CHAPTER 4
DISPLAY POWER MANAGEMENT (OLED)

Organic Light Emitting Diode (OLED) displays are increasingly replacing traditional LCD and PLASMA screens in the new generation televisions, computers and smartphones. OLED displays are the second most widely used type of displays, next to LCDs, in smartphones. In contrast to uniformly backlit LCD displays, OLED displays are not backlit and their pixels are individually illuminated. Hence, OLED displays are power efficient, thinner in size, flexible than LCD displays and they can show deep black levels with high contrast. For majority of images an OLED display consumes 60-80% of the power of a LCD display. However, OLED display is not efficient in displaying contents with white background as illuminating red, green and blue OLED materials to their maximum levels to produce white color requires more energy. OLED’s color dependent energy consumption is explained in Section 4.2. Our measurements show that, it requires more than three times the power of LCD display to show webpages with white background and black text. Other sources [112] also confirm the inefficiency of OLED display in displaying contents with white background.

Web browsing is one of the most widely used applications in mobile devices [113]. Most of the web pages have white background which consumes more power in OLED displays than in LCD displays. This chapter addresses this problem by mapping the
colours of web pages to power efficient colours for OLED displays while retaining their brand identity, readability and colour harmonicity.

In this chapter, first we introduce OLED display technology in Section 4.1 and our key observations on OLED displays in Section 4.2 then, we describe our algorithms to conserve energy consumption of OLED displays while browsing web pages.

4.1 OLED Display Technology

Due to their thin size, vivid colours, high contrast and power efficiency, OLED screens are increasingly replacing LCD screens in modern smartphones. OLED uses organic compounds (for red, green and blue sub-pixels) which emit light in response to electric current. OLED displays can use either passive-matrix (PMOLED) or active-matrix addressing schemes. Active-matrix OLEDs (AMOLED) require a thin-film transistor back plane to switch each individual pixel on or off, but allow for higher resolution and larger display sizes. AMOLED displays are becoming increasingly popular and have been used in smartphones such as the Google Nexus One and the Samsung Galaxy S (Super Active-Matrix OLED or SAMOLED, a variant of AMOLED). As OLED displays are not backlit and each sub-pixel (made up of the organic compounds for red, green and blue colours) is individually illuminated, the power consumption of OLEDs depends on the luminance of the contents being displayed. OLEDs consume relatively less power to show darker contents than lighter/brighter contents. In addition to luminance, the power consumption also varies depending in the colour of the content being displayed. ..
4.2 Key Observations on OLED Displays

Power consumption of an OLED display depends on the contents being displayed. We observed that the colour and luminance of the contents are key factors that determine the amount of power required. Our observations on OLED power consumption are described below. First, we show the relationship between the display brightness (which is adjustable by the user) and power consumption. Then, we describe the relationship between the content luminance and power consumption. Finally, we depict how colour of the content affects power consumption.

1. To understand the relationship between the power consumption and brightness of the screen, we measured the power consumption on the Google Nexus One smartphone with a 3.7 inch AMOLED (Active-matrix OLED). In this experiment, we kept the displayed image constant and varied the brightness of the display while measuring the energy consumption of the display for 1 minute. Figure 4.1 shows the results of this experiment. As expected, the power consumption of the display varied linearly to the display brightness (255 is the maximum brightness). This is due to the amount of power supplied to each OLED pixel is increased to make the screen brighter. This trend is similar to LCD displays.

If $E_{OLED}$ is the energy consumption of OLED display overtime and $BR_{OLED}$ is the brightness of the display, then,

$$E_{OLED} = \alpha \times BR_{OLED} + \beta \quad (4.2.1)$$
where, $\alpha$ and $\beta$ are device dependent constants. For Google Nexus One smartphone, $\alpha = 0.144$ and $\beta = 21$

2. In the next experiment, we kept the display brightness constant and varied the luminance (brightness) of the image. To avoid pixel saturation while increasing the luminance of the image, we applied non-linear $1/\gamma$ (Gamma correction or simply, Gamma) on the image. As Gamma increases the luminance of the image increases. Figure 4.2 shows the power consumption of the display when different Gamma values (from 1.0 to 2.0) are applied to the displayed image. This suggests that, darker images consume less power.

3. Finally, we observed that the energy consumption of OLED displays is quite sensitive to the colour being displayed. The reason for this non-linearity in
power consumption among colors can be explained at higher level as described below.

OLED material used to produce blue light has the lowest luminance efficiency (measured in lumens/watt) when compared to the materials used to produce red and green light. Hence, higher current is required to match the luminance of blue material with green. Applying higher amount of current on blue material degrades blue material more rapidly than the materials that produce other colours. This results in a faster decrease of blue light output relative to the other colours. Manufacturers address this issue by optimising the size and order of the red, green and blue sub-pixels to reduce the current density through the sub-pixels, in order to equalise lifetime at full luminance. For example, a blue sub-pixel may be 100% larger than the green sub-pixel. A red sub-pixel may be 10% smaller than the green sub-pixel. Figure 4.3) [114] shows one such
arrangement known as RGBG Pentile matrix where each pixel is represented by two subpixels instead of conventional three subpixels. This leads to an uneven power consumption by objects with different colours (while their luminance is constant). In this case, an image with a dominant blue shade consumes more power than an image with a dominant red or green shade.

To demonstrate this non-linearity and to find the relationship among colours, we measured the base energy consumption of the Nexus One’s OLED display for a period of one minute with the red, green, and blue colour intensities all set to zero (i.e., we displayed a completely black image. This is base power consumption reference point).

Next, we gradually changed only the red colour intensity (with green and blue intensities both set to zero) and measured the power consumption of the red display components at each intensity level. We then repeated this experiment
for just the blue and green colours. After each experiment, we subtracted the power measurements from the base power consumption (black image) to get the incremental power consumption caused by that colour and intensity.

The results depicted in Figure 4.4 show that red consumes the least energy with green consuming approximately 1.5 times more energy than red, and blue consuming approximately 2.1 times more energy than red. The lines are non-linear as Gamma correction is applied in the process of mapping the pixel values to electrical power to illuminate the OLED materials. In addition, we also discovered that power consumption of a pixel is equivalent to the power consumption of individual subpixels (red, green, and blue subpixels) of the pixel. Moreover, we found that power consumption of an image can be predicted using power consumption of all pixels that collectively make that image. The relationship between power consumption and colour can be generalised as shown in Equation 4.2.2.

If $E_{\text{pixel}}$ is the power consumption of a pixel in OLED display and $R, G, B$ are the values of the colours red, green and blue in RGB colour space, then,

$$P_{\text{pixel}} = a_1.R^2 + a_2.R + b_1.G^2 + b_2.G + c_1.B^2 + c_2.B + d \quad (4.2.2)$$

where, $a_1, a_2, b_1, b_2, c_1, c_2$ and $d$ are device dependent constants.

While an OLED will consume around 40% of the power of an LCD displaying an image which is primarily black, for the majority of images it will consume 60 to 80% of the power of an LCD. However it can use over three times as much power
to display an image with a white background such as a document or website. This can lead to reduced real-world battery life in mobile devices. OLED display power consumption can be minimised by proper colour transformations [55, 56, 115] to these websites.

![Energy Vs RGB Sub-Pixel Values](image)

**Figure 4.4.** Energy Vs RGB Sub-Pixel Values

From these observations, we can infer that to reduce the power consumption of OLED displays one should reduce the screen brightness, luminance of the contents and use energy efficient colours. Screen brightness is a user adjustable parameter in smartphones. Modern smartphones have built-in mechanism for ambient light based automatic screen brightness adjustment. Hence, in our work we assume that the screen brightness is set to some constant value by the user (or smartphone OS) and vary only the luminance and colour of the contents to save energy.

### 4.3 Power Optimisation for Webpages - Texts

As described above web browsing is one of the most common and widely used application in mobile phones. Most of the mobile webpages are made up of texts
and images. In this section we describe our approach for mapping colours of HTML texts to power efficient versions and in the next section we describe about handling images in the webpage. The two variables which affect the power consumption of OLED displays are luminance and colour. Therefore, the basic question we address in our system is: Given set of colours, how to map these colours to power efficient versions such that, the quality of the pages in a website are not adversely affected?.

We define quality of a page with respect to colours using three important properties - colour harmonicity, brand colour and readability (or legibility). A generally accepted understanding of colour harmony among researchers is, Colours seen together to produce pleasing affective response are said to be in harmony [116]. Colour is one of the powerful tools in corporate branding, for eg., Coke is red, UPS is brown and IBM is blue. Brand colours appear on all their promotional materials including, logo, banners, product packaging and webpages. WWW (World Wide Web) organisation suggests minimum, Chromatic Contrast (CC) (Difference in Hue) and Achromatic Contrast (ACC) (or Colour Brightness Difference) between the background and text colour for better readability [117].

4.3.1 Colour Harmony

A plethora of theories and studies exist that focus on the relationship between colour and aesthetic response as well as the construction of colour harmony. However, consensus regarding colour harmony is lacking in the literature leaving designers and architects with colour harmony information that is contradictory and ambiguous. As colour harmony is based on various factors including the Human Visual System (HVS) characteristics, cultural differences etc. it is not possible to make a list of rules to
describe the harmonious or disharmonious set of colours. Only the human eye can judge the final artistic result [118]. However, designers use some common methods and tools for selecting colour harmony.

The most common tool for selecting harmonious colours is the colour wheel which shows the hue of colour in order. Colour wheel in RGB (Red, Green, Blue) colour space is shown in Figure 4.5. The outermost circle shows the primary (Red, Green, Blue) and secondary hues (Yellow, Magenta, Cyan). The secondary hues are derived by mixing equal amount of adjacent primary hues. The inner circles shows the tints (lighter version) and shades (darker version) of the hues.

The following colour schemes derived from the colour wheel are commonly known and used as harmonious colours [118].

1. *Analogous scheme*: uses any three consecutive hues or any of their tints and shades on the colour wheel

2. *Complementary scheme*: uses direct opposites on the colour wheel
3. Clash scheme: combines a colour with the hue to the right or left of its complement on the colour wheel

4. Monochromatic scheme: uses one hue in combination with any or all of its tints and shades

5. Split complementary scheme: consists of a hue and the two hues on either side of its complement

In this work, we have used monochromatic and analogous scheme for background hues and complementary scheme for foreground hues. We have used only these three schemes as there is a good chromatic contrast between a hue and its direct opposite hue in the colour wheel. Chromatic contrast is one of the requirement for better readability. In addition, most common background colour scheme in webpages are monochromatic. In this work we used five out of the eight harmonic types (Figure 4.6) defined over the hue channel of the HSV color wheel by Tokumaru et al [119] [120]. Each type is a distribution of hue colors that defines a harmonic color set: colors with hues that fall in the gray wedges of the wheel are defined as harmonic. For details the reader is refered to Tokumaru et al. [119]. For any given hue, to select a set of analogous hues we have used i,V types from the colour wheel depicted in and to select a set of complementary colours we have used types I, Y, X.

4.3.2 Brand Colour & Brand Identity

There are many ways colour helps to communicate a message. Colour can convey meaning, express personality, differentiate, frame, and highlight content. Colour is a crucial element of a brand identity. Companies understand the proper use of colour
is vital to create a positive image among consumers. Furthermore, colour plays a huge role in memory recall. Colours are often associated with words [121] which give meaning to the colours (Figure 4.7). It stimulates all the senses, instantly conveying a message like no other communication method. Most of the websites use colour palettes which are derived from brand colours and they maintain colour consistency across all pages of the site. It makes people to remember the website at first glance. For example, the brand colour of NUS (National University of Singapore) is a shade of Orange (#FF6600) and a shade of Blue (#003399) and these colours are the dominant colours of the NUS logo (Figure 4.8) and these colours form the primary colour palette for NUS website [122]. To make it consistent among all the departments, schools and research institutes of NUS, there is a dedicated website which provides information about the corporate identity [123]. Similarly, Intel Corporation [124] and Nvidia Corporation [125] webpages primarily use a shade of Blue and Green colours respectively (Figure 4.8). These are the main colours in their corporate logos.

![Colours Wheel Types](image)

**Figure 4.6.** Colours Wheel Types
webpages are re-painted with new colour palette which is generated using the brand colours.

**Identifying Brand Colour & Key Image.** Brand colour of a company can be identified using the logo of the company available in its website. However, it requires additional efforts to find the file containing the logo as the resource location and file name of the logo is not standardised. An alternate source is *favicon* (short for favourite icon). Almost all websites use *favicons* today. A *favicon*, also known as a shortcut icon, website icon, (Uniform Resource Locator) URL icon, or bookmark icon, is a file containing one or more small icons, most commonly $16 \times 16$ pixels, associated with a particular website or webpage [126]. Favicons are usually placed in predefined URL `/favicon`, which is relative to the server root. Browsers that provide favicon support typically display the favicon in its address bar and next to the page-name in its list of bookmarks. Browsers that support a tabbed document interface typically show the favicon next to the page-title on the tab. Favicons of many websites are
Figure 4.8. Webpages designed using Brand Colours available in their Logos
made up of brand colours. Most of the time the favicon is simply miniature of the company logo image. As shown in Figure 4.9 NUS, Nvidia and Intel use their logo as favicon. In this thesis, we call the image which is used to find the brand colour as key image. A key image can be the logo, the favicon or any image with the URL '/keyimage' relative to the root of the server.

To extract the brand colour from the key image the following algorithm is used. The image is first quantized to a set of colour bins. We have used 4096 bins to represent all web safe colours. The bin with the highest value represents the dominant colour in the image. As the human visual system is most sensitive to large areas of colour, larger colour patches are the best for harmonization purposes. Hence, the algorithm picks 'n' dominant colours as shown in Figures 4.10 and 4.11. Logo usually have transparent backgrounds (alpha channel value = 0). For such images the histogram is computed only for the non-transparent areas. The parameter $minThreshold$ indicates the minimum required presence of the colour in the image. For example, less than 2% presence of the colour in the image is most likely due to noise in the image which is gathered in processes such as, compression/conversion and edge smoothing process. Moreover these colours do not contribute for colour harmonisation.

**Algorithm: Brand Colour Extraction**

* Create a RGB colour histogram of the Image; exclude the full transparent areas (Alpha channel)
* Quantise to 4096 web safe colour bins ($256 \times 256 \times 256$) colours;
* Rank the colours according to their presence in the key image exclude the colour if ($binValue < minThreshold$)
  and select the top 'n' dominant colours;

If one wants to consider, real colours rather than quantised 4096 colours, he can use more complex colour patch extraction algorithms [127]. However, we do not
Figure 4.9. Logos are Used as FaviconS
need such computationally intensive algorithms as we are interested only in websafe
colours and limited by the resources in the mobile devices.

**Power Efficient Brand Colours.** The next stage is to obtain the power efficient
colours. We compute the power consumption of each colour based on our power model
shown in Figure 4.4. These values are shown in Figures 4.10 and 4.11. The values
represent the power required in $\mu$Watt to display one pixel in the selected colour.
Form this we filter ‘m’ energy efficient colours for colour harmonisation of the webpage
with the key image. According to the requirement of the client a set of colours from
the ‘m’ energy efficient colours are selected for re-colouring the backgrounds and texts
in the webpage.
4.3.3 Chromatic and Achromatic Contrast & Colour Mapping

As described above the background and foreground colours should have sufficient level of chromatic and achromatic contrast for legibility. W3C recommends minimum 125 units of brightness difference and 500 units of colour difference between the two colours for good visibility [117]. The perceived colours brightness of a pixel is determined by equation (4.3.1). The difference between brightness of two colours gives the achromatic contrast [117]. Chromatic contrast between two colours is determined using equation (4.3.2).

\[1\text{PixelBrightness} = \sqrt[2]{0.241r^2 + 0.691g^2 + 0.068b^2}\] (4.3.1)

\[ChromaticContrast = \text{abs}(r_1 - r_2) + \text{abs}(g_1 - g_2) + \text{abs}(b_1 - b_2)\] (4.3.2)

\(r, g\) and \(b\) are values of the red, green and blue subpixels.

\(r_1, g_1\) and \(b_1\) are values of the red, green and blue components of the text colour. \(r_1, g_1\) and \(b_1\) are values of the red, green and blue components of the background colour

**Energy Efficient Colours Mapping.** In the following paragraphs we describe methods to meet the energy efficiency requirement of the client while mapping colours. The energy efficient colour mapping problem can be defined as follows:

\(^1(\text{http://alienryderflex.com/hsp.html})\)
Let $w_1$ be the original webpage, $w_2$ be the power optimised version of the webpage, $w_i[n]$ be the 'n' colours used in a webpage, $\text{pagePower}(w_i)$ be the power consumption of the webpage, $e[m]$ be the 'm' energy efficient colours obtained from the key image, 'acc' be achromatic contrast and 'cc' be chromatic contrast between background (bg) and foreground (fg) colours and '$\tau$' be the energy efficiency factor required by the client. The system should map the colours with the following constraints.

**ColourMappingProcess:**

Map $w_1[n] \rightarrow w_2[n]$

where, $w_2[n] \in e[m]$

and, $\frac{\text{pagePower}(w_2)}{\text{pagePower}(w_1)} \geq \tau$

and, $(\text{acc}(bg_i, fg_i) \geq 125) \land (\text{cc}(bg_i, fg_i) \geq 500)$

If $e[m]$ is not sufficient to meet the power requirement, we use derived colours from $e[m]$ which are monochromatic and complementary hues of $e[m]$. Monochromatic and complementary hues are described in Section 4.3.1.

There are two approaches to compute the power consumption of a webpage (texts and backgrounds). The first approach is to render the page completely and then compute the power consumption of the rendered image. This is computationally intensive task for mobile devices. The second approach makes a coarse approximation by considering average text to background area ratio. We have conducted a short experiment to find the average ratio of text to background in mobile webpages. We
accessed group of 20 text based webpages (some samples are shown in Figure 4.12) with default font sizes in Samsung Galaxy Nexus smart phone (4.65” Super AMOLED screen) at High Definition (HD) resolution (1280 x 720). We have taken a snapshot of these pages and then separated the text pixels based on foreground colour to compute the percentage of area occupied by texts. The results for 20 webpages are shown in Figure 4.13. In all these pages, less than 20% of the area is really used by the texts and the rest goes to background. Using this average ratio, we approximate the power consumption of a page as shown in Equation (4.3.3).

$$\text{pagePower}_{\text{approx.}} = \text{pixelPower}(B_{\text{Color}}) \times R \times 0.80 + \text{pixelPower}(F_{\text{ColorHigh}}) \times R \times 0.20$$  \hspace{1cm} (4.3.3)

Where, $B_{\text{Color}}$ is the background colour of the body of the page. This is the primary background colour. $F_{\text{ColorHigh}}$ is one of the foreground colours which consumes the highest power. $R$ is screen resolution in number of pixels per screen (800x480). The pixelPower() function represents the power model (Figure 4.4) of the device.

We first compute the $\text{pagePower}(w_1)$ using Equation (4.3.3). We divide the energy efficient colour set $e[m]$ into two halves. The first half, $e[m_b]$ is a set of low power consuming colours for background. The second half, $e[m_f]$ is a set of relatively high power consuming colours for foreground. Then, for each possible combination of background and foreground colours from the sets $e[m_b]$ and $e[m_f]$ that guarantees minimum ACC and CC, we compute pagePower consumption using the Equation (4.3.3). Finally, the colour combinations that meets energy efficiency requirement $\tau$ are selected for mapping. **Variation 1:** If the combinations do not meet ACC
Figure 4.12. Background vs Text Area (After Excluding Images) - Sample Webpages
and CC requirement, we generate new set of $e[m_f]$ for foreground colour. These new foreground colours are complementary colour (I,Y,X) types in Figure 4.6) to the selected background colours. **Variation 2:** If the combinations do not meet the energy efficiency requirement $\tau$, we create low power alternative colours of $e[m_b]$ for background. These alternative colours are monochromatic or analogous colours (i, V types in Figure 4.6) to $e[m_b]$. Hence, the hue of the background will have very small degree of change.

4.4 Power Optimisation for Webpages - Images

Images are the second widely used contents in webpages, next to texts. As shown in previous studies [128], some of the HTML files refer to more than 200 images. Unlike text colours, the colour fidelity of the images (in particular, for foreground images of the webpages) should be retained by any colour mapping process. Hence,
we cannot make large hue changes to images. As discussed above in Section 4.2, power consumption of OLED display, depends on two properties of the content. They are luminance (Figure 4.2) and colour (Figure 4.4) of the content. Basic approaches to save energy relies only on the luminance property. These approaches simply make the images darker to save energy as described below.

**Basic Approach 1 - Linear Darkening.** There is a linear relationship between the luminance of a content and the R,G,B subpixel values as shown in (4.4.2). Linear darkening approach simply reduces the RGB subpixel values uniformly by a constant value to reduce the brightness as shown in Equation (4.4.1). In this approach, saturation of pixel values will result in poor content quality (the image will look overly dark in some areas as shown in Figure 4.15b). If the image is already dark, a large number of pixels will saturate resulting in a flat image with loss of contrast compared to the original image.

\[
\begin{align*}
    r &= r - x \\
    g &= g - x \\
    b &= b - x 
\end{align*}
\] (4.4.1)

**Basic Approach 2 - Gamma Compression.** As discussed in Section 3.3, using $\gamma$ compression the brightness of the content can be reduced without saturating the pixels. However, the image looses its contrast much faster due to compression, resulting in a flat image (Figure 4.15c). If the image is already dark it will get overly saturated even for a small amount of $\gamma$ compression. We have also conducted experiments to study the effect of gamma compression on image quality. In this
experiment, we decreased Gamma from 1 to 0 (Gamma compression) in gradual increments and measure the contrast change of the resulting image. As shown in Figure 4.14 decreasing Gamma (gamma compression) has a gradual yet increasing effect on the contrast.

![Figure 4.14. Change in Contrast vs Gamma](image)

We have developed a new approach to reduce power consumption of images based on both luminance and colours of the image. Our approach handles both properties (luminance and colour) by leveraging on the non-linear response of human eyes to these properties. We call it as Human Visual System (HVS) based colour mapping algorithm. The HVS based colour mapping algorithm uses luminance adaptive colour transformation with minimum loss to the contrast as described in the following paragraphs.

### 4.4.1 Luminance Adaptive Colour Transformation

There is a large difference between the image we display and the image we actually perceive. Human eyes have non-linear response to colour and luminance. For example, if we double the luminance of the display, this does not imply that the perceived
Figure 4.15. Effects of basic approaches on Image Contrast
brightness is doubled too. Biological Visual Systems detect certain wavelengths of light better than other. How well a visual system is able to detect light of a certain wavelength is known as *luminance sensitivity* of the visual system. For example, the luminance sensitivity of the HVS is shown in Figure 4.17. From this we can make the following observations. Human eyes can see light of wavelength 530nm (‘green’ colour) much better than 470nm (‘blue’ colour) and 660nm (‘red’ colour). This means that, a small change in green colour is highly noticeable than red or blue [129]. In addition, a change in red color is relatively better noticeable than a change in blue color. Hence, in our algorithm we apply higher amount of reduction to blue than red and green. Interestingly, this non-linear response of HVS system has a positive effect on OLED power saving. In OLED displays, as shown in Figure 4.16, blue colour consume the highest amount of power across different OLED phone models. With this we can infer that, better energy saving can be achieved by reducing blue intensity with minimum impact on the human perceived quality of the image. However, to implement this we need to determine the ratio of change among the values of R, G and B. To estimate this, we leverage on the ITU-R Recommendation BT.709 [130] to compute the relative luminance from R, G and B values (shown in Equation (4.4.2)). It should be noted that, this formula is derived based on the luminance sensitivity function of HVS (green light contributes the most to the luminance perceived by humans, and blue light the least) [130]. One can also interpret the rationale as follows. The reduction in the value of blue colour has minimum effect on the overall perceived luminance (brightness) as contribution of blue colour to the luminance is very low.

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Figure 4.16. Pixel power models of Goole Nexus One, Samsung Galaxy S and Nokia N85 OLED displays. Axis X represents gamma-corrected linear RGB values [6]

We have derived R,G and B reduction ratio directly from the Formula (4.4.2) as 79:28:93 respectively (shown in Equation (4.4.3)). If the colour is other than red, green and blue, the ratio is interpolated. For example, let the base brightness reduction required be 50. A pure green pixel (0,255,0) is reduced by a value of $50 \times 28 / 255 \times 100\% = 14$. A pure white pixel (255,255,255) is reduced by a value of $50 \times 66.7\% = 33$. Note: $66.7\% = (79 \times (255/255)+28 \times (255/255)+93 \times (255/255))/3\%$.

In general, if a pixel value is $r_1, g_1, b_1$ the percentage of reduction is $(79 \times (r/255)+28 \times (g/255)+93 \times (b/255))/3\%$. In all cases, the amount of reduction applied to each individual subpixel is same. Hence, it retains the hue. Changing R,G,B in different amount will cause a change in hue which results in loss in colour fidelity of the image. However, reducing the pixel values will saturate some pixels and results in loss of contrast. The following paragraph describes mechanisms to minimise contrast loss.
Figure 4.17. Human Visual System Sensitivity

\[ Br = 0.2126 \ r' + 0.7152 \ g' + 0.0722 \ b' \]  \ (4.4.2)

where, \( Br \) is brightness and,

\( r', g' \) and \( b' \) are gamma corrected values of the red, green and blue sub pixels.

\[ \text{ratio}_R : \text{ratio}_G : \text{ratio}_B = (1 - 0.21) : (1 - 0.72) : (1 - 0.07) \]  \ (4.4.3)

**Minimising Contrast Loss.** As shown in the beginning of this section, reducing the brightness of a content results in saturation of pixels which in turn reduces the contrast. HVS is more sensitive to local contrast over global contrast [131, 132]. Perceived brightness of an object depends on the local contrast. For example, Figure 4.18 shows two squares of equal luminance, each with a local background of different luminance [133]. The square appears brighter with dark background as the contrast between them is high. We preserve local contrast by creating a contrast mask of
the image and apply minimum changes to the pixels whose values are important for retaining the local contrast. For example, these pixels could be the pixels in the border between two objects. To generate the contrast mask, we pass the image through a low pass filter such as, Gaussian blur filter suitable blur radius which reduces the image’s high-frequency components. Each pixel value of the blurred copy is then subtracted from the corresponding pixel value of the image to generate the contrast map. (Figure 4.19). The values of the pixels in the local contrast map are normalised and then they are subtracted from the highest value (one) to obtain the local contrast mask (That is, Inverse of the contrast map). The local contrast mask acts as a weight map for applying colour transformation. Each value in the weight map corresponds to a weight, \( W(i) \) that gives the amount of transformation can be applied for pixel \( i \).

### 4.4.2 HVS based Colour Transformation Algorithm

The final colour transformation algorithm which is adaptive to the human eye’s sensitivity to colours and contrast is given in Figure 4.20. The details of the steps in this HVS based colour transformation process is given below.
Figure 4.19. An Image and its Contrast Map
• Generate the contrast mask of the Image and assigns a weight (W) to each pixel $i$.

• Using the HVS based ratio given in Equation (4.4.3), obtain the percentage of intensity reduction ($HVS_P$) for each pixel $i$ as given below.

$$HVS_P(i) = \frac{79 \cdot \frac{r_i}{255} + 28 \cdot \frac{g_i}{255} + 93 \cdot \frac{b_i}{255}}{3}$$

(4.4.4)

where, $r_i$, $g_i$ and $b_i$ are red, green and blue subpixel values of the pixel $i$.

• Adjust the weight W of each pixel $i$ using the percentage of intensity reduction $P(i)$ as follows:

$$W'(i) = W(i) \cdot HVS_P(i)$$

(4.4.5)

• Let $T_P$ be the target power saving to be achieved for the Image. Distribute $T_P$ to all pixels based on each pixel's adjusted weight $W'(x)$.

$$S_P(i) = P_T \cdot \frac{W'(i)}{\sum_{x=0}^{N} W'(x)}$$

(4.4.6)

where, $S_P(i)$ is the amount of power to be saved by pixel $i$.

• Finally, the original $rgb$ values for each pixel $i$ will be reduced according to assigned pixel power saving, $S_P(i)$ to get final $r'g'b'$ values:

$$r' = r \cdot d, \quad g' = g \cdot d, \quad b' = b \cdot d$$

(4.4.7)

with $d$ determines the percentage drop in $rgb$ value for pixel $i$ corresponding to the pixel power saving, $S_P(i)$. 

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4.4.2.1 Algorithm Alternative

An alternative approach is to use the power model of the platform (for example, Figure 4.4 gives the power model for Google Nexus One) to obtain energy efficient colours for each pixel in the image. We call it as *Power Model (PM) based Colour Mapping*. PM based colour mapping process described below can map pixel colours to energy efficient colours while retaining the luminance of the image. However, as it tries to keep the luminance, hue and saturation of the colours close to the original, it can save only a minimum amount of energy ($P_M$). It reduced power consumption by an average of 5%. If the amount of power saved $P_M$ is lower than the $P_T$ (required target power saving discussed above), then the resulting image is darkened further to meet $P_T$ while minimising contrast loss using *local contrast mask*.
**PM based Colour Mapping.** Given a power model for an OLED display, a one-to-one mapping from the original colours to energy efficient colours is generated with some constraints on luminance, hue and saturation of the original colours.

For each colour $C_0$, we want to map it to a $C' = (r', g', b')$ with minimum power consumption subjected to some constrains on the differences between $C_0$ and $C'$. Specifically, given $C_0 = (r_0, g_0, b_0)$, we want to find,

$$C' = \arg \min_C E(C)$$

subject to

$$L(C) \geq L(C_0)$$

$$|H(C) - H(C_0)| \leq a$$

$$|S(C) - S(C_0)/S(C_0)| < b$$

We call this as *energy minimisation problem*. In this problem, $a, b$ are configurable parameters that controls the strictness of the constraints. In our implementation, $a = 9$ and $b = 0.25$ provides the optimal balance between power saving and image distortion. The function $E(\cdot)$ gives power consumption of a pixel in microwatts as given below.

$$E(C = (r, g, b)) = E_R \cdot r + E_G \cdot g + E_B \cdot b.$$  

(4.4.8)

where $r, g, b$ are the gamma-corrected linear $r, g, b$ values of the colour $C$. $E_R, E_G,$ and $E_B$ are platform dependent constants derived from the power model of the platform (Figure 4.4).
The function $L(C)$ is the perceived brightness of colours $C$ derived from equation (4.4.2). The functions $H(C)$ and $S(C)$ are the hue and saturation component of the HSV (Hue, Saturation and Value) colours space. $H(C)$ and $S(C)$ can be computed from RGB colour space as given below:

Hue, $H(C)$, measures the similarity of colours $C$ to well described colours such as red, yellow, magenta, green and blue.

\[
H(C) = \text{atan2}(\sqrt{3} \cdot (g - b), 2 \cdot (r - g - b))
\] (4.4.9)

Saturation, $S(C)$, describes the colourfulness of colours $C$ from greyscale to pure colours.

\[
S(C) = \frac{\max(r, g, b) - \min(r, g, b)}{\max(r, g, b)}
\] (4.4.10)

**Power Model Aware Greedy Search.** The most straightforward solution to the energy minimisation problem is an exhaustive search (brute-force), in which for each pixel its colour $C_0 = (r_0, g_0, b_0)$ is mapped to an energy efficient colour $C' = (r', g', b')$, by searching all possible combinations of $r, g, b$. Though it guarantees to find the optimal solution, its computation time is unacceptably long when the image size is big. For an image of size $n$ pixels, the computational complexity is $O(n \times r_l \times g_l \times b_l)$ where, $r_l, g_l$ and $b_l$ are the number of intensity levels of red, green, and blue components, respectively. Given, the number of levels for $r, g, b$ are same in RGB based colour models, the complexity is, $O(n \times (sp_l)^3)$ where, $sp_l$ is number of
levels for a subpixel.

We can use a greedy algorithm to improve the performance. In our greedy approach, we first consider the high power consuming subpixel colour (for eg. blue). We vary blue gradually, while retaining the green and blue values to find the minimum value of blue which satisfies the constraint. We map \( C_0 = (r_0, g_0, b_0) \) to \( C_g = (r_0, g_0, b_g) \) where, subscript \( g \) stands for potential partial solution obtained through our greedy approach. Then, we consider the next high power consuming colour (for eg. red). We vary red gradually, while retaining the original green \( (g_0) \) and potential blue \( (b_g) \) values to find the minimum value of red which satisfies the constraint. Then finally we fix blue and red to \( (b_g) \) and \( (r_g) \) respectively and gradually reduce green to obtain potential green \( (g_g) \). The potential colour \( C_g = (r_g, g_g, b_g) \) is returned as the result of the greedy algorithm. However, it should be noted that the greedy approach do not yield optimal energy efficient colour. It gives one of the best possible colours. The computational complexity is significantly reduced to \( O(n \times 3(sp)) \).

For a given device power model (Figure 4.4), the mapping of a colour to its energy efficient version is always constant (that is, given colour is always mapped to the same energy efficient colour). Hence, colour mapping for all possible colours in RGB colour space can be precomputed in a powerful computer and stored in the mobile device for runtime application. In such cases, the run time colour mapping of an image to power efficient version can be done in \( O(n) \), where \( n \) is the image size in pixels.
For most of the smartphones the blue pixels consume approximately two times the power of red and blue pixel. Hence, the power model (Figure 4.4) can be easily generalised for most other OLED smartphones with minimum errors (which are device dependent). With such generalisation, the mapping of all colours in RGB colour space to their energy efficient version need to be computed only one and reused in all devices.

**4.4.3 Adapting to Other Contents**

Our algorithm can be adapted to other contents such as video, flash contents and games. For stored video each frame can be pre-processed to generate power efficient versions. For live video streaming, performance is critical. As the average changes between the successive frames in a typical video are minimum, we can store the computed contrast mask values of current frame and apply the same values to the successive frames which are similar to the current frame. Such data are easily obtainable in widely used video streaming formats such as MPEG-2. MPEG-2 stores video frames in GOP (group of pictures) structure, where each GOP contains an I frame and a set of P and/or B frames [134]. I frame (index frame) stores full details about the scene, P frame (predictive frame) store the difference of current frame from the previous I frame, and B frame (backward looking frame) is generated by interpolating current P frame to previous P frame or I frame. The frames are arranged in either I-B-P or I-P-P format, depending on the compression and quality requirements. We can apply our algorithm on the I frames only, and then store the computed contrast mask values in a buffer. These values are applied directly over B and P frames within the same GOP without any re-computation. For a GOP with 15
frames, our computations are done only once. For a 30 fps video, we need to compute values only for 2 frames in a second.

For games, most of the time the maps forming background of a scene is static. Hence, it can be either pre-processed as a single big frame or divided into grids and each grid can be independently pre-processed. As the dynamic parts (moving avatars, weapons etc) are not occupying significant portions of the game screen, their contribution for the OLED power consumption is low.

In addition, saliency features can be used. The studies of psychology and cognitive science have shown that the human perception is attention-based and selective. When watching videos or playing games, not every pixel on the screen is of equal importance to us. In most cases, our visual attention mainly focuses on a salient sub-region of an image. Particularly, in computer games, an user’s attention is focused on the current task, and task-irrelevant details remain unnoticed. These tasks are usually in line with the game’s objective. For example, in first player games (FPS), user’s attention is concentrated in the same direction as his weapon. In adventure games, user’s attention will be scattered. The other factors which define the focus of user’s attention include enemy location, treasure location and other game objective details.

4.5 System Implementation

The text and image colour transformation for smartphone OLED power efficiency can be realised in two different architectures. The complete transformation process can be performed either in a server (centralised) or distributed between the client
Figure 4.21. Centralised Colour Transformation

(smartphone) and server. In the centralised architecture (shown in Figure 4.21), both text and image transformations are done in the central server and the browsers in the client can be simply configured to access the web contents through the central server. There are major advantages with the centralised architecture. Centralised architecture does not cost any additional processing to the client side and is browser independent. However, there will be additional round trip delays. In addition, it should maintain the client state in order to do transformations according to the client’s requirements such as, power efficiency requirement of the client. Frequently accessed contents can be cached to avoid repeated transformations for the same content. The cache helps to reduce the overall energy consumption of the whole system instead of simply mitigating the energy consumption from client to the server side. More cache hits will result in better end-to-end (over all) power saving.
In the distributed architecture (shown in Figure 4.22) the text colour transformation can be done in the client itself. This requires significant changes in the browser engine and the solution becomes browser dependent. In this approach, the additional round trip delay for html texts are eliminated. However, the additional delay to access the energy efficient images remains the same as centralised architecture. Though text colour mapping is not computationally intensive, for some lower end smartphones it introduces more computational latency.

In our current implementation we have implemented the service as a Cloud Service (called, *El-pincel*) which uses centralised architecture discussed above.

### 4.6 Evaluation Methodology

In this section, we present our evaluation methodology. Our goal was to measure the amount of power saved by our system and its impact on the quality of the content.
4.6.1 Quality Measurements - Objective Metrics

As recommended by W3C (discussed in Section 4.3), Chromatic Contrast (CC) (Difference in Hue) and Achromatic Contrast (ACC) (or Colour Brightness Difference) are used as metrics to measure the quality of text in terms of legibility. Traditional metrics for image quality measurement such as, Mean Square Error (MSE) and Peak Signal to Noise Ratio (PSNR) tend to ignore the attributes of HVS perception. As described in Section 4.4, HVS has different levels of sensitivity to different colours and different luminance levels. Hence, we used Global Contrast Loss (GCL) and Structural Similarity Index (SSIM) as metrics to measure the image quality. We define global contrast as the standard deviation among all the pixel values in the image. A low contrast results in the image appearing ”washed out” as all the pixels look similar. For example, if the image is more or less flat (pixel values are close to each other), saturating x% of pixels makes the image complete black. We define GCL as the loss in global contrast between the modified and original content.

To account for HVS, we used SSIM, a more complex metric which accounts for human perception, and is gaining increasing popularity among the image processing community. A detailed description on SSIM is presented in Section 3.4.3.

4.6.2 Quality Measurements - Subjective User Study

As our content transformation techniques are HVS based, the study on the perceived quality with actual human subjects is essential to validate the approach. We did two user studies with 72 student users with different backgrounds. As our service is developed for mobile devices, we let the users view the original and modified contents over the WWW (accessible by any internet connected devices including smartphones).
in various lighting conditions (e.g. office, outdoor, day/night) to validate the practical usability of our service. This Web based application first collects unanimous data about the users and then provides necessary instructions to complete the survey. The user demography is shown in Table 4.1. Appendix C provides more details about the survey application and questionnaire presented to the participants.

<table>
<thead>
<tr>
<th>Total Number</th>
<th>72 (in age group 19-35)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Gender</td>
<td>Male (59), Female(13)</td>
</tr>
<tr>
<td>Photography Experience</td>
<td>Beginner (35), Amateur (28), Semi-professional (7), Professional (2)</td>
</tr>
<tr>
<td>Photo Editing Tool</td>
<td>Photoshop (32), Paintshop Pro (3), others (44). [some use more than 1]</td>
</tr>
<tr>
<td>Web Development Experience</td>
<td>Beginner (34), Amateur (25), Semi-professional (12), Professional (1)</td>
</tr>
<tr>
<td>Web surfing per day using smartphones/tabs</td>
<td>Never (17), 1-5 Hrs (47), 5-10 Hrs (1), more than 10 hrs (2)</td>
</tr>
</tbody>
</table>

**Table 4.1.** Demographics Statistics for the User Study

Our first user study compares the original and the modified versions of web pages for various energy efficiency settings. Users were asked to rank the readability of the text with 3-point Likert Scale, where one indicates hard to read, two indicates readable with some efforts and three indicates clearly readable. The users also ranked harmonicity of the colours of the page contents with 3-point Likert Scale, where one indicates not harmonious, two indicates somewhat harmonious and three indicates harmonious. Each user was presented with 20 web pages from a pool of original, 20%,
Figure 4.23. Study on Readability and Colour Harmonicity

40%, 60% and 80% power saving versions of the web pages. A sample screenshot for one of the pages is shown in Figure 4.23.

Our second user study compares our image manipulation technique with the basic approaches. We gave a pair of images from a pool of 20%, 40%, 60% and 80% power saving versions of images generated using simple darkening, relative darkening, our HVS based approach and its variation PM based approach. We presented 40 image pairs in random order to the users. A sample of which is shown in Figure 4.24. The users were asked to select the most visually appealing image in each pair. The background was set to pure black to avoid distraction while comparing the images.
4.7 Evaluation Results

In this section we first describe the results for colour transformed webpages as a whole including text, background and images. Then, we present additional results on the HVS based image manipulation algorithm.

4.7.1 Evaluation Results of Colour Transformed Webpages

The results of accessing web pages on a Google Nexus One smart phone with and without the cloud service are given in Figure 4.25. The results are shown for saving around 20%, 40% and 60% power. The power saving level is a user selectable parameter in the cloud service. The chromatic contrast of the texts in original pages are 700-800 and that of the modified pages are 650-700. The achromatic contrast (brightness contrast) are 200-250 and 175-220 for original and modified pages respectively. W3C recommended values for minimum chromatic and a chromatic contrast are 500
and 125 respectively [117]. The transformed pages maintain this requirement while saving required amount of display power.

We have used a mixed set of popular and unpopular websites for the user study. These sites are wordpress.com, apple.com, netlingo.com, foohack.com, anuflora.com and clickbank.com. We have selected the pages with less Flash contents as the service is yet to evolve to handle Flash. After removing six invalid users (selected same option for all) with biased entries, the final results are presented in Figure 4.26. The score is the sum of the Likert scale options (three, two or one) selected by users, where three indicates the best quality. The pages are displayed in random. For up to 60% energy saving, the transformation achieves good legibility and harmonicity score close to or higher than the original version while up to 80% is acceptable for most users.

### 4.7.2 Evaluation results of HVS based Image Manipulation Algorithm

We have selected a random set of six images from Kodak test image database [136] for evaluation. For objective analysis we have applied all these approaches on the original images while keeping constant power saving. Power and quality measurement for three images (out of six due to space constraint) and their power optimised versions are shown in Figure 4.27. All approaches are calibrated to consume roughly same amount of power. As expected the linear darkening approach provides lower GCL. However, it experiences lower PSNR and MSSIM. The gamma compression approach gives better MSSIM while its GCL is high making the images flat. However, our approaches (HVS based and PM based) perform better in both the parameters and ensures better visual quality.
Figure 4.25. Web Page Transformation with El-pincel
Scores for Readability: 1 - hard to read, 2 - readable with some efforts and 3 - clearly readable.
Scores for Harmonicity: 1 - not harmonious, 2 - somewhat harmonious and 3 - harmonious.

power(xx%) - is the amount of power saved by the transformed page.

Figure 4.26. Web Page Transformation - User Study