Ground-based Vision Cloud Image Classification based on Extreme Learning Machine

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Abstract: Cloud radiation properties and distribution significantly affect the forecasting accuracy, climate monitoring effectiveness and global climate’s change. A simple method proposed to automatically recognize four different sky conditions (cirrus, cumulus, stratus and clear sky) by means of extracting some features from vision images and that be useful for training classifier. In this paper, texture features, color features and SIFT features are extracted and extreme learning machine are used to cloud-type classification under different experimental conditions. The experiment results show that the proposed approach using texture features, color features and SIFT features together get better performance than using these features alone or any two of them together, the accurate identification rate of cirrus, cumulus, stratus and clear sky are 87.67%, 90.75%, 74.50% and 93.63%, with an average of 86.64%. Under the same experiment condition, the proposed method outperform artificial neutral network (ANN), k-nearest neighbor (KNN) and support vector machine (SVM).

Keywords: Cloud classification, texture features, color features, sift features, extreme learning machine.

1. INTRODUCTION

Clouds are important part of the earth’s heat balance and hydrological cycle, clouds change determine the earth’s radiation balance and interaction with solar and at the same time play an important role in global climate change [1, 2]. As we know, different cloud-type reflects different shape, size, physical structure and features of weather through movement of atmosphere. However, the net effect of clouds is still not clear and will cause large uncertainties in climate models and climate predictions [3]. Recently, the observations of the amount of cloud, cloud form and height of cloud base are based on the visual judgment of the meteorological observers and satellite remote sensing. Human observations, however, will bring high costs so that the development of automatic devices to detect and quantify cloud amount and type become inexorable trend [4].

Satellite cloud images can provide a wide range of large scale distribution of the cloud structure information, but in thin clouds and low clouds is limited by spatial resolution and unknown surface effects; And the range of ground-based observation is small, which can provide local distribution information such as clouds size, arrangement and cloud height distribution. In recent years, a lot of ground-based sky imaging instruments have been developed, with respect to the improvement of both the hardware [e.g., charge-coupled devices (CCDs) and digital image processing (DIP)] techniques. These instruments include whole sky imager (WSI) [5], total sky imager (TSI) [6], whole sky infrared cloud measuring system (WSIRCMS) [7], and ground-based total-sky cloud Imager (TCI) [8]. At present, research of the ground-based total-sky cloud classification mainly concentrated in the visible cloud images. Buch et al. [9] using WSI data, presented a binary decision tree model to distinguish five sky types: cirrus, cumulus, stratus, altocumulus and clear sky based on analysis of texture features, brightness information and location information. Peura et al. [10] extracted features like cloud edge sharpness, boundary shape, different degree of fibrous and edge information from all-sky cloud images, dividing the cloud into ten types, using K-means clustering and total accuracy rate reached 65%. Singh and Glennen [11] presented an approach of cloud classification for common digital images that extracting numerous features from the grayscaled images, and using K-nearest neighbor and neural network method to distinguish five different sky conditions, but the authors acknowledge their results as modest. Calbo and Sabburg [12] used some possible criteria for whole sky-images
to classify eight predefined sky conditions, which include statistical features, features based on Fourier transform, and features that need prior distinction between clear and cloudy pixels. But this method only achieved an accuracy of 62%. Heinle et al. [13] used K-nearest neighbor method for classification based on the spectral features and gray level co-occurrence matrix texture features. Kazantzidis et al. [14] based on Heinle’s work, not only using texture and statistical color features, but also taking account the solar zenith angle, the cloud coverage, the visible fraction of solar disk and the existence of raindrops in seven kinds of sky.

In this paper, we present global features and local features that extracted from digital images of the sky and which can be useful for cloud-type classification, based on recent cloud classification research status at home and abroad. In section 2, the texture features, color features and SIFT features are extracted from cloud images. In section 3, we introduced the clouds classifier-extreme learning machine. Under different experiment conditions, the performance and results of the algorithm are discussed in section 4. Finally, in section 5 we summarize the conclusions of this research and suggest possible future investigations on cloud-type identification from ground-based sky images.

2. FEATURES FOR CLOUD-TYPE RECOGNITION

2.1. Texture Features

Texture features reflect the visual features of images through the pixels and distribution regularity of its surrounding grayscale space. It describes the local characteristics of the image, according to the local mode number, type and their relationship of texture texton to describe the texture. Texture analysis mainly has four methods [15], including statistical analysis method, structural analysis method, model based analysis and signal analysis method. This paper use statistical analysis approach, adopting two texture features: Haralick [16] proposed gray-level co-occurrence matrix (GLCM) and Tamura et al. [17] based on the visual perception texture features.

2.1.1. Gray-level Co-occurrence Matrix

Gray-level co-occurrence matrix reflects the joint probability occurrence of gray levels i and j for two pixels with a defined spatial relationship in an image. Element[i,j] of the matrix is defined by counting the probability of a pixel with value i is adjacent to a pixel with pixel j. The probability called \( P(i,j,\delta,\theta) \) is defined as:

\[
P(i,j,\delta,\theta) = \left\{ \left( x, y \right) \mid z(x,y) = i, z(x+Dx,y+Dy) = j; x,y = 0,1,2,\cdots,N - 1 \right\}
\]

(1)

Here, \( \delta = (Dx, Dy) \) and the direction \( \theta \) is always set as: \( 0^\circ, 45^\circ, 90^\circ, 135^\circ \). Also, six features are used: energy, contrast, entropy, homogeneity, correlation and moment of inertia.

2.1.2. Tamura’s Texture Features

Tamura puts forward six basic texture features based on human subjective psychological measurement: coarseness, contrast, directionality, line likeness, regularity and roughness. Generally, the first three components is especially important for image retrieval. Coarseness describes significantly spatial changes of grey levels, contrast measures the brightness of image, and directionality refers to the direction of the grey values in image. In this paper, these three features are used as Tamura texture feature.

2.2. Color Features

Color feature is a global feature, which describes the surface properties of the object or scene included in image. Comparing to other features, color features has a high robustness because of the small dependence of size, direction and angle of image itself. Expression of color features need to consider two questions: first, choose the appropriate color space to describe the color features; second, the quantitative method will be used in transform color features expression to the form of vector. This article using color moment to express image color, which was proposed by Stricker and Orengo [18]. This method utilizes the concept of the moment in linear algebra, the distribution of colors in an image expressed in the moment. Due to color distribution information is concentrated in the lower order moments, here we only use the first order moments (mean), the second order moments (variance) and the third order moment (skewness) to describe the color distribution. Unlike color histogram, we could use color moment to describe image without quantitative image features.

2.3. SIFT Descriptor

In this work, we use bag of words model to process sift descriptor. The basic idea of BOW is regarded images as orderless collection of independent local image block and has shown impressive levels of performance [19-21], and built a description for each image block [22]. Clustering the description and we can get a dictionary which contains visual vocabulary (usually SIFT keypoints). A BOW is then built as histogram over visual word occurrences. Then according to the high dimension vector representation of training set, classifier is generated and we can use it to classify the image.

Main steps of constructing a BOW descriptor:

1) The detection of image block and generate descriptors. In this paper, we use dense sampling because research by Fei-Fei et al. [23] had founded that dense features work better for some classification and that random sampling of key-points function nearly as well as keypoints selected by detectors [24]. The overlapped grid is 16×16 pixels, with a spacing of 8 pixels. Then we use Low’s high dimensional SIFT descriptor to describe each of 16×16 patches. Each descriptor consists of 128 dimensions, these vectors represent local invariant point in the image.

2) Gather the feature point vector and K-means [25] clustering is then utilized to group similar image patches (SIFT descriptor format) into M bins, where M is the vocabulary size for our experiments.
3. EXTREME LEARNING MACHINE

In this work, we take extreme learning machine as classifier. As a kind of single hidden-layer feed-forward network, compared to traditional methods, it can randomly select the number of hidden layer neurons in the network, the input weights and hidden layer deviation can be random assignment, output layer weights can be calculated by the least squares method. ELM has fast learning speed with a higher generalization performance than traditional gradient-based learning algorithms, and solves the common problem of learning epochs, learning rate, stopping criteria, and local minima [26].

Suppose there are N distinct samples \( (x_i, t_i) \), \( x_i = [x_{i1}, x_{i2}, \cdots, x_{in}]^T \in \mathbb{R}^n \), \( t_i = [t_{i1}, t_{i2}, \cdots, t_{im}]^T \in \mathbb{R}^m \). The standard SLFN with \( N' \) hidden neurons and activation function \( g(x, y) \) are mathematically modeled as

\[
\sum_{i=1}^{N'} \beta_i g_i(x_j) = \sum_{i=1}^{N'} \beta_i g(w_i \cdot x_j + b_i) = o_j, \quad \text{where} \quad w_i = [w_{i1}, w_{i2}, \cdots, w_{in}]^T \text{is the weight vector connecting the ith hidden neurons and the input neurons,} \quad \beta_i = [\beta_{i1}, \beta_{i2}, \cdots, \beta_{im}]^T \text{is the weight vector connecting hidden neurons and the output neurons, and} \quad b_i \text{is the threshold of the ith hidden neurons.} \quad w_i \cdot x_j \text{indicates the inner product of} \quad w_i \text{and} \quad x_j. \quad \text{As show in (Fig. 1), Network structure diagram is characterized of three layers.}
\]

\[\text{Fig. (1). The structure of ELM model.}\]

That the standard SLFNs can approximate these N samples with zero error means that \( \sum_{i=1}^{N'} \| o_j - t_j \| = 0 \). Thus, there also exist \( w_i, \beta_i \) and \( b_i \) such that

\[
\sum_{i=1}^{N'} \beta_i g(w_i \cdot x_j + b_i) = t_j \quad j = 1,2,\cdots,N
\]

According to the above N equations, we can get

\[
H\beta = T
\]

Where \( H \) is called the hidden-layer output matrix, the ith column of \( H \) denotes the ith hidden neuron output with respect to inputs \( x_1, x_2, \cdots, x_n \)

\[
H = \begin{bmatrix}
g(w_1 \cdot x_1 + b_1) & \cdots & g(w_{N'} \cdot x_1 + b_{N'}) \\
\vdots & \ddots & \vdots \\
g(w_1 \cdot x_n + b_1) & \cdots & g(w_{N'} \cdot x_n + b_{N'})
\end{bmatrix}
\]

\( \beta = [\beta_1^T, \beta_2^T, \cdots, \beta_{N'}^T]^T \quad T = [t_1^T, t_2^T, \cdots, t_N^T]^T \quad (4)
\]

If the activation function \( g \) is infinitely differentiable, according to the theorem of extreme learning machine [27], we can get the equation

\[
\|H\beta - T\| = 0 \quad (6)
\]

Therefore, training an SLFN is equivalent to finding a least squares solutions \( \beta \) of the linear system \( H\beta = T \), i.e. \( \hat{\beta} = HT \). \( H^T \) is the Moore-Penrose generalized inverse of matrix \( H \).

Based on above knowledge, the steps of algorithm are as follows:

1) Use the original data to train a neural network. \( x_i = [x_{i1}, x_{i2}, \cdots, x_{in}]^T \) is the training set, \( g(x, y) \) is activation function and \( N' \) is hidden neurons. Randomly assign input weight \( w_i \) and bias \( b_i \), we can calculate output matrix \( H \) according to equation (4).

2) Calculate the output weight \( \beta \).

3) Send the testing data to ELM, four classification values can be obtained. Choose the maximum value as the final classification result.

4) Repeat steps 1-3 \( S \) times, then compute the average of these \( S \) predicting values as the classification accuracy.

The proposed cloud-type identify research processes is shown as (Fig. 2).

4. RESULTS AND DISCUSSION

4.1. Cloud Classification based on Texture Feature

In this work, nine parameters of texture features are selected for cloud-type recognition, where the hidden neurons \( N' \) of ELM is respectively take 12, 15, 20, 25, 30, 35 and the recognition rates for four sky-types are 63.93%, 65.23%, 67.63%, 67.45%, 72.02% and 71.76% respectively. When \( N' = 30 \), we have a higher average recognition rate. Table 1 shows the recognition rate and misjudgment rate of all kinds of sky-types when \( N' = 30 \). From Table 1, the overall success rate is about 72.02%, but only 61.63% correct classification rate is obtained for stratus, where 26.5% and 10.02% are mistaken recognition rate for cirrus and cumulus respectively. According to this results of Table 1, the recognition rates only based on texture features can not get good performance.
Table 1. Confusion matrix using texture features alone when \(N'\) is set to 30.

<table>
<thead>
<tr>
<th></th>
<th>Cirrus</th>
<th>Clear sky</th>
<th>Cumulus</th>
<th>Stratus</th>
<th>Mean</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cirrus</td>
<td>0.7025</td>
<td>0.0020</td>
<td>0.3139</td>
<td>0.2650</td>
<td></td>
</tr>
<tr>
<td>Clear sky</td>
<td>0.0721</td>
<td>0.9619</td>
<td>0.0007</td>
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<tr>
<td>Cumulus</td>
<td>0.1154</td>
<td>0.0186</td>
<td>0.6002</td>
<td>0.1002</td>
<td></td>
</tr>
<tr>
<td>Stratus</td>
<td>0.1100</td>
<td>0.0172</td>
<td>0.0852</td>
<td>0.6163</td>
<td>0.7202</td>
</tr>
</tbody>
</table>

Table 2. Confusion matrix using color features alone when \(N'\) is set to 12.

<table>
<thead>
<tr>
<th></th>
<th>Cirrus</th>
<th>Clear sky</th>
<th>Cumulus</th>
<th>Stratus</th>
<th>Mean</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cirrus</td>
<td>0.5769</td>
<td>0.0150</td>
<td>0.2269</td>
<td>0.0886</td>
<td></td>
</tr>
<tr>
<td>Clear sky</td>
<td>0.1259</td>
<td>0.9653</td>
<td>0.0031</td>
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<td></td>
</tr>
<tr>
<td>Cumulus</td>
<td>0.2354</td>
<td>0.0022</td>
<td>0.5683</td>
<td>0.1459</td>
<td></td>
</tr>
<tr>
<td>Stratus</td>
<td>0.0617</td>
<td>0.0174</td>
<td>0.2017</td>
<td>0.7305</td>
<td>0.7103</td>
</tr>
</tbody>
</table>

4.2. Cloud Classification based on Color Features

There are nine color features used to identify the cloud type, where the hidden neurons \(N'\) of ELM is respectively take 8, 10, 12, 15, 20, 25, 30, and the recognition rates for four sky-types are 6.21%, 69.61%, 71.03%, 70.29%, 69.97%, 70.73% and 70.28% respectively. When \(N' = 12\), we have a higher average recognition rate. Table 2 gives the recognition rates and misjudgment rates for four different sky-types when \(N = 12\). Compared with texture features, the average accuracy is similar, but the recognition rates for cirrus and cumulus are only 57.69% and 56.83 respectively, they have respectively 23.54% and 22.69% are mistaken as cumulus and cirrus, resulting in great confusion.

4.3. Cloud Classification based on Sift Features

In this paper, we use BOW model to process sift descriptors and the value of \(M\) for k-means is 500, then we get the histogram of bin=500, and then normalized. Finally, the 500 dimensional vector can be used to represent the image. When the hidden neurons \(N'\) of ELM is respectively
take 1200, 1500, 1800, 20, 2500, 3000, and the recognition rates for four sky-types are 80.66%, 81.89%, 82.49%, 82.95%, 83.82%, 83.49%. When \( N = 2500 \), we have a higher average recognition rate. Table 3 gives the confusion matrix using sift features with \( N = 2500 \). Compared to the texture and color results, the overall performance is better, and the recognition rate for clear sky is slightly higher than the other three kinds of sky type.

**4.4. Cloud Classification based on Texture Features and Color Features**

For texture features and color features, 18 components are used for cloud type classification. When the hidden neurons \( N \) of ELM is respectively take 12, 15, 20, 25, 30, 35, 40, and the recognition rates are 70.32%, 73.03%, 75.33%, 76.35%, 76.81%, 71.23%, 71.12% respectively. As shown in Table 4, the recognition rates for four cloud types using texture and color features are better than that only using any one of them. The cloud misjudgment, however, for each other still exists and more than 20% of cumulus are mistaken for cirrus.

**4.5. Cloud Classification based on Color Features and Sift Features**

Color features and sift features have 509 components for classification. When the hidden neurons \( N \) of ELM is respectively take 900, 1200, 1400, 1500, 1800, 2000, 2500 and the recognition rates are 82.59%, 83.59%, 84.63%, 84.91%, 85.59%, 85.79%, and 85.89% respectively.

When \( N = 2500 \), we have a higher average recognition rate of 85.89%. Table 5 is confusion matrix when \( N = 2500 \). The results illustrates that using the two features together is better than that only using color features or sift features. This shows that combine two features can be useful for improving the recognition rate.

**4.6. Cloud Classification based on Texture Features and Sift Features**

Based on 9 components of texture features and 500 components of sift features, when the hidden neurons \( N \) of ELM is respectively take 900, 1200, 1500, 1800, 2000, 2500,

<table>
<thead>
<tr>
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<th>Clear sky</th>
<th>Cumulus</th>
<th>Stratus</th>
<th>Mean</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cirrus</td>
<td>0.8311</td>
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<td>Clear sky</td>
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<td>0.8574</td>
<td>0.0005</td>
<td>0.0006</td>
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<td>Cumulus</td>
<td>0.0474</td>
<td>0.0598</td>
<td>0.8381</td>
<td>0.1087</td>
<td></td>
</tr>
<tr>
<td>Stratus</td>
<td>0.0068</td>
<td>0.0007</td>
<td>0.0526</td>
<td>0.8260</td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th></th>
<th>Cirrus</th>
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<th>Cumulus</th>
<th>Stratus</th>
<th>Mean</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cirrus</td>
<td>0.8177</td>
<td>0.0092</td>
<td>0.2420</td>
<td>0.1848</td>
<td></td>
</tr>
<tr>
<td>Clear sky</td>
<td>0.0001</td>
<td>0.9899</td>
<td>0.0007</td>
<td>0.0004</td>
<td></td>
</tr>
<tr>
<td>Cumulus</td>
<td>0.1607</td>
<td>0.0008</td>
<td>0.5806</td>
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<tr>
<td>Stratus</td>
<td>0.0215</td>
<td>0.0008</td>
<td>0.1767</td>
<td>0.6841</td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th></th>
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<th>Cumulus</th>
<th>Stratus</th>
<th>Mean</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cirrus</td>
<td>0.8741</td>
<td>0.0344</td>
<td>0.0734</td>
<td>0.1357</td>
<td></td>
</tr>
<tr>
<td>Clear sky</td>
<td>0.0026</td>
<td>0.9499</td>
<td>0</td>
<td>0.0304</td>
<td></td>
</tr>
<tr>
<td>Cumulus</td>
<td>0.0955</td>
<td>0.0146</td>
<td>0.8109</td>
<td>0.0332</td>
<td></td>
</tr>
<tr>
<td>Stratus</td>
<td>0.0278</td>
<td>0.0012</td>
<td>0.1157</td>
<td>0.8008</td>
<td></td>
</tr>
</tbody>
</table>

Table 3. Confusion matrix using sift features alone when \( N \) is set to 2500.

Table 4. Confusion matrix using texture features and color features when \( N \) is set to 30.

Table 5. Confusion matrix using color features and sift features when \( N \) is set to 2500.
The recognition rates for four cloud types are 79.39%, 80.49%, 81.10%, 81.76%, 82.41%, 82.16%. From the results we see the overall accuracy is better than only using texture features. The results of recognition rates and misjudgement rates for four different cloud types are shown in Table 6. From the confusion matrix, it can be seen that the recognition rate for cirrus, clear sky and cumulus is higher, but for stratus is lower.

### 4.7. Cloud Classification based on Texture Features, Color Features and Sift Features

Combine texture features, color features and sift features, there are 518 components. When the hidden neurons $N'$ of ELM is respectively take 1200, 1400, 1500, 1800, 2000, 2500, 3000, the recognition rates for four cloud types are 85.69%, 86.02%, 85.59%, 86.22%, 86.64%, 86.33%, 86.60%, the overall performance is better than any discussed above. The highest recognition rate is 86.64% with $N' = 2000$. Table 7 gives confusion matrix using these three features, and for four kinds of sky type the recognition rate reached more than 70%, achieved good results. This illustrates that global features and local features combined together is more conducive to improve the recognition rate, and enhance the classification performance.

### 4.8. Experimental Comparison and Misjudgment Analysis

Since the support vector machine (SVM), k-nearest neighbor algorithm (KNN), and Back Propagation (BP) artificial neural network are popular methods for cloud classification, so the proposed approach of this work is benchmarked against KNN, SVM and BP. Fig. (3) shows the classification results for KNN, SVM, BP and ELM. The proposed method is proved to be more robustness for cloud type classification.

![Classification results for different methods](image)

<table>
<thead>
<tr>
<th>Cirrus</th>
<th>Clear sky</th>
<th>Cumulus</th>
<th>Stratus</th>
<th>Mean</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cirrus</td>
<td>0.8767</td>
<td>0.0375</td>
<td>0.0583</td>
<td>0.1061</td>
</tr>
<tr>
<td>Clear sky</td>
<td>0.0044</td>
<td>0.9363</td>
<td>0.0017</td>
<td>0.0037</td>
</tr>
<tr>
<td>Cumulus</td>
<td>0.0946</td>
<td>0.0209</td>
<td>0.9075</td>
<td>0.1452</td>
</tr>
<tr>
<td>Stratus</td>
<td>0.0243</td>
<td>0.0054</td>
<td>0.0326</td>
<td>0.7450</td>
</tr>
</tbody>
</table>

Table 7. Confusion matrix using texture features, color features and sift features when $N'$ is set to 2000.
resulting in misjudgment. Fig. 4(a) shows the sample that cirrus is mistaken for cumulus. At the same time, 2.43% cirrus are mistaken as stratus, the body of these samples covered the sky, showing the layered characteristics. Fig. 4(b) shows the sample that cirrus is mistaken for stratus.

For the classification of cumulus, there are 5.83% samples are misjudged as cirrus, and found that these samples have common characteristic of fragmented body. There are 3.26% samples are misjudged as stratus, we can find that the body of these samples covered the sky, showing the layered characteristics. Fig. 5 shows the cumulus sample mistaken for cirrus and stratus.

For the classification of stratus, there are 10.61% samples are wrongly recognized as cirrus, these cloud samples are irregular fragments and some bits and pieces under the cloud. Fig. 6(a) shows the stratus sample mistaken for cirrus. Also, 14.52% samples are mistaken for cumulus, and analysis these samples find that the body of these cloud samples covered the sky, but still exist some massive cloud body, showing the cumuliformis characteristics. Fig. 6(b) shows the stratus sample mistaken for cumulus. And there are little samples of cumulus, stratus and cirrus misjudged as clear sky because of too little cloud cover in image.

CONCLUSION

Cloud classification is an important part of automatic observation of sky, and accurate and quantitative automatic cloud observation are useful for numerous climatic model, hydrologic and atmospheric research. In this paper, we proposed a cloud classification method to automatically recognize different kinds of digital sky images. Among the article, we not only discuss global features of cloud image, i.e. texture features and color features, but also process sift features by means of BOW model. Finally, we have realized a detailed analysis of cloud image with three features and extreme learning machine. Experimental results demonstrate that combining these three features for classification better than using only one feature or any two of them.

In nature, the sky often present a wide series of different cloud type at the same time, such as cirrus and cumulus or...
cirrostratus and stratocumulus frequently appear together. In order to avoid misclassification caused this phenomenon, we suggest that when partition image to subimages initially, the blocks can be smaller. And that it is important to check if these blocks have enough information for assign the image blocks to a cloud type. We are sure that through the above suggestions, an improved algorithm is feasible. In addition, other, not mentioned features, such as LBP features and shape features, may also improve the algorithm's performance. In this work, however, we just discuss single type of sky cloud images, while the sky types are often complex. Therefore, future research are needed for automatic identification of complex cloud image.

CONFLICT OF INTEREST

The authors confirm that this article content has no conflict of interest.

ACKNOWLEDGEMENTS

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Fig. (6). Stratus are mistaken for cirrus (left) and cumulus (right).


