He et al.
EURASIP Journal on Advances in Signal Processing (2023) 2023:11
https://doi.org/10.1186/s13634-023-00971-x

EURASIP Journal on Advances in Signal Processing

RESEARCH Open Access

Evaluation method for the hyperspectral image camouflage effect based on multifeature description and grayscale clustering

Zhenxin He, Yuanying Gan*, Shixin Ma, Chuntong Liu and Zhongye Liu

*Correspondence: yiran_gan@sina.cn

School of Missile Engineering, PLA Rocket Force University of Engineering, Xi'an 710025, China

Abstract

Hyperspectral images have a special attribute with both spectral and spatial information, which is of great significance for the evaluation of the stealth performance of camouflaged targets. Aiming at the problems of a single evaluation index and the low credibility of traditional optical camouflage evaluation methods, this paper proposes a grayscale clustering camouflage effect evaluation method based on multifeature descriptions of hyperspectral images using similarity indicators that reflect different spectral characteristics of the target and background. From the perspective of spectrum and human visual contrast, a comprehensive evaluation index system including spectral distance feature, spectral derivative feature, curve shape feature and spatial texture feature is constructed by combining spatial–spectral multi-feature constraints. At the same time, an improved Delphi method is proposed to simulate the expert decision-making process, and better evaluation weights are obtained by comparison and screening. The comprehensive evaluation of camouflage effect based on whitening function gray clustering is realized. The proposed method can not only give the "excellent" and "bad" of camouflage effect qualitatively, but also calculate the comprehensive score of camouflage effect by model.

Keywords: Hyperspectral image, Camouflage evaluation, Whitening weight, Grayscale clustering

1 Introduction

The emergence of hyperspectral remote sensing has led to a revolution in the remote sensing field. It mainly uses hyperspectral detection equipment to obtain narrowband spectral information to achieve ground object detection [1–3]. Compared with traditional optical images, hyperspectral images contain not only the spatial information of the ground feature distribution, but also the unique spectral information of the ground features. It has strong technical advantages for camouflage and the identification and detection of military targets, making it a new type of military reconnaissance method [4]. In the modern military battlefield, "attack" and "defense" are always a pair of "spear" and "shield." Improving the stealth capability of military targets means improving the survivability of the battlefield, which is important for winning military wars in the new situation. Therefore, using the full-band characteristics of hyperspectral to evaluate the stealth effect of camouflaged targets has extremely high application value [5, 6].

2 Related work

In recent years, some domestic scholars have begun to pay attention to the stealth effect of camouflage targets under hyperspectral reconnaissance methods and have launched research on the evaluation methods of camouflage effects based on hyperspectral images. It mainly includes two types based on image processing and spectral characteristics. The literature [7, 8] adopts the idea of principal component analysis processing (PCA), which uses wavelet transform to extract the four components of low frequency, horizontal high frequency, vertical high frequency and diagonal high frequency from the first principal component as a camouflage effect. The evaluation index of the company has achieved a certain comparative effect. However, this method is still essentially an image-based camouflage evaluation method, which does not make full use of the spectral information of hyperspectral images. The literature [7] combines the characteristics of high spectral resolution of hyperspectral images, and uses Euclidean distance to calculate spectral features to quantify the camouflage effect under hyperspectral imaging. In literature [9], anomaly detection algorithm is introduced into camouflage effect evaluation. Similarly, Euclidean camouflage coefficient is defined to quantitatively analyze camouflage effect. The literature [10] proposed a hyperspectral camouflage effect evaluation method based on intuitionistic fuzzy decision. In literature [11], combined with the finite time search strategy, a camouflage evaluation method based on hyperspectral image detection is proposed, which has certain rationality and feasibility. However, the above methods do not make full use of the spectral feature information of hyperspectral images, and the calculation of similarity is only through simple linear weighting. The results have certain objectivity, but the reliability is not strong.

The core idea of camouflage effect evaluation method based on spectral features is to mine different similarity indexes in spectral dimension. In addition to the commonly used spectral angular distance [12, 13] and spectral derivative vector [14, 15], the literature [16] considers the similarity of the shape of the spectral curve on this basis. In essence, the correlation degree of the slope of each point of the two spectral curves is used as the basis for camouflage evaluation, and the results have certain reliability. However, the practicability and innovation of the overall evaluation method are still relatively lacking.

In summary, the existing evaluation methods are roughly divided into two categories. One relies only on spatial dimension features (such as hue, brightness, texture, and patches), and the other relies too much on spectral dimension features and ignores the spatial features between the target and the background. At the same time, the traditional camouflage effect evaluation method is dependent on the observer's eye discrimination, with a strong subjective color. In order to avoid this situation, a large number of researchers set the discriminant indicators as the quantized eigenvalues, which completely lost the professional judgment opinion. Overall, there is little research on camouflage effect evaluation technology based on hyperspectral images at home and abroad, and it is still mainly based on the comparison of simple similarity indicators. It is difficult to intuitively and quantitatively evaluate the camouflage effect from the overall perspective of spatial and spectral characteristics. Therefore, this paper adopts a hierarchical weighted comprehensive evaluation method based on image camouflage evaluation theory. First, the similarity characteristics of the image are constructed, and on this basis, the improved Delphi method is used to simulate the expert decision-making process to determine the weights of different indicators, construct the evaluation index matrix and combine the grayscale clustering comprehensive evaluation method to give a comprehensive evaluation result.

The major contributions of this paper are as follows:

1. We propose a camouflage effect evaluation method based on hyperspectral spatial–spectral similarity feature multi-index joint, which combines spectral similarity and spatial feature similarity, and solves the problem of single and one-sided evaluation index of traditional evaluation methods.
2. We introduce multiple sets of weight data to select the optimal value to replace the traditional expert decision-making, effectively ensuring the objective fairness of decision-making; based on the whitening weight function, the decision matrix is constructed, and the gray level is defined to realize the process of evaluating the camouflage effect from fuzzy to clear.
3. Based on the proposed hyperspectral camouflage effect evaluation method, the camouflage performance of a certain camouflage strategy under different backgrounds can be given. It can also judge the order of different camouflage strategies in the same background. That is to say, it can be qualitatively described by hierarchical division, or quantitatively evaluated by comprehensive decision-making measurement results.

3 Methodology

3.1 Image-similarity features

1. *Spectral Distance Feature*: In hyperspectral image processing, the spectral angle cosine (SAC) [17] is often used to calculate the similarity of two spectral curves. Assuming that x and y represent the average spectral vector of the target and background in a certain area, respectively, the calculation formula of SAC is:

$$s_{\mathrm{SAC}}(x,y) = \cos\langle x,y\rangle = \frac{\langle x,y\rangle}{\sqrt{\langle x,x\rangle}\sqrt{\langle y,y\rangle}} \tag{1}$$

It can be seen from the above formula that the spectral angle distance is actually the cosine of the generalized angle between the two spectral curve vectors. Obviously, the higher the similarity between the two spectral curves, the greater the cosine value of the included angle, which reflects the better camouflage effect of the target. At the same time, it can also be seen that the size of the spectral angular distance is only a measure of curve similarity. In the high-dimensional space, it only reflects the parallelism of the two eigenvectors. It has nothing to do with the size and can effectively avoid the interference caused by factors such as the sun's incident angle and brightness. As a distance measurement method, spectral angular distance has strong objectivity and reliability in camouflage evaluation.

2. *Spectral Derivative Feature*: Spectral derivatives can reduce the characteristic interference caused by partial atmospheric transmission and have some superiority in geophysical spectral morphological analysis [18]. The spectral derivative characteristic (SDC) can reflect subtle changes in the spectral curve, mainly in the slope, gradient and other information. This change is able to highlight the absorption characteristics of the material in the characteristic band and better express the essential characteristics of the target and the background. Considering the hyperspectral image $X = \{x_i\}_{i=1}^{n}$ with d bands and n pixels, the spectral derivative of the first image element can be defined as:

$$x_i' = \mathrm{d}x_i / \mathrm{d}\lambda \tag{2}$$

For the discretization of the previous test, the differential expression of x_i' can be obtained:

$$x_i' = \left[\left|x_{i,2} - x_{i,1}\right|, \left|x_{i,3} - x_{i,2}\right|, \ldots, \left|x_{i,d} - x_{i,d-1}\right|\right] \tag{3}$$

Similarly, the average spectral derivatives x' and y' correspond to the target and background, respectively, which are used to compute generalized cosine values:

$$s_{\mathrm{SDC}}(x, y) = \cos\left\langle x', y' \right\rangle = \frac{\left\langle x', y' \right\rangle}{\sqrt{\langle x', x' \rangle}\sqrt{\left\langle y', y' \right\rangle}} \tag{4}$$

The spectral curve variation information, reflected by the spectral derivative feature, is essentially a way to evaluate the camouflage effect from the perspective of the curve shape. Therefore, describing the similarity of the target and background using spectral derivative features is important to enhance the objective of camouflage effect evaluation.

3. *Curve Shape Feature*: Different from the spectral derivative feature, the spectral correlation coefficient (SCC) can be obtained for the "slope" of each point; the spectral vector information can be integrated, and the absolute correlation degree of the spectral curve (ASC) can be used. The degree of similarity between two spectral curves can be determined [16].

Deviation standardization was used to normalize the target spectrum and background spectrum:

$$Y_i = \frac{x_i - \min(x_i)}{\min(x_i) - \max\left(y_i\right)} \tag{5}$$

For the average spectral derivative of the background and target and the sum of the normalized spectral data, the spectral correlation coefficient is calculated as:

$$\xi\left(j\right) = 1 / \left[1 + \left|x'\left(j+1\right) - y'\left(j+1\right)\right|\right] \tag{6}$$

where $j = 1, 2, \ldots, d-1$. Combining the information of the optical correlation coefficient, we obtain the average, namely the absolute correlation of the spectral curve, which can be expressed as:

$$s_{\mathrm{ASC}} = \frac{1}{d-1}\sum_{j=1}^{d-1}\xi\left(j\right) \tag{7}$$

The absolute correlation calculated by the above formula reflects the spectral line shape characteristics of the two spectral curves and is comparable. It can be seen that the greater the value of the absolute correlation, the higher the spectral similarity between the target and the background; otherwise, the smaller the absolute correlation value, the worse the similarity, indicating a poor camouflage effect.

4. *Spatial Texture Feature*: Texture is a visual feature that reflects grayscale statistics and distribution characteristics and spatial arrangement structure, which is different from image features such as grayscale and color. For hyperspectral data, the texture structure reflects the spectral difference between different spatial pixels and reflects the spatial transformation law of the spectrum. Therefore, using spectral data to express the spatial texture structure and establishing a camouflage evaluation index based on spatial texture features is of great significance for distinguishing camouflage from background.

Principal component analysis is the most commonly used feature extraction algorithm, and the obtained first principal component reflects the maximum amount of information of the spectral data. Therefore, the spectral data can be converted into a grayscale image through the dimensionality reduction method, and then the texture extraction algorithm can be used to obtain the largest feature of the grayscale image.

The wavelet transform [19] is the most commonly used feature extraction algorithm in the process of obtaining texture structures. Multilayer wavelet decomposition is used for the first principal component, and four wavelet components are used as variables to extract texture features:

$$\begin{cases} T_1 = (cH_m + cV_m + cD_m)\big/\, cA_m \\ T_2 = cH_m\big/\, cV_m \end{cases} \tag{8}$$

where cH_m,cV_m , and cD_m are the horizontal, vertical, and diagonal wavelet components, respectively; T_1 is the ratio of high-frequency components and low-frequency components after wavelet transformation, which is used to express the spatial frequency characteristics of image texture; T_2 is the ratio of horizontal and vertical components after wavelet transformation, which is used to express the differentiation direction characteristics of image texture. Then, the spatial texture feature (spatial texture feature, STF) can be expressed as the weighted sum of, namely:

$$T = K(T_1, T_2) \tag{9}$$

The difference (T_x, T_y) between the spatial texture characteristics of the target and the background is used as the similarity index:

$$s_{\mathrm{STF}} = 1\big/\left(1 + \left|T_x - T_y\right|\right) \tag{10}$$

3.2 A comprehensive evaluation index system

Different similarity characteristics reflect the camouflage characteristics of the target relative to the background from different angles. On this basis, it is necessary to integrate the characteristics of various indicators to find a comprehensive measurement method that can better reflect the camouflage characteristics of the target. The difficulty of comprehensive evaluation lies not in the "cognitive uncertainty" in fuzzy mathematics but in how to obtain the inherent meaning of the camouflage characteristics from the indicators that have been obtained. Gray system theory has strong superiority in solving this problem.

The comprehensive evaluation is based on the multifeature description of the background and camouflage images, and the ultimate goal is to give a comprehensive decision measure result of the camouflage effect. Among them, based on improving the weight construction of the Delphi method and the gray clustering comprehensive evaluation method based on the whitening weight function is two important links, in essence through the simulation of the expert decision-making process, combined with the gray evaluation clustering characteristics and the more intuitive and detailed comprehensive camouflage effect evaluation index, that explain the "advantages and disadvantages" of the camouflage effect.

1. *Linear Normalization*: To achieve the consistency of each index in the multi-index system, all indices are required to have the same dimension, order of magnitude and unit. Therefore, different index data need to be standardized.

Consider three normalization methods: normalization, scale transformation and range transformation. Because the scale transformation can retain the original feature difference to the greatest extent, it also has different data requirements (trending to "0," toward "1" and toward the center). Different nondimensional processing methods are used, and the nondimensional processing method of linear proportional transformation is used here.

Linear scale transformation mainly includes the lower limit measure, central measure and upper limit measures; different measurement methods reflect the different application scope, and the upper limit measurement method does not change the original index discrimination direction, for the camouflage effect evaluation index, has the tendency of "1" characteristics, to reflect the difference as far as possible between target and background. The upper-limit measure method is used here.

$$\delta_{ki} = d_k^i \Big/ \max_k d_k^i \tag{11}$$

2. *Delphi Tips for Weight Construction*: For a multi-index evaluation system, the selection of weights is of great significance. Different indices can easily lead to deviations in evaluation results and sometimes interfere with decision-makers' decision-making and causes them to obtain incorrect decision-making results. Delphi is a more commonly used weight construction method, but its essence is a survey method for collecting expert opinions. It involves the processing and analysis of expert opinions. It is affected by the number of experts and the degree of expertise of the experts. It is easy to cause inconsistencies in the weighting results. This paper uses big data to simulate the expert decision-making process and obtains the best evaluation weights through comparison and screening [20].

If the initial weight of each index is $w^* = \{w_i^*\}_{1\times n}$, the weight vector construction result of each index can be normalized:

$$
\begin{aligned}
w &= \left\{ \frac{w_1^*}{\sum_{i=1}^{n} w_i^*}, \frac{w_2^*}{\sum_{i=1}^{n} w_i^*}, \ldots, \frac{w_n^*}{\sum_{i=1}^{n} w_i^*} \right\} \\
&= \{w_1, w_2, \ldots, w_n\}
\end{aligned}
\tag{12}
$$

3. *Comprehensive Evaluation of Gray Clustering*: The so-called "gray" refers to the knowledge and unknown of the judgment process. In the actual camouflage evaluation process, the characteristic description of things is often known, and how to evaluate or evaluate the results is often unknown. Gray clustering [21] uses known observation indicators to classify unknown results through custom categories, in which "category" represents the "good or bad" difference of the expert decision layer, which is actually a hierarchical discrimination method with index direction. Gray clustering mainly includes the following steps:

Step 1: Establish an indicator set

Suppose that there are n objects and m evaluation indices, and establish an evaluation index matrix $U = [u_1, u_2, \cdots, u_n]^T$ where is the eigenvector of the *i*'s object.

Step 2: Normalization of the indicator characteristics

The directly obtained raw data are inconsistent in terms of magnitude and unit, making it difficult to equally evaluate target camouflage performance; therefore, the raw data should be normalized before using each metric. To better unify the metrics, the central effect measure normalization method of the linear scale transformation is used here.

Step 3: Construct the whitening weight function and set the evaluation level.

The process of evaluating things from fuzzy to clear corresponds to the gray evaluation system, which is equivalent to the process of grayscale changing from "gray" to "white," in which the whitening weight function plays a key role.

The evaluation grade is delimited from best to inferior according to the evaluation requirements, and s gray classes must be determined according to the number of evaluation grades. Based on this, you can divide the range $[a_1, a_{s+1}]$ for an indicator into subsets:

$$
\begin{aligned}
&[a_1, a_2], [a_2, a_3], \ldots, [a_{k-1}, a_k], \ldots \\
&[a_{s-1}, a_s], [a_s, a_{s+1}]
\end{aligned}
\tag{13}
$$

Determine the triangulated whitening function of *k*'s class as:

$$
f_j^k(\cdot) \quad \left(j = 1, 2, \ldots, m; k = 1, 2, \ldots, s\right)
\tag{14}
$$

Assuming that the observed value of the *k*'s index is, the membership degree of the category can be calculated by the following formula:

$$
f_j^k(x) = \begin{cases} \frac{x - a_{k-1}}{\lambda_k - a_{k-1}}, & x \in [a_{k-1}, \lambda_k) \\ \frac{a_k - x}{a_k - \lambda_k}, & x \in [\lambda_k, a_k] \end{cases}
\tag{15}
$$

Step 4: Constructing the index weights

Weights were determined by using a modified Delphi method, using multiple sets of weight data experiments instead of expert decisions, to obtain reliable weight vectors $w = (w_1, w_2, \ldots, w_m)$.

Step 5: Calculate the samples' decision coefficient matrix

The decision coefficient for judging whether object i belongs to category k can be expressed as:

$$\sigma_i^k = \sum_{j=1}^{m} f_j^k \left(x_{ij} \right) w_j \tag{16}$$

The sample decision coefficient matrix can be obtained as follows:

$$\Sigma = \left(\sigma_i^k \right) = \begin{bmatrix} \sigma_1^1 & \sigma_1^2 & \cdots & \sigma_1^s \\ \sigma_2^1 & \sigma_2^2 & \cdots & \sigma_2^s \\ \vdots & \vdots & & \vdots \\ \sigma_n^1 & \sigma_n^2 & \cdots & \sigma_n^s \end{bmatrix} \tag{17}$$

Step 6: Determine the gray class grade.

The matrix $\sum$ is normalized by rows, and the normalized unit decision coefficient matrix can be obtained:

$$\delta_i^k = \frac{\sigma_i^k}{\sum_{k=1}^{s} \sigma_i^k} \tag{18}$$

If $\max_{1 \le k \le s} \left\{ \delta_i^k \right\} = \delta_i^{k^*}$, k^* is the category to which i's object belongs (i.e., the evaluation level).

Step 7: Determine the comprehensive decision-making degree

After determining the evaluation rating of all the objects, it is still impossible to compare with the objects of the same level, so the comprehensive decision degree needs to be introduced. Assuming there is the decision coefficient η, it is necessary to combine the adjustment coefficients of the different decision classes.

$$\begin{cases} \eta_1 = (s, s-1, s-2, \ldots, 1) \\ \eta_2 = (s-1, s-1, s-2, \ldots, 2) \\ \eta_3 = (s-2, s-1, s-1, \ldots, 3) \\ \vdots \\ \eta_4 = (1, 2, 3, \ldots, s-1, s) \end{cases} \tag{19}$$

$\eta_1, \eta_2, \ldots, \eta_s$ are then called the adjustment coefficients of class 1, class 2, ..., class s, respectively.

Step 8: Comprehensive evaluation results

Define comprehensive decision measures for objects 1 and 2 of the same hierarchy:

$$\begin{cases} \varepsilon_1 = \eta_k \delta_1^T \\ \varepsilon_2 = \eta_k \delta_2^T \end{cases} \tag{20}$$

If

$$\begin{cases} \max\limits_{1 \le k \le s} \left\{ \delta_{i_1}^k \right\} = \delta_{i_1}^{k^*} \\ \max\limits_{1 \le k \le s} \left\{ \delta_{i_2}^k \right\} = \delta_{i_2}^{k^*} \\ \varepsilon_1 > \varepsilon_2 \end{cases} \tag{21}$$

Then, it is judged that Target 1 is better than Target 2.

4 Experimental results and analysis

4.1 Experimental data

The experimental data were taken by the gaiasky series on-mounted spectroscopy imaging system (DJI m600 pro on the airborne platform), with parking coverage in the visible and near-infrared bands (396.4 1024.8 nm) and can be used to analyze the camouflage characteristics of stealth targets in the visible and near-infrared range of the high spectrum. In addition, there are a total of 256 bands, the spectral detection rate of 2.2 to 2.3 n m, the image size and the spatial resolution of 60 m height of 1.92 cm.

The experimental data have high spectral differentiation and spatial resolution, which can be used to calculate the spectra and texture of camouflage targets and background and then finely analyze the camouflage performance of stealth targets, which has strong reliability.

4.2 Assessment of camouflage effect

The background of the camouflage target is mainly vegetation and grass grassland. To compare the camouflage background and camouflage effect, typical objects are selected for camouflage analysis.

As shown in Fig. 1, a total of five typical objects are selected, among which the camouflage net and the car are the target objects to analyze and compare the stealth ability before and after vehicle camouflage; locust tree and spruce, as two typical vegetation backgrounds and cement land as the road background, are used to analyze and compare the stealth ability of the camouflage network in different ground backgrounds.

The camouflage network adopts the jungle camouflage network produced by Taizhou Huayi Equipment Technology Co., Ltd. The size of the camouflage network is $6{:}8 \times 6{:}8$ m, and the color can match various background colors. The near-infrared spectral reflectivity of green spots is not less than 0.5, with certain visible light and near-infrared camouflage characteristics.

Fig. 1 Hyperspectral scene. Objects represented by the label: (1) camouflage net, (2) cars, (3) wutong, (4) spruce, (5) cement

1. *Evaluation index system*: Four characteristics of spectral distance, spectral derivative, curve shape and spatial texture were selected as evaluation indicators to calculate the characteristic similarity of the camouflage net, automobile and locust tree, spruce, grassland and cement by the linear normalization method, and finally establish the evaluation index system shown in Table 1.

2. *Determine the weight*: For the comprehensive evaluation method of grayscale clustering, the weight of various indicators is the problem that must be solved, and the weighted model directly determines the camouflage evaluation effect. Therefore, this section starts from the reliability of the camouflage method and selects a large number of target points and background points to simulate the expert decision of the Delphi method to obtain an optimized weighted model.

The comprehensive camouflage coefficient is used as an index to evaluate the rationality of the weight:

$$s_{\text{total}} = w_1 s_{\text{SAC}} + w_2 s_{\text{SDC}} + w_3 s_{\text{ASC}} + w_4 s_{\text{STF}} \tag{22}$$

The so-called expert decision of the simulated Delphi method is the process of judging the rationality of the comprehensive camouflage coefficient based on the known prior camouflage properties. A set of 30 data points was selected from the hyperspectral images. When the target points were unchanged, grass, various vegetation and vehicles were selected. Almost reliable weight parameters were obtained through a large number of experiments, and the weights were accurate to those after the decimal point. The weight ratio results as shown in Table 2.

3. *Determine the camouflage evaluation rating level*: According to the effect of camouflage, four evaluation grades "excellent, good, medium and poor" are determined and extended to six grades from left to right. Then, the corresponding number of categories is set to $k=0, 1, 2, 3, 4, 5$. Referring to Eq. (15), the extended triangular whitening weight function $f_j^k(x)$ is shown in Fig. 2.

As shown in Fig. 2, there is a decision ambiguity for each category membership. Assuming that the value of the function variable is normalized, the coefficient of the whitening weight function $f_j^s(s = 6)$ is determined according to the six camouflage levels, then $a_k(k = 0, \ldots, 6) = [0.15, 0.3, 0.45, 0.6, 0.75, 0.9, 1.05]$. The whitening weight functions $f_j^k(x)$ corresponding to each category are shown in Table 3.

Table 1 Evaluation index system

Evaluation Index	Target	Background			
		Spruce	Wutong	Grass	Cement
Spectral Distance	Camouflage Net	1	0.8323	0.9679	0.3241
	Cars (Black)	0.2679	0.1562	0.7490	1
Spectral Derivative	Camouflage Net	0.7962	1	0.8005	0.4358
	Cars (Black)	0.3762	0.3219	0.3773	1
Curve Shape	Camouflage Net	0.6946	0.5190	1	0.2561
	Cars (Black)	0.4924	0.2828	0.1351	1
Spatial Texture	Camouflage Net	1	0.9542	0.6937	0.0323
	Cars (Black)	0.4321	0.5791	0.1345	1

Table 2 Approximately optimal weight results

Point location		Camoufalge coefficient				
		Spectral distance	Spectral Derivative	Curve Shape	Spatial Texture	Comprehensive index
Weight		0.4	0.1	0.2	0.3	–
A	Target point: (200, 180)	0.978	0.163	0.656	0.888	0.805
	Background point: (190, 60)					
B	Target point: (200, 180)	0.013	0.151	0.264	0.879	0.326
	Background point: (200, 260)					
C	Background point: (200, 180)	0.982	0.160	0.786	0.541	0.728
	Background point: (330, 200)					

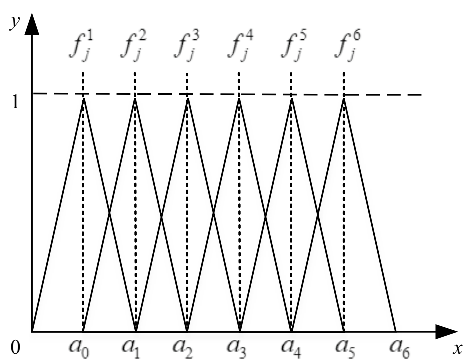

Fig. 2 Triangular whitenization weight function diagram

Table 3 Corresponding whitening weight functions

Class	Gray whitening weight function	Class	Gray whitening weight function
0	$f_j^0(u_{ij}) = \begin{cases} \frac{u_{ij}-0.75}{0.9-0.75}, & u_{ij} \in (0.75, 0.9] \\ \frac{1.05-u_{ij}}{1.05-0.9}, & u_{ij} \in (0.9, 1.05] \\ 0, & u_{ij} \notin (0.75, 1.05) \end{cases}$	1	$f_j^1(u_{ij}) = \begin{cases} \frac{u_{ij}-0.6}{0.75-0.6}, & u_{ij} \in (0.6, 0.75] \\ \frac{0.9-u_{ij}}{0.9-0.75}, & u_{ij} \in (0.75, 0.9] \\ 0, & u_{ij} \notin (0.6, 0.9) \end{cases}$
2	$f_j^2(u_{ij}) = \begin{cases} \frac{u_{ij}-0.45}{0.6-0.45}, & u_{ij} \in (0.45, 0.6] \\ \frac{0.75-u_{ij}}{0.75-0.6}, & u_{ij} \in (0.6, 0.75] \\ 0, & u_{ij} \notin (0.45, 0.75) \end{cases}$	3	$f_j^3(u_{ij}) = \begin{cases} \frac{u_{ij}-0.3}{0.45-0.3}, & u_{ij} \in (0.3, 0.45] \\ \frac{0.6-u_{ij}}{0.6-0.45}, & u_{ij} \in (0.45, 0.6] \\ 0, & u_{ij} \notin (0.3, 0.6) \end{cases}$
4	$f_j^4(u_{ij}) = \begin{cases} \frac{u_{ij}-0.15}{0.3-0.15}, & u_{ij} \in (0.15, 0.3] \\ \frac{0.45-u_{ij}}{0.45-0.3}, & u_{ij} \in (0.3, 0.45] \\ 0, & u_{ij} \notin (0.15, 0.45) \end{cases}$	5	$f_j^5(u_{ij}) = \begin{cases} \frac{u_{ij}-0}{0.15-0}, & u_{ij} \in (0, 0.15] \\ \frac{0.3-u_{ij}}{0.3-0.15}, & u_{ij} \in (0.15, 0.3] \\ 0, & u_{ij} \notin (0, 0.3) \end{cases}$

4. *Evaluation level*: The results of the evaluation index in Table 1 are replaced with the corresponding whitening weight function to obtain the whitening result $a(\cdot)$ of the gray number index, where $(\cdot)$ represents the category corresponding to the bleaching results. Table 4 gives the results for the calculation. In addition, the "Classes" in Table 3 represent the pros and the cons of camouflage effects. To facilitate statistics, we put six grades (0, 1,

Table 4 Evaluation index system

Index	Target	Background			
		Spruce	Wutong	Grass	Cement
Spectral Distance	Camouflage Net	0.3333 (0)	0.5487 (0) 0.4513 (1)	0.5473 (0)	0.1607 (3) 0.8393 (4)
	Cars (Black)	0.7860 (4) 0.2140 (5)	0.0413 (4) 0.9587 (5)	0.9933 (1) 0.0067 (2)	0.3333 (0)
Spectral Derivative	Camouflage Net	0.6920 (1) 0.3080 (0)	0.3333 (0)	0.6633 (1) 0.3367 (0)	0.9053 (3) 0.0947 (4)
	Cars (Black)	0.5080 (3) 0.4920 (4)	0.1460 (3) 0.8540 (4)	0.5153 (3) 0.4847 (4)	0.3333 (0)
Curve Shape	Camouflage Net	0.6307 (1) 0.3693 (2)	0.4600 (2) 0.5400 (3)	0.3333 (0)	0.7073 (4) 0.2927 (5)
	Cars (Black)	0.2827 (2) 0.7173 (3)	0.8853 (4) 0.1147 (5)	0.9001 (5)	0.3333 (0)
Spatial Texture	Camouflage Net	0.3333 (0)	0.6387 (0)	0.6247 (1) 0.3753 (2)	0.2153 (5)
	Cars (Black)	0.8807 (3) 0.1193 (4)	0.8607 (2) 0.1393 (3)	0.8967 (5)	0.3333 (0)

2, 3, 4, 5) from good to bad corresponding to "A, B, C, D, E, F." As given in Table 4, there are two levels of data corresponding to most evaluation indicators (e.g., under the background of phoenix trees, the spectral distance similarity of camouflage net corresponds to excellent and better camouflage levels). Therefore, the uncertainty of camouflage level is solved by constructing sample decision matrix.

4.3 Comprehensive decision

The decision coefficient matrices Σ_1 and Σ_2 of camouflage nets and black sedans are obtained by weighting the whitening indexes of different targets and backgrounds by category, and the weights are $w = [0.4, 0.1, 0.2, 0.3]$. In the decision coefficient matrix, "row" represents the four background of spruce, sycamore, grassland and cement land, and "column" represents the evaluation category of camouflage effect of "A(0), B(1), C(2), D(3), E(4) and F(5)."

1. *Camouflage Net*: The decision coefficient matrix of the camouflage net is calculated as follows:

$$\Sigma_1 = \left(\sigma_i^k\right) = \begin{bmatrix} 0.2641 & 0.1953 & 0.0739 & 0 & 0 & 0 \\ 0.4444 & 0.1805 & 0.0920 & 0.1080 & 0 & 0 \\ 0.3192 & 0.2537 & 0.1126 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0.1548 & 0.4867 & 0.1231 \end{bmatrix} \tag{23}$$

The maximum value is available for each line:

$$\begin{cases} \max\limits_{1 \le k \le 6} \left\{ \sigma_1^k \right\} = 0.2641 = \sigma_1^0 \\ \max\limits_{1 \le k \le 6} \left\{ \sigma_2^k \right\} = 0.4444 = \sigma_2^0 \\ \max\limits_{1 \le k \le 6} \left\{ \sigma_3^k \right\} = 0.3192 = \sigma_3^0 \\ \max\limits_{1 \le k \le 6} \left\{ \sigma_4^k \right\} = 0.4867 = \sigma_4^4 \end{cases} \tag{24}$$

To see, in comparison, the camouflage net in the spruce, wutong, grassland three land background, the evaluation level is "A," reflecting the best camouflage performance; and in the cement background, the evaluation level is "E," as it can be seen that there is basically no camouflage effect.

To more carefully express the camouflage performance of the camouflage net under the background of spruce, wutong and grassland, the comprehensive decision measure under three different backgrounds can be calculated. According to the adjustment coefficient principle of the category in the grayscale clustering, the comprehensive decision measure of the three samples can be calculated as:

$$\begin{aligned} \varepsilon_1 = \eta_1 \delta_1^T = [6, 5, 4, 3, 2, 1] \begin{bmatrix} 0.4952 \\ 0.3662 \\ 0.1386 \\ 0 \\ 0 \\ 0 \end{bmatrix} \\ = 5.5366 \end{aligned} \tag{25}$$

$$\varepsilon_2 = \eta_2 \delta_2^T = 5.1645 \tag{26}$$

$$\varepsilon_3 = \eta_3 \delta_3^T = 5.3014 \tag{27}$$

where η_i is the adjustment coefficient vector for the gray class, and δ_i is the decision coefficient vector after σ_i's normalization.

The evaluation results of different backgrounds of this camouflage net are "spruce > grass > wutong."

2. *Cars (black)*: The decision coefficient matrix of the resulting car is calculated as follows:

$$\begin{aligned} \Sigma_2 = \left(\sigma_i^k \right) = \begin{bmatrix} 0 & 0 & 0.0565 \\ 0 & 0 & 0.2582 \\ 0 & 0.3937 & 0.0027 \\ 0.3333 & 0 & 0 \end{bmatrix} \cdots \\ \cdots \begin{bmatrix} 0.4585 & 0.3994 & 0.0805 \\ 0.0564 & 0.1196 & 0.4064 \\ 0.0485 & 0 & 0.4490 \\ 0 & 0 & 0 \end{bmatrix} \end{aligned} \tag{28}$$

The maximum value is available for each line:

$$
\begin{cases}
\max\limits_{1\le k\le 6}\left\{\sigma_1^k\right\} = 0.4585 = \sigma_1^4 \\
\max\limits_{1\le k\le 6}\left\{\sigma_2^k\right\} = 0.4064 = \sigma_2^5 \\
\max\limits_{1\le k\le 6}\left\{\sigma_3^k\right\} = 0.4490 = \sigma_3^5 \\
\max\limits_{1\le k\le 6}\left\{\sigma_4^k\right\} = 0.3333 = \sigma_4^0
\end{cases}
\tag{29}
$$

Vehicles without the camouflage net basically do not have any stealth ability under the vegetation background. Therefore, the camouflage net has an important role in improving the camouflage ability of the car.

4.4 Result interpretation

It can be seen from the experimental results in the comparative condition of multibackground or multiobjective objects that when given a camouflage strategy, the method can give the camouflage performance of the camouflage strategy in different backgrounds, and then it can determine the order of different camouflage strategies. It can be qualitatively given through hierarchy or quantitative evaluation through the results of comprehensive decision measures.

However, the method still has obvious disadvantages. First, the comprehensive evaluation method establishes a decision index system through multifeature description. It ignores the characteristic bands of spectral curves but only gives quantitative results, while the reconnaissance method is only for some characteristic bands. Second, the result of the method is only a comparison result under different conditions, which obtains the order of target_1 and target_2, but cannot judge the level of target_1 and target_2 alone or the degree of reliable camouflage of the whole band.

Figure 3 shows the comparison of the spectral curves of camouflage net and black car under the four backgrounds of spruce, wutong, grassland and cement. It can be seen that the camouflage net has higher similarity with the spectral curve of vegetation compared

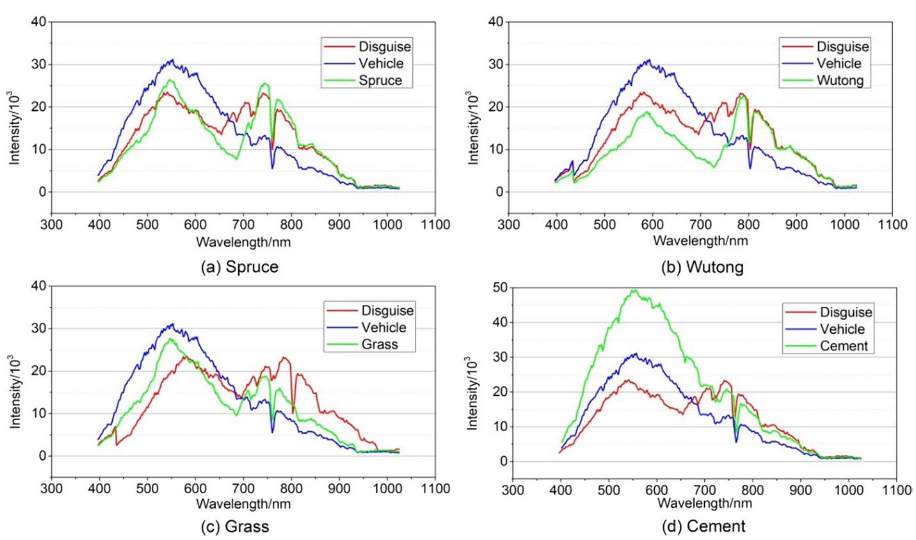

Fig. 3 Comparison plots of spectral curves of camouflage nets and vehicles in different backgrounds

with the car. It has a certain camouflage effect on the visible and near-infrared bands of the spectral dimension of hyperspectral images, but there are obvious characteristic differences in the transition period (reflected in the band range between 650 and 750 nm). Intuitively, the spectral similarity of spruce background is better than the other three backgrounds, which is basically consistent with the results of comprehensive evaluation.

5 Conclusion

The goal of this article is to establish a camouflage-effect evaluation method for camouflage targets, in which we use a grayscale clustering method based on multiple hyperspectral similarity features. Experiments proved that this method has strong reliability, not only because it can qualitatively give the "excellent" and "bad" of the camouflage effect, but also because of the quantitative comprehensive scores of the camouflage effect, which we can compute by the model. Among them, we improved the weight construction of the Delphi method and used a gray clustering comprehensive evaluation method based on the whitening weight function, which are two key points for grayscale clustering. Despite this, more information on both targets and background is more fundamental in all evaluation systems. Therefore, introducing more spectral indicators may be the development direction of camouflage evaluation based on hyperspectral images in the future.

Acknowledgements
The authors like to thank the editor and the reviewers for their thorough and constructive comments, which helped a lot to enhance the quality of the manuscript.

Author contributions
ZH contributed to the conception of the study; SM performed the experiment; YG contributed significantly to analysis and manuscript preparation; YG and ZL performed the data analyses and wrote the manuscript; ZH and CL helped perform the analysis with constructive discussions. All authors read and approved the final manuscript.

Funding
Not applicable.

Availability of data and materials
The datasets used or analyzed during the current study are available from the corresponding author on reasonable request.

Declarations

Competing interests
The authors declare that they have no competing interests.

Received: 21 August 2022 Accepted: 5 January 2023
Published online: 17 January 2023

References

1. C. Yu, M. Zhao, M. Song, Y. Wang, F. Li, R. Han, C.-I. Chang, Hyperspectral image classification method based on cnn architecture embedding with hashing semantic feature. IEEE J. Sel. Top. Appl. Earth Obs. Remote Sens. **12**(6), 1866–1881 (2019)
2. P. Ghamisi, N. Yokoya, J. Li, W. Liao, S. Liu, J. Plaza, B. Rasti, A. Plaza, Advances in hyperspectral image and signal processing: a comprehensive overview of the state of the art. IEEE Geosci. Remote Sens. Mag. **5**(4), 37–78 (2017)
3. M.E. Paoletti, J.M. Haut, R. Fernandez-Beltran, J. Plaza, A. Plaza, J. Li, F. Pla, Capsule networks for hyperspectral image classification. IEEE Trans. Geosci. Remote Sens. **57**(4), 2145–2160 (2019)
4. A. Zavvartorbati, H. Dehghani, A.J. Rashidi, Evaluation of camouflage effectiveness using hyperspectral images. J. Appl. Remote Sens. **11**(4), 1 (2017)
5. M. Kastek, T. Piatkowski, R. Dulski, M. Chamberland, V. Farley, Multispectral and hyperspectral measurements of soldier's camouflage equipment. Proc. SPIE Int. Soc. Opt. Eng. **8382**, 83820K (2012)
6. V. Kumar, J.K. Ghosh, Camouflage detection using mwir hyperspectral images. J. Indian Soc. Remote Sens. **45**(1), 139–145 (2017)

7. W.S. Hua, J. Yang, X. Liu, Z. Ma, Camouflage assessment based on hyperspectral characteristics. J. Appl. Opt. **34**(006), 964–967 (2013)
8. H. Zhu, S. Yu, Camouflage assessment based on wavelet texture characteristics. Comput. Eng. **34**(16), 227–229 (2008)
9. K. Wang, Research on hyperspectral image anomaly target detection and application of spectral imaging in camouflage evaluation. NanJing University of Science & Technology, 2015.
10. H. Fang, A.H. Li, T. Wang, H.W. Chang, Synthetic evaluation method of hyperspectral camouflage effect based on intuitionistic fuzzy decision. Laser Optoelectron. Prog. **56**(5), 81–88 (2019)
11. S.X. Ma, C.T. Liu, H.C. Li, H. Wang, Z.X. He, Camouflage effect evaluation based on hyperspectral image detection and visual perception. Acta Armamentarii **40**(7), 1485–1494 (2019)
12. B. Tu, C. Zhou, W. Kuang, L. Guo, X. Ou, Hyperspectral imagery noisy label detection by spectral angle local outlier factor. IEEE Geosci. Remote Sens. Lett. **15**(9), 1417–1421 (2018)
13. M.K. Tripathi, H. Govil, P. Diwan, Comparative evaluation threshold parameters of spectral angle mapper (sam) for mapping of chhabadiya talc minerals, Jahajpur, Bhilwara, India using hyperion hyperspectral remote sensing data," in *2019 2nd International Conference on Intelligent Communication and Computational Techniques (ICCT)*, pp. 70–74, 2019.
14. S. Bao, C. Cao, W. Chen, T. Yang, C. Qiu, F. Zhu, Mulberry identification based on spectral derivative and support vector machine, in *IGARSS 2018—2018 IEEE International Geoscience and Remote Sensing Symposium*, pp. 5315–5318, 2018.
15. D. Liu, L. Han, Spectral curve shape matching using derivatives in hyperspectral images. IEEE Geosci. Remote Sens. Lett. **14**(4), 504–508 (2017)
16. T. Guo, W. Hua, X. Liu, X. Liu, Z. Cui, Comprehensive evaluation of optical camouflage effect on hyperspectral image. Laser Optoelectron. Prog. **53**(10), 7 (2016)
17. M.H. Fang, W.M. Ju, W.F. Zhan, T. Cheng, F. Qiu, J. Wang, A new spectral similarity water index for the estimation of leaf water content from hyperspectral data of leaves. Remote Sens. Environ. **196**, 13–27 (2017)
18. J. Bao, M. Chi, J.A. Benediktsson, Spectral derivative features for classification of hyperspectral remote sensing images: experimental evaluation. IEEE J. Sel. Top. Appl. Earth Obs. Remote Sens. **6**(2), 594–601 (2013)
19. F. Meng, Y. Shi, N. Wang, M. Cai, Z. Luo, Detection of respiratory sounds based on wavelet coefficients and machine learning. IEEE Access **8**, 155710–155720 (2020)
20. W. Ji, J. Wang, X. Fang, S. Gu, Improved delphi method with weighted factor and its application, in *2013 9th Asian Control Conference (ASCC)*, pp. 1–5, 2013.
21. X. Naiming, S. Bentao, C. Nanlei, Construction mechanism of whitenization weight function and its application in grey clustering evaluation. J. Syst. Eng. Electron. **30**(1), 121–131 (2019)

Publisher's Note