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Multi-feature similarity-based evaluation of camouflage effectiveness

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Abstract
Camouflage plays a crucial role in countering reconnaissance and concealing military objects. In the defense industry, camouflage techniques, such as camouflage nets and patterns, aim to minimize detectability by reducing distinctive features. However, existing evaluation methodologies face challenges, including inconsistent visual perception and incomplete evaluation indices. This study proposes a comprehensive similarity-based approach for assessing camouflage effectiveness using both objective and subjective evaluation methods. The objective evaluation quantifies camouflage similarity by analyzing four key indices: image color, brightness, texture, and structure. These are represented as the color similarity index (S_C), luminance similarity index (S_L), structure similarity index (S_S), and texture similarity index (S_T). The entropy weighting method (EWM) is employed to optimize feature weighting and extract meaningful information. The subjective evaluation assesses detection time and perceived similarity based on a user study involving 20 participants across four different camouflage scenes. Results indicate that the comprehensive similarity model outperforms conventional evaluation methods, demonstrating superior predictive accuracy. Among the indices, S_C plays a dominant role, highlighting the significant impact of color on human visual perception. This study demonstrates that a visual perception-based approach enhances camouflage evaluation accuracy and provides a robust, reliable framework for assessing camouflage performance.

Keywords
Camouflage effectiveness, Similarity index, Objective evaluation, Subjective evaluation, Feature vector, Visual perception.

1.Introduction
Camouflage is the process of blending objects into their surrounding environment using a combination of materials, patterns, and coloration to reduce detectability. It has a broad range of applications in robotics, bionics, and defense [1]. The effectiveness of camouflage can be pre-assessed to determine the likelihood of target exposure [2]. Assessing camouflage effectiveness is critical for camouflage patterns and material design [3, 4]. The universal image quality index (UIQI) approach evaluates camouflage by considering the human visual system (HVS) and image structure, and the results align with the subjective evaluation [5]. The structural similarity index (SSIM) was used to assess the degree of blending between the stimuli and background, considering human visual perception [6]. Image quality metrics employed feature extraction, analysis, and fusion as evaluation tools for camouflage [7].

Lin et al. [8] initially proposed an evaluation approach based on HVS after consideration of the observer's psychological aspects; however, the outcomes are still very subjective. Wang et al. [9] effectively evaluated five significant parameters: brightness, edge shape, color and texture characteristics, and spot size, and assessed the camouflage performance employing grayscale theory, yielding more objective outcomes. Rong et al. [10] modelled dynamic background differences and applied dynamic target detection to assess the impact of a camouflage pattern. To evaluate the effectiveness of camouflage, vision-based detection techniques are used to differentiate targets from their backgrounds [11]. These methods focus on texture, brightness, and intensity [12–15], especially the mean absolute error (MAE) and peak signal-to-noise ratio (PSNR), which may not sufficiently account for HVS perception [16, 17]. However, the camouflage image has complex spatial features and no uniform color blocks. Visual perception of image color is inaccurate in CIELAB [18]. The camouflage evaluation

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technique relies on human visual perception to accurately capture its effects [19]. High observer subjectivity and poorly repeatable weather influences make this approach difficult. Digital images aid objective and subjective visual assessment. This method prevents subjective error and provides scientific precision, although it lacks HVS sensitivity. Therefore, further research is necessary for objective evaluation that incorporates subjective perception [20].

Color, brightness, texture, and structure are all essential features of images that play a significant role in camouflage design. Therefore, a model that comprehensively examines multiple parameters yields superior results compared to one that focuses on a single parameter. This study proposes a camouflage target evaluation index based on the analysis of color, brightness, texture, and structure features and incorporates a subjective evaluation test to validate the relationship.

This work primarily contributes to the following areas: it proposes a comprehensive approach for assessing artificial camouflage targets based on multi-feature analysis. The entropy weight method (EWM) is utilized to compute overall camouflage performance. A visual experiment was conducted to assess target blending level with the surrounding environment according to the human visual perception mechanism.

The remaining paper is organized as follows: Section 2 discusses the literature review. Section 3 elaborates on the proposed method, while Section 4 presents its experiments. Section 5 summarizes the significance of proposed work. Section 6 concludes the work with its future scope.

2.Literature review

This section examines the many studies on assessing the effectiveness of camouflage with its background. It provides a comprehensive overview of objective evaluations based on various image features, as well as subjective evaluations based on HVS considerations and feature fusion strategies, along with their limitations.

Xue et al. proposed the gradient magnitude similarity deviation (GMSD) method, which was based on modeling the HVS. Image processing and machine vision disciplines frequently use it [21], as it efficiently extracts texture features from the image. Using the S-CIELAB color system, the camouflage similarity index (CSI) [22] can be used to measure the differences in color between a hidden target and its background. It works better than the UIQI. When used for identifying an object from a similar background, CSI performs well. This paper suggests four single index models and three comprehensive index models to measure how well camouflage works. The subjective and objective evaluation results are then compared using the Pearson correlation coefficient (PCC) [23].

This study suggested a way to test the grayscale clustering camouflage effect that takes into account the different spectral properties of the target and the background. This approach is based on multi-feature descriptions of hyperspectral images, employing similarity indicators. By integrating spatial–spectral multi-feature restrictions, a comprehensive assessment index system is developed, incorporating derivative features, spectral distance, spatial texture, and curve shape features while considering the spectrum and human visual contrast [24]. Multi-attribute decision-making, neural network modelling, linear weighted models, and human visual attention mechanisms are all used in objective evaluation techniques. The multi-attribute decision-making model [25] enables the evaluation of camouflage between multiple targets and backgrounds. The Hausdorff distance and the color difference minimal principal color similarity vector technique [26] are used to find the degree of distortion and the similarity between the target and center background. But the computational requirements for these methods can be high, and they provide only small improvements in performance. The luminance and chromatic adaptations have been combined to propose a new color appearance model. The brain actually perceives the appearance of color, including the effects of illumination and the environment [27, 28]. A multi-feature camouflage fused index (MF-CFI) [29] was suggested that is based on how different the background and target are in terms of texture, color, and grayscale. The authors conduct eye movement experiments to compare the proposed index. The results reveal that the MF-CFI and the eye movement data have the highest PCC. Yang et al. proposed the logarithmic amplification probability, based on the correlation of features between the target and background. It computes the probability density of the joint distribution. Based on the statistics, the level of camouflage was described [30, 31]. An assessment approach was developed for hyperspectral camouflage based on detection and perception theory. By employing a multi-feature description approach, the proposed technique resolves the issue of a single evaluation index in conventional evaluation methods [32]. The proposed approach considers human visual and cognitive processes. This study used electroencephalography (EEG) signals produced by presenting images with different camouflage effects to observers in order to build a brain functional network [33]. In the study, a technique for evaluating camouflage was presented that is based on the degree to which the camouflage target's edge contours resemble each other. In order to assess the effectiveness of the camouflage effect, the research integrates the Sobel and Canny algorithms to extract the target's edge contour. It then uses the Euclidean distance to determine the similarity of the target's edge contour to its environment after camouflage [34]. A new framework, based on the SSIM index, was proposed using the assumptions of the HVS [35–37], for obtaining statistical structural information. Song and Geng [38] proposed a framework for assessing camouflage textures based on the SSIM index with the aim of identifying the differences between camouflage textures and background images. The effectiveness of a camouflaged target significantly influences its detection, indicating the potential for enhancing the target detection algorithm to assess the camouflage effectiveness [39]. The infrared camouflage test effect was tested using three evaluation indexes that included a wide range of color, brightness, and texture features [40]. The color-tone similarity index (CSIM) and picture similarity index (PSIM) were introduced as methods to quantify the similarity between two color images [41]. This work focuses on identifying patterning targets within a background, then generating a saliency map through appropriate processing. Compared to other saliency map generation methods, the results derived from this approach are easier to interpret and more visually distinct [42].

This section examines various methods used for assessing camouflage effectiveness. Furthermore, there are particular drawbacks in existing approaches for evaluating camouflage effectiveness. The selection of a single feature for evaluating camouflage effectiveness may result in poor accuracy. On the other hand, the previously discussed evaluation method employs a fusion strategy that integrates several features, thus yielding more objective outcomes. These methods strongly suggest that the essential features of images play a vital role in assessing the camouflage effect. Color, luminance, structure, and texture are important in camouflage design. Additionally, the proposed method is better than other methods because of two factors: the feature fusion strategy, which makes the evaluation more objective, and the multi-feature model, which prevents single features from being biased. Therefore, a model that comprehensively evaluates all features yields superior results compared to alternative methods. Hence, this work utilizes multi-feature constraints to evaluate the level of camouflage between the target and its background.

3.Methods

3.1Overview

The image feature information directly reflects the degree of camouflage target fusion in the background. In order to effectively conceal the target, camouflage simulates the color, structure, and texture of the natural background. Concerning the HVS mechanism, the observer possesses a strong capability to perceive features such as color, structure, texture, and brightness. Therefore, the evaluation of the camouflage effect relies heavily on the similarity between the target and the background, which is based on image feature information. Four fundamental visual features are comprehensively evaluated: color, brightness, texture, and structure. *Figure 1* illustrates our proposed approach for evaluating the effectiveness of camouflage. The model has the different background images (N), and artificial camouflaged target images (M) are used as input. Firstly, the four metrics were calculated: image color similarity index (S_C), luminance similarity index (S_L), structure similarity index (S_S), and texture similarity index (S_T). The proposed model determined the proportions of weights using the objective information entropy approach. The subjective tests were conducted to validate the camouflage effect. Further, the level of camouflage was analyzed.

Algorithm 1 evaluates camouflage performance by computing similarity indices (S_C, S_L, S_T, S_S) between a target and its background. It converts images to appropriate color spaces, applies entropy weighting, calculates comprehensive similarity, assigns a camouflage level, and validates results using subjective evaluation.

Algorithm 1: Performance of the camouflage

Step 1: Input image a) Camouflage target image b) Background Image

Step 2: if (Similarity index=S_C and S_L)

    Image=RGB to LAB color space

    Compute S_C and S_L

    Else (Similarity index=S_T and S_S)

Image=RGB to Gray color space
Compute S_T and S_S
end
Step 3: Calculate Weight using entropy weighting method
Step 4: Calculate the Objective Comprehensive similarity
Step 5: Assign the Level of camouflage
Step 6: Evaluate using Subjective model

3.2Color similarity index (S_C)

The color is analyzed using S_C. In order to calculate the S_C, all red-green-blue (RGB) images of backgrounds and camouflage are converted to S-CIELAB space. The standard deviation of the distance in S-CIELAB space is then used to calculate the color difference between each background and camouflage image. Because it takes into account both the HVS's spatial and color perceptions, S-CIELAB space is better than other color spaces for analyzing color similarity [43]. The CIELAB space is superior to other color spaces for measuring color similarity, as it considers both the color perceptions of the HVS and spatial perception [43]. Prior to preprocessing image pairings with S-CIELAB, it is essential to convert RGB input images into CIE XYZ tristimulus values [44]. Subsequently, the background image and camouflage must be converted into the opponent's color space. The hue-saturation-value (HSV) model can be seen as a low-pass filter (LPF) within the context of image processing, analyzing the LPF for each color channel [45]. The images are then converted back into S-CIELAB space after spatial filtering, which has color channels, where brightness is represented by L*, the green-to-red distance is represented by a*, and the blue-to-yellow distance is represented by b*. The pixel (x,y) values in Equation 1 show the distance (m) between the camouflage target image and the target-overlapping area of the background image in S-CIELAB color space. This distance determines the image color similarity (ICS).

$$ICS(x,y) = \sqrt{(L_i^* - L_j^*)^2 - \left(a_i^* - a_j^*\right)^2 + \left(b_i^* - b_j^*\right)^2} \quad (1)$$

The color difference's standard deviation was calculated since it gives a more comprehensive evaluation than the mean. Equation 2 shows the S_c.

$$S_C = \sqrt{\frac{1}{x \times y}\sum_{x=1}^{x}\sum_{y=1}^{y}\left(ICS(x,y) - \frac{1}{x \times y}\sum_{x=1}^{x}\sum_{y=1}^{y} ICS(x,y)\right)^2} \quad (2)$$

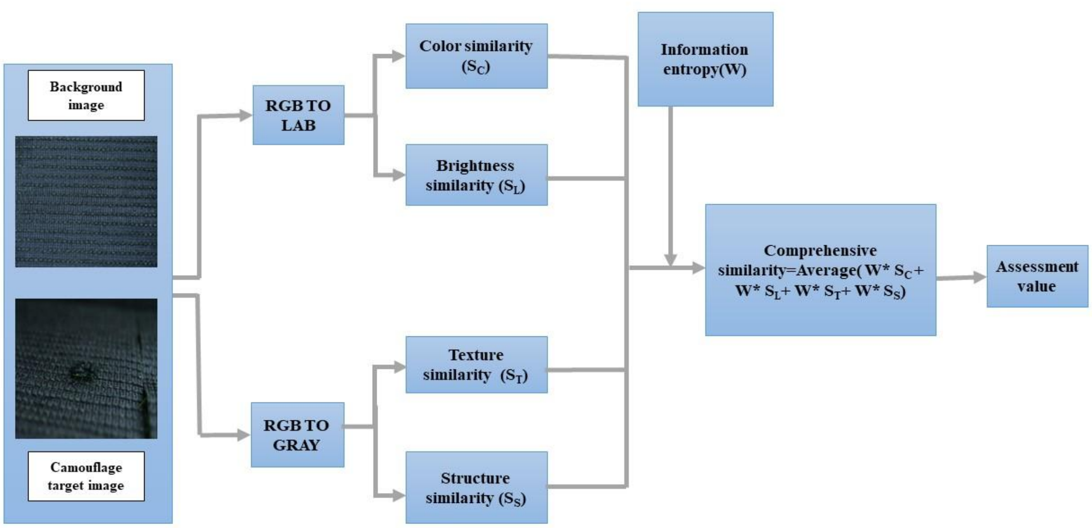


Figure 1 Flowchart of the objective evaluation method for assessing camouflage effectiveness

3.3Luminance similarity index (S_L)

The feature similarity index (FSIM) was developed for the brightness elements in color images. FSIM considers the following two factors: FSIM computes the local quality map using phase congruency (PC) and gradient magnitude (GM) [46]. PC model, is a form of edge detection that is especially resistant to variations in lighting and contrast, is a measure of feature significance in computer pictures. The PC model [47] is a frequency-based framework of visual processing. According to the PC model, the Fourier components' maximum phase includes the points where HVS detects features. The reference and test images are first applied with quadrature pair of filters to produce a collection of response vectors at the coordinates (x), scale (s), and orientation (o). Second, the local amplitude particularly at orientation (o) and scale (s) of these vectors is determined. Additionally, it computes the local energy at orientation (o). The following Equation 3 is used to determine the PC value at position (x).

$$PC(x) = \frac{\sum_j E_{\theta_j}(x)}{\varepsilon + \sum_n \sum_j A_{n,\theta_j}(x)} \quad (3)$$

Where the local energy along orientation θ_j is represented as $E_{\theta_j}(x)$ and local amplitude on scale (n) and orientation (θ_j) is represented as $A_{n,\theta_j}(x)$

Image gradient computation is traditional area of image processing. Convolution masks can be used to represent gradient operators. The Sobel gradient operator was used in this technique. Using the Sobel gradient operators, the image's partial derivatives $G_x(x)$ in the horizontal and $G_y(y)$ in the vertical directions were derived. The GM of f(x) is defined as follows in Equation 4.

$$G = \sqrt{G_x^2 + G_y^2} \quad (4)$$

An FSIM for measuring image similarity is presented using the extracted PC and GM feature maps. PC and GM features are derived from their luminance channels. The PC of the two images, the test image (f_1) and the reference image (f_2), are denoted as PC_1 and PC_2, respectively. The GM maps G_1 and G_2, as well as the PC maps, were also extracted from the images: f_1 and f_2. T_1 is a positive constant that increases the stability of S_{PC}. T_2 is a positive constant, which depends on the dynamic range of the GM values. PC_1, PC_2, G_1, and G_2 will be used to define and calculate FSIM.

The FSIM index computation consists of two steps: first, the similarity map is calculated; second, the similarity map is combined into a single score.

The following Equation 5 defines the similarity metric for $PC_1(x)$ and $PC_2(x)$:

$$S_{PC} = \frac{2PC_1PC_2 + T_1}{PC_1^2 + PC_2^2 + T_1} \quad (5)$$

The following Equation 6 defines the similarity metric for $G_1(x)$ and $G_2(x)$:

$$S_G = \frac{2G_1 2G_2 + T_2}{G_1^2 + G_2^2 + T_2} \quad (6)$$

Combining the similarity measures of $S_{PC}(x)$ and $S_G(x)$ yields Equation 7, which represents the $S_L(x)$ similarity of $f_1(x)$ and $f_2(x)$.

$$S_L(X) = [S_{PC}(X)]^{\alpha}.[S_G(X)]^{\beta} \quad (7)$$

3.4Texture similarity index (S_T)

GMSD is used for texture analysis [15]. The convolution of the background and camouflage target images was done using the Sobel operator to extract the GM images separately. The standard deviation of the magnitude difference in Equations 8 and 9 is used to show the texture difference between the gradients of the background and camouflage images.$S_i(u,v) = \sqrt{(s_h \otimes I_i(u,v))^2 + (s_v \otimes I_i(u,v))^2}$ (8)

$$S_j(u,v) = \sqrt{(s_h \otimes I_j(u,v))^2 + (s_v \otimes I_j(u,v))^2}$$

$$s_h = \begin{bmatrix} -1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{bmatrix} \; s_v = \begin{bmatrix} -1 & -2 & -1 \\ 0 & 0 & 0 \\ 1 & 2 & 1 \end{bmatrix} \quad (9)$$

After that, standard deviations were added to obtain the overall GMSD, which measures the texture similarity between the background and camouflage images. Equation 10 shows the texture similarity of gradients, and Equation 11 shows the GMSD.

$$GMS(u,v) = \left(2S_i(u,v) \cdot S_j(u,v)\right) / \left(S_i^2(U,V) \cdot S_j^2(U,V)\right) \quad (10)$$

$$GMSD_{ij} = \sqrt{\frac{1}{UV} \sum_{u=1}^{u=U} \sum_{v=1}^{v=V} (GMS(u,v) \frac{\sum_{u=1}^{u=U} \sum_{v=1}^{v=V} GMS(u,v)}{uv})} \quad (11)$$

3.5Structure similarity index (S_S)

The structure of the image reflects its overall framework. People frequently employ image structure analysis to evaluate the quality of images. The SSIM index measures the degree of visual similarity between the background image and the camouflage target image. The development of SSIM relied on fundamental assumptions of the HVS. In order to calculate the SSIM value, this quantitative measure considers three factors: brightness, contrast, and structural information between the two pictures [48]. The SSIM algorithm divides the similarity measurements into three parts: luminance, contrast, and structure [49]. The mean intensity of the two images determines the brightness between them. The standard deviation defines the contrast. The correlation between the two images defines the structure. These three elements are multiplied to form

SSIM (x, y). Equation 12 represents the structure's similarity.

$$SSIM = \frac{(2\mu_x\mu_y+c_1)(2\sigma_{xy}+c_2)}{(\mu_x^2+\mu_y^2+c_1)(\sigma_x^2+\sigma_y^2+c_2)} \quad (12)$$

Where the is the pixel sample mean of x, is the pixel sample mean of y, is the variance of x, is the variance of y, and is the covariance of x and y. c_1 and c_2 are constants defined by the dynamic range of pixel values**.**

3.6Estimation of weights

The objective weighting method commonly uses entropy theory as an approach. Entropy represents the quantity of useful information present in uncertain data. The main benefit of the EWM over other subjective weighting models is its elimination of human factors influencing indicator weights, thereby enriching the objectivity of the comprehensive evaluation outcomes. EWM assesses value by quantifying the degree of differentiation. A higher degree of dispersion in the measured value correlates with increased index differentiation, yielding more information. For parameters that provide more information, weights are higher.Using the similarity approaches, x_{ijk} is given by taking the differences between the i-th camouflaged target and j th background image, where k = 1 for the S_C and S_L and 2 for the S_T and S_S, respectively. Thus, the ratio of the i th camouflaged target image to the j-th background image computed using the k-th technique can be stated as follows. Equation 13 represents the entropy formula.

$$p_{ijk} = x_{ijk} / \sum_{i=1}^{M} x_{ijk} \quad (13)$$

The entropy theory [18] provides an equation to compute each metric's weight, representing the entropy as $p_{ijk}\ln(p_{ijk})$ in Equation 14, the weight as W_j in Equation 15, and the similarity index as V_j in Equation 16.

$$E_j = \frac{1}{\ln n}\sum_j^n p_{ij} ln(p_{ij}) \quad (14)$$

$$\omega_j = \frac{1-E_j}{n-\sum_j^n E_j}, 1 \le j \le n \quad (15)$$

$$v_j = \sum_{k=1}^{2}\sum_{i=1}^{M} w_k x_{ijk} \quad (16)$$

By calculating the average values of four similarity indices, the proposed method obtained the final camouflage effectiveness value.

3.7Comprehensive similarity measure

This method uses the entropy weight approach to calculate the weights of each feature, such as color, brightness, texture, and structure, based on their similarity. The comprehensive similarity measurement value of the camouflage target is obtained by averaging all similarity indices.

In Equation 17, the overall comprehensive similarity value is represented as comprehensive similarity of objective methods (CS_{obj}).

$$CS_{obj} = \text{Average}\ (S_C+S_L+S_T+S_S) \quad (17)$$

In Equation 18, the comprehensive similarity of non-spatial relationship similarity indices is represented as comprehensive similarity of non-spatial relationship parameter (CS_{NSR})

$$CS_{NSR} = \text{Average}\ (S_C+S_L) \quad (18)$$

In Equation 19, the comprehensive similarity of spatial relationship similarity indices is represented as comprehensive similarity of spatially related parameter (CS_{SR})

$$CS_{SR} = \text{Average}\ (S_T+S_S) \quad (19)$$

A difference of less than 25% between two images [50], may be considered similar. *Table 1* [2] illustrates that the grade levels for the correlation coefficient of the target fusion degree can be adjusted.

Table 1 Standard level of camouflaged target effect

Percentage of target fusion	Level of camouflage
Greater than or equal to 95%	I
Greater than or equal to 85%	II
Greater than or equal to 75%	III
Less than 75%	IV

3.8Subjective evaluation method

To validate the proposed method, an experiment was conducted to collect various artificial camouflage target patterns using a camera. *Figure 2* illustrates the subjective evaluation process of the experiment. Twenty observers aged 23 to 35 with normal color vision participated in the experiment. Each camouflage image was evaluated 20 times, and the average value of each subjective evaluation index was calculated. The camouflage target image was displayed, and the observer was seated 1.5 meters away from the screen. Observers need to evaluate two subjective assessment criteria: detection time and subjective similarity. The observers evaluated the search time by searching the camouflage target and clicking the mouse. The detection time is the duration required to locate a camouflaged target through clicking a mouse. By pressing the numbers 1 through 7, the observers evaluated the subjective similarity between the camouflaged target and the background image. At the valuation step, the psychophysical evaluation scale approach is used, with a seven-point rating scale ranging from least similarity (1) to extreme similarity (7).

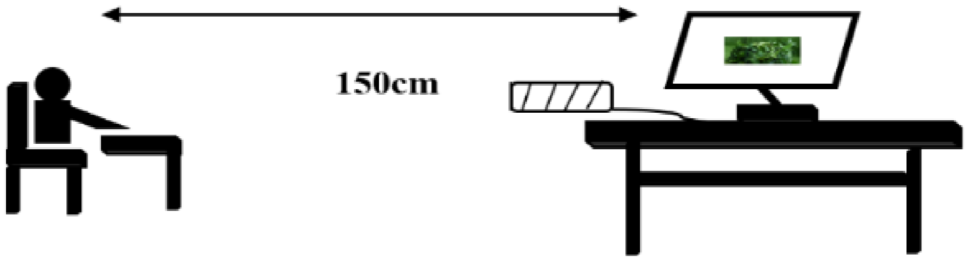


Figure 2 Experimental process of subjective evaluation

4.Results

The experiment utilized four different backgrounds. Camouflage material samples were collected from an indoor environment. For each sample type, three images were captured and augmented to create 60 samples. Two camouflage samples were obtained using Army and black camouflage clothing. The jungle camouflage background contained forest leaves and grass, while the terrain camouflage consisted of stones. *Figure 3* presents images of the samples.

(a) (b) (c) (d)

Figure 3 (a) Army camouflage (b) dark camouflage (c) Jungle camouflage (d) Terrain camouflage

4.1Objective evaluation metrics validity

Based on features, the similarity measurement value of the target is obtained, as shown in *Table 2*. Seven objective models and subjective evaluation indices were employed to predict camouflage effectiveness. There are four single index evaluation models (S_C, S_L, S_T, S_S) and three comprehensive index models (CS_{NSR}, CS_{SR}, CS_{Obj}) among the seven predictors. S_C, S_L, S_T, S_S are objective metrics; the weights were determined using entropy.

The color and brightness are not spatially related similarity parameters, and the texture and structure are the spatially related.

Table 2 Similarity statistics of four features

Target Images	**S_C**	**S_L**	**S_T**	**S_S**
Army Camouflage	0.9826	0.9624	0.9908	0.9197
dark Camouflage	0.8909	0.8672	0.9129	0.8913
Jungle camouflage	0.8523	0.7839	0.7951	0.7837
Terrain Camouflage	0.7165	0.7235	0.6872	0.7302

4.2Analysis of comprehensive similarity measure

CS_{NSR}, CS_{SR}, and CS_{Obj} perform as objective indicators. CS_{NSR} is derived from the average of S_C, S_L, and CS_{SR} is derived from the average of S_T, S_S. The average of S_C, S_L, S_T, and S_S yields CS_{Obj}.

Table 3 indicates that army camouflage has more effectiveness compared to other camouflage designs. The army camouflage target exhibits a greater degree of fusion with its surroundings compared to other camouflage targets. The effectiveness of camouflage patterns is maximized when the degree of target fusion with its background is great, while lower effectiveness is observed when this integration is low. The computation and analysis of camouflage images, along with *Table 3*, reveal the effect of the camouflage target on the background and assess the degree of camouflage.

Table 3 Statistical analysis of comprehensive similarity

Target image	CS_{NSR}	CS_{SR}	CS_{Obj}	Comprehensive result in %	Camouflage level
Army Camouflage	0.9725	0.9552	0.9638	96.38	I
Dark Camouflage	0.8790	0.9021	0.8905	89.05	II
Jungle camouflage	0.8181	0.7894	0.8037	80.37	III
Terrain Camouflage	0.7200	0.7087	0.7144	71.44	IV

5.Discussion

Feature analysis provides a viable method for assessing the effectiveness of camouflage. However, this objective evaluation method lacks a clear counterpart in human vision. A psychophysical assessment approach is represented by the use of eye movement data to assess the effectiveness of camouflage. Several investigations have shown a correlation between various eye movement metrics and the detectability of targets. However, assessing camouflage efficiency is an intricate process that includes feature analysis and human perception. To comprehensively account for the complexities of human vision involvement in evaluating camouflage effectiveness, this study proposed a model for assessing the camouflage effectiveness of a target using multi-feature analysis. This model consists of four essential feature indices: S_C, S_L, S_T, and S_S. This study conducts several subjective evaluation tests to validate the objective evaluation performance. This study selects various images for testing and visualizes the results to demonstrate the effectiveness of camouflage. As shown in *Figures 4* and *5 (a)* and *5(b)*, the objective evaluation parameters are chosen to examine the relationship with the two subjective evaluation parameters (search time and subjective similarity) extensively. The horizontal axes in *Figures 4* and *5 (a)* and *5(b)* represent the Comprehensive Similarity Index CS_{Obj}, CS_{NSR}, and CS_{SR}, while the vertical axis represents the subjective evaluation results of four camouflage images.

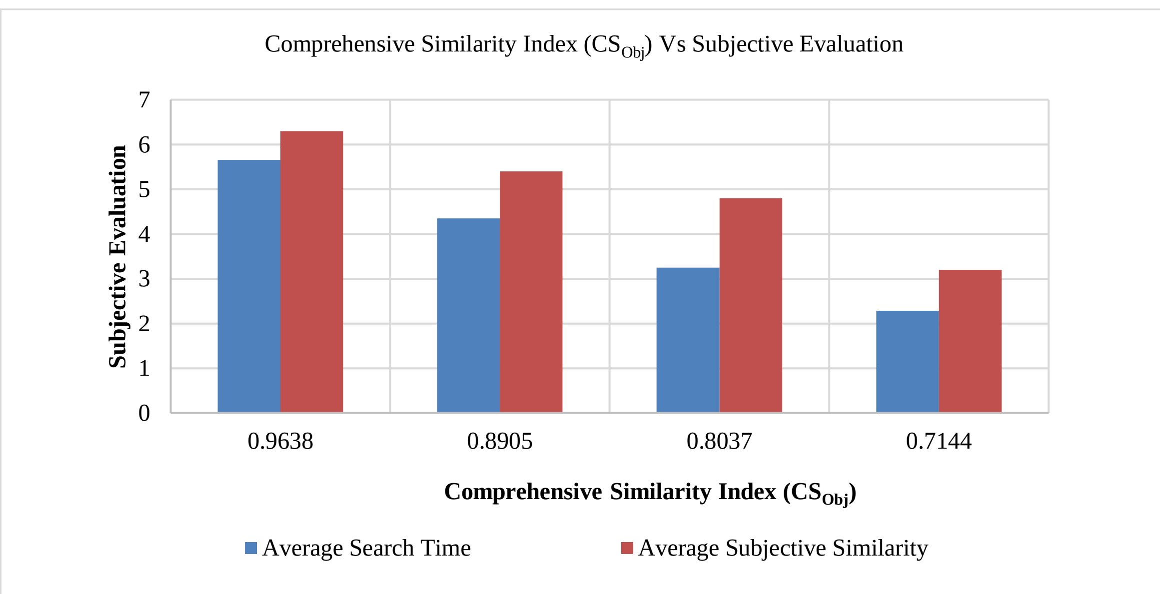
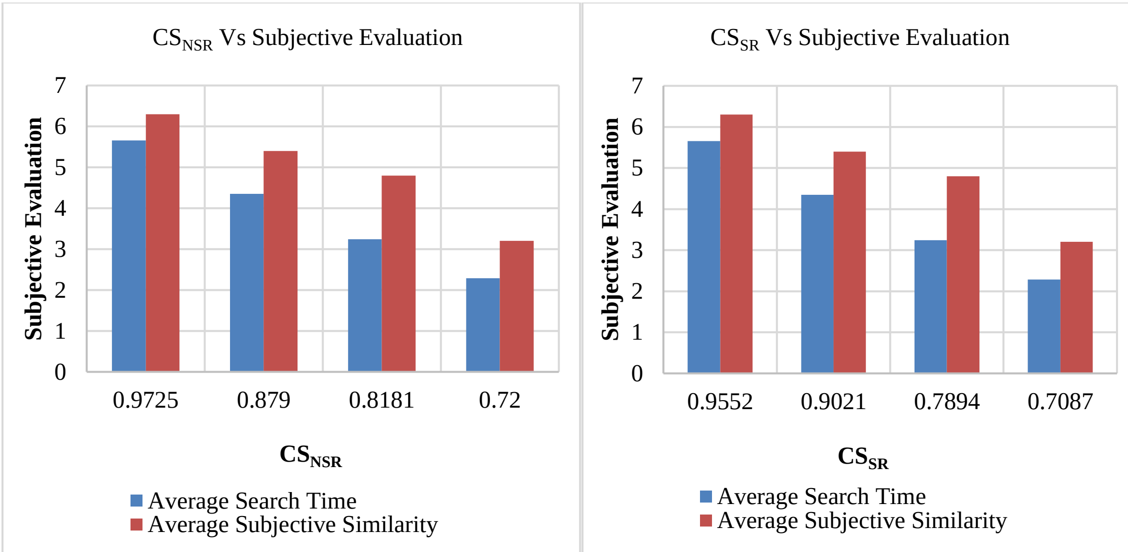


Figure 4 The correlation between Comprehensive similarity Index and Subjective evaluation



(a) (b)

Figure 5 (a) The correlation between CS_{NSR} and subjective evaluation (b) The correlation between CS_{SR} and subjective evaluation

The detection time and subjective similarity ratings of the observers showed a strong linear trend based on the target's similarity to the background. For the army camouflage, which is a highly similar target (CS_{obj} =0.9638), the observers took a longer time to detect the target and gave a higher similarity rating compared to the detection times and similarity ratings for the comparatively less similar target of dark camouflage (CS_{obj} =0.8905). Similarly, for the dark camouflage (CS_{obj} =0.8905). The average detection time taken to detect the target and the average subjective similarity rating given by the observers were comparatively higher than the average detection time and average subjective similarity rating for the comparatively less similar target of jungle camouflage (CS_{obj} =0.8037). and so on.

The comprehensive model demonstrates improved evaluation performance compared to the single index model, based on the subjective evaluation results. The findings correspond to the conditions: higher camouflage between the background and target correlates with greater assessment similarity, increased search time, and lower detection probability. Compared to the other methods, the proposed approach shows a stronger linear relationship, as shown in *Figures 4* and *5 (a)* and *(b).* The results demonstrate that the proposed camouflage effectiveness assessment method is the most effective, yielding outcomes consistent with human visual perception.

In the military field, these findings can improve target fusion by strategically designing a multi-featured pattern. Real-world applications can use it to evaluate visible light camouflage technology and study camouflage materials.

5.1Limitations

This study has certain limitations. Collecting camouflage data is more challenging than acquiring standard target detection datasets. Future research may focus on collecting additional artificial camouflage data to address this challenge. Response time in subjective assessments of camouflage recognition may vary based on a person's age and position relative to the display. This can be mitigated by establishing specific guidelines for seating posture and visual ability. Additionally, as the experiment was conducted in a laboratory setting, caution is required when applying the findings to real-world combat scenarios. Battlefield conditions, including safety concerns and the significant psychological and physical demands on soldiers, may influence their interactions with camouflaged targets and environments. A complete list of abbreviations is listed in *Appendix I.*

6.Conclusion and future work

A multi-feature-based comprehensive model was used to assess camouflage effectiveness, outperforming existing methods. To determine camouflage performance, four single-index models are employed: S_C, S_L, S_T, S_S, and three comprehensive models: CS_{NSR}, CS_{SR}, CS_{Obj}. The outcomes show that the comprehensive models exhibit superior predictive performance due to their ability to represent more features. The multi-feature-based comprehensive assessment method for camouflaged target effectiveness calculates the degree of fusion between the target and background. The model considers image color, brightness, structure, and texture, rendering it more comprehensive and associated with the HVS. The subjective model based on human visual evaluation experiments may be employed as a reliable assessment model for camouflage performance, as it addresses the limitations of the existing evaluation model, including incomplete evaluation indices and insufficient consistency with visual perception. The correlation between proposed CS_{Obj} results and the subjective test results suggests that this approach has the finest evaluation performance. The proposed comprehensive assessment methodology can accurately and objectively describe the level of camouflage for a target in varied environments. Future studies will aim to identify additional features that capture the saliency of camouflage patterns.

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Conflicts of interest
The authors have no conflicts of interest to declare.

Data availability
The data are not publicly available. However, the data may be provided by the corresponding author upon reasonable request.

Author’s contribution statement
K. Karthiga: Experimental design, Algorithm development, Performing experiments, Writing – original draft. **A. Asuntha:** Supervision, Writing – review and editing.

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Appendix I

S. No.	Abbreviation	Description
1	CS_{Obj}	Comprehensive Similarity of Objective Methods
2	CS_{NSR}	Comprehensive Similarity of Non-spatial Relationship Parameter
3	CS_{SR}	Comprehensive Similarity of Spatially Related Parameter
4	CSI	Camouflage Similarity Index
5	CSIM	Color-tone Similarity Index
6	EWM	Entropy Weight Method
7	EEG	Electroencephalography
8	FSIM	Feature Similarity Index
9	GMSD	Gradient Magnitude Similarity Deviation
10	HSV	Hue-Saturation-Value
11	HVS	Human Visual System
12	ICS	Image Color Similarity
13	LPF	Low-Pass Filter
14	MAE	Mean Absolute Error
15	MF-CFI	Multi-Feature Camouflage Fused Index
16	PC	Phase Congruency
17	PCC	Pearson Correlation Coefficient
18	PSIM	Picture Similarity Index
19	PSNR	Peak Signal-to-Noise Ratio
20	RGB	Red-Green-Blue
21	SSIM	Structural Similarity Index
22	S_C	Color Similarity Index
23	S_L	Luminance Similarity Index
24	S_S	Structure Similarity Index
25	S_T	Texture Similarity Index
26	UIQI	Universal Image Quality Index