Texture Feature Extraction Method for Ground Nephogram Based on Hilbert Spectrum of Bidimensional Empirical Mode Decomposition

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ABSTRACT

It is important to recognize the type of cloud for automatic observation by ground nephoscope. Although cloud shapes are protean, cloud textures are relatively stable and contain rich information. In this paper, a novel method is presented to extract the nephogram feature from the Hilbert spectrum of cloud images using bidimensional empirical mode decomposition (BEMD). Cloud images are first decomposed into several intrinsic mode functions (IMFs) of textural features through BEMD. The IMFs are converted from two- to one-dimensional format, and then the Hilbert–Huang transform is performed to obtain the Hilbert spectrum and the Hilbert marginal spectrum. It is shown that the Hilbert spectrum and the Hilbert marginal spectrum of different types of cloud textural images can be divided into three different frequency bands. A recognition rate of 87.5%–96.97% is achieved through random cloud image testing using this algorithm, indicating the efficiency of the proposed method for cloud nephogram.

1. Introduction

The global radiation budget and hydrological cycle are highly influenced by the variability and potential trends of cloud properties. Clouds can provide abundant information on climate change in the past, present, and future (Heintzenberg and Charlson 2009). Therefore, clouds are part of the essential elements of meteorological observations.

Nowadays, land-based weather stations and satellites are all part of integrated monitoring systems. However, land-based images have not been carefully analyzed so far. Automated ground-based cloud recognition is difficult because instruments cannot detect cloud structural characteristics as easily as human eyes can (Liu et al. 2011).

Automated cloud observation systems have been developed based on a number of visible light– or infrared-based measuring equipment, such as the whole-sky imager (WSI), total sky imager (TSI), all-sky digital camera, infrared cloud analyzer, infrared cloud imager, micropulse lidar (MPL; e.g., Zhao et al. 2014a), and Millimeter cloud radar (MMCR; e.g., Garrett and Zhao 2012). This equipment has provided quantitative measurements of cloud cover. However, there are limited studies on automated identification of cloud type at present, and only a simple classification exists, which identifies from three to four kinds of typical clouds. Buch et al. (1995) classified altocumulus, cirrus, stratus,
and cumulus based on the WSI, using a binary-tree strategy with success rates of 43%, 35%, 54%, and 46%, respectively. They suggested some texture-related features and obtained a misclassification rate of 39% of their test pixels when compared with visual classification. Peura et al. (1996) outlined a classification method for land-based images that extracted several features like clarity, size, fiber, physical level, and edge information from the WSI for identification of cloud type. The overall accuracy of this method is about 65%, but it does not effectively identify stratocumulus, cumulonimbus, and altocumulus because the recognition rates are only 38%, 0%, and 44%, respectively. Wang and Sassen (2001) classified clouds observed from MMCR and MPL into nine types based on radar reflectivity, cloud temperature, and so on. This classification has been widely used by cloud-related studies such as Zhao et al. (2014b). Singh and Glennen (2005) used five-feature extraction methods in the K-nearest neighbor and neural network classifier to recognize cumulus and cumulonimbus clouds with the recognition rates of 86.3% and 83.3%, respectively, from digital camera cloud images. Calbó and Sabburg (2008) extracted several characteristics that are useful in cloud type classification and identification of eight categories of sky conditions according to their definitions from the TSI and the WSI. Sun et al. (2009a) analyzed the local binary pattern (LBP) spectra and variance (VAR) characteristics for five cloud classes—cirrus, undulatus, cumulus, stratus, and clear sky—based on a whole-sky infrared cloud image. The classification success rates for the above-mentioned five classes in the class recognition of 274 cloud image samples are 100.0%, 84.2%, 70.3%, 64.7%, and 99.0%, respectively, with an overall average of 87.2%. Sun et al. (2009b) proposed a method using a fuzzy uncertainty texture spectrum and essential information of cloud images to identify cumulus, altocumulus, and cirrus, and the recognition rates are 100%, 90%, and 100%, respectively, from the whole-sky infrared cloud image. Heinle et al. (2010) presented a set of statistical features about the color of the cloud image and distinguished seven sky conditions: high patched cumuliform clouds, high thin clouds, stratiform clouds, stratocumulus clouds, low cumuliform clouds, thick clouds, and clear sky. The success rates of identification for random images reached 75%–88%. Zhang et al. (2010) recognized cloud types by neural network and co-occurrence matrices. Liu et al. (2011) discovered that several structural features are effective for identifying cumuliform, cirriform, and waveform clouds, with a recognition accuracy of 90.97%.

These methods have provided some interesting cloud detection results, but they can only identify several kinds of typical clouds and the recognition rates are not sufficiently high.

A thermal imaging camera is very expensive, and its sensitivity is greatly reduced for high (cold) clouds such as cirrus. Smith et al. (2004) showed the advantages of visible cloud detection, which is inexpensive and has higher resolution. Therefore, a study on the identification of visible clouds is necessary and urgent. Our analysis in this study involves the visible cloud images taken by digital camera on the ground. It is more difficult to recognize a visible channel cloud image without adequate multichannel data analysis. Automatic identification of clouds using computers faces enormous challenges for the ever-changing shape of clouds. Although the texture of a cloud is exceedingly rich and relatively stable, the frequency information of different clouds varies greatly. It is just an effective method based on the spatial frequency domain analysis of texture. This method is similar to the human visual perception system, which automatically decomposes an image into different frequency and direction components when watching texture images (Shan et al. 2007).

The bidimensional empirical mode decomposition (BEMD) and the Tamura texture feature method (Chen et al. 2010) refer to the features of cloud image. Then, the average sample method is used for classification. However, the recognition rate is still not satisfactory because these features extracted from images are ineffective for identifying some clouds. Considering the fact that a cloud is first divided into categories and further judged by the observer in human observation, cloud images are then divided into three main types of cloud. The features of cloud images are extracted by the Hilbert spectrum method of BEMD to facilitate cloud classification and to improve the recognition rate.

Compared to the algorithms in the literature, our method provides a novel means to classify a sky image by extracting the frequency information of cloud. This method has obvious advantages in terms of objectivity and resolution. In addition, a test run of random images is presented, which outperforms existing algorithms by yielding a higher success rate. The paper is organized as follows. The cloud image data are introduced in section 2. Section 3 describes the proposed algorithm. In section 4, the experimental results are presented. The conclusions are summarized and the method is discussed in section 5.

2. Data

The 115 cloud images used in the study are obtained from the National Weather Service website, and their types are clearly labeled. The format of each image is Joint Photographic Experts Group (jpeg), and the
3. Methodology

a. BEMD texture analysis

Empirical mode decomposition (EMD), proposed by Huang et al. (1998), is a time–frequency analysis tool. For signal processing, it decomposes data into several intrinsic mode functions (IMF) by a sifting process. It is completely driven by data, with good localization and adaptability.

BEMD can be applied for analysis in the spatial frequency domain, because of its advantage in texture image analysis and in multiscale decomposition of a texture image. Nunes et al. (2003) derived a useful algorithm of BEMD. The extreme value is detected by the morphological operator method in the bidimensional sifting process. Radial basis functions are used to obtain surface interpolation for regional maxima and minima. It is a new and promising method for decomposing an image into multiple scales and extracting unique features while avoiding choosing a wavelet base, as required by wavelet transform for BEMD. We use this method to preprocess cloud images.

First, the cloud image is transformed to grayscale format. Thenceforward, it is decomposed into three IMFs and residue using BEMD. The sifting process is defined as follows (Long et al. 2009):

The original image is \( M \times N \) in pixels, with a gray value of \( f(x,y) \) for \((x = 1, \ldots, M, y = 1, \ldots, N)\).

1) Initialization:

\[
\text{Ires}_{ij}(x,y) = \text{Ir} = f(x,y), \quad (1)
\]

where \( \text{Ires}_{ij}(x,y) \) is the sifting result in the \( j \)th iteration, \( \text{Ir} \) is the residue, \( i \) is the number of layers of decomposition of the IMF, and \( j \) is the iteration times used to seek the IMF.

2) Search for the local maxima and minima of \( \text{Ires}_{ij}(x,y) \).

3) Fit the extreme points and form the envelopments.

Calculate the average of the top and bottom envelopes:

\[
m_{ij}(x,y) = \frac{\text{Top}_{ij}(x,y) + \text{Bottom}_{ij}(x,y)}{2}. \quad (2)
\]

4) Extract the details:

\[
\text{Ires}_{ij}(x,y) = \text{Ires}_{ij}(x,y) - m_{ij}(x,y). \quad (3)
\]

5) Repeat steps 2–4 until \( m_{ij} \) satisfies the iteration criteria:

\[
\text{imf}_{ij}(x,y) = \text{Ires}_{ij}(x,y). \quad (4)
\]

The standard deviation (SD) is computed from the two continuous sifting results to stop the IMF extraction as follows:

\[
\text{SD} = \sum_{x=0}^{X} \sum_{y=0}^{Y} \left( \frac{[\text{Ires}_{ij-1}(x,y) - \text{Ires}_{ij}(x,y)]^2}{[\text{Ires}_{ij-1}(x,y)]^2} \right) < \varepsilon, \quad (5)
\]

where \( \varepsilon \) is typically less than 0.3. BEMD is stopped, and then several IMFs are obtained. The selection of \( \varepsilon \) determines the number and quality of IMF for the BEMD. A smaller \( \varepsilon \) gives more detail of how IMFs are decomposed (Song and Yu 2010). To better reflect the detail of various clouds, \( \varepsilon \) is set to 0.0003 in this study.

6) \( \text{Ir}(x,y) = \text{Imf}_{ij}(x,y) + \text{Ir}_{N}(x,y) \) and \( \text{res}_{ij}(x,y) = \text{Ir}(x,y) \).

7) Repeat steps 2–6; the image can be decomposed into

\[
f(x,y) = \sum_{j=1}^{N} \text{imf}_{ij}(x,y) + \text{Ir}_{N}(x,y). \quad (6)
\]

In Eq. (6), \( \text{imf}_{ij}(x,y) \) is the \( j \)th IMF for the decomposition and \( \text{Ir}_{N}(x,y) \) is the monotonous residual function.

It is a fundamental step for BEMD to solve the discrete data interpolation problem. In this study, the two-dimensional envelope construction method based on radial basis function interpolation is used (Gao 2008).

BEMD is based on the following assumptions (Hu 2008). Any signal is made up of different IMFs. Each IMF, linear or nonlinear, has the same number of zero-crossing and extreme points. There is only one extremum in the adjacent zero crossing. Modes are independent of each other.

In this way, the signal would be decomposed into the sum of several IMFs. The data must be able to represent the overall texture characteristics of an image, which is
Fig. 1. The images of 10 types of ground nephogram samples: (a) cumulus humilis, (b) cumulonimbus, (c) cirrus, (d) stratus, (e) nimbostratus, (f) altostratus, (g) cirrostratus, (h) stratocumulus, (i) altocumulus, and (j) cirrocumulus.
computed for texture classification. The characteristic scale is defined by the extreme distance of BEMD; that is to say, extreme spacing reflects the scale features of the IMFs. The original texture image is decomposed into several periodical, stationary processes of the IMFs that are self-adaptive. The IMFs represent the characteristics of the texture image from high to low frequency.

The IMFs manifest different frequency characteristics in the texture image (Hu 2008). In this experiment, it is found that the unique frequency information for some textures decomposed by BEMD can be identified effectively. The detailed texture of each IMF varies within the diverse types of clouds. For instance, Fig. 2a is the image of an altocumulus at 250 × 250 pixels. Figures 2b–d show the amplitude and frequency character of altocumulus clouds from three IMFs of the BEMD algorithm. The main texture information is focused in the second (Fig. 2c) and third (Fig. 2d) IMFs, different from a cumulonimbus that is concentrated in the first IMF. It is shown that the details of their textures are concentrated in different frequencies. This helps us to improve the recognition rate of cloud classification.

Some features of instantaneous amplitude can be used as a texture classification method (Shan et al. 2007). However, the identification results of cloud image feature extraction based on these characteristics are
unsatisfactory (Chen et al. 2010). The discrimination of some clouds is not good using these features.

Clouds can be divided into cumuliform, waveform, and stratiform clouds according to genetic-cloud formation and evolution in the actual ground detection. This classification is more suitable than the idea that a cloud can be identified by image texture. A cumuliform cloud is a gigantic cloud formed by vertical air convection condensation and includes cumulus, cumulonimbus, and cirrus. A waveform cloud is an undulating cloud formed by fluctuation of the air, including cirro-cumulus, altocumulus, and stratocumulus. The identification of the three clouds is not good using these features. Additional features include cirrostratus, and stratus. Identification of the three clouds can be further accomplished with additional features.

b. The Hilbert spectral analysis

Texture frequency distribution characteristics of various types of cloud images can be clearly seen, and amplitude and frequency information can be extracted from the Hilbert spectrum and the Hilbert marginal spectrum.

The Hilbert–Huang transform (HHT) is a new adaptability time–frequency analysis method with clear physical meaning for nonlinear and nonstationary signals. The time–frequency–amplitude distribution of the signal can provide rich information to HHT.

It is well known that the resolutions of time and frequency in the preceding time–frequency analysis are incompatible because of the restrictions of Heisenberg’s uncertainty principle. However, the advantage of HHT is that the Hilbert spectrum can be obtained from the instantaneous frequency and amplitude of the IMFs. Thus, the resolutions of time and frequency are independent of each other in HHT.

The Hilbert transform is a linear transformation with a focus on local properties that thus avoids the excentric and inexistent high- and low-frequency components of the Fourier transform for fitting the original sequence. Although a two-dimensional Hilbert transform is feasible, some studies have shown that the Hilbert spectrum can be derived from the IMF of EMD by the Hilbert transform, whose input is a one-dimensional array. However, the IMF of BEMD is a two-dimensional array and should be first converted to a one-dimensional array. Then, the Hilbert spectrum can be obtained by the Hilbert transform.

The IMFs from BEMD must be converted to one dimension, so the two-dimensional array of 50 pixels × 50 pixels needs to be converted to a one-dimensional array of 2500 pixels. The method of conversion is as follows.

The matrix size of the IMF component is 50 pixels × 50 pixels—that is

\[
X = \begin{bmatrix}
  x(1,1) & x(1,2) & \cdots & x(1,50) \\
  x(2,1) & x(2,2) & \cdots & x(2,50) \\
  \vdots & \vdots & \ddots & \vdots \\
  x(50,1) & x(50,2) & \cdots & x(50,50)
\end{bmatrix},
\]

where \( X \) is converted to a one-dimensional array \( X' \), where \( X' = [x(1,1), x(1,2), \ldots, x(1,50), x(2,1), x(2,2), \ldots, x(2,50), \ldots, x(50,1), x(50,2), \ldots, x(50,50)] \).

The Hilbert spectrum and the Hilbert marginal spectrum of various types of cloud images are obtained by the Hilbert transform for \( X' \).

The texture frequency of the decomposed cloud image is spatial rather than time frequency. The spatial frequency domain is the spatial frequency (wavenumber) characteristic that is an independent variable that describes the image. The change of pixel values in space can be decomposed into a linear superposition of harmonic vibration function with different amplitude, spatial frequency, and phase. The composition and distribution of the spatial frequency components of the image are called the spatial frequency spectrum. The decomposition, processing, and analysis of the spatial frequency characteristics of the image are referred to as the spatial frequency or wavenumber domain processing. Similar to the time–frequency transformation, the spatial domain and the spatial frequency domain can also be converted to each other. In this paper, the units of spatial frequency, namely, the texture frequency, are per meter.

The Hilbert transform cannot be used for \( I_{I_2}(x, y) \) because its monotonocity does not reflect the oscillation mode of the signal. First, each intrinsic mode component \( \text{imf}_j(x, y) \) is converted to a one-dimensional array \( \hat{\text{imf}}_j(t) \) (with \( t = t_x \times t_y \), \( t_x \), and \( t_y \) for image pixel rows and columns, respectively), then \( \hat{\text{imf}}_j(t) \) can be obtained for \( \hat{\text{imf}}_j(t) \) by the Hilbert transform (Chen et al. 2009):

\[
\hat{\text{imf}}_j(t) = \frac{1}{\pi} p \cdot v \int_{-\infty}^{+\infty} \hat{\text{imf}}_j(t) \frac{1}{t - \pi} dt
\]

where \( p \cdot v \) denotes the integral principal value.

Then, the analytic signal is constructed using

\[
z_j(t) = \text{imf}_j(t) + j \cdot \hat{\text{imf}}_j(t) = a_j(t)e^{j\phi_j(t)},
\]

where \( a_j(t) = \sqrt{\text{imf}_j^2(t) + \hat{\text{imf}}_j^2(t)} \), and \( \phi_j(t) = \arctan[\text{imf}_j(t)/\hat{\text{imf}}_j(t)] \).
Further, the instantaneous frequency can be obtained using

\[ f_i(t) = \frac{1}{2\pi} \omega_i(t) = \frac{1}{2\pi} \frac{d\phi_i(t)}{dt}. \]  

(10)

So, \( H(\omega, t) \) becomes

\[ H(\omega, t) = \operatorname{Re} \sum_{j=1}^{N} a_j(t)e^{\text{i} \phi_j(t)} = \operatorname{Re} \sum_{j=1}^{N} a_j(t)e^{\int \omega_j(t)dt}. \]  

(11)

Equation (11) is called the Hilbert spectrum. The signal amplitude variation with time and frequency in the entire frequency band is described by \( H(\omega, t) \). The instantaneous frequency has a definite physical meaning after BEMD is introduced into the HHT. The frequency of HHT is the best sine approximation for the local waveform. Therefore, the frequency can be defined at every point of the waveform rather than as a global sine function.

The amplitude of the IMF is displayed by grayscale on the frequency–time–amplitude diagram, that is, the Hilbert spectrum. The gray level indicates amplitude: the brighter the scale, the greater amplitude. Frequency variation with time and the relative change of energy can be revealed by the Hilbert spectrum. The Hilbert spectrum amplitude is the normalized value. The relative change of the amplitude is represented by the relative change of the color. The Hilbert spectrum is the time–frequency distribution based on a profile or a skeleton diagram to describe the signal energy, and it changes instantly with the frequency distribution.

The characteristics of cloud image texture frequency and intensity with spatial variation can be clearly distinguished by the Hilbert spectrum, which reveals the energy distribution on the surface of the three-dimensional time (spatial) frequency (Xiong et al. 2002).

c. Hilbert marginal spectrum

The Hilbert marginal spectrum can be derived from the time integration of the Hilbert spectrum (Nunes et al. 2005) using

\[ h(\omega) = \int_{0}^{T} H(\omega, t) dt. \]  

(12)

The amplitude of instantaneous frequency is acquired from the Hilbert marginal spectrum, which describes the cumulative amplitude distribution of each frequency point for all data with statistical significance. The amplitude of a certain point in the Fourier spectrum represents the trigonometric function component containing this frequency in the entire signal. The greater the amplitude, the greater the possibility of local existence in the entire data. A fast Fourier transformation (FFT) represents the possibility of energy distribution in a frequency, while the Hilbert spectrum describes the accumulative amplitude of instantaneous frequency of the entire data.

The meaning of the (instantaneous) frequency in the Hilbert spectrum and the Hilbert marginal spectrum is different from the frequency in the Fourier analysis (Fourier frequency). The presence of energy in a frequency for Fourier analysis denotes a sine or cosine wave present in the entire timeline. A greater Hilbert marginal spectrum indicates a greater probability of the frequency.

The texture frequency distribution characteristics of various cloud images can be more clearly revealed, and the amplitude and frequency information by the Hilbert spectrum and the Hilbert marginal spectrum can be easily extracted.

4. Results

Texture classification is an important branch of texture analysis and an important research area in machine vision. The characteristics of different textures in an image are first determined. These characteristics are used to classify in view of classification and discrimination, and the feature vectors are obtained to build the classifier. The feature vectors in the training set are trained with a classifier, and finally the test set is classified using the trained classifier.

a. Feature extraction

First, each cloud image is decomposed by BEMD; that is, the image is converted into grayscale and decomposed to three IMFs and the residual. Then, the two-dimensional data are transformed into the one-dimensional data to calculate the Hilbert spectrum and Hilbert marginal spectrum. After that, the features are extracted, and a gross error test is performed. At last, the cloud image is classified.

The Hilbert spectrums of the 10 types of ground nephogram samples derived by the HHT are shown in Figs. 3a–j. The number of pixels of the space is used as the abscissa in Fig. 3, and there are a total of 2500 pixels. The ordinate is the spatial frequency (wavenumber; per meter).

The characteristic of the IMFs by BEMD is shown in Fig. 3 in a graph with high resolution. The depth of color represents the energy level in the color bars. The red pixels mean that the energy level is relatively higher, and
FIG. 3. (a)–(j) The Hilbert spectrums of the 10 types of ground nephogram samples derived from the HHT. The abscissa denotes the number of pixels, and the ordinate represents the spatial frequency (wavenumber, m⁻¹).
the blue pixels mean that the energy level is lower; it is not very obvious in the limited resolution of the image, seen more clearly in the three-dimensional time (space)–frequency Hilbert spectrums. We can see that the frequency of the IMF is not a constant value but fluctuates around the central frequency—the higher the frequency, the greater the volatility (Zhao et al. 2005). The figure shows a detailed IMF component frequency change that accurately reflects the time–frequency characteristics. The signal discontinuity of frequency in time can be clearly identified, and the main frequency can be accurately distinguished without cross terms. In addition, the time–frequency concentration appears very well.

The Hilbert spectrum of various types of cloud images indicates that the number of pixels of some clouds is fewer, as in Figs. 3d–g. The high energy of the cloud image signal in the Hilbert spectrum is mainly concentrated in the low frequency within 50 m$^{-1}$ because the cloud images are uniform, curtainlike. Thus, stratiform clouds are easy to identify from the other clouds according to the Hilbert spectrum. The energy in Fig. 3a is primarily concentrated within 150 m$^{-1}$, but its pixels are relatively denser.

The Hilbert spectrum of other types of cloud images can be divided into two categories based on their concentration, although the pixels are dense. The number of pixels for the first category of clouds is very dense, and the frequency of the signal mainly changes from 0 to 500 m$^{-1}$, such as in altocumulus (Fig. 3i) and cirrocumulus clouds (Fig. 3j), which all belong to the wave cloud. Their texture frequency distribution becomes wider because of the volatility of the cloud image texture. The number of pixels for the second category of clouds is moderately dense, and the frequency of the signal mainly changes from 0 to 300 m$^{-1}$, as shown in cumulonimbus (Fig. 3b), cirrus (Fig. 3c), and stratocumulus clouds (Fig. 3h). The first two clouds belong to the cumuliform cloud, and the third (stratocumulus) is a wave cloud.

The above-mentioned cloud classifications are in accordance with the genetic-cloud classification, but there are still two other types of clouds that are different from those already discussed. First, stratocumulus cloud, which belongs to the wave cloud, is classified as the last category. The reason for this is that its overall shape is characterized by wave cloud, while its local form is similar to cumuliform cloud and only partial cloud images are selected as the cloud image sample for the calculation, thus resulting in the classification of cumuliform cloud. Second, cumulus humilis, which belongs to the cumuliform cloud, is classified as stratiform cloud. This is mainly because cumulus humilis only covers the sky partially, and the texture information of the sky is more uniform and similar to the stratiform cloud.

Therefore, according to the texture frequency of the Hilbert spectrum, clouds can be basically divided into three main types—that is, stratiform, cumuliform, and wave cloud.

To further describe the accumulated amplitude distribution of cloud image in each frequency and to effectively extract the Hilbert spectrum information of different clouds, the Hilbert marginal spectrums of the 10 types of ground nephogram samples are derived from time integration of the Hilbert spectrum in Figs. 4a–j. The abscissa denotes the spatial frequency (wave-number; per meter), and the ordinate represents the amplitude.

The texture frequency distribution characteristics of the three types of cloud images are shown in Fig. 4. Several typical cloud images can be further identified by the Hilbert marginal spectrum. The frequency distribution range of the three main types of clouds can be more clearly seen from the information of the amplitude and frequency in the Hilbert marginal spectrum. The texture frequency range of stratiform cloud, such as stratus (Fig. 4d), nimbostratus (Fig. 4e), altostratus (Fig. 4f), and cirrostratus (Fig. 4g), varies from 0 to 150 m$^{-1}$. The frequency of the most amplitude accumulation is within 10 m$^{-1}$, and the frequency changes comparatively monotonically. The texture frequency range of cumulus humilis of cumuliform cloud (Fig. 4a) is from 0 to 150 m$^{-1}$, but its frequency is much more varied. The texture frequency range of cumulonimbus (Fig. 4b), cirrus (Fig. 4c), and stratocumulus (Fig. 4h) is from 0 to 300 m$^{-1}$. The texture frequency range of wave cloud, such as altocumulus (Fig. 4i) and cirrocumulus (Fig. 4j), is from 0 to 500 m$^{-1}$.

To further extract information, the texture frequency is filtered when its amplitude is less than 10% of the maximum. Therefore, the maximum frequency is extracted as the eigenvalue for the amplitude information.

b. Classification process

In the classification process, a target cloud image is first decomposed by BEMD, and its Hilbert spectrum and Hilbert marginal spectrum are calculated. Then, the texture frequency is filtered to extract the maximum frequency as eigenvalue. Finally, the target cloud is classified into a category according to its main feature.

After repeated experiments, clouds are divided into three categories according to the eigenvalues: less than 150, between 150 and 300, and larger than 300 m$^{-1}$.

c. Recognition results

According to the above-mentioned analysis, 115 cloud images samples were identified and the experimental
FIG. 4. (a)–(j) The Hilbert marginal spectrums of the 10 types of ground nephogram samples derived from the time integration of the Hilbert spectrum. The abscissa denotes the spatial frequency (wavenumber; m⁻¹), and the ordinate represents the amplitude.
results are displayed in Table 1. It is the confusion matrix of classification. Three different clouds are distinguished: low-, mid-, and high-frequency clouds. Among them, low-frequency clouds include stratus, nimbostratus, altostratus, cirrostratus, and cumulus humilis. Mid-frequency clouds include cirrus, cumulonimbus, and stratocumulus. High-frequency clouds include altocumulus and cirrocumulus.

The experimental results show that the typical ground-based cloud images are preliminary classified using this method. The cloud classification is exceedingly complicated. First, the cloud is divided into categories, and then subdivided according to other characteristics. This method coincides with the idea of a weather observer.

Figure 5 shows an original sample of altostratus, the associated Hilbert spectrum, and the Hilbert marginal spectrum decomposed by the BEMD algorithm. In Fig. 5b, the abscissa denotes the number of pixels and the ordinate represents the spatial frequency (wavenumber; per meter). In Fig. 5c, the abscissa denotes the spatial frequency (wavenumber; per meter) and the ordinate represents the amplitude. Further study finds that the distribution of the pixels in the Hilbert spectrum can well describe the uniformity of the cloud image grayscale texture, such as the altostratus in Figs. 2f and 5a. Their Hilbert spectrum and Hilbert marginal spectrum are compared. Few pixels are found in the mid-frequency of Fig. 5b compared to Fig. 3f, and two extra peaks appear in Fig. 5c compared to Fig. 4f. The altostratus in Fig. 5a contains the outline of the sun. Thus, the sun in the background of altostratus can also be recognized by the frequency distribution of the Hilbert spectrum and the Hilbert marginal spectrum.

5. Conclusions

In this paper, we presented a cloud image feature extraction method based on the Hilbert spectrum of BEMD that can efficiently extract the minutiae of a texture image. The experimental results showed that

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<tr>
<th></th>
<th>Low-frequency clouds</th>
<th>Mid-frequency clouds</th>
<th>High-frequency clouds</th>
<th>Total</th>
<th>Correct rate (%)</th>
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<td>1</td>
<td>58</td>
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<tr>
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<td>1</td>
<td>33</td>
<td>96.97</td>
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<tr>
<td>High-frequency clouds</td>
<td>—</td>
<td>3</td>
<td>21</td>
<td>24</td>
<td>87.50</td>
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this method is a simple but effective one for cloud image feature extraction. The time–frequency density and the trend of the energy with time–frequency can be easily identified from the Hilbert spectrum because of its high time–frequency resolution and superior capability of describing local time–frequency characteristics. The HHT is applied to the ground-based cloud image analysis and processing. The precise time–frequency structure of the cloud image texture can be obtained by HHT to facilitate ground-based cloud image recognition.

There are still some problems with the HHT, however, such as the end effect, the interpolation method, parametric forms, and normalization processing, among others. It takes a longer time for complex BEMD. Therefore, considerable research is needed to refine the algorithm in order to increase the rate of decomposition in the future.

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