Establishment and Analysis of Passingness Evaluation Index of off-Road Vehicle Based on PCA

Rundong Xu\textsuperscript{a}, Wei Wang\textsuperscript{b}

Department of Artillery Engineering. The Army Engineering University of PLA.
Shijiazhuang, China

\textsuperscript{a}1135565552@qq.com, \textsuperscript{b}17692178689@163.com

Abstract. The cross-country passing ability of vehicles refers to the ability to pass complex terrain and soft ground with a certain average speed under rated load. For quantitative investigation off-road vehicle through indicators, this article from the perspective of the terrain, the first seven terrain factors determined by access to information, the second of ASTER GDEM elevation data to spatial analysis, get 7 class data, finally using the principal component analysis (PCA) to 7 kinds of terrain factor has carried on the correlation analysis and factor analysis, reflect the off-road vehicle is established evaluation index of complex terrain through sexual - integrated terrain index $Tr$. The results show that the comprehensive terrain index $Tr$ can account for 87.623% of the total variance of the original variable, and can integrate a single terrain factor.

1. Introduction

Cross-country vehicle passability [1] refers to the vehicle's ability to pass complex terrain and soft ground at a certain average speed under rated load [2,3], which is divided into geometric passability and support passability. The geometric permeability is related to the fluctuation of the surface, and the supporting permeability is related to the soil characteristics. The research on vehicle passability at home and abroad started in the 1970s, focusing on the study of ground characteristics and vehicle structure: g.y.bialadi summarized various prediction technologies used to solve cross-country movement problems, and gave the required terrain data types [1]. Ji xuewu et al. studied the effects of soil characteristics and vehicle structure on the passability of wheeled vehicles [2]. Liu Jude studied several key technologies of vehicle driving in sandy land environment [3]. Li Yang et al. simulated the climbing ability of crawler vehicles on hard road, clay road, heavy clay road and dry sand road, and analyzed the climbing ability of some crawler walking mechanisms under working conditions [4]. In recent years, with the development of GIS technology, scholars at home and abroad began to conduct qualitative and quantitative evaluation of vehicle passability from the perspective of terrain. James J.D ’onlon constructed a qualitative cross-country passability inference model based on location vocabulary using GIS technology [5]. Liu huajun proposed a cross-country terrain description method based on elevation map and evaluated the terrain feasibility according to fuzzy rules [6]. Fan linlin built a cross-country traffic model based on hexagonal grid and studied the shortest path planning algorithm [7]. However, the author found that most of the researchers did not objectively explain the selection of terrain factors when selecting terrain factors to evaluate the vehicle's passability, which could easily lead to
incomplete information in the evaluation model of vehicle's cross-country passability. Therefore, in this paper, the correlation analysis of terrain factors that affect vehicle cross-country passability was carried out, and the factors with higher vehicle correlation degree were screened and integrated by using the idea of "dimensionality reduction" of principal component analysis method, so as to provide a decision basis for quantitative evaluation of vehicle cross-country passability.

2. Knowledge of principal component analysis

2.1. Principle of principal component analysis

Principal components analysis (PCA) was invented by Carl Pearson in 1901, which was used to analyze data and establish mathematical models [8]. In multivariate statistical analysis, the principal component analysis method is often used to reduce the dimensionality of the data set while maintaining the feature that the difference in the data set contributes the most [8, 9]. Assume that the data set is a matrix of order $n \times p$:

$$X = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1p} \\ x_{21} & x_{22} & \cdots & x_{2p} \\ \vdots & \vdots & \ddots & \vdots \\ x_{n1} & x_{n2} & \cdots & x_{np} \end{bmatrix}$$ (1)

The number of indicators in the original data set was $p$, and the evaluation indicators were $x_1, x_2, \ldots, x_p$. After the dimension reduction by principal component analysis, the new evaluation index becomes $y_1, y_2, \ldots, y_q$, ($q < p$), namely:

$$\begin{cases} y_1 = l_{11}x_1 + l_{12}x_2 + \cdots + l_{1p}x_p \\ y_2 = l_{21}x_1 + l_{22}x_2 + \cdots + l_{2p}x_p \\ \cdots \cdots \cdots \cdots \cdots \cdots \cdots \cdots \cdots \\ y_q = l_{q1}x_1 + l_{q2}x_2 + \cdots + l_{qp}x_p \end{cases}$$ (2)

The determination principle of coefficient $l_{ij}$ is as follows:

1. $y_i$ and $y_j$ ($i \neq j, i, j=1,2,\ldots,q$) irrelevant;
2. $y_1$ is the largest variance of any linear combination of $x_1, x_2, \ldots, x_p$; $y_2$ is the largest variance of any linear combination of $x_1, x_2, \ldots, x_p$ except of $y_1$; $y_q$ is related to $y_1, y_2, \ldots, y_{q-1}$ all unrelated $x_1, x_2, \ldots, x_p$. All linear combinations of $x_p$ are the worst. Among the new evaluation indicators, $y_1, y_2, \ldots, y_q$ is called the original evaluation indexes’ $(x_1, x_2, \ldots, x_p)$ principal component. From the above theoretical analysis, it can be concluded that the essence of principal component analysis is to realize dimensionality reduction and convert $p$ variables in the original evaluation index into $q$ variables that are unrelated ($q < p$), so as to ensure that the constructed new variables can contain the main information of the initial $p$ variables.

2.2. The calculation process of principal component analysis

2.2.1. Standardize the raw data. The units of evaluation indicators in the original data are often different, and some of them are different by several orders of magnitude. Direct correlation analysis on them will make the results inaccurate. Therefore, in order to eliminate the impact of different units, it is necessary to first conduct standardized processing on the original data. The standardized calculation formula is as follows:
3

\[ x_i = \frac{X_i - \overline{X}_i}{S_i} \]  

(3)

Where, \( x_i \) is the value after standardization, \( X_i \) is the original value, is the mean value of the sample data, and \( S_i \) is the variance of the sample data.

2.2.2. Calculate the correlation coefficient matrix. The expression of correlation coefficient matrix is as follows:

\[
R = \begin{bmatrix}
R_{11} & R_{12} & \cdots & R_{1p} \\
R_{21} & R_{22} & \cdots & R_{2p} \\
\vdots & \vdots & \ddots & \vdots \\
R_{p1} & R_{p2} & \cdots & R_{pp}
\end{bmatrix}
\]  

(4)

Where \( r_{ij} \) \((i, j = 1, 2, \ldots, p)\) is the correlation coefficient between the original variable \( x_i \) and \( x_j \), \( r_{ij} = r_{ji} \), and its calculation formula is

\[
r_{ij} = \frac{\sum_{k=1}^{n} (x_{ik} - \overline{x}_i)(x_{jk} - \overline{x}_j)}{\sqrt{\sum_{k=1}^{n} (x_{ik} - \overline{x}_i)^2} \sqrt{\sum_{k=1}^{n} (x_{jk} - \overline{x}_j)^2}}
\]  

(5)

Where, \( \overline{x}_i \) and \( \overline{x}_j \) is the mean value of standardized values.

2.2.3. Solve for eigenvalues and eigenvectors. If you want to solve eigenvalues and eigenvectors, you can solve eigenequations \( |\lambda I - R| = 0 \) by using Jacobi method to get eigenvalues and arrange them in order of size as follows:

\[
\lambda_1 \geq \lambda_2 \geq \cdots \geq \lambda_p \geq 0
\]  

(6)

Then figure out the eigenvectors for \( \lambda_i \), then solve for the eigenvector \( e_i \) \((i = 1, 2, \ldots, p)\), requirements \( \|e_i\| = 1 \), namely:

\[
\sum_{j=1}^{p} e_{ij}^2 = 1
\]  

(7)

Where: \( e_{ij} \) represents the first \( j \) component of vector \( e_i \).

2.2.4. Solve the principal component contribution rate and cumulative contribution rate. The calculation formula of principal component contribution rate is as follows:
The formula for calculating the cumulative variance contribution rate is as follows:

$$\sum_{k=1}^{p} \frac{\lambda_k}{\sum_{k=1}^{p} \lambda_k} (i = 1, 2, \cdots, p)$$

(8)

The formula for calculating the cumulative variance contribution rate is as follows:

$$\sum_{k=1}^{p} \frac{\lambda_k}{\sum_{k=1}^{p} \lambda_k} (i = 1, 2, \cdots, p)$$

(9)

Generally, the characteristic value with the cumulative variance contribution rate over 80% is taken. Express the first, second... the m (m≤p) principal component.

2.2.5. The principal component loads and the principal component scores were calculated. The calculation formula of principal component load is as follows:

$$l_{ij} = p(z_i, x_j) = \sqrt{\lambda_i} e_{ij} (i, j = 1, 2, \cdots, p)$$

(10)

The obtained principal component score is taken as the coefficient before the original index of each principal component, and the expression is as follows:

$$Z = \begin{bmatrix} z_{11} & z_{12} & \cdots & z_{1m} \\ z_{21} & z_{22} & \cdots & z_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ z_{n1} & z_{n2} & \cdots & z_{nm} \end{bmatrix}$$

(11)

3. Topographic factors that describe ground complexity

3.1. Terrain factor classification

Terrain factor is a major component of surface morphology analysis and is widely used to describe ground complexity [5]. There are many topographic parameters used to describe topographic features and spatial distribution. For example, according to the geological application category, it is divided into general topographic attributes and hydrological characteristics; According to the complexity of terrain elements, it can be divided into single factor and compound parameter.; according to the information of the spatial structure can be divided into the microscopic factor, macro factor and other related information factor three categories, including micro factors, including slope, slope direction, ground curvature macroeconomic factors including relief degree, surface roughness, etc., other related information factors including solar radiation flux density, reflection coefficient, etc. [6]. For cross-country vehicles, surface information is mainly considered, so the analysis of terrain factors should start with micro and macro factors [7].

3.2. Microtopographic factor

Microtopographic factors include slope, slope direction, ground curvature, etc. What they describe and reflect are the topographic information characteristics of specific ground points.
3.2.1. Slope factor. Slope can be expressed as: the Slope of a certain point on the ground is the Angle between the tangent plane passing the point and the horizontal ground. Is the maximum rate of change in height, indicating the degree of inclination of the ground surface at this point. The essence of ground slope is a differential concept, which treats the ground as an infinite number of points, each of which has its own slope.

The slope $S$ of a point on the surface is a surface function $Z=f(x,y)$ on behalf of the elevation change rate of surface from east to west, from north to south. The mathematical expression of slope algorithm is

$$S = \arctan\left(\frac{p}{q}\right) \times \frac{180}{\pi}$$

(12)

Where, $S$ refers to the slope, $p$ is the rate of elevation change in the x direction, and $q$ is the rate of elevation change in the y direction. Therefore, the key to solving the slope at a certain point on the slope is to solve $p$ and $q$.

3.2.2. Aspect factor. The Angle between the normal projection of the tangent plane of any point on the ground and the due north direction passing the point is called the slope direction of the point. Calculated in a clockwise direction, the slope direction value range is 0°-360°. The mathematical expression of slope direction is:

$$\text{Direction} = \arctan\left(\frac{p}{q}\right)$$

(13)

Where, $p$ is the rate of elevation change in the x direction, and $q$ is the rate of elevation change in the y direction.

3.2.3. Ground curvature. Ground curvature is a representation of the degree of bending change at each point on the ground surface. The components of ground curvature in vertical and horizontal directions are plane curvature and section curvature respectively.

Ground curvature refers to the terrain surface, specific to any point, refers to the used point along the horizontal slice of the proceeds of the terrain surface plane of the curve at that point the curvature of the value, also is every bit of ground contour curve degree, use this numerical to quantitative description of the surface surface along the horizontal direction of bending, and the complexity of the ground were characterized. From another perspective, the plane curvature of the surface surface is also a measure of the degree of curvature of the curve perpendicular to the slope, and its mathematical expression is as follows:

$$Kh = \frac{q^2r - 2pqs + p^2t}{(q^2 + p^2)\sqrt{1 + p^2 + q^2}}$$

(14)

Where, $Kh$ refers to plane curvature, $p$ is the rate of elevation change in the x direction, $q$ is the rate of elevation change in the y direction, $s$ is the slope of the point, and $r$ is the radius of curvature of the point.

Section curvature refers to the curve that intersected with the normal direction of the point and the maximum elevation change direction in the small range at any point on the topographic surface. The curvature value of the curve at the point is section curvature. This value is used to quantify the bending and variation of surface surface in the vertical direction, so as to characterize the complexity of the ground. From another perspective, the section curvature of surface surface is also a measure of the rate of change of surface slope along the direction of maximum slope, and its mathematical expression is as follows:
\[
K_v = \frac{p^2 r + 2 pqs + q^2 t}{(q^2 + p^2)^2 \sqrt{1 + p^2 + q^2}} \tag{15}
\]

Where, \(K_v\) refers to section curvature, \(p\) is the rate of elevation change in the x direction, \(q\) is the rate of elevation change in the y direction, \(s\) is the slope of the point, and \(r\) is the radius of curvature of the point.

3.3. Macrotopographic factor
Macrotopographic factors include topographic relief degree, surface roughness, elevation variation coefficient, etc., which describe and reflect the macro topographic features in the large area of ground.

3.3.1. Topographic relief. Topographic relief, also known as relief or relief energy, local terrain, relative height, refers to the difference between the elevation of the highest point and the elevation of the lowest point in a specific area. It is a macroscopic indicator describing the topographic features of a region, and its mathematical expression is as follows:

\[
R = H_{\text{max}} - H_{\text{min}} \tag{16}
\]

Where, \(R\) represents topographic relief, \(H_{\text{max}}\) represents maximum elevation value within unit area, and \(H_{\text{min}}\) represents minimum elevation value within unit area.

3.3.2. Ground roughness. Ground roughness is an index reflecting the fluctuation and erosion degree of the surface. It is generally defined as the ratio of surface area of surface element to its projected area on the horizontal surface. Its mathematical formula is expressed as follows:

\[
R = \frac{S_{\text{surface}}}{S_{\text{level}}}, \quad 1 / \cos(Slope) \tag{17}
\]

Where, \(S_{\text{surface}}\) refers to the surface area of surface element, \(S_{\text{level}}\) refers to the projected area of surface element on the horizontal surface, and \(\text{Slope}\) refers to the surface Slope.

Surface roughness is a macro topographic factor that can reflect the fluctuation and erosion degree of terrain. In regional studies, surface roughness is an important quantitative index to measure the intensity of surface erosion. It is also of great significance to study surface roughness when studying soil and water conservation and environmental monitoring.

3.3.3. Variance Coefficient in Elevation. Variance Coefficient in Elevation is an index reflecting the relative change of Elevation within a certain distance of the surface, expressed by the ratio of Elevation standard deviation and mean value of the region. Its mathematical expression is:

\[
VCE_i = \frac{S_i}{\bar{Z}_i} \tag{18}
\]

Where, \(VCE_i\) refers to the variation coefficient of terrain elevation in the statistical region; \(S_i\) refers to elevation standard deviation of statistical region; \(\bar{Z}_i\) means of statistical region elevation; \(i\) is a natural number and refers to a statistical region.
4. Principal component analysis of terrain factors

4.1. Data source and preprocessing
The data used in this paper is derived from geospatial data cloud (http://www.gscloud.cn/). The original data is ASTER GDEM elevation grid data, with a spatial resolution of 30 meters and a spatial range of N35 to N37 in the north-south direction and E112 to E114 in the east-west direction, as shown in figure 1.

ARCGIS software was used to calculate the slope, slope direction, plane curvature, section curvature, topographic relief, surface roughness and elevation variation coefficients of the region. Raster data is converted into point elements, and the attribute list of point elements is derived to obtain the terrain factor value of this region. The pre-processing process is shown in figure 2.

Fig. 1 ASTER GDEM Elevation raster data

Fig. 2 Pre-processing flowchart
As the number of point elements in this region exceeds tens of millions, such a large sample data is not needed for principal component analysis. Therefore, in order to reduce the data processing time while ensuring accuracy, 200 data for each terrain factor are selected as samples for analysis, some of which are shown in table 1.

### Tab. 1 Partial terrain factor raw data

| Slope  | Asp ect | Ground curvature | Section curvature | Surface relief | Ground roughness | Variance Coefficient in Elevation |
|--------|---------|------------------|-------------------|----------------|-----------------|----------------------------------|
| 3.516  | 210.96  | 0.00000          | 2.96964           | 2.50000        | 1.00188         | 0.0008826                       |
| 9.348  | 219.81  | 0.00000          | 0.86614           | 5.33337        | 1.01345         | 0.0008826                       |
| 10.94  | 209.36  | 1.53431          | -4.15749          | 5.33337        | 1.01852         | 0.0008826                       |
| 11.91  | 182.86  | 0.00000          | -0.37121          | 3.16663        | 1.02200         | 0.0035902                       |
| 9.860  | 165.96  | -0.34646         | 0.51969           | 2.55554        | 1.01498         | 0.0035902                       |
| 5.549  | 192.53  | 1.12846          | -1.59371          | 3.00000        | 1.00470         | 0.0035902                       |
| 3.438  | 217.88  | -0.62289         | -0.12795          | 3.77771        | 1.00180         | 0.0094263                       |
| 2.298  | 336.80  | -0.72872         | 1.86971           | 3.27783        | 1.00080         | 0.0094263                       |
| 4.762  | 341.57  | 0.12374          | 1.11361           | 2.11108        | 1.00346         | 0.0094263                       |
| 4.387  | 344.06  | 0.00000          | -0.86614          | 1.11108        | 1.00294         | 0.0227967                       |
| 2.488  | 345.96  | 0.42070          | -0.32171          | 0.77771        | 1.00094         | 0.0227967                       |
| 0.603  | 270.00  | -0.24855         | -0.61976          | 2.44446        | 1.00006         | 0.0227967                       |
| 3.248  | 158.20  | -0.31097         | 1.29759           | 4.77783        | 1.00161         | 0.0057498                       |
| 6.799  | 135.00  | -0.60121         | -0.35374          | 6.00000        | 1.00708         | 0.0057498                       |

4.2. Calculate the correlation coefficient matrix

Before the principal component analysis, the correlation analysis of 7 terrain factors [10-12] was firstly conducted to determine whether the 7 factors were suitable for principal component analysis by comparing the correlation. Correlation coefficient matrix is shown in table 2.

As can be seen from table 2, the correlation coefficient of slope, surface fluctuation and surface roughness is over 0.7, presenting a very high correlation. The correlation coefficient between plane curvature and section curvature is -0.679. There is correlation between slope direction and slope slope, surface fluctuation and surface roughness, but the correlation degree is relatively low, which should be abandoned. The correlation between elevation variation coefficient and other 6 terrain factors is poor and should be abandoned. From the perspective of vehicle passability, slope information should be retained, so slope, ground undulation and surface roughness are selected for principal component analysis.
Tab. 2 Correlation coefficient matrix

| correlation coefficient | Slope | Aspect | Ground curvature | Section curvature | Surface relief | Ground roughness | Variance Coefficient in Elevation |
|-------------------------|-------|--------|------------------|-------------------|--------------|------------------|----------------------------------|
| Slope                   | 1.000 |        |                  |                   |              |                  |                                  |
| Aspect                  | 0.152 | 1.000  |                  |                   |              |                  |                                  |
| Ground curvature        | 0.081 | -0.122 | 1.000            |                   |              |                  |                                  |
| Section curvature       | 0.001 | 0.091  | -0.679           | 1.000             |              |                  |                                  |
| Ground relief           | 0.753 | 0.294  | -0.053           | 0.007             | 1.000        |                  |                                  |
| Ground roughness        | 0.958 | 0.153  | -0.110           | 0.031             | 0.725        | 1.000            |                                  |
| Variance Coefficient in Elevation | 0.012 | -0.072 | -0.032           | -0.087            | 0.050        | 0.032            | 1.000                            |

4.3. **Principal component analysis**

Principal component analysis was carried out on slope, surface relief and surface roughness, and the results were shown in table 3.

Tab. 3 Principal component variance and cumulative variance

| composition | Initial eigenvalue | Extract sum of squares and load |
|-------------|--------------------|---------------------------------|
|             | eigenvalue | variance % | cumulative value % | eigenvalue | variance % | cumulative value % |
| 1           | 2.629      | 87.623    | 87.623              | 2.629      | 87.623    | 87.623              |
| 2           | 0.330      | 11.000    | 98.623              |            |           |                    |
| 3           | 0.041      | 1.377     | 100.000             |            |           |                    |

According to the principle that the eigenvalue is greater than 1, a principal component is extracted, which explains 87.623% of the total variance of the original variable (80%~85% is better, which can represent the majority of the information of the original index).

According to table 4 after rotation of factor load matrix,

Tab. 4 The rotated factor load matrix

| Terrain factor | The first principal component |
|----------------|------------------------------|
| Slope          | 0.969                        |
| Surface relief | 0.876                        |
| Ground roughness | 0.960                    |

The first principal component and the degree of slope, surface relief and surface roughness were positively correlated, it mainly lies in the degree of slope, ground ups and downs and the significance of integrating the surface roughness, and form a composite index of characterization of topographic information, so can use the principal component known as the composite terrain index, the index contains information slope, height difference and surface roughness information, to a large extent determines the off-road vehicle complex terrain through capacity.

Table 5 is the principal component score calculated according to the regression algorithm, namely the coefficient of the score function.
### Tab. 5 Principal component score

| Terrain factor       | The first principal component |
|----------------------|-------------------------------|
| Slope                | 0.369                         |
| Surface relief       | 0.333                         |
| Ground roughness     | 0.365                         |

According to table 5 score function of available components:

\[ Tr = 0.369 \times \text{Slope} + 0.333 \times R_1 + 0.365 \times R_2 \]

Where, \( R_1 \) is ground fluctuation, and \( R_2 \) is surface roughness.

#### 4.4. Results

In order to verify whether the comprehensive terrain index \( Tr \) has guiding value, ARCGIS software is used to conduct data processing on an area with the comprehensive terrain index \( Tr \) as the index, and the results are shown in figure 3:

![Fig. 3 Comprehensive terrain index result map of a region](image)

It can be seen that by using the comprehensive terrain index \( Tr \) to evaluate the terrain, the results obtained in the figure can identify the impossible passage areas of cross-country vehicles such as rivers and reservoirs. At the same time, for the passing zone, the comprehensive terrain index is classified. The green to red indicates that the passing zone is more difficult for cross-country vehicles. Therefore, the passing zone can be evaluated by using this index.

#### 5. Conclusion

Under the background of modern science and technology, more and more attention has been paid to the cross-country vehicle's ability to pass complex terrain. With the development of GIS technology, it is of guiding significance to objectively evaluate the cross-country vehicle's ability to pass terrain from the perspective of terrain.

In this paper, using principal component analysis method, the four kinds of micro terrain factor and three macro terrain factor was analyzed, and the analysis results show that the slope, the ground fluctuation degree is higher, and the surface roughness of correlation slope and elevation variation coefficient and other related basic terrain factor does not exist, cannot be used for principal component analysis, surface curvature and the section curvature has a high correlation, but ups and downs and slope, ground and surface roughness is not relevant. Slope information is very important when investigating the cross-country passing ability of vehicles. In this paper, the characteristic value and principal component score of terrain factors including slope, ground fluctuation and surface roughness are calculated comprehensively. According to the calculation results, the first eigenvalue contains 87.623% of the three terrain factors, which can be used as a comprehensive attribute set of slope,
ground fluctuation and surface roughness. The first characteristic value was named as comprehensive terrain index Tr, in which slope accounted for 36.9%, ground undulation for 33.3%, and surface roughness for 36.5%. By using the comprehensive terrain index Tr and ARCGIS software, the cross-country passability of vehicles in a certain region was evaluated, and the evaluation results could correctly distinguish the passable area from the non-passable area, and the passable area was graded.

The focus of the next study will be to make a cross-country thematic map that conforms to the passing ability of cross-country vehicles based on the comprehensive terrain index Tr and relying on GIS tools.

6. References
[1] Li shiwu, Zhang zhaoli, Yang chunwei, et al. Analysis of vehicle passability on ramp and path optimization [J]. Science, technology and engineering, 2018, 18(22): 144-149.
[2] Fan zhitao. Performance analysis and development prospect of off-road vehicle [J]. Shandong industrial technology, 2018, (21): 51.
[3] Yao ming, He jianqing, He ren, et al. Determination of vehicle speed in mobility evaluation of off-road vehicle [J]. Automotive engineering, 2012, 34(10): 885-888.
[4] Baladi G J O T. Terrain evaluation for off-road mobility[J], 1987, 24(2): 127-140.
[5] Ji xuewu, Fan huwen, Zhao liuqi. The performance analysis of wheeled cross-country vehicle [J] Petroleum geophysical equipment, 1996, (02): 1-10.
[6] Liu jude. Discussion on several key issues in the research on the passability of vehicle sand [J] Automotive engineering, 1996, (02): 103-107+76.
[7] Li ming. Research on obstacle avoidance path planning and lateral control of intelligent vehicles [D]. Dalian university of technology, 2013.
[8] Donlon J, Forbus K D. Using a geographic information system for qualitative spatial reasoning about trafficability [C]. Proc. of the Qualitative Reasoning Workshop, 1999.
[9] Liu huajun. Research on road environment understanding technology for intelligent vehicles [D]. Nanjing university of science and technology, 2007.
[10] Fan linlin. Research on cross-country path planning based on hexagonal grid [D]. PLA information engineering university, 2017.
[11] Gan yan, Wei yan, Yang you. The application of SVM method combined with PCA in school financial risk early warning [J] Journal of chongqing university of science and technology (natural science edition), 2014, 16(04): 143-146+161.
[12] Dong jianwei, Chen yanmei, Meng pan. A method for determining the weight of influential factors of PM2.5 based on principal component analysis [J]. Journal of guangdong normal university of technology, 2016, 37(11): 25-28+52.
[13] Yang shuju. The application of principal component analysis in student achievement evaluation [J]. Practice and understanding of mathematics, 2012, 42(16): 103-112.
[14] Yang rongfeng, Yang kun, Hong liang, et al. Topographic factor analysis and comparison based on different spatial resolution DEM [J]. Journal of yunnan normal university (natural science), 2018, 38(05): 75-78.
[15] Liu xinhua. Topographic factor analysis and extraction of regional soil erosion [D]. Northwest a & f university, 2001.
[16] Wang yan. Topographic information extraction and landscape spatial pattern analysis based on DEM [D]. Southwest university, 2006.
[17] Wang liangyu, Xia qile, Chen jiabing, et al. Study on adaptability of citrus juice preparation based on principal component analysis [J]. Journal of fruit trees: 1-17.
[18] Chen zhen, Ma xixia, Zhang xiaolei. Risk assessment of mountain flood disaster in small watershed based on PCA and AHP [J]. Hydropower energy science, 2018, 36(11): 56-59.
[19] Shu tianzhu, Wang xiaohong. The correlation between topographic relief and regional soil erosion based on 3S technology [J]. Soil and water conservation research, 2017, 24(04): 127-132.