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Application of a Cloud-Texture Analysis Scheme to the Cloud Cluster Structure Recognition and Rainfall Estimation in a Mesoscale Rainstorm Process

SHOU Yixuan*[1] (寿亦萱), LI Shenshen[1] (励申申),
SHOU Shaowen[1] (寿绍文), and ZHAO Zhongming[2] (赵忠明)

[1] *Nanjing University of Information Science and Technology, Nanjing* 210044

[2] *Institute of Remote Sensing Applications, Chinese Academy of Sciences, Beijing* 100101

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ABSTRACT

It is thought that satellite infrared (IR) images can aid the recognition of the structure of the cloud and aid the rainfall estimation. In this article, the authors explore the application of a classification method relevant to four texture features, viz. energy, entropy, inertial-quadrature and local calm, to the study of the structure of a cloud cluster displaying a typical meso-scale structure on infrared satellite images. The classification using the IR satellite images taken during 4–5 July 2003, a time when a meso-scale torrential rainstorm was occurring over the Yangtze River basin, illustrates that the detailed structure of the cloud cluster can be obviously seen by means of the neural network classification method relevant to textural features, and the relationship between the textural energy and rainfall indicates that the structural variation of a cloud cluster can be viewed as an exhibition of the convection intensity evolvement. These facts suggest that the scheme of following a classification method relevant to textural features applied to cloud structure studies is helpful for weather analysis and forecasting.

Key words: infrared (IR) images, textural features, cloud classification, rainfall estimation, meso-scale torrential rainstorms

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1. Introduction

With enhancement in the spatial-temporal resolution, satellite images can provide more detailed atmospheric information. The concomitant issues on how to extract the effective information, which is helpful for weather analysis, have received much attention from academicians around the world. Among them, the problems such as cloud classification, rainfall estimation and cloud phase etc. are some hot topics, which are in general based on precise segmentation of the satellite images.

It is known that a cloud cluster is an object having a semi-fluid property. It is influenced not only by environmental air but also by the disturbing air inside itself. The airflow often brings moisture to the different levels of the troposphere to form different types of hydrometeors, such as water droplets, snow flakes and ice crystals, etc., and it is made up of distinct kinds of cloud such as cirrus, stratus, cumulus, and cumulonimbus, etc. A cloud cluster is often composed of a variety of clouds, which are often mixed together without obvious divisions, so it is difficult to distinguish the structure of a cloud cluster precisely from satellite images (Lin et al., 2001; Kambhamettu, 1994). In the past years, some researchers have tried to apply some classical image processing methods to cloud structure recognition and classification on the basis of spectral characteristics, but the results have not been satisfactory (Corpetti et al., 2002; Grazinni et al., 2002). Recently, scientists have come to recognize that clouds in nature, as any other object, also have their own intrinsic textural characteristics. The texture is an important visual property of an object, which is often used for image analysis. As for its definition, a uniform one has not yet been agreed upon. Generally, it is defined as a recurrent pattern composed of many elements, which are bordered upon and knitted with each other (Zhang, 1999). Study on the segmentation of satellite images based on texture began in the

*E-mail: yixuan_s@nsmc.cma.gov.cn

1980s or even earlier (Baraldi and Parmigianni, 1995; Gu et al., 1991; Welch et al., 1988). Their applications in weather analysis are mostly effective, especially in the recognition and classification of macro-scale cloud cluster structure (Lakshmanan et al., 2000; Papin et al., 2000; Arnaud et al., 1992; Peak and Tag, 1994; Jobard and Desbois, 1993). Based on statistics, disasters caused by rainstorms, hail, tornados, and thunderstorms comprise a large portion of the major annual natural disasters around the world. With regards to the mechanism, these severe weather phenomena are closely related to the meso- and micro-scale systems that are incorporated as some meso- and micro-scale cloud clusters embedded in a macro-scale cloud system on satellite images. Therefore, it is worth furthering the study of designing methods for understanding the structure of meso- and micro-scale cloud clusters.

In this paper, we apply a neural network based on textural characteristics to cloud classification using infrared satellite images (IR images). Herein, this method will be tested on a rainstorm process. Furthermore, the relationship between precipitation and the structure of a cloud cluster will be discussed to get a better understanding of the meaning of this work.

The paper is organized as follows. Descriptions of the classification algorithm are given in section 2. An application of the method will be provided in section 3. To further understand the influence of the structure on the heavy rainfall, an empirical function of rainfall and texture is presented in section 4. Finally, section 5 gives the conclusions of the whole paper.

2. Cloud classification based on textural features

2.1 *Textural Features*

As a certain visual property of an object, a textural feature is often expressed in terms of a quantity. A textural descriptor can indicate the extent of smoothness, sparseness or regularity of a certain area on an object (Wechsler, 1980). Generally, textural feature description methods can be divided into spectral, structural and statistical categories (Zhao and Zhao, 1998). The proposed cloud-texture classification here is based on the statistical approach, which first sets up a matrix called the Gray Level Co-occurrence Matrix (GLCM).

The GLCM is a matrix which expresses the distribution density of pixels on an image, and each element therein denotes the probability of concurrence of two pixels with a distance interval of δ pixels and an angle difference of θ degrees respectively (Zhang, 2003). According to this matrix, lots of textural characteristics can be derived based on the principles of statistics. Among them, there are four parameters: energy, entropy, inertial-quadrature, and local calm, and these are used most frequently in describing the textural characteristics of clouds (Zhao and Zhao, 2000). The functions are shown respectively as formulas 1–4, where i and j are gray scales of any two pixels within the study area, and δ and θ represent respectively the distance and angle intervals between these two pixels. Here $P(i,j|\delta,\theta)$ prescribe the probability of concurrence of two pixels with gray scale i and j having a distance interval δ and an angle difference of θ degrees.

$$f_1=\sum_i\sum_j[P(i,j|\delta,\theta)]^2\ , \tag{1}$$

$$f_2=\sum_i\sum_j[P(i,j|\delta,\theta)\times\lg P(i,j|\delta,\theta)]\ , \tag{2}$$

$$f_3=\sum_i\sum_j[(i-j)^2P(i,j|\delta,\theta)]\ , \tag{3}$$

$$f_4=\sum_i\sum_j\frac{1}{1+(i-j)^2}P(i,j|\delta,\theta)\ . \tag{4}$$

2.2 *Cloud Classification*

With respect to the methods of classification, they are often divided into two major types: supervisory and non-supervisory. In the former, the minimum distance or maximum likelihood classifier, for instance, seeks to build up a set of samples and a discriminant before classification. In contrast, a non-supervisory classifier, such as ISODATA (Iterative Organizing Data Analysis Technique) or the K-means classifier seeks to automatically make a threshold selection based on the likelihood between two pixels on an image. Generally, for bypassing the procedure of setting transcendental samples, a non-supervisory classifier becomes much more simple and effective than a supervisory one, and this has been noted by many scientists and applied to cloud classification. For example, Grazzini and his colleagues once studied a K-means classifier, which is based on textural features, and tested its effect on cloud cluster classification in an infrared satellite image (Grazzini et al., 2002). The result shows that the K-means classifier is not better than a normal supervisor classifier for cloud classification, regardless of whether it is based on the spectral characteristics or textural features. As the authors have analyzed recently in their paper, classic methods such as the K-means classifier, etc., are not so efficient because of the multi-scale properties of the turbulent flows. In view of this, we decided to use a supervisory classifier based on textural features.

The neural network is a relatively new classifier compared to other supervisory classification methods. It shows an unusual extensive ability to work with unknown input data and its parallel structure is beneficial for a system with multi-components (Dai, 2000). These highlights nicely meet the requirements of cloud

Table 1. The textural features of the cirrus, cumulus, cumulonimbus, stratus and cloudless areas.

	Cirrus	Cumulus	Cumulonimbus	Stratus	Cloudless area
Energy	0.047–0.66	0.017–0.045	0.08–0.260	0.068–0.078	1
Entropy	3.17–3.45	> 3.53	2.01–2.91	2.87–3.25	0
Inertial-quadrature	4.21–7.78	> 8.05	0.975–2.74	2.22–2.77	0
Local Calm	0.45–0.516	0.23–0.44	0.56–0.73	0.51–0.58	∞

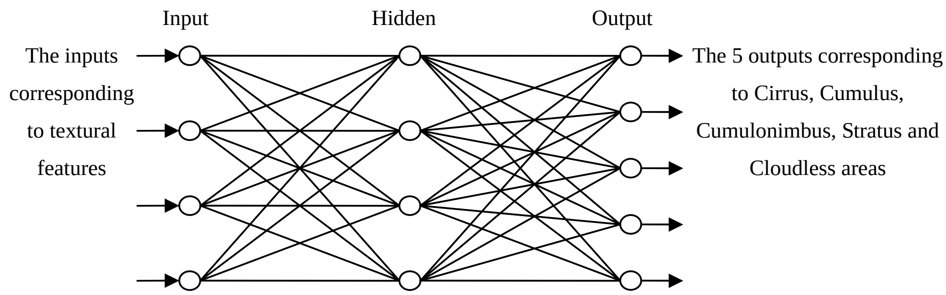

Fig. 1. The BP neural network.

classification, especially for the recognition of the structure of meso- and micro-scale convective cloud which characteristically has multi-scale properties. Thus we design a texture-based BP neural network for the classification.

Because the neural network is one of the supervisory classification methods, a volume of samples should be selected from the research areas to initially make a training field. The samples are collected manually according to the characteristics of different cloud types on infrared satellite images depicted in *Satellite Meteorology* (Chen, 1989). Experimentally, the areas of the infrared satellite images are roughly divided into five areas: cloudless, cumulus, cirrus, cumulonimbus and stratus areas. Generally, the more samples there are, the higher the precision of the classification will be. As a test in this paper, a total of 500 sample areas are selected from infrared satellite images during June 2003. Each of the five cloud types mentioned above has 100 samples respectively.

In order to study the distributions of these samples' textural characteristics and their relationship with the object types, a distance operator is applied to cluster all the textural characteristics of the sample areas. The Mahalanobis distance operator is used in this paper, for it considers not only the scatter of the data in a dataset but also the correlation of the population distribution between each axis, which is suitable for the datasets with a super-ellipsoid structure such as the textural characteristics matrix (Gao and Xie, 1999). The formula of the Mahalanobis distance can be expressed as (5). Here d_{ij} is the Mahalanobis distance, X_i, X_j represent two elements in a textural characteristics matrix, and C^{-1} is the converse matrix of the standard covariance matrix C.

$$(d_{ij})^2 = (X_i - X_j)^{\mathrm{T}} C^{-1} (X_i - X_j)\ . \tag{5}$$

Table 1 gives the results of the cluster. From each row of the table we can see that the watershed between each type is obvious, which means the four textural characteristics used in this paper can each depict one kind of area effectively.

According to the input and the output data, the BP neural network in this paper is designed as shown in Fig. 1, whose inputs correspond to the four textural characteristics and outputs correspond to the five areas, viz. the cloudless, cirrus, cumulus, cumulonimbus, and stratus areas.

The sample dataset is first input into the network to produce a discriminant. Differing from the other supervisory classifiers in producing a discriminant, the neural network builds it up by iterating and adjusting the weight coefficients on each branch of the net until the error between two iterations is less than ε. After several sets of experiments, when the momentum of the network α is set to 0.5, the training tempo η to 0.05 and the critical error ε to 0.01, the network works more effectively. Once the discriminate function is set, the automatic classification can be done through this net. Details about the algorithm can be found in the flowchart of the BP neural network training and classification as shown in Fig. 2.

3. Case study

To examine the effectiveness of the above method, we apply it to an analysis of a rainstorm process that occurred during 4–5 July 2003 in the middle-lower

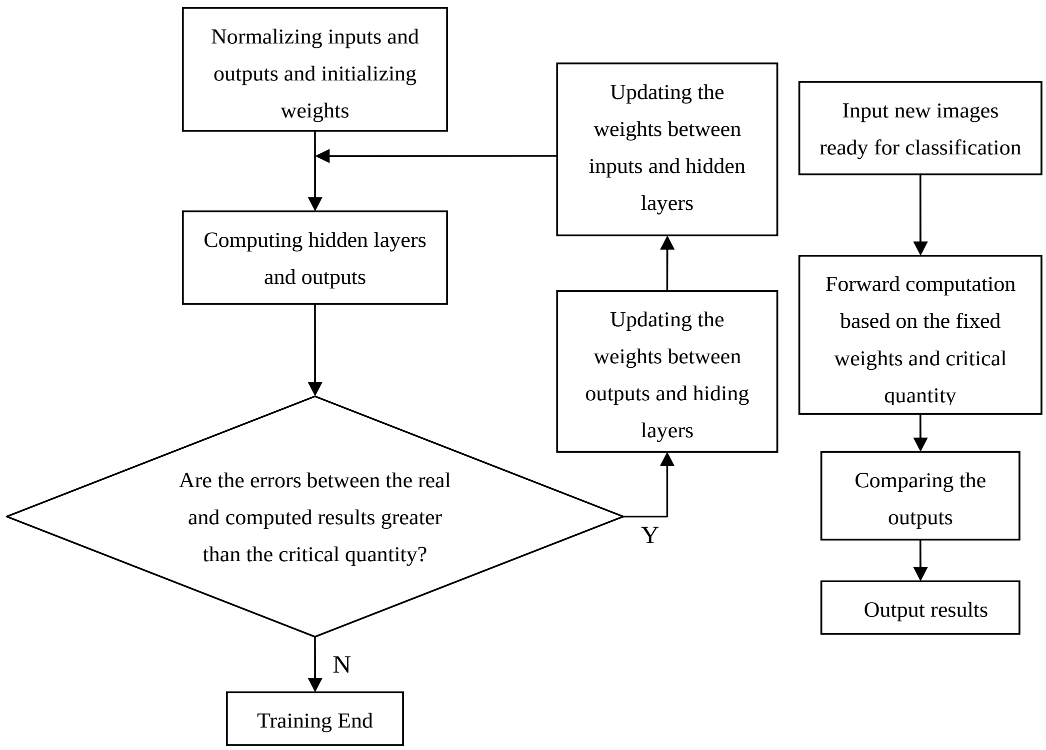

Fig. 2. The flowchart of the BP neural network training and classification.

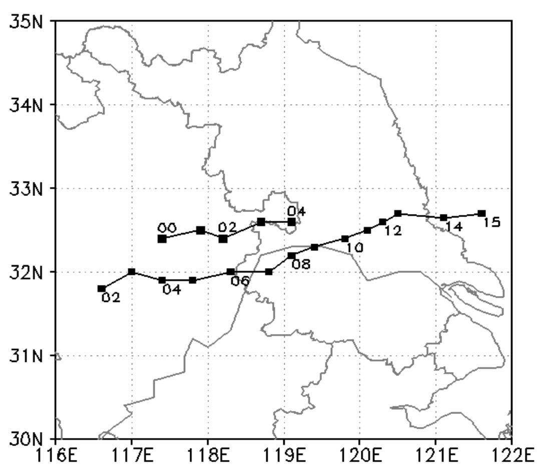

Fig. 3. The path of the rain clusters during 4–5 July 2003.

Yangtze River basin in China. The infrared satellite images during this period are supplied by the National Satellite Meteorological Center of the China Meteorological Administration (NSMC-CMA).

3.1 *Case Introduction*

The rainstorm process that occurred in the middle-lower Yangtze River basin from 2100 LST 4 July–1900 LST 5 July 2003 is a typical abnormal summer rainfall event. It was observed that the rain belt was about 200 km wide and 1000 km long, extending from west to east (Fig. 3). The rainfall center was located near Nanjing city (Fig. 4). According to the observation data, the 24-hour rainfalls in more than seven cities in the middle-lower Yangtze River basin were over 200 mm, some even beyond 300 mm, which caused flash floods in the Huaihe, Chuhe and Lixiahe River basins (Liao and Shou, 2004; Yan and Shou, 2005; Shou et al., 2005).

3.2 *Analysis and Results*

According to the location of this rainstorm, the study area is set within 20°–40°N, 105°–126°E. For segmenting the satellite image, we first calculate the textural characteristics for every 8×8 pixel-sized window area. Figure 5 shows the textural features of the

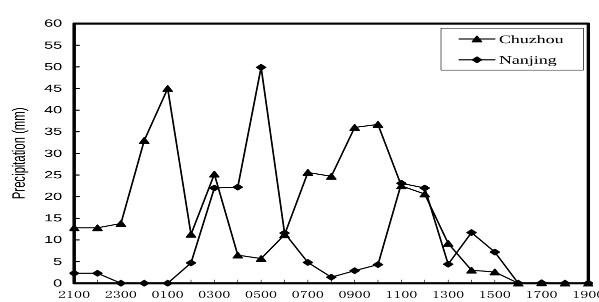

Fig. 4. Rainfall of Chuzhou and Nanjing during the period 2100 LST 4 July–1900 LST 5 July 2003.

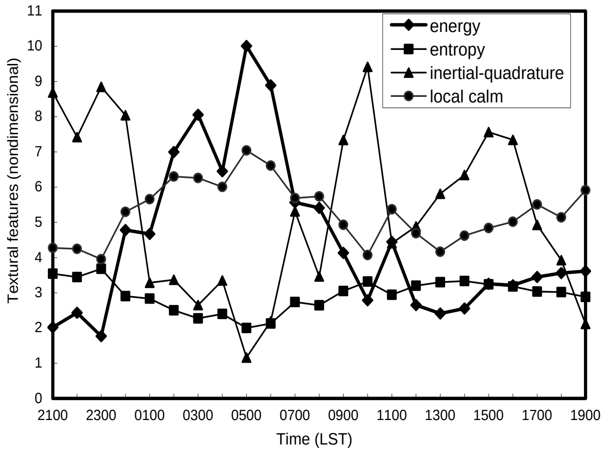

Fig. 5. The cloud textural features of the area centered at (32°N, 119°E) from 2100 LST 4 July to 1900 LST 5 July 2003 (Energy and local calm are multiplied by 50 and 10 respectively).

area centered at (32°N, 119°E) from 2100 LST 4 July to 1900 LST 5 July.

Based on the network parameters such as α, η and ε mentioned in section 2, each area on the images can be classified as soon as the newly-computed textural characteristics are input. Figures 6 and 7 show the original infrared satellite images and classification results, respectively, every 4 hours from 2000 LST 4 July to 0800 LST 5 July. After a careful examination, we find that the classification results are well matched with the original images. Furthermore, the meso-scale structure of the cloud which stayed over Jiangsu and Anhui provinces during 4–5 July 2003 is obviously seen in Fig. 7. As seen from its structural evolvement, the cloud cluster is mainly composed of cumulus and cirrus and is pushed from southwest to northeast by the upper-level flows during the earlier stages (Figs. 7a, b). With the enhancement of the convection intensity, the proportion of cumulonimbus in the cloud cluster begins to increase. At the strongest stage of the convection (Fig. 7c), the cumulonimbus expands to its maximum extent and forms as a convective cloud belt covering Jiangsu and Anhui provinces. At 0800 LST 5 July 2003, the weakening period, the cumulonimbus shrinks to disappearance (Fig. 7d). These points of evidence suggest that the convection varies with the evolvement of the

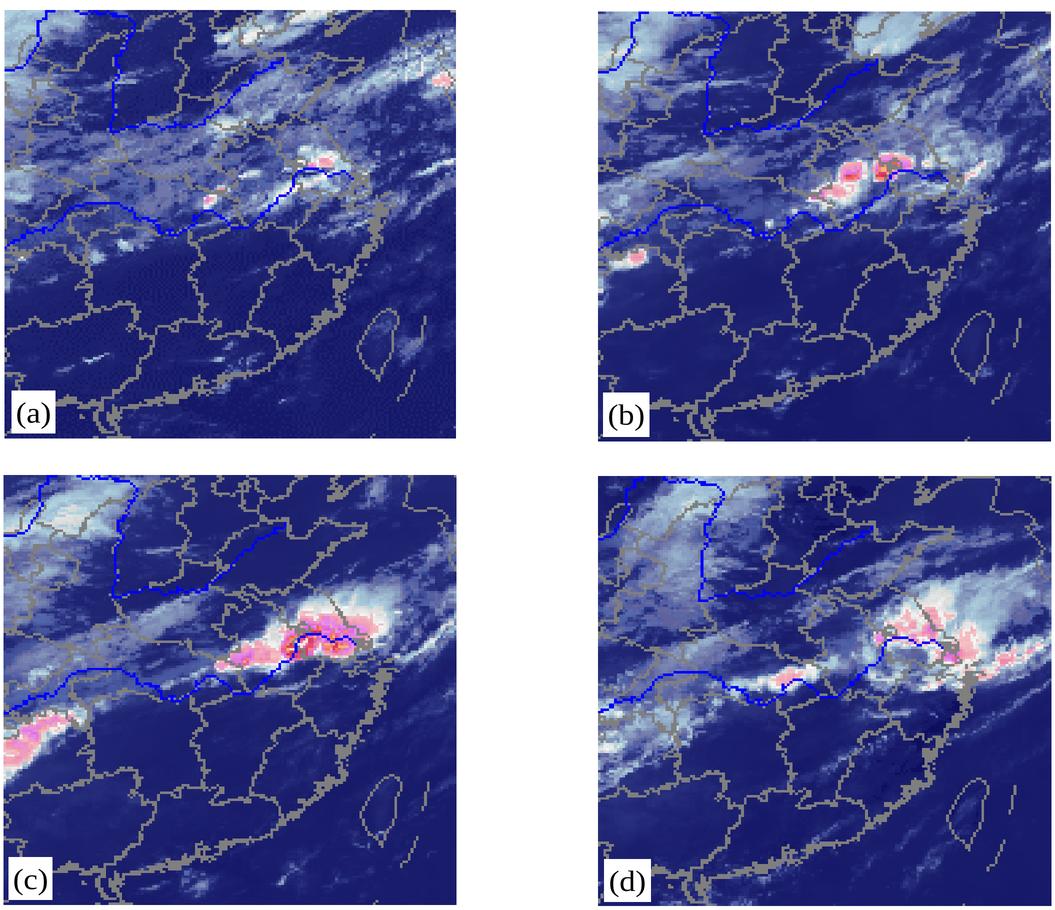

Fig. 6. IR cloud images every 4 hours from 2100 LST 4 July to 0800 LST 5 July [(a) 2000 LST 4 July (b) 0000 LST 5 July (c) 0400 LST 5 July (d) 0800 LST 5 July].

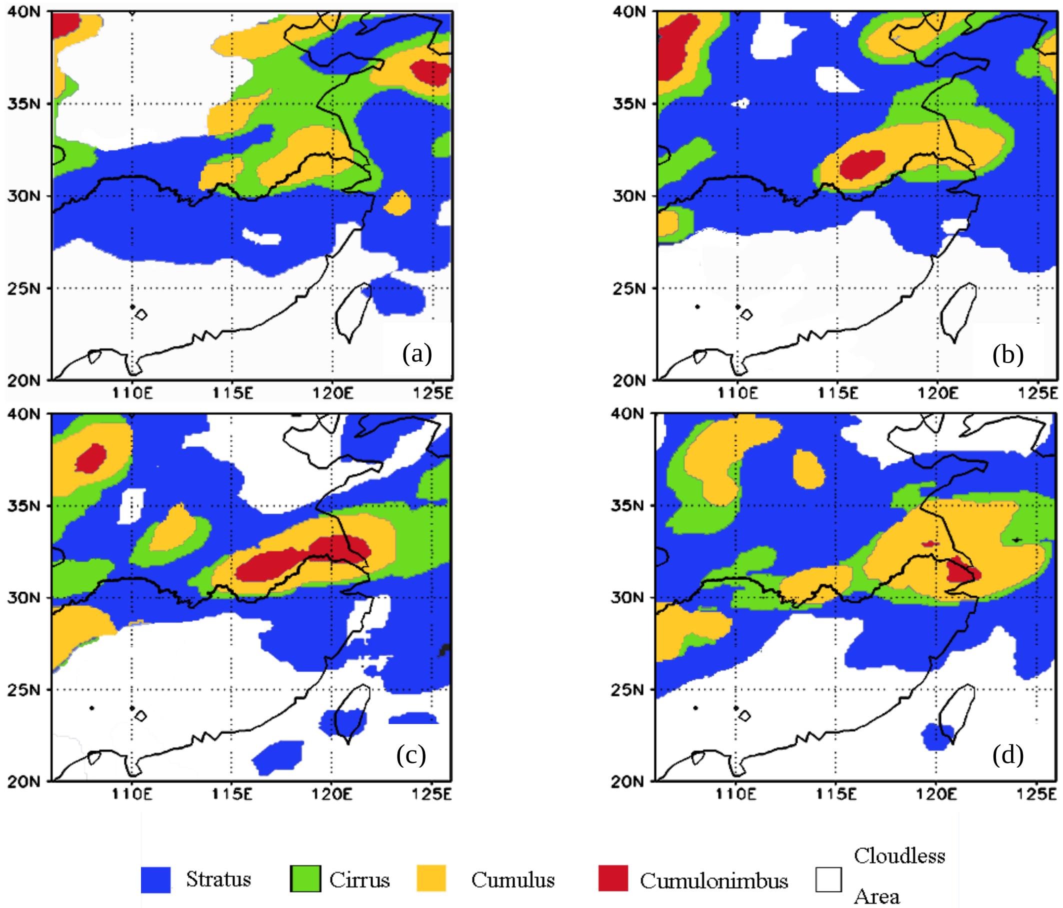

Fig. 7. Cloud textural classification every 4 hours as in Fig. 6.

cumulonimbus in the cloud cluster. Now, we will discuss whether there is some relationship between the cloud structural evolvement and the precipitation in the following paragraphs.

4. Rainfall estimation based on texture features

As we know, not all kinds of cloud can produce torrential rainfall. Cirrus, for instance, is a type of cloud that cannot make rainfall, which means that clouds with different properties may contribute differently to the rainfall. So it is worthwhile to enquire further into the relationship between the cloud structural evolvement and the precipitation.

In the 20th century, some scientists discovered the relationship between infrared brightness temperature (TBB) and the ground rainfall. In 1998, Vicente et al. expressed this kind of relation by an equation, which is expressed as:

$$r = c_1 \times \exp(c_2 \times T^{c_3}) , \tag{6}$$

where r is the precipitation rate, T is the infrared brightness temperature, and c_1, c_2, c_3 are constants. However, TBB is a physical quantity which only represents the temperature of the object on infrared satellite images, however it has no ability to reflect the properties of a cloud directly. Illuminated by the effect of textural features in cloud classification, we try to set up a relation between a textural characteristic and the rainfall.

After studying the distribution of the four textural characteristics against TBB, we find that, compared to the other three textures, the textural energy has the best relationship with TBB (Fig. 8), which is a negative correlation, with one increasing as the other decreases. Through a regression analysis, this relation is assigned to a power law equation as follows:

$$T = c_4 E^{c_5} , \tag{7}$$

where E is textural energy, T is TBB, and c_4 and c_5 are constants.

By substituting (7) into (6) we can get the following:

$$r = c_1 \times \exp[c_2 \times (c_4 E^{c_3})^{c_3}] . \tag{8}$$

Equation (8) suggests that once the optimal parameters $(c_1, c_2, c_3, c_4, c_5)$ are given, the rainfall caused by

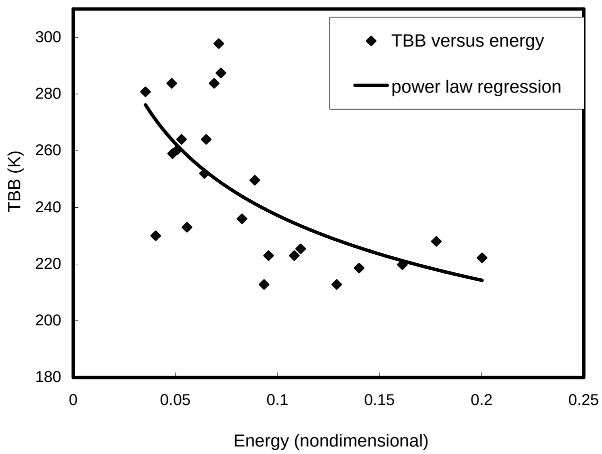

Fig. 8. Distribution of texture energy against TBB.

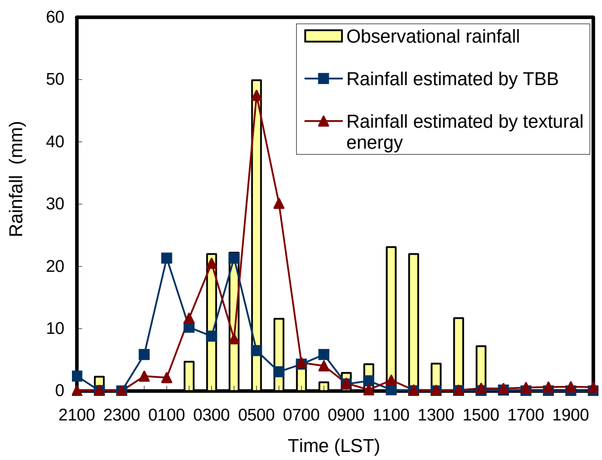

Fig. 9. Rainfall estimated by TBB and textural energy as well as the observational rainfall at Nanjing during 2100 LST 4 July to 2000 LST 5 July 2003.

different types of cloud can be estimated. With reference to the parameters given by Vicente et al. (1998), the coefficients in formula (8) are finally determined as (1.1183×10^{11}, 3.6382×10^{-2}, 1.2, 163.1, -0.1465).

Figure 9 gives the hourly rainfall estimations at (32°N, 119°E) around Nanjing during 2100 LST 4 July to 2000 LST 5 July according to the formulas (6) and (8). From the figure, we can see that the rainfall estimated by textural energy matches better with the observations than that by TBB. Combined with the classification results above, the proportion of the cumulonimbus in the convective cloud cluster varies synchronously with the rainfall, i.e., the more intense the precipitation, the bigger the proportion of the cumulonimbus in the convective cloud cluster.

Moreover, the cloud types shown on the classification time-series images are also seen increasing synchronously with the rainfall, which indicates that the vertical motion in the cloud cluster increases continuously during the torrential rainfall process. The more violent the vertical motion, the stronger the mixture between the upper and lower atmospheric levels. As such, being synchronously provided with sufficient moisture and vertical motion, the hydrometeors at the upper level will circulate in the air and grow significantly. Once there is an imbalance between the buoyant force and gravity, a large number of hydrometeors within the clouds will drop down into the low level to cause an increase in rainfall (Shou et al., 2003). This suggests that the structural variation of a cloud cluster can be viewed as an exhibition of the convection intensity evolvement, which may be helpful for weather analysis and forecasting.

5. Conclusions

In this article, we have first particularized to a cloud classification method relevant to four textural features, viz. energy, entropy, inertial-quadrature and local calm, in the infrared satellite images. Then we applied it to a study of a cloud cluster displaying a typical meso-scale structure. The application of the classification method shows that the detailed structure of the cloud cluster that caused the rainstorm in the Yangtze River basin during 4–5 July 2003 can obviously be seen after classification. To further study the relationship between the cloud structure and the rainstorm, a rainfall estimation formula based on textural energy was given. According to the case documented in this paper, the evolvement of the cumulonimbus in the cloud cluster is closely related to the convection intensity. This suggests that the structural variation of a cloud cluster can be viewed as an exhibition of the convection intensity evolvement, which may be helpful for weather analysis and forecasting.

Although the scheme in this paper has proved to be meaningful to weather analysis and forecasting, there are still many issues that should be improved upon in the future, such as increasing the amount of the sample data, comparing this scheme to some other correlative methods in use today, and combining this with some other methods such as numerical modeling.

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