Quality Assessment of Images Illuminated by Dim LCD Backlight

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ABSTRACT

We consider the quality assessment of images displayed on a liquid crystal display (LCD) with dim backlight—a situation where the power consumption of the LCD is set to a low level. This energy saving mode of LCD decreases the perceived image quality. In particular, some image regions may appear so dark that they become non-perceptible to human eye. The problem becomes more severe when the image is illuminated with very dim backlight. Ignoring the effect of dim backlight on image quality assessment and directly applying an image quality assessment metric to the entire image may produce results inconsistent with human evaluation. We propose a method to fix the problem. The proposed method works as a precursor of image quality assessment. Specifically, given an image and the backlight intensity level of the LCD on which the image is to be displayed, the method automatically classifies the pixels of an image into perceptible and non-perceptible pixels according to the backlight intensity level and excludes the non-perceptible pixels from quality assessment. Experimental results are shown to demonstrate the performance of the proposed method.

Keywords: Image quality assessment, dim backlight

1. INTRODUCTION

Image quality assessment is needed in many applications. Ideally we want the image quality assessed by computer to be consistent with that by human eye. Peak signal-to-noise ratio (PSNR) and structure similarity (SSIM) index [1] are among the image quality metrics that have been widely used. PSNR calculates the distortion of every pixel of a test image, whereas SSIM uses a modified measure of spatial correlation between the original image and the test image to quantify the structural distortion of the test image. It is often a common practice to uniformly apply such image quantify metrics to all image pixels. The implication of this operation is that the entire image under test is perceptible. However, it is not necessarily true, especially for the case considered in this work, where the LCD is operated in the low power mode.

We consider the quality assessment of images displayed on LCDs. Specifically, we consider the case where the backlight of the LCD is set to a low power level [2], [3]. With this energy saving mode, the perceived image quality decreases with the intensity of the backlight. In particular, some image regions may appear so dark that they become non-perceptible to human eye when the backlight is very dim. Ignoring this very fact and directly applying an image quality assessment metric to the entire image may produce results inconsistent with human evaluation of the image. A simple experiment was set up to illustrate this point. The picture in Fig. 1(a) is a dimmed image, and the one in Fig. 1(b) is the image generated by adding impulse noise to the dimmed image. The noise was added to dark pixels, and its intensity was controlled so that human eye cannot tell the difference between the two images. Though these images are perceptually identical, the SSIM value is 0.854, not 1.0 as it is supposed to be.

To fix this problem, we propose a precursor for image quality assessment. Specifically, given an image and the backlight intensity level of the LCD on which the image is to be displayed, the precursor automatically classifies the pixels of an image to perceptible and non-perceptible pixels and excludes the non-perceptible pixels from quality assessment. The technique does not impose any limitation on the particular quality metric used for image quality assessment. The technique is simple and easy to implement. Besides, it works effectively.

The idea behind the technique and the implementation are describe in Sec. 2. The evaluation of the performance of the technique is described in Sec. 3. Finally, the concluding remarks are drawn in Sec. 4.

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(a) (b)

Figure 1. Quality assessment of dimmed images: (a) the reference image and (b) the test image generated by adding impulse noise to the reference image. Most noise is added to dark pixels of the image, and the intensity of the noise is controlled so that human eyes cannot distinguish between the two images.

2. METHODOLOGY

Our technique involves the application of a perceptible luminance threshold to discriminate non-perceptible (dark) pixels from perceptible ones. The non perceptible pixels are masked in the image quality assessment process. In other words, they do not contribute to the final quality value. This section describes the details of the technique.

2.1 Determination of image luminance

We note that it is the displayed image to be evaluated, not the source image. In practice, however, the image available for quality assessment is the source image. We estimated the displayed image from the display model. Specifically, the following display model [11] is used:

$$L_d = L_b + p^{\gamma}(L_m - L_b) + L_a, \tag{1}$$

where L_d is the luminance value of the displayed image, L_b is the luminance of the black level of the display, L_m is the maximum luminance of the display, p is the normalized pixel value of the source image, γ is the gamma parameter, and L_a is the ambient light reflected from the display panel. L_a is related to the ambient illuminance E_a (described in lux) by

$$L_a = \tfrac{k}{\pi} E_a, \tag{2}$$

where k is the reflectivity of the display panel.

The values of γ, L_m, and L_b, have to be determined before we apply (1) to determine the displayed pixel value. For this, we use a luminance meter (LAIKO DT-101) to measure the luminance for each normalized pixel value and determine γ, L_m, and L_b by linear regression under the uniform backlight assumption that every pixel in the display are the same. As shown in Fig. 2, the resulting γ, L_m, and L_b are 0.444, 191.33 and 0.25, respectively.

2.2 Minimum perceptible luminance determination

We adopt the light adaptation model of Valeton *et al*. [4] to determine the threshold for discriminating perceptible pixels from non-perceptible pixels. This model relate the response of cone photoreceptors to the intensity of perceived light by

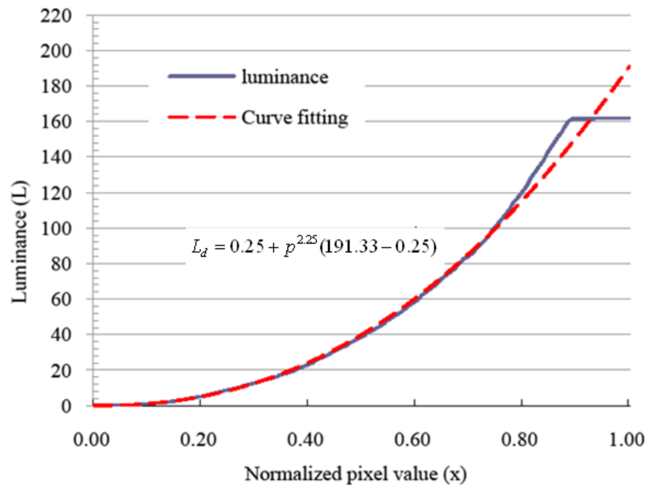


Figure 2. Determining the maximum backlight L_m, luminance of the black level of the display L_b, and gamma correction coefficient γ by linear regression. In this example, L_m=191.33, L_b=0.25 and γ=2.25.

$$\frac{V}{V_m} = \frac{L^{0.74}}{L^{0.74} + \sigma^{0.74}}, \tag{3}$$

where V/V_m is the normalized response, L is the intensity of the perceived light, and σ is the half saturation intensity adaption parameter (a larger σ corresponds to a brighter backlight). In our implementation, we set σ to be the average luminance value of the displayed image. The threshold of minimum perceptible luminance is empirically determined to be the luminance value corresponding to 0.01 cone response.

2.3 Non-perceptible pixel masking

The masking of dark pixels consists of the following four steps:

1) Obtain the luminance value for both the reference and test images.
2) Determine the minimum perceptible luminance using the method described above.
3) Pixels with luminance smaller than the minimum perceptible luminance are set to 0 luminance value.
4) Assess the processed images with the conventional image quality assessment metrics.

3. PERFORMANCE EVALUEATION

We set up two experiments to evaluate the performance of the proposed technique. In the first experiment, we show that the preprocessing stage improves the performance of both PSNR and SSIM on dimmed images with hardly perceptible noises. In the second experiment, we further verify our idea on non-dimmed images from LIVE image database.

3.1 Experiment on dimmed images

This experiment is set up to illustrate the necessity of such discriminative quality assessment. The picture in Fig. 1(a) is a dimmed image, and the one in Fig. 1(b) is the image generated by adding impulse noise to the dimmed image. The noise was added to dark pixels, and its intensity was controlled so that human eye cannot tell the difference between the two images. The pictures in Figs. 3–5 were generated in the same way as those in Fig. 1. The results of image quality assessment are shown in Table I, where "without masking" refers to the non-discriminative quality assessment and "with masking" to discriminative quality assessment. We can see that the discriminative quality assessment leads to much

(a) (b)

Figure 3. Quality assessment of dimmed images: (a) the reference image and (b) the test image generated by adding impulse noise to the reference image. Most noise is added to dark pixels of the image, and the intensity of the noise is controlled so that

(a) (b)

Figure 4. Quality assessment of dimmed images: (a) the reference image and (b) the test image generated by adding impulse noise to the reference image. Most noise is added to dark pixels of the image, and the intensity of the noise is controlled so that human eyes cannot distinguish between the two images.

(a) (b)

Figure 5. Quality assessment of dimmed images: (a) the reference image and (b) the test image generated by adding impulse noise to the reference image. Most noise is added to dark pixels of the image, and the intensity of the noise is controlled so that human eyes cannot distinguish between the two images.

Table 1. Performance comparison between discriminative and non-discriminative quality measurements.

	PSNR		**SSIM**	
	Without masking	With masking	Without masking	With masking
Fig. 1	39.44	51.07	0.854	0.963
Fig. 3	39.79	51.79	0.827	0.954
Fig. 4	51.25	97.27	0.939	1.000
Fig. 5	52.69	80.16	0.961	1.000

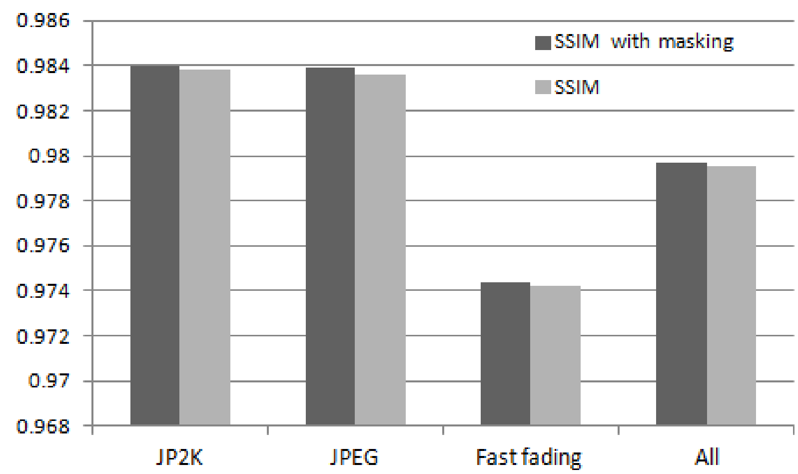
higher PSNR and SSIM values than the non-discriminative quality assessment. This strongly indicates that the discriminative quality assessment is indeed closer to human evaluation. The results also indicate that the method becomes more effective as the image has lots of dark (below-threshold) pixels. For example, the image in Fig. 3 has more dark pixels than that in Fig. 1 and hence the amount of improvement of Fig. 3 is greater than that of Fig. 1.

3.2 Experiment on bright images

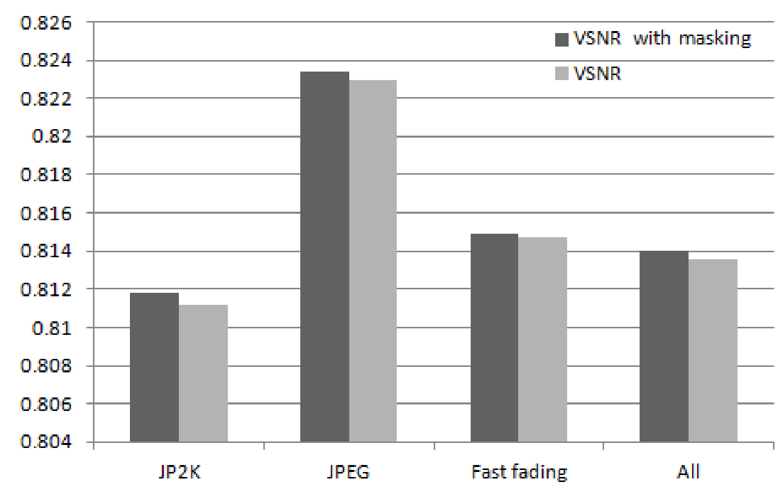
We also test the proposed method on the LIVE image database [3], [5], [6]. Three types of distortions: JPEG compression, JPEG2000 compression, and bit errors in JPEG2000 bit stream (fast fading distortion) are considered in this experiment. The quality of each resulting image is evaluated using the VSNR [7], SSIM, and VIF [8] metrics. The performance of the proposed method is measured by the Spearman rank-order correlation coefficient (SROCC) [9]. It should be noted that most of the images in the LIVE dataset are "bright" images as opposed to dimmed images, and the subjective evaluation results released are for displays with full backlight level as opposed to low backlight level. Nevertheless, the bar charts in Fig. 6 shows that our method makes the VSNR, SSIM, and VIF evaluations more closer to human evaluation for all the three types of distortions. Furthermore, the improvement in the SROCC value is considered significant according to the Hotelling-Williams t-test (p-value<0.025) [10].

4. CONCLUSION

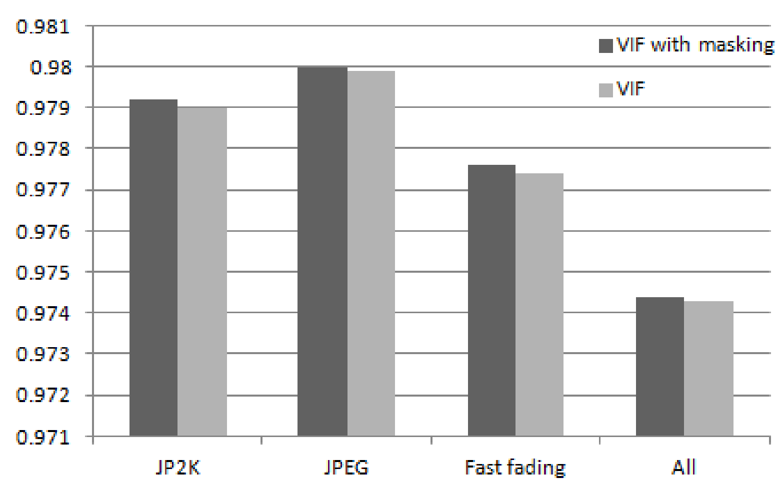
We argue in this paper that, when the backlight is dim, the perceptibility of pixels displayed on an LCD has to be considered before a quality metric is applied to the image. This is because that, under dim backlight, some image regions



(a)



(b)



(c)

Figure 6. Performance comparison between discriminative and non-discriminative quality measurements using the Spearman rank-order correlation coefficient (a) SSIM (b) VSNR (c) VIF.

may appear so dark that they become non-perceptible to human eye. Ignoring this very fact and directly applying an image quality assessment metric to the entire image may produce results inconsistent with human evaluation of the image. We illustrate the necessity of such discriminative preprocess and show that the problem can be satisfactorily addressed by augmenting a preprocessing stage to the regular quality assessment process. By discriminating non-perceptible pixels from perceptible ones, the proposed technique makes the quality assessment more consistent with human evaluation. We also test the proposed technique using LIVE image data base, where most images are “bright” images as oppose to dimmed images. The experimental results show that the proposed technique significantly improves the SSIM, VSNR, and VIF values according to the Hotelling-Williams t-test (p-value<0.025).

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