Hindawi
Modelling and Simulation in Engineering
Volume 2022, Article ID 2986346, 12 pages
https://doi.org/10.1155/2022/2986346

Research Article

Digital Camouflage Pattern Design Based on the Biased Random Walk

Yuanying Gan, Chuntong Liu, Zhenxin He, Hongcai Li, and Zhongye Liu

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

Correspondence should be addressed to Yuanying Gan; yiran_gan@sina.cn

Received 1 February 2022; Revised 8 May 2022; Accepted 26 May 2022; Published 16 June 2022

Academic Editor: Fahad Al Basir

Digital camouflage is a common countermeasure against military reconnaissance. In the face of high-tech imaging reconnaissance, battlefield detection means tend to be automated and refined. In order to adapt to the concealment requirements under various environmental backgrounds, combined with the camouflage performance of digital camouflage and its feedback mechanism in camouflage pattern design, this paper proposed a digital camouflage pattern design method based on biased random walk. Firstly, the original background is preprocessed, and the background texture's direction, corner, step length, and pixel intensity difference are statistically analyzed, and the boundary probability between pixel nodes is estimated. Then, a biased random walk is used to outline the camouflage patches. The edge scatter is enriched according to the density of the patches, and the camouflage patches are filled according to the proportion of the main color of the background. Finally, a digital camouflage pattern is obtained. The quantitative analysis results show that the mean heart rate of the digital camouflage pattern based on multiscene design is at least 31.0% higher than that of the original background segmentation texture, and the standard deviation index of equivalent diameter is increased by 14.9% on average. In addition, the results of simulation camouflage image detection in multiple scenes show that the proposed method can effectively deal with camouflage target detection on the basis of fully retaining the original background texture information and has strong camouflage concealment effect in the scene.

1. Introduction

In optical images, pixels are regarded as the smallest indivisible unit in the whole image. The mosaic generated based on pixels is disordered. Compared with the smooth edge of traditional camouflage, the digital camouflage composed of mosaics of different shapes and sizes shows better camouflage effect in major scenes [1–4]. The digital camouflage design mainly includes two parts: the extraction of background tone and the design of camouflage patches [5]. The main color extraction of background images generally adopts K-means clustering method [6–11], color histogram [12, 13], and other methods. According to the similarity rule, the classification of image colors can obtain the main representative colors in the background image, and filling the designed digital patches can increase the similarity between the digital camouflage pattern and the original background and enhance the camouflage effect of the target.

Yan [8] pointed out that a good camouflage pattern should not only be similar to the scene in color but also be in harmony with the background in texture characteristics. Yu et al. [5] proposed a method for designing camouflage patches based on background color and edge information, which got rid of the inherent dependence on the designer's experience and enhanced the camouflage effect. Bai et al. [14] segmented the background based on the watershed algorithm to obtain the blob shape. Wang Zhan et al. used the mean shift and minimum spanning tree algorithm to extract the background image blobs. Yun-xiang et al. [15] used the fractal Brown model to study the generation of digital camouflage patterns. The above methods are based on statistical background characteristics and have a high similarity with the background image.

Considering the invariance of two-dimensional plane digital camouflage, Wu et al. [16] proposed a stereoscopic camouflage imaging algorithm based on background depth information and formed a raster image theory based on parallax factors to produce a digital camouflage pattern with three-dimensional dynamic effect. The three-dimensional and dynamic effects will be significantly weakened with the increase of the reconnaissance distance, and the operability and applicability are not strong. Based on this, Zhou et al. [17] introduced texture lines covered by optical illusion strips and arranged and combined them according to certain rules to generate camouflage patterns, which stimulated human vision to form visual perception deviations and increased the camouflage target to some extent. The deceptive observation angle weakens the similarity between the digital camouflage pattern itself and the background.

In order to make the designed digital camouflage pattern not only retain the certainty of the original background texture but also show the randomness of the camouflage patches, Qi et al. [18] used the Markov random field model to simulate the characteristics of the regional background, generated a two-dimensional texture matrix, and initially solved the subjective and random problems of camouflage spots. Bi et al. [19] used the random midpoint displacement method to generate fractal curves to simulate complex and irregular geometric shapes in nature, but this lacked the constraints of background information on texture curves.

Armi and Fekri-Ershad [20] analyzed many texture features and found that affected by noise, illumination, scale, rotation, viewpoint, and other factors, texture presents diversity and complexity, which provides ideas for our texture design method. In recent years, random walk algorithms have achieved outstanding results in the fields of image dehazing [21, 22], image segmentation [23, 24], and evolutionary images [25]. The biased random walk [26] is based on satisfying a certain trend law but also meets the characteristics of random walk. This concept fully conforms to the design concept of digital camouflage texture. This paper simulates the trend of irregular texture based on the random walk algorithm, estimates the boundary probability between pixel nodes by defining the trend function, outlines the digital camouflage patches, and finally fills the main color of the background to distort the surface features of the target and realizes the design of digital camouflage patterns.

2. Camouflage Patch Design

2.1. Random Walk Motion Hypothesis. Assume that each pixel in the background image is node $N_{x,y}$ (x and y represent the row and column coordinates of the image matrix, respectively). We define the connection between nodes as edge $E(N_{x,y}, N_{x',y'})$ and segment the image through the connection between nodes and edges to obtain digital camouflage patches. A good digital patch should have both the certainty of the background texture and the randomness of the target survival scene. Therefore, the selection of nodes and the direction of edges are the key points in the process of camouflage patch generation. If a pixel is randomly selected as the moving point M, the running trajectory of the moving point M in the image is piecewise linear.

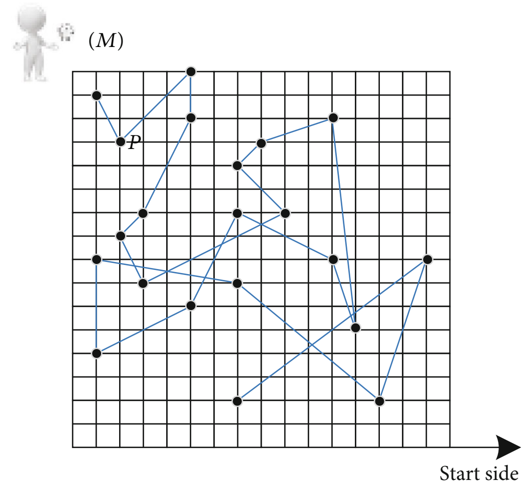


Figure 1: Schematic diagram of random walk piecewise linear motion.

According to the general assumption of the type of motion, this "linearity" depends on the time and position of each point's motion. If mapped in an image, it is equivalent to node $N_{x,y} = (x, y)$ coordinates and edge lengths $E(N_{x,y}, N_{x',y'})$. The "piecewise "is reflected in the angle between the edge and the edge; that is, the current node is the vertex, the moving point M moves to the next node as the end point, and the ray from the vertex to the horizontal right side of the image is set as the starting edge. The connecting line from the vertex to the end point is the end edge, and the angle between the end edge rotated clockwise to the direction of the start edge is recorded as the rotation angle θ. So far, the texture curve drawn in the image is the digital camouflage patch.

Assuming that the number of points obtained by a person throwing a dice once is the moving point motion step, and the number of points obtained by throwing the dice twice is converted into an angle, then the random walk of the moving point M in the image is shown as the running trajectory in Figure 1. Theoretically, the node position that the moving point M will reach next is the product of the random probabilities of two dice throws, and the obtained probability is a set of random variables. Therefore, the moving point trajectory in Figure 1 is a completely unconstrained random process.

2.2. Biased Random Walk. From the point of view of a single event, the ideal random walk motion does not have any regularity. After the digital patches generated based on random walk are colored, it can show good destructiveness in the whole scene but ignores the original texture trend of the background pattern. The biased random walk is based on the irregular random walk, and it also satisfies some specific trends. Therefore, the limited condition of the background texture feature is used as a constraint function, which not only retains the background feature but also satisfies the randomness. The resulting camouflage patches can have more advanced camouflage effects.

2.2.1. Random Walk Dependency Model. The general idea of a random walk is to stop at (x_l, y_l) with a given probability $P(x, y, \theta, l)$ (l is the movement distance). The probability distribution $q_{x,y,\theta}(l)$ of the motion unit that starts to move along θ and moves a distance l at the position (x, y) is

$$q_{x,y,\theta}(l) = \exp\left(-\int_0^l P\left(x + \zeta_{\bar{x},y,\theta}(s), y + \zeta_{x,\bar{y},\theta}(s), \theta, s\right) ds\right), \tag{1}$$

where $\zeta_{x,y,\theta}(s)$ is expressed as the vector of the motor unit from the point (x, y) in the distance interval $[x + s_x, y + s_y]$; $\zeta_{x,y,\theta}(s) = s \cdot \angle\theta$; based on the chemokine ρ with biased characteristics, a simple functional correlation can be derived:

$$P(x, y) = P(\rho(x, y)). \tag{2}$$

This means that each motor unit can only be affected by chemokines at a specific location. Based on this, we assume a simplest dependency model:

$$\begin{gathered} \beta(x, y, \theta) = \beta_0\left(\rho(x, y), D^\theta \rho\right), \\ D^\theta \rho = \partial_x \rho + \partial_y \rho + c\theta \cdot \nabla_l \rho, \end{gathered} \tag{3}$$

where c is a constant.

Combined with the above-mentioned dependency models, the chemotactic function $\rho(x, y)$ can be enriched by establishing various mathematical model mechanisms, so as to realize the control of biased random walk of seeds in the motor unit.

2.2.2. Mathematical Model Mechanism. Considering that the camouflage patches need to retain the original background texture information, the constraint function must first learn the prior information of the background texture. Perform image segmentation processing on the original background, remove noise points, count the obtained edge point information of each segmentation, and iterate the 8 neighborhood directions of each pixel point. If it is the same as the previous step, the statistical step size is $l + 1$. If they are different, calculate the rotation angle θ, and after traversing the entire image, obtain the statistical values of the step length and direction rotation angle, calculate the ratio of the different step length l and the direction angle θ, and obtain the final probability distributions P_l andP_θ:

$$\begin{cases} P_l = \{p_{l1}, p_{l2}, \cdots, p_{l\,\max}\}, \\ P_\theta = \{p_1, p_2, \cdots, p_8\}. \end{cases} \tag{4}$$

The definition of the direction angle is shown in Figure 2. As can be seen from the figure, there is a positional correspondence between the pixels in the same straight line direction, and there will be repeated calculations when the direction corners are counted. Therefore, when we set the random walk prerequisites, the 8 directions in the direction corners are converted into 4 directions, and batch iterations are considered, which not only ensures that there are no gaps in each direction but also prevents the phenomenon of reentry and overlap in the adjacent steps of the random walk.

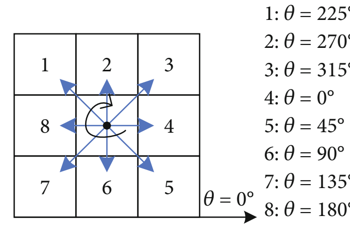


Figure 2: Schematic diagram of direction angle definition.

2.3. Build Weight Coefficients. According to the segmentation result of the original background image, the step size information $\mathbf{L} = \{l_1, l_2, \cdots l_{\max}\}$ is obtained, the frequency of occurrences corresponding to different step sizes is counted, and the probability value $\mathbf{P}_l$ of the step size is calculated. Finally, the walk step size is randomly generated according to the probability and normalized, and the step size parameter S_{stepPara} is obtained as

$$S_{\text{stepPara}} = R_{\text{Random}}(\Phi(\mathbf{L}), \mathbf{P}_l), \tag{5}$$

where $\Phi(\cdot)$ represents the normalization process, namely, $\Phi(\mathbf{L}) = \{l^\phi\}$ and $l_i^\phi = l_i / l_{\max}$, and $R_{\text{Random}}(\mathbf{A}, \mathbf{B})$ represents that a certain data in the corresponding set $\boldsymbol{A}$ is generated according to the probability value in the set $\boldsymbol{B}$, where $\boldsymbol{A}$ and $\boldsymbol{B}$ are the corresponding relationship.

The core of realizing random walk is to obtain the weight of each texture edge (straight edge). In order to fully describe the background information, the pixel value and geometric distance (step size and direction) of the current position are comprehensively considered. Convert all pixel coordinates in the image to line indices $E(x, y)$, set the edge indices in the order of coordinates, and calculate the pixel difference of each potential edge according to the edge index assumption in the image, and normalize it. The pixel parameters V_{valPara} is

$$V_{\text{valPara}} = \Phi\left(\sqrt{\sum \left(I_{\text{val}}(E(x, y)) - I_{\text{val}}\left(E\left(x', y'\right)\right)\right)^2}\right), \tag{6}$$

where I_{val} is the current position pixel value.

Finally, the Gaussian weight W is calculated, that is,

$$W = \exp\left(-\left(\alpha \cdot V_{\text{valPara}} + \beta \cdot S_{\text{stepPara}}\right)\right) + C, \tag{7}$$

where α and β are the coefficients of the V_{valPara} and S_{stepPara} parameters, respectively. In this paper, the parameter α is set to 0.8, and the parameter β is set to 0.2, so that the obtained weight result highlights the pixel change law, and C is the

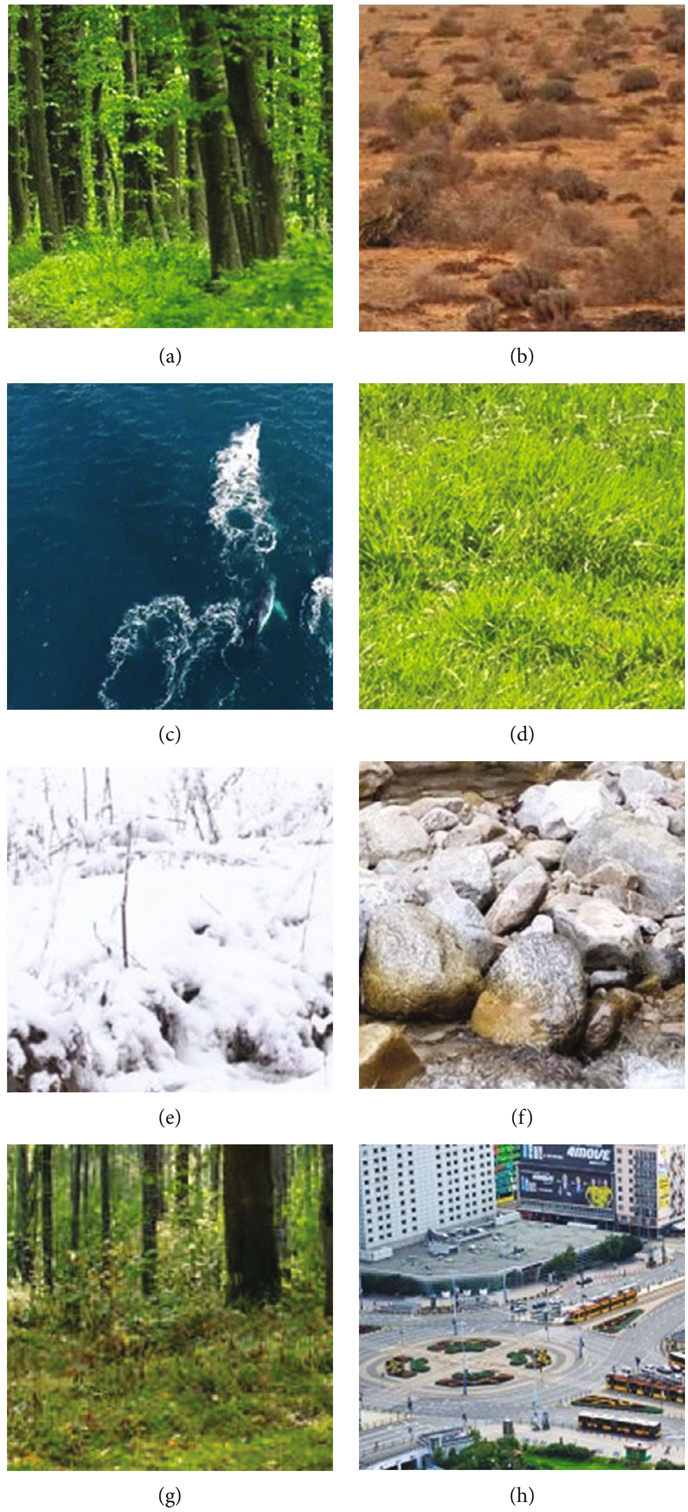


FIGURE 3: Original background image. (a) Forest, (b) desert, (c) ocean, (d) grassland, (e) snow, (f) gravel, (g) woodland, and (h) city.

minimum optional constant (this paper sets $C = 10^{-5}$) to ensure numerical stability.

2.4. Dirichlet Problem. The Dirichlet problem is the solution of the harmonic function at the boundary. Let the boundary of the region D be Q, and find the solution of continuous boundary value on Q, satisfying the given condition in D. In the image, the boundary of the patch is composed of texture, then the area D must be bounded, and the boundary points are all regular points. Combined with the conditional function, set up the Dirichlet problem to solve the camouflage patch boundary, first initialize the boundary, construct a diagonal

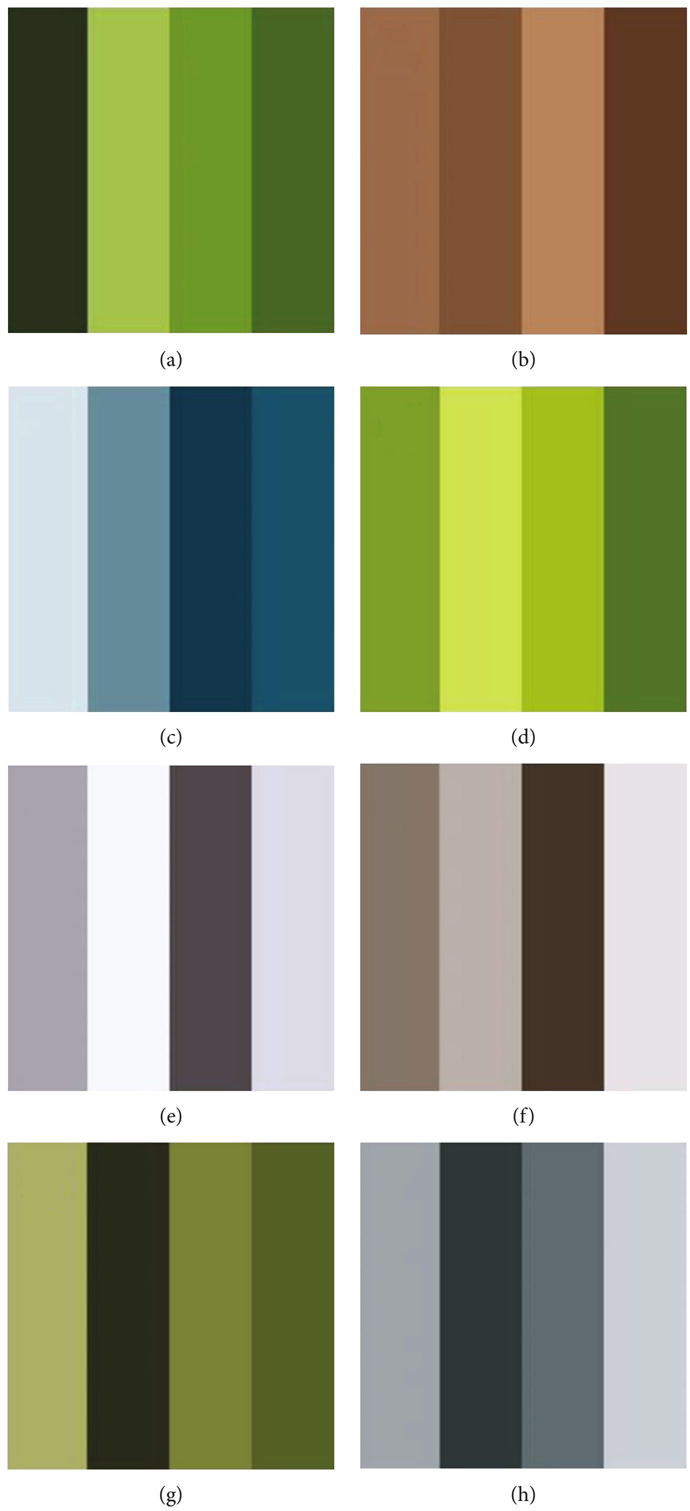


Figure 4: Four main color extraction. (a) Forest, (b) desert, (c) ocean, (d) grassland, (e) snow, (f) gravel, (g) woodland, and (h) city.

matrix from all the seed points in the sample image according to the label size, and regard it as the initialization boundary Q_0.

Construct a Laplace sparse matrix $\mathbf{\Gamma}$ according to the weight information corresponding to each edge, set up the Dirichlet problem, solve the random walk probability by solving the combined Dirichlet problem, obtain the probability matrix, and match texture patch markers based on the maximum values of rows and columns returned and index information.

$$\mathbf{\Gamma} = \mathrm{diag}\left(\sum \mathbf{S}\right) - \mathbf{S}, \tag{8}$$

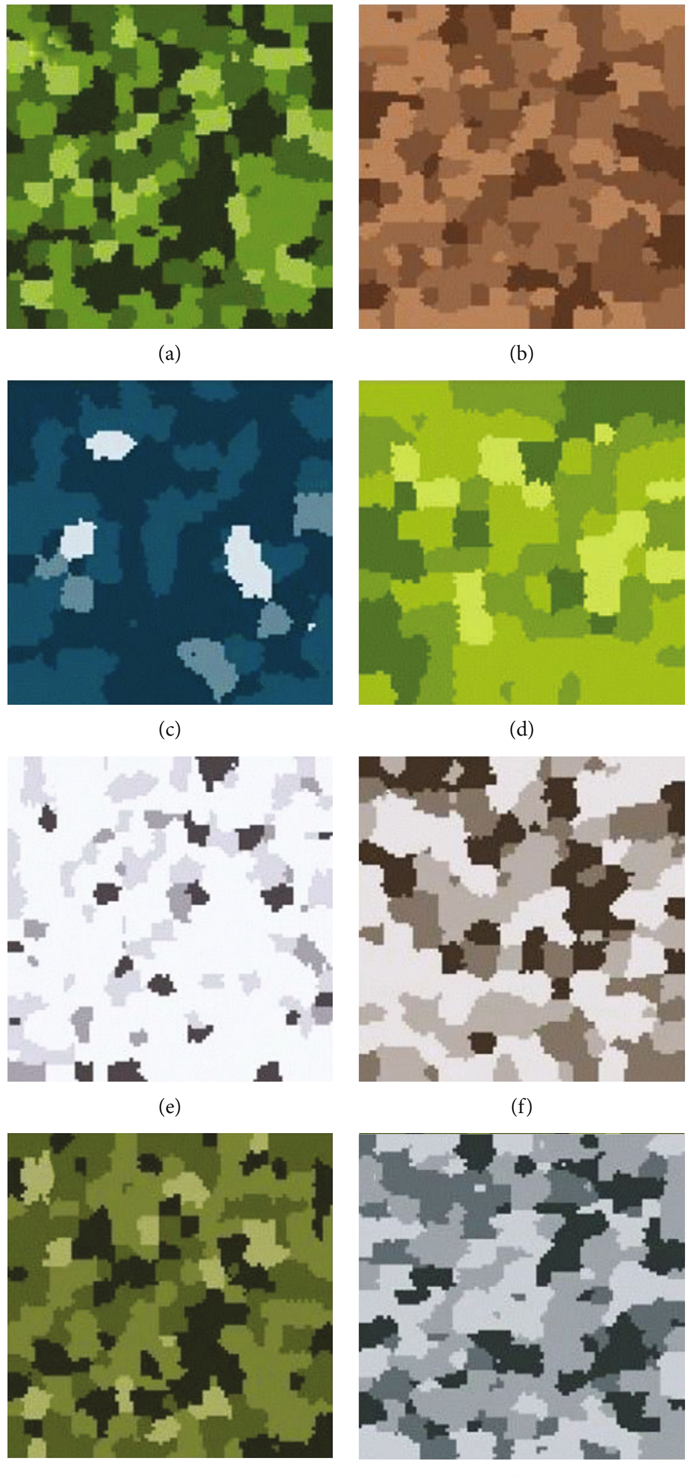


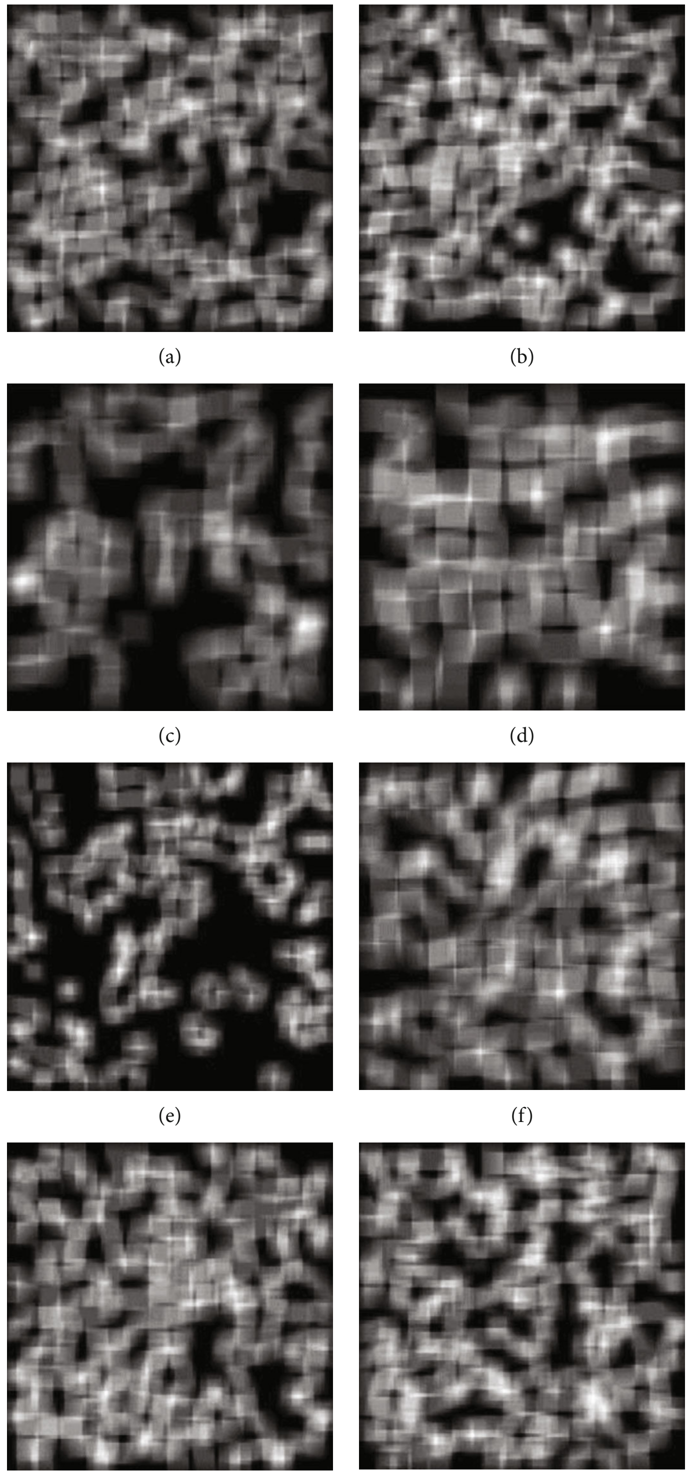
Figure 5: Texture patch map. (a) Forest, (b) desert, (c) ocean, (d) grassland, (e) snow, (f) gravel, (g) woodland, and (h) city.

where $\boldsymbol{S}$ is composed of edge index and corresponding edge weight information, the row and column are equivalent to the sparse square matrix of the total number of pixels, and diag $(\cdot)$ indicates that the diagonal matrix is constructed.

So, the matrix $\mathbf{Z}$ for estimating texture patch edges can be expressed as

$$\mathbf{Z} = -\boldsymbol{\Gamma}_{\overline{\text{core}}} / (\boldsymbol{\Gamma}_{\text{core}} \cdot \mathbf{I}_k), \tag{9}$$

where $\boldsymbol{\Gamma}_{\text{core}}$ is the sparse matrix containing the core pixels of k camouflage patches, $\boldsymbol{\Gamma}_{\overline{\text{core}}}$ is the noncore sparse matrix, and $\mathbf{I}_k$ is the k-order unit matrix.



(a) (b) (c) (d) (e) (f) (g) (h)

Figure 6: Texture patch dense map. (a) Forest, (b) desert, (c) ocean, (d) grassland, (e) snow, (f) gravel, (g) woodland, and (h) city.

3. Camouflage Pattern Fill

3.1. Camouflage Patch Main Color Fill. Some animals in nature can change the pigmentation state of their skin to hide in the background. The protective prey can "distort" their body contours, making predators appear visual fragments and improving the animal's own survivability.

Different combat environments require different main colors of digital camouflage. The original image contains N pixels, and each pixel value is between [0,1]. Four clustering

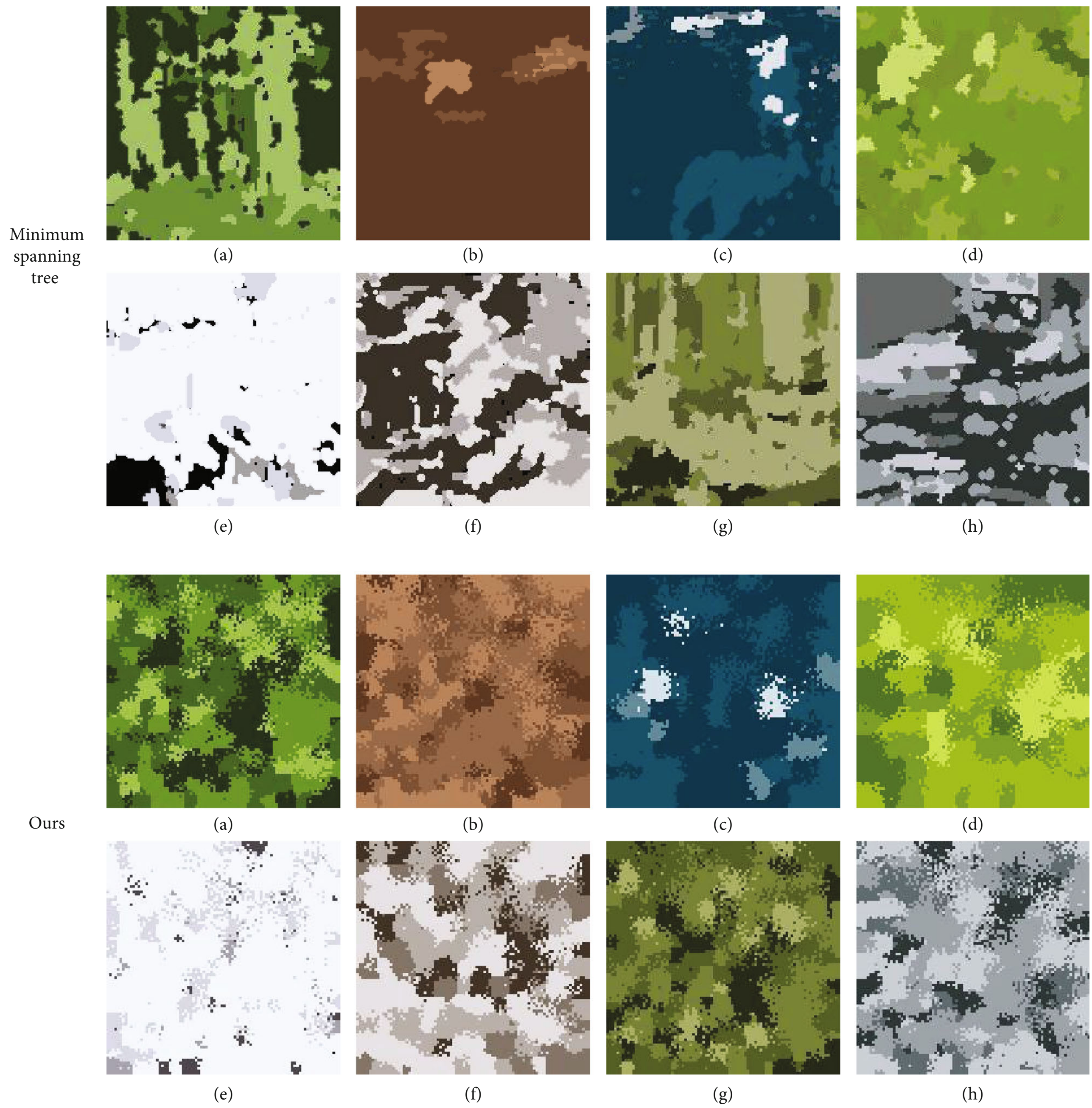


FIGURE 7: Camouflage pattern. (a) Forest, (b) desert, (c) ocean, (d) grassland, (e) snow, (f) gravel, (g) woodland, and (h) city.

centers (pixel values) are randomly initialized. According to the clustering idea, four main colors are extracted, which are used as digital camouflage coloring options to enhance the target camouflage effect. The specific idea is that the pixel values with similar sizes are grouped, and the pixel values corresponding to the clustering center are relocated through iteration. After the iteration process converges, the final four pixel values are the four main colors of digital camouflage. Filling the extracted background main color to the digital camouflage patch can increase the hiding performance of the target to a certain extent. K-means clustering algorithm is one of the simplest and most effective unsupervised algorithms at present. Using this algorithm, it can realize eight typical scenes such as forest, desert, ocean, grassland, snow, gravel, woodland, and city (Figure 3) to extract the color and generate the main color cluster diagram; the result is shown in Figure 4.

The background is analyzed according to the mathematical model in Section 2, followed by a biased random walk strategy, to generate camouflage patches and fill the patches with four main tones. The results are shown in Figure 5.

It can be seen from Figure 5 that the generated camouflage pattern, because of the strong difference in the main color, makes the inner edge of the pattern obvious, and the texture information is very easy to obtain, forming a new exposed feature of the camouflage target.

Table 1: Mean eccentricity comparison statistics.

Method	Forest	Desert	Ocean	Grassland	Snow	Gravel	Woodland	City
Water divide [14]	0.2488	0.2608	0.2302	0.1570	0.2200	0.2836	0.1933	0.3445
Markov [18]	0.1670	0.1151	0.1637	0.1200	0.1751	0.1828	0.1300	0.1867
DSH [15]	0.3853	0.4699	0.3770	0.3316	0.4619	0.3855	0.4481	0.4590
Ours	0.6803	0.6845	0.5722	0.6619	0.6808	0.7218	0.6898	0.6907

Table 2: Equivalent diameter standard deviation comparison statistics.

Method	Forest	Desert	Ocean	Grassland	Snow	Gravel	Woodland	City
Water divide [14]	4.0819	6.0444	4.0608	4.8725	4.6106	14.0797	5.0899	5.4081
Markov [18]	9.3463	10.4637	6.9831	7.5966	10.5611	14.1472	11.9873	7.8641
DSH [15]	6.8744	11.1016	17.7655	2.2917	17.6447	11.7586	6.1297	9.0849
Ours	10.7921	11.3147	27.6717	16.2704	17.9355	13.3947	11.7163	11.5464

3.2. Destructive Edge Design. Inspired by "camouflage masters" in animal worlds such as chameleons and cuttlefish and considering the destructiveness of gradient edges to textures, it is proposed to add random scattered points to the edges of patches. Since the label of the marked image in the background image area reflects the distribution of the patches in the background, the density is calculated according to the patch size information. The texture patch density map corresponding to each background image is shown in Figure 6.

In order to make the designed camouflage pattern destructive to the target, this paper increases its randomness from two aspects. One is to convert the texture patch density map into a probability map; that is, the area with higher brightness of the dense map indicates that the patch size is small and the texture density is high. Therefore, this paper adapts the size of the design area scatter template according to this rule; the second is to calculate the proportion of the extracted background main color in the original background and generate probability random numbers according to the proportion, so that the background color distribution is satisfied when filling the main color, and the camouflage effect of the digital pattern is increased. The final generated camouflage pattern is shown in Figure 7.

4. Comparative Results Analysis

4.1. Analysis of Camouflage Pattern Design. In order to intuitively reflect the effectiveness and robustness of the algorithm in this paper, it is compared with the fusion mean shift and minimum spanning tree scheme proposed in Reference, and the results are shown in Figure 7.

The method proposed in this paper has obvious advantages over the minimum spanning tree algorithm in the degree of edge damage and has better robustness. In multiple typical scenarios, digital patterns can show good randomness. In order to further illustrate the superiority of the algorithm in this paper, we use intuitive values for quantitative analysis.

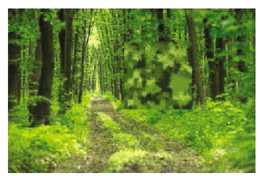
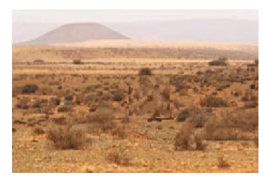
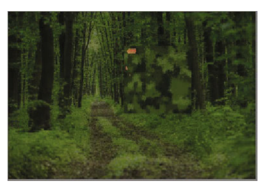
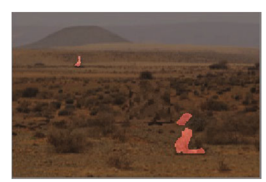
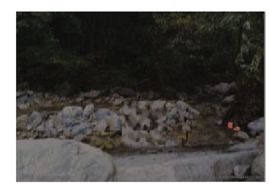
4.2. Quantitative Analysis. Eccentricity is a measure of the flatness of an ellipse. Generally speaking, the greater the eccentricity, the flatter the ellipse. Mapped to the image, the larger the eccentricity of the ellipse with the same standard second-order central moment as the patch area, the more distorted and irregular the texture patch is. The diameter of the circle with the same area as the patch area represents the size of the patch formed by the texture. The standard deviation of the equivalent diameter of all patches in the image is counted, which intuitively reflects the fluctuation amplitude of the size of all patches in the image.

In this paper, forest, desert, ocean, grassland, snow, gravel, woodland, and city represent 8 typical background environments, including different texture density types. To intuitively reflect the superiority of the algorithm in this paper, two characteristic parameters of mean eccentricity and equivalent diameter are analyzed under eight backgrounds and compared with several existing classical algorithms. The results are shown in Tables 1 and 2.

It can be seen from Table 1 that the texture image generated in eight different types of backgrounds, compared with the three typical algorithms, the ellipse second-order center distance, and the corresponding eccentricity are larger, and the corresponding texture patch shape is more distorted. In multiple scenarios, the eccentricity index is increased by at least 31.4%. Table 2 intuitively reflects the fluctuation of texture patch shape. Although the standard deviation of equivalent diameter of texture pattern designed by Markov algorithm is higher in gravel and woodland scenarios, the standard deviation of equivalent diameter increases by 14.9% on average. Overall, the robustness of digital camouflage design scheme based on biased random walk is better.

The obtained digital camouflage pattern is combined with the scene to obtain a camouflage simulation image, and the camouflage target is segmented by using the SINet network framework [27] proposed by the Media Computing Laboratory of Nankai University. The results are shown in Table 3.

Table 3: Multiscene simulation image target detection results.

Result	Scene: Forest	Desert	Gravel	Snow
Camouflage simulation image				
SINet test results				

The test results in Table 2 show that the camouflage pattern obtained based on the biased random walk digital camouflage pattern design scheme and even the extremely robust SINet network cannot completely segment the digital camouflage target and even completely miss the detection phenomenon. In addition, combined with human eye interpretation, it may be found that the camouflage simulation areas of different scenes have obvious concealment.

5. Conclusion

This paper proposed a digital camouflage pattern design method based on a biased random walk strategy. First, we segment the original background, count the pixel and edge information, and complete a biased random walk based on the estimated boundary probability to obtain the prototype of the camouflage patch. Then, according to the patch density distribution, the scatter and distortion effect in the local area of the texture is mapped, and the camouflage pattern is optimized. Finally, the K-means clustering algorithm is used to extract the main color of the background, and the camouflage patches are randomly filled according to the proportion of the color to complete the digital camouflage pattern design that conforms to the background characteristics. Quantitative analysis of characteristic parameters shows that the camouflage patches generated by the algorithm in this paper are distorted and irregular and exhibit strong randomness. At the same time, the detection results of camouflage targets based on camouflage simulation images show strong concealment, which is in line with the camouflage performance of digital camouflage.

The method proposed in this paper is mainly based on the random walk characteristics of the texture inside the pattern and the principle of edge destruction. The digital camouflage pattern designed in this paper has strong confusion under visual observation. However, from the perspective of practical application, the camouflage also needs to effectively deal with infrared reconnaissance, radar reconnaissance, and hyperspectral reconnaissance, which need to be combined with a large number of actual detection data for analysis and verification. It is difficult to obtain the experimental data of multi-reconnaissance cooperative detection, which also brings difficulties to the research of this problem.

Data Availability

The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

References

[1] J. Yu, Q. Zhang, Z. Chen, L. Zhang, and J. Dai, "A mosaic algorithm of digital camouflage," *Optical Technique*, vol. 43, no. 4, pp. 339–342+347, 2017.

[2] A. A. Hejrandoost and R. Safabakhsh, "Thinning based multi-purpose camouflage pattern design," in *2011 7th Iranian Conference on Machine Vision and Image Processing*, pp. 1–5, Iranian, 2011.

[3] Y. Gan, C. Liu, Z. He, H. Li, Z. Liu, and X. Yao, "Image texture synthesis method based on the trend function constraint," in *2021 IEEE 3rd International Conference on Frontiers Technology of Information and Computer (ICFTIC)*, pp. 525–528, Qingdao, China, 2021.

[4] Y. Wang, L. I. Ming, L. I. Junhua, C. Zhang, and H. Chen, "Texture image classification based on BoF model with multi-feature fusion," *Journal of Beijing University of Aeronautics and Astronautics*, vol. 44, no. 9, pp. 1869–1877, 2018.

[5] J. Yu, W. X. Yang, Z. Y. Hu, and H. Chen, "Research of digital camouflage generation algorithm," *Opto-Electronic Engineering*, vol. 37, no. 11, pp. 110–114, 2010.

[6] R. Wu, *Study on a Method for the Design of the Digital Camouflage*, Nanjing University of Aeronautics and Astronautics, Nanjing, 2016.

[7] Q. Jia, Z. Lin, J. Hu, J. Liu, L. Zhu, and J. Liu, "Design and evaluation of facial camouflage pattern," in *Proceedings of the 2019 International Conference on Artificial Intelligence and Computer Science (AICS)*, pp. 818–821, Wuhan, Hubei, China, July 12–13, 2019.

[8] F. Yan, *Research on Extraction Algorithm of Main Color of Camouflage Background*, Xi'an Technological University, Xi'an, 2011.

[9] T. W. Chen, Y. L. Chen, and S. Y. Chien, "Fast image segmentation based on K-means clustering with histograms in HSV color space," in *2008 IEEE 10th Workshop on Multimedia Signal Processing*, pp. 537–576, Cairns, QLD, Australia, 2009.

[10] J. H. Chen, H. H. Wei, C. L. Chen, H. Y. Wei, Y. P. Chen, and Z. Ye, "A practical approach to determining critical macroeconomic factors in air- traffic volume based on K-means clustering and decision-tree classification," *Journal of Air Transport Management*, vol. 82, article 101743, 2020.

[11] Z. W. Chen and J. Z. Ni, "Research on the visible camouflage pattern of the marine background texture of the unmanned boat," *Shipbuilding of China*, vol. 61, no. S01, pp. 198–203, 2020.

[12] Z. Wang, Y. H. Yan, and K. C. Song, "Texture synthesis method based on pixel adaptive neighborhood," *Journal of Northeastern University(Natural Science)*, vol. 35, no. 9, pp. 1257–1261, 2014.

[13] W. J. Cho, W. Ahn, M. S. Kim, J. Park, S. Kim, and K. H. Han, *Making Pixel Patterns Automatically for Camouflage-Using Color Information from Their Background*, vol. 174, Springer, Berlin Heidelberg: CCIS, 2011.

[14] W. M. Bai, F. Run, and J. Yu, "Application of VC and MATLAB in designing camouflage spots," *Computer & Digital Engineering*, vol. 39, no. 3, pp. 144–147, 2011.

[15] C. A. Yun-xiang, X. U. Shi-qiang, Z. H. Zhi-yong, and H. U. Yun, "Study of digital pattern generation method based on fractal Brown model," *Acta Armamentarii*, vol. 37, no. 1, pp. 186–192, 2016.

[16] W. U. Guo-jing, L. Y. Xu-liang, X. U. Wei-dong, L. I. Ling, and W. E. Xiao-di, "Research on 3D dynamic imaging algorithm for digital camouflage," *Acta Armamentarii*, vol. 37, no. 11, pp. 103–108, 2016.

[17] Y. Zhou, Z. P. Xie, and X. J. Jiang, "Simulation design method of camouflage target concealing strategy based on evolutionary

computation," *Acta Armamentarii*, vol. 42, no. 9, pp. 1987–1997, 2021.

[18] J. Qi, L. Xu-Liang, W. Chao, and R. Xian-Hui, "Application of Markov random field and pyramid structure in the design of digital pattern painting," *Journal of Applied Sciences*, vol. 30, no. 6, pp. 624–628, 2012.

[19] S. H. Bi, L. Zheng, and Y. W. Wu, "Research on computer-aided designing system of camouflage pattern," *Journal of System Simulation*, vol. 25, no. 9, pp. 2164–2170, 2013.

[20] L. Armi and S. Fekri-Ershad, "Texture image analysis and texture classification methods - a review," *International Online Journal of Image Processing and Pattern Recognition*, vol. 2, no. 1, pp. 1–29, 2019.

[21] C. Qu, D. Y. Bi, S. W. Yan, and L. Y. He, "Random walk image dehazing through a priori of light and dark pixel," *Systems Engineering and Electronics*, vol. 39, no. 10, pp. 2368–2375, 2017.

[22] C. Qu and D. Y. Bi, "Clearness for foggy and noisy image based on lazy random walk," *Acta Optica Sinica*, vol. 38, no. 4, article 0410001, 2018.

[23] M. Lu, L. Chen, and J. Tian, "Broken region connection method for curved objects based on biased random walk," *Computer Engineering and Design*, vol. 40, no. 10, pp. 2922–2927, 2019.

[24] J. Shen, *Research on Target Segmentation Method of Curved Structure Based on Conditional Constrained Random Walk*, Wuhan University of Science and Technology, Wuhan, 2021.

[25] A. Neumann, B. Alexander, and F. Neumann, "Evolutionary image transition using random walks. Evolutionary and biologically inspired music, sound," in *International Conference on Evolutionary and Biologically Inspired Music and Art*, pp. 1–34, Amsterdam, The Netherlands, 2017.

[26] W. Alt, "Biased random walk models for chemotaxis and related diffusion approximations," *Journal of Mathematical Biology*, vol. 9, no. 2, pp. 147–177, 1980.

[27] D. P. Fan, G. P. Ji, G. Sun, M. M. Cheng, J. Shen, and L. Shao, "Camouflaged object detection," in *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, pp. 2777–2787, Seattle, WA, USA, 2020.