# Research on the classification of terrain texture from DEMs based on BP neural network

LIU Kai
Nanjing Normal University
Nanjing, P. R. China.
liukaigiser@163.com

TANG Guo'an
Nanjing Normal University
Nanjing, P. R. China.
tangguoan@njnu.edu.cn

JIANG Sheng
Nanjing Normal University
Nanjing, P. R. China.
baobiaojc@163.com

*Abstract*—**Terrain texture is an important natural texture. DEM based terrain texture attracts more and more attention in the research area for its purity in representing surface topography and tis derivability in terrain analysis. In this paper, eight sample areas from different landform types of Shaanxi Province in China are selected to make a classification analysis on the terrain texture by Gray level co-occurrence matrix (GLCM) model and BP neural network. First, GLCM was used to extract the feature parameters of the terrain texture from DEMs and its derivative data. Then, the quantitative analysis was conducted by using difference value between the variation coefficient among class and variation coefficient within class in order to find the optimal parameter combination. At last, the BP neural network was applied to classify the terrain texture. The highest recognition rate is 90% which shows a great potential in landform recognition and classification.**

## INTRODUCTION

Under the inner and outer geological forces, terrain surfaces show the complex morphological characteristics. The research on analysis and quantification of morphology and spatial structure of terrain surface not only play an important role in national economy, but also have actual values in scientific research on landform formation, development and evolution. The existing researches of morphological characteristics of landform mostly discuss landform changes recur to the spatial variable characteristics of topographic factors on micro scale, which can well describe the local morphological characteristics of terrain surface. But the knowledge of morphological characteristics of landform on macro scale is still insufficiency. And recently effective analysis methods of morphological and structural characteristics of landform on macro scale are still in shortage.

As a kind of significant features, texture has been widely used in digital image processing. Haralick (1973) and Ilea (2011) discussed the concept and connotation of the texture. Some texture analysis methods can be adopted such as statistical texture analysis methods, structural methods, methods based on model and frequency domain methods. Recently, Much effort has been devoted to extracting effective and efficient texture operators from remote sensing images (Wood et al., 2012), and image textural analysis has been the important basis for object identification and classification.

Digital elevation models (DEMs), as the major information source in describing surface morphological characteristics, is widely applied in GIS based digital terrain analysis (DTA). Recently, significant achievements have been made in DEM based digital terrain analysis, such as basic theory of DTA, landform morphological characteristic investigation, landform classification and cartography (Ian S, 2011).Compared with remote sensing images, DEMs are grid cell-based expression of the land surface where buildings and vegetation have been removed, representing bare-ground topography (Anders et al., 2011). Thus, terrain textures from DEMs have purer geomorphological significance than remote sensing images.

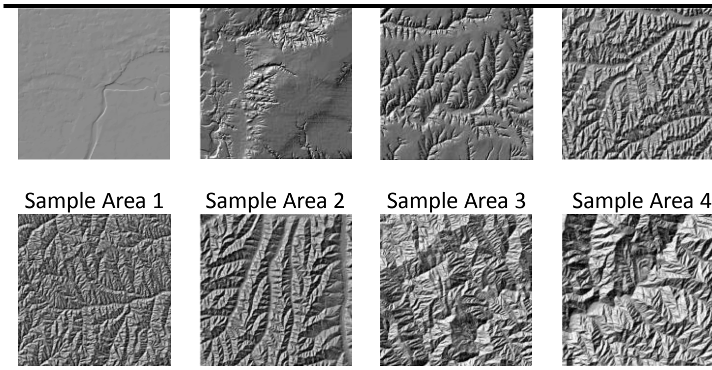
This paper firstly discusses the terrain texture characteristics, then, the Grey Level Co-occurrence Matrix (GLCM), a common textural analysis method, is applied to study the terrain texture from DEMs and its derivatives. At last, the back-propagation (BP) neural network is applied to classify the terrain texture.

## MATERIALS AND METHODS

### *Study areas and data*

In this paper, 8 sample areas from different landform types of Shaanxi province in China are selected to make a classification analysis. Each study area is divided into fifteen blocks as test samples with an area of 12 km ×12 km. DEM data in this research is from the contours of 1:50000 topographical maps and produced by the National Geomantic Center of China with a spatial resolution of 25m.The basic morphological characteristics of each sample area are shown in Table Ⅰ.

TABLE I. HILLSHADE MAPS OF SAMPLE AREAS




*Establishment of GLCM based on DEMs*

The Construction of GLCM based on DEMs is on the three-dimension curve described by DEM elevation matrix. It regards XOY-plane as a coordinate plane, and then puts forward a series of hypothesis as follows: pixel size equals to r, pixel numbers of horizontal direction equals to Mx, pixel number of vertical direction equals to My, the space domain of horizontal direction is Sx= {1, 2, …, Mx}, the space domain of vertical direction is Sy= {1, 2, …, My}, z is the elevation coordinate axis.

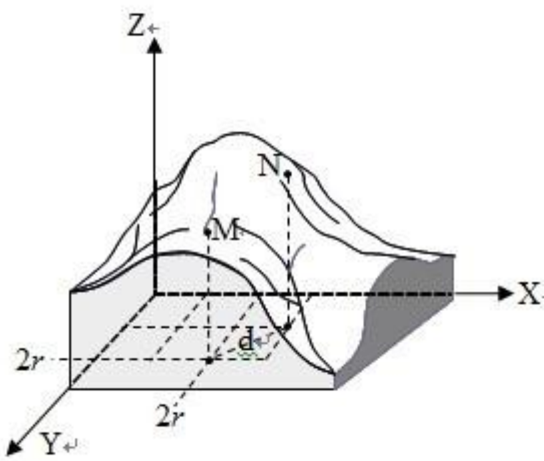



Figure 1. Space expression of dot pair in DEM

Hypothesizing the distance (project distance) between a pair of pixels equals to d, the direction angle of dot pair equals toθ, then when the direction is parallel with X-axis, θ equals to 0 and counterclockwise rotation around z-axis takes the positive direction. Choose a pair of pixels with direction θ and distance d from texture image and then statistics the joint conditional probability density, then a GLCM model C (d,θ) could be structured. Based on GLCM, Haralick proposed 14 textural features. According to existing research, this paper select 10 features to analysis the terrain characteristics.

*Parameter screening*

The parameter should satisfy the requirements of maximizing internal homogeneity while minimizing external homogeneity. In this paper we use the coefficient of variation. The equation is as follows:

$$CV = \frac{\sigma}{\mu} \times 100\%$$

Where σ is standard deviation and μ is the mean value. The smaller the CV value within class is, the more stable the feature will be. The bigger the CV value among class is, the more strong separating capacity the feature will be. Hence, we use the difference value between the CV value among class and the CV value within class to assess the discriminative capacity of each parameter.

*Establishment of BP model*

BP network is basically a gradient decent algorithm designed to minimize the error function in the weights space. During training of the neural network, weights are adjusted to decrease the total error. In principle, it has been proved that any continuous function can be uniformly approximated by BP network model with only one hidden layer. So a three-layer BP model is employed in our study. It is easy to determine the number of neurons in the input layer and output layer during applications. In this paper, the input neurons number depends on the texture parameters joined in the classification experiments and the output neurons number is eight which depends on the classification categories. However, it is not easy to choose the appropriate number of neurons in the hidden layer and in this paper it is determined by trial-and-error method.

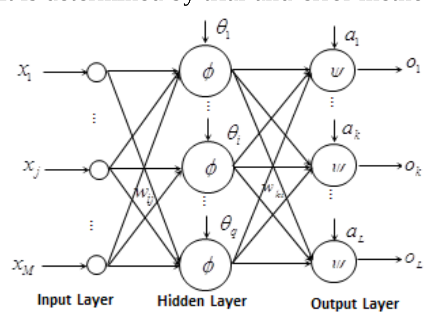



Figure 2. BP neural network structure

RESULT

Table Ⅱ shows the difference value between the CV value among class and CV value within class, the value varies in different parameters from different data. Some value is negative which means that the CV value with class of such parameter is greater than the CV value among class, and it is unsuited to classification experiments.

TABLE II. DIFFERENCE VALUE BETWEEN CV VALUE AMONG CLASS AND CV VALUE WITHIN CLASS

| | DEM | Hillshde | Slope | Curvature |
|---|---|---|---|---|
| **Angular Second Moment** | 0.168581 | 1.25958 | 1.259767 | 0.229531 |
| **Contrast** | 0.343481 | 0.29671 | 0.344383 | 0.112854 |
| **Variance** | -0.10602 | 0.008394 | 0.361408 | -0.05802 |
| **Inverse Different Moment** | 0.0551 | 0.191398 | 0.183427 | 0.051564 |
| **Average** | -0.05771 | 0.0135 | 0.280301 | -0.03641 |
| **Sum Variance** | -0.13523 | 0.10284 | 0.368139 | -0.05132 |
| **Sum Entropy** | 0.027231 | 0.283655 | 0.237616 | 0.106881 |
| **Entropy** | 0.054366 | 0.290388 | 0.27177 | 0.112752 |
| **Different Variance** | 0.18413 | 0.65725 | 0.607766 | 0.221478 |
| **Different Entropy** | 0.221065 | 0.260702 | 0.267087 | 0.137527 |

In this paper, BP neural network is applied to classify the terrain texture. Each study region contains 15 samples, 10 samples are selected as the training samples and the rest 5samples are chosen as the test samples.

Table Ⅲ shows the classification accuracy by using single data without parameter screening. The accuracy of slope data is the highest, while the accuracy of DEM data is the lowest which indicates that the texture form slope data is more suitable for terrain classification.

TABLE III. CLASSIFICATION ACCURACY BY USING SINGLE DATA

| DEM | Hillshade | Slope | Curvature |
|---|---|---|---|
| 52.5% | 62.5% | 77.5% | 55% |

Figure 3 shows the classification accuracy by using multiple data with parameter screening. According to the difference value in Table one, priority should be given to the parameter with high different value. Classification accuracy varies with parameter number changes but in any case, it is higher than the accuracy by using single data. The accuracy reaches the peak when using seven parameters and it could be regarded as the optimal parameter combination.


Figure 3. Classification accuracy as change of parameter number

## CONCLUSIONS

In oreder to overcome the shortcoming of describing the terrain characteristics on macro scale, in this paper, the GLCM model and BP neural network are introduced into digital terrain analysis. The results show that texture analysis starts from human vision perceptive mechanism can effectively analyze and quantify the morphological and structural characteristics of terrain surface and such method could be used and improved to reveal the morphological and structural characteristics of landform on macro scale, which can be recognized as a new thinking for the quantification and classification of landform morphological characteristics. In the further, some other complex textural analysis methods and classifiers should be applied, and it could reveal the morphological characteristics of landform in a more painstaking level.

## ACKNOWLEDGMENT

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