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OLED power consumption model and its application to a perceptually lossless power reduction algorithm

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Abstract

OLED display technology is gaining popularity among original equipment manufacturers (OEM). Production costs are decreasing, making this technology more readily available. OLED displays have a better contrast, no backlight and the ability to estimate the contribution of each pixel to the power of the display. This feature allows to experiment spatial algorithms to improve the image quality in relation to its power consumption.

In this article we present a framework to evaluate the performance of spatial algorithms such as just noticeable distortion and saliency maps on OLED displays. We introduce a comprehensive power model that takes into account each pixel value and the display screen brightness. We validate the effectiveness of this model by implementing a power reduction method based on power saving and perceptual quality metric.

Introduction

OLED displays have several advantages over LCD displays. They offer a better contrast, deeper blacks – a black pixel is not emitting any light – but have a peak of energy consumption to display bright images. Unlike LCD displays they do not have back-light system – a fix energy cost for those displays – and therefore the cost of displaying an image is content dependent. Actually below a certain average picture level (APL) around 65% – where 100% means white image – the same image displayed on an OLED display cost less than on a LCD display (at the same display resolution and comparative hardware).

The life time (LT) of an OLED display is shorter than of an LCD display. The LT value of a display is expressed in hours of usage and describes the amount of time for this display to have its maximum intensity reduced to $X\%$ of its original maximum intensity (LT50 means 50%). The LT evaluation of an OLED display is complicated because it is related to the type of usage and the content displayed [7, 6, 8]. It is, however, generally accepted to say that limiting high intensity should help the display to last longer or avoid burned pixels. The challenge being to reduce the pixel values – globally or locally in the image to be displayed – without loosing information as image quality degradation is not a solution.

It's important to distinguish between types of OLED displays. In this work we are focused on predicting the power consumption of mobile displays such as smart-phone, RGB OLED devices that rely on battery to function, we are not presenting a model for TV display where often RGBW OLED technology is chosen.

Among the three color channels (red, green and blue) the blue channel is the one that at equivalent digital value requires more energy to emit light, so dimming the blue pixels arbitrarily or perceptually can be interesting [8] to reduce over energy usage of this channel. Following that concepts spatial algorithms can be developed where the dimming can be applied on all channels, e.g. aiming at reducing image intensity within perceptual threshold.

There are some redundant spatial and temporal information existing in the image and video frames that are not perceivable by the human visual system (HVS) [9]. For instance, we can alter the luminance of a pixel while keeping the perceptual quality of the image, and in videos, we can adapt the frame rate by predicting the similarity between consecutive frames [10]. Since the power cost of an image in an OLED display depends mainly on the content and the RGB values of the individual pixels, we can reduce the power consumption of the displayed images by modifying the pixels values in such a way that the resulting image would be indistinguishable from the original image.

These perceptual redundancies are mainly due to the psychophysical properties of the HVS and the mechanisms of visual attention [11]. The first concept is related to the fact that the human eye cannot detect changes in the visual stimuli below the just noticeable distortion (JND) threshold due to the spatial and temporal sensitivities of the HVS [12]. JND has become a very promising way to model the perceptual redundancies in visual content and JND models have been applied to a variety of perceptual image and video processing algorithms such as compression, visual watermarking, and perceptual visual quality.

The second concept is related to visual attention which is the set of mechanisms of the human visual system that optimize and control the search processes inherent in vision [13]. By selecting only spatial regions of interest, it effectively solves the bottleneck of limited resources in the human visual system [14]. Thus, understanding the underlying mechanisms of the visual attention has become a fundamental problem that has been studied by several scientists working on different domains, such as neuroscience [14], psychology[17], and computer vision[15]. Researchers in computer vision have focused in both developing computational models to simulate the human visual attention process[16] and detecting salient regions in a scene[15]. Since a visual saliency map provides a measure of how important a subset of contents from a scene to the human visual system, it helps on reducing the scope of visual processing and saving computational resources.

Previous studies [19, 20] demonstrated that visual saliency has an effect on the spatial and temporal sensitivities of the HVS. For instance, JND thresholds in non salient regions are higher than in salient regions [19]. This means that visual saliency acts as a modulation factor for the JND thresholds, and taking into account its effects provides a more accurate JND model.

Also it's important to note that we are focusing on modeling the cost at display level, what we call *display cost* and that we do not take into account the image *processing cost* before display. Modifying images to improve their quality and visibility using a spatial algorithm is obviously content dependent and has a separate *processing cost* that will need to be taken into account when this algorithm will be applied in real time.

In this article we present an applied research framework [2] to evaluate the power consumption of OLED display as well as a general concept for developing spatial correction algorithms that benefit from this model. Novelty for the model comes from taking into account the RGB pixels values and the display screen brightness *(scBr)* as input. The *scBr* is the display parameter that defined the maximum display intensity, e.g this parameter will be modified by simple auto-brightness algorithm. Most of the described OLED power consumption models are based on assuming a display functioning at maximum $scBr = 1$ and independence between the color channels [5, 3].

This paper is organized as follows, the first part introduces the experimental steps to build the display power consumption model and its evaluation. The second presents the general form of a spatial algorithm and how to evaluate its performance with the display power consumption model (DPCM). Finally an experiment is ran over a series of images where we compare the display cost as well as the visual quality of algorithms aiming at reducing the display power consumption.

Display power consumption model

The model approach is to sum up each pixel contribution of a given image. Let's start by improving the existing model by taking into account different *scBr* values, therefore an image cost can be expressed as follows:

$$\mathbf{cost} = \sum_{i=1}^{N} \mathbf{fun}_R(r_i, scBr) + \sum_{i=1}^{N} \mathbf{fun}_G(g_i, scBr) + \sum_{i=1}^{N} \mathbf{fun}_B(b_i, scBr) \tag{1}$$

where each function $\mathbf{fun}_R$, $\mathbf{fun}_G$ and $\mathbf{fun}_B$ describes the relationship between pixel values r_i, g_i, b_i and their respective power consumption. This requires to measure a few pixel combinations of pure red, pure green and pure blue as it is described in [5, 3]. The same operation needs to be repeated for each *scBr* we want to make simulations for.

At this stage channel independence is still assumed and Figure 1 illustrates the limitation of this approach as the cost prediction of a gray-scale ramp is not the summation of pure red, pure green and pure blue ramps. We can see that the channel independence assumption overestimates the display cost of an image, unless the test images are almost monochromatic red, green or blue.

Figure 2 illustrates how interpolation technique can be used to predict the cost of gray-scale images where each pixel will have the same amount of red, green and blue. It has obviously limitations as we want to make power consumption prediction for any types of content. Therefore we decided to add more reference points to feed our interpolation solution and Figure 3 reveals how we are sampling the RGB cube to add those missing points.

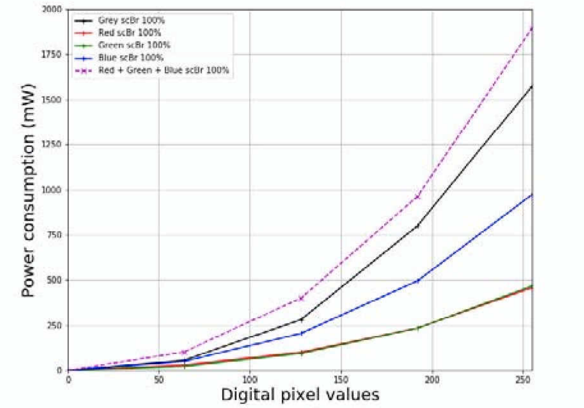

Figure 1. *Power consumption of ramps of pure red, green, blue, gray (in black) and simulation of the gray ramp with model in 1 for* $scBr = 1$ *(in magenta) for the BLU Vivo device. We can observe the over-simulation of this model, the predictions are higher than the measurements.*

In an attempt to be more generic about the DPCM, we want to have a solution under the following form:

$$\mathbf{cost} = \mathbf{FUN}(image,\ scBr) \tag{2}$$

where *image* is the image content in pixel values and *scBr* the screen brightness as a global parameter, both $\in [0,1]$. More precisely the power consumption cost is the sum of contribution of each pixel $P_i = (r_i, g_i, b_i)$ at a given *scBr*:

$$\mathbf{cost} = \sum_{i=1}^{N} \mathbf{fun}(r_i, g_i, b_i, scBr) \tag{3}$$

where N is the total number of image pixels. This later proposed DPCM doesn't assume channel independence. The power estimation of a *RGB* pixel combination and a given *scBr* is then solved using interpolation tools in 4 dimensions for which we use Python programming.

Measuring the power consumption of an image

To measure the power consumption of an image on an OLED display we used an high voltage power monitor (HVPM) from *Moonson Solutions Inc.* [5]. We have conducted our measurements on two devices (BLU VIVO and Google Pixel) having OLED display technology and running Android OS.

As we can't be sure to measure only the display cost, we need to put those devices in flight mode, stop all non-necessary applications running [4, 5] in order to have repeatable measurement sessions and to limit the background cost to the image viewer application.

The battery of the device is directly connected to the HVPM, itself connected to a computer where we can read the power consumed by the display device when an image is displayed.

Following those steps we can define an offset cost when we measure a black image. In our model a black image has a luminance of 0 **lux** and a power consumption of *offset* **mW**.

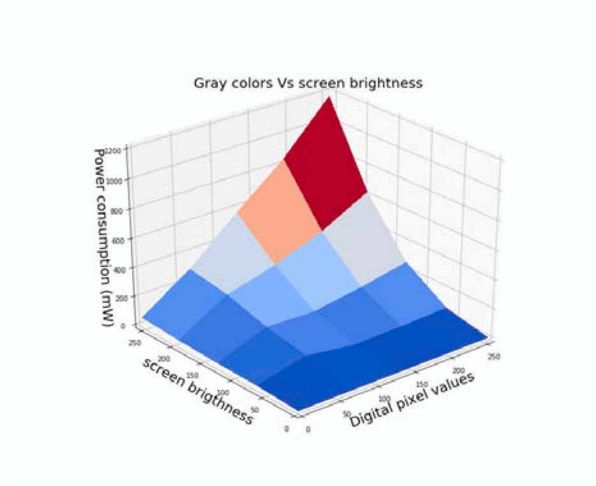

Figure 2. Visualization of the power measurement for a Google Pixel device in mW of gray pixels (on each point red, green and blue pixels have the same digital value) from black to white for different scBr.

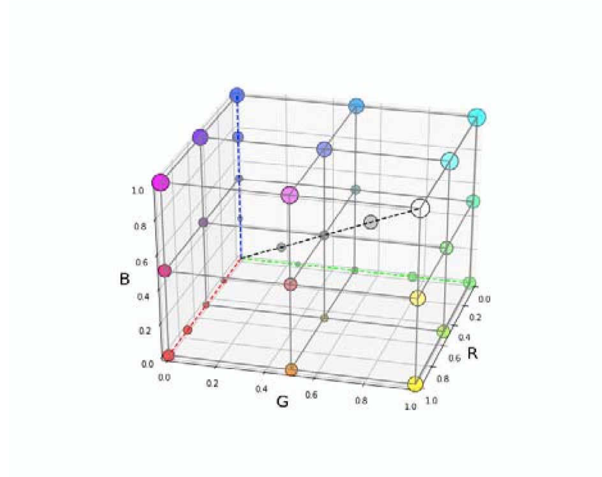

Figure 3. Visualization in 3D of the RGB points for the interpolation with non-regular sampling, points laying on the colored lines in red, green, blue and black.

Building and using the model

To obtain accurate estimation cost we need to take into account various combination of red, green and blue pixels and as well several *scBr* values. That is to say we need to sample the **RGB** cube and repeat those measurements for several *scBr* values.

This measurement procedure is time consuming. We need to display all the reference images at the desired *scBr*, each measure takes at least $30s$ until the device has reach stability. This operation is repeated at least three times per sample. Figure 2 presents the measurements of gray pixel combinations from black to white and *scBr* from 0 to 1 for a Google Pixel device. The offset has been removed from the measurements such that a black image has consumption cost of 0 mW.

Once we have a set of reference data points in **4D** we can make use of fitting methods. Each image pixel becomes an entree point $[r, g, b, scBr]^T$ for which we want to know the power cost estimation using Eq. 3. We use the function *scipy.interpolate.griddata* from the Python module *SciPy* [1] to perform this operation.

Interpolation from non regular sampling

This interpolation only uses $[17 * 5]$ reference points in **4D** space, axis of pure red, pure green, pure blue and pure gray as presented in Figure 3 in *RGB* space for a given *scBr* value. At each point is associated a measured power consumption in *mW*. 17 points in the *RGB* cube times five $scBr = [0,\ 0.25,\ 0.5,\ 0.75,\ 1]$ values for a total of 85 reference points.

These data are providing reasonable accuracy for our configuration test such as image content representing a typical webpage or social media content, it's usually the combination of very saturated colors (i.e. pixel on the *RGB* cube edges).

Interpolation with regular sampling

This should give much better accuracy than the previous approach, but it requires to take many more measurements. Ideally if all parameters $R, G, B, scBr$ can take n different values, all combination of them means to measure $n*n*n*n$ images. If $n = 5$ then we have $5^4 = 625$ reference points. Figure 3 illustrates how we will sample the *RGB* cube with the colored dots with the assumption that the relationship is linear.

DCPM comparison

An experiment was conducted where the power consumption of 6 images at 6 different $scBr = [0.39,\ 0.58,\ 0.68,\ 0.75,\ 0.78,\ 1]$ were measured and compared to three DPCMs: one assuming channel dependence with regular sampling, a second assuming channel dependence with non regular sampling of the *RGB* cube both following Eq. 3 and a third one assuming channel independence following Eq. 1.

Measurements and simulations correspond to a Google Pixel device having $[1280x720]$ for maximum resolution. The images were resized to the display resolution, in case of the image hasn't reach the exact display dimension, a black pixel border was added to reproduce what the display image viewer will do on the device when displaying full-screen.

Results for this comparison are presented in Figure 4. The first three groups - left to right - of bars are for natural content images, groups 4 and 5 for social content type of images and last group to the right corresponds to a very dark image. In the simulation case using the model as in Eq. 3 is closer to the measurements. It slightly over predicts the power consumption but remains acceptable for our use. The distortion we observed is probably due to the missing reference points in the *RGB* cube. Having all edges measurements and not only the axis colored in Figure 3 should improve the model performances.

Spatial algorithm

In this section, the proposed application framework is presented. First, we describe the spatial algorithms to model the perceptual redundancies of the HVS. More specifically, JND modeling in the DCT domain and the pixel domain will be introduced.

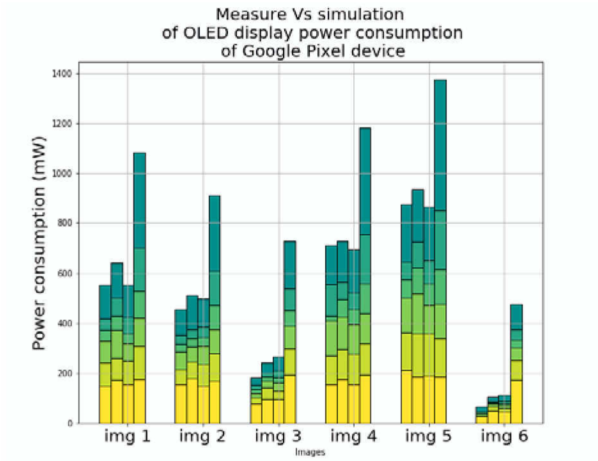

Figure 4. *Measurement and simulations by group of four bars per image, left to right: measurement, simulation with channel dependence regular sampling, simulation with channel dependence non regular sampling and simulation with channel independence. From top to bottom, yellow to green colors correspond to low to maximum scBr. Image 1 to 3 represent natural images, image 4 and 5 internet browsing type of content and image 6 a natural dark image.*

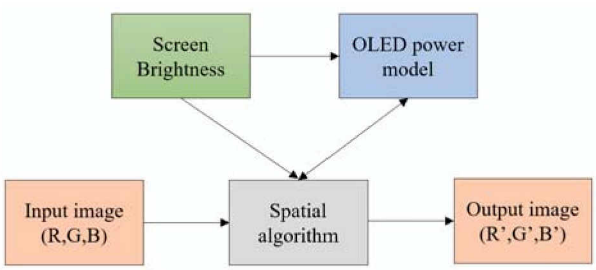

Figure 5. *Basic framework for the evaluation of power consumption and image quality of spatial algorithm on OLED display.*

Second, we explain how saliency information can be incorporated. Finally, the approach for optimizing OLED power consumption will be presented. A diagram of the general framework is presented in Figure 5.

JND Models

The Estimation of the JND thresholds is generally performed by modeling the spatio-temporal relationship between the human visual sensitivity and the masking effects. There have been several JND models developed in the last decade, which can be classified into two main categories [25]: sub-bands based and pixels based depending on whether the JND threshold are obtained in the compressed domain or directly estimated for each pixel in the image domain.

DCT based JND

Typical JND models in the DCT domain consider three important factors of the HVS: contrast sensitivity function (CSF), Luminance adaptation (LA), and Contrast Masking (CM) [22]. The CSF is a measure that characterizes the human spatial vision and is usually determined by estimating individual thresholds for patterns with different spatial frequencies expressed in cpd (cycles/degree) [27]. To take into account the effect of the spatial CSF, the image luminance channel is divided into $N \times N$ blocks and a base threshold t_{Base} is estimated.

The factor t_{Base} is for the intensity value of 128. To account for the fact that the visibility thresholds in very bright and very dark regions are lower than in the medium gray region, the base JND is multiplied by a modification factor f_{L_a}[28].

Contrast masking refers to the reduction in the visibility of one visual signal in presence of another one [29]. The masking effect is strongest when the two signals are of the same location, orientation, and spatial frequency. The sensitivity of the HVS to distortions is generally lower in the texture or disorderly region and higher in smooth or orderly regions. In [22], contrast masking is obtained by introducing an orientation regularity term into the block classification.

The final JND threshold is obtained by combining the base threshold t_{Base}, the luminance adaptation factor f_{L_a}, and the contrast masking factor F_{C_m}

$$dct_{Jnd} = \alpha . t_{Base} . F_{L_a} . F_{C_m} \tag{4}$$

where α is a summation effect factor determined by experiment.

Pixel based JND

JND models in the pixel domain generally consider two main factors: luminance masking and contrast masking. In [23], an image-domain JND model is devised with the nonlinear additivity model for masking (NAMM). A control gain reduction parameter that accounts for the overlapping effect in masking is introduced that allows for the co-existence of luminance masking and contrast masking. A further improvement of this model was done by [24] and [26]. In [24], a JND model based on the free energy principle is introduced, which decomposes an image into orderly and disorderly content. An auto-regressive model is used to predict the orderly regions $Jnd_o(x)$, and a disorderly concealment effect is devised to better estimate the JND thresholds of the disorderly regions $Jnd_d(x)$. The overall JND threshold is calculated as:

$$pix_{Jnd}(x) = Jnd_o(x) + Jnd_d(x) - C \times min\{Jnd_o(x), Jnd_d(x)\} \tag{5}$$

where C is the gain reduction parameter due to the overlapping between $Jnd_o(x)$ and $Jnd_d(x)$.

Recently, Wu *et al.* [26], improved the spatial masking $M_s(x)$ by introducing a pattern complexity factor which is measured as the sparsity of the gradient orientations histogram. By taking into account the luminance adaptation effect $F_{L_a}(x)$, the final JND is calculated using NAMM as:

$$pix_{Jnd}(x) = F_{L_a}(x) + M_s(x) - C \times min\{F_{L_a}(x), M_s(x)\} \tag{6}$$

Visual saliency factor

Visual saliency is the measure of propensity for drawing visual attention, and salient objects are those that stand out the most in a scene. Possible factors that contribute to determine saliency include color, contrast, size, orientation, motion, depth, and context [18]. Visual saliency was originally brought up by psychologists in the study of attention, while the concept of saliency map was introduced by Koch et al. [30] and later implemented by Itti et al.[16] who proposed a computational model to estimate the saliency map by defining image saliency using central-surrounded differences across multi-scale image features. Since this seminal work, there have been a continuously increasing interest in this field, and various approaches have been proposed.

As mentioned earlier, the saliency information could be used as modulation factor to adjust the JND thresholds inside and outside of the salient areas in images. Moreover, [19] showed that the sensitivity with spatial frequencies is elevated by visual attention. To take into account those effects, we follow the methodology developed in [31] and [32], the spatial frequency $\rho_{i,j}$ and the JND thresholds in the DCT domain dct_{Jnd} are modified using two functions $f_P(s_n,\theta_P)$ and $f_{dct_{Jnd}}(s_n,\theta_{dct_{Jnd}})$ [31, 32]:

$$\rho^s_{i,j} = \rho_{i,j} \times f_P(s_n,\theta_P) \tag{7}$$

$$dct_{SJnd}(\theta) = dct_{Jnd} \times f_{dct_{Jnd}}(s_n,\theta_{dct_{Jnd}}) \tag{8}$$

where s_n is the normalized saliency map of the n_{th} block.

The parameters $\theta = (\theta_P, \theta_{dct_{Jnd}})$ of the two modulation functions $f_P(s_n,\theta_P)$ and $f_{dct_{Jnd}}(s_n,\theta_{dct_{Jnd}})$ can be determined experimentally as in [31] or are obtained through an optimization framework [32].

Once the JND thresholds in the compressed domain have been estimated using equation 4 or 8, a conversion to the pixel domain is necessary in order to use the JND map in the power reduction procedure. The authors of [33] provide an approach to estimate the JND thresholds in the pixel domain from the JND thresholds in the DCT domain

$$pix_{Jnd}(x) = IDCT(dct^{'}_{Jnd}) \tag{9}$$

where $dct^{'}_{Jnd}$ is given by:

$$dct^{'}_{Jnd} = \begin{cases} sign(\mathbf{DCT(Y)})dct_{Jnd} & |\mathbf{DCT(Y)}| \geq dct_{Jnd} \\ 0 & \text{otherwise.} \end{cases} \tag{10}$$

Power reduction method

In this section, the method of reducing the image power cost is detailed. As mentioned previously, the power cost of displaying an image in an OLED display depends mainly on the display screen brightness and the RGB values of the individual pixels, more specifically on the image luminance component Y. Moreover, the JND threshold for a specific pixel provides a measure of how much we can change its luminance to have a resulting image perceptually indistinguishable from the original.

Let I be the original color image. First, we estimate the JND thresholds in the pixel domain $pix_{Jnd}(x)$ using equations 5, 6, or 9. Let $I_{YC_bC_r} = (Y,C_b,Cr)$ be the original color image in the YCbCr perceptual color space, where Y is the luminance component, C_b and C_r are the chroma channels. Given $pix_{Jnd}(x)$, a resulting color image is generated by subtracting $pix_{Jnd}(x)$ from the luminance component:

$$I^{'}_{YC_bC_r} = (Y - \gamma \times pix_{Jnd}(x), C_b, Cr) \tag{11}$$

where $\gamma \geq 0$ is a parameter that controls the visual quality of the resulting image. Choosing $0 < \gamma \leq 1$ would result in an image that is perceptually indistinguishable from the original while using less power since its luminance component is reduced. Choosing $\gamma > 1$ allows for a better power saving but with an acceptable loss of quality.

Figure 6. Visual results showing the quality of the power reduction method. Left column: the original image. Middle column: processed image for $\gamma = 1$, power saving: 8.01% for $scBr = 1$ and $SSIM = 0.98$. Right column: processed image for $\gamma = 2.5$, power saving: 19.4% and $SSIM = 0.93$. The savings are for the Google pixel.

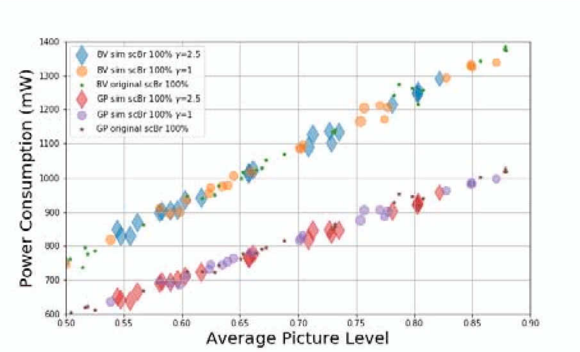

Figure 7. This figure presents the results of two simulations for both devices at scBr $= 1$. The X-axis stands for Average Pixel Level and the Y-axis stands for the DPCM output in mW. We can observe how the γ parameter has an impact on the image display cost as the diamonds and circles are shifted toward bottom left direction.

Experiment and discussion

In the following experiment we want to evaluate the power consumption of images before and after being processed. Two test cases are simulated where the parameter γ was set to 1 and 2.5, the screen brightness to $scBr=0.5$ and full $scBr = 1$.

We run the experiment on 40 images simulating the display cost on both Google Pixel and BLU Vivo devices. The Table 1 presents the results showing how much is saved in term of display cost in average and how its quality is conserved or decreased depending of the approach chosen. The images chosen represent different type of content, from natural image scenes to internet browser-like type of images simulating typical used in smartphone.

Figure 6 shows a visual example comparing the original

Device	γ	SSIM	saving mW (%)	
			scBr = 0.5	scBr = 1
Google Pixel	1	0.9835	6.45	7.19
	2.5	0.9359	16.09	17.7
BLU Vivo	1	0.9835	4.89	5.26
	2.5	0.9359	11.76	12.6

The table above presents the average performances of our experiment. Not surprisingly higher γ value means higher power saving but loss of image quality. The differences between the two devices can be explained by their different power consumption properties.

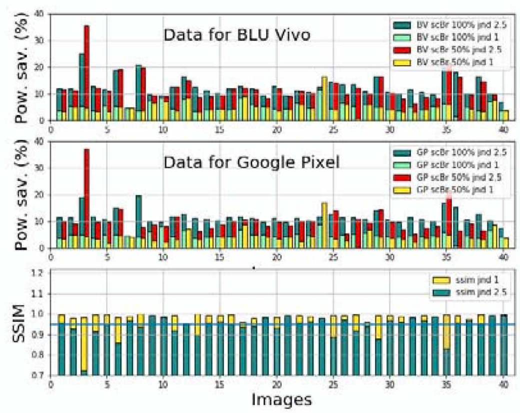

Figure 8. This figure presents the power saving and SSIM results versus the test images on the X-axis. In the two above bar charts, each image power saving is representing by a pair of overlapping bar chart: light and dark green for scBr $= 100\%$, $JND = 1, 2.5$, *yellow and red for scBr* $= 50\%$, $JND = 1, 2.5$. *Only two bar chars overlapping for the SSIM per image as the same image is displayed for both scBr values tested.*

image with the processed images by the power reduction method using the JND model from equation 4 for two different values of the control parameter γ. Figure 7 confirms that applying spatial algorithms that aim at decreasing the luminance will reduce the average picture level (APL) and therefore decrease the image power consumption. Non modified images are displayed on that graph as small colored stars. After the algorithms being applied their new cost are displayed as circles or diamonds with their size being function of product power consumption times structural similarity (SSIM [21]) score. We can observe that all costs are shifted to the left and down meaning a global reduction of the display cost for all types of images.

Figure 8 is a good additional information to evaluate the overall performances of our spatial algorithms. We can more easily spot the outliers and verify with our database of test images. For example in the three sub-figures we can observe that image 3, 5 and 8 on the x-axis have good potential power saving but a certain loss of quality according to the SSIM score. Those images represent a mixed of natural and purely graphical or textual content, i.e. internet page browsing type of content. This information can help us to adapt the strategies to decrease the display power consumption depending of the content displayed.

Conclusion

We have presented a new model for evaluating the display power consumption of an image on OLED display. This display technology allows to estimate the display cost of a given image by summing the contribution of all pixels. Our multi-dimensional approach doesn't assume independence between the color channels which in addition to the *scBr* values gives reasonable accurate predictions. This later aspect is very interesting because it allows to investigates more complex algorithms such as spatial algorithms and estimate potential improvement on the display power consumption. Another and not negligible aspect is the gain of time to obtain this information as we don't need to measure each image.

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