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A Camouflage Texture Evaluation by Weighted Structural Similarity Index Method and Natural Parameters.

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Abstract
Traditional evaluation method of camouflage texture effect is subjective evaluation. It's very tedious and inconvenient to direct the texture designing. In this project, a systemic and rational method for direction and evaluation of camouflage texture designing is proposed. A camouflage texture evaluation method based on WSSIM (Weight structural similarity) is given to access the effects of camouflage texture at first. Then nature image features between the camouflage texture and the background image are calculated to help direct the designing camouflage texture [7, 8]. In this project, we focus on the essential of the human visual system, and its relative significance of the different factors of affecting camouflage texture. The proposed method developed a computational vision model to evaluate the perceived differences between camouflage texture image and background image. And a variety of features, measuring thresholds for discriminating small changes in naturalistic images have been studied to direct the camouflage texture designing. Primary experimental results show that the proposed method is helpful for evaluation and design of the camouflage texture.
Keywords: *WSSIM: Weighted structural similarity*

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I. INTRODUCTION

Camouflage texture is used to increase the survivability of soldiers and mission effectiveness by preventing visual observation and other military sensors from detecting both the soldiers and their equipment's. Camouflage texture achieves the purposes by breaking the target contour and blending the target with the background. So it is very important to evaluate whether camouflage texture spots are consistent with the background in the shape, size, color and spatial distribution [1, 2]. Traditionally, the evaluation is conducted by groups of observers, who rate the effectiveness of camouflage texture. The actual camouflage effects can be reflected in subjective evaluation, but some shortcomings and limitations, such as psychological factors of the observers and testing environment, in image quality subjective evaluation. It is very difficult in practical applications.

In this project, we focus on the essential of the human visual system, and its relative significance of the different factors of affecting camouflage texture. The proposed method developed a computational vision model to evaluate the perceived differences between camouflage texture image and background image. And a variety of features, measuring thresholds for discriminating small changes in naturalistic images have been studied to direct the camouflage texture designing.

The role of images in present day communication has been steadily increasing. In This context the quality of an image plays a very important role. Different stages and multiple design choices at each stage exist in any image processing system. They have direct bearing on the quality of the resulting image. Unless we have a Quantitative measure for the quality of an image, it becomes difficult to design an ideal image processing system. Though subjective quality assessment is an alternative, it is not feasible to be incorporated into real world systems. Hence, objective quality metrics play an important role in image quality assessment.

In the last two decades a lot of objective metrics have been proposed to access image quality. The most widely adopted statistics feature is the Mean Squared Error (MSE). However, MSE and its variants do not correlate well with subjective quality measures because human perception of image distortions and artifacts is unaccounted for. MSE is also not good because the residual image is not uncorrelated additive noise. It contains components of the original image. A detailed discussion on MSE is given by Girod . [3, 4].

A major emphasis in recent research has been given to a deeper analysis of the Human Visual System (HVS) features. There are lot of HVS characteristics that may influence the human visual perception on image quality. Although HVS is too complex to fully understand with present psychophysical means, the incorporation of even a simplified model into objective measures reportedly leads to a better correlation with the response of the human observers . However, most of these methods are error sensitivity based approaches, explicitly or implicitly, and make a number of assumptions , which need to be validated. These methods suffer from the problems like the natural image complexity problem, Minkowski error pooling problem, and cognitive interaction problem.

Structural similarity based methods of image quality assessment claim to account for the fact that the natural image signal samples exhibit strong dependencies amongst themselves, which is ignored by most of these methods. Structural similarity based methods replace the Minkowski error metric with different measurements that are adapted to the structures of the reference image signal, instead of attempting to develop an ideal transform that can fully decouple signal dependencies.

However, Vision models , which treat visible distortions equally, regardless of their location in the image, may not be powerful enough to accurately predict picture quality in such cases. This is because we are known to be more sensitive to distortions in areas of the image to which we are paying attention than to errors in peripheral areas.

1.1 Structural Similarity:

Based on the assumption that the HVS is highly adapted to extract structural information from the viewing field, a new philosophy of SSIM for image quality measurement was proposed by Wang et al . Let x and y be two discrete non-negative signals x = { Xi / I =1,2,...N,} and y = {Yi / i 1,2,...,N} that have been aligned with each let $\bar{x}, \sigma_x^2$ and σ_{xy} be the mean of x , variance of x , and the covariance of x and y respectively. $\bar{x}, \sigma_x^2$ are the estimates of the luminance and contrast of x , and σ_{xy} measures the tendency of x and y to vary together, which is an indication of structural similarity. SSIM index is given as shown below where, C1,C2 and C3 are small constants introduced to avoid instability when the denominator is close to zero.

$$SSIM(x,y) = \frac{(2\mu_x\mu_y + C_1)(2\sigma_{xy} + C_2)}{(\mu_x^2 + \mu_y^2 + C_1)(\sigma_x^2 + \sigma_y^2 + C_2)} \qquad (1)$$

1.2 WEIGHTED STRUCTURAL SIMILARITY INDEX

At first, the original and distorted images are divided into 8 x 8 non-overlapping blocks. The SSIM for each block is computed using equation (1), to form a matrix S as shown below where each element Sij represents the SSIM between corresponding blocks of the original and distorted images with coordinates (i , j)

$$1 \le i \le m = \lfloor H/8 \rfloor \quad \text{and} \quad 1 \le j \le m = \lfloor W/8 \rfloor$$

Where H and W represent the height and width of the image respectively. Psycho visual studies reveal that human eye is very sensitive to the edge and contour information of the image. Edges per unit area e , was determined by detecting edges in an image, using the Canny extension of the Sobel operator [14] and then congregating the edges detected within an 8x8 block. The value of e is normalized to the range [0 1]. A block without edges will have a value of 0.

Secondly, the visual regions of interest map E as specified above is obtained for the original image as shown below. The values Eij represents degree of visual importance of each block with coordinates (i , j) as defined earlier

$$S = \begin{pmatrix} s_{11} & s_{12} & . & . & s_{1n} \\ s_{21} & s_{22} & . & . & s_{2n} \\ . & . & . & . & . \\ . & . & . & . & . \\ s_{m1} & s_{m2} & . & . & s_{mn} \end{pmatrix} \qquad E = \begin{pmatrix} e_{11} & e_{12} & . & . & e_{1n} \\ e_{21} & e_{22} & . & . & e_{2n} \\ . & . & . & . & .. \\ . & . & . & . & . \\ e_{m1} & e_{m2} & . & . & e_{mn} \end{pmatrix}$$

We define Weighted Structural Similarity index WSSI as the weighted average of the structural similarity indices Sij in each local block with coordinates (i,j) where each Sij is weighted with the corresponding visual region of interest values Eij . Equation (4) gives the expression for WSSIM

$$WSSI = \frac{\sum_{i=1}^{m}\sum_{j=1}^{n} S(i,j)E(i,j)}{\sum_{i=1}^{m}\sum_{j=1}^{n} E(i,j)} \qquad (2)$$

II. Experimental Results :

The proposed quality index was tested using LIVE image database [15]. The database consists of twenty-nine high resolution 24-bits/pixel RGB color images (typically 768 x 512), distorted using five distortion types: JPEG2000, JPEG, White noise in the RGB components, Gaussian blur in the RGB components, and bit errors in JPEG2000 bit stream using a fast-fading Rayleigh channel model. Each image was distorted with each type, and for each type the perceptual quality covered the entire quality range. Difference Mean Opinion Score (DMOS) value for each distorted image was computed based on the perception of quality of the images by observers.

We tested the proposed method on all the images and distortions available in the LIVE database, after converting the color images to gray level images. In order to provide quantitative measures on the performance of the objective

quality assessment models, different evaluation metrics were adopted in the Video Quality Experts Group (VQEG) Phase-I test [16]. We performed non-linear mapping between the objective and subjective scores, using 4-parameter logistic

function of the form shown in Equation (3).

$$y = a/(1.0 + e^{-(x-b)/c}) + d \qquad (3)$$

After the non-linear mapping, the Correlation Coefficient (CC), the Mean Absolute Error (MAE), and the Root Mean Squared Error (RMS) between the subjective and objective scores are calculated as measures of prediction accuracy. The prediction consistency is quantified using the outlier ratio (OR), which is defined as the percentage of the number of predictions outside the range of 2 ± times the standard deviation. Finally, the prediction monotonicity is measured using the Spearman rank-order-correlation coefficient (ROCC). To evaluate the performance of the proposed metric, we considered two image quality assessment models, PSNR and MSSIM.Table 1 shows the evaluation results for the models being compared with that of the WSSI for different types of distortions. For each of the objective evaluation criteria, WSSI outperforms the other models being compared across different distortion types. Figure 1 shows the scatter plots of DMOS versus WSSI for different kinds of distortions.

TABLE 1. PERFORMANCE COMPARISON OF IMAGE QUALITY ASSESSMENT MODELS ON LIVE IMAGE DATABASE [15].

(A) JPEG2000 (B) JPEG (C) WHITE NOISE (D) GAUSSIAN BLUR (E) FAST FADING

Model	CC	ROCC	MAE	RMS	OR%
PSNR	0.859	0.851	6.454	8.269	5.917
MSSIM	0.899	0.894	5.687	7.077	2.366
WSSI	0.931	0.925	4.773	5.929	4.142

(a)

Model	CC	ROCC	MAE	RMS	OR%
PSNR	0.842	0.828	6.636	8.622	6.285
MSSIM	0.891	0.863	5.386	7.236	5.714
WSSI	0.917	0.882	4.563	6.377	6.857

(b)

Model	CC	ROCC	MAE	RMS	OR%
PSNR	0.922	0.938	4.524	6.165	5.555
MSSIM	0.94	0.914	4.475	5.459	2.777
WSSI	0.962	0.9545	3.526	4.367	4.166

(c)

Model	CC	ROCC	MAE	RMS	OR%
PSNR	0.744	0.725	8.395	10.50	3.448
SSIM	0.947	0.940	3.992	5.027	3.448
WSSI	0.968	0.963	3.168	3.897	4.137

(d)

Model	CC	ROCC	MAE	RMS	OR%
PSNR	0.857	0.859	6.383	8.476	6.896
MSSIM	0.956	0.945	3.806	4.799	5.517
WSSI	0.962	0.960	3.656	4.467	2.758

(e)

III. Proposed Methods

3.1. CAMOUFLAGE TEXTURE EVALUATION METHODS

3.1.1 WSSIM Texture Evolution Model

Human visual model is based on knowledge of primary visual cortex, which recognizes a visual image by processing in parallel by channels or neurons with different optimal spatial frequencies [7.] Based on human visual model, we propose a camouflage texture assessment framework to get the differences of background image and camouflage textures. Meanwhile, human eyes do not pay an equivalent attention to different regions in an image In the assessment framework, different attention weights are applied to different regions of image. Fig.1 illustrates the camouflage texture assessment framework based on human visual model.

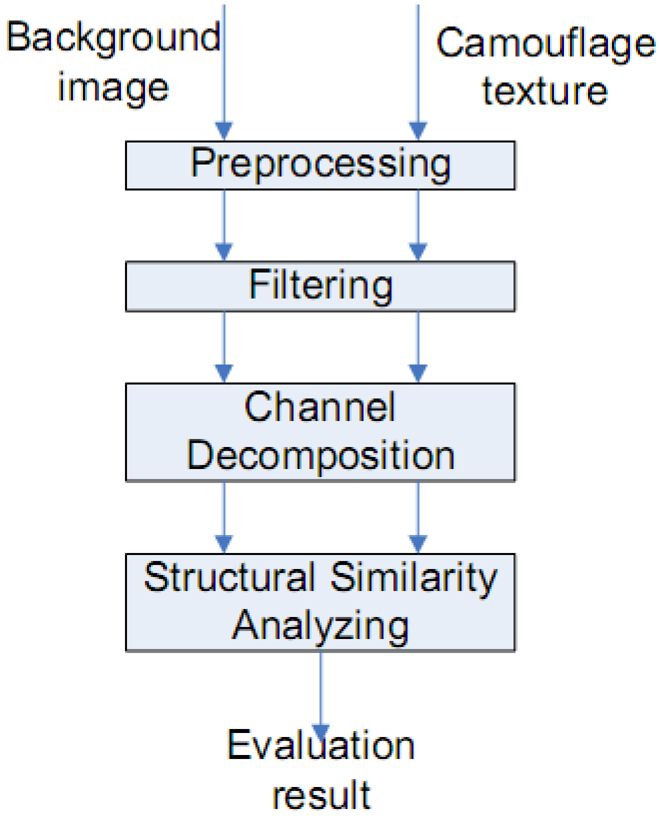


Fig. 3.1.1WSSIM Texture Evolution Model

Fist, a variety of basic operations is performed to eliminate distortions from background image and camouflage texture. And a low-pass filter simulating the point spread function of the eye optics may be applied. Second, the luminance of camouflage texture and background image is compared as follows:

$$l(x,y) = \frac{2\mu_x\mu_y + C_1}{\mu_x^2 + \mu_y^2 + C_1} \qquad (4)$$

Where $l(x,y)$ is the luminance comparison function of the mean intensity μ_x and μ_y of the camouflage texture x and background image y respectively. C1 is included to avoid instability, here we choose 6.5025.
The contrast comparison function is given as follows:

$$c(x,y) = \frac{2\sigma_x\sigma_y + C_2}{\sigma_x^2 + \sigma_y^2 + C_2} \qquad (5)$$

where σ_x and σ_y is the stand deviation and we choose C_2 58.5225.
We define the structure comparison function as follows:

$$s(x,y) = \frac{2\sigma_{xy} + C_3}{\sigma_x\sigma_y + C_3} \qquad (6)$$

where σ_{xy} is the covariance and we choose C_3 58.5225.
At last, the structural similarity (SSIM) index between x and y can be drawn as

$$SSIM(x,y)=l(x,y)c(x,y)s(x,y) \qquad (7)$$

The camouflage texture is compared with each block of the background with same size to get the whole evaluation result by Weight-SSIM as follows:

$$WSSIM(X,Y)=\frac{1}{M}\sum_{j=1}^{M} w_j SSIM(x_j,y_j) \qquad (8)$$

where Wj is the weight of different block of background and M is the sum of the blocks. WSSIM is calculated three times on each pair of background image and camouflage texture for the red green and blue channels. The value will show the differences between the background image and the camouflage textures in RGB channels.

2) Nature Image Feature Analysis

Natural image signals are highly structured [1,11] their pixels exhibit strong dependence which carries important information about the structure of the objects in the visual scene. Structural features of natural images can be used to evaluate the effects of camouflage texture. We select some nature image features for directing the design of camouflage texture. The selected features are summarized in the following

- Average Luminance:

$$\mu=\frac{1}{N}\sum_{i=1}^{N} x_i \qquad (9)$$

Where N is the sum of image pixel

- Standard Deviation:

$$\sigma_x=\left(\frac{1}{N-1}\sum_{i=1}^{N}(x_i-\mu_x)^2\right)^{1/2} \qquad (10)$$

- Correlation Length: Correlation length, which can be convenient from the image Fourier spectrum:

$$r=10.0/W \qquad (11)$$

where

$$W^2=\frac{\sum (U^2+V^2)\left|F(U,V)\right|^2}{\sum \left|F(U,V)\right|^2} \qquad (12)$$

where F (V, U) with U and V as (frequency) variables is the image Fourier spectrum.

- Texture Direction: which is the angle of the peak of the power spectrum

$$P(u,v)=\left|F(U,V)\right| \qquad (13)$$

- Image Entropy:

$$H(I)=-\sum_{i=0}^{L-1}\frac{c_i}{N}\log_2\left(\frac{c_i}{N}\right) \qquad (14)$$

Where N is the sum of image pixels, L is the sum of classes, and c is the pixels number of every class.

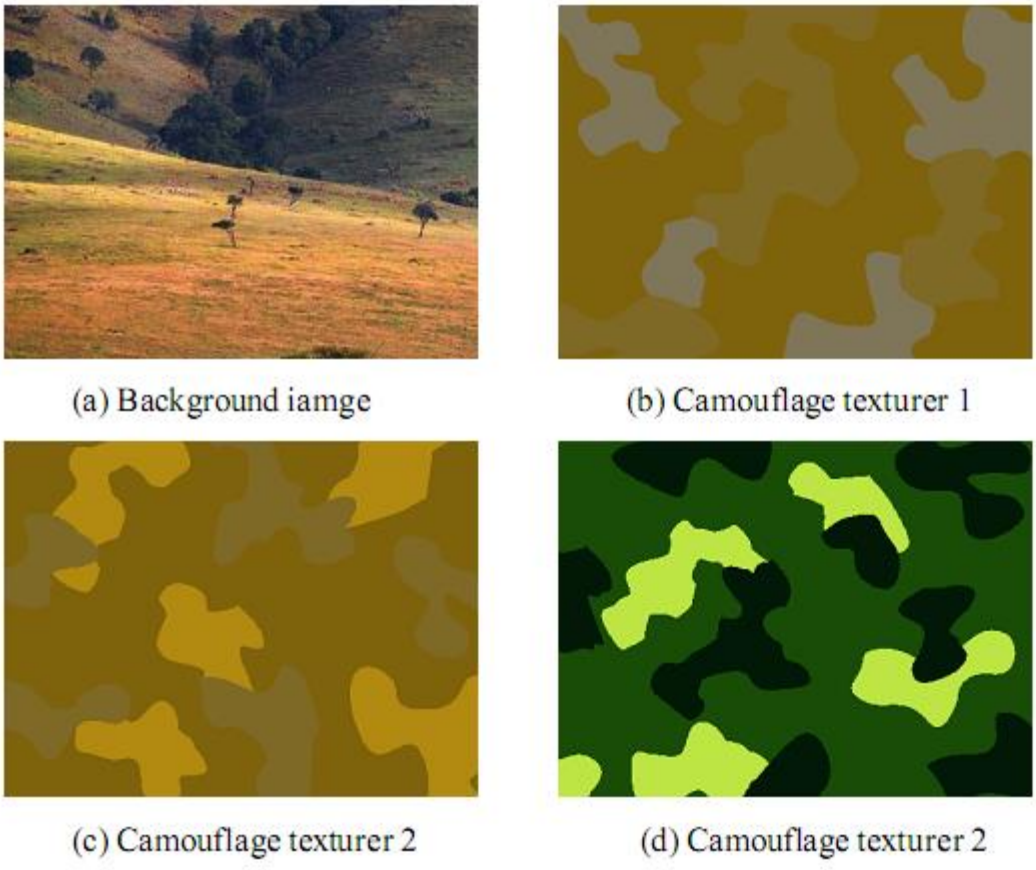
• By edge detection, the number of closed areas and the length of edge can be got. Background image and camouflage textures are treated with Canny edge detector [12] to extract the image edges. These features need to be normalized to ensure different Feature vector with similar effect. Gaussian normalization method is chosen because it can deal ultra-large or ultra-small element values. The function is given by:

$$Z = ((X - \mu)/(3 * \sigma) + 1)/2 \qquad (15)$$

where μ is the mean and σ is the covariance.
These normalized features can measure the differences between camouflage texture and the background image, so according to the differences (e.g. luminance etc.) designers are able to improve the camouflage textures.

3.1.2. WSSIM Test

The camouflage texture is evaluated based on the WSSIM. Fig.2 (a) is the background image and Fig.2 (b) (c) and (d) are the camouflage textures for evaluation. . We calculate the differences between the background image and the camouflage textures in RGB channels. [4,7]



(a) Background iamge (b) Camouflage texturer 1 (c) Camouflage texturer 2 (d) Camouflage texturer 2

Figure 2. Background image and camouflage textures

IV.CONCLUSION

In this paper, a new WSSIM camouflage texture evaluation method based on human visual model is proposed to access the camouflage textures And the nature image feature model is used to analyze of images to understand what features of camouflage texture have the greatest effect on detection [1,4]. Primary experimental results, although not perfect, are very promising and further validation tests will be undertaken to test the method in a greater variety of naturalistic background.

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