A novel hybrid statistical model for camouflaged target detection

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ABSTRACT

Camouflage is a defense mechanism employed as a concealing technique to reduce the possibility of the target being identified. In order to complete military tasks accurately, the detection of camouflaged targets in different scenarios plays a crucial role. Traditional target detection systems have the problem of detecting camouflaged targets in complex environmental conditions. There are various challenges in camouflage target detection system development, such as size, random texture, and recognition accuracy. To resolve these issues, a hybrid statistical model is proposed to identify the target from camouflage images. In this work, hybrid statistical model consists of two modules. A feature extraction module is utilized to extract the low-level features of the image based on texture and scale. A segmentation module is utilized to extract the target region and enhance the boundaries based on seed point selection and detection of edges. Further, the use of morphological processes to highlight the target region. Experiments demonstrate that the proposed hybrid statistical model performs well in camouflage detection in different environments.

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1. INTRODUCTION

Camouflage is a natural phenomenon. In defense applications, humans use this mechanism to disguise the appearance of an object by blending with the surrounding environment on the battlefield. Rapid detection of camouflage targets on a dynamic battlefield is frequently required for defense applications. Furthermore, the military target detection has high-quality requirements. Detecting and identifying the existence of camouflage targets from the environment plays a crucial role in grasping the battlefield situation [1]. The vision characteristics of a camouflaged target are highly similar to the environment, and its color, and texture have been altered to mingle with its surroundings. Detection of targets in camouflage images is a challenging task in machine vision applications.

There are several possible solutions from literature for object detection in the environment of camouflage. Literature [2] proposed a constructive method by statistical modelling of camouflage images in texture smoothing conditions and entity-texture characterization. Literature [3] presented a textural smoothing method followed by statistical characteristics used to detect camouflage targets. The literature [4] performs camouflage object detection by employing non-linear models to smooth the texture and characterize the objects using statistical approaches. The literature [5] developed a dense deconvolution network (DDCN) by presenting short connections during the deconvolution phase and also created a dataset of camouflaged people in various environmental conditions. To identify camouflaged target people in an end-to-end architecture, literature [6] developed a strong semantic dilation network (SSDN) to completely use semantic information. Literatures [7], [8] developed a framework that extracts numerous visual aspects and uses the saliency detection approach in non-linear fusion to quantitatively compute and fuse local and global saliency maps in order to evaluate the effectiveness of camouflage pattern.

A search identification network (SINet) were presented in literature [9] in order to detect camouflaged targets. The dataset COD10K was constructed and contains more than 78 kinds of camouflaged objects. SINet [10] initially employs a search module to localize the interested regions of the targets that are concealed. After that, it uses an identification module for the purpose of precisely identifying the camouflaged target. In their previous work, Zhao *et al*. [11] acquired the hyperspectral images of the five different backgrounds using the hyperspectral imaging system, including jungle background, desert background, jungle camouflage clothing, desert camouflage netting, and jungle camouflage netting. De-noising and black-and-white corrections were applied to samples for pre-processing. Then, using principal component analysis (PCA), examined the region of interest (ROI) in training samples. The wavelet transform based texture feature extraction method provides excellent texture descriptors by exploring the advantages of multi-scale analysis properties, better time-frequency localization [12]. The intensities and relations between an image's pixels define its texture. Since, texture features that describe the relations between pixel intensities, such as gray level co-occurrence matrices (GLCM), Markov random field, local binary pattern (LBP), some LBP versions [13], contourlet transform [14], [15], and wavelet transforms, have shown excellent discriminative performance in texture classification. Despite consistently using conventional wavelet transformations to extract texture features, filter banks implicitly consider the local structure of a texture. To solve the foreground recognition issue in camouflaged scenes, Li *et al.* [16] introduced a texture-guided weighted voting technique in the wavelet domain. A decision theory for classifying the background and foreground in modelling was developed using the Bayesian framework [17]. To smooth the edges of big object regions while removing small free regions, Shen *et al*. [18] suggested and implemented object region extraction based on morphological procedures. To facilitate the network's ability to distinguish the camouflaged targets from the background, the authors extract textural information and enhance the texture difference between the background and the camouflaged target [19]. It is still challenging to identify camouflaged target from images because of the following issues.

a. The position of the target, the random texture of the environment, and the size of the target present challenges in the development of the camouflage target detection system.
b. It lacks enough data to train a deep model compared to other target identification tasks. The datasets such as ImageNet, AlexNet, MobileNet, and visual object classes (VOC), cannot be used.

To address the issues mentioned above, we propose a novel hybrid statistical model to detect camouflaged targets from different environments. Our study is based on a hybrid model which obtains feature information of the image using the feature extraction module, then accurately locates the object that has been disguised using the segmentation module. The contributions of this work summarize as:

a. First, we design a hybrid feature extraction module based on Scale invariant texture feature to effectively use low-level features containing key descriptors and texture information.
b. Second, we design a segmentation module to extract the camouflaged target region and applies the morphological process to highlight the target data.
c. We supplement artificially collected camouflage target data and evaluate using a proposed system.

There are four sections in this paper, including the introduction section. Section 2 proposes the hybrid statistical model for camouflage detection. The obtained results are discussed in the section 3 and section 4 concluded the work.

2. METHOD

The goal of camouflage is to blend an object or person into its surroundings and keep it hidden from the opponent to maximize the likelihood of survival. Therefore, detecting the camouflaged target is more challenging than conventional methods. However, because the human visual system can fully utilize the low-level features, humans are still able to localize those finely concealed targets in most circumstances [10]. This motivates us to focus on extracting the target texture feature for detection of camouflaged targets. In this section, we propose hybrid model to perform extracting statistical features and segmenting the camouflaged target region. Figure 1 illustrates the camouflaged target extraction process.

2.1. Pre-processing

Consider a camouflage image of different dimensions and then resized into 512×512. To enhance processing, convert the selected color image into a grayscale image. The proposed statistical model works based on the fixed window size technique. The resized 512×512 image is split into a size of 32×32 sub-images to obtain 256 sub-images. The dimension of the object and image determine the block size. We must process each sub-image separately in the subsequent steps after obtaining the sub-images.

2.2. Wavelet transform

Each sub-block in the image is then deconstructed using 2-D DWT after the input image has been divided into sub image blocks. Wavelet transform is a technique to transform images into pixels. There are different wavelets to apply such as Meyer, Haar, Symlets, Daubechies and Morlett. The Haar wavelet, which has an order of 2, is used in the proposed method. For the purpose of multi-resolution analysis, a small number of levels of decomposition are sufficient if the subblock size is greater than a certain threshold [20]. For this system, the decomposition level is 2. We obtain wavelet coefficients after decomposition. In decomposition, the coarse-level coefficients represent the approximation coefficients at the lower levels, and the fine-scale wavelet coefficients represent the detail coefficients at the higher levels. There are 256 sub-images are obtained if an image is resized to 512×512 and divided into 32×32 sub-images. After that, 256 wavelet coefficient vectors are generated after using DWT decomposition.

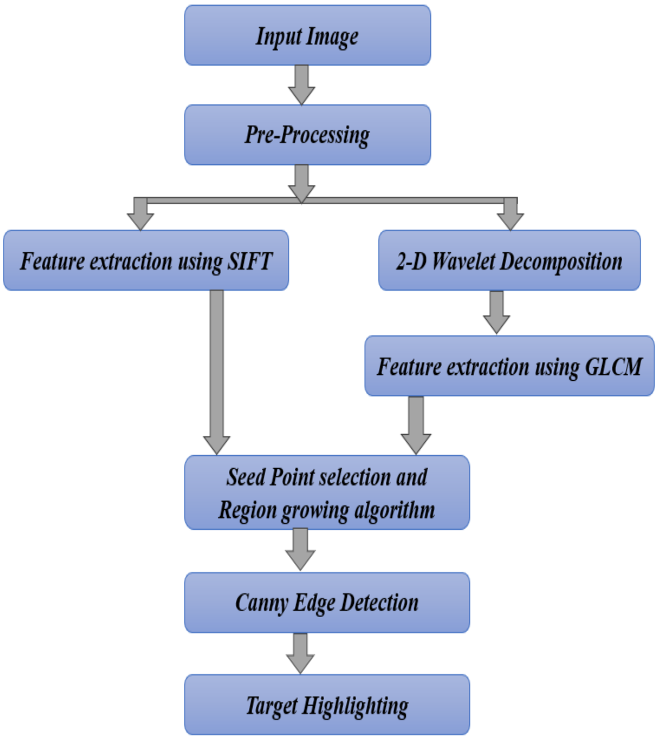


Figure 1. An illustration of a camouflage target extraction process

2.3. Texture feature

Statistical methods assess features from the transformed sub-block of the camouflage image to discover the seed block details for further processing. The texture feature describes the spatial arrangement of colors or intensities in an image. Texture is a measure of each surface regularity, coarseness, and smoothness in all directions [21]. Gray level co-occurrence matrix is a kind of statistical model used to determine features. It is based on the likelihood that gray tone values will occur. The statistical GLCM properties of cluster prominence, cluster shadow, and cluster contrast are utilized to assess the seed block from a group of sub-blocks. The highest sum of statistical features and feature descriptor in each sub-block is used to determine the seed block.

2.4. Scale invariant feature transform feature

A feature extraction technique called scale invariant feature transform (SIFT) reduces the content of an image to a collection of points. High distinctive invariant features have been extracted from image data using the SIFT. SIFT is robust to noise, fluctuations in illumination, partial occlusion, and changes in the viewpoint in images, and it remains invariant to both scale and orientation [22]. There are two main steps in it: i) key-point localization and ii) descriptor generation. The SIFT detector uses the difference of Gaussian (DoG) function to find local maxima at various image sizes under consideration. Each sample point is compared with all of its neighbors in order to find the local maxima and minima. The potential feature points are the estimated extreme values [23]. The point can be considered as the possible key point if it is a local extremum. The orientation histogram is utilized to count the gradient direction of surrounding pixels when sampling is done around the neighbor of the key point location. Subsequent modifications to the image's orientation, scale, and position provide invariance to the transformation. To ensure rotation invariance, a neighbor is taken around the key point, and a local coordinate is produced with the key point's primary direction at 0 degrees. The SIFT feature describes the gradient direction and magnitude around the significant locations. The SIFT technique in this system produces a feature descriptor. The descriptor assigns to each region, describing its appearance.

2.5. Region growing

A region-based sequential technique for image segmentation is known as region growing. Based on predetermined parameters, such as a seed point, threshold and adjacency, sub-regions are grown into larger regions. The proposed methodology uses the mean distance approach as the basis for the region-growing algorithm, designating the window with the highest value as the seed window by first sorting the feature values of all sub-image blocks in ascending order. The average (A) of the first n% of the windows is used to determine the threshold, which are adaptively selected based on the target image. The statistical characteristic values, such as cluster details and contrast, of each of the eight neighboring blocks are now compared to the Shigh value and the average value (A). The window that has a value that is nearer to Shigh (acquired from the seed block) will be combined with the seed window. For each of the 8 adjacent blocks, this procedure is repeated. The procedure ends if no window is combined from the eight neighboring blocks. If at least one window is combined from the 8 neighboring sub-blocks, the process described above will be repeated with the subsequent 16 neighboring sub-blocks, and so on [24].

2.6. Canny edge detection

The canny edge detector was one of the effective edge detection methods for obtaining edge information [25]. To locate the edges in the region-grown image, we now employ a canny edge detection technique. It will highlight every edge in the image that is present in the region-grown image. It illustrates the target edges present in the environment.

2.7. Morphological process

After segmentation process, morphological techniques can be used to remove imperfections in the segmented image and provide details about the structure and shape of the image. Morphology is an image processing method based on the form and shape of objects. When using morphological approaches, a structuring element is added to an input image to produce an output image of the same size. Mathematical morphology defines a wide range of practical operators. They are dilation, erosion, opening, and closing. The edges of objects in an image adds pixels as a result of dilation. Dilation can fix breaks and intrusions. Color maps, which translate data values into colors, control the interpretation of plotted data. Color maps play a crucial role in visualization because they increase the effectiveness and efficiency of data perception. This study highlights the segmented target region using a color map.

3. RESULTS AND DISCUSSION

The proposed hybrid model implemented in MATLAB 2019b. The proposed method has been tested on different types of images, that consist of different sizes and in different contexts. In this work, we collected camouflage images in different scenes and meticulously annotated them and carried out camouflaged target detection experiments on this data. These images have different patterns such as army camouflage, black camouflage, jungle camouflage, terrain camouflage. Any resolution and color or grayscale images can be used as input. All images are resized to 512×512 before processing. Experiments are conducted based on extracting key descriptors, texture feature and segmentation. In this section, we employ the proposed approach to identify camouflaged targets in different environments (army, dark, jungle, and terrain) and visualize the outcomes. In addition, the target that needs to be identified differs in size and posture from each other. Considering that in practical application, this paper only uses a small number of samples as camouflaged target data of camouflage target detection. We collected the samples using various types of clothing, sand, and grass. Figure 2 shows some artificially collected camouflage target data. The input images with different environments are considered with pre-processing. Figure 3 illustrates the camouflaged target in different scenes.

Table 1 illustrates the statistical analysis of the target. The first column shows the type of camouflage pattern, the second column represents the simulation of wavelet-based texture feature profiles such as contrast, cluster shade, and cluster prominence. Contrast feature is normalized linearly and the other two features are normalized logarithmically. The highest possible feature sum of the sub-image block is treated as a seed block, and the center of the seed block is known as a seed point. The seed point is used as input in the region-growing algorithm. Table 2 shows the seed block details.

Table 3 illustrates various camouflage patterns in the first row, from the simulation the second row shows a region-grown image; the third row shows an edge-detected image using Canny; and the fourth row shows the highlighted target image. As shown in the fourth row of Table 4 the camouflaged target region is extracted from a complex environment. The proposed method has demonstrated its ability to complete the detection task from images captured by the camera in a random environment. To validate our hybrid model performance, we conducted comparison with the existing detection approach based on texture statistical features [2]. The outcomes of these comparisons can be found in Table 4. The table shows that the proposed hybrid model is outperforming constructive approach in terms of overall accuracy. TP=the number of processed pixels in the foreground target is equal to the ground truth; FP=the number of processed pixels in the foreground target is not equal to the ground truth; FN=the number of processed pixels in the background is not equal to the ground truth.

$$Precision = TP/(TP + FP) \tag{1}$$

$$Recall = TP/(TP + FN) \tag{2}$$

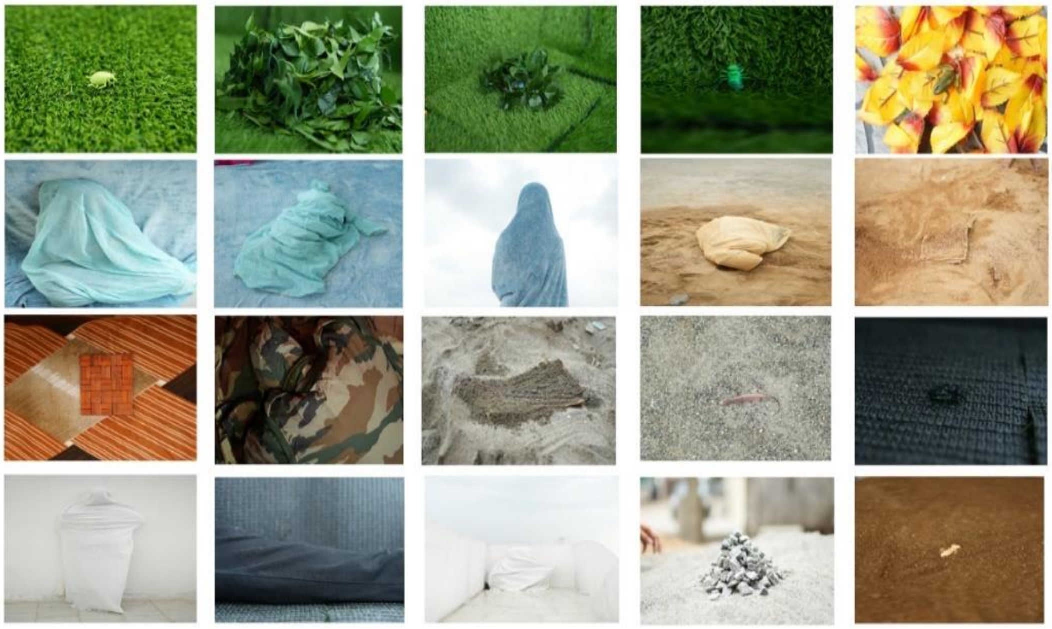


Figure 2. Artificial camouflage patterns and targets

Army camouflage | Dark camouflage | Jungle camouflage | Terrain camouflage

Figure 3. Camouflaged targets in different scenes

Table 1. Statistical feature extraction using GLCM

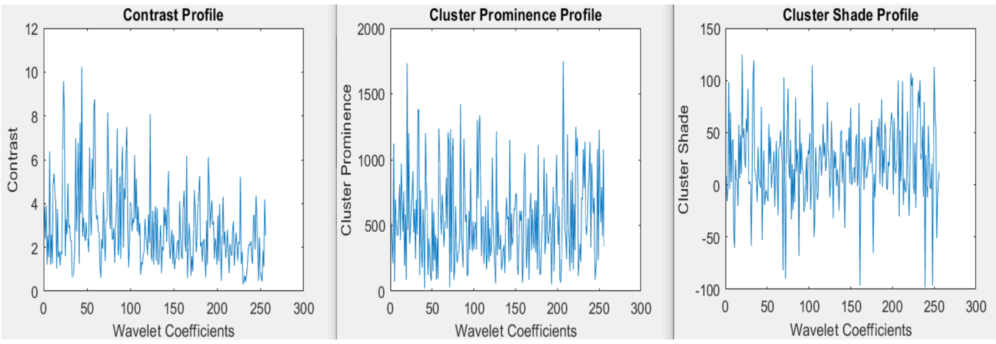
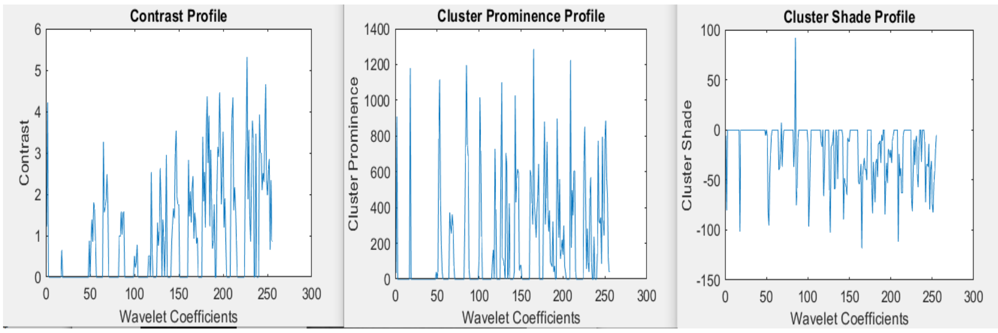
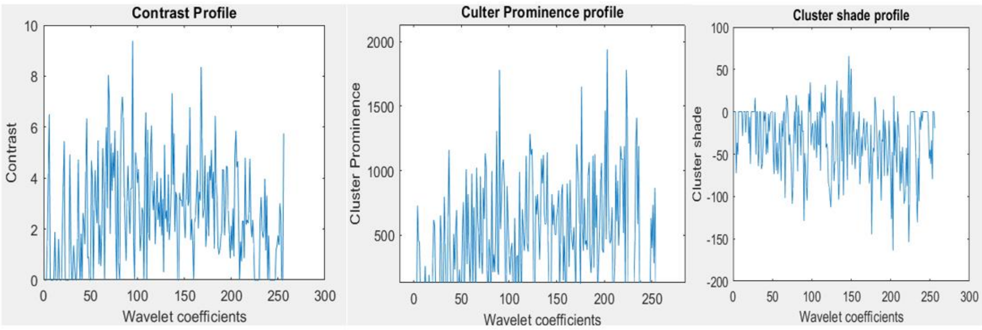
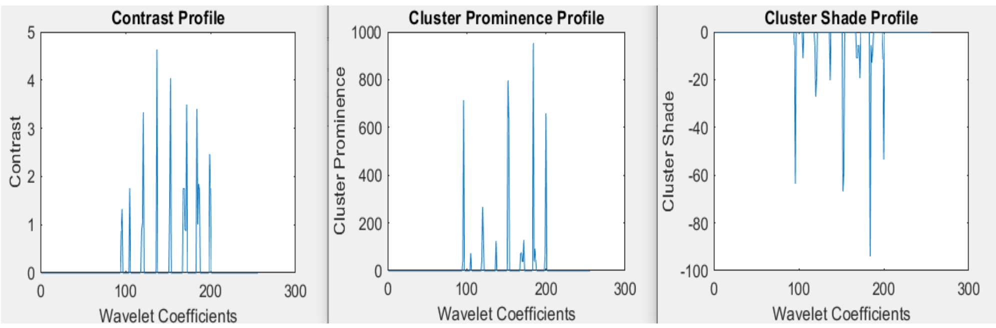
Target image/GLCM features	Statistical features
Army camouflage	
Dark camouflage	
Jungle camouflage	
Terrain camouflage	

Table 2. Seed block and seed point details

Target image	Seed block	Seed point
Army camouflage	20	156,129
Dark camouflage	85	227,92
Jungle camouflage	203	237,205
Terrain camouflage	184	137,51

Table 3. Segmentation and target highlighting

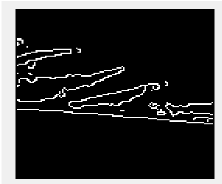
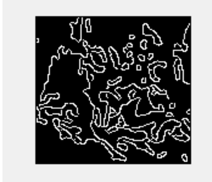
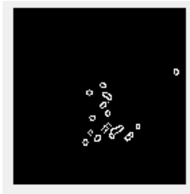
Target image	Army camouflage	Dark camouflage	Jungle camouflage	Terrain camouflage
Region-grown image				
Edge detection				
Target highlighting				

Table 4. Comparison of performance metrics

Target image	Accuracy (hybrid statistical model)	Accuracy (texture statistical features)	Recall (hybrid statistical model)	Recall (texture statistical features)
Army camouflage	0.913	0.851	0.846	0.796
Dark camouflage	0.861	0.798	0.899	0.774
Jungle camouflage	0.924	0.834	0.861	0.816
Terrain camouflage	0.959	0.872	0.919	0.851

4. CONCLUSION

Aiming at the underlying issues with the detection of camouflaged targets in random environments, this paper designs a novel hybrid statistical model for the detection of camouflaged targets by extracting low-level features. Our primary approach is to extract the key descriptors and texture features of the camouflaged targets and their surroundings, which will help to distinguish camouflaged targets from the background. In this work, we implement a module for feature extraction that computes key-point descriptors and extracts the texture features. The highest sum of features selected as a seed point. By the use of seed point details in the region growing algorithm, the segmentation module segments the target region from the background and the edges of the region grown image are computed. Further, the morphological process is used to highlight the target region. The detection model validates the experimental outcomes of images. The visualization effect has demonstrated that the proposed hybrid statistical model outperforms various environmental conditions, such as size, illumination, and random texture. The proposed method for detection of camouflage enriches the application scenario of the defense sector.

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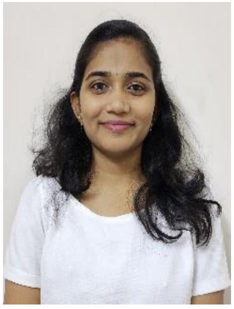
BIOGRAPHIES OF AUTHORS



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