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MEASUREMENT OF JUST NOTICEABLE COLOR DIFFERENCE UTILIZING FREE-ENERGY PRINCIPLE IN UNIFORM COLOR SPACE

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The human visual system (HVS) has a limited sensitivity in perceiving visual information such that visual masking estimation is helpful to improve the performance of image processing techniques. Most existing research efforts only focus on the methods of assessing the visual masking for gray images. In this paper, a spatial masking estimation utilizing the free-energy principle to measure just noticeable color difference (JNCD) in the uniform color space is explored for color images. According to the free-energy principle introduced recently, the HVS is sensitive to the orderly stimulus possessing structural regularity which is easily to be predicted and is insensitive to the disorderly stimulus containing structural irregularity. We reasonably deduce that the spatial masking in color images may be overestimated in the region with orderly structures and underestimated in the region with disorderly structures. Based on a simple prediction model imitating the brain works of the HVS, the structural irregularity is computed to formulate a more accurate spatial masking function of color images in the uniform color space for measuring variable just noticeable color difference (JNCD). The estimated variable just noticeable color difference is further extended to build a color visual model of estimating the visibility thresholds of color images for performance comparison. Simulation results demonstrate that the proposed spatial masking estimation for color images has better consistency with the HVS than the existing method.

Keywords: HVS; JNCD; free-energy; uniform color space; structural regularity.

1. Introduction

For the growing amount of digital images transmitted over the internet, it becomes important for designing image processing techniques to consider the characteristics of the mechanism in the human visual system (HVS) directly. The well-known properties that the HVS has a limited sensitivity in perceiving visual information are always utilized to represent images more efficiently. Through assessing the human visual sensitivity inherent in images, the performance of many techniques of saliency detection [Tian et al 2014], quality assessment [Sheikh and Bovik 2006, Zhang et al 2011], image compression [Höntsch andKaram 2000, Yang et al 2005, Chou and Liu 2008], and watermarking [Nguyenet al 2013, Zebbiche and Khelifi 2014,Liu 2014] et al. has been improved in the perceptual research community. Quantitatively, the human visual sensitivity can be measured by the visual masking estimation. All of these researches, however, concentrated only on the estimation and exploitation of the human visual masking inherent in gray-scale images.

The human visual masking inherent in color images results in that the HVS does not respond to small stimuli and is not able to discriminate color signals of small differences. The perceptual image processing application for color images can be found in [Chou and Liu 2008, Liu 2014, Chou and Hsu 2013, Zhu and Karam 2014, Hsieh et al 2014], some of which [Chou and Liu 2008, Chou and Hsu 2013, Zhu and Karam 2014, Hsieh et al 2014] take the characteristics of the human visual perception of color stimuli into account. By using different levels of just noticeable color difference, a simplified visual model introduced in [Chou and Liu 2008] for estimating the perceptual redundancy for each color pixel as the visibility threshold of color difference was proposed to modify the coding efficiency of two existing image coders. In [Chou and Hsu 2013], a metric for assessing the quality of color images was proposed. The metric measures the average perceptible distortion in terms of the quantized distortion, according to the perceptual error map converting the color difference to the objective score of perceptual quality assessment. Zhu and Karam [Zhu and Karam 2014] proposed a perceptual based no-reference objective image quality metric by integrating perceptually weighted local noise into a probability summation model. Unlike existing objective metrics, the proposed no-reference metric is able to predict the relative amount of noise perceived in images with different content, without a reference. In [Hsieh et al 2014], a copyright identification scheme for color images that takes advantage of the complementary nature of watermarking and fingerprinting was proposed to embed the watermark into the less sensitive R and B channels of the host image in the RGB color space. To gain high performance in color image processing, the properties of the human visual perception of color stimuli must be well utilized in exploring the spatial masking estimation of color images.In the latest research of quality metric proposed in [Frackiewicz andPalus 2016],a new image quality metric was presented for measuring color quantization algorithms.In [Lee andPlataniotis 2016],parametric models were proposed for describing the general characteristics of chromatic data in natural images. Many informative cues are provided for quantifying visual discomfort caused by the presence of chromatic image distortions.Thecharacteristics of human visual contrast sensitivity used to design a novel color image compression algorithm can be found in [Yao and Liu 2016].

The newest research efforts declare that effective analysis of the image structures can be used to deduce accurate estimation of visual masking. The concept of the free-energy principle indicates the brain works actively predict the input scenes and avoids the residual uncertainty/disorder [Knill and Pouget 2004, Friston 2010]. In this paper, the free-energy principle is utilized to estimate spatial masking for color images. Based on a simple prediction model, the luminance dominated structural irregularity is taken into account to explore a more strict spatial masking function in color images for just noticeable color difference (JNCD) in the uniform color space, while only background non-uniformity and texture content are used in the prior works. To avoid underestimating or overestimating the spatial masking effect in the region with structural uncertainty, the nonlinear additivity model is adopted to build a new masking function. By using the estimated variable JNCD, the visibility thresholds of color images are estimated for performance comparison under a fair viewing test.

2. Improved Spatial Masking Estimation Basedon Structure Information

In this section, the analysis of structural irregularity for image perception is extended to color images for spatial masking estimation. According to the free-energy principle recently introduced in [Friston 2010], the input scene information received by human eyes is not fully processed by the HVS and some information with structural irregularities is avoided and hard to be predicted. The HVS is highly adaptive to extract orderly structures and tries to avoid disorderly structures or structural irregularity [Wu et al 2013]. That is, the human visual perception of brain works understands the orderly stimulus which is easily to be predicted and ignores the structural irregularity which is hard to be precisely predicted. To accurately measure the perceptual redundancy of color images, the structure information is utilized to improve the spatial masking estimation in the color image.

In [Chou and Liu 2008], the spatial masking effect considering the local color image context is exploited to calculate variable variable JNCD (VJNCD) of each color pixel in the uniform CIELAB color space. By using the colors on the surface of the VJNCD sphere, the perceptual redundancy inherent in each color pixel in color images can be estimated. In this section, the structural irregularity is incorporated to improve the prior texture masking function, $s_L(E(L_x), \Delta L_x)$, for pixel x of the color image in the CIELAB color space, where the function is primarily induced by average background luminance $E(L_x)$ and luminance gradient ΔL_x of the pixel. The new spatial masking function is defined and given by

$$M(x) = s_L(E(L_x), \Delta L_x) + s_U(LR_x) - g \cdot \min(s_L(E(L_x), \Delta L_x), s_U(LR_x)) \tag{1}$$

where $s_U(LR_x)$ is the corresponding structure-based adjustment caused by considering the amount of luminance residual LR_x, and g the gain reduction parameter used to control the overlapping between $s_L(E(L_x), \Delta L_x)$ and $s_U(LR_x)$. For simplicity, only the luminance dominated structural irregularity inherent in the color image is investigated, while considering the fact that the human eye is more sensitive to luminance than to chrominance.

As mentioned above, the structural irregularity of an image is from the uncertain information which is hard to be predicted for the HVS. We reasonably regard the uncertain information of the image as the residual part between the image and its prediction part [Wu et al 2013]. An computational prediction autoregressive (AR) model for the luminance component of the color image is therefore exploited and given by

$$L'_x = \sum_{x_i \in \Re} p_i L_{x_i} + \nu_x \tag{2}$$

where L'_x is the predicted luminance value of pixel x, x_i the *i*-th neighboring pixel in the surrounding region $\Re = \{x_1, x_2, \ldots, x_N\}$and *i*=1 to N (such as *N*=8 for a 3×3 surrounding square region), and $\{p_i\}$the model coefficients which are determined by minimizing the variance of the white noise$\{\nu_x\}$. The residual part is then computed as follows:

$$LR_x = |L_x - L'_x| \tag{3}$$

Based on the free-energy principle, the HVS tries to avoid structural irregularity while receiving the input scene. That is, the signal in the irregular region can mask or conceal more noise without noticing by the human visual perception. Therefore, a pixel in the image with large residual value means the pixel is difficult to be predicted and has high uncertainty with large structural irregularity. The relation between the structure-based adjustment and the residual part of the pixel in the image is simply deduced by

$$s_U(LR_x) = \sqrt{\kappa \cdot LR_x} \tag{4}$$

where κ is the parameter used to make a trade-off between the visual quality and structure-based masking adjustment. It is obtained by the subject viewing tests and the experimental results.

3. Verification of the Improved JNCD

The performance of the proposed structure-based spatial masking adjustment is verified by incorporating Eq. (1) into Chou's model [Chou and Liu 2008] to compare the accuracy of estimating the visibility thresholds of color images. For a particular color pixel, the perceptual redundancy is quantitatively measured by analyzing the loci of colors which are perceptually indistinguishable from this color. In [Wu et al 2013], the loci form a sphere centralized at this color's coordinate with the radius of VJNCD in the uniform CIELAB color space and used to compute the visibility thresholds of color pixels in color images. By using Eq. (1), the VJNCD of the color pixel *x* within a complex image is redefined as

$$VJNCD_x = JNCD_{Lab} \cdot s_c(a_x, b_x) \cdot M(x) \tag{5}$$

where

$$s_c(a_x, b_x) = 1 + 0.045 \cdot \sqrt{(a^2 + b^2)} \tag{6}$$

is a weighting function used by the CIE94 color difference equation for adjusting the dimension of the ellipsoid along the chroma*a*, b axis and $JNCD_{Lab}$ is the basic visibility threshold of color difference in the CIELAB space. The basic threshold has been found around 2.3[Mahy 1994].

The procedure for estimating the perceptual redundancy of a pixel in an arbitrary color space is firstly to transform the color pixel to the CIELAB space. By using Eq. (5)

(a)

(b)

Fig. 1.(a) Original color image of “Pepper” and (b) itsnoise contaminated image (PSNR=33.20dB)

that utilizes the improved spatial masking function in this paper, the corresponding VJNCD threshold is obtained. Under the perceptually conservative restriction controlled by the luminance, some critical colors on the surface of the VJNCD sphere are selected to transform back to the target color space. Finally, an approximate rectangular subspace is obtained to quantify the perceptual redundancy and the visibility thresholds of the color pixel for each color channel are calculated.

(a)

(b)

Fig. 2.(a) Original color image of “Tulips” and (b) itsnoise contaminated image (PSNR=35.27dB)

The performance of the improved spatial masking for color images is justified by comparing the accuracy of estimating the visibility thresholds of color images in each color component. Herein, a subjective test is conducted to inspect if the estimated visibility thresholds is consistent with the HVS. Suppose a test image is represented in the YCbCr color space, the visibility threshold for each color pixel in each color component of the color image is randomly added to or subtracted from the corresponding color pixel. While the visual quality of the contaminated image has nearly the same as the original image under the specified viewing condition, the accuracy degree of estimating the visibility thresholds is better if the PSNR of the contaminated image is lower.

4. Simulation Results

In the simulation, the spatial masking estimation is carried out for a variety of color images of size 512×512. The color pixels are represented in 24-bit YCbCr format. 16 subjects who have normal eyesight or had been corrected to be normal take part in test. In the viewing test, the original color image and its noise contaminated image are randomly placed side by side on the monitor (ViewSonic VX2363). The test is carried out in the dark room when the subject observes the image pair on the monitor at a viewing distance of six times the image's height.

Table 1.PSNR comparison of the noise contaminated color images

Channels	Chou's model	Proposed method
Lena	35.34dB	34.18dB
F16	34.49dB	33.31dB
Tulips	37.17dB	35.27dB
Zuerst	36.87dB	34.95dB
Goldhill	34.92dB	33.81dB
Pepper	34.75dB	33.20dB

In Fig. 1, the original color image of "Pepper" (Fig. 1a) and its noise contaminated version (Fig. 1b)of PSNR=33.20dB by the associated visibility thresholds in three color components are shown, while the two images are perceptually indistinguishable from each other under the viewing condition mentioned above. The same tests applied to the color image "Tulips" (Fig. 2a) are shown in Fig. 2 where the noise contaminated "Tulips" image of 35.27dB is demonstrated in Fig. 2b. To achieve a fair comparison for verifying the improvement of the existing spatial masking, the simulation results are compared with the color visual model proposed in [Chou and Liu 2008]. The PSNR comparison of the noise contaminated color images are shown in Table 1, from which the improved spatial masking estimation based on the free energy principle indeed achieve larger noise concealment in the regions with structural irregularity, while the visual quality of the contaminated image has nearly the same as the original image under the specified viewing condition. The proposed spatial masking adjustment successfully shows better performance than the masking estimation presented in [Chou and Liu 2008].

5. Conclusions

In this paper, the improved spatial masking estimation based on the free-energy principle is presented for color images. By using the brain works of the human visual perceptionwhichis sensitive to the orderly stimulusthat is easily predicted and is insensitive to the disorderly stimulus, the estimation is incorporated with a simple prediction model to effectively obtain a new spatial masking function. We use the function to compute the visibility thresholds of color images for performance comparison. With the new spatial masking function, the proposed spatial masking adjustment successfully shows better performance than the existing masking estimation.

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