Visual quality analysis for dynamic backlight scaling in LCD systems

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***Abstract*—With the trend toward high-quality large form factor displays on high-end handhelds, LCD backlight accounts for a significant and increasing percentage of the total energy budget. Substantial energy savings can be achieved by dynamically adapting backlight intensity levels while compensating for the ensuing visual quality degradation with image pixel transformations. Several compensation techniques have been recently developed to this purpose, but none of them has been fully characterized in terms of quality losses considering jointly the non-idealities present in a real embedded video chain and the peculiar characteristics of the human visual system (HVS). We have developed a quality analysis framework based on an accurate embedded visualization system model and HVS-aware metrics. We use it to assess the visual quality performance of existing dynamic backlight scaling (DBS) solutions. Experimental results show that none of the DBS techniques available today is fully capable of keeping quality loss under control, and that there is significant room for improvement in this direction.**

I. Introduction

Despite the constant evolutions in Liquid Crystal Display's (LCD) technology, LCD power consumption is still one of the major limitations to the battery life of mobile appliances, such as portable media players, smart phones, navigation and gaming devices [14]. Pushed by the market of multimedia applications, portable devices need to render high definition videos and pictures on larger and larger screens. Since LCD power consumption depends on backlight and pixel matrix driving circuits, which are both proportional to the panel area, LCD contribution to the total system power consumption is going to be considerable even in future mobile devices.

Several techniques have been proposed to face the issue of LCD power. The most promising ones achieve substantial savings by dynamically adapting backlight intensity levels while compensating for the ensuing visual quality degradation with image pixel transformations. Due to the display system non-idealities, this kind of techniques unfortunately produces a quality degradation in the rendered images. Overall quality loss depends on several factors: the pixel transformation, the final backlight intensity level, the LCD display electrical and optical properties, and finally the human visual system (HVS) features. Indeed, due to the high non-linearities and complexity of the HVS, the same distortion level of physical quantities, such as luminosity or chromatic differences, can be perceived in different ways [9].

Two main approaches have been developed to control the visual quality loss in DBS techniques. The first is image dependent, as depicted in Figure 1.a: it computes on-line the amount of backlight scaling on every frame using a simple image distortion metric as a constraint. Techniques following this approach aim at keeping a constant distortion by maintaining the frame-by-frame computed quality performance metric as constant as possible [1], [2], [7], [8]. Unfortunately the simplified quality metrics adopted do not account for both the HVS peculiarities and the display system non-idealities. Hence there is no formal relationship between the adopted distortion metrics and the real perceived quality degradation.

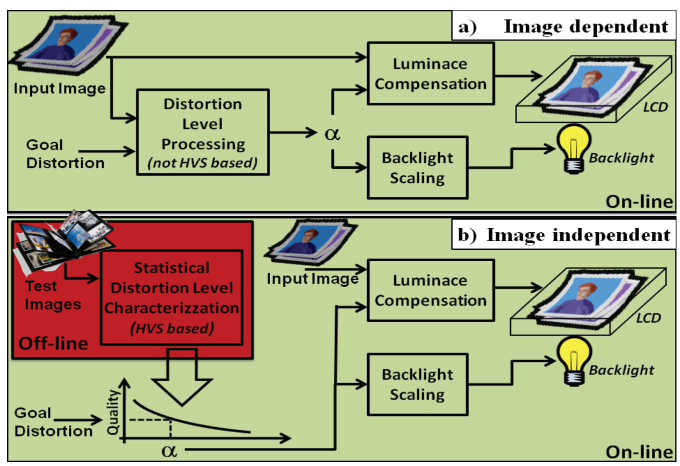

Fig. 1. DBS technique approaches : image dependent (a) vs image independent(b)

Accounting for both the HVS peculiarities and the display system non-idealities in the on-line visual quality distortion metric is very hard, due to their computational complexity. Therefore, image independent approaches have been developed, in which the relationship between perceived image

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distortion and DBS transformation is statistically analysed off-line (Figure 1.b). These approaches consider image degradation as dependent only on the applied DBS transformation. Authors in [3], [4], [5], [6] use a set of benchmark images to calculate an image-independent empirical function which relates the image degradation levels to the transformation parameter applied to the image itself. The distortion degradation level is calculated off-line through a quality metric which considers the HVS peculiarities. This approach does not consider the perceived image distortion as a function of the image itself, in other words it implicitly assumes that a constant backlight reduction would produce, after compensation, a constant quality degradation. This assumption has not been accurately assessed and validated: it is not clear if this methodology produces different perceived distortion levels over different images while aiming at keeping it constant.

The main contribution of this work is the development of a new framework to asses the visual quality performance of backlight scaling algorithms. Our framework considers both the real embedded video chain non-idealities and the HVS insights. The real embedded video chain non-idealities are accounted through an accurate display model performed on a real embedded platform for multimedia application [11]. The HVS peculiarities are considered in the implemented image quality metric. This metric compares the original and the DBS distorted images, thus producing an index which is proportional to the perceived degree of similarity between the two images [9].

This framework has been validated and utilized to analyse the behaviour of state-of-the-art DBS techniques. Experimental results show that none of the DBS techniques available today is fully capable to provide a controlled, constant quality loss, and that there is significant room for improvement in this direction.

II. Framework for Visual Quality Performance Evaluation

The evaluation of the visual quality performance for dynamic backlight scaling algorithms is not trivial due to LCD display non-idealities and HVS peculiarities. We developed a complete Matlab-based framework to overcome these difficulties. Figure 2 shows the framework block diagram.

We can identify three main blocks:

1) DBS transformation: this block processes the original image or video frame with the DBS image transformation. The outputs are a modified image with increased pixels luminance and the related new backlight scaled value.
2) The LCD model: this block models the behaviour of a real embedded LCD panel and its non-idealities. From the RGB image and the backlight level produced by the DBS transformation block, it generates an image representing how the target image itself will look like on the LCD panel. This step is done for both the images: original and DLS transformed one.
3) HVS QoS metric: this block implements the HVS peculiarities and evaluates the differences between the two images from the LCD model block.

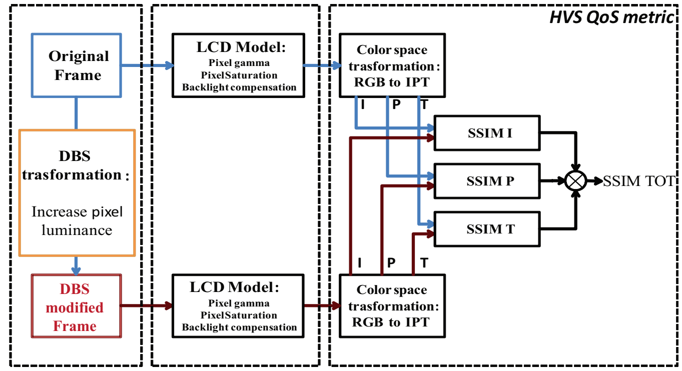

Fig. 2. QoS matlab framework block diagram.

A. LCD Model

From the LCD physics[6] we can write the luminance emitted from the x pixel of the LCD panel equal to:

$$L(x) = f(BL) * g(x) \qquad (1)$$

Intuitively, this equation shows that the luminance emitted from a pixel depends on functions *f()* of the backlight (BL) and *g()* of the pixel value itself, which sets its transmittance. These two functions are related to the LCD panel used, and generally are non-linear.

1) LCD display characterization: This section describes our LCD characterization methodology focused on quantifying the LCD optical properties and to evaluate the non-linearity effects existing between real displayed quantities and digital values descriptions. More in detail, to analyse:

1) The relationship between pixel digital values in RGB space and emitted light intensities, *g()*.
2) The relationship between backlight values and emitted light intensities, *f()*.

As reference case we apply this general methodology to a TFT LCD display (Sharp LQ035Q7DB02). We displayed a set of images on the LCD and measured the emitted light with a light sensor. To get a set of consistent measurements, the ambient light contribution was eliminated performing the tests within a dark room[15].

For the first test, we used a photodiode IPL 10530DAW as light sensor. The light sensor produces as output a voltage linearly proportional to the intensity of the incident light, emitted by the LCD. We measured the emitted light from the LCD displaying a monochromatic image which has only one RGB component which varies from 0 to 255, and the remaining components set to 0 (i.e. (RGB=X,0,0), (RGB=0,X,0), (RGB=0,0,X)).

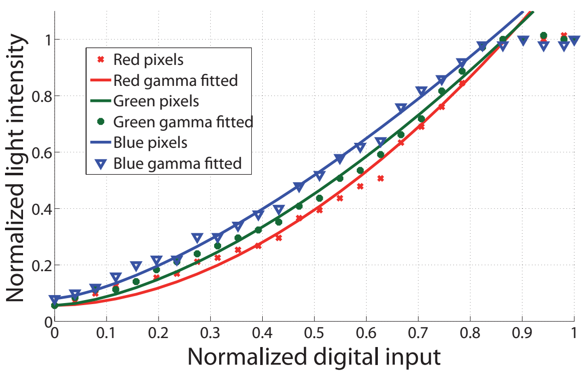

Fig. 3. Light intensities for R,G,B pixels and relative gamma fit.

Figure 3 shows the normalized light intensities on the y-axes and the normalized value of the three RGB components (X/255) on the x axes. The plot shows that the light emitted by pixels is non-linear with the digital RGB value, but it matches a polynomial law. We fitted[15] the measured value (the dots in the plot) with the function:

$$L(x) = offset + K * (R,G,B)^{\gamma_{R,G,B}} \tag{2}$$

The backlight effect has been quantified by measuring the emitted light for different backlight values using the photo-diode as light sensor. The results of this characterization are shown in Figure 4: the dots show the measured data and the line shows the fitted equation.

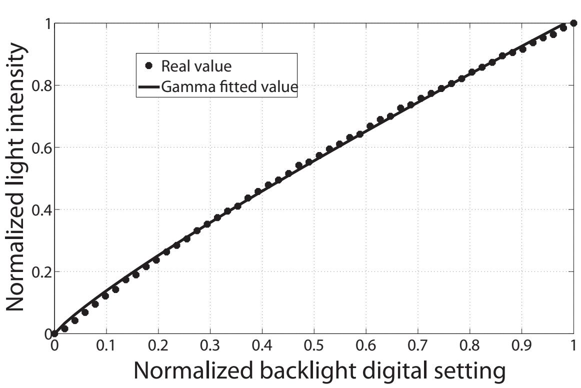

Fig. 4. Normalized light intensity vs. normalized digital backlight value.

The curve was obtained with the power fit:

$$L(x) = K * (Backlight)^{\theta} \tag{3}$$

2) LCD Model: We modeled the LCD panel behaviour using the results from the LCD characterization phase (see Section.II-A1). The model takes as input an RGB image and a backlight value, and it produces as output a trichromatic image which has each pixel component proportional to the light intensity produced by the component itself.

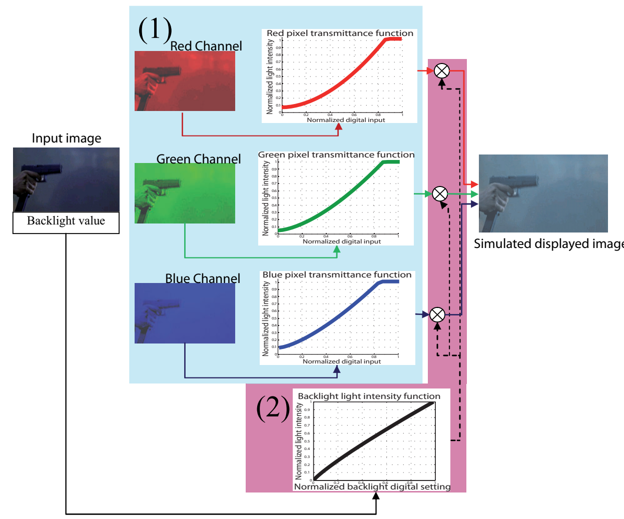

Fig. 5. LCD model schematic.

The model can be split in three main blocks (see Figure 5):

1) The incoming image is transformed by the set of Equations 2, which account for the non-linearity of LCD light transmittance.
2) The input backlight is used to obtain a new value which considers the non-linearity showed in Eq.3.
3) The model combines the transformed image and the new backlight value to compute the simulated displayed image.

B. DBS transformation

The overall goal of a DBS transformation is to dim the backlight while at the same time scaling the pixel transmittance in order to re-equilibrate the target pixel luminance. In the proposed framework we adopt a DBS technique that aims to preserve the pixel luminance and chroma, considering the display non-linearities highlighted in Section.II-A1. The DBS transformation presented is a linear transformation of the pixels value, and can be applied through a pixel matrix operation that is suitable for an implementation on a real embedded system. From Eq.1, 2 and 3, we can formulate:

$$\begin{cases} L_R(x) \propto (R)^{\gamma_R} * (Backlight)^{\theta} & (4) \\ L_G(x) \propto (G)^{\gamma_G} * (Backlight)^{\theta} & (5) \\ L_B(x) \propto (B)^{\gamma_B} * (Backlight)^{\theta} & (6) \end{cases}$$

If we dim the Backlight value of a scaling factor β, we need also to scale each RGB pixel component by a set of α factor in order to obtain the same target luminance:

$$\begin{cases} L'_R(x) \propto (\alpha_R R)^{\gamma_R} * (Backlight/\beta)^{\theta} & (7) \\ L'_G(x) \propto (\alpha_G G)^{\gamma_G} * (Backlight/\beta)^{\theta} & (8) \\ L'_B(x) \propto (\alpha_B B)^{\gamma_B} * (Backlight/\beta)^{\theta} & (9) \end{cases}$$

From 4, 5, 6 and 7, 8, 9 we obtain:

$$\begin{cases} {\alpha_R}^{\gamma_R} = \beta^{\theta} \Rightarrow & \alpha_R = \beta^{\theta/\gamma_R} & (10) \\ {\alpha_G}^{\gamma_G} = \beta^{\theta} \Rightarrow & \alpha_G = \beta^{\theta/\gamma_G} & (11) \\ {\alpha_B}^{\gamma_B} = \beta^{\theta} \Rightarrow & \alpha_B = \beta^{\theta/\gamma_B} & (12) \end{cases}$$

The last equation shows that, for a given β backlight scaling factor, we need to compensate each component by a α_X [1] factor. Due to the bounded digital range [0..255] for each component, this operation is not able to compensate the luminance in the top end values, thus introducing a saturation effect. This can produce both a luminance dynamic range compression and a color distortion. The proposed framework considers all these distortion effects.

C. HVS QoS metric

This block evaluates the perceived quality degradation introduced in the final rendered image by the DBS technique. We used a well established visual QoS index : the structural similarity index metric (SSIM). This index has been demonstrated to be able to quantify the HVS perceived differences between two images [12] [9].

SSIM is based on the assumption that the human visual system is efficient in extracting structural information from the viewing field. The structural information of an image is an attribute which describes the structure of objects in the scene independently from average luminance and contrast. In Figure 6 we can see the schematic implementation of the SSIM metric. The average luminance, contrast and structural information are computed for both target and sample images and then combined together to produce the quality index.

SSIM index for monochromatic images is made of three similarity indices, accounting for luminance, contrast and structural similarity, $l(X,Y)$, $c(X,Y)$ and $s(X,Y)$ respectively.

$$SSIM(X,Y) = l(X,Y) * c(X,Y) * s(X,Y) \quad (13)$$

To apply SSIM to color images, we first transformed the LCD model output images from the trichromatic (RGB) color space to the IPT color space [10] [13]. In IPT each quantity is correlated to perceive lightness, chroma and hue. Then the

[1] For simplicity in the following sections we will use only α_B,and we will call it α.

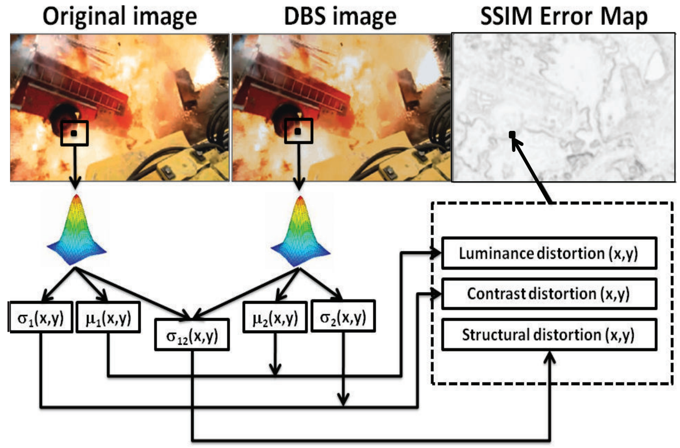

Fig. 6. Diagram of (SSIM) structural similarity measurement system.

SSIM index is computed for each I,P,T, component ($SSIM_I$, $SSIM_P$, $SSIM_T$). Finally we combine them together:

$$SSIM = SSIM_I * SSIM_P * SSIM_T \quad (14)$$

III. EXPERIMENTAL RESULTS

A. QoS framework performance

The presented framework has been tested to verify how our QoS index is sensitive to visual distortion. We asked to a set of human users to asses the visual similarity, in a side by side comparison, between original and distorted images at different SSIM quality levels. Results lead to two important findings: first a constant SSIM index for different images means constant perceived distortion. Second, we correlated human observer scores with the SSIM index results. This helped indentifying four macro-regions in the SSIM index range: each region specifies a quality level. Table.I shows the quality levels and their SSIM ranges. Figure 7 shows a visual example of the four quality regions for three test images.

SSIM Range	Quality Level
1 - 0.98	High quality
0.98 - 0.96	Medium quality
0.96 - 0.94	Low quality
$\leq$ 0.94	Unacceptable

TABLE I
QoS FRAMEWORK OUTPUT QUALITY REGIONS.

B. Image independent DBS techniques

One approach to solve the DBS problem adopted in literature [3] [4] [5] [6], considers the distortion introduced by luminance dynamic range reduction ($\propto \alpha$) independent from the image content and only related to α (see Section.II-B). As already shown in Figure 1.b this is done in two steps:

Fig. 7. Images at different distortion levels: a) Original images; b) High quality (SSIM = 0.98); c) Medium quality (SSIM = 0.96); d) Low quality (SSIM = 0.94); e) Unacceptable (SSIM 0.90).

- off-line: it consists of characterizing the relationship between different image quality loss and different compensation levels, for an image benchmark set by means of a HVS aware distortion metric. The relationship is obtained as statistical fitting function of the test results.
- on-line: the relationship in the off-line step is then used to univocally select the proper compensation value for the target tolerated distortion level in a not-content image aware fashion.

The main hypothesis behind this approach relies to the assumption that applying the same compensation factor to different images produces a constant visual quality loss. We validated and analysed this approach exploiting our framework. In order to do that, we applied the same compensation level to each frame of the video test benchmark chosen (i.e. Terminator 3 movie trailer).

Figure 8 shows the output SSIM index generated by the proposed QoS framework (y-axes) vs. the video frame index (x-axes). In the plot each line refers to a specific compensation level (α). Since each of these lines is not straight, but it crosses different quality regions, we can state that an invariant compensation level applied to every image does not lead to a constant perceived distortion level.

Image independent DBS techniques are incapable of keeping the perceived QoS constant. By the way the plot shows that it is possible to achieve a constant distortion level by dynamically adapting the compensation level (α) frame by frame while considering the image spatial properties.

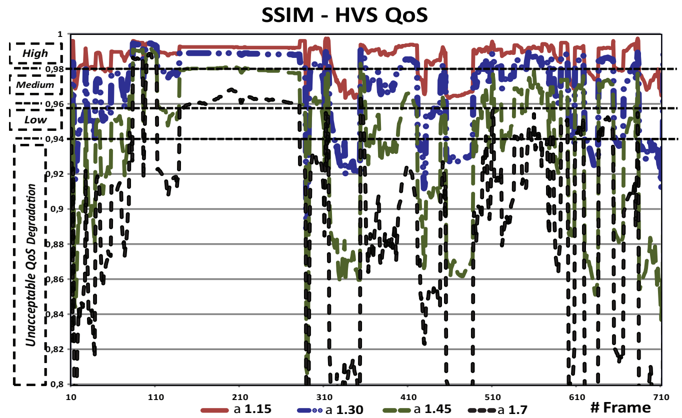

Fig. 8. Image independent DBS technique: QoS framework output vs frame index.

C. Image dependent DBS techniques

A different approach is to consider the distortion introduced by DBS proportional to image dependent key features, as shown in Figure 1.a . The most used technique considers the final perceptual degradation level proportional to the amount of oversaturate pixels on the compensated image [1] [2] [8]. According to this approach, a constant perceived degradation level for different images can be obtained by keeping constant the saturated pixel percentage.

We use our framework to evaluate if this approach really lead to a constant perceived image degradation. For each frame of the video test benchmark we generate the R,G,B pixel value histograms. We scan them in order to find the maximum compensation factor (α_X) that keeps the percentage of pixel saturated below a selected level. Finally we select the most conservative α value between them. We then apply the compensation factor to evaluate the QoS SSIM index for the target images. In the plots in Figure 9 on the x-axes is represented the video frame index and on the y-axes are reported the saturated pixel-percentages generated by the DBS transformation, the backlight level and the SSIM QoS index associated for each frame. On each plot, each line refers to a different maximum level of saturated pixels, namely 4%, 8%, 20%.

We can see from the central plot that the backlight scales dynamically to keep the number of saturated pixels constantly below the specified levels for all the video frames, as reported in the top plot. But this does not lead to a constant visual distortion level, since in the bottom plot each line is not straight but cross different quality regions. This means that controlling the percentage of pixels saturated is not enough to maintain constant the perceived quality distortion. This bad behaviour is due to the evidence that the applied distortion level processing is not HVS aware.

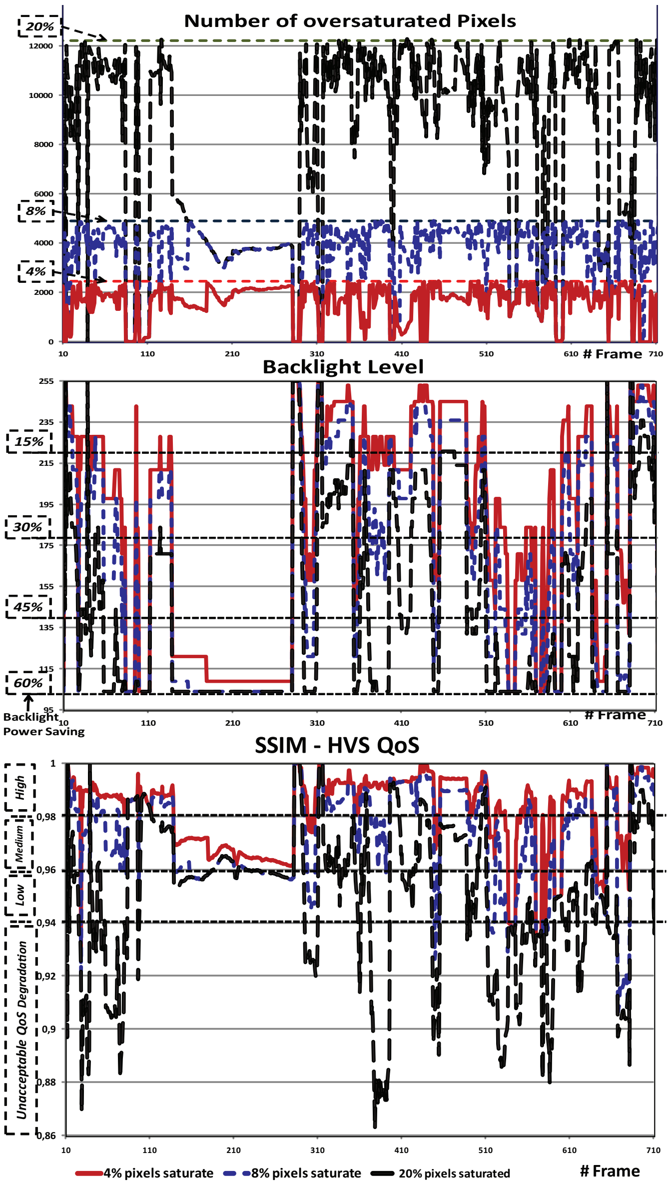

Fig. 9. Image dependent DBS technique: QoS framework output vs frame index.

IV. Conclusion

We proposed a framework to measure the perceived distortion for rendered images on LCD when a DBS technique is applied. We then apply this framework to analyse the QoS performance for the two most up to date DBS techniques. The first technique considers the perceive distortion level directly proportional to the dynamic range and not dependent to image content. We demonstrate that this approach is not capable of keeping the perceived distortion level under control, because the image spatial information cannot be neglected. The second technique instead considers the perceived distortion level directly proportional to the number of saturated pixels and not related to the spatial distribution of them. We demonstrate that keeping constant the percentage of saturated pixels does not lead to produce constant perceived image distortion. Both these results suggest that in order to obtain a constant image degradation while saving the maximum allowed power, DBS solutions need to account the image pixels locality information and HVS peculiarities.

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References

[1] Chang N., Choi I. and Shim H. DLS: dynamic backlight luminance scaling of liquid crystal display. In Very Large Scale Integration (VLSI) Systems, IEEE Transactions on, ISSN:1063-8210, VOL.12, NO.8, PAGE.837–846. (2004)

[2] Shim H., Chang N. and Pedram M. A Backlight Power Management Framework for Battery-Operated Multimedia Systems. In IEEE Des. Test, ISSN:0740-7475, VOL.21, NO.5, PAGE.388–396 (2004).

[3] Iranli A. and Pedram M. DTM: dynamic tone mapping for backlight scaling. In Proceedings of the 42nd Annual Conference on Design Automation. DAC '05, 612-617. 2005.

[4] Iranli A., Fatemi H. and Pedram M.. HEBS: Histogram Equalization for Backlight Scaling. Design, Automation and Test in Europe, 2005. Proceedings, pp. 346-351 Vol. 1, 2005.

[5] Iranli A., Lee W. and Pedram M. Backlight dimming in power-aware mobile displays. In Proceedings of the 43rd Annual Conference on Design Automation. DAC '06. 2006.

[6] Iranli A., Lee W. and Pedram M. HVS-Aware Dynamic Backlight Scaling in TFT-LCDs. IEEE Trans. on Very Large Scale Integration (VLSI) Systems, Vol. 14, N.10, 2006.

[7] Cheng L., Bossi S., Mohapatra S., El Zarki M., Venkatasubramanian N. and Dutt N. Quality Adapted Backlight Scaling (QABS) for Video Streaming to Mobile Handheld Devices. citeseer.ist.psu.edu/722345.html.

[8] Cheng W. and Chao C. Perception-guided power minimization for color sequential displays. In Proceedings of the 16th ACM Great Lakes Symposium on VLSI, 290-295, 2006.

[9] Wang Z., Bovik A. C., Sheikh H. R. and Simoncelli E. P. Image quality assessment: From error visibility to structural similarity. IEEE Trans. on Image Process., Vol. 13, no. 4, pp. 600-612, Apr. 2004.

[10] Ebner F. and Fairchild M. D. Development and testing of a color space (ipt) with improved hue uniformity. 6th IST/SID Color Imaging Conference, pp 8-13, 1998.

[11] i.MX31: Multimedia Applications Processor. http://www.freescale.com.

[12] The SSIM Index for Image Quality Assessment. http://www.ece.uwaterloo.ca/ z70wang/research/ssim/.

[13] Bonnier N., Schmitt F., Brettel H. and Berche S. Evaluation of Spatial Gamut Mapping Algorithms. 14th IST/SID Color Imaging Conference, 2006.

[14] Findlay Shearer. Power management in mobile devices. Elsevier LTD, Oxford.

[15] Ruggiero M., Bartolini A. and Benini L. DBS4video: dynamic luminance backlight scaling based on multi-histogram frame characterization for video streaming application. In Proceedings of the 8th ACM EMSOFT, Atlanta, GA, USA, pp 109-118, 2008.