Objective Quality Assessment for Color to Gray Image Conversion

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Abstract - Color-to-gray (C2G) image conversion is one way of transforming a color image into a grayscale image. In real-world applications the usage is broadened, little work has been dedicated to compare the performance of C2G conversion algorithms. Subjective evaluation is reliable but is also inconvenient and time consuming. Here, we make one of the first attempts to develop an objective quality model that automatically predicts the perceived quality of C2G converted images. Inspired by the philosophy of the structural similarity index, we propose a C2G structural similarity index, which evaluates the luminance, contrast, and structure similarities between the reference color image and the C2G converted image. The three components are then combined depending on image type to yield an overall quality measure. Experimental results show that the proposed C2G-SSIM index has close agreement with subjective rankings and significantly outperforms existing objective quality metrics for C2G conversion.

Keywords: C2G Conversion, SSIM, Quality Assessment, Perceptual Image Processing.

I. INTRODUCTION

Digital images and videos are omnipresent in daily life and the importance of visual data is still growing: According to [1], by 2020, nearly a million minutes of video content is estimated to cross the internet every second.

Typically, video and image signals are intended to be ultimately viewed by humans. For transmission or storage, most signals are compressed in order to meet today's channel and/or storage demands. Compression as well as transmission errors can introduce distortions to video or image signals that are visible to human viewers.

Image quality assessment methods typically belong to one of three categories with different challenges and scopes of applications: Full reference (FR) image quality assessment approaches require and utilize the availability of a reference image. Reduced reference (RR) methods exploit a small set of features extracted from the reference image. No reference (NR) approaches estimate the perceived quality of a possibly distorted image solely from the image itself [2].

The simplest FR image quality metric is the mean squared error (MSE), which is defined as the average of the squared differences of the reference and the distorted image. Although being widely used, it does not correlate well with perceived visual quality [3]. More sophisticated approaches towards perceptually accurate image quality assessments (IQA) typically follow one of three strategies. Bottom-up approaches explicitly model various processing mechanisms of the human visual system (HVS), such as masking effects [4], contrast sensitivity [5], or just-noticeable-distortion [6, 7] in order to assess the perceived quality of images. For instance, the adaptivity of the HVS to the magnitude of distortions is modeled explicitly by the concept of most apparent distortion (MAD) [8] in order to apply two different assessment strategies for supra- and near-threshold distortions.

However, the method proposed in this paper as well as most image quality metrics developed recently follow a top-down approach. There, general functional properties of the HVS are assumed in order to identify and to exploit image features corresponding to the perceived quality. The SSIM [9] aims at taking into account the sensitivity of the human visual system towards structural information. This is done by pooling three complementary components, namely luminance similarity (comparing local mean luminance values), contrast similarity (comparing local variances) and structural similarity, which is defined as the local covariance between the reference image and its perturbed counterpart.

II. RELATED WORK

A. Existing Color-to-Gray Algorithms

Most existing C2G conversion algorithms seek to preserve color distinctions of the input color image in the corresponding grayscale image with some additional constraints, such as global consistency and grayscale reservation. This algorithm tends to produce artificial edges in the C2G image. Rasche et al. incorporated contrast preservation and luminance consistency into a linear programming problem, where the difference between two gray values is proportional to that between the corresponding color values [3]. Gooth et al. transformed the C2G problem into a quadratic optimization one by quantifying the preservation of color differences between two distinct points in the grayscale image [4]. More recently, Eynard et al. assumed that if a color transformed image preserves the structural information of the original image, the respective Laplacians are jointly diagonalizable or equivalently commutative. Using Laplacians commutativity as the criterion, they minimized it with respect to the parameters of a color transformation to achieve optimal structure preservation .

B. The SSIM Index

Suppose **x’** and **y’** are local image patches taken from the same location of two images being compared, the local SSIM index computes three components: the luminance similarity *l*(**x’**, **y’**), contrast similarity *c*(**x’**, **y’**) and structure

similarity *s*(**x’**, **y’**)

$$l(\mathbf{x}', \mathbf{y}') = 2\mu_{x'}\mu_{y'} + C_1\mu^2_{x'} + \mu^2_{y'} + C_1, \quad (1)$$

$$c(\mathbf{x}', \mathbf{y}') = 2\sigma_{x'}\sigma_{y'} + C_2\sigma^2_{x'} + \sigma^2_{y'} + C_2, \quad (2)$$

$$s(\mathbf{x}', \mathbf{y}') = \sigma_{x'y'} + C_3 2\sigma_{x'}\sigma_{y'} + C_3, \quad (3)$$

where μ, σ and $\sigma_{x'y'}$ denote the mean, standard deviation (std) and covariance of the image patches, respectively [19].

C_1, C_2 and C_3 are small positive constants to avoid instability, when the denominators are close to 0. Finally, the three measures are combined to yield the SSIM index

$$\mathrm{SSIM}(\mathbf{x}', \mathbf{y}') = l(\mathbf{x}', \mathbf{y}')_\alpha \cdot c(\mathbf{x}', \mathbf{y}')_\beta \cdot s(\mathbf{x}\_, \mathbf{y}\_)_\gamma, \quad (4)$$

where $\alpha > 0$, $\beta > 0$ and $\gamma > 0$ are parameters used to adjust the relative importance of the three components, respectively.

By setting $\alpha = \beta = \gamma = 1$ and $C_3 = C_2/2$, the simplified SSIM index that is widely used in practice is given by

$$\mathrm{SSIM}(\mathbf{x}', \mathbf{y}') = \frac{(2\mu_{x'}\mu_{y'} + C_1)(2\sigma_{x'y'} + C_2)}{(\mu^2_{x'} + \mu^2_{y'} + C_1)(\sigma^2_{x'} + \sigma^2_{y'} + C_2)} \quad (5)$$

It is widely recognized that SSIM is better correlated with the human visual system (HVS) than MSE and has a number of desirable mathematical properties for optimization purposes.

III. THE C2G-SSIM INDEX

The diagram of the proposed C2G-SSIM index is shown in Fig. 1. First, we transform both the reference color image and the test C2G image into a color space, where the color representation is better matched to the HVS. Next, we measure luminance, contrast and structure distortions to capture perceived quality changes introduced by C2G conversion. Finally, we combine the above three measurements into an overall quality measure based on the type of image content.

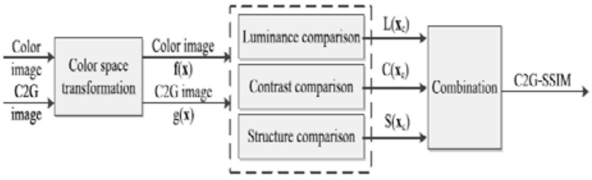
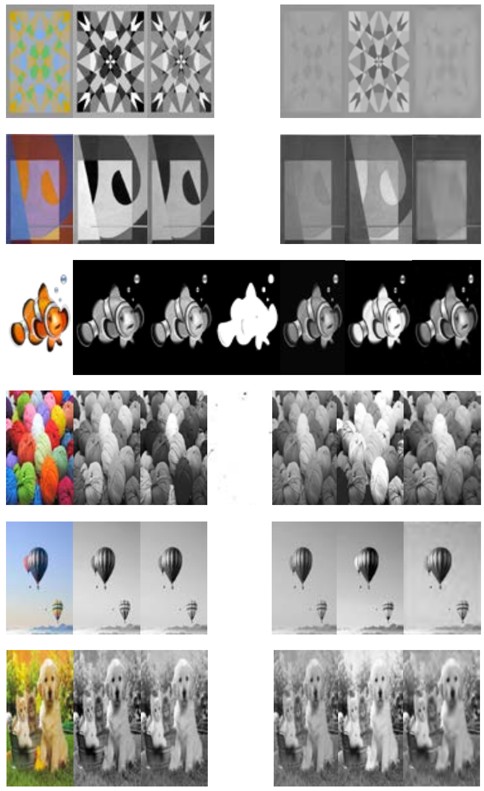


Fig. 1. Three-stage structure of C2G-SSIM.

IV. SIMULATION/EXPERIMENTAL RESULTS



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

Fig 1.(a) Original image, (b) CPR image, (c) RTCP image, (d) L component, (e) Y component, (f) JPEG compression (g) EZW component

TABLE 1. QUALITY FACTORS

IMAGE	QUALITY FACTORS					
	CPR	RTCP	L	Y	JPEG	EZW
IMAGE1	0.965	0.930	0.792	0.787	0.858	0.781
IMAGE2	0.962	0.961	0.916	0.931	0.935	0.903
IMAGE3	0.949	0.943	0.814	0.931	0.920	0.877
IMAGE4	0.798	0.704	0.398	0.758	0.620	0.442
IMAGE5	0.980	0.978	0.876	0.968	0.952	0.936
IMAGE6	0.865	0.868	0.531	0.812	0.762	0.633

V. CONCLUSION

Here we developed an objective IQA model, namely C2G-SSIM, to assess the perceptual quality of C2G images using the original color image as reference. C2G-SSIM evaluates luminance, contrast and structure similarities between the reference color image and the C2G image. Image type dependent combination is then applied to yield an overall quality measure. The proposed C2G-SSIM index compares and significantly outperforms existing objective quality metrics for C2G conversion.

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