Ground-Based Cloud Using Exponential Entropy/Exponential Gray Entropy and UPSO

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Abstract: Objective and accurate classification model or method of cloud image is a prerequisite for accurate weather monitoring and forecast. Thus safety of aircraft taking off and landing and air flight can be guaranteed. Thresholding is a kind of simple and effective method of cloud classification. It can realize automated ground-based cloud detection and cloudage observation. The existing segmentation methods based on fixed threshold and single threshold cannot achieve good segmentation effect. Thus it is difficult to obtain the accurate result of cloud detection and cloudage observation. In view of the above-mentioned problems, multi-thresholding methods of ground-based cloud based on exponential entropy/exponential gray entropy and uniform searching particle swarm optimization (UPSO) are proposed. Exponential entropy and exponential gray entropy make up for the defects of undefined value and zero value in Shannon entropy. In addition, exponential gray entropy reflects the relative uniformity of gray levels within the cloud cluster and background cluster. Cloud regions and background regions of different gray level ranges can be distinguished more precisely using the multi-thresholding strategy. In order to reduce computational complexity of original exhaustive algorithm for multi-threshold selection, the UPSO algorithm is adopted. It can find the optimal thresholds quickly and accurately. As a result, the real-time processing of segmentation of ground-based cloud image can be realized. The experimental results show that, in comparison with the existing ground-based cloud image segmentation methods and multi-thresholding method based on maximum Shannon entropy, the proposed methods can extract the boundary shape, textures and details feature of cloud more clearly. Therefore, the accuracies of cloudage detection and morphology classification for ground-based cloud are both improved.

Key words: detection of ground-based cloud; multi-thresholding of cloud image; exponential entropy; exponential gray entropy; uniform searching particle swarm optimization (UPSO)

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1 Introduction

Due to the neglect of the weather reason, there are a large number of aviation accidents. Real-time and accurate weather forecasting is an important guarantee of aviation safety. Cloud has penetrated into many research fields of atmospheric science as a meteorological element. Different types of clouds reflect different weather and climate. Objective and accurate classification model or method of cloud image is a prerequisite for accurate weather monitoring and forecast. In recent years, extensive research on recognition of satellite cloud images was conducted[1-2]. However, the cloud parameters are also often needed to be aquired by ground-based observation in the actual meteorological service. Currently, observation and detection of the shape and cloudage of

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ground-based cloud depend more on artificial judgment. The observation and detection results are susceptible to human psychology and eyesight condition, and the recorded results are relatively simple. It is difficult to realize accurate and real-time detection when the weather conditions are complex[3-4]. Therefore, the automatic detection and classification method of cloud should be studied to realize automation of observation and detection of ground-based cloud. Thresholding is a kind of simple and effective cloud detection method[5-7]. It can divide a cloud image into background region and cloud region according to the gray level, which facilitates the subsequent cloud classification and recognition. Currently, thresholding methods of ground-based cloud consist of fixed threshold method[8] and Otsu method[9] based on the red and blue bands of image. However, the actual ground-based cloud image is complex. Satisfactory results cannot be achieved using the above-mentioned methods when the image contains ground or the sky is not clear. In order to adapt to ground-based cloud images with complex background under different weather conditions, multi-thresholding methods based on entropy are considered to segment the above ground-based cloud images. The concept of information entropy was firstly introduced into thresholding by Kapur, et al[10]. The proposed thresholding method based on maximum Shannon entropy catches the most attention because it is simple and relatively effective. It is then extended to multi-threshold selection. As the number of thresholds increases, the amount of computation increases substantially. In order to reduce the computation, iterated conditional modes algorithm[11], genetic algorithm[12], global transformation algorithm[13], basic particle swarm optimization (PSO) algorithm[14] are adopted to search the optimal thresholds of the thresholding method based on maximum Shannon entropy. They accelerate the running speed in varying degrees.

However, the above defined Shannon entropy has the defects of undefined value and zero value. Therefore, exponential entropy was defined by Pal, et al.[15] under the same assumption of Shannon logarithmic entropy. Meanwhile, bi-level thresholding method based on exponential entropy is proposed to make up for the defects. In addition, the above thresholding methods based on logarithmic entropy and exponential entropy solely depend on the gray histogram distribution. The gray level within the object region and background region is unable to be kept relatively uniform. Therefore, Wu Shihua, et al.[16] defined exponential gray entropy on the basis of exponential entropy, and derived bi-level thresholding method based on exponential gray entropy. Better segmentation effect can be obtained for some images using the method. For segmentation of the actual ground-based cloud image, textures and details feature are needed to be extracted for the subsequent accurate classification of cloud. If the cloud image is simply segmented with only one threshold, there is confusion and misclassification of the cloud area and background area. Many textures and details of cloud is lost, which results in reducing the cloud classification accuracy. Therefore, multiple thresholds must be selected to achieve more accurate multi-thresholding of ground-based cloud image. Among the algorithms of searching optimal thresholds, the basic PSO algorithm[17] can obtain better optimization result because of its higher search speed and fewer tuning parameters. However, the search accuracy is not satisfactory due to the nonuniformity while searching between the local optimal solution and the global optimal solution.

Based on the above-mentioned analysis and the characteristics of ground-based cloud image, bi-level thresholding based on exponential entropy and exponential gray entropy are extended to multi-thresholding, respectively. Multi-thresholding methods of ground-based cloud image based on exponential entropy/exponential gray entropy are proposed in the paper. The criterion based on exponential entropy and exponential gray entropy can make up for the defects of undefined value and zero value in Shannon logarithmic entropy, and consider the uniformity of gray level within the cloud cluster and background cluster of ground-based cloud image. The criterion together with the multi-thresholding strategy can adapt to the segmentation of complex ground-based cloud images under different weather condition, facilitating subsequent cloud shape identification and cloudage detection. In order to search for the optimal thresholds of multi-thresholding methods of ground-based cloud image based on exponential entropy/exponential gray entropy more efficiently, the uniform searching particle swarm optimization (UPSO) algorithm[18] is further adopted in the paper. The particle swarm in the algorithm searches uniformly between the local optimal solution and the global optimal solution. Compared with the basic PSO algorithm, the UPSO algorithm further simplifies the parameters. Thus the search speed and accuracy of the particles are both improved greatly. The detailed steps of the proposed multi-thresholding methods are given in the paper. The experimental results show the segmentation effect of cloud images and running time required by the proposed method, and comparisons are made with six methods such as the segmentation methods of ground-based cloud image using fixed threshold method[8] or Otsu mothod[9] based on the red and blue bands, bi-level thresholding method using exponential entropy/exponential gray entropy, bi-level thresholding method using Shannon entropy and multi- thresholding method using Shannon entropy[14].

2 Multi-thresholding of Ground-Based Cloud Based on Exponential Entropy

Assume that a ground-based cloud image f has L gray levels. The gray level of the pixel (m, n) is denoted by $f(m,n)$. In the cloud image, The occurrence frequency and probabilities of gray level are denoted by h_i and p_i, respectively. In the gray level range $[0, L-1)$, a certain threshold t is selected to divide the cloud image into a background area C_B and a cloud area C_O, whose gray level ranges are in $[0,t]$ and $[t+1, L-1]$. The probability distributions of background area C_B and cloud area C_O are $\left\{\frac{p_0}{P_t}, \frac{p_1}{P_t}, \cdots, \frac{p_t}{P_t}\right\}$ and $\left\{\frac{p_{t+1}}{1-P_t}, \frac{p_{t+2}}{1-P_t}, \cdots, \frac{p_{L-1}}{1-P_t}\right\}$, respectively, where $P_t = \sum_{i=0}^{t} p_i$, $1-P_t = \sum_{i=t+1}^{L-1} p_i$, $t \in [0, L-1)$.

To the ground-based cloud image, the exponential entropy of background area and cloud area are defined as

$$H_{E,B}(t) = \sum_{i=0}^{t} \frac{p_i}{P_t} e^{1-\frac{p_i}{P_t}} \tag{1}$$

$$H_{E,O}(t) = \sum_{i=t+1}^{L-1} \frac{p_i}{1-P_t} e^{1-\frac{p_i}{1-P_t}} \tag{2}$$

The total exponential entropy of cloud image is written as

$$H_E(t) = H_{E,B}(t) + H_{E,O}(t) = \sum_{i=0}^{t} \frac{p_i}{P_t} e^{1-\frac{p_i}{P_t}} + \sum_{i=t+1}^{L-1} \frac{p_i}{1-P_t} e^{1-\frac{p_i}{1-P_t}} \tag{3}$$

When $H_E(t)$ attains maximum, the corresponding threshold T_E is the optimal threshold which can distinguish between cloud and background effectively.

$$T_E = \arg \max_{0 \leqslant t < L-1} \{H_E(t)\} \tag{4}$$

The typical ground-based cloud image consists of ground background, sky and cloud, which occupy different ranges of gray levels. In addition, due to the variation of light and cloud thickness, the cloud itself forms several areas of different gray level ranges. In order to identify the cloud type more accurately, bi-level thresholding based on exponential entropy is extended to multi-thresholding which can identify a variety of objects and backgrounds. Thus complex ground-based cloud images can be segmented efficiently. Assume that select n thresholds $t_1, t_2, \cdots, t_n$ $(0 \leqslant t_1 < t_2 < \cdots < t_{n-1} < t_n < L-1)$, and the cloud image is segmented into $n+1$ gray level intervals. Let

$$p(0, t_1) = \sum_{j=0}^{t_1} p_j$$

$$p(t_{k-1}+1, t_k) = \sum_{j=t_{k-1}+1}^{t_k} p_j \qquad k = 2, 3, \cdots, n$$

$$p(t_n+1, L-1) = \sum_{j=t_n+1}^{L-1} p_j$$

Then the total exponential entropy of cloud image is written as

$$H_E(t_1,t_2,\cdots,t_n)=\sum_{i=0}^{t_1}\frac{p_i}{p(0,t_1)}\mathrm{e}^{1-\frac{p_i}{p(0,t_1)}}+\sum_{i=t_1+1}^{t_2}\frac{p_i}{p(t_1+1,t_2)}\cdot\mathrm{e}^{1-\frac{p_i}{p(t_1+1,t_2)}}+\cdots+\sum_{i=t_{n-1}+1}^{t_n}\frac{p_i}{p(t_{n-1}+1,t_n)}\mathrm{e}^{1-\frac{p_i}{p(t_{n-1}+1,t_n)}}+\sum_{i=t_n+1}^{L-1}\frac{p_i}{p(t_n+1,L-1)}\mathrm{e}^{1-\frac{p_i}{p(t_n+1,L-1)}} \quad (5)$$

When $H_E(t_1,t_2,\cdots,t_n)$ reaches maximum, the corresponding thresholds $(T_{E,1},T_{E,2},\cdots,T_{E,n})$ are the optimal thresholds of multi-thresholding method of ground-based cloud based on exponential entropy.

$$(T_{E,1},T_{E,2},\cdots,T_{E,n})=\arg\max_{0\leqslant t_1<t_2<\cdots<t_{n-1}<t_n<L-1}\{H_E(t_1,t_2,\cdots,t_n)\} \quad (6)$$

3 Multi-thresholding of Ground-Based Cloud Based on Exponential Gray Entropy

If the pixel (m,n) of cloud image is in the background area, let

$$p_{m,n}=\frac{f(m,n)}{\sum_{(x,y)\in C_B}f(x,y)} \qquad (m,n)\in C_B \quad (7)$$

Obviously, $p_{m,n}$ satisfies $p_{m,n}\geqslant 0$ and $\sum_{(m,n)\in C_B}p_{m,n}=1$. There is a one-to-one correspondence between the probability $p_{m,n}$ and the gray level $f(m,n)$ in the background area C_B. The more uniform the gray level within the background area reaches, the more similar the value of $f(m,n)$ as well as the value of $p_{m,n}$ is.

The exponential gray entropy of background area can be defined as

$$H_{G,B}=\sum_{(m,n)\in C_B}p_{m,n}\mathrm{e}^{1-p_{m,n}}=\sum_{(m,n)\in C_B}\frac{f(m,n)}{\sum_{(x,y)\in C_B}f(x,y)}\cdot\mathrm{e}^{1-\frac{f(m,n)}{\sum_{(x,y)\in C_B}f(x,y)}}=\sum_{i=0}^{t}h_i\frac{i}{\sum_{j=0}^{t}h_j\cdot j}\mathrm{e}^{1-\frac{i}{\sum_{j=0}^{t}h_j\cdot j}}=\sum_{i=0}^{t}\frac{h_i\cdot i}{u(t)}\mathrm{e}^{1-\frac{i}{u(t)}} \quad (8)$$

where $u(t)=\sum_{j=0}^{t}h_j\cdot j$.

If the pixel (m,n) of cloud image is in the cloud area, let

$$p_{m,n}=\frac{f(m,n)}{\sum_{(x,y)\in C_O}f(x,y)} \qquad (m,n)\in C_O \quad (9)$$

Obviously, $p_{m,n}\geqslant 0$, $\sum_{(m,n)\in C_B}p_{m,n}=1$. Similarly, the more uniform the gray level within the cloud area reaches, the more similar the value of $p_{m,n}$ is.

The exponential gray entropy of cloud area can be defined as

$$H_{G,O}=\sum_{(m,n)\in C_O}p_{m,n}\mathrm{e}^{1-p_{m,n}}=\sum_{(m,n)\in C_O}\frac{f(m,n)}{\sum_{(x,y)\in C_O}f(x,y)}\cdot\mathrm{e}^{1-\frac{f(m,n)}{\sum_{(x,y)\in C_O}f(x,y)}}=\sum_{i=t+1}^{L-1}h_i\frac{i}{\sum_{j=t+1}^{L-1}h_j\cdot j}\mathrm{e}^{1-\frac{i}{\sum_{j=t+1}^{L-1}h_j\cdot j}}=\sum_{i=t+1}^{L-1}\frac{h_i\cdot i}{u(L-1)-u(t)}\mathrm{e}^{1-\frac{i}{u(L-1)-u(t)}} \quad (10)$$

Then the total exponential gray entropy of cloud image is written as

$$H_G(t)=H_{G,B}+H_{G,O}=\sum_{i=0}^{t}\frac{h_i\cdot i}{u(t)}\mathrm{e}^{1-\frac{i}{u(t)}}+\sum_{i=t+1}^{L-1}\frac{h_i\cdot i}{u(L-1)-u(t)}\mathrm{e}^{1-\frac{i}{u(L-1)-u(t)}} \quad (11)$$

When $H_G(t)$ becomes larger, the sum of the gray level differences within the cloud area and those within the background area becomes smaller. In other words, the gray levels within the above two areas both become more uniform. When $H_G(t)$ reaches maximum, the corresponding threshold T_G is regarded as the optimal threshold.

$$T_G=\arg\max_{0\leqslant t<L-1}\{H_G(t)\} \quad (12)$$

Unlike the Shannon entropy and the exponential entropy which both solely depend on the gray histogram distribution, exponential gray entropy takes into account the uniformity of gray levels within the cloud area and the background area.

In order to adapt to segmentation of complex ground-based cloud images, the above bi-level thresholding Eqs. (11, 12) based on exponential gray entropy are extended to multi-thresholding. Select n thresholds $t_1,t_2,\cdots,t_n$, which satisfies $0\leqslant t_1<t_2<\cdots<t_{n-1}<t_n<L-1$, and the cloud image is segmented into $n+1$ gray level intervals. Let

$$u(0,t_1)=\sum_{j=0}^{t_1}h_j\cdot j$$

$$u(t_{k-1}+1,t_k)=\sum_{j=t_{k-1}+1}^{t_k}h_j\cdot j\qquad k=2,3,\cdots,n$$

$$u(t_n+1,L-1)=\sum_{j=t_n+1}^{L-1}h_j\cdot j$$

Then the total exponential gray entropy of cloud image can be depicted as

$$H_G(t_1,t_2,\cdots,t_n)=\sum_{i=0}^{t_1}\frac{h_i\cdot i}{u(0,t_1)}\mathrm{e}^{1-\frac{i}{u(0,t_1)}}+\sum_{i=t_1+1}^{t_2}\frac{h_i\cdot i}{u(t_1+1,t_2)}\mathrm{e}^{1-\frac{i}{u(t_1+1,t_2)}}+\cdots+\sum_{i=t_{n-1}+1}^{t_n}\frac{h_i\cdot i}{u(t_{n-1}+1,t_n)}\mathrm{e}^{1-\frac{i}{u(t_{n-1}+1,t_n)}}+\sum_{i=t_n+1}^{L-1}\frac{h_i\cdot i}{u(t_n+1,L-1)}\mathrm{e}^{1-\frac{i}{u(t_n+1,L-1)}}\tag{13}$$

The criterion function of multi-threshold selection based on exponential gray entropy is written as

$$(T_{G,1},T_{G,2},\cdots,T_{G,n})=\arg\max_{0\leqslant t_1<t_2<\cdots<t_{n-1}<t_n<L-1}\{H_G(t_1,t_2,\cdots,t_n)\}\tag{14}$$

When the total exponential gray entropy $H_G(t_1,t_2,\cdots,t_n)$ of cloud image reaches maximum, the corresponding thresholds $(T_{G,1},T_{G,2},\cdots,T_{G,n})$ are the optimal thresholds of the multi-thresholding method based on exponential gray entropy. At this time, the areas of different gray level ranges can be distinguished more precisely. To the segmented cloud image, the gray levels of pixels within the same class of cloud area or background area tend to be uniform. Thus the cloud can be extracted from the complex background more accurately.

4 UPSO Algorithm Steps of Multi-thresholding Method Based on Exponential Entropy/ Exponential Gray Entropy

In order to reduce the computation of multi-thresholding methods of ground-based cloud based on exponential entropy/ exponential gray entropy, the UPSO algorithm is adopted to find the optimal thresholds. Assume that in n^*-dimensional solution space, a swarm of particles are initialized. The position and velocity vectors of the particle l in d-dimensional solution space are depicted as $\boldsymbol{X}_l=(X_{l1},X_{l2},\cdots,X_{ln^*})$ and $\boldsymbol{V}_l=(V_{l1},V_{l2},\cdots,V_{ln^*})$, respectively. In the t-th iteration, the best solution $\boldsymbol{B}_l(t)$ of the particle l is called individual extremum, while the best solution $\boldsymbol{G}(t)$ of all particles is called global extremum. The iteration formulae of the position and velocity are given by

$$\boldsymbol{V}_l(t+1)=w\boldsymbol{V}_l(t)+c[r\cdot\boldsymbol{B}_l(t)+(1-r)\boldsymbol{G}(t)-\boldsymbol{X}_l(t)]\tag{15}$$

$$\boldsymbol{X}_l(t+1)=\boldsymbol{X}_l(t)+\boldsymbol{V}_l(t+1)\tag{16}$$

where c is the learning factor and $c=1.3$, r the random number obeying uniform distribution in $(0,1)$, and w the inertia weight and $w=0.78$.

Compared with the basic PSO algorithm, the particle swarm in the UPSO algorithm searches uniformly between the individual extremum and the global extremum. The particles avoid gathering around the individual extremum and the search accuracy is increased. In addition, the UPSO algorithm further simplifies the tuning parameters. Thus the search efficiency is also improved.

By using the UPSO algorithm, the detailed steps of multi-thresholding method of ground-based cloud based on exponential entropy/ exponential gray entropy are written as follows:

Step 1 Input a ground-based cloud image, and convert it to a grayscale image.

Step 2 A swarm of particles are initialized. The number of particles is 20. The initial position and velocity of each particle are generated randomly in $[0,L-1)$ and $[-10,10]$, respectively.

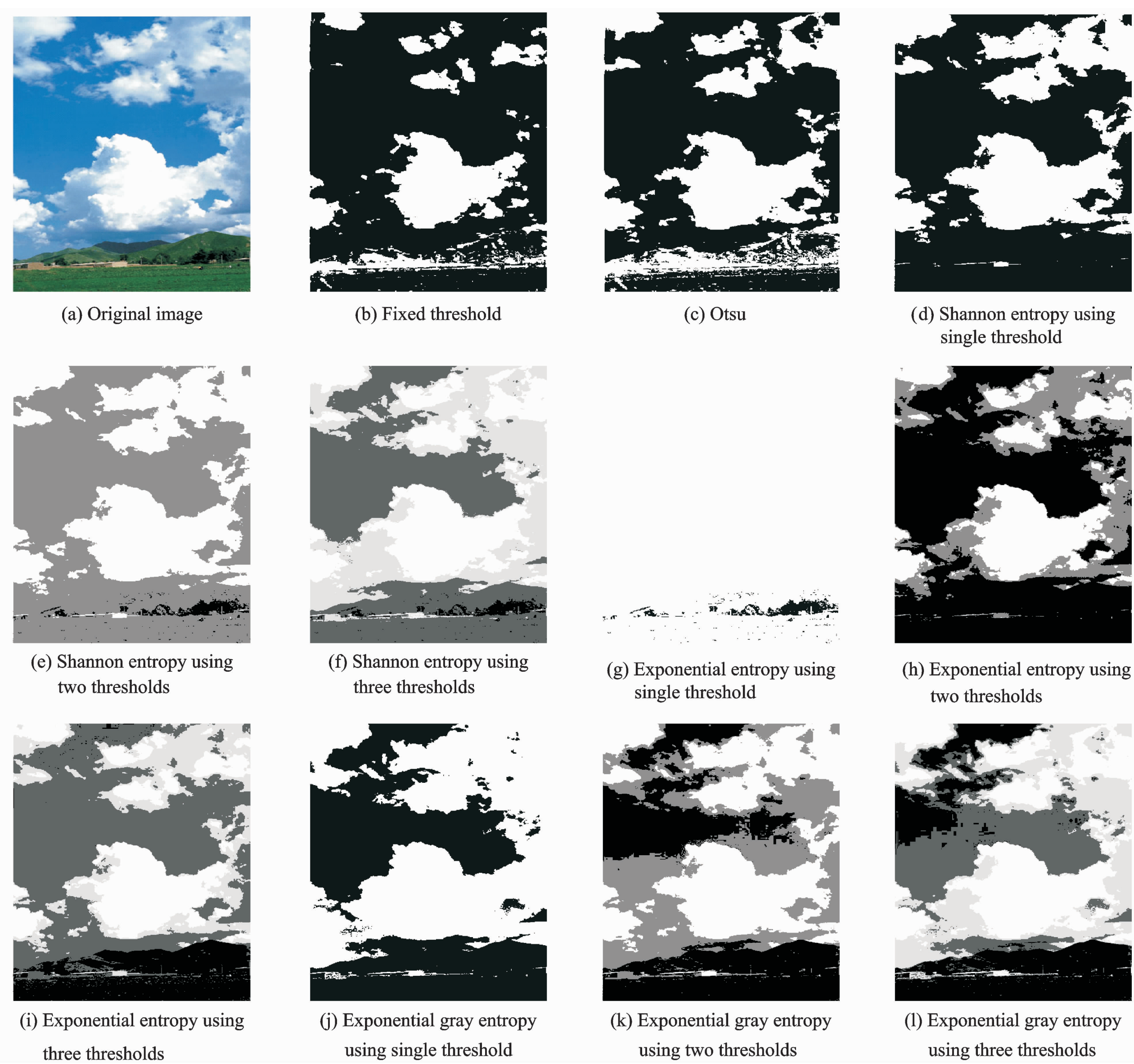
Step 3 Evaluate the fitness value of each particle according to Eq. (5) of the multi-thresholding method based on exponential entropy (or Eq. (13) of the multi-thresholding method based on exponential gray entropy).

Step 4 The velocities and the positions of each particle are updated according to Eqs. (15, 16), respectively.

Step 5 If the maximum iteration times 50 is met, the update stops and the global optimal positions are obtained, corresponding to the optimal thresholds of multi-thresholding method. Then, the ground-based cloud image is segmented using the optimal thresholds. Otherwise, return to Step 3.

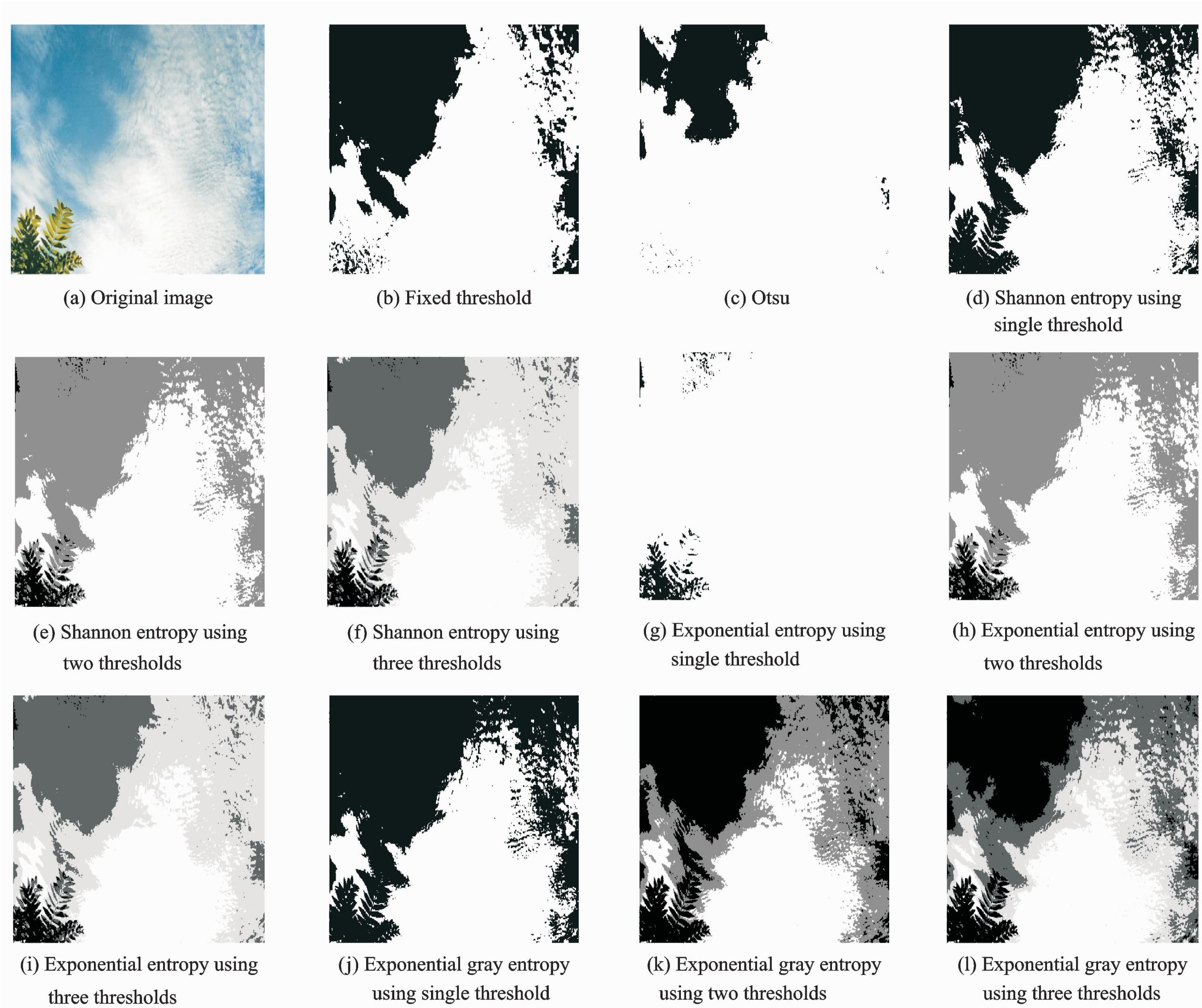
5 Experimental Results and Analysis

To verify the effectiveness of the proposed multi-thresholding method of ground-based cloud image based on exponential entropy/ exponential gray entropy, a large number of segmentation experiments are carried out. Segmented images, optimal thresholds and running time are given. Comparisons are made with six segmentation methods such as fixed threshold method[8], Otsu method[9] based on the red and blue bands of image, bi-level thresholding method using exponential entropy/exponential gray entropy, bi-level thresholding method using Shannon entropy and multi-thresholding method using Shannon entropy[10]. The experiments are carried out under the following environment: Intel(R) Core(TM) 2, 2.00 GHz, 2 GB memory, Matlab R2009a. For lack of space, take two ground-based cloud images as examples to illustrate the effectiveness of the proposed method. Figs. 1,2 are cumulus congestus image and cirrocumulus image, with the size of 360×514 and 500×307. The segmentation results are shown in Figs. 1,2.



(a) Original image (b) Fixed threshold (c) Otsu (d) Shannon entropy using single threshold
(e) Shannon entropy using two thresholds (f) Shannon entropy using three thresholds (g) Exponential entropy using single threshold (h) Exponential entropy using two thresholds
(i) Exponential entropy using three thresholds (j) Exponential gray entropy using single threshold (k) Exponential gray entropy using two thresholds (l) Exponential gray entropy using three thresholds

Fig. 1 Cumulus congestus image and segmentation results



(a) Original image (b) Fixed threshold (c) Otsu (d) Shannon entropy using single threshold

(e) Shannon entropy using two thresholds (f) Shannon entropy using three thresholds (g) Exponential entropy using single threshold (h) Exponential entropy using two thresholds

(i) Exponential entropy using three thresholds (j) Exponential gray entropy using single threshold (k) Exponential gray entropy using two thresholds (l) Exponential gray entropy using three thresholds

Fig. 2 Cirrocumulus image and segmentation results

Fig. 1 is a cumulus congestus image and its segmentation results. Unlike cumulus humilis, cumulus congestus is thick, dense and large. As the sunlight is difficult to get through, the concave and convex cloud surface have obvious shadows. The parts of sunlight are white and the shading parts are dark. In Fig. 1, the original image also contains cumulus fractus in the upper part. The existing segmentation methods of ground-based cloud image using fixed threshold method and Otsu method based on the red and blue bands both mistakenly regard ground background as cloud. After segmentation, large amount of cloud information is lost in the top right part of image, which affects the subsequent cloud shape identification and cloudage detection seriously. While the bi-level thresholding methods based on entropy can distinguish between the cloud and ground background. However, the boundary and shape of cloud still cannot be extracted accurately. When the quad-level thresholding method based on maximum Shannon entropy is adopted, as the Shannon entropy has the defects of undefined value and zero value, the contours of ground background are not clear. The sky near the ground background is mistakenly regarded as cloud. Multi-thresholding method based on exponential entropy can extract the boundary and shape of cloud more accurately. The contours of cloud and background are both visible. Multi-thresholding method based on exponential gray entropy can segment the cloud parts of sunlight and the shading cloud parts accurately. The cumulus fractus in the upper part can also be shown clearly. The boundary shape, textures and details feature are clearer.

Fig. 2 is a cirrocumulus image and its segmentation results. Cirrocumulus is generated by the wave action as the upper atmosphere is unstable. The clouds are small, and most of them distribute in the upper air in lines or groups with a corrugated appearance. The segmentation methods of ground-based cloud image using fixed threshold method and Otsu method based on the red and blue bands both mistakenly regard parts of ground background and sky as cloud. The cloudage detection error is high. The clouds are together, completely losing the feature of corrugated shape. Among all the bi-level thresholding methods, the method based on exponential gray entropy is more superior. Simply selecting one threshold cannot extract the boundary and shape of cloud from the ground background and sky. For the original image in Fig. 2, the multi-thresholding methods based on Shannon entropy and exponential entropy perform similarly. The extraction of the boundary and shape is relatively accurate and the cloudage detection error is low. When the multi-thresholding method based on exponential gray entropy is adopted, information of textures and details is rich. The feature that the clouds distribute with a corrugated appearance is shown clearly. Thus the type of cloud is easy to be identified according to the feature.

The above analysis shows that, compared with six segmentation methods such as fixed threshold method, Otsu method based on the red and blue bands of image, bi-level thresholding method using exponential entropy/exponential gray entropy, bi-level thresholding method using Shannon entropy and multi-thresholding method using Shannon entropy, the multi-thresholding method based on exponential entropy has higher accuracy of cloudage detection. While the multi-thresholding method based on exponential gray entropy can show the boundary shape, textures and details feature more clearly, which is most helpful to cloud morphological classification.

The running time of the fixed threshold method and Otsu method based on the red and blue bands are both short. However, to complex cloud images containing ground background, the detection errors of cloud shape and cloudage are high. The thresholding methods based on entropy perform better. The optimal thresholds, cloudage, detection error and running time of the thresholding methods based on entropy are listed in Table 1.

It can be seen from Table 1 that, among all the multi-thresholding methods, compared with the method based on Shannon entropy and basic PSO, the proposed methods based on exponential

Table 1 Performance comparison of three methods based on entropy

Image		Bi-level thresolding			Tri-level thresolding			Quad-level thresolding		
		Shannon entropy	Exponential entropy	Exponential gray entropy	Shannon entropy	Exponential entropy	Exponential gray entropy	Shannon entropy	Exponential entropy	Exponential gray entropy
Cumulus congestus	Thresholds	151	46	117	(46,146)	(131,189)	(93,149)	(45,108 173)	(103,152,200)	(89,116,168)
	Cloudage/%	34.53	98.43	51.01	36.13	20.83	34.94	40.25	43.43	51.40
	Detection error /%	25.77	111.56	9.65	22.34	55.22	24.90	13.49	6.66	10.47
	Running time /s	0.144	0.080	0.079	0.518	0.209	0.498	0.623	0.234	0.517
Cirrocumulus	Thresholds	166	94	176	(93,174)	(93,176)	(156,196)	(92,148,200)	(92,149,201)	(140,175,209)
	Cloudage/%	57.73	97.06	49.19	50.49	48.82	32.95	70.84	70.29	49.64
	Detection error/%	11.57	48.82	24.96	22.39	24.96	49.36	8.89	8.04	23.70
	Running time/s	0.072	0.031	0.069	0.598	0.181	0.389	0.699	0.228	0.393

entropy/exponential gray entropy and UPSO require shorter running time. Because exponential entropy and exponential gray entropy both avoid the logarithmic computation in Shannon entropy. The adopted UPSO algorithm can find the optimal thresholds quickly and accurately. The running time of the exhaustive multi-thresholding method is reduced greatly. Thus the fast processing of cloud shape identification and cloudage detection can be realized. The analysis of cloudage detection data shows that the multi-thresholding method based on exponential gray entropy is adapted to the cumulus congestus image. However, when the cirrocumulus image is detected using the method, some clouds are mistakenly regarded as sky. Bi-level thresholding method based on exponential entropy has high detection error. When the method is extended to quad-level thresholding, the cloudage detection errors of the above two images are 6.66% and 8.04%, respectively. The data is far less than that of other methods. Thus conclusions can be drawn that the multi-thresholding method based on exponential entropy has high accuracy of cloudage detection for complex ground-based cloud image.

6 Conclusions

To guarantee the safety of aircraft taking off and landing and air flight, multi-thresholding methods of ground-based cloud based on exponential entropy/ exponential gray entropy and UPSO are proposed, which can realize automated ground-based cloud detection and cloudage observation. Exponential entropy and exponential gray entropy both make up for the defects of undefined value and zero value in Shannon entropy. In addition, exponential gray entropy takes into account both of the grayscale probability and the uniformity of gray levels within the cloud cluster and background cluster. Cloud regions and background regions of different gray level ranges can be distinguished more precisely using the multi-thresholding strategy. Furthermore, the boundary shape of cloud can be extracted accurately. Multi-thresholding can also distinguish the cloud areas of different brightness, which are formed due to variable sunlight and thickness. To reduce the computation of exhaustive multi-thresholding method, UPSO algorithm is adopted to find the optimal thresholds quickly and accurately. Thus the real-time processing of multi-thresholding can be realized. Compared with the existing segmentation methods of ground-based cloud image using fixed threshold mothod and Otsu method based on the red and blue bands, and the method based on Shannon entropy and basic PSO, the proposed methods have significant superiority. The multi-thresholding method based on exponential entropy can better distinguish cloud from sky and ground background. The boundary shape can be extracted clearly, and the accuracy of cloudage detection is satisfactory. While the multi-thresholding method based on exponential gray entropy can show the boundary shape, textures and details feature more clearly, which is more helpful to the subsequent cloud morphological classification.

The proposed multi-thresholding methods based on exponential entropy/ exponential gray entropy and UPSO have been applied to digital cloud image segmentation in ground-based cloud identification, and excellent segmentation effect has been achieved.

References:

[1] Gomez-Chova L,Camps-Valls G, Bruzzone L, et al. Mean map kernel methods for semisupervised cloud classification [J]. IEEE Transactions on Geoscience and Remote Sensing, 2010, 48(1): 207-220.

[2] Gonzalez A, Perez J C, Munoz J, et al. Watershed image segmentation and cloud classification from multispectral MSG-SEVIRI imagery [J]. Advances in Space Research, 2012, 49(1):135-142.

[3] Yang Jun, Lv Weitao, Ma Ying, et al. An automatic ground-based cloud detection method based on the local threshold interpolation [J]. Acta Meteorologica Sinica, 2010, 68(6): 1007-1017. (in Chinese)

[4] Lu Xiaofeng. Ground nephogram classification based on textural feature extraction and analysis [D]. Nanjing: Nanjing University of Information Science & Technology, 2011. (in Chinese)

[5] Wu Yiquan, Zhu Zhaoda. 30 years (1962—1992) of the developments in threshold selection methods in image processing(2) [J]. Journal of Data Acquisition & Processing, 1993, 8(3): 268-282. (in Chinese)

[6] Ranjani J J, Thiruvengadam S J. Fast threshold selection algorithm for segmentation of synthetic aperture radar images [J]. IET Radar, Sonar & Navigation, 2012, 6(8): 788-795.

[7] Huang Qian, Wang Shaolong, Xu Daolei, et al. Adaptive threshold approach for night-sky cloud inspection [J]. Journal of Image and Graphics, 2012, 17(8): 960-965. (in Chinese)

[8] Huo Juan, Lv Daren. Characteristics and distribution of all-sky radiance by libradtran modeling: For cloud determination algorithm in all-sky images [J]. Acta Meteorologica Sinica, 2006, 64(1): 31-38. (in Chinese)

[9] Yang Jun, Lv Weitao, Ma Ying, et al. An automatic ground-based cloud detection method based on adaptive threshold [J]. Journal of Applied Meteorological Science, 2009, 20(6): 713-721. (in Chinese)

[10] Kapur J N, Sahoo P K, Wong A K C. A new method for gray level picture thresholding using the entropy of histogram [J]. Computer Vision, Graphics and Image Processing, 1985, 29(1): 273-285.

[11] Luo Xiping, Tian Jie. The ICM algorithm for multi level threshold selection by maximum entropy criterion [J]. Journal of Software, 2000, 11(3) : 379-385. (in Chinese)

[12] Wang Yi, Fan Yangyun, Niu Yilong, et al. Effective immune genetic algorithm for segmentation of 3D brain images [J]. Journal of System Simulation, 2008, 20(15): 4136-4140. (in Chinese)

[13] Davies E R. Stable bi-level and multi-level thresholding of images using a new global transformation [J]. IET Computer Vision, 2008, 2(2): 60-74.

[14] Wei Miaomiao, Jiang Mingyan. Multilevel thresholding methods for image segmentation based on particle swarm optimization [J]. Journal of Shandong University: Engineering Science, 2005, 35(6): 118-121. (in Chinese)

[15] Pal N R, Pal S K. Entropic thresholding [J]. Signal Processing, 1989, 16(2): 97-108.

[16] Wu Shihua, Zhang Xiaojie, Wu Yiquan. Two-dimensional exponential gray entropy image thresholding based on decomposition [J]. Chinese Journal of Stereology and Image Analysis, 2010, 15(4): 351-358. (in Chinese)

[17] Wu Yiquan, Ji Shouxin, Wu Shihua. Gray entropy image thresholding based on 2-dimensional histogram vertical and oblique segmentation [J]. Journal of Tianjin University, 2011, 44(12): 1043-1049. (in Chinese)

[18] Wu Xiaojun, Yang Zhanzhong, Zhao Ming. A uniform searching particle swarm optimization algorithm [J]. Acta Electronica Sinica, 2011, 39(6): 1261-1266. (in Chinese)

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