IEEE Access
Multidisciplinary ⋮ Rapid Review ⋮ Open Access Journal

Received April 19, 2021, accepted April 22, 2021, date of publication May 4, 2021, date of current version May 12, 2021.
Digital Object Identifier 10.1109/ACCESS.2021.3077258

A Novel Method for Automatic Camouflage Pattern Synthesize

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ABSTRACT Camouflage plays an indispensable role in modern military. Generally, a camouflage pattern includes a plurality of shapes units, which are split by elemental colors. The fixed camouflage pattern is low adaptability and concealability for changeable battlefields. Moreover, the conventionally camouflage design is time and resource consuming for manual drawing. In this paper, we propose a dynamic camouflage synthesizing method. Firstly, the texture patterns of one class of battlefield images is extracted using convolutional transfer network. We use 3*3 convolution kernels to extract texture features. And the covariance matrix is used as loss function to calculate the loss of different image texture features. Colors construction and their distribution of the specified battlefield images is extracted according to a clustering-based algorithm. Finally, the statistical color units are embedded into the texture patterns. We assess the adaptability and the concealability of synthesized camouflage using Eye Tracking based criteria. Comparing to the People's Liberation Army Type 87 woodland pattern and the digital camouflage pattern synthesized using our previous method, testing results of our synthesized camouflage patterns were better in different saccade indicators. This demonstrates camouflage pattern synthesize proposed got better concealment and the validity of proposed method. Besides, we also compared our method with local binary pattern for extracting texture features. The experiments results indicated the method proposed had better consistency to the scene images.

INDEX TERMS Camouflage pattern, convolution neural networks, computer aided design, style transfer.

I. CAMOUFLAGE DESIGN

Camouflage is part of the art of military deception [1]. In World War I, the frequent use of various optical reconnaissance equipment and means resulted in that monochrome uniforms were difficult to adapt in the battlefield environment [1]. The camouflage patterns of many countries were mainly hand-painted and spraying, between the World War I and World War II. The conventional camouflage pattern was based on a number of irregular spots or stripes, consisting mainly of random combinations of similar colors, not only with smooth edges but also explicit colors. The design of camouflage is commonly divided into two parts: texture shapes and colors. The camouflage pattern is designed to blend into battlefield background. Conventional handmade camouflage designs have undergone a long evolution [2]. The main feature of the original camouflage is the use of larger camouflage spots with rounded edge contours. The large spots of three and four colors could better divide the target profile contour, and the combination of these different spots is more effective in camouflage against short distance and lower resolution. The subsequent conventional camouflage with a four-color geometric deformation design, which combines four deformation patches of dark green, yellow-green, brown and black. It is more suitable for summer, but not as effective in concealing in areas lacking vegetation cover [3]. At present, the conventional camouflage still adopts irregular camouflage blocks of several different colors, and the colors and texture shapes are mainly determined by the specific battlefield scenes through the designer's observation and experience. In the conventional camouflage design method, the designer's experience is dominant. And the camouflage patterns are designed through manual drawing methods. However, the conventional camouflage design method is hard to meet the modern military demands of concealability, adaptability as well as efficiency.

Conventional camouflage is simply designed to adapting the specific battlefield background. In order to resist closer

The associate editor coordinating the review of this manuscript and approving it for publication was Mingbo Zhao.

visual reconnaissance and high-resolution imaging reconnaissance, the conventional method is gradually replaced by computer aided digital camouflage. Digital camouflage is arranged by pixel units of different colors including square or triangle according to certain arrangement rules [2], which better combines the imaging principle of computer pixel array and the visual perception characteristics of human eyes. Digital camouflage improves concealability through multi-scale patterns, color dithering and edge effects. In addition, the boundary between different colors of different camouflage targets could be broken by digital camouflage, which makes them blurred and broken to achieve better concealability. The earliest digital camouflage design was born in the 1970s [4]. Initially, it still focused on the research of theoretical part. Some foreign experts and scholars combined with visual psychology to study camouflage design and camouflage pattern layout. Nowadays, various kinds of digital camouflage have been proposed and applied. The most common design method of digital camouflage mainly includes the following steps [3]: firstly, collecting real battlefield images, then generating random color and texture patterns through different sampling methods, combining them and finally projecting or mapping the patterns onto the surface of 3D objects to evaluate the concealability of these patterns and further adjust the camouflage patterns. The overall process is shown in FIGURE 1.

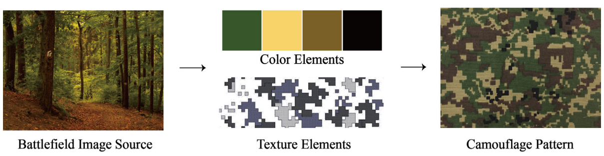

FIGURE 1. **Conventional digital camouflage design process.**

Liang *et al.* adjusted the generated camouflage by building different evaluation systems, such as multi-indicator gray clustering algorithm [4]. Digital technology plays an important part in the design and evaluation of camouflage patterns. With the development of computer technology, a very large number of digital camouflage design methods have emerged. Some similar digital camouflage design methods were proposed in [5]–[7], these methods were based on visual and psychological principles. They used computer technology to extract battlefield backgrounds and form camouflage patterns through various pixel dots. James Kilian [8] presented an application of image-based analysis technique for constructing a computer-based system for camouflage evaluation, which was limited to the target acquisition reduction performance of camouflage to the human visual system, and they also described the methods used for data acquisition, reduction, processing and evaluation. Hogervorst *et al.* [9] derived a number of camouflage styles from a series of battlefield background datasets and then evaluated the styles according to human observation. To solve the artifact problems caused by object movement, Samuel *et al.* proposed a dizzy camouflage style in [10]. In [6], Xue *et al.* changed the salient feature map of the feature style to enhance the hidden effect of the camouflage style. Besides, a novel algorithm based on speckle template distribution was proposed by FengXu *et al.* in [11]. Zhang [12] proposed a camouflage style design method based on Fourier transform and Gaussian low-pass filter with spatial triple primary color mixing angular frequency, and this method achieved very good concealability for a specific battlefield environment. With the advancement of computer technology and image processing technology, Prasetyo *et al.* proposed a completely new method in [13], which was based on the response surface method in CIELAB color space, and it was used to enhance camouflage features. Lin *et al.* enhanced the camouflage by using particle swarm optimization in [14]. However, all of these methods have the same problem. They have particularly good concealability in specific war scenarios. But these camouflage patterns are less adaptable and not applicable to more war scenarios. These methods take a long time to generate camouflage patterns. Therefore, in our previous work [15] a new automatic design method was proposed. We extracted camouflage suitable from a large number of battlefield images through convolutional neural networks. Although this method greatly improves the concealability and the adaptability of the camouflage pattern, this method still took a long time to design one camouflage pattern.

In this paper, we present an automatic method to generate camouflage patterns dynamically along with the battlefield backgrounds, the process of which includes: texture extraction, color clustering and analysis and camouflage synthesis, shown in FIGURE 2.

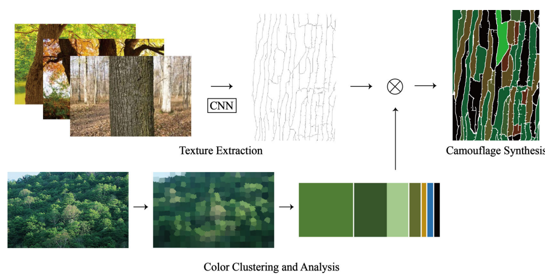

FIGURE 2. **Flowchart of the proposed method.**

The texture feature pattern of the basic scene is obtained by feature extraction of multiple battlefield images through convolutional transfer network. Then a number of texture pattern regions of different sizes and shapes are formed form texture patterns according to the edges of the generated texture feature patterns. Finally, according to the colors of the dynamic battlefield images, a clustering algorithm is used to approximate the color synthesis of each texture pattern. This method combines the texture and color features of the battlefield, which greatly improves the concealability and adaptability of the camouflage patterns.

II. TEXTURE FEATURES EXTRACTION USING CONVOLUTIONAL TRANSFER NETWORK

A. RELATED WORKS

With the emergence of artificial intelligence, a convolutional neural network, such as LeNet-5 [16] appeared. Conventional neural network has emerged to allow computer to better identify objects and allow computer to better accomplish more complex classification and prediction. With the development of artificial intelligence, there have been many cross-collisions between artificial intelligence and the art fields. But for the art fields, the style of an image is a very abstract concept. And style is different from ordinary objects and cannot be described by simple features such as shape, size. Gatys *et al.* firstly proposed a new method of style transfer in [17], so-called style migration. It referred to the use of algorithms to learn the style of famous paintings and then applied the learned style to new different images. They separated images into image content and image style, style of which refers to the overall feeling similar to an image (e.g., abstractionist style) and content referred to the actual objects in an image, such as people or other objects in an image. They performed the extraction of content features and style features through a VGG network. VGG19 [18] is mostly used for image feature extraction owing to its 3*3 small convolutional kernels and deep structure, which can better extract deep features of images. And for style transfer, it can also better extract abstract styles. In addition, they also divided the loss function into content loss and style loss. Restoring image content with content loss and image style with style loss. And they used different loss functions. For content loss, different feature maps are obtained by convolutional layers of different depths. And the accuracy of content in style migration is ensured by calculating the similarity between the feature maps of different layers. For style, the accuracy of style is ensured by calculating the Gram matrix between each dimension of different feature images. And finally the total loss function is calculated by assigning different weights to the content and style losses. Justin [19] proposed a fast style migration algorithm based on Gatys's work, which speeded up the style transfer by calculating the perceptual loss and employing pre-trained loss networks, where CNNs were used to capture the texture of an image and then transform it into a target image. They also achieved good results. In [20], the authors applied the style migration algorithm to videos and also obtained good results. After that, related style migration algorithms [21]–[23] were also proposed. All of them were modified and adjusted on the basis of the method proposed by Gatys *et al.* And the fast camouflage pattern generation method proposed in this paper also referred to the style transformation method of them.

In the meantime, we also refer to some other articles on textures. Shervan Fekri-Ershad proposed a method with high accuracy based on the improved local ternary patterns for bare texture classification in [24], the results by this method are high classification accuracy and noise resistance. Fuzhi Yang *et al.* had a great research aim to recover realistic textures from a low-resolution image to super-resolution, they proposed a learnable texture extractor in [25]. Mutasem K. Alsmadi used content-based image retrieval systems to extract the color signature, the shape features, and texture feature in [26]. Laleh Armi and Shervan Fekri-Ershad discussed the various methods used for texture analysis in details in [27], a brief review is also made on the common classifiers used for texture image classification. And in this paper, we mainly use the texture feature of some basic scenes. There are many conventional digital image processing technology, Shervan Fekri Ershad proposed an approach which has an overall process on the images of textures based on Local binary pattern and Gray Level Co-occurrence matrix by edge detection. Finally, extracting the statistical features from the images would classify them in [28]. Kaplan *et al.* used LBP (Local Binary Pattern) to acquire texture features to classify the bearings in [29]. They experimented on stone textures and good results were obtained. However, these texture extraction methods are not suitable for camouflage synthesizing. In our experiments, we also compare the similarities and differences between this approach and our proposed method.

Style transfer is dedicated to transforming the style of an image. Style transfer modifies the color characteristics of an image through the network. Its essence lies in the adjustment of the image color features. Our work focuses on extracting a common texture features for one kind given scene through a convolutional transfer network and replacing the random pixel texture of conventional and new digital camouflage with these common texture features. These texture features contain the features of different scenes, and the most basic and general representative texture features of a certain scene. And then the color features are extracted by the specific scene to compose the camouflage pattern. The essence lies in the extraction and combination of image texture features and color features. Improvements of the proposed method are listed as follows.

1) Style transfer is dedicated to transferring an image color features to another content image. Our jobs take a set of images and extract the common and universally adaptable texture feature.
2) The style transfer targets two RGB inputs, one for the content image and one for the style image. An output is a content image with the target style. Especially, the style is mainly about the color features. Our method has multiple gray inputs for the target texture images. The network proposed has only one output, the output contains the common and universally adaptable texture features of the target inputs. Our network is used to extract the common and universally adaptable texture features to improve the adaptability of the camouflage.
3) For the loss function, style transfer has separated different loss functions as well as network parameters, and the number of network layers. In style transfer networks two loss functions are implemented: content loss and style loss. Style transfer adjusts the final output by adjusting the different weights of the loss function.

For our convolutional transfer network, we build it using Siamese networks, keeping the weights of network shared, and by having the same number of network layers, aiming to ensure the reciprocity of the extracted features, and the same receptive field.

B. NETWORK STRUCTURE

The texture design of conventional camouflage is mostly irregular ovals and other irregular patterns. And the choice of texture is mainly determined by the design experience of the camouflage pattern designer. Digital camouflage is designed by computer-based technology. In this paper, texture convolutional transfer network is proposed to generate camouflage texture pattern by Siamese networks and classical convolutional neural networks. We perform the construction of Siamese networks by using VGG19, in which the networks are symmetrical and the parameters are shared. In order to keep the features extracted from different pairs of input images with the same perceptive, and thus further ensuring the symmetry of different images in the texture pattern design. We use VGG19 as baseline for feature extraction. The small convolutional kernel of 3*3 and the deep network can extract the deep texture features of the input image better, in addition to the primary image content. In convolutional transfer network, we generate a random noise image of the same size as the original input image as another input image. The shape of the random input is same as the inputs to keep the same scale and receptive field. We acquire the feature map of these two input image through some 3*3 convolutional kernels and max pooling. Then we adjust the random input via calculating the difference of feature maps, and the random and original input are made maximally feature similar by back-propagation iteratively, so as to obtain the adjusted output. The texture convolutional transfer network structure is shown in FIGURE 3. In convolutional transfer network, we use convolutional kernels of 3*3, and all pooling layers use a max pooling of 2*2. In this method, we all use a 3-channel image of 512*512 size.

Firstly, we use one original input image of whole datasets to generate a random noise image. The parameters of network are adjusted by calculating the difference of feature maps between the original input and the random noise image through the texture transfer network to iterate and back-propagate to adjust the random image. In advance, we convert the images to gray images, and maximize the feature similarity between the original input and the random image to obtain the adjusted output. Meanwhile, we randomize the image order in the dataset as the next original input, and continue to adjust the adjusted output, which is the new input, to obtain the new adjusted output. By disrupting the texture input images and iterating the whole dataset several times. We get a adjusted output with similar features to all original inputs. The common texture features of our entire images in the dataset.

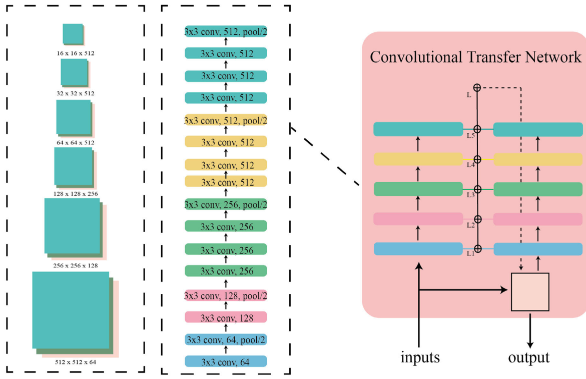

FIGURE 3. Structure of texture convolutional transfer network.

C. LOSS FUNCTION

In texture convolutional transfer network, Siamese network contains a pair of symmetrical convolutional neural networks. The covariance matrix of the feature map obtained after the image has been convolved with layers can well characterize the texture features of the image. The covariance matrix is used to describe the autocorrelation of global features in [18]. The texture loss function is showed in (1). The F_{ik}^{l} and the F_{jk}^{l} mean the vector of l layer feature maps flattened well.

$$L = \frac{1}{4N_l^2 M_l^2} \sum_{ij} (\sum_{k} (F_{ik}^{l} F_{jk}^{l}) - A_{ij}^{l})^2 \tag{1}$$

For the texture feature loss function of each convolutional neural network, if two images have the same representation, it means that the two images are similar. We calculate the covariance matrix of the input image through the feature map of the convolutional layer of one layer of the network and the generated texture feature map in the same layer as the loss function. We adjust the network parameters by feedback propagation and gradient descent method to minimize the loss function. Meanwhile, we make the transferred texture and the input image being most similar. F_{ik}^{l} and F_{jk}^{l} mean transvection in L layer. k denotes the corresponding element in feature map. N_L^2 is the number of feature maps of the layer, M_L^2 is the size of each feature map. The overall loss function is calculated by giving different weights to the two parts of the Siamese network. The weight values can be adjusted so that the features of the input image have different proportion of the results in the texture convolutional transfer network. Otherwise we can adjust the same parameters so that the features of the input image remain consistent. In this paper, we keep the weights same.

D. COLOR FILL BLOCKS DIVISION

The camouflage texture is mainly composed of pixel blocks with quadrilateral shapes. We use texture pattern blocks generated by the texture convolutional transfer network to instead of normal pixel block to achieve better concealability of camouflage. A block is the smallest unit of the area array camera image plane. Although using pixel regions as textures can better meet the requirements of the camouflage, it still destroys the edges of the object. Instead, texture pattern blocks are small regions and edges formed by the texture convolutional transfer network, which can protect edges and features better. These small regions preserve the effective information of image features without destroying the edges of the objects in the image and eliminating abnormal pixels. The use of texture pattern blocks instead of pixel regions as camouflage texture can greatly improve the concealability of camouflage. We remove the smaller regions of the texture patterns generated using texture convolutional transfer network by image filtering and image binarization. Then close the texture regions to form texture blocks based on morphology methods. FIGURE 4 shows the basic process of texture patterns design.

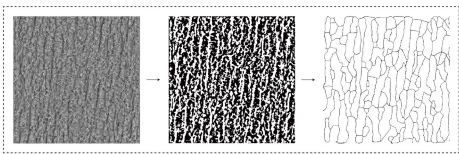

FIGURE 4. Process of the texture pattern generation.

III. DYNAMIC COLORS FILL

In order to make camouflage design in dynamic, color features generation is designed as an online method. We use a K-means-based clustering algorithm [30] to cluster dynamic input images, which is faster and has higher memory utilization, and more importantly, the process does not change the pattern itself. And the weighted distance measure combines color and spatial proximity and control the size and compactness of the texture patterns. K-means clustering is an unsupervised clustering algorithm that allows for fast and accurate clustering by specifying the distance and number of centers of clusters. We perform color clustering on different dynamic input images and extract the basic colors of them by adjusting the clustering parameters. However, the wrong color elements are excluded, because of the bad influence of noise. The color elements are then filled into the delineated texture pattern regions using the labeling method to obtain the final camouflage pattern. We set the number and distribution of colors in the final camouflage pattern. FIGURE 5 shows the process of dynamic color fill.

We use color clustering method to extract the basic color information of input image. All color elements are selected from clustering image, but exclude the wrong color elements, such as the white and pink color elements to acquire the final color elements. Consequently the color elements are randomly filled into the texture patterns according to the weights calculated from the instant battlefield image to form the final camouflage pattern.

IV. CAMOUFLAGE EVALUATION USING EYE MOVEMENT INDICATORS

A. IMAGE SOURCE AND SYNTHESIZED CAMOUFLAGES

Since the standard battlefield environment camouflage datasets are not available for general researches. In this

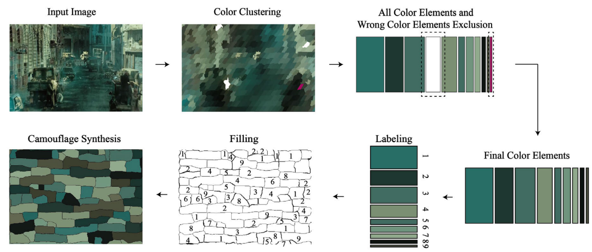

FIGURE 5. Process of dynamic colors fill.

paper, we simulate the specified scenes using web images. We collected three categories of war scenes forest, city, and rock land. In addition, the category of forest contains different broad-leaved forests and coniferous forests, etc. To improve the adaptability of the texture features extracted by our method, we choose some war movies and documentary series to capture the images of battlefield environment scenes. We convert the images to gray scales. Then input four-fifths of the images from these classes into the texture convolutional transfer network for processing, to generate four general initial texture patterns. We randomly selected some war scene images among the remaining images for the color clustering and analysis. FIGURE 6 shows two cases of automatic synthesized camouflages. The top row demons the case of forest scene and the bottom row demons the rock scene. The first column lists the textures generated from the same class of battlefield images. The second column lists the dynamic battlefield images and its corresponding color clustering images. The third column lists the synthesized results using the generated texture with the same color distribution of dynamic battlefield image.

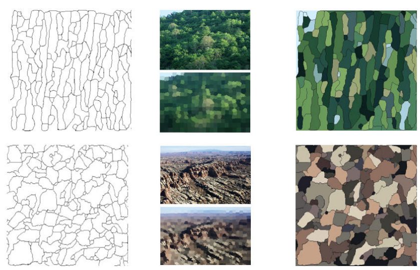

FIGURE 6. Two cases of automatic synthesized camouflages.

B. QUALITY INDIES

Saccade is an index to describe a rapid movement of the eye between fixation point, which are considered as the most important indicator in eye movement measurement. Many other related indicators are developed on its basis. Saccades are rapid eye movements designed to shift the fovea to objects of visual interest. Generally, abnormalities of saccades offer important clues in the diagnosis of a number of movement disorders. Pichet Termsarasab *et al.*, they studied horizontal and vertical saccades, discussed their usefulness, and examined how saccadic abnormalities can aid in diagnosis in [31].

Two kinds of eye movement metrics were applied in their works: visual metrics and quantitative metrics. The visual metrics are more oriented to the observation of trajectories, while the statistical type metrics are oriented to the analysis of data. In experiments, the basic eye movement quantitative indicators are compared to draw experimental conclusions. We utilize three eye movement metrics proposed in [32], [33] to access the quality of our synthetic camouflage.

1) Number of saccades: the eye movement between two gaze points is often referred to as saccade. The higher the number of saccades indicate the longer the eye searches. In our experiment, it represents the concentration of the eye to observe the target, the more times, the more focused of the eye observes, the more confusing the target is, and the harder the target is to find from the background.
2) Amplitude of first saccade: the range of eye rotation when the eye focuses on the screen for the first time. The greater the amplitude, the more meaningful targets or clues are found in the area or location. In our experiment, it represents the first time the eye looks at the screen as a whole, the larger the range, the wider the distribution of the observed target and the easier the target is to be observed from the background.
3) Duration of interval: the time interval of each saccade. The longer the gaze, the more difficult it is for the eye to extract information, and the more attractive a target is. In our experiment, it represents the length of gaze time in the temporal region of interest, the larger the interval, the longer the gaze, and the more difficult it is to discriminate the camouflage target from the background.

C. EXPERIMENTS

In order to verify the concealability of our quick design, we made the camouflage concealability experiment. Firstly, we selected three kinds of methods: the conventional manual method (People's Liberation Army Type 87 woodland pattern), the method proposed in [15] denoted as auto-design below, and our proposed method. And we compared the effects designed by these three different methods in the same forest battlefield environment. For a more accurate comparison, we mapped all of these camouflage patterns onto the surface of a soldier model of the same size and shape. We randomly distributed 20 targets in the same background. Finally, we used the Eye Tracker to analyze and evaluate the results of experiments.

1) TEXTURE FEATURE COMPARISON EXPERIMENT

LBP (Local Binary Pattern) is an operator used to describe the local texture features of an image. It has significant advantages such as rotation invariance and gray scale invariance. It is used to extract the local texture features of an image and keep the position information of texture features. The LBP operator used in the experiment are grayscale values of 8 neighboring pixels with their grayscale values within a 3*3 window, using the center pixel of the window as the threshold. If the surrounding pixel value is greater than the center pixel value, the position of the pixel is marked as 1, otherwise it is 0. In this way, the 8 points in the 3*3 neighborhood can be compared to produce 8-bit binary numbers (usually converted to decimal numbers, i.e., LBP codes, of 256 kinds), i.e., the LBP value of the center pixel of the window, and this value is used to reflect the texture information of the region. FIGURE 7 shows the result of LBP and our proposed method for the same input image.

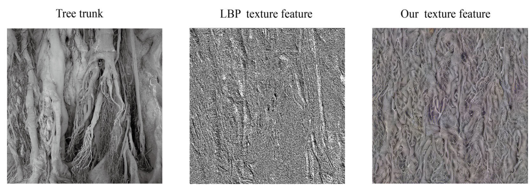

FIGURE 7. Texture feature results of LBP and our proposed method.

Although features extracted by LBP is closer to content of the image. Our proposed method can better extract the input images with more details and smaller textures, and remove the location information and keep only the texture features. The extracted features are closer to the original input image. For better comparison of the results, we used the SSIM (Structural Similarity) algorithm for the analysis of the extracted texture features results. And we provide a basic introduction in the discussion section. We use the input image and the texture feature images extracted by both methods for the computation. The similarity between the results of our proposed method and the original image reached 44.5%. While the LBP method is only 4.6%. The similarity of our results is almost 10 times higher than that of the LBP algorithm. In addition, the LBP algorithm can only extract texture features of a single input, but cannot process multiple input images at the same time. Our proposed method can handle single input as well as multiple image inputs, not only can extract the feature texture of a single image, but also the common texture features of a class of images. For the camouflage design, too much positional information will lead to a decrease in the adaptability of the camouflage. The location features of the original image are removed by our proposed convolutional transfer network. The results show that our proposed method is more applicable to the design of camouflage patterns.

2) ESTIMATION OF TEXTURE SIZE

In the conventional style transfer algorithm, controlling stroke size in style conversion is still a daunting task. In texture pattern design, efficiency, flexibility, and diversity should be considered to fit for the various battlefield scenes. Lingchen Yang *et al.* proposed a recurrent convolutional neural network to control the stroke size in style transfer in [34]. In order to verify the effect of camouflage patterns, we mapped the designed camouflage pattern onto

3D surface. The 3D images of different angles are obtained by 3D mapping. Hence, a similar problem should be considered, which is the size of the texture pattern. If texture features were designed too small and the observation may be only a single color. If the texture features were too large, the camouflage will be less concealed. Therefore, it is important to design a suitable and reasonable texture size. In actual combat, the effective concealment range is of distance from 5m to 15m. Therefore, the design of this experiment simulates the pixel size of the target in the image approximate 10m. The final design of the texture size is decided by actually taking pictures to compare the real camouflage uniforms and the relationship between the distance of the object and the pixels on the image. In addition, we tried to confirm the texture of the design is clearly visible. FIGURE 8 shows 5 different camouflage patterns and 3D models from different scenes. we acquired different camouflages in one kind of scene according different specific battlefield.

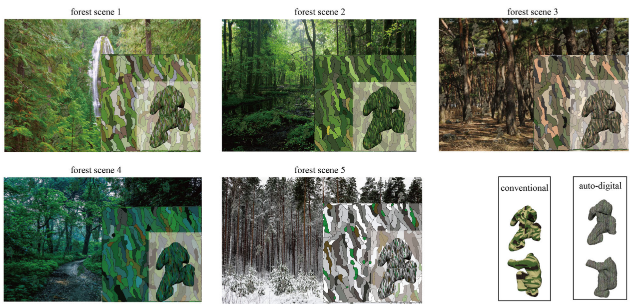

FIGURE 8. Five 3D camouflage test models.

3) TESTING PROCESS

10 undergraduate and graduate students were selected as participants, average age of which is 20 years old. In addition that we set up the same experimental environment, such as the same illuminate condition, to avoid some unnecessary disturbances. The experimental requirements and steps were described in detail to the participants to ensure that they could complete the test in a calm and comfortable state. The experiment needed to be conducted, in the same experimental location. The experiment required each participant to find all the camouflage targets from three images by three times, as shown in FIGURE 9. A total of 5 sets of experiments are required. It is obvious that the pattern synthesized using proposed method has better concealability and adaptability in human visual observation. But we verify it by recording the related data. Required equipment: (1) Laptop for participants to view the simulated images. (2) Tobii Pro glasses2, Eye Tracker for recording eye movement data.

4) RESULTS

TABLE 1 records the experimental results of the concealability experiment, where the Eye Tracker is able to collect the gaze duration in the region of interest and the number of eye rotations, etc. until the eyes are fixed on the region of interest. The duration of gaze time is related to the difficulty of participants to spot the targets.

TABLE 1. Quality results.

	Duration of Interval(s)		Number of Saccades(qty)		Amplitude of First Saccade(px)	
	Avg.	Std.	Avg.	Std.	Avg.	Std.
Conventional Manual	29.540	12.842	33.511	17.746	13.603	2.636
Auto-design	29.883	13.931	34.024	18.937	5.685	1.947
Proposed Method	75.534	58.970	102.555	99.256	2.701	2.072

When participants were skeptical of the target, the longer the gaze time would be. From the table above, we can see that the camouflage we designed is hard to be detected against the forest background, which indicates that the pattern we designed is better concealed. According to the statistic results, the number of saccades in our camouflage is about 3 times more than other methods on average. Amplitude of first saccade is also 3 to 10 smaller than other methods on average. The duration of interval in our designed camouflage is 2 to 3 times as long as the camouflage pattern of conventional manual and computer-aided digital methods. It indicates participants made multiple observations for targets and saw our camouflage targets for the first time more than other methods fewer and took longer to go from one target to another. We found that participants consumed more time looking for all targets across the background in the quick camouflage we designed, i.e. it is more difficult to find targets under our camouflage method. FIGURE 10 shows the box plots of the results of different indicators.

The 'o' represents outliers in the data that does not fit the distribution. The '×' represents the mean value of the data in each group. The middle of the box has a line that represents the median of the data. The upper and lower bar of the box-plot means that the arrangement contains 50% of the data. Therefore, the height of the box reflects to some extent the degree of fluctuation of the data. The upper and lower edges then represent the maximum and minimum values of the set of data. For duration of interval, the data resulting from our proposed method are more evenly distributed, with median values above the mean. This implies that the experimental participants needed more time to discriminate the target from the background. For number of saccades, the data resulting from our proposed method are more evenly distributed, with median values above the mean and some skewed data appearing. This suggests that the experimental participants needed more saccades to find the target. For amplitude of first saccade, our proposed method yielded a more concentrated distribution of data with a median value above the mean. This indicates that a relatively large number of experimental participants needed to have difficulty detecting the camouflage target designed by our method at first glance. In contrast, we achieve better concealability than conventional manual and computer-aided digital methods.

5) SAMPLES AND TIMES

In order to have a clear comparison of adaptability and design period, we used different battlefield environments to design

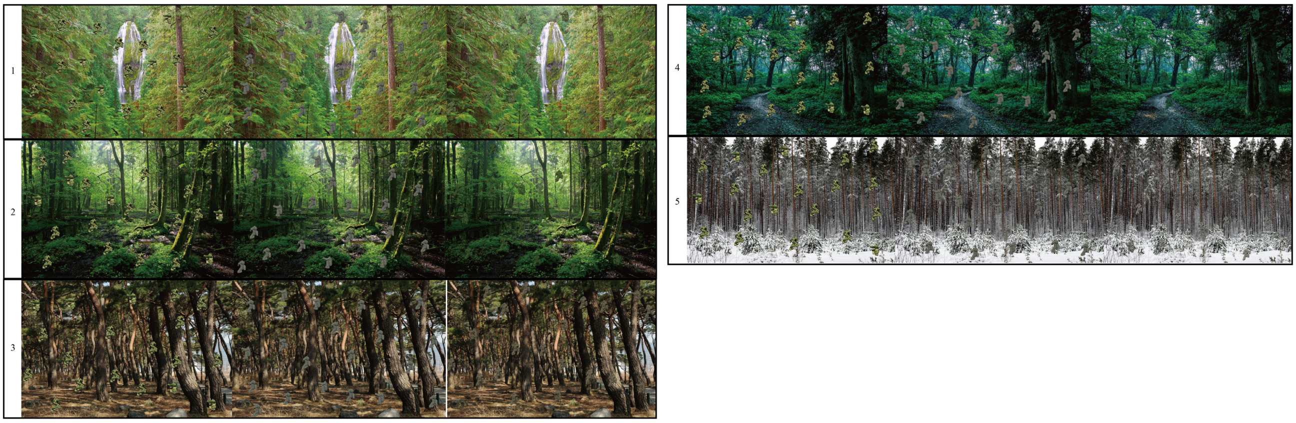

FIGURE 9. Testing illumination of five different battlefield scenes in these three camouflage patterns.

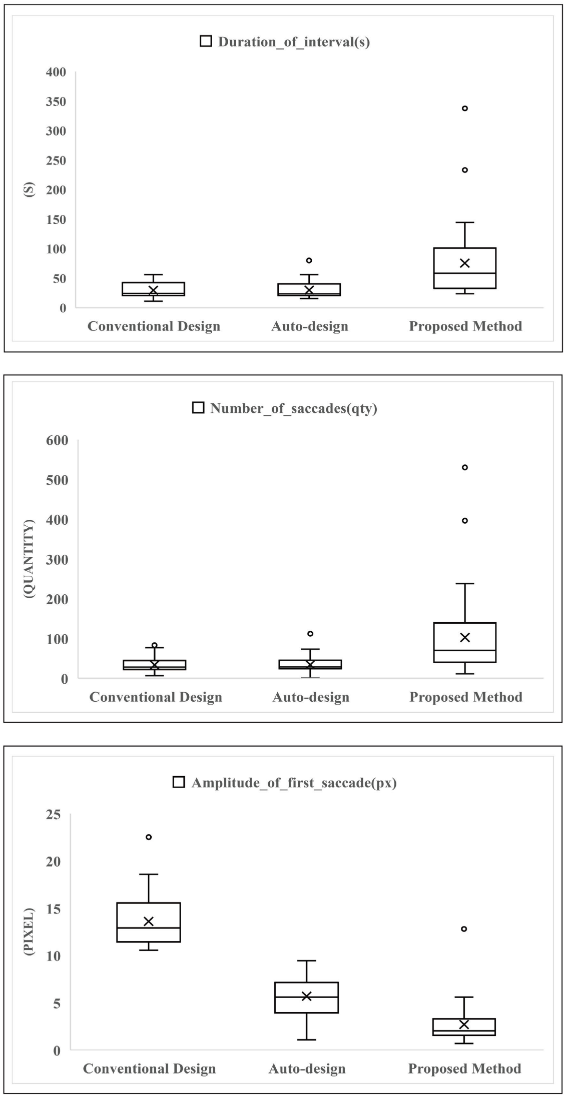

FIGURE 10. Compared results of three indicators.

different camouflage patterns in the same forest, but the same scene differ a lot in weather and season. And the results shows that our design have a better adaptability. FIGURE 11 shows a sample of conventional manual design (People's Liberation Army Type 07 woodland pattern) and the synthesized patterns using proposed method.

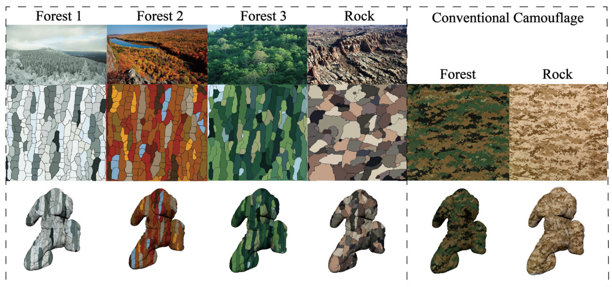

FIGURE 11. Samples of different forest scenes, rock scene, and conventional camouflage patterns.

Currently, all camouflage design methods are designed by offline mode and cannot be transformed in dynamic, whereas our method achieves dynamic camouflage design for the first time.

V. DISCUSSION AND CONCLUSION

A. DISCUSSION

In the camouflage design process, we mainly adjusted the parameters of two parts. As mentioned above, the epoch in the neural network, the neural network needs to be trained to achieve the best performance and find the right parameters. Hence the extracted features results are parameters dependent. In addition, we also verified whether the different order of the input battlefield images would affect the texture pattern of the camouflage.

Different epochs produce different features, when epoch size is large the loss value becomes smaller. And the closer the extracted features will be to the real image, which is the most similar to the battlefield environment. When it reaches a boundary point, the extracted features will be the most similar to the input battlefield environment. We selected 12 battlefield environments as inputs and trained our Siamese network for thousands of times. The experiments show that the network reaches equilibrium near 1800 iterations.

In this method, we collected many battlefield environments to design camouflage texture features and combined dozens of different images from the same battlefield environment to generate camouflage texture features. However, there is a question that whether the different order of the images input to the network will affect the final texture features. Theoretically, the Siamese network we used keeps the same receptive and the same parameters so the input order should not have an effect on the final results. In the experiment, we randomly selected some battlefield environments and conducted experiments in different input orders to generate multiple rock texture features. We choose two methods for image similarity discrimination. SSIM (Structural Similarity), proposed in [35], [36], is a full-reference image quality evaluation index that measures the similarity of images in terms of brightness, contrast, and structure. Cosine similarity [37]–[39], which represents the image as a vector and characterizes the similarity of these two images by calculating the cosine distance between the vectors. And the results (only three orders are shown) are shown in TABLE 2. The average value of similarity between these two methods is about 99.5%, which indicates that allowing for minor distortions. The order of the inputs has only a negligible effect on the results.

TABLE 2. Results of Comparison.

Order	I	II	III
SSIM	99.52%	99.67%	99.87%
COSIN	99.35%	99.17%	99.22%

B. CONCLUSION

In this paper, we proposed a novel dynamic camouflage pattern synthesize method by reconstruct texture features offline and fill color features according to the battlefield scene online. It greatly improves the concealability and adaptability of camouflage pattern. Firstly, we use convolutional transfer network to design texture features of camouflage pattern and replace the conventional irregular textures and normal pixel blocks of digital camouflage patterns to enhance the adaptability of camouflage patterns. The 3×3 convolutional kernels and 2×2 max pooling are used to extract deep texture features. Comparison results proved that our method is more suitable for camouflage design than other image processing algorithms. Then we use clustering-based method to extract basic color features of one specific battlefiled image. Labeling method is used to distribute the basic color elements into texture patterns extracted before to acquire final camouflage pattern. Moreover, we also map the camouflage patterns onto the surface of 3D models and analyze the results between proposed method and other methods. The eye tracker measurement is applied to evaluate the results, to substitute the traditional detection methods in camouflage detection. The results show that the method proposed achieves dynamic synthesize of camouflage patterns by combining texture features of different battlefield environments and color features of specific battlefield environments, which significantly improves in adaptability and concealability of camouflage.

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