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RESEARCH ARTICLE

Landform classification based on optimal texture feature extraction from DEM data in Shandong Hilly Area, China

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Abstract Texture and its analysis methods are crucial for image feature extraction and classification. Digital elevation model (DEM) is the most important data source of digital terrain analysis and landform classification, and considerable research values are gained from texture feature extraction and analysis from DEM data. In this research, on the basis of optimal texture feature extraction, the hilly area in Shandong, China, was selected as the study area, and DEM data with a resolution of 500 m were used as the experimental data for landform classification. First, second-order texture measures and texture image were extracted from DEM data by using a gray level co-occurrence matrix (GLCM). Second, the variation characteristics of each texture measure were analyzed, and the optimal feature parameters, such as direction, gray level, and texture window, were determined. Meanwhile, the texture feature value, combined with maximum information, was calculated, and the multiband texture image was obtained by resolving three optimal texture measure images. Finally, a support vector machine (SVM) method was adopted to classify landforms on the basis of the multiband texture image. Results indicated that the texture features of DEM data can be sufficiently represented and measured via the quantitative GLCM method. However, the feature parameters during the texture feature value calculation required further optimization. Based on the image texture from DEM data, efficient classification accuracy and ideal classification effect were achieved.

Keywords DEM data, image texture, feature extraction, Gray Level Co-occurrence Matrix (GLCM), optimal parametric analysis, landform classification

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1 Introduction

Texture, which is based on the periodicity and regular permutation of texture primitives (Hawkins, 1970), is a characteristic index of images, and it is often used to map the attributes of an object’s surface or structure. The image texture with wide use can reflect the spatial distribution of gray scale, and it appears as an external expression of the statistical rule of gray scale between pixel pairs (Zheng and Zhou, 1997). The reasons for its wide use are that texture information, which is regarded as spatial grayscale information, can enhance feature structures and shape features in ground object recognition (Lefebvre and Corpetti, 2017), can improve the homogeneity within the class in region segmentation (Kim et al., 2009), and can distinguish the objects whose spectra are easily confused in classification (Ouma et al., 2008). Texture analysis methods include statistical, structural, model, and signal processing methods (Materka and Strzelecki, 1998). Image texture has the characteristics of local random and global regular, which determines that a statistical method is an appropriate texture analysis method. Moreover, the statistical method can represent the homogeneity within the region and the heterogeneity between regions and can effectively describe the macroscopic characteristics of images. Gray level co-occurrence matrix (GLCM) is an example of a statistical method; it considers the comprehensive information of pixel gray scale in terms of direction, adjacent interval, and other aspects (Haralick and Shanmugam, 1973). GLCM is the basis for analyzing the local patterns and arrangement rules of image texture. To date, the GLCM method is widely used in remote sensing images for segmentation, classification, and ground object recognition. For instance, on the basis of the texture measures and feature values, the practicability of the classification method of combining spectral and textural characters was discussed to improve classification accuracy in a remote sensing image (Puissant et al., 2005;

Ota et al., 2011). From previous research, it can be learned that classification accuracy is directly affected by texture feature parameters when the GLCM method is used. Therefore, the research on optimal texture feature parameters has become a difficult and widely discussed topic in image classification. In recent years, numerous scholars have studied texture feature parameters in detail, such as direction and gray level, and several achievements have been obtained. For example, texture parameters for retrieving forest age and generating geological mapping have been determined through quantitative analysis (Arebey et al., 2012; Champion et al., 2014; Radford et al., 2018). In the case of image texture combined with different feature parameters, such as direction and distance, the specific pattern image based on structure feature was identified (Srivastava et al., 2018). The variance of texture feature values in different window parameters was utilized in landscape recognition from remote sensing images (Hall-Beyer, 2017). With the advantages of remote sensing data, such as multi-source and high resolution, the GLCM method has attracted great attention in landform classification (Chowdhury et al., 2007).

Formerly landforms are depicted on a map. Now, however, landforms are more closely imitated by digital images (Ballantine et al., 2005; Smith and Pain, 2009; Nair et al., 2018). Landform classification has been the focus of surveying and mapping science, cartography, and geomorphology. Beyond that, landform classification and segmentation are conducive for studying the spatial distribution and structure of landform, as well as terrain features (Zhu et al., 2018a). These processes can also facilitate the exploration of the mutual relations between landform and other natural geographical elements and provide important basis for land use, hydrological analysis, and urban planning. There are many methods used in landform classification. Martins et al. (2016) extracted terrain factor from digital terrain model data for landform classification; unsupervised and supervised classification methods, which together with the terrain factors, were employed to classify landform (Prima et al., 2006; Piloyan and Konečný, 2017); some scholars applied the object-oriented, topography position index, and geomorphological approach for landform classification (Drăguț and Blaschke, 2006; Ho and Umitsu, 2011; Mokarram et al., 2015). However, the problems of the landform classification method mentioned above are as follows: The segmentation threshold of a large scale classification system is unsuitable for small-scale contexts, In addition, the analysis window leads to the uncertainty expression of terrain factors. Moreover, the degree of automatic classification is low. Thus, the terrain texture is introduced for landform classification. The benefits of terrain texture are clear for distinguishing different landform features, and texture feature values can improve the precision of landform classification in images. With respect to vegetated areas in remote sensing imagery, texture reflects the differences in vegetation morphology on the terrain surface because terrain relief causes texture variation in expressing a geomorphologic landscape. However, this terrain relief information is insufficient for direct acquisition from remote sensing images. Consequently, the application of remote sensing images is limited in terrain feature analysis. Opposite to remote sensing images, DEM data represent actual surface elevation and transform elevation information into terrain texture, visualized in the way of a remote sensing image. The difference is that terrain textures from DEM data have purer landform importance than those from remote sensing imagery, and surface coverings are removed in DEM data (Singh et al., 2014). Suppose that terrain textures showed the same grayscale in DEM data, the texture features will share similarities. On the contrary, texture features exhibit regional differences. Therefore, different landform types can be distinguished and identified in DEM data by selecting quantitative models and measures of terrain texture (Bugnicourt, 2018).

In recent years, numerous researchers have studied the terrain texture feature extraction and classification in DEM data on the basis of the GLCM method. The main results are as follows: The feature parameters of GLCM were preliminarily discussed for quantitatively expressing terrain textures in DEM data (Liu et al., 2012, 2017), and then landform segmentation was conducted (Wang et al., 2015; Tian et al., 2016). The uncertainty of texture measures and feature values caused by the change in DEM data resolution was analyzed (Huang et al., 2015). Texture derivatives with the random forest (RF) method (Zhao et al., 2017) and drainage basin object-based method with decision tree (Lv et al., 2017; Xiong et al., 2018) have been used for landform classification. These methods apply remote sensing texture analysis technology to DEM digital terrain analysis, which is not only a breakthrough in macroscopic terrain feature quantization and identification but also a valuable research proposition. Based on the above-mentioned analysis, the current research on landform classification only expands from a few texture measures or a single feature parameter object in remote sensing image. Few scholars have focused on multiple texture feature values and parameters from DEM data. An urgent problem to be solved is whether we can center on the existing issues noted previously to explore the laws of texture feature values and select the optimal texture measures that can identify different landform types for classification on the basis of the difference of texture feature values. Following this idea, DEM data were adopted for extracting three landforms in Shandong Province. The mean and standard deviation value of eight texture measures were calculated using the texture analysis method of GLCM. The different laws and characteristics of texture feature values in various landforms were explored, and the optimal feature parameters were determined. In addition, texture measures that can finely efficiently identify regional landform types were selected to form a multiband image for landform classification. Finally, the accuracy of the classification results was evaluated and then verified.

2 Materials and methods

2.1 Study area and data

The study area is located in Shandong hilly area, where the comprehensive effects of internal and external geological processes are evident. The Earth's internal forces, named plate movement, can lead to the relief of the surface and the development of typical hilly landform types, such as mountains, hills, and plains. These landforms create abundant terrain textures in Shandong Province. According to the classification scheme of digital land geomorphology of 1:1,000,000 in China (Zhou et al., 2009), the study area was divided into three types (plain, hill, and mountain) in line with the altitude and morphological indices of relief. Three different spatial location areas, which can reflect the regional characteristics of texture, were selected: 1) the northwest plain of Shandong Province, 2) the hilly area of Jiaodong, and 3) the central mountain of Shandong Province. Figures 1(a)–1(c) show the location distribution. Table 1 presents the sample areas and their landform characteristics of morphological indices. On the basis of the repeatability of texture primitives and the stability of statistical texture features, the image range was defined as 120 × 120 pixels. The study data used in the experiment were DEM data with a scale of 1:1,000,000 and a resolution of 500 m, which were provided by the National Geomatics Center of China. This scale of DEM data not only can analyze the distribution of macroscopic geomorphology but also plays the role of smoothing texture and reduces the random noise caused by high-precision DEM data.

2.2 Experimental methods

Figure 2 illustrates the flowchart of quantitative extracting texture feature for landform classification in this study. In Fig. 2, a texture image is calculated using the GLCM method, and the statistical second-order texture measures and feature value are extended on the basis of GLCM. The

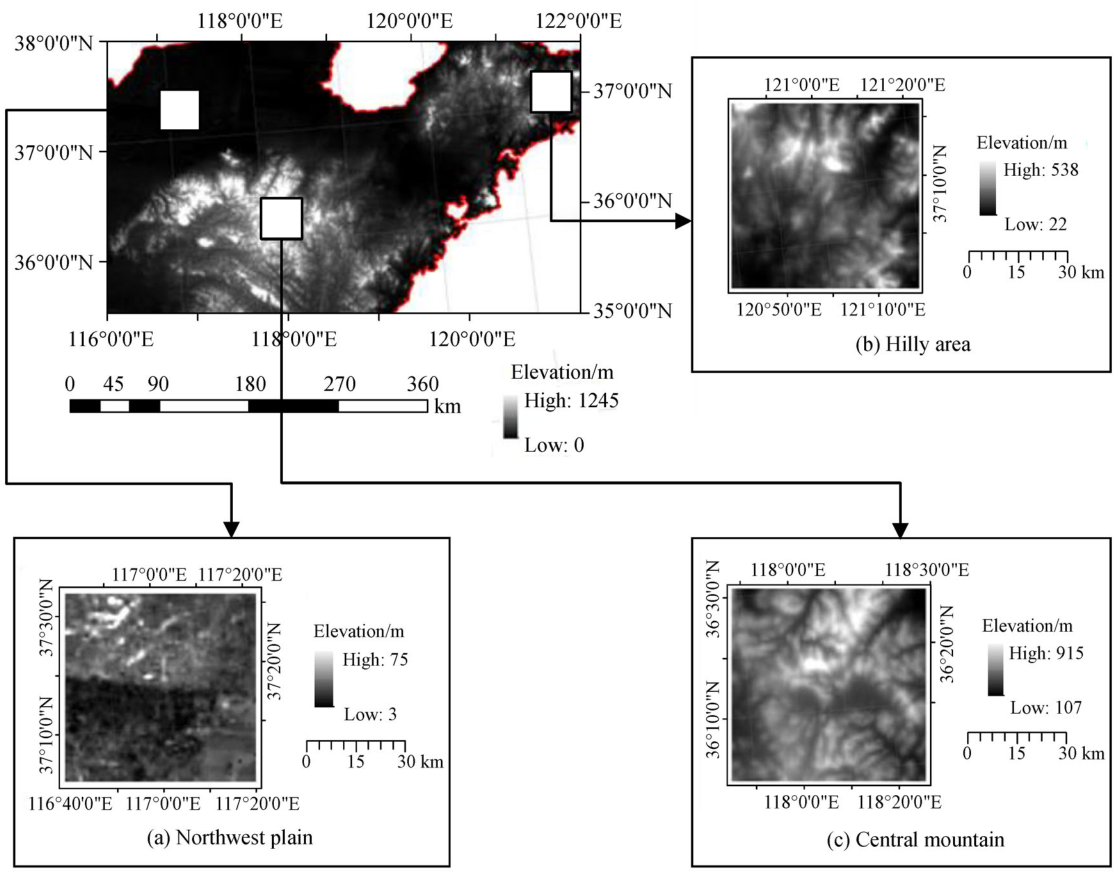

Fig. 1 Distribution of three sample areas study area.

Table 1 Major landform characteristics of three sample areas in Shandong Province, China

Test area	Area/km^2	Altitude/m	Relief/m	Average altitude/m	Average relief/m
TA-a	3600	3–75	0–50	15	4.78
TA-b	3600	22–538	0–225	155	37.04
TA-c	3600	107–915	2–237	402	60.17

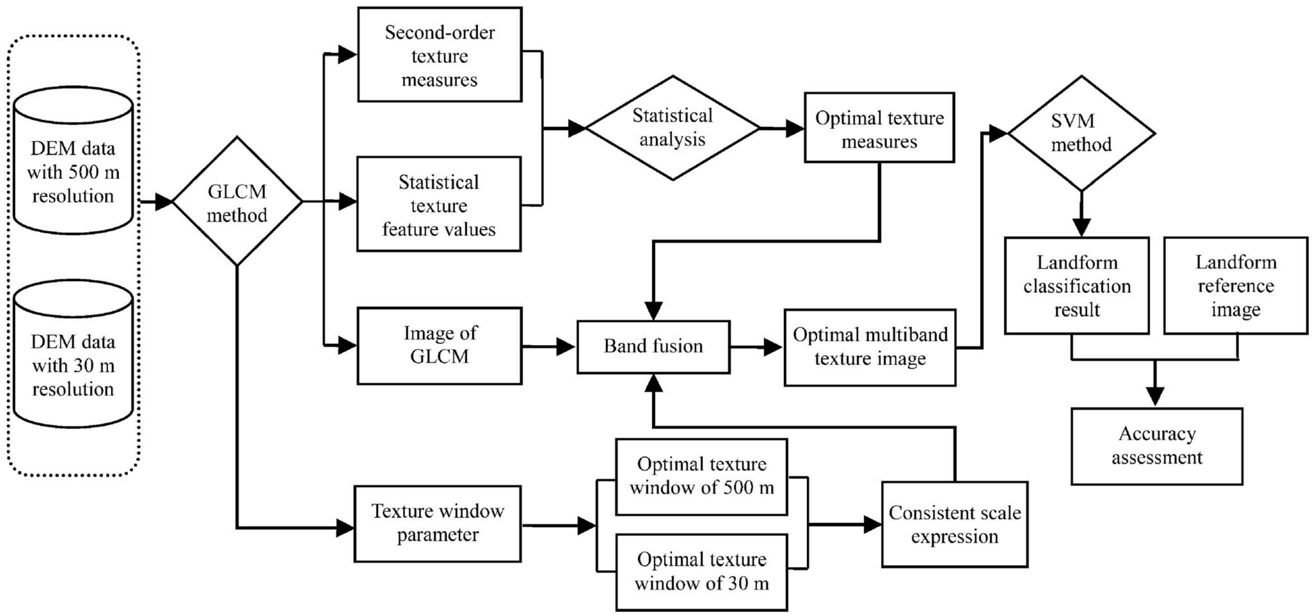

Fig. 2 The flowchart of quantitative extracting texture feature for landform classification.

optimal texture measures were determined in different landforms by using the principle of maximum difference between texture feature values. Moreover, DEM data with the resolutions of 30 and 500 m were utilized to determine the optimal texture window, thereby proving a consistent scale expression. The texture images corresponding to the texture measures were fused into a multiband texture image for classifying landforms, which was based on the SVM method. The analysis results indicated that the spatial distribution structure of different landforms was conducive to quantitative express landforms. The main adoption methods are described as follows.

2.2.1 GLCM

GLCM, which studies gray spatial correlation, is a common method for describing texture. Assume that the image size is $M \times N$ and the gray level is L. The image can be represented as $G(x, y)$. The GLCM is defined as the joint probability density $P(i, j, d, \theta)$ between a pair of pixels, where d is used to measure neighboring distance between pixels i and j, and θ is used to quantize directions. Eq. (1) is expressed as follows (Haralick and Shanmugam, 1973):

$$\begin{gathered} P(i, j, d, \theta) = \#\{[G(k, l) = i, G(m, n) = j], \\ dis((k, l), (m, n)) = d\} \\ 0 \leqslant i, j \leqslant L-1, (k, l), (m, n) \in M \times N, \\ \theta \in (0°, 45°, 90°, 135°), \end{gathered} \tag{1}$$

where $\#(x)$ denotes the number of elements in the set and $dis(\cdot)$ represents the distance function.

GLCM, which was proposed by Haralick (1979), is a second-order statistical texture quantization method for further expressing texture features. The commonly used texture measures, such as Mean, Variance (Var), Homogeneity (Hom), Contrast (Con), Dissimilarity (Dis), Entropy (Ent), Angular Second Moment (ASM), and Correlation (Cor), were selected to calculate the results of texture feature values. The detailed formula and significance of texture can be seen in Haralick's study (1973, 1979).

2.2.2 Statistical analysis

Statistical analysis begins with the range of texture feature value. Values of the mean, standard deviation, and variation coefficient (VC), which are the basis for distinguishing different texture measures or areas, were quantitatively analyzed.

The texture feature value was computed from the formula of texture measure, and each pixel in the study area had a texture feature value by using a statistical method. In this study, the mean and standard deviation values within sample areas were regarded as texture feature values (Eqs. (2) and (3)). The mean and standard deviation values belong to 1D statistical information, which can easily be obtained through calculation. In addition, the mean value can reflect the concentration degree of feature values in an area, whereas the standard deviation can reflect the degree of dispersion and stability of feature values.

$$\overline{X} = \Sigma_1^n x_n / n, \tag{2}$$

$$S = \Sigma x^2 - \frac{\Sigma x^2}{n} / n - 1. \tag{3}$$

VC is a statistic that measures the variation of observed values in data. The optimal texture window size could be determined using the VC value in accordance with its stability, and VC is defined as follows (Puissant et al., 2005):

$$\mathrm{VC} = \mathrm{S}/\overline{X}, \tag{4}$$

where S is the standard deviation, $\overline{X}$ denotes the mean value, x represents the sample value, and n indicates the number of samples (pixels).

With the use of texture information for classification, the result largely depended on the size of the texture window (Ferro and Warner, 2002). Thus, determining the optimal texture window was a premise for improving classification accuracy.

2.2.3 SVM method

The SVM is a supervised classification method that is based on statistical learning theory (Vapnik, 1963). In the current study, the idea of SVM is straightforward: to maximize the margin between classes and separate samples on the basis of the optimal decision surface. This experiment applied the SVM method for image classification. The theory of SVM is mature because it can convert a low-dimensional classification problem into a high-dimensional one. In addition, the SVM can support multi-class classifier strategies and small training samples and solve the problem of nonlinear, overlearning phenomenon, as well as local minimum (Chang and Lin, 2011). Furthermore, the classification accuracy of the SVM method can be determined by selecting diverse support vectors and kernel functions (Kavzoglu and Colkesen, 2009). Hence, the effective kernel function, namely, radical basis function (RBF), is adopted (Subasi and Gursoy, 2010; Zakaria and Shabri, 2012). The RBF includes penalty factor C and nuclear parameter g (Vapnik, 1997), which allow misclassification to a certain extent and are crucial to non-separable training data. Figure 3 shows the training process of the classification method, and good classification results can be obtained from complex data.

Other parameters were set as follows: the pyramid level was set to 0, that is, data processing was at raw resolution. The classification probability threshold was 0, that is, if a pixel calculated for obtaining the total probabilities was less than 0, then it would not be classified.

3 Results and analysis

3.1 Determination of texture feature parameters of DEM data

DEM data were used to generate GLCM and extract texture features, and the main parameters in the calculation are direction, distance, gray level, texture window, and second-order texture measures.

3.1.1 Distance and direction

Texture information will be lost due to the far distance between pixels. Consequently, texture features cannot be extracted effectively. Considering that the spatial resolution of DEM data was 500 m, a distance parameter of 1 pixel ($d = 1$) was adopted in texture analysis (Rodriguez-

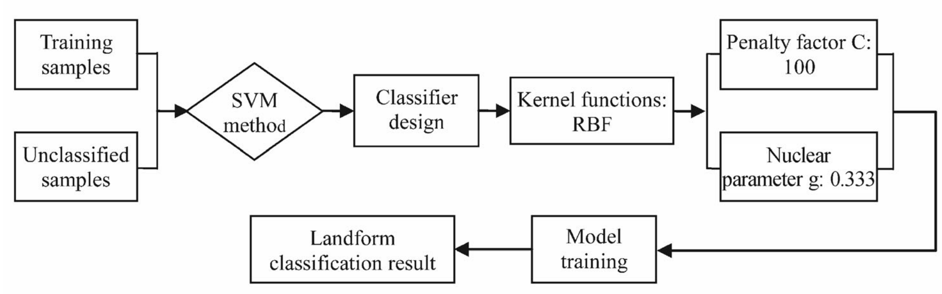

Fig. 3 Training process of SVM method.

Galiano et al., 2012). This distance parameter can meet the basic principle of spatial correlation, that is, the closer the distance, the stronger the spatial correlations. Direction was recorded in detail by Haralick and Shanmugam (1973). Different directions had varied texture features during the extraction of texture information. For example, 0° and 90° were suitable for horizontal and vertical texture features, respectively. However, 45° and 135° were suitable for diagonal texture features. The texture features which quantitatively represented by the texture feature values were studied among different directions. Figure 4 presents the texture feature values results of four directions in sample areas.

After several experiments on texture directions, the texture features of 64-bit gray level and 7 × 7 texture window were used for illustration (the gray levels of the other windows had the same rule). In the four directions, the texture feature values among texture measures held steady except for contrast measure, which had the greatest difference in texture feature value as shown in Fig. 4. These results implied that the mean values of texture features, except contrast, that came from the same landforms were not affected by angles, and the directivity was not noticeable within the landform. The texture features of contrast were simply the opposite; contrast measure dramatically changed in the 45° direction. Thus, it would be arbitrary to select the mean of four directions as texture feature considering the goal of extracting the optimal feature parameter. On the basis of the directivity of texture measure, only the texture feature value of contrast was considered in selecting the direction parameter, as shown in Fig. 5. The 0° and 90° directions did not meet the requirement of distinguishing different landforms because of the same mean value as Fig. 5(a) shows. Thus, the optimal direction was determined by calculating the relative change rate of the standard deviation (Zhang et al., 2015). The maximum difference change of the texture feature values was in 135° direction as Fig. 5(b) shows. For coarse texture areas, previous studies suggested that the value of GLCM concentrates on the diagonal direction. The experiment and theory indicate that the optimal direction of 135° was determined for texture extraction.

3.1.2 Gray level

The gray level determines the GLCM size. Reduction in gray level can improve the computing speed and reduce space. However, a low gray level can destroy useful texture components and lead to the loss of image information (Mohanaiah et al., 2013). Therefore, determining the optimal gray level was indispensable in texture research for expressing landform features. Figure 6 displays the mean value of the texture features in different gray levels.

In the texture feature extraction process, the gray level had common laws in different texture windows. Only the texture window of 7 × 7 was selected for investigation. The texture feature values of hills and mountains were larger at the gray level of 256 bit as the first row in Fig. 6 exhibits, which inconveniently analyzed the GLCM and largely increased the calculation amount. Therefore, the gray level of 256 bit was rarely used. The image gray level must be reduced before calculating the GLCM. The second row in Fig. 6 illustrates the comparisons of three gray levels. When the gray level was greater than 16 bit, the mean values of homogeneity, angular second moment, and correlation measures were less affected in different windows; thus, the texture feature value was stable. The other values, especially the mean values of mean, variance, and contrast measure, were affected considerably; they became increasingly noticeable with the increase of gray level. However, changes in the texture feature value at 256-bit gray level were inappropriate for the plain area. This area had relatively constant texture attributes and would not change dramatically with the gray level. For guaranteeing texture information and feature value in the study areas, the 64-bit gray level was selected as the reasonable representation of the mean, variance, and contrast measure. The use of a 64-bit gray level could also help distinguish different landforms through statistical analysis, thereby supporting the scientific practicability of this study.

3.1.3 Optimal texture window

The texture window size was closely related to the spatial resolution of the image and the reflection of the landform types in texture analysis. If the texture window was small, the extracted texture information would have enriched details and then lead to a serious spot phenomenon. Conversely, the information of small objects would be easily filtered out, thereby causing fuzzy boundaries. As stated in Section 2.2.2, Fig. 7 shows the VC of the texture feature value in different windows.

A high VC causes a wide variation range, poor integrality, and low stability, and a low VC is reversed. For this reason, the optimal texture window was determined when the VC tended to stabilize. In various landform types, the VC of different texture measures varied with the texture window size. As the texture window size increased, the VC of the mean, entropy, and angular second moment measures changed from small to large and then tended to stabilize. Meanwhile, the VC of the variance, contrast, and dissimilarity measures changed from large to small and then tended to stabilize. Homogeneity and correlation measures had a similar trend to the variance. The only difference was that the change of homogeneity and correlation from large to small was slower than that of variance. The window interval where the VC remained stable ranged from 7 to 15. Considering the comprehensive change of each landform type, the optimal texture window size of 7 × 7 was selected.

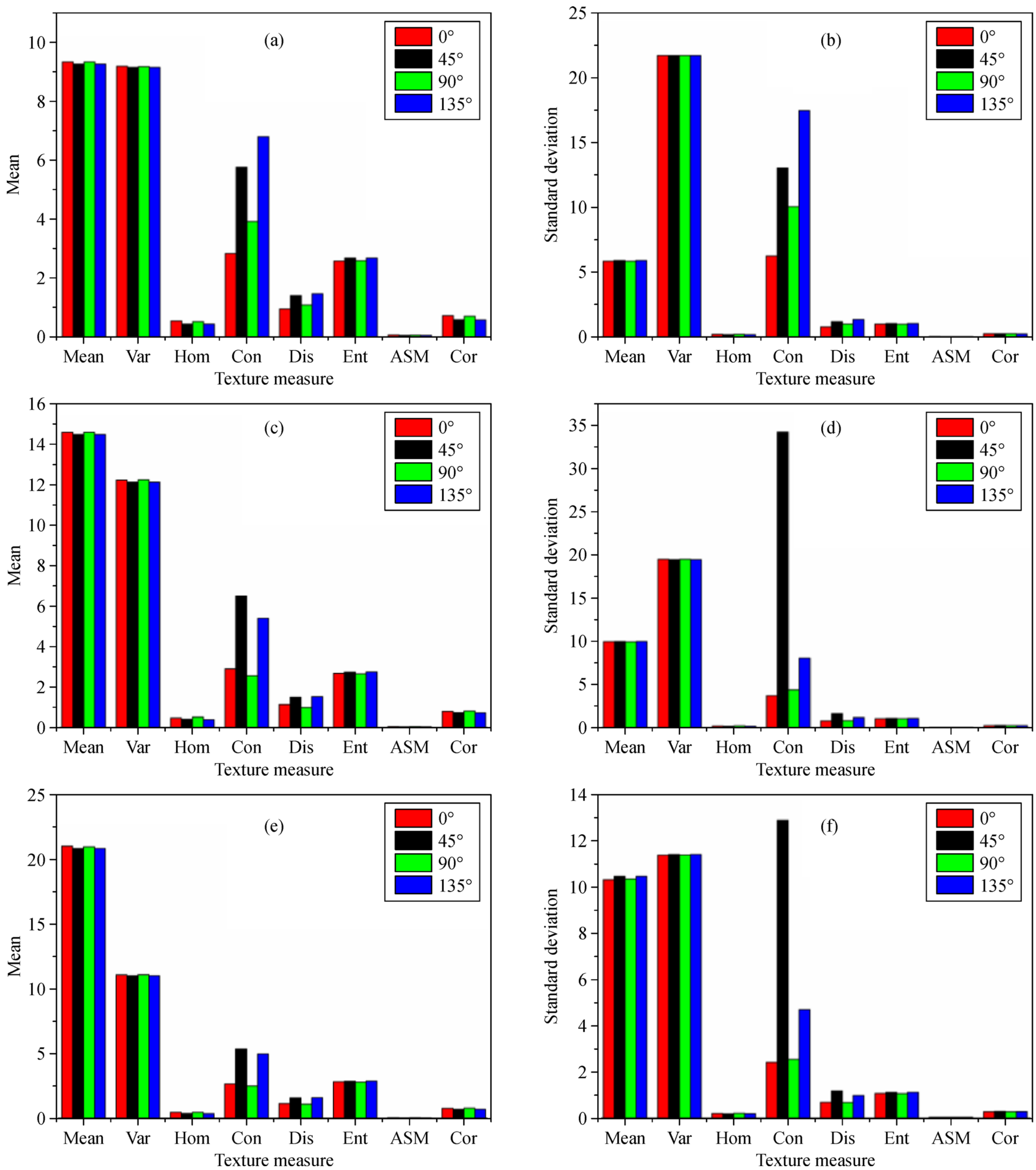

Fig. 4 The texture feature value of four directions in sample areas: (a, b) northwest plain; (c, d) hilly area; (e, f) central mountain.

3.2 Results and analysis of DEM image texture

3.2.1 Changes of texture feature values in different texture windows

Changes of texture feature value in different texture windows are shown in Fig. 8, and the variation trend of the texture features are distributed as Fig. 8 showing.

The various changes in different texture windows were discussed, which are based on the mean value of texture feature. The mean values of mean and contrast measures decreased with increased texture window size, the mean value of variance and entropy measure increased with the growing texture window, and the mean values of homogeneity, dissimilarity, angular second moment, and correlation measures were nearly independent of the

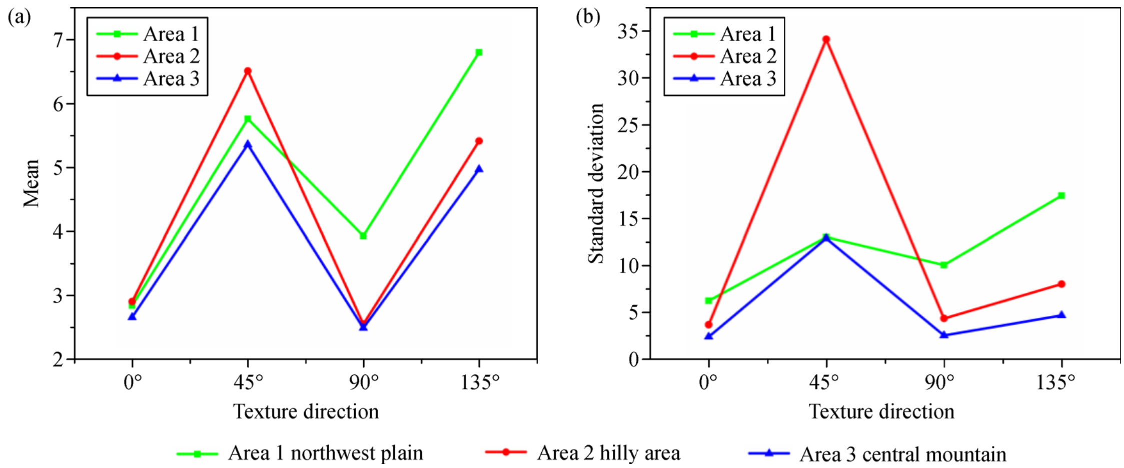

Fig. 5 The texture feature values of contrast in different landforms: (a) the mean value of texture feature; (b) the standard deviation value of texture feature.

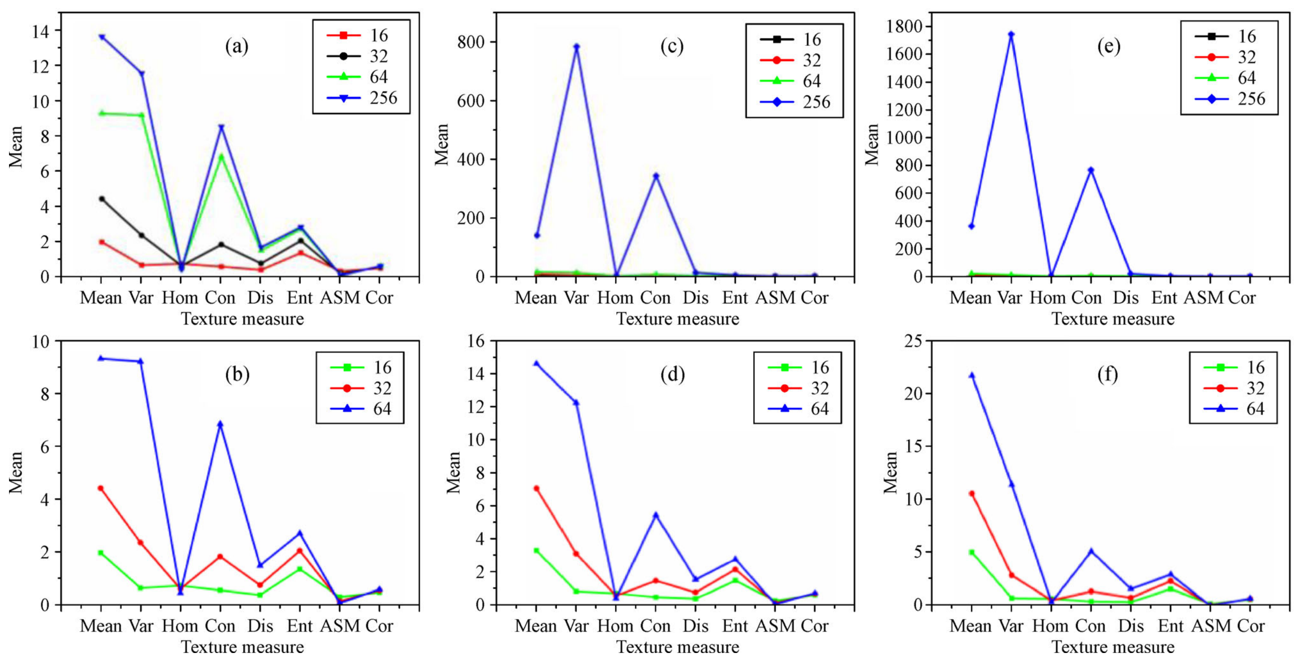

Fig. 6 The mean value of texture features in different gray levels among three sample areas: (a, b) Northwest plain; (c, d) hilly area; (e, f) central mountain.

growing texture window. A comparison of the same texture measure from various landforms showed some differences in the mean value of texture feature. For the mean measure, the mean values arranged from largest to smallest are mountains, hills, and plains. According to the significance of texture measure, the texture was disordered because plains had the smallest mean value. For the variance measure, the mean values arranged from largest to smallest are hills, mountains, and plains. In other words, hills and mountains had larger texture periodicity than plains. For the contrast measure, the mean values arranged from largest to smallest are plains, hills, and mountains. The contrast of mountains and hills was similar. By contrast, plains had the largest contrast, as shown in Fig. 1(a). When the resolution was reduced, the discrimination capability of contrast measure was considerably enhanced in the messy texture. The mean values of homogeneity, dissimilarity, entropy, and angular second moment measures had inconspicuous difference. The texture was considerably disordered that the homogeneity measure has a low mean value. The local gray difference of the three sample areas was small, thereby leading to a low

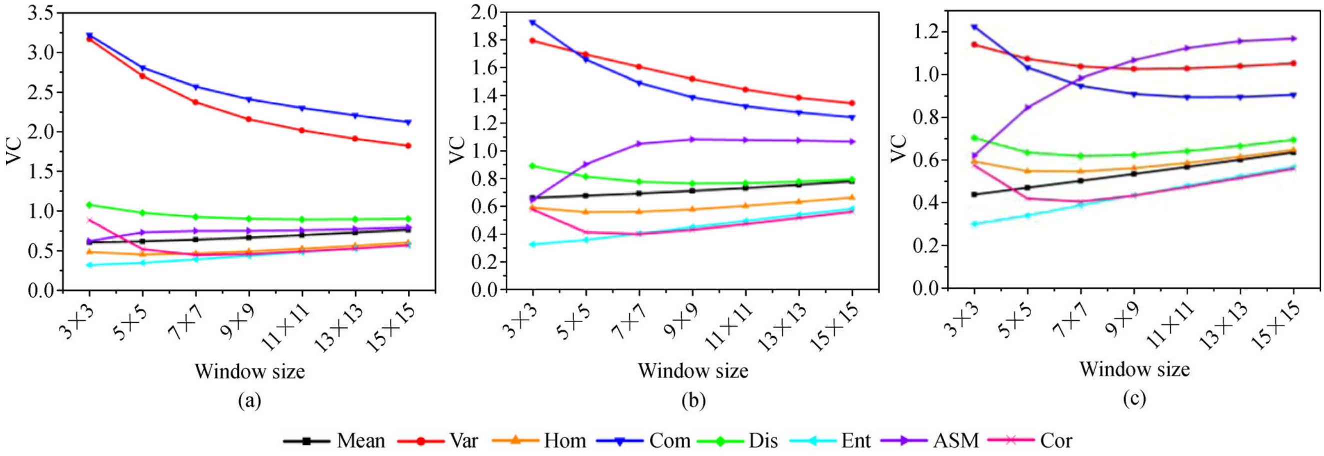

Fig. 7 VC of the texture feature value in different windows: (a) northwest plain; (b) hilly area; (c) central mountain.

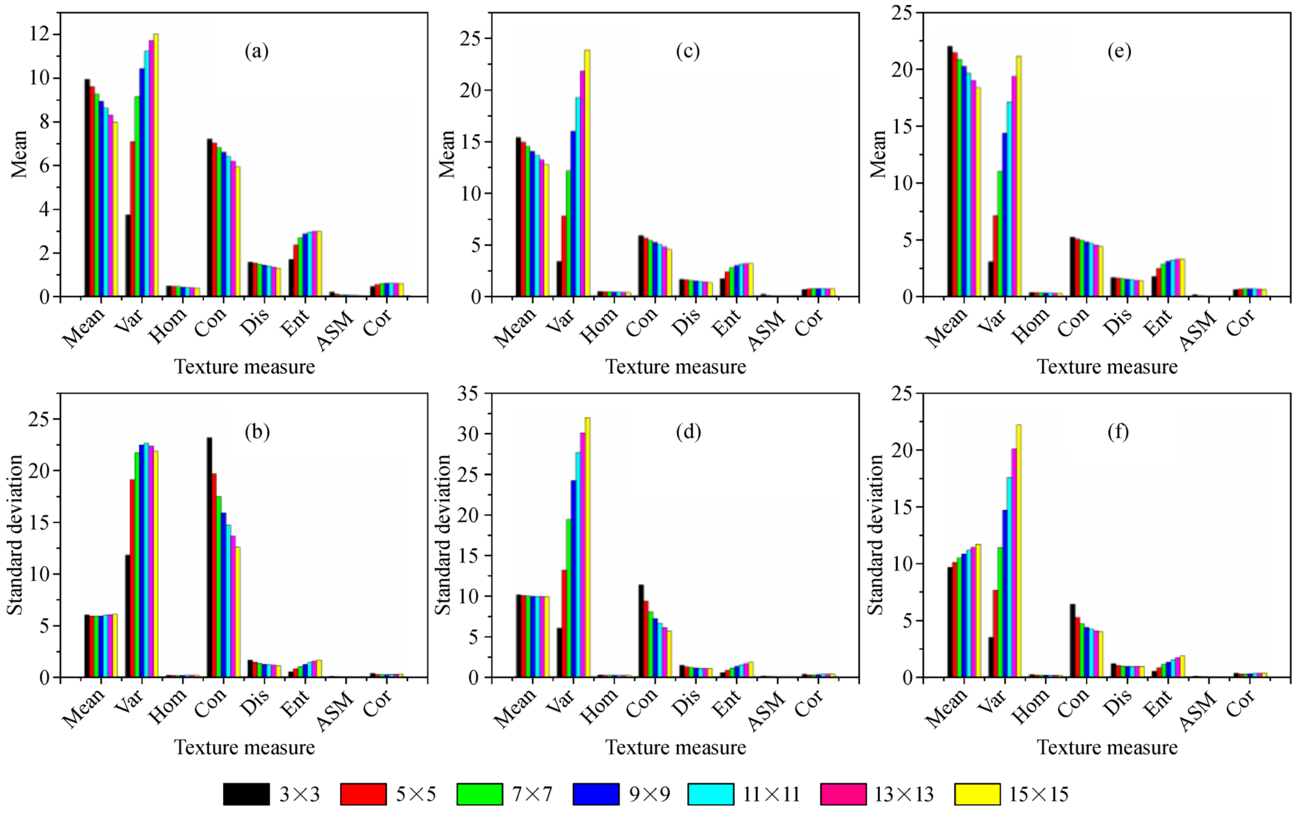

Fig. 8 Changes of texture feature value in different texture windows: (a, b) Northwest plain; (c, d) hilly area; (e, f) central mountain.

texture feature value of the dissimilarity measure. Gray scale was uniformly distributed in the three landforms, and pixels had the same gray value in the coarse texture, thereby resulting in a low mean value of entropy measure. Angular second moment measure was sensitive to the resolution change and exceptional at distinguishing detailed texture. Hence, such measure has poor discrimination capability for distinguishing landforms with a 500 m DEM resolution. Correction measure had a high mean value on account of the similar and uniform local gray value.

3.2.2 Optimal texture measure

In Fig. 8, the standard deviation value of texture feature was used to expresses the dispersion degree between samples. In this paper, samples refer to the texture measures. A high standard deviation value signifies a large sample difference and separation. As described in Section 3.2.1, the mean values of mean, variance, and contrast were different in the three landforms. On the basis of these three texture measures mirrored by the mean and the standard deviation value difference in three landforms, the capability to distinguish landforms was explored in the optimal texture window. Hence, the mean measure could be used to distinguish the plain area, the variance measure could distinguish the mountainous area, and the contrast measure could distinguish the plain, hill, and mountainous areas. Thus, the mean, variance, and contrast measures were adopted as the optimal texture measures, since they meet classification requirements.

3.3 Landform classification based on texture image from DEM data

Eight texture images were calculated using the GLCM method. However, owing to the principle of optimal measures, three texture images, namely mean, variance, and contrast, were selected as samples. These samples images, which exhibited in Fig. 9 ((1) mean, (2) variance, and (3) contrast texture images), were used to fuse a multiband image for landform classification, and Figure 9 showed the details of landform classification. Furthermore, ROIs are equally extracted from the three sample areas and then details of classification in training and testing are divided into three steps:

1) On the multiband texture image, according to prior knowledge, the number of training samples selected in the plain, hilly and mountainous area is 189, 247, and 46 respectively;

2) The samples are trained using the classification method of SVM;

3) The other texture primitives of the whole texture image are used as the test samples, and the computer automatically determines what landform it belongs to.

To classify the entire Shandong hilly area, the landform samples were trained using the SVM method in the texture image. Figure 10(a) shows the landform classification map result.

Using the DEM data with a 500 m resolution, the classification scheme of digital land geomorphology of 1:1,000,000 in China based on the altitude and morpho-

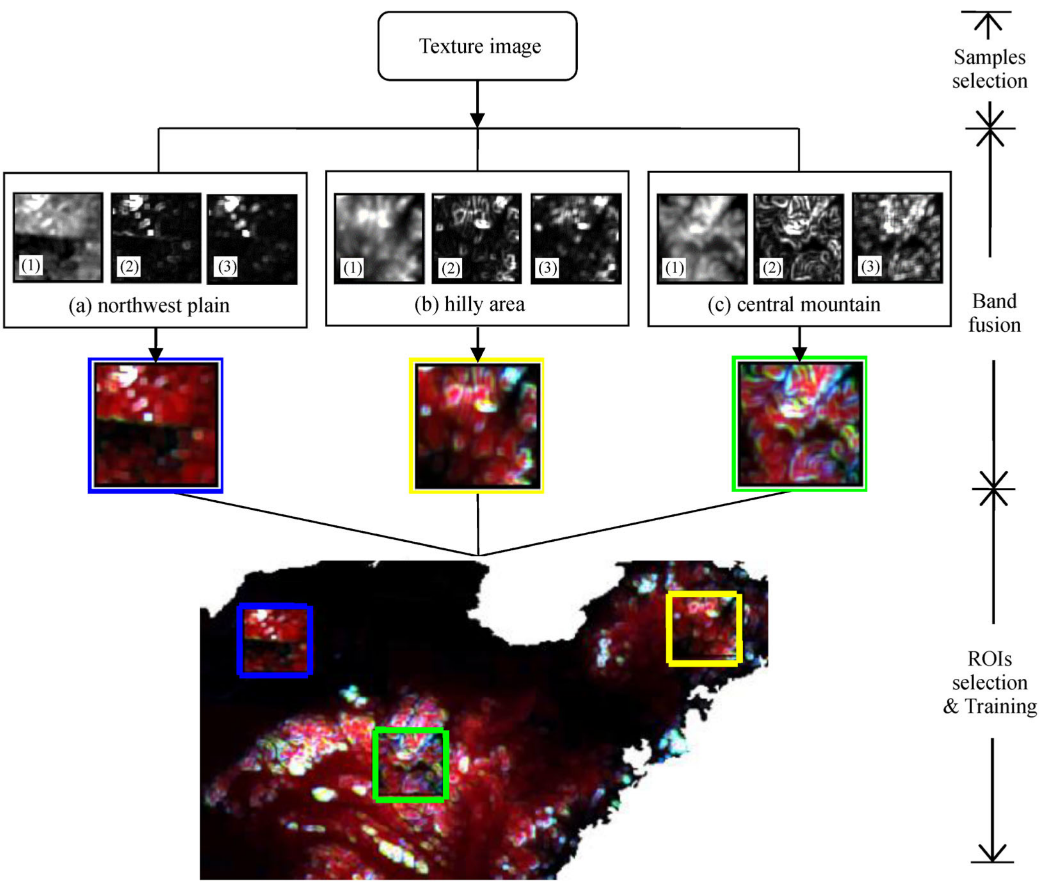

Fig. 9 Details of landform classification.

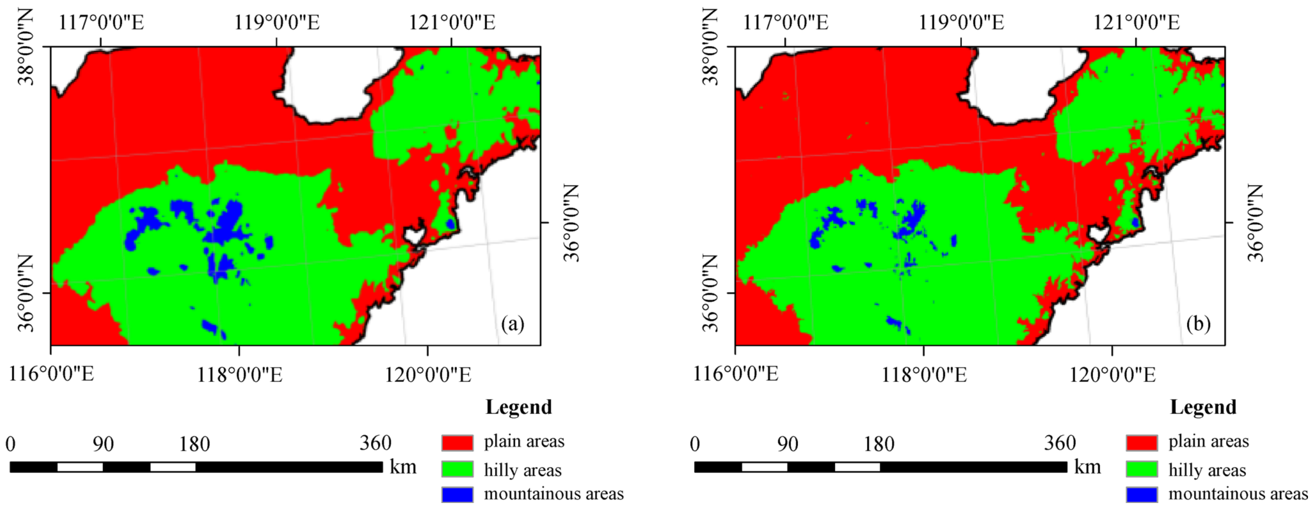

Fig. 10 Landform classification result: (a) classification map; (b) reference map.

logical indices of relief were adopted to produce the landform class table of reference map (Zhou et al., 2009). This reference map was used for testing classification accuracy, as shown in Table 2. Some indices were slightly adjusted to satisfy landform characteristics in Shandong Province. Figure 10(b) presents the landform classification result of reference map.

4 Discussion

4.1 Comparison of texture feature extraction

In this research, a shared statistical method was adopted for extracting second-order texture feature values from DEM data. Previous works (Karahaliou et al., 2007; Wang et al., 2015), only discussed the mean values of texture features. The present study further introduced standard deviation values to account for the difference between texture features and to reduce the influence of directivity. Generally, using DEM data and GLCM methods for landform classification that greatly focused on the areas of Shaanxi Province, China (Liu et al., 2012; Ding et al., 2018), can help explore the development and evolution of geomorphology. Nevertheless, our study aims to investigate the relationship between macroscopic geomorphology and natural elements to lay a foundation for the application of human geography. To some degree, related studies on landform classification relied on several texture measures, such as angular second moment, entropy, contrast, and correlation, due to their mutual independence on the texture feature value (Puissant et al., 2005; Ding et al., 2016). However, the difference in how these texture measures distinguish ground objects has not been considered. Only a few researchers have directly used DEM data and the strategy of texture feature optimization to classify landforms (Ding et al., 2016). In conclusion, utilizing DEM data, multiple feature values and parameters, and the discernment of texture measures can directly classify landforms by terrain texture. Another point of innovation of this thesis is the finding that texture primitives of DEM data can improve classification accuracy better than remote sensing images (Blaschke et al., 2014).

4.2 DEM resolution influence on texture expression

Scale is the basic attribute for expressing and describing spatial entity and phenomena (Zhu et al., 2018b). This experiment analyzed the texture window size of DEM data with a resolution of 30 m to verify the consistency scale when expressing ground objects. In Fig. 11, the value point where the VC value changed from large to steady or from small to steady was selected as the optimal texture window size.

Using the hilly area in Jiaodong as an example, the optimal texture window of 30 m resolution was confirmed from the DEM data (the laws of the mountainous and plain areas were consistent with those of hilly area). The aim is to prove that the texture window of 7 × 7 was an appropriate scale for expressing ground objects in 500 m resolution DEM data. In terms of VC stability, the optimal texture window of 11 × 11 was determined in 30 m resolution DEM data. The scale expression of 500 m resolution DEM data was 3.5 km, whereas the scale expression of 30 m resolution DEM data was 3.3 km. These findings indicated that the scale expression was consistent even in different windows and resolutions.

Table 2 The landform class table

Landform types	Altitude/m	Relief/m	Attribute
Plain areas	0–50	< 30	Lower altitude plain area
Hilly areas	51–500	30–200	Lower altitude hilly area
Mountainous areas	501–1500	200–500	Small relief mountain

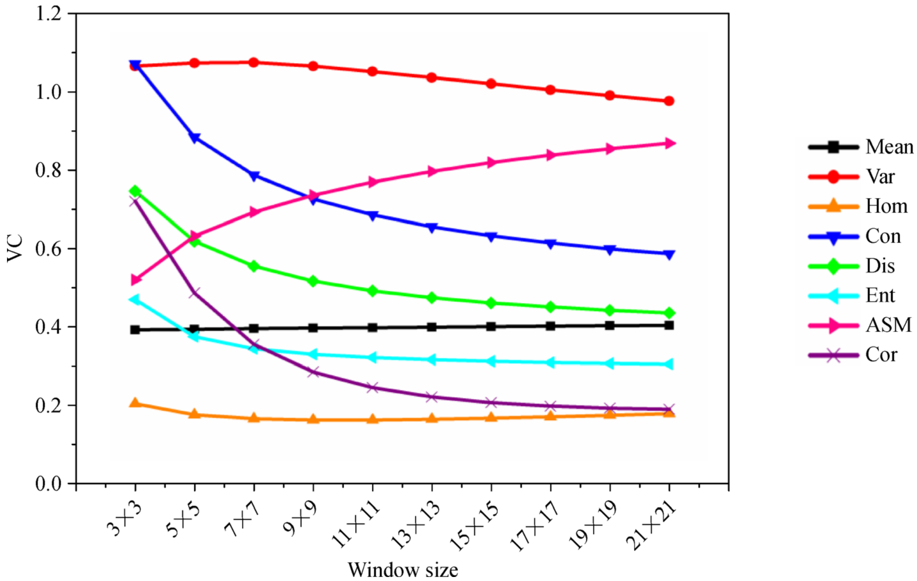

Fig. 11 VC of the texture feature value in DEM data with a resolution of 30 m.

Supposing that data had a high resolution and small texture window, the spatial information in reflecting ground object features would be insufficient for full extraction. On the contrary, when the image had a low resolution and large texture window, the wrong texture information would be extracted because the spatial difference of two ground objects had cover up. Therefore, a reasonable scale expression can acquire abundant texture information, and a texture window of 7 × 7 can be employed to band fusion.

4.3 Reliability of landform classification accuracy based on DEM image texture

The confusion matrix was established by testing samples and included two precision indices, namely, overall classification accuracy and kappa coefficient. The kappa coefficient was applied to measure the consistency between the classification map and reference data. A kappa coefficient greater than 0.8 implied that a high consistency existed between the classification map and reference data or fine classification accuracy was produced. To prove that the texture information can improve classification accuracy, the texture image classified by texture feature value information is compared with DEM data classified only by elevation information, which is based on the texture image of DEM data and only DEM data, respectively. Using SVM method, Table 3 expresses the classification accuracy in different data sources.

In Table 3, the overall accuracy and kappa coefficient of the texture image of DEM data and only DEM data are greater than 90%, which indicated that landform classification in the Shandong hilly area received efficient results. As for producer accuracy, by analyzing the correct classified counts in two data, we can realize the following. The pixel number of plains and mountains in the texture image of DEM data are lower than pixel numbers in only DEM data, whereas the pixel number of hills presents an opposite case. Results illustrated that the texture expression capability is poor for areas with large terrain relief, such as mountains. Although the correct pixels of plain areas are low in the texture image of DEM data, the experiment area is mainly composed of plains and hills; thus, the producer accuracy hardly suffered influence. Producer accuracy can also reflect the number of omission pixels for one class. As shown in Table 3, plains and mountains had similar producer accuracy in two data, while omission pixels of hills are high in only DEM data, resulting in low producer accuracy. User accuracy can reflect the commission pixels for one class. As shown in Table 3, the user accuracy of hills is essentially equal in two data. However, the user accuracy of plains in the texture image of DEM data is higher than that of only DEM data, which implies that pixels in plains were less incorrectly classified as compared to other areas. As

Table 3 Landform classification accuracy in different data sources

Data sources	Landform types	Accuracy assessment		Correct classified counts	Total pixel counts
		Producer accuracy/%	User accuracy/%		
Texture image extracted from DEM data	Plain areas	99.46	94.17	328917	330694
	Hilly areas	90.72	99.28	254133	280131
	Mountainous areas	98.96	53.24	6405	6472
	Total	1)		589455	617297
Only DEM data	Plain areas	100	91.97	330694	330694
	Hilly areas	88.85	100	248892	280131
	Mountainous areas	100	73.14	6472	6472
	Total	2)		586058	617297

several pixels in mountains were incorrectly classified to other areas, user accuracy in the texture image of DEM data is lower than that of only DEM data. Due to discrete distribution and high relief, mountainous areas could not be classified well in two data. The quantity of correct classified counts played a dominated position, causing the overall accuracy and kappa coefficient in texture image of DEM data to be higher than those of only DEM data by 1.09%. Therefore, using texture is an effective method for improving landform classification accuracy.

5 Conclusions

Terrain texture is a crucial basis for distinguishing different landforms, and DEM data are the key to analyzing terrain texture. The data used in the study were DEM data with a scale of 1:1,000,000 and a resolution of 500 m. By using the texture feature values of GLCM as the research object, the variations of texture features on distance, direction, gray level, and texture window were analyzed in detail. Moreover, the SVM method was adopted to classify landforms in texture image formed by texture measures. In the coarse resolution of DEM data, the main results and conclusions of this study were as follows:

1) On the basis of the GLCM method, the influence of each feature parameter on the texture feature value was tested to establish the optimal feature parameter value. In the same landform, the texture feature values of all directions were similar, and no substantial difference was observed in directivity (except for contrast). According to the relative change rate of standard deviation, the direction parameter of 135° was confirmed. Considering that the resolution of DEM data is 500 m, a distance parameter of 1 pixel was adopted. To ensure maximum texture information and reduce computation time, the optimal gray level of 64 bits was adopted. Finally, the optimal texture window of 7×7 was determined by VC stability.

2) In different landform areas, the texture measure's capability to distinguish objects was diverse, especially the texture measures of mean, variance, and contrast. The mean measure could distinguish plain areas, the variance measure could distinguish mountainous areas, and the contrast measure could distinguish plain, hilly, and mountainous areas. Applying the optimal texture measures for band fusion could form a multiband texture image. As texture feature value can quantitatively express the texture information, efficient landform classification results could be obtained via the SVM method in texture image.

Given the limitation of experimental sample areas and the rich influence of DEM data, DEM resolution will render the texture feature extraction uncertain. Thus the obtained conclusion in this study must still be tested and verified. Meanwhile, the texture analysis on multi-scale DEM data must be complemented, and the changes in texture feature values should be discussed in detail. Eventually, DEM digital terrain analysis method can be used for landform classification for the entirety of China.

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1) Overall Accuracy 95.48% Kappa Coefficient 0.91
2) Overall Accuracy 94.93% Kappa Coefficient 0.89

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