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Identification of Precipitation-Clouds Based on the Dual-Polarization Doppler Weather Radar Echoes Using Deep–Learning Method

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ABSTRACT The dual-polarization Doppler weather radar is a kind of radio-frequency sensor that can provide abundant information about atmospheric particle scattering behavior. The identification of the precipitation cloud type based on dual-polarization Doppler weather radar echoes is a study that classifies precipitation clouds based on the scattering theory of precipitation cloud particles to polarized electromagnetic waves. In recent years, the Doppler weather radar has been widely used in quantitative precipitation estimation, and the accurate identification of precipitation cloud types plays an essential role in improving the accuracy of precipitation estimation. The accuracy of the conventional precipitation cloud identification method relies on the number of features that are identified by human eyes, and it greatly reduces the operation efficiency. In order to improve the accuracy and efficiency of the precipitation cloud identification, a methodology of precipitation cloud identification based on deep learning is proposed in this paper. The method mainly consists of three major parts, which are constant altitude plan position indicator data inversion, zero-layer bright band identification, and precipitation-cloud classification by using the deep learning network model. At last, this paper evaluates the identification effect of this method through a real precipitation process. The results show that this method can distinguish the stratiform clouds and convective cloud precipitation in the precipitation area in real time, and it is in good agreement with the ground observation data. This method is very useful for improving the accuracy of the quantitative precipitation estimation of the Doppler weather radar.

INDEX TERMS CAPPI, deep learning, identification, precipitation cloud, zero-layer bright band.

I. INTRODUCTION

The capability of microwaves to penetrate cloud and rain has placed the weather radar in an unchallenged position for remotely surveying the atmosphere. Although visible and infrared cameras on satellites can detect and track storms, the radiation sensed by these cameras cannot probe inside the storm's shield of clouds to reveal, as microwave radar does, the storm's internal structure and the hazardous phenomena that might be harbored therein. The Doppler radar is currently the primary tool that can detect tracers of wind and measure their radial velocities, both in the clear air and inside heavy rainfall regions veiled by clouds. So it can be claimed that Doppler radars are the most important sensors for atmosphere sounding. The The dual linear polarization Doppler weather radar is a kind of radio frequency sensor capable of transmitting two linear polarizations of electromagnetic wave and provides several additional parameters of interest to the meteorologist. It can transmit the horizontal and vertical polarization waves alternately or simultaneously, and adopt different signal processing in two polarization channels, therefore it can derive several polarimetric measurements, such as horizental reflectivity (Z_H), differential reflectivity factor (Z_{DR}), differential propagation phase constant (K_{DP}), linear depolarization ratio (LDR), correlation coefficient ($\rho_{HV}(0)$) and so on. These polarimetric measurements reflect the characteristics of the size, shape, phase and orientation of the precipitation particles in the atmosphere, and promote the development of quantitative precipitation estimation and hydrometeor classification [1]–[5]. Compared with the Z-I relationship of the conventional Doppler weather radar, the quantitative precipitation estimation based on dual-polarization Doppler weather radar has obvious advantages [6], [7].

Precipitation is a kind of common weather phenomenon. According to the different types of precipitation clouds, they can be divided into three precipitation types, which are stratiform cloud precipitation, convective precipitation and convective stratiform mixed cloud precipitation [8]. The stratiform cloud precipitation is caused by the vertical rising movement of the air in a wide range. In generally, stratiform cloud has a large horizontal scale, but with small vertical scale. The intensity of precipitation caused by stratiform cloud is relatively weak, but with long duration, and the radar echo presented as flakes, which is accompanied by the phenomenon of the bright-band [9], [10]. The convective cloud precipitation is caused by the air vertical movement due to the instability of the atmosphere. Its horizontal scale is small, and the vertical convection is strong, often accompanied by storm, rainstorm, hail, and other disastrous weather [11]. Therefore, the accurate identification of stratiform clouds and convective clouds is helpful for understanding the formation mechanism of precipitation cloud and improving the ability of estimating rainfall intensity by Doppler weather radar.

In 2003, Ikeda and Brandes [12] analyzed the characteristics of the polarization parameters of the precipitation particles in the melting layer, and they obtained the distribution of the polarimetric parameters such as Z_H, Z_{DR}, LDR and $\rho_{HV}(0)$ in the melting layer. In 2005, Rico-Ramirez *et al.* [13] utilized the fuzzy logic method to identify the zero-layer bright band on the basis of these distribution laws, and the recognition results are used in the classification of hydrometeors such as rain, snow and snowmelt.

In 2008, Wang J et al. utilized back propagation artificial neural network (BP-ANN) method to realize the classification of precipitation clouds. The BP-ANN takes reflectivity and reflectivity gradient as input, and the input data is processed by the hidden layer. Finally, the membership degree of three kinds of precipitation cloud types can be obtained by the BP-ANN method [8]. In 2011, based on the precipitation data in Singapore for many years, Kumar analyzed the drop distribution of the precipitation particles during the precipitation process of stratiform clouds and convective clouds in this area. Meanwhile, they realized the classification of precipitation cloud type, and derived corresponding Z-R relation of different types of precipitation clouds by using the parameters of rain rate R, reflectivity Z, median volume diameter D_0, N_W that is generalized number concentration of an exponential DSD having the same liquid water content W and mass-weighted diameter D_{m} as the actual DSD, and the gamma model parameter μ [14].

In 2006, an article published in Science by Hinton et al. opened up a new door of deep learning in the field of machine learning. Deep learning, as a new kind of multilayer artificial neural network learning algorithm, solves the defects of the traditional neural network algorithm, such as overfitting, gradient diffusion and local optimization, and it has been widely used in machine learning and computer vision, and has aroused wide attention in various fields [15]–[18]. In 2016, Tao *et al.* [19] utilized the deep learning algorithm to extract useful features from the multispectral satellite information, and retrieved the rainfall in the local area at that time with the extracted feature parameters. In 2017, Wang H et al. utilized the convolution neural network algorithm to extract the features from the polarimetric measurements of dual-polarization Doppler weather radar. The extracted features were classified by Softmax classifier, and the precipitation particles are divided into rain, snow, hail, ice crystals and other categories [20].

This paper presents a new identification method for precipitation clouds, based on the data of CINRAD-SA dual-polarization Doppler weather radar in China and the study of the characteristics of precipitation cloud. In this method, the Vertical and Horizontal Interpolation (VHI) method is used to interpolate the radar scanning volume data to obtain the CAPPI data at any altitude. Considering the similarity of the echo characteristics between the zero-layer bright band and the convective cloud precipitation, this paper uses the fuzzy logic method to identify the zero-layer bright band in order to remove them from the CAPPI data. Then, this study uses the CNN network model to discriminate the precipitation clouds. In the end, the identification result of precipitation cloud at several altitudes have been merged into a complete precipitation cloud distribution map.

II. DATA

In this research, we collected a large amount of precipitation data from the CINRAD-SA dual-polarization Doppler weather radar in Guangdong province of China, and the radar parameters are shown in Table 1. The data include Z_H, Z_{DR}, LDR, $\rho_{HV}(0)$, Φ_{DP} and K_{DP}, which reflect the detailed precipitation process between March 2017 and July 2017 in Guangdong province of China.

TABLE 1. The main technical indicators of CINRAD-SA dual polarized weather radars.

Number	Project	Radar（CINRAD-SA）
1	Transmitter Wave type	S-band（2885Mhz）
2	Transmitter Peak power	800Kw
3	Antenna type	Parabolic antenna
4	Antenna Gain	45db
5	Operation mode	Horizontal / vertical polarization
6	Signal processing mode	PPP/FFT
7	Beam width	0.95°
8	Pulse resolution	1.57us
9	Detection range	400Km
10	Range Bin	250m

Polarization refers to the vibration direction of electromagnetic waves in the propagation, and when the electric field vibrates in the horizontal direction, it is named the horizontal polarized wave. Otherwise, if in the vertical direction, it is named the vertical polarized wave. The CINRAD-SA dual-polarization Doppler weather radar transmits the vertical and horizontal polarization waves at the same time or alternately. Due to the inhomogeneous distribution of spread medium in space, the different polarization signal attenuation and phase shift will be different, so the attenuation difference and phase shift difference of two polarization waves can be obtained. A series of polarimetric measurements data can be obtained by the corresponding data processing and calculations of the attenuation difference and phase shift difference. This section will introduce the major polarimetric measurements and their characteristics in detail.

A. HORIZONTAL AND VERTICAL REFLECTIVITY FACTORS (Z_H AND Z_V)

Usually, the dual linear polarimetric Doppler weather radar alternately transmits horizontal and vertical polarization waves to obtain the horizontal and vertical reflectivity, respectively. When the horizontal polarization waves are transmitted, the horizontal reflectivity is defined by equation 1.

$$Z_H = \int_0^{D_{\max}} N(D) \bullet D_H^6 d_D \tag{1}$$

Where D is the diameter of precipitation particles, D_H is the projection of D in horizontal polarization direction, and $D_{\max}$ is the max diameter of these precipitation particles. $N(D)$ is the drop distribution of the precipitation particles, and it is a function of D. When the radar transmits vertically polarized waves, the vertical reflectivity is given by equation 2.

$$Z_V = \int_0^{D_{\max}} N(D) \bullet D_V^6 d_D \tag{2}$$

where D_V is the projection of D in vertical polarization direction. Thus, it is obvious that the horizontal and vertical reflectivity factors are the functions of the particle diameter, drop distribution and dielectric constant. For the rainfall, the effect of particle diameter on the horizontal reflectivity factor is greater, and the larger particle size produces the larger the horizontal reflectivity factor. Therefore, the size of the precipitation particles can be inferred. Besides, the reflectivity factor is also affected by the dielectric constant for different types of precipitation particles, such as hail and raindrops.

B. DIFFERENTIAL REFLECTIVITY FACTOR Z_{DR}

Z_{DR} is computed by horizontal and vertical reflectivity factor:

$$Z_{DR} = 10 \bullet \log\left(\frac{Z_{\mathrm{H}}}{Z_V}\right) \tag{3}$$

Equation 3 shows that Z_{DR} is related to particle size and axial ratio (axial ratio is defined by α/b, where α is horizontal axial radius, and b is vertical axial radius). Therefore, differential reflectivity factor is the function of particle size, shape and dielectric constant. For the spherical particles, $Z_{\mathrm{H}} = Z_V$, and $Z_{DR} = 0$. For the non-spherical particles, the larger the eccentricity, the farther the differential reflectivity factor deviates from the 0 value, so the differential reflectivity factor can be used to distinguish different precipitation particles.

C. DIFFERENTIAL PROPAGATION PHASE Φ_{DP} AND DIFFERENTIAL PROPAGATION PHASE CONSTANT K_{DP}

The difference of the phase between the horizontally and vertically polarized waves is called the differential phase, which is given by equation 4.

$$\Phi_{DP} = \Phi_{HH} - \Phi_{VV} \tag{4}$$

Where Φ_{HH} and Φ_{VV} are respectively the two-way phase angle at a certain distance from the arrival of the antenna when the radar signal is in the horizontal and vertical polarization. The specific differential phase $K_{DP}$is defined by equation 5.

$$K_{DP} = \frac{\Phi_{DP}(r_2) - \Phi_{DP}(r_1)}{2(r_2 - r_1)} \tag{5}$$

K_{DP} is the difference between the propagation constants of horizontally and vertically polarized waves, and it contains the difference between isotropic particles and anisotropic particles. Isotropy means that the physical and chemical properties of the object do not change with the direction. In other words, the characteristics of electromagnetic scattering echo of the precipitation particles in different directions should be the same. Therefore, the isotropic particles will produce similar phase shifts for horizontal and vertical polarization waves, and the difference of K_{DP} is attributed to anisotropic particles. In general, K_{DP} increases as the dielectric constant and eccentricity increase, and it depends on the number density of particles.

D. ZERO LAG CORRELATION COEFFICIENT $\rho_{HV}(0)$

The correlation coefficient at zero lag is defined by the amplitude of zero lag cross correlation coefficient of the received horizontally and vertically polarized signals, whose expression is given by equation 6.

$$\rho_{HV}(0) = \frac{\left\langle S_{VV} S_{HH}^* \right\rangle}{\left[\left\langle |S_{VV}|^2 \right\rangle \left\langle |S_{HH}|^2 \right\rangle\right]^{\frac{1}{2}}} \tag{6}$$

where S_{HH} and S_{VV} can be equivalent to the polarized echo signal in horizontal and vertical direction, and $\rho_{HV}(0)$ reflects the correlation of the backscattering characteristics of horizontal and vertical polarization waves. Thus, correlation coefficients are closely related to the shape, density and spatial orientation of precipitation particles. As mentioned above, these polarimetric measurements reflect the size, shape, density, and orientation of precipitation particles in atmospheric space. The comprehensive utilization of these polarimetric measurements makes it possible to classify the type of precipitation clouds precisely.

III. METHOD

A. THE INVERSION OF CAPPI

In china, the main operational radar of China Meteorological Administration is Doppler weather radar, which can not only obtain the distribution information of precipitation particles in atmosphere, but also provide the information of the atmospheric wind field. During the Doppler weather radar operation process, VCP21 working mode is a common choices for meteorological service. It can complete a volume scan in 6 minutes, and each volume scan consists of 9 elevation. For each elevation, the Plane Position Indicator (PPI) scan mode is adopted. As shown in Figure 1, the radar antenna captures precipitation data in the atmosphere in a fixed elevation, omni-directional scanning mode, and in polar coordinates (radar-centered) with different color scales to indicate the magnitude and direction of the values. This scanning method is called PPI scanning. In other words, radar can acquire the information of precipitation particles in a three-dimensional space in 6 minutes, which provides guarantee for the real-time prediction in weather operation. In the process of identifying the precipitation cloud, in order to describe the vertical and horizontal characteristics of the precipitation cloud system more intuitively, the PPI data of all elevations need to be processed through spatial interpolation to obtain the information of the precipitation particles at a certain altitude, namely CAPPI data.

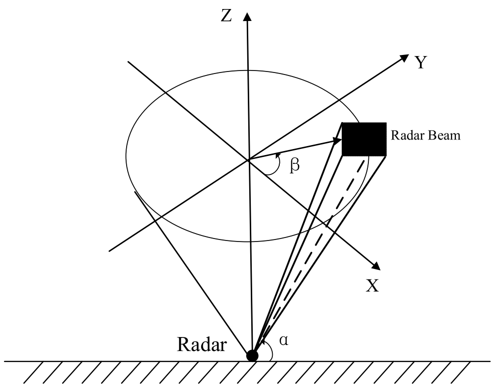

FIGURE 1. The schematic diagram of PPI scan mode.

In the detection stage of dual-polarization Doppler weather radar, the noise of radar system itself, the interference of ground clutter and the attenuation of radar signal will lead to the data quality decline, which seriously affects the credibility of the final identification result. Therefore, some meteorological data quality control methods is applied to improve the accuracy of detection data, mainly including ground clutter rejection, systematic error correction, and attenuation correction.

VHI is a commonly used linear interpolation method, as shown in Figure 2, where Z is the radar reflectivity, R is the distance from the radar site to the target, θ is the azimuth angle of the target, and ϕ is the elevation angle of the target. For a data point to be interpolated $Z(R, \theta, \phi)$, it is

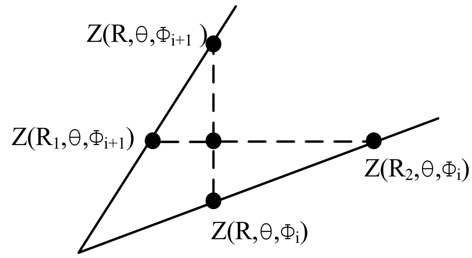

FIGURE 2. The interpolation schematic of VHI.

linearly interpolated by the data below its elevation, namely $Z(R, \theta, \phi_i)$ and $Z(R_2, \theta, \phi_i)$, and the data above its elevation, namely $Z(R, \theta, \phi_{i+1})$ and $Z(R_1, \theta, \phi_{i+1})$.

$$Z(R, \theta, \phi) = \frac{W_{\phi_i} \cdot Z(R, \theta, \phi_i) + W_{\phi_{i+1}} \cdot Z(R, \theta, \phi_{i+1})}{W_{\phi_i} + W_{\phi_{i+1}} + W_{R_1} + W_{R_2}} + \frac{W_{R_1} \cdot Z(R, \theta, \phi_{i+1}) + W_{R_2} \cdot Z(R, \theta, \phi_i)}{W_{\phi_i} + W_{\phi_{i+1}} + W_{R_1} + W_{R_2}} \quad (7)$$

where W_{ϕ_i} and $W_{\phi_{i+1}}$ are the interpolation weights of $Z(R, \theta, \phi_i)$ and $Z(R_1, \theta, \phi_{i+1})$, which are given by equation 8. W_{R_1} and W_{R_2} are the interpolation weights of $Z(R_1, \theta, \phi_{i+1})$ and $Z(R_2, \theta, \phi_i)$, which are given by equation 9.

$$\begin{cases} W_{\phi_i} = (\phi_{i+1} - \phi)/(\phi_{i+1} - \phi_i) \\ W_{\phi_{i+1}} = (\phi - \phi_i)/(\phi_{i+1} - \phi_i) \end{cases} \quad (8)$$

$$\begin{cases} W_{R_1} = (R_2 - R) \,/\, (R_2 - R_1) \\ W_{R_2} = (R - R_1) \,/\, (R_2 - R_1) \end{cases} \quad (9)$$

From table 1, the maximum effective detection range of the radar data is 400 km, and the range bin is 250 meters with 1 degree beam width. In this paper, the CAPPI data of Z_H, Z_{DR}, $K_{DP}$and $\rho_{HV}(0)$ has been rebuilt by using VHI method, and the minimum resolution is 100-meter.

B. IDENTIFICATION OF BRIGHT BAND

1) ZERO-LAYER BRIGHT BAND

The zero-layer bright band is an important feature of stratiform cloud precipitation. It mainly refers to a phenomenon that a strong echo bright band or a bright circle appears on the high elevation angle radar echoes. During the process of falling of solid precipitation particles such as snowflakes or ice crystals, when the ambient temperature is above 0°C, the surface of the ice particles is melted and a layer of outsourced water film is formed. Due to the difference of the complex refractive index of the liquid water and the ice phase particle, the reflectivity of the melting particles increases dramatically.

The zero-layer bright band reflects the obvious ice-water conversion process during the stratiform cloud precipitation process. Many kinds of precipitation particles exhibit in the zero-layer bright band, and their physical properties are complex and changeable. At the same time, some characteristics are very similar to the convective clouds, which bring difficulties to the accurate identification of the precipitation cloud.

Therefore, it is of great significance to accurately distinguish the position of the zero-layer bright band to improve the accuracy of cloud identification and quantitative precipitation estimation. In recent years, research on the identification of the zero-layer bright band based on dual-polarization radar data has yielded fruitful results. A large number of studies show that in zero-layer bright band, as the altitude increase, the horizontal polarization reflectivity Z_H and differential reflectivity factor Z_{DR} increase firstly and then decrease, and horizontal/vertical zero lag correlation coefficient $\rho_{HV}(0)$ decrease firstly and then increase. In general, in the products of S-band polarimetric radar, Z_H in the zero-layer bright band mainly distributes from 30 to50 dBZ, and Z_{DR} is mainly from 1 to 3.5dB, and $\rho_{HV}(0)$ is mainly from 0.7 to 0.95.

2) DESIGN OF THE METHOD FOR IDENTIFYING THE ZERO-LAYER BRIGHT BAND

This paper chooses the fuzzy logic algorithm to identify the zero-layer bright band, which was proposed by Zadeh in 1965 firstly. The traditional fuzzy logic algorithm mainly includes: fuzzification, inference, aggregation, and defuzzification. As discussed in section 3.2.1, the input parameters include the polarimetric measurements, such as Z_H, Z_{DR} and $\rho_{HV}(0)$, and so on. At the same time, considering that the zero-layer bright band also has the obvious altitude characteristic, we also take the height as an input parameter. In the method of identification of zero-layer bright band based on fuzzy logic, the input parameters are processed by fuzzification, inference, aggregation and defuzzification, and the final output is 1 (zero-layer bright band) or 0 (non-zero-layer bright band). The schematic diagram is shown in Figure 3.

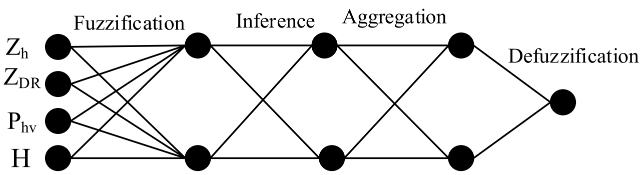

FIGURE 3. The structure of bright band identification system based on fuzzy logic.

a: FUZZIFICATION AND MEMBERSHIP FUNCTION SELECTIONS

When fuzzy logic algorithm is applied for the identification of the zero-layer bright band, firstly, we need to process fuzzification for the four input parameters. Namely, the original input data are converted into fuzzy basis by membership function, and a certain input data can belong to different fuzzy basis, and it also corresponds to different membership degrees in different fuzzy basis [20]. It is obvious that the most important step is the construction of membership function. Through a large number of experiments, it is found that the performance of the beta membership function is the best, and the beta function is given by equation 10.

$$\beta(x, a, b, m) = \frac{1}{1 + \left|\frac{x-m}{a}\right|^{2b}} \tag{10}$$

Where x is the input parameter, and $a$is the function width, and b is the slope and m represents the center point of the function. The output of the beta function lies between 0 and 1. The value of a, b, m correspoding to 4 input parameteors are shown in Table 2.

TABLE 2. The parameteor of Beta membership function corresponding to the polarimetric measurements.

Parameteor	a	b	m
Z_H	14	9	40
Z_{DR}	1.3	11	2.1
$\rho_{HV}(0)$	0.15	10	0.815
H	2.5	9.5	3.75

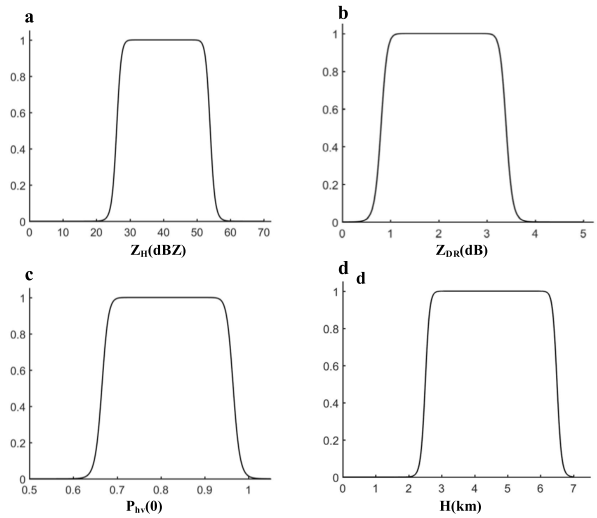

FIGURE 4. The diagram of Beta membership function corresponding to the polarimetric measurements. a the membership function of Z_H. b the membership function of Z_{DR}. c the membership function of $\rho_{HV}(0)$. d the membership function of H.

b: INFERENCE

Through the analysis by the former researchers, the core of classifier based on fuzzy logic mainly lies in the construction of membership functions and fuzzy rules, which can be described as follows in logical language.

IF (X_1 IS MBf_1 AND X_2 IS MBf_2 AND X_3 IS MBf_3 AND X_4 IS MBf_4)

THEN Output IS 1

Where, MBF_i $(i = 1, 2, 3, 4)$ represents the degree of membership function corresponding to the four input parameters. Therefore, the intensity R of the precipitation particles belonging to the bright band can be expressed by the following expression:

$$R = \sum_{i=1}^{4} [W_i \bullet \mathrm{MBf_i}(X_i)] \tag{11}$$

Where W_i is the contribution of the i-th input parameter to the bright band, and $W_i = 0.25$ $(i = 1, 2, 3, 4)$.

Moreover, $MBF_i(X_i)$ indicates the degree of membership function of the input parameter X_i, and it corresponds to the bright band.

c: AGGREGATION

Here, we select the strength R as the only parameter to determine whether the particle belongs to the zero-layer bright band or not.

d: DEFUZZIFICATION

Strength R is the only parameter to determine whether the particle belongs to the zero-layer light band or not. In this paper, through a large number of experimental analysis, we found that the identification effect is better when the Tdd-offset is equal to 0.95. Therefore, when $R \geq 0.95$, the output is 1, otherwise the output is 0.

The fuzzy logic algorithm is applied to identify the bright band, and it is mainly because that this method obtains the classification results based on the degree of membership function rather than the specific values. Moreover, this method is not limited by the statistical formula and the final result is not affected by the inaccurate value of some parameters.

C. CLASSIFICATION OF PRECIPITATION CLOUDS BASED ON DEEP LEARNING

The stratiform cloud precipitation is caused by a large range of vertical movement of air, with a certain vertical velocity. During the radar detection, its reflectivity is relatively small, and the gradient of the horizontal reflectivity is relatively small. The vertical thickness is relatively thin, and the top is relatively flat. If precipitation at the ground is liquid, it is often accompanied by the phenomenon of the zero-layer bright band. The convective precipitation is produced by the air vertical movement caused by the atmospheric instability. Its reflectivity factor is stronger, and the horizontal reflectivity gradient is larger. The vertical thickness is thicker, and the top is uneven. These features play an important role in the identification of stratiform clouds and precipitation of convective clouds. In this paper, the Convolutional Neural Network (CNN) is used to identify the types of precipitation clouds, and we utilize a large number of stratiform and convective cloud precipitations to train and test the neural network, so that it can meet the requirements of accurate identification.

Convolutional Neural Network (CNN) is a multi-layer sensor and it is inspired by the biological visual neural mechanism. it is composed of multiple convolution and sub-sampling layers, which has the ability of automatically extracting sample features. In the convolution layer, the neuron of each network layer is only connected with the neurons in a small neighborhood of the upper layer. Through the local sensor, each neuron can extract the primary visual feature and guarantee the spatial structure relation of the original signal, so that the image can be directly used as the input of the neural network. It avoids complex feature extraction and data reconstruction process in traditional recognition algorithm. In the pooling layer, the original data is compressed by sampling, which reduces the computational complexity and constructs the invariance of the spatial structure. In addition, CNN makes it more similar to the biological neural network through the weight sharing network structure that reduces the complexity of the network model and the number of weights. Therefore, it has become an important research tool in many fields such as the image recognition and the automatic speech recognition.

1) SELECTION OF SAMPLE DATA

As stated in section 2.2, the polarimetric measurementsis processed for each cell through CAPPI inversion by VHI method in this paper, and the cell size is 0.1×0.1 km^2, including polarimetric data such as Z_H, Z_{DR}, and $\rho_{HV}(0)$ and so on. It is well known that the precipitation clouds are distributed in a layered form in the atmosphere. In this study, the paper takes the 10 km^2 (32×32 cells) reflectivity Z_H data as input, and utilize CNN algorithm to classify the types of precipitation clouds in this area.

Combining the horizontal and vertical structure characteristics of stratiform clouds and convective clouds, and based on a large number of stratiform and convective cloud precipitations, and mixed cloud precipitation data, this paper takes the CAPPI reflectivity data between 3-7 km. We select 1200 reflectivity matrices (each matrix with a size of 32×32 cells) with typical stratiform cloud and convective cloud precipitation characteristics to establish a database for the training and testing of convolutional neural network of precipitation cloud type recognition system.

2) DESIGN OF PRECIPITATION CLOUD TYPE IDENTIFICATION METHOD

This paper presents a cloud type identification algorithm based on CNN, which is an algorithm that is a typical supervised deep learning algorithm, relying on a large number of tagged sample data to train the model. Using the Python+Pytorch development platform, this paper constructs a precipitation cloud type identification model based on CNN, and its flow diagram is shown in Figure 5.

As shown in Figure 5, the precipitation cloud identification system is mainly composed of input and output layer, two convolutional layers, two residual block layers, two full connection layers, and a Sofatmax classifier. The system input is a reflectivity matrix with a size of 32×32 cells, which passes through convolutional layer, two residual block layers (each consists of one convolutional layer, one InstanceNorm layer, and one ReLU active layer), and another convolutional layer. Finally, we obtain 16 feature maps with a size of 3×3 cells. The system utilizes two full connection layers to convert the 16 feature maps into 1×64 feature vector, which is used by Sofatmax classifier to classify the types of precipitation clouds.

In our research, we take nearly 2400 samples to train and test the identification system, contains 1200 stratified

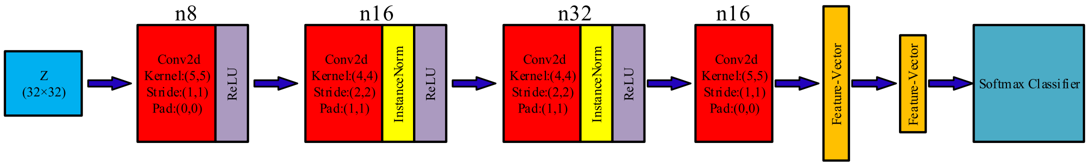

FIGURE 5. The flow chart of precipitation cloud type identification algorithm based on CNN.

cloud data matrices and 1200 convective cloud data matrices, which are extracted from a large number of scaning data by human eyes. Moreover, the stratiform cloud samples have been marked as 0, and the convective cloud samples have been marked as 1.

a: TRAINING PROCESS

The training process is mainly through BP algorithm to adjust the parameters of the system based on a large number of tagged sample data, so that each parameter in the system can achieve the optimal value. The training set consists of 1000 stratified cloud samples and 1000 convective cloud samples. The training steps are given as follows.

Firstly, as shown in Figure 5, input the tagged sample data into the identification system, where each sample data is 32×32 reflectivity matrices. The input data pass through multiple processes such as convolution, normalization and activation and so on. Finally, the system obtain 16 feature maps with a size of with a size of 3×3 cells.

Secondly, the obtained feature maps are converted into a feature vector, and the Sofatmax classifier is used to classify it, and finally the type of precipitation cloud corresponding to the input data is obtained.

Finally, the result of the precipitation cloud identification and the samples are compared and analyzed, so the corresponding output error is obtained. The output error is back propagated to the input layer through the hidden layer, and the error is distributed to all the units of each layer, thus the error signal of all units is obtained. Finally, the weights of each unit are corrected by this error signal.

b: TESTING PROCESS

The testing process is to use a small amount of sample data used in the system for the identification of precipitation cloud type. By comparing the result from the model output to the known categories, we can evaluate the accuracy of the system.For the completed convolutional neural network model, the parameters of each unit have been determined. The test sample data can be input into the system, and then propagate through each layer and finally reach the output layer to obtain the result of classification. In this paper, 200 stratiform clouds and convective cloud sample data are selected to test the system, and the accuracy of the test process can reach 90.2%.

D. SYSTEM DESIGN

This paper constructs a precipitation cloud identification system, which takes the original detection data of weather radar as input, and finally outputs the type of precipitation cloud through CAPPI inversion, identification of zero-layer bright band, and classification of precipitation clouds based on CNN. The schematic diagram is shown in Figure 6.

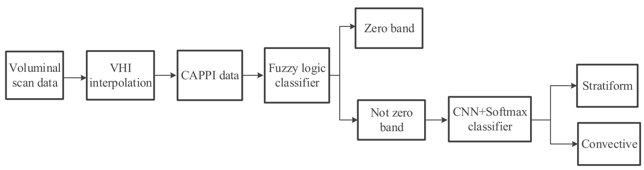

FIGURE 6. The schematic diagram of precipitation cloud identification system.

As shown in Figure 6, the system realizes the identification of the precipitation cloud type. As discussed in section 2.2, the paper utilize the VHI method to process CAPPI inversion for the volume scanning data of the dual-polarization Doppler weather radar, and obtains the horizontal distribution of the Z_H, Z_{DR}, $\rho_{HV}(0)$ and the other polarization parameters at any altitude.

In the southwest area of China, the precipitation clouds are usually distributed in altitude from 2 to 7 kilometers. Thus, for the identification of precipitation clouds types, the CAPPI data in the range of 2-7 kilometers are chosen to analyze. In the altitudes range of 2.5-5 kilometers, zero-layer bright band is relative active, and it can cause large interference for precipitation cloud identification. As stated in section 3.1, this paper utilizes a fuzzy logic algorithm to identify the zone of the zero-layer bright band through combing the distributions law of Z_H, Z_{DR}, $\rho_{HV}(0)$ and H of the particles in the zero-layer bright band.

For non-zero-layer bright band, the paper utilized the CNN network model to identify the precipitation cloud type. Because this module belongs to the category of deep learning, its accurate identification of precipitation cloud type depends on the training of large batch sample data. As described in section 3.2, the paper selects 2000 sample data matrices with typical stratiform and convective cloud precipitation characteristics from the radar in 2017 to train and test the CNN network, so as to realize the accuracy requirement of identifying stratiform and convective clouds.

IV. RESULTS

In this paper, the performance of the system is evaluated by the data detected in a mixed cloud precipitation process by using the CINRAD-SA dual-polarization Doppler weather radar which is upgraded in China. On 16 June 2017, a heavy rainfall process were detected by the CINRAD-SA radar, which is located in Guangzhou, Guangdong, China (23°01′N, 113°35′E). The radar indicators are shown in Table 1. The period of the rainfall was from 2000UTC on June 16th, 2017 to 0500 UTC on April 17th, 2017. The precipitation range covered almost all areas of Guangdong province, and the intensity of rainfall reaches 45mm for Guangzhou, which was classified as a heavy rainfall process. The paper uses the precipitation cloud identification system described in section 3.4 to identify the precipitation cloud types in the process of rainfall, and analyzes the identification result with the ground precipitation data. Moreover, this paper verifies the correctness of the identification result. The detailed process is given as follows.

In this paper, the CAPPI inversion with VHI method is used to process volume scan data. Figure 7 is CAPPI distribution map of the Z_H, Z_{DR} and $\rho_{HV}(0)$ at 4 km altitude. The paper only processed the data in the area within 300 km. The data resolution is 100 × 100 meters, and the distance between adjacent circle is 75 km.

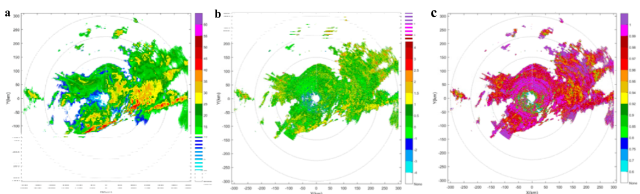

FIGURE 7. **The CAPPI distribution of polarimetric parameters correspoding to a Z_H b Z_{DR} c $\rho_{HV}(0)$ at 4 km altitude.**

As shown in Figure 7, in the vicinity of the radar station (picture center point), the data in the area is less reliable due to the existence of blind zone and the influence of ground clutter, which has been removed by the article in the 10 km area. As mentioned in section 3.4, in the southwest region of China, the zero-layer bright band is active in the precipitation area with a altitude of 2.5-5 km, and it is necessary to preprocess the zero-layer bright band when the precipitation cloud type is identified in the region. The paper uses the CAPPI data mentioned above to identify the type of precipitation cloud at 2-6km altitude. Considering the interference caused by the zero-layer bright band, the paper uses the fuzzy logic algorithm to identify the area of the zero-layer bright band, and then uses the deep learning network to identify the type of the precipitation cloud, and the final identification result correspoding to 4km altitude is shown in Figure 8.

As shown in Figure 8, the red area is a zero-layer light band. Corresponding to the Figure 6, in this area, Z_H is from 35 to 40 dBZ, Z_{DR} is from 2 to 3 dB, and $\rho_{HV}(0)$ is 0.85-0.94, which are fully consistent with the distribution law of the polarimetric parameters of the precipitation particle in the zero-layer bright band zone described in section 3.2. It proves that the correctness of the identification result of the zero-layer bright band. The yellow area in the Figure 8 is the precipitation area of convective clouds, which can be

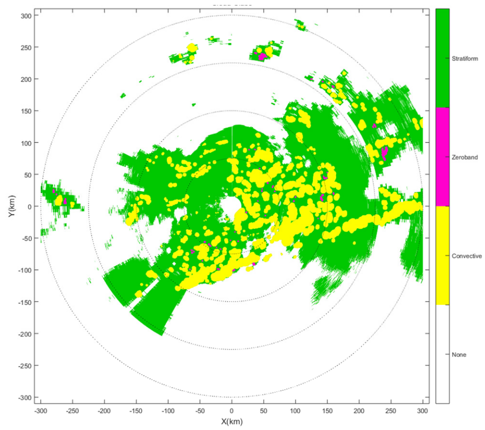

FIGURE 8. **The precipitation cloud map at 4 km altitude.**

referred from Figure 7 (a). The echo intensity Z_H in this region has the following characteristics, the center intensity of the echo is greater than the 40 dBZ, or the echo intensity of the surrounding precipitation region has a large gradient. For the region with Echo center intensity greater than 40 dBZ, it corresponds to the development of the mature convective cloud. For the latter echo, it corresponds to the developing convective bubbles. Thus the identification result of the precipitation cloud type is reasonable.

In order to improve the accuracy and reliability of the final identification result, this paper selects another five CAPPI data in different altitudes in the range of 2-7km to identify the types of precipitation cloud. The identification results are shown in Figure 9.

The Figure 9 (a), (b), (c), (d) and (e) correspond to the CAPPI distribution map of reflectivity of precipitation data at 2, 3, 4, 5, and 6 km altitudes, and (a′), (b′), (c′), (d′), and (e′) are the distributions of precipitation cloud types at the corresponding altitudes.

In order to obtain a more complete distribution map of precipitation clouds in this area. the 5-altitude precipitation cloud distribution is merged. As described in Section 3.3, the CNN is applied to identify the type of precipitation clounds. For each input data (32 × 32 reflectivity matrix), the features are extracted by multiple convolution kernels to judge whether convection exists in the region, so as to realize the identification of precipitation cloud types. For convective clouds with a height of 3 km and below, it will directly lead to convective cloud precipitation. For convective clouds above 3 km altitude, convective cloud precipitation will only occur if convective intensity is large. Therefore, in the process of data fusion, for a certain region, when there are convective clouds at (a′) or (b′), or the precipitation clound types of (c′), (d′), and (e′) all are convective cloud, it can be judged as convective clouds, otherwise it can be judged as stratiform clouds. The fusion result is shown in Figure 10.

The yellow area in Figure 10 is the precipitation area of convective clouds, located in Guangzhou, Shantou and its surrounding areas of Guangdong province, China. Comparing to

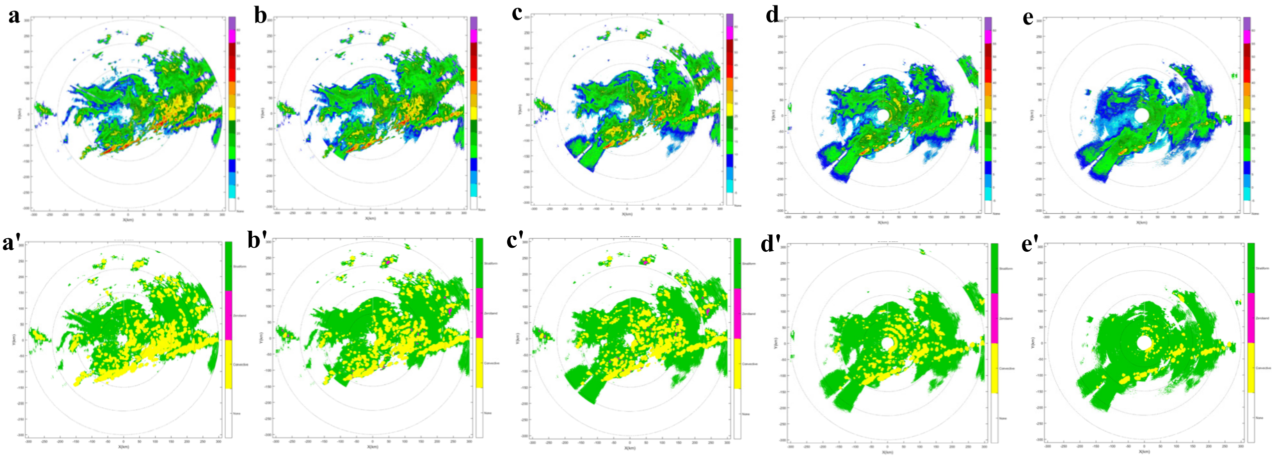

FIGURE 9. The precipitation cloud map at multiple altitudes.

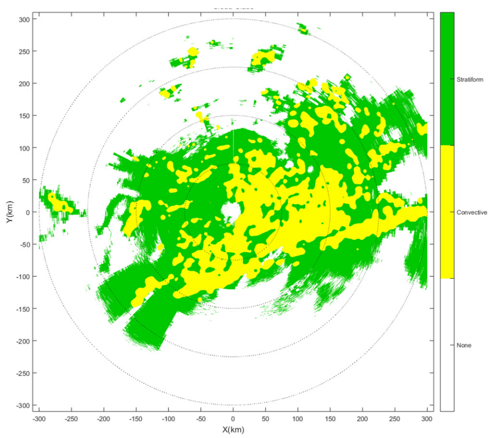

FIGURE 10. The distribution map of precipitation cloud type.

the Figure 9 (a), the reflectivity is ranging from 25 to 50 dBz at the height of 2 km. Moreover, through checking the ground precipitation observation data in the area, it is found that in the process of precipitation, the cumulative precipitation in Guangzhou and Shantou is 45mm and 39mm respectively, and the duration is about 3 $\sim$ 4 hours. Therefore, It can be inferred that the precipitation process should belong to the convective precipitation, which is in correspondence with the classification result of the system, thus verifying the accuracy of the identification result.

V. CONCLUSION

A new deep learning method of precipitation cloud type identification is proposed in this paper, based on the data of the upgraded CINRAD-SA type dual-polarization Doppler weather radar in China. Compared with the traditional method of precipitation cloud type identification, the method does not need artificial searching for the characteristic parameters of the precipitation cloud type, such as the maximum reflectivity, the reflectivity gradient, and the top echo characteristics. In this method, the CNN algorithm is applied to extract the features from CAPPI data, which comes from the original scaning data and is processed by VHI menthod. Moreover, the softmax classifier is applied to classify the type of precipitation cloud based on the the extracted features. In the process of the precipitation cloud identification, considering the similarity of the echo characteristics between the zero-layer bright band and the convective cloud precipitation, the final identification result is interfered. The zero-layer bright band is identified and removed, and the accuracy and credibility of the identification result are greatly improved.

This paper takes a mixed cloud precipitation process in Guangdong Province as a case, and the specific process of this method is introduced in detail. The final identification result is analyzed theoretically, and the rationality of the recognition result is verified. Secondly, the paper verifies the identification results based on the actual ground precipitation data in this area. The accuracy of the identification is proved. This method is a good reference for improving the accuracy of quantitative precipitation estimation of the Doppler weather radar.

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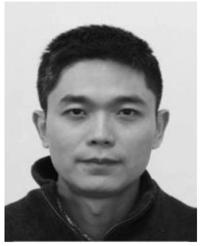

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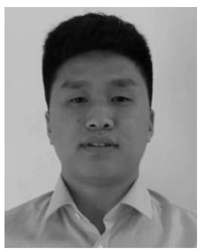

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