
7: $D_t = C_t$;			
8: for j=1, 2,, m:			
9: $G_{t}, h_t = GRUcell_j(D_t, h_{t-1});$			
10: $G_t = ReLU_j(G_t);$			
11: end for			
12: <i>end for</i>			
13: $Y = ReLU(W^*G_t + b);$			
14: return Y			

3.3 QPE-Net22

Similarly, QPE-Net22 employs a 22-layer network structure. As opposed to the QPE-Net8 network, QPE-Net22 first implements multi-scale feature recognition of image features in space, and each layer of time series operations uses the sampling results of the spatial feature layer. Multi-scale feature fusion, the connection of the spatial feature layer and the temporal feature layer runs through the entire network model; at the same time, downsampling is used to reduce redundant information to form a tighter expression, making the output feature map more accurate. The overall structure of the network is divided into two parts: feature extraction and sampling layer. Prior to each upsampling, ConvGRU is integrated to perform timing operations. There are four downsampling operations in the feature extraction layer, and the output of each sampling is set to Y_{i+1} . Then:

$$Y_{i+1} = \begin{cases} z & i=1\\ \sigma(C(w_i * Y_i + b_i)) & i=2,3,4 \end{cases}$$
(10)

The timing layer has two layers of results. Unlike QPE-Net8, the timing result of each layer uses the sampling result Y_{i+1} of the corresponding layer from bottom to top. the timing structures of the first layer and the second layer are easily derived using Eqs. (6) and (7).

(The first layer)

$$r_{1}^{t} = \sigma \left(w_{r,1} \cdot \left[h_{1}^{t-1}, Y_{5+1}^{t} \right] \right)$$

$$z_{1}^{t} = \sigma \left(w_{z,1} \cdot \left[h_{1}^{t-1}, y_{5+1}^{t} \right] \right)$$
(11)
$$\tilde{h}_{1}^{t} = tanh \left(w_{\tilde{h},1} \cdot \left[r_{1}^{t} * h_{1}^{t-1}, y_{5+1}^{t} \right] \right)$$
(The second layer)
$$r_{2}^{t} = \sigma \left(w_{r,2} \cdot \left[h_{2}^{t-1}, Y_{4+1}^{t} + h_{1}^{t} \right] \right)$$

$$z_{2}^{t} = \sigma \left(w_{z,2} \cdot \left[h_{2}^{t-1}, y_{4+1}^{t} + h_{1}^{t} \right] \right)$$
(12)

$$\widetilde{h_2}^t = tanh\left(w_{\tilde{h},2} \cdot \left[r_2^t * h_2^{t-1}, y_{4+1}^t + h_1^t\right]\right)$$

The structure of OPE-Net22 is shown in Fig. 4. Taking the first six layers from the

The structure of QPE-Net22 is shown in Fig. 4. Taking the first six layers from the preprocessed radar echo data as the channel, by inputting the radar data of 10 continuous time, each time passing through two convolutional layers, and then learning the multi-level features through the downsampling (the largest pooling layer). Each time the downsampling size is changed to half of the original. When upsampling, the ConvGRU unit is used for timing calculation, and then the same number of channels corresponding to the feature extraction part are fused, and finally the rain data corresponding to the hour is generated. QPE-Net22 is a network parameter configuration table as shown in Tab. 2.

Input size	Kernel type	Kernel size	Output size
224×224×6	Conv2d	3×3	224×224×64
224×224×64	Downsampling conv2d	3×3	112×112×128
112×112×128	DownSampling conv2d	3×3	56×56×256
56×56×256	DownSampling conv2d	3×3	28×28×1
28×28×1	DownSampling conv2d	3×3	14×14×1
14×14×1	Upsampling deconv2d	3×3	28×28×1
28×28×1	Upsampling deconv2d	3×3	56×56×1

 Table 2: QPE-Net22 Network parameter





A typical calculation flow of the QPE-Net22 network model is as follows:

Algorithm2 QPE-Net22 Input: Training data $D_i = \langle Z_1, Z_2, \dots, Z_T \rangle, i = 1, 2, \dots, k$ Output: *The rainfall Y* 1: *for t=1, 2, ..., T*: 2: *for i*=1, 2, ..., *n*: $C_i = DownConvs_i(Z_t);$ 3: 4: end for 5: $D_t = C_n;$ 6: *for i*=1, 2, ..., *n*: 7: $D_t = UpConvs_i(C_{n-j-1}, D_t);$ G_{t_t} , $h_t = GRUcell_i (D_{t_t}, h_{t-1});$ 8: 9: $G_t = ReLU_j(G_t);$ 10: end for 11: end for12: $Y = ReLU(W^*G_t + b);$ 13: return Y

3.4 Training algorithm

The ST-QPE algorithm's radar quantitative estimation of precipitation training process on these two structures mentioned above is listed:

Algorithm3 ST-QPEInput: Training data $< D_i, \hat{R}_i >, D_i =< Z_1, Z_2, \cdots, Z_T >, i = 1, 2, \cdots, k$ Output: The model parameter $\theta =< W, b >$ 1: $f \leftarrow QPENet8$ or QPENet22;2: Initial θ ;3: Do while itertime \leq epoch and $\Delta > \varepsilon$:4: $L(\hat{R}_i, D_i, \theta) \leftarrow \hat{R}_i - f(D_i, \theta);$ 5: $\Delta = \|\hat{R}_i - f(D_i, \theta)\|;$ 6: $\theta \leftarrow \theta - \eta \cdot \nabla L(\hat{R}_i, D_i, \theta);$ 7: EndDo8: Output θ

After obtaining training samples, the algorithm selects an appropriate number of batches from the training set, use the back-propagation algorithm to find the optimal parameters, input the training set into the ST-QPE algorithm, and iterate through the epoch to the model convergence. ST-QPE algorithm training is actually a process of seeking the optimal parameters. The loss function is used as the training target during model training. this paper uses Mean Square Error (MSE) as our loss function to evaluate accuracy of model training. The calculation formula is as Eq. (13):

$$L = \frac{1}{n} \sum_{i=1}^{n} (y - y')^2$$
(13)

where n is the total number of experimental samples, y is the actual rainfall value, and y' is the result value reversed by the model.

3.5 Back propagation and parameter update

Similar to Shin et al. [Shin, Ahn, Lee et al. (2019)], we adopt Rectify Linear Unit (ReLU) as the activation function, which helps to solve the convergence of deep networks, also to improve the model expression ability. Because of the piecewise linear characteristics of the ReLU function, the network does not easily lose information during forward and backward propagation. The expression of the ReLU function is as Eq. (14):

$$f(x) = \begin{cases} 0, \ x \le 0 \\ x, \ x > 0 \end{cases}$$
(14)

For the ST-QPE algorithm, the loss function is defined as $L(\theta)$, and the gradient of the parameter θ is obtained by the loss function. To facilitate the derivative operation, the calculation formula of the loss function has been improved. The back-propagation process is as Eqs. (15) to (17):

$$L(\theta) = \frac{1}{2n} \sum_{i=1}^{n} (y - y'(\theta))^2$$
(15)

$$\frac{\partial L}{\partial \theta} = \frac{1}{n} \sum_{i=1}^{n} (y - y'(\theta)) \frac{\partial y'}{\partial \theta}$$
(16)

$$\nabla_{\theta} L(\theta) = \frac{\partial L}{\partial \theta} \tag{17}$$

After obtaining the gradient of each layer, we use the stochastic gradient descent algorithm to update the parameters of each layer so that the objective function converges. the magnitude of the parameter change is adjusted by referring to the learning rate η according to the gradient, as shown in the Eq. (18):

$$\theta = \theta - \eta \cdot \nabla_{\theta} L(\theta) \tag{18}$$

An inappropriate value of η can introduce issues. The network may converge too slow if the value is too small, or may never converge if the value is too large. Empirically, the learning rate of this paper is best when it is set to 0.001.

4 Experimental results and analysis

The method is implemented using python with a deep learning framework pytorch on pycharm. To demonstrate the method, we also take the advantage of GPU computing architecture to gain higher performance by using CUDA 9.0 and CUDNN. We conducted experiments for analysis of QPE-Net8 and QPE-Net22 on a computer with an NVIDIA GTX 1080Ti card.

4.1 Dataset

Meteorological observation data is a collection of various raw data observed by conventional meteorological instruments and professional meteorological equipment.

The meteorological element sequences accumulated from continuous observations at fixed points, cannot directly represent the characteristics of regional climate change in climate analysis and numerical simulation, due to limitations such as uneven station spatial distribution, uneven sequence lengths instability of observation equipment in performance. Therefore, such data encounters many restrictions in practical applications. Motivated by these limitations, this paper systematically integrates and perform quality control on the experimental samples. We choose radar data and rainfall data from February to October 2018 as experimental data. The string-matching algorithm is used to select the effective samples of the radar data. 7450 consecutive valid samples are selected among 11162 samples; thus 745 rainfall sets of data. In order to speedup reading, the original radar echo data and the rainfall data that covers the whole province are cropped with a smaller size of 45×45 (550 to 595, 840 to 885). The size of original coverage is 224×224 (550 to 774, 700 to 924). The radar echo data values are normalized, level by level to between 0 and 1 using Eq. (19):

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$$x'_{i} = \frac{x_{i} - x_{min_{i}}}{x_{max_{i}} - x_{min_{i}}} \quad (0 \le i \le 6)$$
(19)

where x is the original radar echo data, x_{min} and x_{max} are the minimum and maximum values respectively, x'_i is the normalized value, and *i* denotes the radar layer number.

After data preprocessing steps described above, a set of standard data is built, where the ratio of data for to data for test is 7:3. The data set consists of ten consecutive radar samples and corresponding rain labels within one hour. The data set is defined as:

$$D = \{(x_1, y_1), (x_2, y_2), \cdots, (x_i, y_i), \cdots, (x_t, y_t)\}$$
(20)

In Eq. (20), $x_i (i = 1, 2, 3, \dots, t)$ is the input data(all radar echo data), $y_i (i = 1, 2, 3, \dots, t)$ is the output data. The target data set represents the hourly rainfall value of the automatic weather station.

4.2 Experimental results

Once the model training is done, the current optimal model and loss function graphs on the training and test sets are recorded. The QPE-Net8 structure and QPE-Net22 loss function graphs are depicted in Figs. 5-8.









Figure 7: QPE-Net22 training loss

Figure 8: QPE-Net22 testing loss

150 epoch 200

250

300

50

3.0 2.5 1.5 0.5 0.5 0.5

Figs. 5-8 shows the changes of the loss values of QPE-Net8 and QPE-Net22 after 300 iterations. It can be seen from the figure that as the number of iterations increases, the loss values of the two structures gradually decrease and tend to be stable.

Now we can draw the inversion rainfall map based on the optimal model. Fig. 9 is a comparison of rainfall images retrieved from radar echo maps between CMPA, QPE-Net8 and QPE-Net22. Darker colors indicate greater rainfall intensity. By having the loss maps of both two structures, the QPE-Net8 and QPE-Net22 network structures are able to learn the radar data characteristics to get inversed rainfall maps that are more similar to and the real rainfall maps.



Figure 9: The rainfall images retrieved from radar echo maps. (a) the CMPA hourly fusion live rainfall map (the label), (b) the rainfall map retrieved by QPE-Net8, (c) the rainfall map retrieved by QPE-Net22

Then, we use the MICAPS, a comprehensive analysis and processing system for weather information, to visualize the map on July 6, 2018 at 05:00, where the size is 45×45 with the grid interval of 0.05, longitude from 112° E to 114.2° E and latitude from 27.5° N to 29.7° N. The result is then converted into Micaps fourth type data format. The data is arranged in the wise of first weft and backward meridian. Next, data from label, QPE-Net8, and QPE-Net22 are imported into the Micaps system with the region set to Hunan. The results are shown in Fig. 10 and the enlarged area is shown in Fig. 11.



Figure 10: The result comparison in MICAPS



Figure 11: The enlarged area map

As can be seen from Figs. 11 and 12, a clearer and more intuitive understanding of the results can be developed, by visualizing CMPA fusion hourly live, and results of QPE-Net8 and QPE-Net22 inversion. Compared with the CMPA actual situation, results show that the QPE-Net8 and QPE-Net22 models have better responses in several heavy precipitation centers, therefore better reflect the heavy precipitation area where the overall deviation of precipitation is relatively small. Fig. 11 shows the QPE-Net8 underestimates the heavy rainfall center, while the QPE-Net22 model based on multi-scale fusion is stronger than the CMPA live and QPE-Net Net8 model has better stability.

4.3 Test of results

In order to describe the error and accuracy characteristics of radar retrieval rainfall effect, this paper uses the Mean-Square Error (MSE), Mean Error (ME) and Relative Error (RE) to statistically evaluate these two models by Eqs. (21)-(23). RMSE is used to measure the similarity between predicted results and label values, which is commonly used in regression problems in the field of machine learning. Use RMSE to evaluate the dispersion of QPE-Net8, QPE-Net22 and CMPA live rainfall. If the RMSE is smaller, it means that the distribution is more concentrated. The average error is used to estimate the overall data difference. The closer the ME is to 0, the smaller the overall data difference; The relative error is used to estimate the reliability of the data.

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (y - y')^2}$$
(21)

$$ME = \frac{1}{n} \sum_{i=1}^{n} (y - y')$$
(22)

$$RE = \frac{\frac{1}{n} \sum_{i=1}^{n} |y - y'|}{\frac{1}{n} \sum_{i=1}^{n} y'} \times 100\%$$
(23)

where *n* represents the total number of samples, *y* is the sample label, and y' is the value inversed by the model.

In order to ensure the evaluation objectivity of, this paper divides rainfall into light rain (less than or equal to 2.5 mm), moderate rain (2.6~8.0 mm), heavy rain (8.1~15 mm), and torrential rain (more than or equal to 16 mm) according to the one-hour rainfall level.), the rainfall inversion of the two models is analyzed for each group.QPE-Net8 and QPE-Net22 models and CMPA live rainfall scatter plots are given in Fig. 12. The closer-the points lie on a scatter plot with respect to the straight line, the better the radar rainfall inversion quality is. Points above and under the line indicate overestimation and underestimation become more obvious as the amount of rainfall increases. the correlation coefficient between QPE-Net22 and CMPA live rainfall is slightly higher than that of QPE-Net8, indicating that QPENet22 has a better correlation with CMPA live distribution, as a more concentrated distribution can be observed, which effectively improves the accuracy of rainfall estimation. Therefore, the QPE-Net22 network gives inversion closer to the CMPA hourly live than QPE-Net8 does.



Figure 12: The scatter plot of CMPA live, QPE-Net8 estimated rainfall and QPE-Net22 estimated rainfall

Then, based on the rainfall level, we give the error analysis of QPE-8 and QPE-Net22 models, as shown in Tab. 4.

Model		<2.5 mm	2.6~8.0 mm	8.1~15 mm	>16 mm
QPE-Net8	RMSE	2.4608	7.8636	14.641	19.789
	ME	0.1976	-0.0668	0.0106	0. 1093
	RE	0.5129	0.3088	0.0339	0.0942
	RMSE	2.4873	7.8636	14.556	17.609
QPE-Net22	ME	0.0393	-0.0103	0.0314	0. 0297
	RE	0.1732	0.0378	0.0942	0.0275

Table 4: The analysis of radar inversion rainfall error for different rainfall levels

According to Tab. 4, QPE-Net8 and QPE-Net22 overestimate the rainfall more often for light rain, heavy rain and torrential rain, but highly underestimate moderate rain. The QPE-Net22 model has an average error of 0.0297 mm and a relative error of 0.0275, In this order of magnitude, rainfall is better than the QPE-Net8 model, and the average error of QPE-Net8 overestimation of heavy rain is 0.0106 mm and the relative error is 0.0339, which is better than the QPE-Net22 model. Overall, QPE-Net22 has average and relative retrieval errors on cases of light rain, moderate rain, and heavy rain lower than QPE-Net8. For moderate rain, heavy rain, and torrential rain, the mean square error generated by-QPE-Net22 is also smaller than QPE-Net8, which indicates that QPE-Net22 has a higher degree of fit for heavy rainfall and torrential rainfall.

Finally, we use the objective weather testing methods for ConvGRU, QPE-Net8 and QPE-Net22, including the Probability of Detection (POD), the False Alarm Ratio (FAR), and the Critical Success Index (CSI) [Lu, Ren, Sun et al. (2018)]. The calculation formulas are shown in Eqs. (24)-(26).

$$POD = \frac{TP}{TP + FN}$$
(24)

$$FAR = \frac{FP}{TP + FP} \tag{25}$$

$$CSI = \frac{TP}{TP + FN + FP}$$
(26)

where TP, FN and FP respectively represent the number of points in cases of the success, false and missing reports on the inverse rainfall map.

According to the information of radar and the rainfall label, the corresponding hourly rainfall maps are inverted, and the two network structures of QPE-Net8 and QPE-Net22 are tested and evaluated. The inversed results are tested by calculating the rainfall in each grid cell. Evaluation and comparison analysis are performed against with the existing ConvGRU network model. The final evaluation results are shown in Tab. 5.

Model	POD	FAR	CSI
ConvGRU	0.6342	0.2351	0.5472
QPE-Net8	0.5991	0.0246	0.5902
QPE-Net22	0.5255	0.0103	0.5226

 Table 5: Comparison of inspection results

It can be seen from Tab. 5 that POD and CSI values of QPE-Net8 and QPE-Net22 are less than those of ConvGRU, which indicates that the rainfall results reversed by the ST-QPE model are more stable, especially for the case of missing reports, which is referred to FAR Evaluation. QPE-Net8 and QPE-Net22 results are significantly better than ConvGRU. In summary, QPE-Net22 provides results that are closer to the ground truth rainfall value than the other two methods.

Fig. 13 shows a schematic diagram of the rainfall changes at 12, 14, 17 and 18 o'clock on 8th July, 2018. A rainfall zone including Yiyang and Yueyang is involved. As time

advances, the rainfall has changed significantly. At 14:00, 17:00, and 18:00, rainfall of more than 10mm appeared, followed by two zones with heavy rainfall greater than 16mm at 17:00 and 18:00. The hourly precipitation evolution chart shows that the center of precipitation gradually moves westward and northward over time. Fig. 13 contains the live rainfall map obtained from the automatic station, the CMPA live area zoomed-in map, the QPE-Net8 reversed area zoomed-in map, and the QPE-Net22 reversed area zoomed-in map. Compared with the real station rainfall, the CMPA live rainfall, QPE-Net8 inversion rainfall and QPE-Net22 inversion rainfall precipitation distribution and landing area are more consistent, which further verifies the reliability of the method presented in this paper.



Figure 13(a): The rainfall data of Hunan Province Automatic Observation Station in hour



Figure 13(b): CMPA Live Rainfall



Figure 13(c): The rainfall inversion by QPE-Net8 model



Figure 13(d): The rainfall inversion by QPE-Net22 model

Figure 13: Diagram of rainfall process from 12:00 pm to 18:00 pm on July 8, 2018

In terms of the effect of the inversion of rainfall given in Figs. 13(c) and 13(d), the overall performance of both models is relatively stable, especially for moderate rain, heavy rain and storm in the northeast border area of Hunan. In contrast to the automatic station live and CMPA live rainfall, the area and intensity of different grades of rainfall have better improvements. The spatial and temporal characteristics of QPE-Net8 are generally poorer, resulting in a narrow precipitation range and large instability. Another concern is that QPE-Net22 can generate results closer to the CMPA reality, and it is able to better grasp the northward movement of rainfall zones. The area and range of the rainstorm are more consistent with the automatic station reality and the CMPA reality. The model inversion effect better.

5 Conclusion and future work

In this paper, an algorithm of radar echo precipitation based on spatiotemporal network is proposed to meet the high resolution in radar quantitative precipitation estimation which is difficult to achieve by traditional methods. The convolutional neural network was used to extract the spatial and temporal characteristics of the radar echo map, two different network structures have been designed for inversion experiments, and the ST-QPE algorithm inversion was analyzed using statistical tests and weather methods. The simulation results include the indicators and correlation coefficient diagrams of the two models for different rainfall distributions. The experimental results show that the ST-QPE algorithm can better reflect the rainfall information corresponding to the current hourly radar echo and improve the accuracy of the quantitative rainfall estimation. Therefore, useful practical guidance for small areas without radar stations and early warnings of extreme weather can be provided more efficiently.

There are several avenues for future works. We would like to design a data set that includes multiple meteorological elements (such as temperature and humidity), and construct a network model that integrates attention mechanisms, optimizes network parameters. Also, improvements to the spatial and temporal characteristics can likely to be considered.

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