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Simulation Evaluation Method for Fusion Characteristics of the Optical Camouflage Pattern

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Abstract
A comprehensive evaluation system for a camouflage design combining local effect evaluation and global sampling is developed. Different from previous models, this method can sample and evaluate target camouflage in a wide range of combat areas, thereby obtaining a comprehensive evaluation effect. In evaluating local effects, the Gaussian pyramid model is adopted to decompose the image on a multi-scale so that it can conform to the multi-resolution property of human eyes. The Universal Image Quality Index (UIQI) conforming to features of eye movements is then adopted to measure the similarities between multi-scale targeted and background brightness, color and textural features. In terms of the imitation camouflage pattern design algorithm, uniform sampling is used to obtain the evaluation distribution in the background; while for the deformation camouflage pattern, the sampling distribution is improved to make it conform to the movement rule of the target in the background. The evaluation results of the model for different designs were investigated. It is suggested by the experimental results that the model can compare and evaluate the indicators involved in the process of camouflage design, including integration, polychromatic adaptability and algorithm stability. This method can be applied in the evaluation and contrast of camouflage pattern design algorithms, in parameter optimisation of camouflage design and in scheme comparison in engineering practice, and can provide support of evaluation methodology for camouflage design theories.

Key words: *camouflage pattern evaluation, effect evaluation, sampling statistics, visual feature.*

Introduction

As one of the significant military disguising technologies, camouflage technology has been used widely in shelter-of-personnel, weaponry and engineering goals. According to various usages or objects of the camouflage pattern, it can be classified as an imitation camouflage pattern for fixed objects and a deformation camouflage pattern for moving targets within a large scope [1, 2]. Hitherto, design methods aiming at these two camouflage patterns have been developed steadily. Meanwhile, various evaluation methods have been proposed. According to the stages of evaluating a camouflage pattern, the evaluation method can be divided into engineering evaluation after completion of the construction and simulation evaluation after completion of the design. As a matter of fact, engineering evaluation generally requires much time and effort, and currently there are few researches on simulation evaluation. Simulation evaluation in the design stage plays a vital role in the performance measurement and comparison of the camouflage design algorithm as well as in quantification of the effect of the deformation camouflage pattern, and thus it could affect the development of camouflage design theory.

At present, camouflage evaluation technologies can be differentiated subjectively and objectively. Subjective evaluation includes mainly traditional detection probability statistics and target significance, both of which require huge financial and material resources in actual operation and have low efficiency. Jia Qi et al. [3] applied Itti's visual attention mechanism model in the extraction of disguise features and fit the features to detection probability parameters with the BP(Back Propagation) network. Lin Wei et al. [4] established the relations between detection probability and the features and fitted the parameters according to the psychological stimulation equation. Objective evaluation is mainly to evaluate the comprehensive similarities between the evaluated background and the target zone based on the similarity measure. The general idea is to decompose the target and background image regions into features such as colour, brightness, texture, shape and structure, and then to establish similarity relationship models using certain measuring methods [5], including the BP neural network method [6], an evaluation method combining colour and distribution information [7], the Gabor wavelet texture-based method [8] and the multi-index evaluation method based on grey theory [9]. Xue Feng et al. [10] designed a camouflage pattern based on the feedback of the evaluation methods, and the evaluation process was extracted and quantised the target boundary characteristics based on the gradient method. Daniela H. et al. [11] evaluated the features of camouflage pattern textures based on a human observer. The above methods have mainly two limitations: First, most of the methods are engineering evaluation methods, in which the objects evaluated are specific targets, and the scope of the evaluation is also local background. The overall performance evaluation of the camouflage pattern and its effects cannot be applied well. Second, the evaluation method is not guided by visual relevance theory when measuring feature similarity. Moreover, all the evaluation processes are not carried out at a multi-scale resolution. For the feature of the multi-resolution of the human eye when observing a target, the fusion of the target and the background cannot be better reflected by those models.

All these limitations have restricted the development of camouflage patterns to some degree. In engineering practice, for the design and application of these two types of camouflage patterns, it is necessary to consider evaluation of the advantages and disadvantages of the imitation camouflage pattern design algorithm, the overall effect of the deformation camouflage pattern against an extensive background, and the adaptability against a complex background. Actually, most of the present camouflage pattern design theories do not offer parallel comparison. Based on the principle of sampling statistics, this work puts forward simulation evaluation theory for camouflage patterns and systematically expounds the evaluation steps. According to the visual observation mechanism, the theory of local fusion measurement of camouflage patterns is studied. The contribution mainly includes two aspects. One is to propose a sampling theory and statistical method for evaluation of the global camouflage effect, and the other is to improve the local evaluation simulation model to make it more consistent with the human visual characteristic model. By examining local fusion of the camouflage pattern and its statistical characteristics in the background, the overall performance of the camouflage pattern and its design method is given according to the numerical method, which could provide theoretical support for the performance measurement of camouflage pattern effects and its design methods.

Methodology

Fusion characteristic evaluation based on visual features

First it is necessary to classify the target and the background regions. The traditional method is to compare the features of the background and the target within a certain peripheral scope directly. However, during field reconnaissance, the background in far regions has little influence on the target, and the evaluation result is not stable in the case of the main colours of the selected background scope not being single. The eight-way domain partition map method [12] is a relatively rational method to classify the target and the background, which takes the target as the original point and eight regions of equal dimension surrounding the target as the background. To calculate the results, the mean value of all the backgrounds are counted as the effects of local regions.

At present, there are various theoretical methods to evaluate the target and the background. The most common is to decompose the image feature into brightness, colour, texture, structure and shape, which are combined in a certain compound mode. However, there is no theory or experimental study reflecting the advantages and disadvantages of various combination modes of these characteristic parameters. To conform to low-level visual features, the multi-layer Gaussian pyramid is adopted to decompose the target and background images, for image comparison on a multi-scale can reflect the observation results within different visual scopes. Suppose the initial $A(i, j)$ image is the 0th layer of the pyramid and the next layer image can be obtained by Gaussian filtering and down-sampling the upper layer image. Suppose M and N are, respectively, the length and width of the original image, and the image size of layer l is $2^{-l}M \times 2^{-l}N$. Where, the two-dimensional Gaussian convolution function is as shown in ***Equation (1)***.

$$Gauss(x,y) = \frac{1}{2\pi\sigma^2} e^{-\frac{(x-x_0)^2+(y-y_0)^2}{2\sigma^2}} \tag{1}$$

Extract the brightness, colour and texture features of the images at each layer. ***Equation (2)*** represents the calculation of the feature of brightness. The colour feature is represented by value a and value b with Lab uniform colour space. During colour space conversion, it is necessary to transfer the image to XYZ colour space and then to Lab space. The texture feature is described with the *Gabor* filter, as shown by ***Equations (3)-(5)***. The *Gabor* filter is the result of consine modulation of the two-dimensional Gaussian function, and it has been found by biological experiment that it can approach the one-cellular reception field function better [13-16]. 4 orientations are selected to extract the texture feature, that is, $\theta \epsilon \{0°, 45°, 90°, 135°\}$.

$$I = 0.299r + 0.587g + 0.114b \tag{2}$$

$$G(x,y) = e^{\left(-\frac{x^2}{2\sigma_x{}^2}-\frac{y^2}{2\sigma_y{}^2}\right)} [cos(2\pi f_0 x') + j\, sin(2\pi f_0 y')] \tag{3}$$

$$x' = x\cos\theta + y\sin\theta \tag{4}$$

$$y' = -x\sin\theta + y\cos\theta \tag{5}$$

Similarities between feature results with the same dimensions are investigated. Literature [17] verified the relative superiority of the Universal Image Quantity Index (UIQI) by an eye movement experiment, which has high correlations with the indicators of eye movement and is easy to calculate. However, it is impossible to reveal the influences of chromaticity on visual effects by comparing the results in a grey level image. Calculation of UIQI is as shown in ***Equations (6)-(11)***, where b_{ij} and c_{ij} are, respectively, their corresponding pixel values. With the same scale and their corresponding features, this index is adopted to calculate the similarities between the target and background features.

$$UIQI = \frac{\sigma_{bc}}{\sigma_b\sigma_c} \cdot \frac{2\bar{b}\bar{c}}{\left(\bar{b}\right)^2 + (\bar{c})^2} \cdot \frac{2\sigma_b\sigma_c}{\sigma_b{}^2 + \sigma_c{}^2} = \frac{4\sigma_{bc}\bar{b}\bar{c}}{(\sigma_b{}^2 + \sigma_c{}^2)(\left(\bar{b}\right)^2 + (\bar{c})^2)} \tag{6}$$

$$\bar{b} = \frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N} b_{ij} \tag{7}$$

$$\bar{c} = \frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N} c_{ij} \tag{8}$$

$$\sigma_b = \frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N} (b_{ij} - \bar{b})^2 \tag{9}$$

$$\sigma_c = \frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N} (c_{ij} - \bar{c})^2 \tag{10}$$

$$\sigma_{bc} = \frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N} (b_{ij} - \bar{b})\,(c_{ij} - \bar{c}) \tag{11}$$

Considering that the brightness, colour and texture features are on an equal status for stimulation of the low-level visual sensory, at the same pyramid scale, the average of the three similarity measures is calculated as the evaluation result of this layer. Similarly, the mean values of 2 colour features and the texture features in four directions are taken as the measurement of the feature layer. Thus, the measurement results of the target and background similarity at different scales can be obtained. Since human eyes tend to focus on the whole when observing local effects, it will pay attention to details only when the overall difference is large. Therefore, when integrating the effects between different pyramid layers, the higher the number of the layer is, the greater the weight required to be given, as shown in ***Equation (12)***.

$$g = \frac{\sum_{i=1}^{l} e^{i-l} UIQI_i}{\sum_{i=1}^{l} e^{i-l}} \tag{12}$$

Thus, the local simulation evaluating method for camouflage patterns in the background is represented in the procedure shown in ***Figure 1***. First, classify the target and the background regions according to the eight-connected-region method. Decompose the target and each background region in the Gaussian pyr-

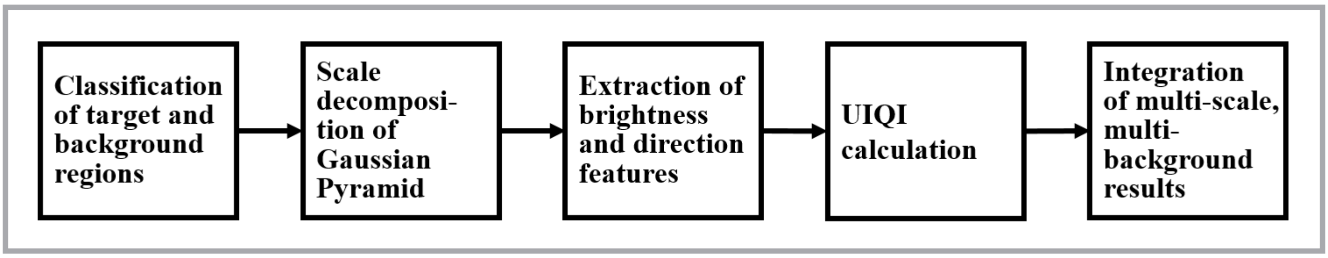

Figure 1. *Flow chart of local evaluation based on visual features.*

amid scale and calculate their brightness, colour and texture features. Then, use UIQI to evaluate the similarities between the same scale and the corresponding features. Last, integrate the results multi-dimensionally and calculate the results of eight backgrounds in turn to obtain the mean value, which is the integration effects of the camouflage pattern.

Evaluation of imitation camouflage pattern design scheme

The camouflage design algorithm is assessed, including the overall effect of the algorithm, its stability, and the complexity of the camouflage pattern, among which the complexity of the camouflage determines the difficulty of the construction and is determined mainly by the size of the spots and the quantity of the main colours. Spot size is deduced according to the reconnaissance conditions, thus the main determinant is the quantity of main colours, which is usually restricted by the construction conditions in practice. Therefore, when conducting theoretical evaluation, it is possible to set 3-5 colours based on experiences [18-20]. Comprehensive evaluation of a camouflage pattern needs to be implemented in a general-purpose environment, so that there would be a common basis for horizontal contrast between different camouflage algorithms. Currently, the most widely used background types include woodland, grassland, desert, and snow, the background data sets of which are selected and constructed according to the actual application of the design algorithm.

$$I_c = f(x, y, I_b) \tag{13}$$

$$E_{(x,y)}[g(x, y, I_c)] = = \frac{1}{S}\sum_{i=1}^{S} g(x_i, y_i, I_{c_i}, I_{b_i}) \tag{14}$$

$$D_{(x,y)}[g(x, y, I_c)] = \frac{1}{S}\sum_{i=1}^{S}(g_i - \alpha)^2 \tag{15}$$

Algorithm 1. *Evaluation procedure of imitation pattern scheme.*

Require: Background data set D, type number of main colour n, times of repetition m
//processing
for i = 1, 2, 3, …, m **do**
$I_b \leftarrow$ select randomly from data set D some background image
$(x, y) \leftarrow$ generate uniform sampling successively by the linear congruence method
$I_c \leftarrow$ calculate camouflage pattern by the design algorithm
$g_i \leftarrow$ evaluate the algorithm by the local
$\alpha, \beta \leftarrow$ calculate the mean and variance of with the method of estimation
Return α, β

Uniform sampling is adopted to randomly select the shrouded simulation region and to calculate its local camouflage effect α. The general effect of the algorithm is represented by the expectation of the results, and the stability β of the algorithm is represented by variance. Suppose f is the camouflage design algorithm, g the local evaluation algorithm, I_b the background, and I_c is the designed camouflage pattern. $x \sim U(0, M)$ and $y \sim U(0, N)$. The sampling can be generated by the linear congruence algorithm [21-24], as shown in ***Equations (13)-(15)***. ***Algorithm 1*** represents the details of the algorithm flow.

Evaluation of deformation camouflage pattern

The overall idea of the evaluation of the deformation camouflage pattern is generally consistent with the method mentioned above, that is, the simulation effect is collected statistically using the local effect evaluation method by randomly selecting the coordinates in the background. However, because the deformation camouflage pattern is used for moving objects, there are two differences in its evaluation process. On the one hand, camouflage is mostly applied to a background of the same type, thus it is required to select an appropriate background data set. On the other hand, uniform distribution is not suitable for the sampling of deformation camouflage, and it is required to take the movement rule of the target in the background so as to determine the distribution function. In literature [25], the trajectory of the moving target was considered as the basis for dynamic evaluation of the sample source. This method can only evaluate the regional effect after completion of the construction. Therefore, it is considered in this study to establish the probability of the sampling distribution expression target appearing in different regions based on the probability of occurrence of different colour regions.

Suppose the possibility of the target appearing in the region close to colour $(\bar{r}, \bar{g}, \bar{b})$ is higher than in other regions, the colour tolerance measurement $d(x, y)$ of the background region can be determined by Euclidean distance, as shown in ***Equation (16)***. However, in actual practice, regions with a larger chromatic aberration haveva higher probability of occurrence, thus, ***Equation (17)*** can overturn the chromatic aberration function by the maximum value. Color $(\bar{r}, \bar{g}, \bar{b})$ can be obtained by solving the average colour of the colour lump.

$$d(x, y) = \sqrt{\begin{gathered}(I_{br}(x, y) - \bar{r},)^2 + \left(I_{bg}(x, y) - \bar{g}\right)^2 \\ +(I_{bb}(x, y) - \bar{b})^2\end{gathered}}$$

$$\hat{d}(x, y) = \max_{(x,y)} d(x, y) - d(x, y) \tag{16}$$

$$\hat{d}(x, y) = \max_{(x,y)} d(x, y) - d(x, y) \tag{17}$$

Probability density distribution established based on chromatic aberration

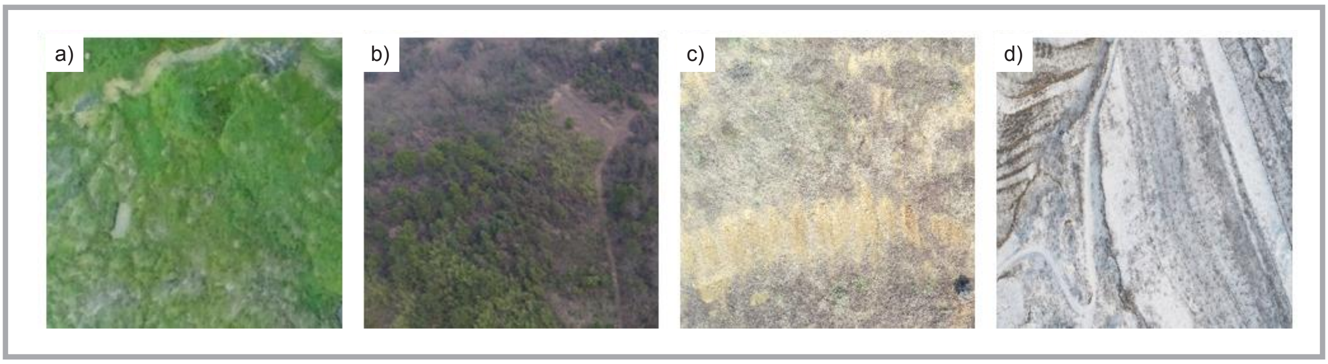

Figure 2. *Demonstration of background data sets: a) data set of grassland, b) data set of forestry, c) data set of deserts, d) data set of snowfield.*

Algorithm 2. *Evaluation procedure of deformation pattern.*

Require: Background image I_b, camouflage pattern I_c, times of repetition m, close colour $(\bar{r}, \bar{g}, \bar{b})$, regulatory factor ω
//processing
1: $s'(x, y) \leftarrow$ gaccording to $(\bar{r}, \bar{g}, \bar{b})$, ω, I_b calculate the probability density function of the background
2: $L \leftarrow max_{(x, y)}\, s'(x, y) \cdot$ MN
3: $q(x, y) \leftarrow$ generate uniform distribution density function according to the size of I_b
4: **for** i = 1, 2, 3, …, m **do**
5: $(x_i, y_i) \leftarrow$ by $x_i \sim U(0, M)$, $y_i \sim U(0, N)$ sampling and obtain
6: $\gamma = \frac{s'(x_i, y_i)}{Lq(x_i, y_i)}$
7: $\mu \leftarrow$ sampling from uniform distribution $U(0, 1)$
8: if $\gamma \le \mu$ then return to step 5
9: $g_i \leftarrow$ evaluate algorithm $g(x_i, y_i, I_c, I_b)$ through the local
10: $\alpha, \beta \leftarrow$ calculate the mean and variance of $\{g_1, g_2, ..., g_m\}$with the moment estimation method
11: **Return** α, β

can be obtained by normalising $\hat{d}(x, y)$, but the distribution thereby established has almost 0 probability of getting the sampling in regions with large chromatic aberration. Therefore, it is considered to modify the scope of difference with factor $\omega \in [0, 1]$ to obtain function $s(x, y)$, and then the probability density function $s'(x, y)$ is attained through normalisation. This procedure is represented by ***Equations (18)*** and ***(19)***. It can be concluded from the calculation process of $s(x, y)$ that the larger ω is, the slower the probability density function $s'(x, y)$ tends to be, and the probabilities of all the regions tend to be equal. When ω is close to 1, $s'(x, y)$ tends to be a uniform distribution. When ω is 0, $s'(x, y)$ is the result of direct normalisation of $\hat{d}(x, y)$. Therefore, the form of $s'(x, y)$ can be controlled by factor ω.

$$s(x, y) = \frac{\hat{d}(x, y) + tan\, \omega \frac{\pi}{2}}{255 + tan\, \omega \frac{\pi}{2}} \tag{18}$$

$$s'(x, y) = \frac{s(x, y)}{\iint s(x, y)} \tag{19}$$

After two-dimensional probability density is determined, the accept-reject method is adopted for sampling [26-28]. (x_i, y_i) is sampled out randomly from the given reference $q(x, y)$, and its probability of acceptance γ can be calculated as:

$$\gamma = \frac{s'(x_i, y_i)}{Lq(x_i, y_i)} \tag{20}$$

Take sample μ randomly from uniform distribution $U(0, 1)$. If $\gamma > \mu$, this sample can be accepted; otherwise, it should be rejected and the sampling restarted. This sampling method can collect the samples required quickly by means of a computer. However, if the scope of parameter L is set irrationally, a large rejection region can be caused, which could lead to a lengthened calculation time. In this work, the coordinate range of (x, y) is fixed after the image is determined, and hence the reference distribution $q(x, y)$ adopts a two-dimensional uniform distribution, as shown in ***Equation (21)***. Calculation of L adopts the method represented by ***Equation (22)*** so as to guarantee the expanded density of the uniform distribution is right to cover the scope of $f(x, y)$.

$$q(x, y) = \frac{1}{MN}\ 0 \le x \le M, 0 \le y \le N \tag{21}$$

$$L = \max_{(x,y)} s'(x, y) \cdot MN \tag{22}$$

The process of calculating and making statistics of the local effects after completion of the sampling is same as that in previous section. It is worth noting that the mean value of the results represents the overall effect of the deformation camouflage pattern in the background, and the variance reflects the adaptability of the camouflage pattern in a multi-colour environment. Recently, study on the deformation camouflage pattern against a multi-colour background has become a hot topic, for it could provide a basis for horizontal comparison between camouflage patterns. Moreover, the stability of the design algorithm of the deformation camouflage pattern can be assessed by one-way analysis of variance. Although there are great difficulties in the automatic design algorithm from the background image to the deformation camouflage pattern, research on this is not common. ***Algorithm 2*** represents the process details of deformation camouflage pattern evaluation.

Experiment and discussion

the experimental process entails a comparative experiment of imitation camouflage and deformation camouflage evaluation. When local fusion evaluation is performed, the number of pyramid layers is set at 3. The size of the camouflage pattern designed is 100*100 pixels. After the sampling in the background is completed, it is covered with the designed camouflage pattern to complete the evaluation process. In cases of full eight-way domain backgrounds not being available when sampling to the boundary, the sample shall be discarded. The sampling times is 50.

Establishment of data set

To demonstrate the evaluation process, a uniform data set is established. As shown in ***Figure 2***, data sets with backgrounds of grassland, forestry, desert and snowfield are established with the method of UAV imaging in the air. The dimension of each data set and the condition to collect the data are basically the same so that the evaluation results can remain steady. Background images within the scope of about 1km are collected for the data set, and the flight height of UAV is kept at about 100 m. The collection time is about 10 am on sunny days.

Evaluation experiment of imitation camouflage pattern design scheme

To create a reference comparison, two different imitation camouflage design schemes are adopted. The number of main colours of all schemes is uniformly set to 5 categories. The first type uses the K-means clustering method to cluster the background in RGB space, and then deletes the spots with too small an area. The second method uses the FCM clustering algorithm to extract the main colour in Lab space [29-31], removes small plaques with the expansion corrosion method, and then determines the plates according to the minimum size of the digital camouflage pattern. The plates are divided, and the main colours within the plates are selected. Both schemes are evaluated according to the procedure in ***Algorithm 1***, and the number of iterations m is chosen to be 50.

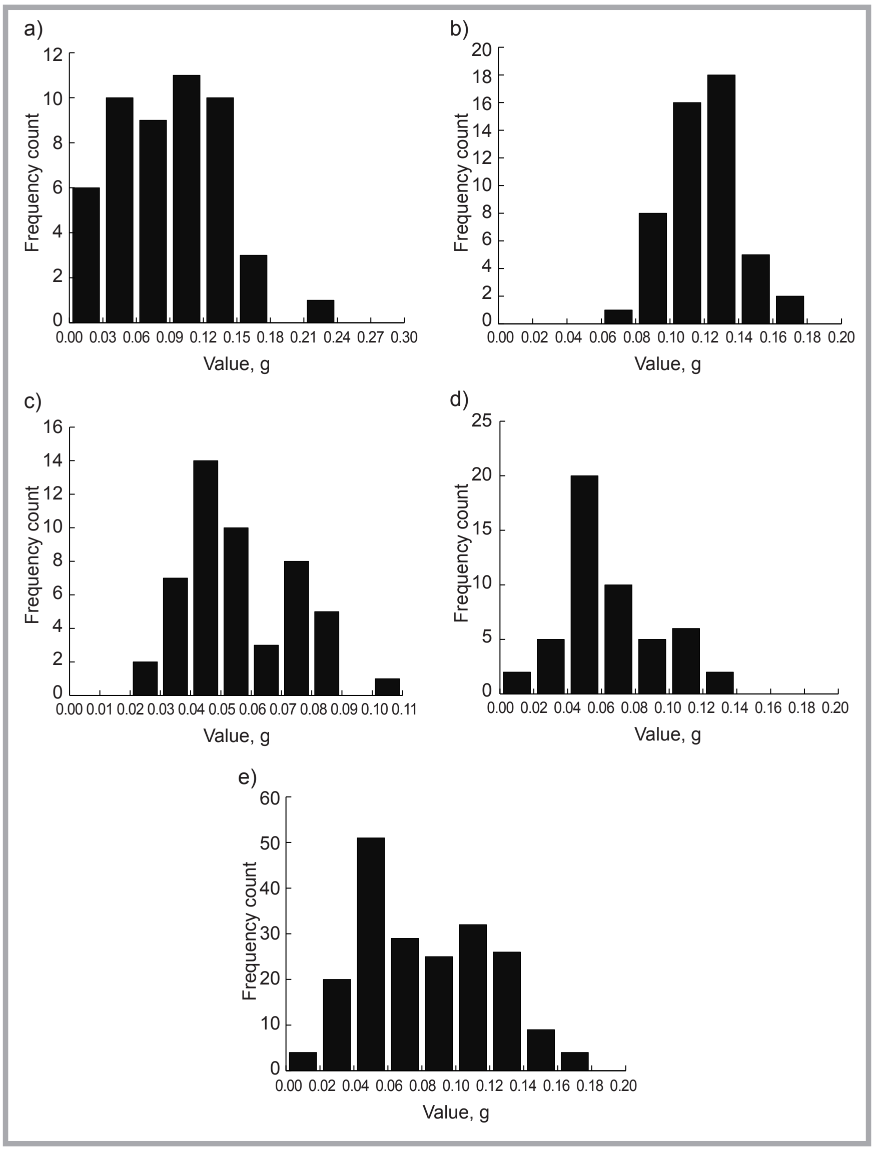

Figure 3. *Statistical histogram of the evaluation results of the first imitation camouflage pattern design scheme: a) sampling result of grassland background, b) sampling result of forestry background, c) sampling result of desert background, d) sampling result of snowfield background, e) combined sampling result of four backgrounds.*

Figures 3 and ***4*** represent the statistical histogram of local sampling of both imitation camouflage design schemes with a sample size of 50, among which, ***a***, ***b***, ***c*** and ***d*** are the statistical results of the evaluation against backgrounds of grassland, forestry, desert and snowfield, while ***e*** is the statistical result of the combination of these four backgrounds. Generally, all the results are within interval [0, 0.22], and the histograms obtained after these four backgrounds are combined are rather similar. Seen from the statistical results of each background, the results of the desert background are concentrated, while those of the grassland background are the most dispersed. This is because the variegation of the desert background is low with a single hue, while the grassland background is quite the reverse. This also suggests that the local evaluation indexes selected are rational and stable, and the results can correctly reflect backgrounds with varying complexities.

Table 1 shows a comparison of results of the evaluation indexes of both camouflage design methods. In terms of the effect, method 2 is better than method 1 in the backgrounds of grassland, desert and snowfield, and thus is the stability of the algorithm. However, in the forestry background, method 1 is slightly better than scheme 2. From ***Figure 4.b*** it can be method the reason why the abnormal phenomenon occurs in the forestry background is that the statistical evaluation results of method 2 have outliers in interval [0.2, 0.22]. Generally speaking, no matter the overall effect or stability of the algorithms, method 2 is better than method 1.

Table 1. *Statistics of effects of the two imitation camouflage design methods in five backgrounds.*

		Grassland	Forestry	Desert	Snowfield	Total
Algorithm 1	α	0.089	0.110	0.056	0.064	0.082
	β	0.047	0.022	0.018	0.027	0.040
Algorithm 2	α	0.087	0.120	0.051	0.057	0.079
	β	0.0410	0.030	0.014	0.022	0.037

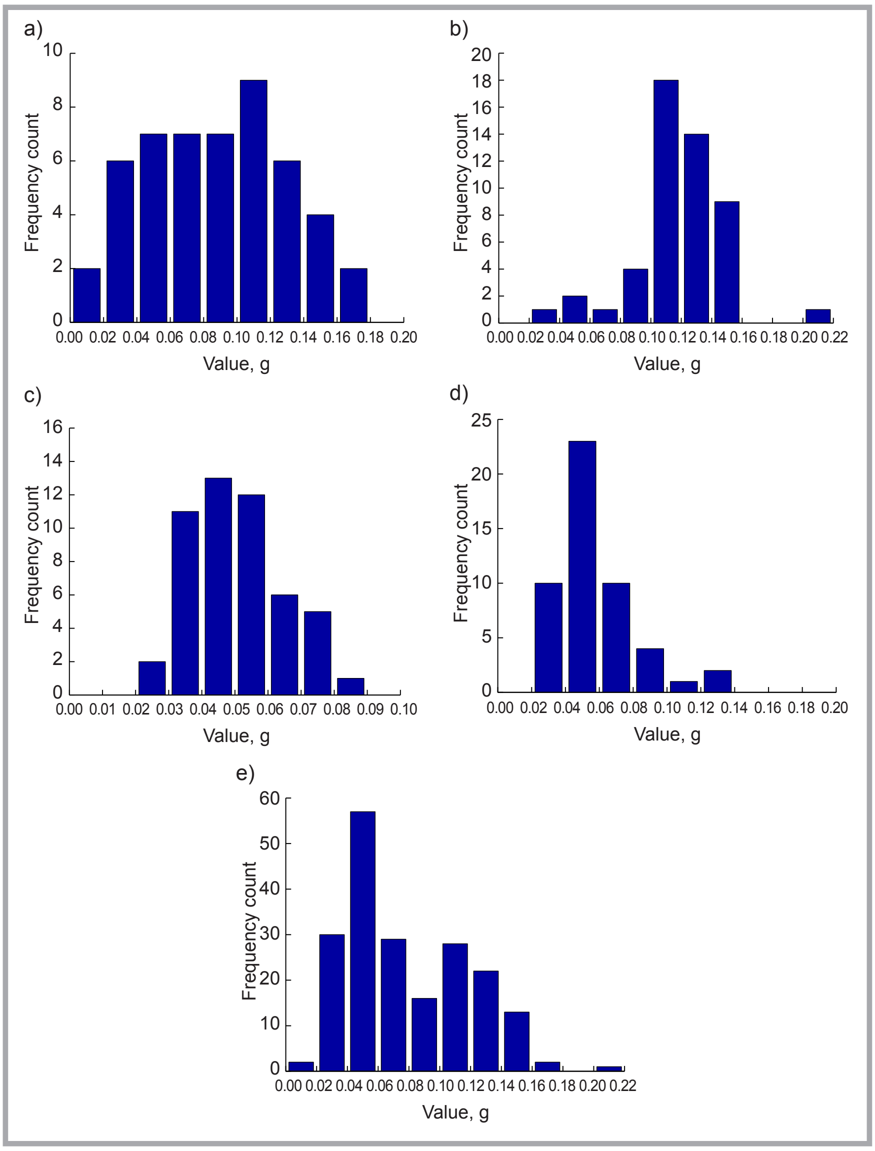

Figure 4. Statistical histogram of the evaluation results of the second imitation camouflage pattern design scheme: a) sampling result of grassland background, b) sampling result of forestry background, c) sampling result of desert background, d) sampling result of snowfield background, e) combined sampling result of four backgrounds.

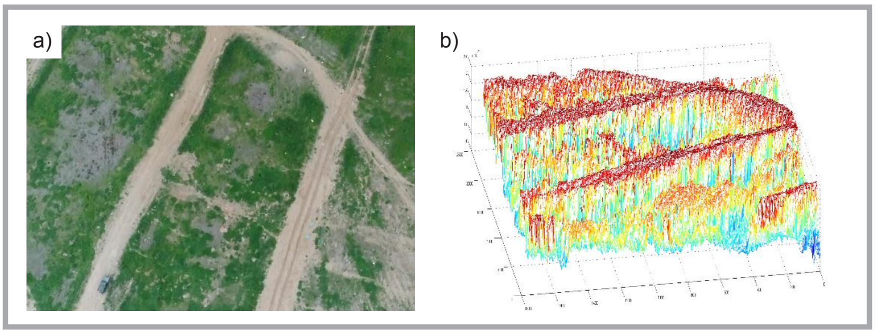

Figure 5. Grassland background region and the established probability distribution: a) image demonstration of forestry background, b) image of two-dimensional sampling probability density function.

Evaluation experiment of deformation camouflage pattern

The deformation camouflage pattern can only be applied in the background of one type, hence the experiment is completed for just the grassland background. First, calculate the sampling distribution of the background according to ***Algorithm 2***. In the grassland background represented in ***Figure 5.a***, it is obvious that the road and the grassland belong to two quite different main colour regions. In engineering practice, the probability of vehicle and weaponry appearing on the road is higher in non-road regions, hence ocher is selected as the close colour in standard camouflage colours based on the colour scope of road. In the case of the regulatory factor being set as 0.6, the two-dimensional sampling probability density function, shown in ***Figure 5.b***, can be obtained according to the computational formula.

Table 2. *Effect statistics of two deformation camouflage patterns in a grassland background.*

	Pattern 1	Pattern 2	Pattern 3
α	0.183	0.211	0.225
β	0.089	0.103	0.093

Reference [32] generates a digital camouflage pattern based on a texture model of the Markov random field. In order to form a comparative experiment, the size of the phase domain was selected to be 4 orders, 5 orders and 6 orders when constructing the texture structure of the Markov random field. With the parameters remaining the same, there are 7 types of main colours after clustering, and the basic pattern pyramid is decomposed into two layers. Deformation camouflage patterns are generated, respectively, as shown in ***Figure 6.a***, ***Figure 6.b*** and ***Figure 6.c***, which are named pattern 1, pattern 2 and pattern 3, respectively. The process of sampling and local effect evaluation is performed according to the process of ***Algorithm 2***, and the statistical data are calculated to obtain the results shown in ***Table 2***. The result shows that the effect of pattern 1 is the optimal. As a matter of fact, in terms of the visual results, the colour distribution of pattern 1 accords more with the principle of background sampling, with the range of the ocher area higher than for the other two patterns. The multi-colour adaptabilities of these three patterns vary less, and the performance of pattern 1 is slightly better than the other two. The overall effect of pattern 2 is better than that of pattern 3, but its multi-colour adaptability is slightly weaker, which indicates that the difference between these two patterns is not significant. It can be concluded from the experimental results that the camouflage pattern designed is the best in the case of the phase field size being 4 orders.

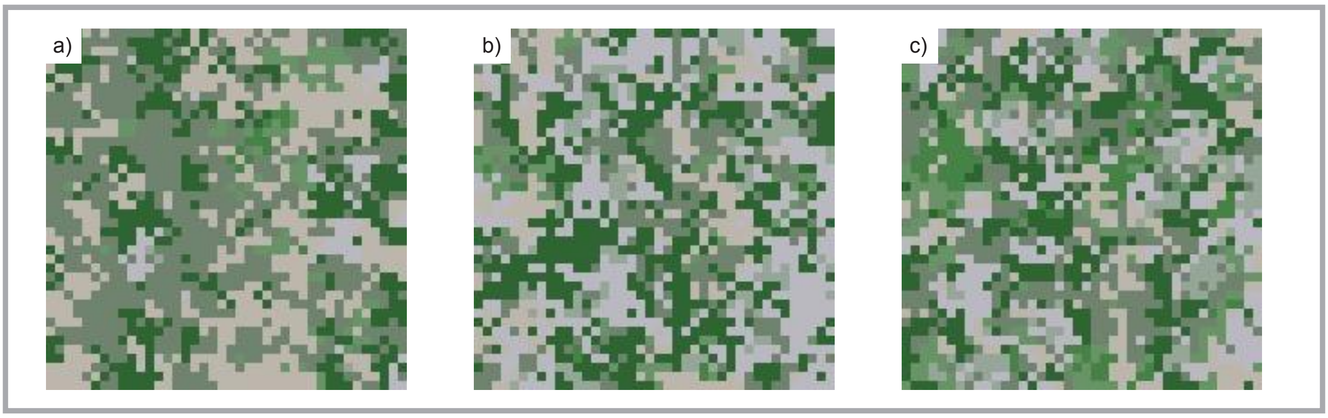

Figure 6. Three designed camouflage patterns: a) camouflage pattern generated with a texture structure phase field of 4 orders, b) camouflage pattern generated with a texture structure phase field of 5 orders, c) camouflage pattern generated with a texture structure phase field of 6 orders.

Conclusions

Based on visual feature extraction and contrast theory, this study implements systematic studies on the fusion feature of the optical camouflage pattern. To make a local evaluation of camouflage pattern effects conform to human visual characteristics, aiming at the target and background patterns, the multi-scale Gaussian pyramid decomposition method is adopted to simulate observation results of the human eye at different resolution scales. The UIQI index conforming to human eye observation characteristics is used as a similarity measure method to evaluate the brightness, colour and texture features between the target and the background on a multi-scale. Results reflecting the local fusion of the camouflage pattern can be obtained by integrating those of the surrounding eight connected regions. To make the evaluation method a reference for camouflage design theory, a method based on global sampling statistics is proposed to evaluate the imitation camouflage design algorithm and the deformed camouflage pattern. Uniform sampling is adopted for evaluation of the imitation camouflage design model, and considering the movement rule of the actual target, a two-dimensional probability density function is constructed to evaluate the deformation camouflage pattern, with the method of accept-reject sampling being adopted for sampling statistics. Grassland, woodland, desert and snow type background datasets are constructed during the experiment, and two groups of comparative experiments are designed. The first group of experiments take the performance of two different imitation camouflage design models in the dataset into consideration, while the second group studies the fusion effect of the deformation camouflage pattern designed in the background under different phase domain parameters. The experimental data are consistent with those of direct visual observation. The experimental results show that the method proposed can effectively compare and evaluate indicators such as fusion, multi-colour adaptability and algorithm stability in the process of camouflage design.

The computation framework proposed in this work could be applied for an evaluation comparison of the camouflage design algorithm, parameter optimisation in the process of camouflage design, and a scheme comparison in engineering practice, which could support, to some degree, the development of camouflage design theory. However, to fit the visual mechanism, the computation of local evaluation is complex, which would be a difficulty to be resolved with emphasis in a future work.

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