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Development of a Perceptually Calibrated Objective Metric for Exposure Quality

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Abstract

This study aims at developing an image quality metric for exposure quality, with a transform to just noticeable differences (JNDs) of quality in pictorial scenes. Such a perceptually calibrated exposure metric would allow the prediction of overall image quality by combining exposure with other image attributes. Eight pictorial images were used in the study, and twenty-one observers participated in the subjective evaluation using a softcopy quality ruler method defined in ISO 20462 Part 3. The image simulation path involved seven levels of exposure manipulation, together with two variations in tone mapping algorithms (a global tone mapping algorithm and a local tone mapping algorithm). For each pictorial scene a second image was captured with an exposure target in the scene, allowing the measurement of the scene exposure level. The results showed that an objective metric based on the green channel intensity of the exposure target could be used to predict the optimal exposure level and the quality falloff due to exposure error.

Introduction

During the last decade, the proliferation of consumer mobile devices, such as smartphones and tablets, has made digital imaging ubiquitous. Image quality of digital captures has also been steadily improving, thanks to the innovation in both camera hardware components and image signal processing (ISP) pipelines. Image quality metrics play an important role in digital imaging. They can be used to optimize and benchmark algorithms, ISP pipelines and imaging systems; dynamically monitor and adjust image quality. The use of objective metrics of image quality provides a more efficient way of optimizing imaging systems compared to the traditional way of conducting psychophysical studies, where human observers are involved in image quality evaluation tasks.

Image quality is a multidimensional problem. There is a long list of image attributes that can influence the perceived image quality, with one of them being exposure quality. Fig.1 shows an example of digital captures at different exposure levels. Over-exposure (right image) may result in loss of highlight details and color saturation, while under-exposure (left image) may result in the loss of shadow details and noisier raw image input to the ISP pipe.

Figure 1. Examples of effect of exposure level on image quality. Left – under-exposed image; Middle – properly exposed image; Right – over-exposed image.

Exposure quality is critical to imaging systems because there is an inherent gap between dynamic range of real world scenes and that of a digital camera. Dynamic range in photography is defined as the ratio between the maximum and minimum measurable light intensities. In real-world scenarios, the luminance dynamic range can span up to 14 orders of magnitude between highlights and shadows in a scene. On the other hand, the dynamic range of CMOS image sensors for mobile applications typically covers only 3 to 4 orders of magnitude, while that of DSLR cameras can go slightly higher (4 to 5 orders of magnitude).

Because of the gap between dynamic range of a digital camera and that in real-world scenes, it is important to appropriately regulate the amount of light reaching electronic image sensor through exposure control. A good exposure control strategy would maximize information preservation of the scene at raw image level, which facilitates the ISP pipeline to create images of optimal system quality [1]. Exposure level can be achieved through the parameter combination among exposure time, lens aperture, and analog/digital gains.

The primary goal of this study is to develop a perceptually calibrated objective metric for measuring the exposure quality of digital cameras. This study was conducted following the framework of IEEE P1858 CPIQ standards [2]. In the CPIQ framework, an image quality metric is perceptually calibrated and a quality loss function is established to link objective measurement to just noticeable differences (JNDs) of quality in pictorial scenes. Such a perceptually calibrated exposure metric would allow the prediction of overall image quality by combining exposure with other image attributes, such as visual noise and color saturation.

In modern digital cameras exposure quality is jointly determined by both front-end camera exposure control and tone mapping operations inside the ISP pipeline. Tone mapping algorithms today fall into two categories: scene adaptive global tone mapping (GTM) algorithms and adaptive local tone mapping (LTM) algorithms. GTM algorithms are designed based on the global statistics of the image, and they apply identical tone mapping strategy to every pixel in the image [3-5]. GTM algorithms are computationally efficient, but they have limited capability in preserving details in highlights and shadows, and they typically reduce mid-tone contrast. LTM algorithms are based on the fact that the vision of an active viewer does not usually adapt to the scene as a whole, but instead more localized regions, since the eyes tend to wander across the scene to search for the points of interest. Therefore, it is the surrounding regions of each spatial focal point that dominate the visual adaptation state of the viewer [6-9]. A well-designed LTM algorithm is typically capable of achieving higher perceptual image quality than a GTM algorithm, at the cost of additional complexity in implementation and reduced speed. Because of the importance of tone mapping algorithms in digital images, we will include in this study a treatment on tone mapping with two levels: a GTM path and a LTM path.

Methods

Image processing

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In this study the test stimuli were generated using real-world scene captures. A Canon EOS 1DX DSLR camera was used for the capture task. The exposure variation was introduced by using a fixed aperture (F/5.6), fixed ISO speed (ISO 50), and varying exposure time. During the capture, the camera exposure metering system was used to estimate a proper exposure level for the particular scene. After metering seven images were captured, with the exposure time spanning minus 3 stops to plus 3 stops around the metered result. Each scene capture was followed by a second capture, in which an X-Rite 24-patch ColorChecker test chart was captured with the same exposure levels as the real-world scene. A neutral patch on this test chart (patch #22) will be used to construct the objective measures for exposure.

Figure 2. Example images of GTM (left image) and LTM (right image) for scene 'Field', based on the same raw input. The enhanced image quality due to LTM is clearly visible in the right image.

The raw images from the camera were processed using an internal image processing pipeline to generate a BMP image for display. This pipeline includes processing steps such as demosaicing, color correction, and tone mapping. Two tone mapping methods were used in the study, a global tone mapping method and a local tone mapping method. The global tone mapping method used a tone curve that was a combination of a sRGB gamma curve and an S-curve for creating an overall pleasing image contrast. The local tone mapping method generated images with better rendering in the image dark regions compared to the global tone mapping method. Fig. 2 shows one raw image being processed in GTM as well as in LTM. The image quality enhancement due to the LTM operation is clearly visible when comparing the two images side-by-side.

To prepare the test images for the subjective evaluation task, the BMP images (5184x3456) were further down-sampled by 4x, then center cropped to ~1MP (1253 x 834). The images were displayed at 100% magnification on a monitor during image evaluation.

Softcopy quality ruler experiment

A softcopy quality ruler method, as depicted in ISO 20462 Part 3, was used in the subjective evaluation task [10-14]. The softcopy quality ruler package was developed for the IEEE P1858 CPIQ standard, and it has been used in developing objective metrics for numerous CPIQ image quality metrics [15-17]. The use of the softcopy ruler method allows an objective metric for an image attribute to be calibrated in the quality JND space, and hence it can be combined with other image quality metrics in predicting the overall image quality via multivariate formulism [18].

In the softcopy quality ruler study, two images were displayed on a monitor side-by-side, a ruler image that varied in sharpness, and a test image that varied in exposure. The subject was asked to adjust the sharpness (and hence quality) of the ruler image to match the quality of the test image. The result of the match was recorded as a calibrated value of the ruler image in display on the Standard Quality Scale (SQS, as defined in ISO 20462 Part 3).

The display used in this study was a Dell UltraSharp U3014 30-inch monitor. It has a resolution of 2560 x 1600 pixels, with a pixel pitch of 0.250 mm. The monitor was calibrated to sRGB color space, and its peak luminance was set at 225 cd/m^2. The viewing distance was set at 864 mm, and controlled by a headrest. The room was dimly lit with an ambient illumination of ~5 lux.

The treatment for each scene included seven exposure levels for the global tone mapping path, and seven exposure levels for the local tone mapping path. In addition, one null level was added to the test set to allow a sanity check on the observers' responses.

Twenty-four observers participated in the subjective evaluation study. All observers had normal color vision and normal or corrected-to-normal visual acuity. After examining responses to the eight null images, data from three observers were removed from the analysis. Two observers had standard deviation of their null responses higher than 3 JNDs, and one observer had a null bias higher than 2.56 JND, clearly separating them from the rest of the group.

Scene selection

Eight real-world scenes were selected for the exposure metric study (see Fig. 3), four had people in them and seven were outdoor captures. The main reason for selecting these test scenes was their similarity in scene contents to the softcopy quality ruler images. In the softcopy ruler method, the observer is asked to match the ruler image and the test image in overall quality. This task would be greatly simplified if the scene contents of the two images are identical or similar to each other.

Figure 3. Test scenes used in the exposure metric study. The scene names are (from top left): Field, Grass_people, FarmStand2, Girl, Mountain, GeorgeEastmanHouse, Flowers, No_parking.

Results

SQS results

There were seven levels of treatment on exposure variations during capture. With the exposure treatment the test images would span a range of under-exposure to proper exposure to over-exposure (see Fig. 1). The responses from the twenty-one observers were recorded on the Standard Quality Scale (SQS), as defined in ISO 20462 Part 3. Fig. 4 shows the recorded observer responses for one scene ('Field', as shown in Fig. 2) for both GTM and LTM processing methods. Each data point represents the mean SQS value from all twenty-one observers.

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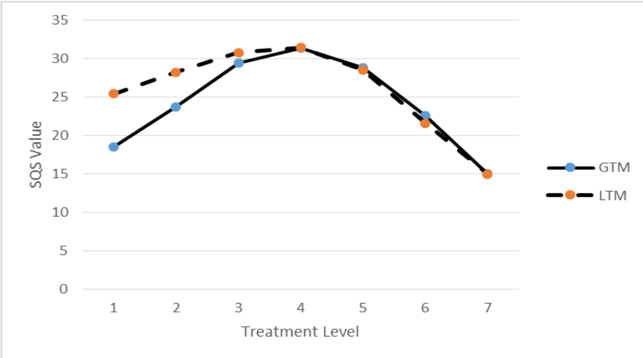

Figure 4. Mean observer responses for scene 'Field', for both global tone mapping (GTM, solid line) and local tone mapping (LTM, dashed line) processing methods.

The response curves have an inverse U shape, suggesting that perceived image quality is poor for both under-exposed and over-exposed images, and with the highest quality in the middle. Furthermore, the LTM method significantly improves the perceived quality of the under-exposed images compared to the GTM method. Interestingly, LTM does little to change the quality of the already-optimally-exposed images or the over-exposed images. A possible explanation can be that in over-exposed images the highlight regions are clipped and details permanently lost. In addition, the results also show that while local tone mapping increases image quality on average, it does not shift the optimal exposure level in relative position in the exposure sequence, as compared to the global tone mapping method. This observation would become important when we attempt to develop an objective metric for exposure quality that can work for both GTM and LTM methods.

Objective metric of exposure quality

In order to construct an objective metric for exposure quality, the SQS results were converted to JNDs of quality loss by subtracting SQS values from the maximum SQS values in the dataset. For this dataset the maximum SQS value was found to be 31.4, indicating that image quality is excellent in the displayed images when the exposure level is set to the optimal position.

The objective metric of exposure quality is based on the measured signals from patch #22 on the X-Rite ColorChecker test chart. The use of this test patch for exposure measurement has been a common practice in industry, with one plausible reason being that the nominal reflectance of this patch (~ 20%) is close to the average scene reflectance in the real world. Three objective measures were considered in this study as the objective metrics for exposure quality, the normalized green channel pixel level Gn, luminance Y, and CIELAB Lightness L*. Gn is defined as green channel pixel level/255. The normalized value was used here rather than the original pixel level because bit-depth for future digital images may differ from what we use today. Y and L* were calculated from the image signals assuming a sRGB display with D65 white point.

A mathematical model was constructed to fit the experimental data, as shown in Eq (1):

$$QL = d * (1 - \exp(-(b * |OM - a|)^c)) \qquad (1)$$

Where QL stands for quality loss; OM stands for objective metric; a, b, c, and d are the fit parameters. Parameter 'a' is of particular importance because it defines the position for optimal exposure, where the quality loss is at its minimum.

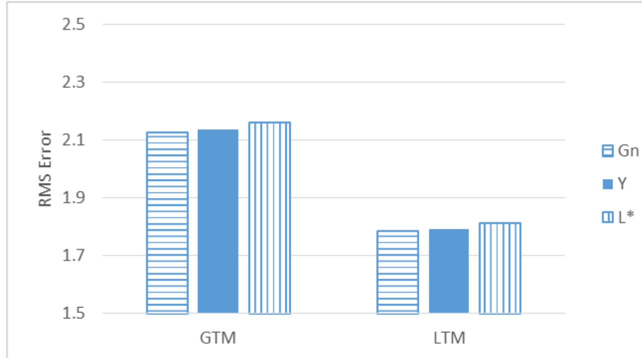

Figure 5. RMS errors for 3 candidate objective metrics and for both GTM and LTM paths. The three candidate metrics are, normalized green channel pixel level Gn, Luminance Y, and CIELAB lightness L.*

Fig. 5 shows the root mean square (RMS) errors for all three candidate objective metrics and for two image processing methods (GTM and LTM). It can be seen that Gn produces the smallest RMS errors for both GTM and LTM methods, suggesting that the normalized green channel pixel level should be used as the objective metric for exposure quality. The data also shows that LTM has smaller RMS errors in general compared to GTM. This is in line with the observation illustrated in Fig. 4 that LTM serves to equalize image quality across varying exposure levels and across scenes.

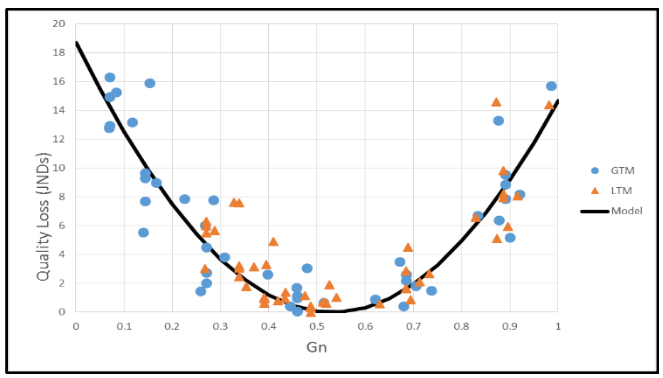

Figure 6. Quality loss as a function of normalized green channel pixel level Gn, for all eight test scenes. Blue circles are experimental data for GTM and orange triangles are experimental data for LTM, from all twenty-one observers. Solid black line represents the mathematical model for quality loss.

Fig. 6 shows the experimental data for both GTM and LTM, using Gn as the objective metric of exposure. The blue circle are GTM data and the orange triangles are the LTM data. The solid line shows the model fitting results for this dataset, using the mathematical equation defined in Eq (1). The fit parameters are: a = 0.537, b = 0.416, c = 1.739, d = 250. The resulting RMS value is 1.992.

Conclusions and Discussions

In this study, a psychophysical study was conducted using the softcopy quality ruler method to determine the aim and the quality loss function for exposure quality. Two tone mapping methods were used, a global tone mapping method and a local tone mapping method. It was found that a single mathematical model would fit both sets of experimental data well. The objective metric for

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exposure was defined using normalized green channel pixel level (Gn). The optimal exposure value, as identified by model fitting, is Gn = 0.537. For an 8-bit digital image the corresponding sRGB green channel pixel level is 0.537 * 255 = 137. In addition, the quality loss curve defined in this study is symmetric to the optimal point in both the under-exposed and the over-exposed directions.

In the public literature there have been existing methods for determining exposure quality. Imatest [19] uses the reference data from X-Rite [20] for the measurement of exposure error. In such a measurement a perfect white diffusive surface (R = 100%) is rendered to G = 255 in sRGB space, and patch #22 should have a green channel value of 122 for correct exposure. Some advanced exposure techniques would also ask for a headroom beyond perfect white to represent specular highlights in the scene. In such cases the patch #22 pixel level should be lower than 122. The results from the current study suggest that to achieve optimal image quality the aim for exposure quality should be set at 137 on patch #22, higher than the values specified in the existing methods.

The exposure quality metric, as defined in the current study, can be used in combination with other perceptually calibrated metrics of image quality to predict overall quality. For example, under low light conditions, an imaging system would typically need to make tradeoffs among color saturation, exposure, noise, and texture details. This perceptually calibrated objective metric of exposure quality can be used together with the CPIQ set of metrics of visual noise, texture blur, and chroma level (to be released in 2016), in measuring and benchmarking camera performance for low light conditions.

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