CAMERA-BASED MEASUREMENT OF RELATIVE IMAGE CONTRAST IN PROJECTION DISPLAYS

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ABSTRACT

This research investigated the measured contrast of projection displays based on pictures taken by un-calibrated digital cameras under typical viewing conditions. A high-end radiometer was employed as a reference to the physical response of projection luminance. Checkerboard, gray scale and color complex test images with a range of the projector's brightness and contrast settings were projected. Two local and two global contrast metrics were evaluated on the acquired pictures. We used contrast surface plots and Pearson correlation to investigate the measured contrast versus the projector's brightness and contrast settings. The results suggested, as expected, the projector contrast has a more significant impact on measured contrast than projector brightness, but the measured contrast based on either camera or radiometer has a nonlinear relationship with projector settings. The results also suggested that simple statistics based metrics might produce a higher Pearson correlation value with both projector contrast and projector brightness than more complex contrast metrics. Our results demonstrated that the rank order of un-calibrated camera based measured contrast and radiometer based measured contrast is preserved for large steps of projector setting differences.

***Index Terms*—** measured contrast, projection display, digital camera, radiometer, metrics, Pearson correlation

1. INTRODUCTION

In the conventional market, LCD displays have been dominating the share for a long time. This is especially true in the desktop and mobile display market. However, nowadays, customers have an increased wish to own a display with higher resolution and larger area to visualize the information in a rich user experience. Due to many manufacturing limitations, it is difficult or not cost effective to produce a large scale display with LCD flat panels, while a projection display has a strong competency of high resolution, portability and flexibility on specifications. The application [1], for example, could be tiling multiple high brightness projectors to produce a large perceptual seamless image. One core research topic for the projection methodology is establishing a systematic approach to quantify and evaluate the quality attributes of projected images in an objective and automatic manner with carefully designed and selected image quality metrics.

In general, Display Image Quality (DIQ) is characterized based on the sets of device dependent and independent attributes. The latter set includes, but is not limited to, the attribute families of brightness, contrast, colors, sharpness and artifacts (such as noise). Based on these attributes, there were many attempts to characterize devices like CRT [2, 3] and LCD [2, 3, 4] displays. The characterization of a projection display shares a lot with these methods. Previous characterizations of projection display focused on black level estimation [5], display uniformity [1, 6, 7] and colorimetry [6, 8, 9], but limited attentions were paid to measured contrast in the actual quality of the displayed image. More specifically, the measured contrast of a displayed image has been shown to be of a significant impact [10] on visual experience. However, apart from subjective observer based evaluation and classic contrast measurement on the display itself there is no convenient method to evaluate this parameter on a displayed image.

This paper presents a study on the measured contrast of projected images. This study aims to understand the basic interactions between brightness and contrast under typical viewing conditions, evaluate the performance of contrast metrics, and correlate projector settings, camera based measured contrast and radiometer based measured contrast of the projected images. In this context, three types of cameras and a radiometer were employed as the DIQ measurement tools. The results of evaluation can be used to improve the design of projection DIQ assessment methods. They can also to be extended in the development and enhancement of general projected image reproduction technologies.

This paper is organized as follows: first, in Section 2, we introduce the background of image contrast and the metrics that were evaluated in this research. Then, in Section 3, a full description of the controlled environment, equipment setup and operation procedure for the contrast measurement is given. With respect to the acquired pictures, a series of discussions upon the interaction between projector settings and measured contrast is presented in Section 4. At last, conclusions are drawn based on the data observations.

2. BACKGROUND

Brightness can be defined as the perceived intensity of light coming from the image itself, rather than any property of the portrayed scene [11]; while we may say that contrast is a measure of the luminance and chromatic variations in one region relative to the average variance in the surrounding region in the same scene. So far, no one could give a convincible standard definition to contrast in a color complex scene. Somehow, contrast in either simple or complex scenes could be measured by metrics at local and/or global levels.

2.1. Global Contrast

One physical definition of contrast is given by Michelson formula [12] for luminance based global contrast:

$$C^M = (L_{max} - L_{min})/(L_{max} + L_{min}),$$

where L_{max} and L_{min} are the minimum and maximum luminance values respectively over all pixels of the entire image. This metric can be implemented easily and is widely incorporated in researches as a reference in the performance evaluation of other contrast metrics. In the family of global contrast metrics, Weber-Fechner [13], Root-Mean-Square (RMS) [14] and other definitions [15, 16, 17] were proposed as well. They share the similar concept with Michelson contrast by taking luminance information of extreme bright and dark pixels into account, but they have problem to deal with measurement noises (illustrated in contrast measurement section) and in many cases the contrast prediction is not appropriate [10].

The chrominance information in image should also contribute to the prediction of perceived contrast. In this context, an alternative metric referred as LAB Variance [18] was proposed:

$$C^{LAB} = \sqrt[1/3]{std^2(L) * std^2(a) * std^2(b)}$$

This metric was defined in the perceptually uniform CIELAB space and it takes simultaneously the luminance and chromatic channels into account. However, the equal weighting on channels does not reflect a well-known fact that luminance has stronger impact on the perceived contrast than chrominance [19, 20, 21].

2.2. Local Contrast

Many researchers realized that perceived contrast is highly local in nature. One of the local algorithms is RAMMG [22], that takes the advantage of multiple pyramid levels of local contrast information. The RAMMG metric subsamples the input image and generates pyramid images in the CIELAB space with nearest neighborhood algorithm. Then the local contrast is calculated by summing up the absolute differences between one pixel and its surrounding pixels in every channel and at every pyramid level. The local contrast values from the same channel would be normalized and finally be weighted. The mean of outputs from all levels would be the prediction of contrast over the entire image:

$$C^{RAMMG} = \frac{1}{N_L} \sum_{i=1}^{N_L} \sum_{j=1}^{3} \sum_{k=1}^{N_p} W_j C_k$$

where N_L stands for the number of pyramid levels, and N_p stands for number of pixels in each pyramid images, C_k stands for the local contrast for each pixel and its surroundings, and W_j stands for the weight of each CIELAB channel. Inspired by the design of RAMMG metric, other improved versions like RSC [23] employed Difference of Gaussians (DOG) formula to calculate the local contrast:

$$DOG(x,y) = \frac{R_c(x,y) - R_s(x,y)}{R_c(x,y) + R_s(x,y)}$$

where (x,y) stands for the spatial location of center point in the respective field, R_c and R_s stands for neuron responses of center and surround component respectively. The DOG formula was employed to take the spatial sensitivity in the center of the receptive field into consideration, and the purpose was to extend the edges and gradient information in the input images.

3. EXPERIMENTAL SETUP

3.1. Projector Setup

We used the SONY APL-AW15 which was a portable three chip LCD high brightness projector. The projector was placed on a flat table in front of the projection screen and was exactly 3m away as it is depicted in Figure 1. The projection principal axis was pointed at the screen and was perpendicular to it. The projection resolution was 1280x768 in pixels. On the screen, the projection size was approximately 2x1.2 meters. The projector was connected to a controlling laptop with a VGA cable. In order to minimize the influence of projector temporally stability, the projector lamp was warmed up at least one hour before each experiment section. All settings related to projector's brightness, contrast and color enhancement were switched off to make sure the input image was projected as it is.

3.2. Digital Camera

Three types of digital cameras were employed in the experiments as the DIQ measurement tools. They were a low-end webcam Logitech QuickCam Pro 9000, a prosumer DSLR Nikon D200 with VR 18-200mm f/3.5-5.6G (VR off) lens and a high-end DSLR Hasselblad H3D II with HC 80mm lens. The resolutions for the three cameras were 3264x2448, 3872x2592 and 6490x4870 in pixels respectively. The webcam was mounted on a table which was 3m away from the

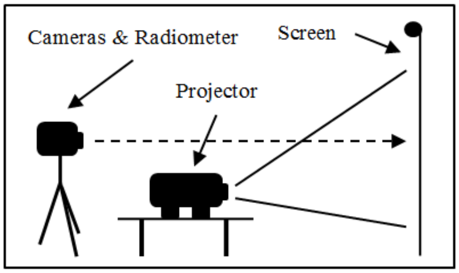


Fig. 1. Projector and camera placement

projection screen, while the other two cameras were both fixed on tripods that were 4m away. All cameras were manually focused with highest possible optical sharpness and all camera settings were fixed at certain values. The principal axes of all cameras were pointed at the center of the projected image and were quasi-perpendicular to it with a slightly varying angle due to the manual setup. The pictures were always taken remotely with software installed on the controlling laptop without physically touching the cameras. In order to confirm the physical responses of projected images on the screen, a radiometer Minolta CS1000 was mounted on a tripod beside the digital cameras as a measurement reference.

3.3. Test Images

Three test images which had a resolution 768x512 were included in the experiments as it is illustrated in Figure 2. They covered the image categories of simple checkerboard, gray complex and color complex. The use of checkerboard was recommended in the projection contrast measurement sections of international standard IDMS [24]. The color complex image was selected from Kodak Photo CD PCD0992 [25] based on which the grayscale version was generated by using Matlab function rgb2gray. The two complex images provides a smooth transition from a laboratory artificial stimuli to a natural scene in a way which people usually perceive and interpret objects in the real environment. The images were always projected at the original resolution on the screen.

3.4. Viewing Conditions

Three typical viewing conditions were considered in the experiments. The projection screen was illuminated by the fluorescent light with fixed luminance values (measured with a light meter at a fixed position) at approximately 0 (low light), 30 (dimmed light) and 300 lux (high light) respectively. A darkroom gives 0 lux luminance. In a dimmed meeting room like environment, the typical luminance is around 30 lux; while in the office like environment in daylight, the luminance could be around 300 lux. Whenever the viewing condition was switched, there was always at least

Fig. 2. Test images

30 minutes idle period between two continuous experiment sections to maximize the illuminant temporal stability.

3.5. Procedures

Since the resolution of original test image was smaller than the projection resolution in the grayscale and color complex cases, the actual image content of pictures taken by cameras were wrapped by the surround. In order to estimate the influence of surround on the measured contrast, in the post-processing step, all pictures taken by cameras were processed with Matlab scripts to generate a cropped version. The cropped version contains only the actual image content without surround or background. In the non-cropped version, the surrounds were simply left as how they were illuminated by the controlled light. Both the cropped and non-cropped picture versions would be input to the metrics.

Finally, for each set of pictures taken (project the same test images that under the same viewing condition), we generated the contrast surface plots with respect to the outcomes of metrics like it is demonstrated in Figure 3a. In our experiments, we evaluated four contrast metrics: Michelson [12], LAB Variance [18], RAMMG [22] and RSC [23]. Since the RAMMG and RSC shared various input parameters, we evaluated several combinations of them which involved: channel weightings: (1, 0, 0), (1/3, 1/3, 1/3), (0.5, 0.25, 0.25), pyramid scales: linear and log based scales, radius of center and surround of receptive field: (1, 2), (2, 3), (3, 4). These parameters were used and recommended by Simone et al. in their investigation of measuring perceptual contrast [26].

Because these metrics had no parameter related to viewing distance which might have influence on the metric selection, we fixed measurement devices at the same location to make sure that they share a constant distance to projection screen. In this case, the influence of viewing distance on measured contrast were equal to all metrics. In order to reduce computational complexity, the level weighting method was always set to variance and pictures were transformed into CIELAB space by the metrics themselves. We also evaluated the performance of metrics by determining the correlation between measured contrast and projector contrast, and the correlation between measured contrast and projector brightness with respect to Pearson correlation coefficient.

4. RESULTS AND DISCUSSION

4.1. Projector

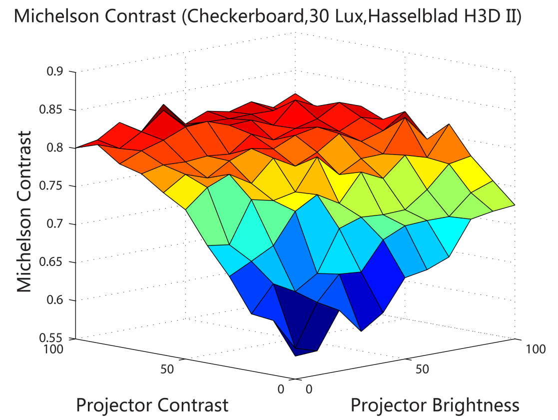
The projector SONY APL-AW15 had a light leak issue due to a fact that it is difficult to completely block the projector's backlight. The black level of the projection increased while the projector brightness increased, and it generated a halo around the image content. This halo should contribute to the perceived contrast, but it is beyond the scope of this article. The solution we adopted was cropping the image content from the pictures and accounting only the pixels in that image. In the case that the image resolution is smaller than projector resolution, both cropped and noncropped (the area other than the image content was black) picture versions were used in the post-analysis step. In the evaluation of the four metrics listed, the absolute values of measured contrast were reduced comparing with non-cropped version but the general shape of normalized contrast surfaces were almost identical. This observation suggests that it is not necessary to crop the image for either global or local contrast metric.

4.2. Digital Cameras

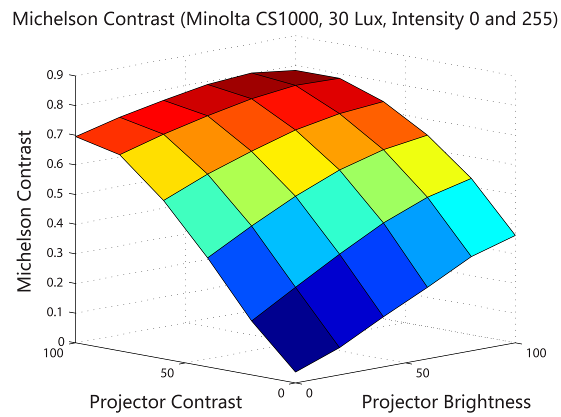
The webcam is not suitable for measuring contrast in the projection system, because the shape of contrast surfaces for the webcam were not consistent under varying viewing conditions. In analogy, the results for Nikon D200 are very similar to the ones for Hasselblad H3D II, except in the case of Michelson contrast under high light environment. In such case, the contrast surface for Nikon D200 is smoother than the one for Hasselblad H3D II. Based on the observations, the consumer DSLR camera Nikon D200 is preferred as a measurement tool for projection contrast. Hasselblad H3D is a little bit more sensitive to small luminance variation especially in the low and high light conditions, but it consumes much more time to take a large volume of pictures.

4.3. Contrast Measurement

Two global contrast metrics: Michelson's definition, LAB Variance, and two local contrast metrics: RAMMG and RSC were evaluated. Under the low light condition, Michelson's definition always gave contrast value 1 for three types of cameras and three types of test images despite the changes of projector contrast and brightness. This metric is very sensitive to measurement noises as it is depicted in Figure 3a and becomes very unstable under high light condition. LAB Variance, RAMMG and RSC metrics all produce logistic shape like contrast surface. The latter two metrics share a general shape of contrast surface despite their radius of receptive center and surround values, somehow the absolute values of measured contrast are different. They are more sensitive to increasing rate of projector brightness and contrast than the



(a)

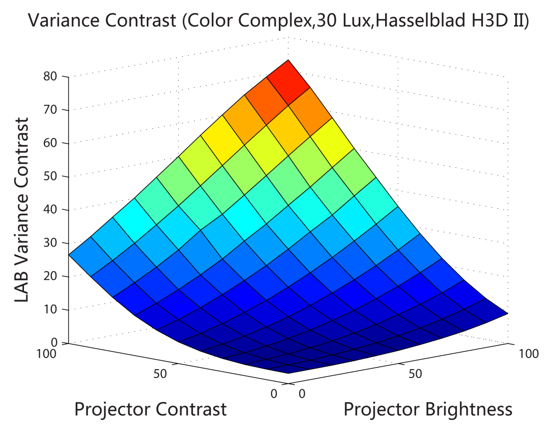


(b)

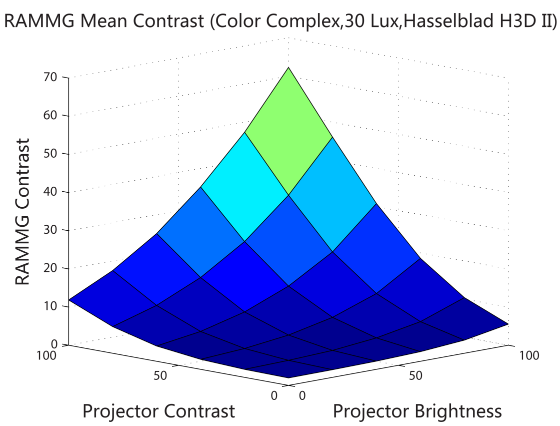
Fig. 3. Michelson contrast surface for checkerboard pictures taken by Hasselblad H3D II (a) and Minolta CS1000 (b) under dim light condition

LAB Variance metric, since the contrast surface appears to be more bended.

Pearson product-moment correlation coefficient was employed to determine the correspondence between measured contrast and projector settings. In Figure 5, we plotted Pearson correlation between radiometer based Michelson contrast and camera based contrast of various metrics. The general tendency of radiometer based contrast correlated well with camera based contrast of RSC metric while remain projector brightness constant. LAB Variance metric produced higher correlation value at low projector contrast but the correlation decreased a lot while projector contrast increased. In the case projector contrast remained constant, the LAB Variance metric gave a higher contrast correlation to radiometer based Michelson contrast. The measured contrast of RAMMG and RSC metrics correlated well with projector contrast and projector brightness, and RSC metric produced approximate 12% higher correlation than RAMMG metric.

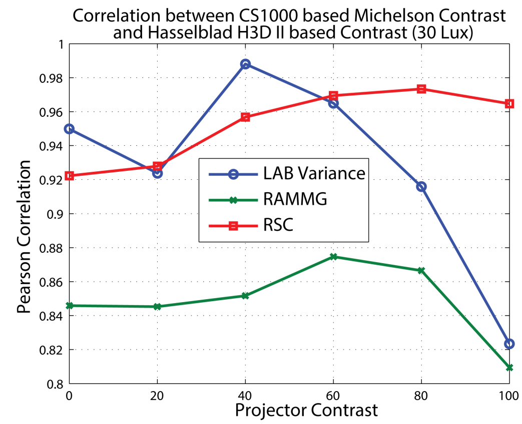


(a)

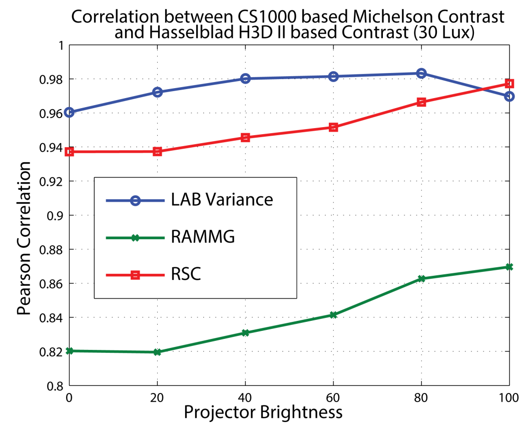


(b)

Fig. 4. LAB Variance (a) and RAMMG (b) contrast surface for color complex pictures taken by Hasselblad H3D II under 30 Lux viewing condition



(a)



(b)

Fig. 5. Pearson correlation between measured contrast and projector settings for color complex pictures taken by Hasselblad H3D II under 30 lux viewing condition

4.4. Generals

Projector contrast has more significant impact than projector brightness on the measured contrast for all metrics as expected. The phenomenon can be observed from the height difference of left most and right most corner points of contrast surface in Figure 3 and Figure 4. It leads to an asymmetric contrast surface. The measured contrast for digital cameras has a consensus with the one for the radiometer. As it is depicted in Figure 3, the general tendency of the two Michelson contrast surfaces are similar to each other despite the contrast value range.

5. CONCLUSIONS AND FUTURE WORKS

In this research, several contrast metrics were evaluated based on pictures taken by un-calibrated digital cameras under typical viewing conditions. The results showed that the projector settings have a great impact on the measured image contrast, and the impact of projector contrast setting is even stronger. Camera based Michelson contrast was proved not to be suitable for projection contrast measurement, while the global metric LAB Variance produces higher Pearson correlation values than the complicated local metric RAMMG and RSC on both brightness and contrast correlations. Thus, we demonstrated that the rank order of un-calibrated camera based measured contrast and radiometer based measured contrast is preserved for large steps of projector setting differences. In the coming future, it will be important to incorporate psychophysical experiments to investigate the correspondence between the perceived contrast and measured contrast.

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