Ground Nephogram Recognition Algorithm Based on Selective Neural Network Ensemble

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Abstract: In view of the low accuracy of traditional ground nephogram recognition model, the authors put forward a *k*-means algorithm-acquired neural network ensemble method, which takes BP neural network ensemble model as the basis, uses *k*-means algorithm to choose the individual neural networks with partial diversities for integration, and builds the cloud form classification model. Through simulation experiments on ground nephogram samples, the results show that the algorithm proposed in the article can effectively improve the Classification accuracy of ground nephogram recognition in comparison with applying single BP neural network and traditional BP AdaBoost ensemble algorithm on classification of ground nephogram.

Keywords: Cloud shape, *k*-means, BP neural network, adaboost.

1 Introduction

In recent years, with the development of image processing and pattern recognition theory, research on automatic classification and recognition of cloud images has become a research hot spot of meteorological applications [Huang and Zhang (2012)]. In the cloud images identification research area, the satellite remote-sensing cloud images recognition is the main focus among the both domestic and international researchers. Satellite cloud observations have achieved good results in the identification of large-scale clouds and measurement of cloud tops. While, ground-based cloud observations have only achieved automatic measurement of cloud volume and cloud height in recent years. However, the shape identification of ground nephogram is still judged by qualitatively nowadays. Due to the wide variety of ground nephogram shape, there are many drawbacks if mainly relying on the experience of the observer to carry out manual observation, such as excessively subjective randomness [Yang, Xue and Song (2008)].

In recent years, domestic and foreign researches on the classification of ground-based cloud shapes mainly use the classification methods based on minimum distance classifier

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and neural network. The support vector machine is selected as the classifier to classify the cloud image [Li, Fu and Deng (2016)]. Extracting texture features by means of autocorrelation, co-occurrence matrix as well as LAW energy has been applied in Singh et al. [Singh and Glennen (2005)], but there are only theory discussion and analysis in the literature. Yang et al. [Yang, Xue and Song (2008)] used the minimum distance classification methods to achieve cloud shapes, but the method relied excessively on the selection of the initial center and easily fell into the local optimum. Lu et al. [Lu and Zhang (2011)] proposed to use BP neural network classifier to automatically classify and identify cloud images, but this method does not overcome the shortcomings of the traditional BP neural network. And it is easy to fall into the local minimum which causes the algorithm to converge slowly, then result in unstable classification results. The traditional BP AdaBoost algorithm can be used for the classification of cloud images. Although it can overcome the disadvantage that a single BP neural network trapped into local minimum values and it also improves the accuracy of cloud image recognition, which weakened the performance of ultimately integrated classifier.

In terms of the above problems, a selective neural network ensemble method based on *k*-means clustering algorithm is proposed in this paper. Based on the BP neural network ensemble model, this method uses *K*-means clustering algorithm to select some individual neural networks with different measurements. Finally, multiple BP neural networks strong classifier with higher precision and diverse differences will come out through the integration of AdaBoost algorithm, which can be applied for the identification and classification of ground-based cloud images.

2 BP neural network and AdaBoost algorithm

2.1 BP neural network

BP neural network is a typical multi-layer feed forward network, which is divided into two stages: forward propagation of information and back propagation of error. In the forward propagation phase, each neuron in the input layer is responsible for receiving input information from the outside world and transmitting it to each neuron in the middle layer. After processing information, the neurons in the intermediate layer transformed and then passed information to the output layer to obtain a prediction result. The errors between the result predicted by output layer and real results are delivered back to the neurons in the middle layer, and then minimizes the square of the error between the network output value and the target value via gradient descent method, thus learning the weight of the network element [Tom (2003)]. Due to its simple structure and strong robustness, BP neural network has solved many complicated engineering problems in the past several years and achieved amazing achievements [Abbas, Bangyal and Ahmad (2010)].

2.2 AdaBoost algorithm principle

The AdaBoost algorithm is an integrated learning algorithm, and the core idea is training different weak classifiers in different sample distributions for the same training set. The performance of these weak classifiers is supposed to surpass random guessing only slightly. Finally, a plurality of such weak classifiers is cascaded into a strong classifier through a weighting mechanism [Xu and Chen (2018)]. The algorithm is essentially implemented by changing the distribution of the sample data. In each iteration, the weight of the sample is determined based on the overall correct rate of the last classification and sample's classification. It increases their weights for samples with incorrect classification, while reduces their weights for samples with the correct classification, thereby obtaining different sample distributions.

2.3 Traditional BP AdaBoost classifier model

The traditional BP AdaBoost models, which consider the BP neural network as the weak classifier, train multiple BP neural network weak classifiers to classify samples under different sample distribution, which are combined into strong classifiers at last via the AdaBoost algorithm [Li and Cui (2018)]. The model based on the traditional BP AdaBoost is used in this paper to recognize cloud shape, and the algorithm flow is shown in Fig. 1.

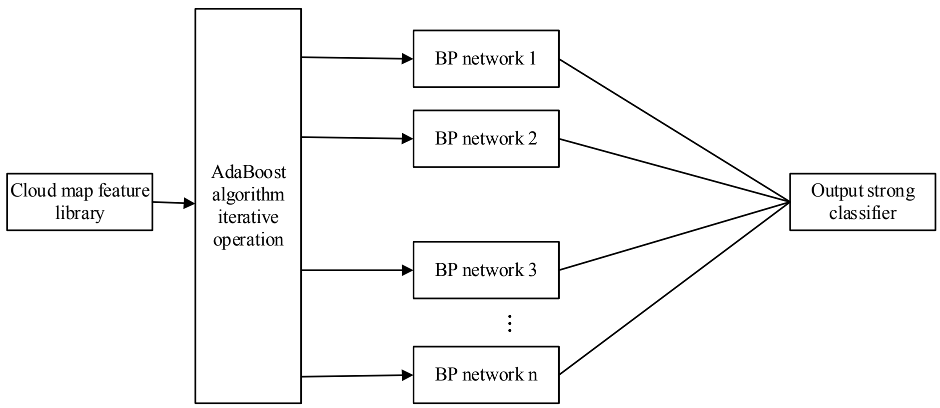

Figure 1: BP AdaBoost classifier for cloud image

As the following, the steps of strong classifier algorithm trained by the BP AdaBoost are:

(1) Selecting data and initializing BP network

The m group training data are randomly selected from the cloud samples, and the distribution weight the AdaBoost algorithm $D_1\left(i\right) = 1 / m$ and the weight and threshold of the BP neural network are initialized. Then, the structure of the neural network is determined by the input and output dimensions of the samples images.

(2) Training weak classifier

When training the t^{th} weak classifier, the training data of the distribution weights after the $t-1^{th}$ training are used as the input of the BP neural network. ε_t is the same of the error of the classifier g_t is calculated as follows:

$$\varepsilon_t = \sum_i D_i(i) \qquad i = 1, 2, \cdots, \mathrm{m}(\mathrm{g}_t(\mathrm{x}_i) \neq y_i) \tag{1}$$

(3) Calculating the weight of the classifier

The weights of each classifier are mainly calculated according to the error of each classifier. The calculation formula of the t^{th} classifier weight is:

$$\alpha_t = \frac{1}{2}\ln(\frac{1-\varepsilon_t}{\varepsilon_t}) \tag{2}$$

(4) Adjusting the weight of training data

Adjusting the weight of the $t+1^{th}$ classifier training samples by the weight α_t of the t^{th} classifier, the weight adjustment formula is:

$$D_{t+1}(i) = \frac{D_t(i)}{Z_t} \times \exp(-\alpha_t y_i g_t(x_i)) \qquad i = 1, 2, \cdots, m \tag{3}$$

In the formula Z_t is the normalization factor, so that the sum of the weights of the samples is 1.

(5) Generating a strong classifier for the cloud image

The AdaBoost algorithm obtains T BP neural network weak classifiers after training for T times. The final strong classifier $h(x)$ is obtained by combining T with weak classifiers:

$$h(x) = \frac{\alpha_t}{\sum_{t=1}^{T}\alpha_t} g_t(x) \tag{4}$$

3 Selective neural network ensemble is based on *K*-means

3.1 K-means clustering

The principle of *K*-means clustering is to classify similar objects into the same cluster and classify dissimilar objects into different clusters by means of similarity calculation methods. This method has specific geometric and statistical significance. In this paper, the trained based on neural network classifiers are clustered by this idea, and the individual classifiers with partial differences are integrated selectively while ensuring accuracy. The working flow of the *K*-means clustering algorithm is as follows:

Input: Training data set $X = \{x_1, x_2, \cdots, x_n\}$, number of clusters k ;

Output: k clusters C_j, $j = 1, 2, \cdots, k$

Step 1. Set $I = 1$, randomly selecting k training samples as the initial cluster center of k clusters $m_j(I)$, $j = 1, 2, \cdots, k$, I is the iteration times of the algorithm is iterated;

Step 2. Calculate the distance $d(x_i, m_j(I))$, $i = 1, 2, \cdots, n; j = 1, 2, \cdots, k$ of each training sample from the centers of the k clusters, if

$d(x_i, m_j(I)) = \min\{d(x_i, m_i(I))\}, j = 1, 2, \cdots, k$, then $x_i \in C_j$;

Step 3. Calculate k new cluster centers

$$m_j(I+1) = \frac{1}{N_j} \sum_{i=1, x_i \in C_j}^{N_j} x_i \quad j = 1, 2, \cdots, k \tag{5}$$

Step 4. If $m_j(I+1) \neq m_j(I), j = 1, 2, \cdots k$, set $I = I + 1$, and jump to Step 2; otherwise the algorithm ends.

3.2 Main idea of selective neural network

Differences in training sets and differences in initial weights and thresholds for each BP network are importantly influencing factors between individual networks. However, the traditional BP Adaboost integration methods may produce neural network classifiers that are very similar to each other because of the randomness of the learning algorithm, while integrating less differentiated classifiers may not necessarily reduce the integration generalization error. It is also possible that the generalization ability of the algorithm is weakened. The higher the accuracy of each network that constitutes the integrated learning model, the greater the difference between the members, and the more favorable the reduction of the integrated learning generalization error [Wu, Zhou and Shen (2000)]. In the case of limited training set, the difference between training sets are obtained by repeating sampling technique, while the raw data may repeating in the sub-training set or not. The Bootstrap technique is used to sample N sets of n training sets and then train the N sets of sample sets by means of the BP neural network to independently obtain the weights and thresholds of each network, and classify the obtained ownership thresholds and obtain the same clustering center as the base classifiers via the *K*-means algorithm. Finally, the weights and thresholds of the individual classifiers close to each cluster center are selected as the initial weights and thresholds of the M base classifiers, thus forming M differential base classifiers through the AdaBoost algorithm. The M base classifiers are cascaded into a final strong classifier to establish classification model for ground based cloud images.

4 Experimental results and analysis

4.1 Experimental data

According to the needs of observation and weather forecasting, the cloud is divided into low, medium and high level by the height of the cloud bottom from the ground. According to the macroscopic characteristics, physical structure and genesis of the cloud, the cloud is divided into ten genus and twenty-nine species [China Meteorological Administration (2004)]. In this paper, four typical cloud classes, such as cumulonimbus calvus, Cu hum, cirrus spissatus and stratus cloud, are selected to establish a classification sample library. The experimental samples are collected by meteorological observation base in the Nanjing University of Information Science and Technology, the cloud data of the official website of the Shanxi Meteorological Bureau, China personal digital camera, and the book of the China Cloud Images. The four typical cloud samples are shown in Fig. 2.

Usually in Fig. 2, the cumulonimbus cloud is thick, large and towering, with varying heights, dark bottoms, and smooth or even texture; The cumulus clouds are generally cumulus clusters with well-defined contours and flat. The cloud is not connected to each other, causing texture fluctuations and uneven boundaries; The texture of the cirrus is white filament or narrow strip, and the distribution is relatively uniform; The bottom of the layer cloud is very low, the texture is evenly layered, like fog, but not connected to the ground, the thickness and height of the cloud top are very small.

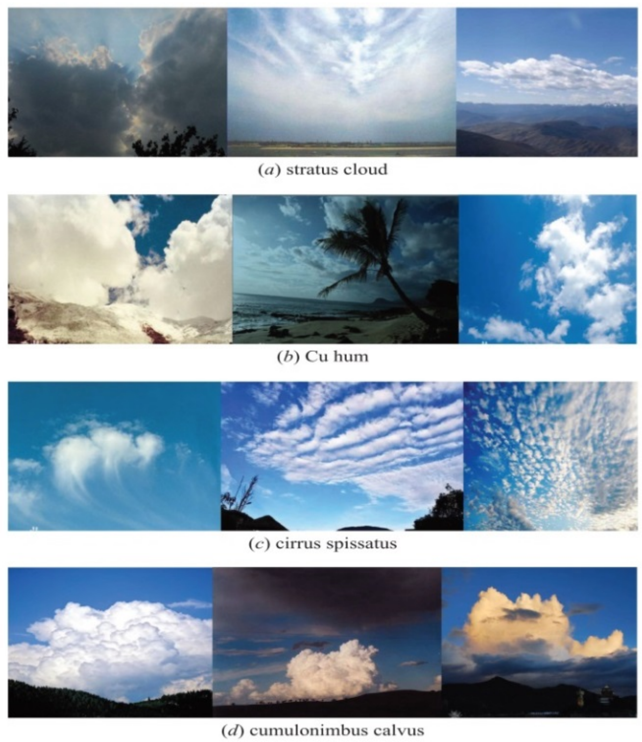

Figure 2: Cloud sample images

4.2 Textures features extraction

Because the physical properties of the surface of the object are different, which will result in different textures, the change of texture in the cloud and the sky is a very effective visual feature information of the cloud classification [Chen and Song (2014)]. Extracting texture features based on gray level co-occurrence matrix has been widely used in the field of image recognition, such as Yu et al. [Yu, Li and Liu (2010); Honeycutt and Plotnick (2008); Kekre, Thepade, Sarode et al. (2010)]. Du et al. [Du, Zhang and Gu (2018)] exhaustively demonstrates the various statistics that can be extracted from the gray level co-occurrence matrix as feature values. It is proposed in Singh et al. [Singh and Glennen (2005)] that the features extracted by the gray level co-occurrence matrix are better for cloud image classification than other texture features. The gradient information of the image to the gray level co-occurrence matrix in Mu et al. [Mu, Bao and Wang (2015); Wang and Dong (2009)], so that the co-occurrence matrix can more closely contain the texture primitives of the images and arrangement information. The determination of the texture features of the cloud images is to extract the cloud images that meets the requirements in the total image feature library, and then analyze the texture features of the image by the specific structure in Duan et al. [Duan, Wang and Yang (2016)]. In this paper, the gray gradient co-occurrence matrix method is used to extract the texture features of the cloud images according to the existing research.

The gray-gradient co-occurrence matrix texture analysis method extracts texture features by means of the comprehensive information of the grayscale and gradient of the images. It is a joint distribution of pixel grayscale and edge gradient size, which reflects the two basic elements in the images, that is, the relationship between the gray level and the gradient of the pixel. The gray level of a pixel is the basis of an images, and the gradient is the element that forms the contour of the edge of the images. Further the gray-gradient space describes the texture of the images well, and clearly showing the distribution of pixel grayscale and gradient within the images. Cui et al. [Cui, McIntosh and Sun (2018)] proposed an effective method for automatically setting PI and CG, which can achieve high-precision recognition of images. And this paper applies image recognition technology to the meteorological field.

The element $h(x, y)$ of the gray-gradient co-occurrence matrix is defined as the number of pixels of the gradient value y and gray value x in the normalized grayscale image $f(i, j)$\right) and its normalized gradient image $g(i, j)$, that is, the number of elements in the set $\{(i, j) \mid f(i, j) = x \cap g(i, j) = y\}$. The gradient image $g(i, j)$ can be calculated from the gray image by a differential operator.

However, the actual situation is to extract the texture features of the cloud image via the gray-gradient co-occurrence matrix. The amount of calculation is determined by the gray level and dimension of the cloud image [Bo, Ma and Jiao (2006)]. In general, the gray level of a cloud image is 256 levels. In order to improve the time efficiency of the overall recognition performance of the cloud image, the gray level of the original cloud image is compressed to 32 gray levels without affecting the texture features in the gray-gradient co-occurrence matrix calculation. From the calculated gray-gradient co-occurrence matrix, 15 common secondary statistical characteristic parameters such as small gradient advantage, large gradient advantage, gray unevenness, gradient inhomogeneity and energy are extracted, and the cloud image sample feature database is established. Before the feature extraction, the necessary pre-processing of the sample initial image is made, so that the texture features of the image are more prominent and the interference of other factors such as noise is minimized, which creates favorable conditions for more accurate extraction of the feature parameters of the cloud images.

4.3 Experiment and analysis of results

In this paper, a total of 800 cloud images were selected. Each type of cloud image sample was 200, where 150 samples selected from each class as training samples, the rest as testing samples. In the algorithm model proposed in this paper, the Bootstrap method is firstly used to generate a $N(N = 200)$ cloud image training set with n size ($n = 150$, sharing the same size as the original training set). Then, each group trains out a neural network weak classifier, and cluster the initial weights and thresholds of each weak classifier generated to obtain M class clusters via the *K*-means algorithm (M shares the same number with the number of base classifiers, which are experimentally explored from base classifiers in the integrated network in this paper, $M = 15$). The initial weights and thresholds of individual classifiers close to the center of M clusters are selected, and their values are used as the initial weights of the integrated network individuals. The threshold is finally integrated into a strong classifier by the AdaBoost algorithm. The error rate comparison between the traditional BP AdaBoost algorithm model and the proposed algorithm model on the cloud images test samples is shown in Fig. 3 (the training error precision value of each base classifier is 0.003) when the number of base classifiers is the same.

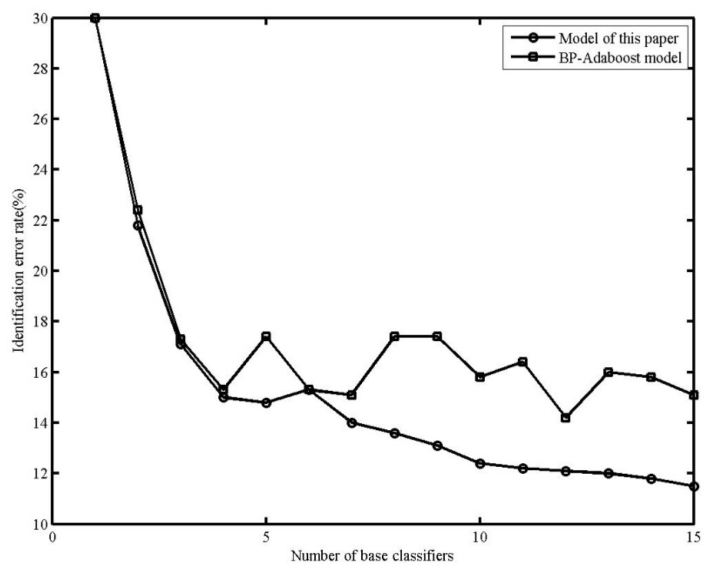

Figure 3: Error rate for two algorithms with the same number of base classifiers

In the traditional BP AdaBoost integration mode, due to the generated randomly initial weights and thresholds of each base classifier, a large difference between the networks is hardly be guaranteed that the differences of the various base classifiers generated by the training are not obvious enough., Integrating these base classifiers does not improve the generalization ability of the entire cloud classifier, and the cloud map test set error rate curve shows a turbulent trend, as shown in Fig. 3. However, the *K*-means algorithm proposed in this paper selectively selects the weights and thresholds of individual networks to train the classifiers, so that the generated base classifiers have certain differences, and the individual networks integrating these differences are used for the Identification of cloud maps identification. The error rate can continue to decrease steadily, which demonstrates in Fig. 3 that the error rate of the strong classifier generated by the algorithm model proposed in this paper is significantly lower than that of the traditional BP AdaBoost algorithm on the cloud test set.

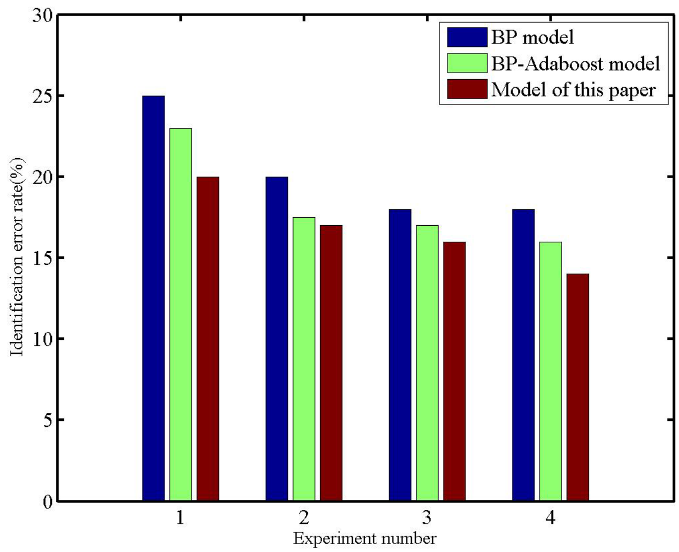

Figure 4: Error rate of different models

This paper also compares the performance of single BP neural network model, traditional BP AdaBoost model as well as the model from this paper based on cloud image classification recognition in different accuracy of training error in the base classifier. For the three models, we conducted a total of 4 time tests, with the training error accuracy value of each base classifier set with 0.04, 0.01, 0.008 and 0.003 in per test. Moreover, in the integration model, the number of basic classifiers is taken with 15, the experimental results are shown in Fig. 4, where the x-axis represents the experimental number, the y-axis is the error rate of the measured test sample. As shown in Fig. 4, the higher the accuracy of the various networks that comprise the integrated learning model, the greater the difference between the memberships, the more conducive to reduce the error in learning generalization integration.

5 Conclusion

This paper constructs a cloud image strong classifier based on *K*-means algorithm for selective integration of BP neural network classification. Compared with the traditional BP AdaBoost algorithm, a now model is put forward in this paper that perform clustering and integrate selectively some partially individual networks several weak classifiers. Finally, model integrate them into a strong classifier through AdaBoost. The experimental results show that the proposed algorithm has high classification accuracy for recognizing cloud images, which can effectively improve the accuracy and stability of cloud images classification and also reduce the generalization error of traditional neural network integration. It is the main content in the next step that how to effectively determine the key features of cloud image classification and determine the number of base classifiers in the integrated classifier.

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