Politecnico di Torino

Energy Management for IoT
01UDGOV

Master's Degree in Computer Engineering

Report lab 2

Energy efficient display

Candidates:
Fabio Delbosco (S322244)
Tommaso Montedoro (S329567)

Referee:
Prof. Massimo Poncino

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CHAPTER 1

Introduction Chapter

The purpose of this laboratory is to prove how manipulation of images can lead to power saving in emissive display. The focus is pointed on the quality vs power saving tradeoff, in the following we examine how different transformation can be implemented to reduce power consumption and what are their impact on the fine image percivance. The report is divided in 2 chapters:

1. Day one - Energy efficient image processing
2. Day two - Dynamic voltage scaling

CHAPTER 2

Preliminary Concepts

When working with OLED displays, the panels consist of millions of pixels made up of Organic Light-Emitting Diodes (OLEDs). Unlike traditional LCDs, they do not require an external backlight; instead, each pixel is composed of three sub-pixels that emit different colors of light: red, green, and blue. Since there is no backlight dominating power consumption, it is evident that color selection directly impacts the energy consumption of the device.

Various techniques can be employed to take advantage of this characteristic and reduce the power consumption of certain pixels. These techniques involve applying transformations in different color spaces. Below, we introduce some of these, which will be used in our work to modify images and analyze the resulting power savings.

2.0.1 RGB Color Space

The RGB (Red, Green, Blue) color space is the most commonly used representation in digital displays. It is an additive color model where different intensities of the three primary colors combine to produce a wide range of colors. In OLED screens, each subpixel (R, G, and B) emits its own light, meaning that power consumption is directly related to the intensity of each channel. Brighter colors, particularly white, require higher energy consumption, whereas black pixels consume almost no power due to the nature of self-emissive OLED technology.

2.0.2 LAB Color Space

The LAB color space is designed to be perceptually uniform, meaning that equal differences in values correspond to equal perceptual differences in color. It consists of three components:

- **L*** (Lightness): Represents the brightness level.
- **a*** (Green-Red axis): Defines color variation between green and red.
- **b*** (Blue-Yellow axis): Defines color variation between blue and yellow.

The LAB space is particularly useful for color correction and perceptual optimization of images. In the context of OLED displays, LAB transformations can be leveraged to adjust brightness and color while minimizing energy consumption.

2.0.3 HSV Color Space

The HSV (Hue, Saturation, Value) color space is often used in image processing because it separates chromatic content from brightness information. It consists of:

- **Hue (H)**: Represents the color type (0-360°).
- **Saturation (S)**: Indicates color intensity (0-100%).
- **Value (V)**: Represents brightness level (0-100%).

Since OLED displays consume less power with lower brightness, HSV-based transformations allow for **power-efficient modifications** by adjusting the Value (V) channel while maintaining color fidelity.

2.0.4 Impact on OLED Power Consumption

Each color space provides different ways to manipulate images while considering power efficiency. The RGB model directly affects OLED power consumption since higher intensity values increase energy usage. LAB and HSV transformations, however, enable techniques such as brightness adjustments and color remapping, which can help **reduce power consumption without significantly affecting visual quality**.

CHAPTER 3

Day one - Energy efficient image processing

This chapter presents the implementation and the result obtained by applying the various strategies, three subsets of images are used to test the various transformations and extract the results. First dataset consist of .tiff image representing people, landscape and object mostly with a wide, flat background. The second one is the biggest one, it contains mainly natural images taken from the BSDS500 training set and the last one is a subset of 5 screens of a laptop. We expect that different types of images will react differently to the various transformations, depending on their conformation and different colour range.

Figure 3.1: Dataset 1

Figure 3.2: Dataset 2

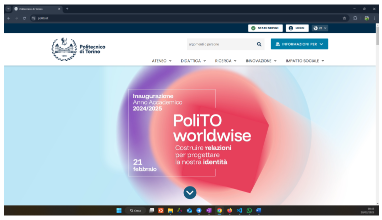

Figure 3.3: Dataset 3

3.1 Image processing workflow

To be able to work with image and estimate the consumption of each we used a power model. Each pixel of the image is analyzed, the power consumed by each of them is given by the formula 3.1. Then each pixel contribution is summed together and added to the static power, independent of the pixels values 3.1

$$P_{pixel} = W_R * R^Y + W_G * G^Y + W_B * B^Y$$

$$P_{image} = W_0 + \sum_{i=1}^{n} \{P_i(R, G, B)\}$$

Y	W_0	W_R	W_G	W_B
0.7755	1.48169521*10-6	2.13636845*10-7	1.77746705*10-7	2.14348309*10-7

The second metrics we used is the image Distortion, this is a quantitative value that represent the difference between 2 images by comparing them in the L*a*b space, a three-dimensional model that encapsulates Lightness (L) and two color-opponent dimensions: Green-Red (A) and Blue-Yellow (B). Thanks to this representation we are able to compute the Euclidean distance between the two and so the Distortion value.

$$\epsilon(image_i, image_j) = \sum_{k=1}^{n}(\sqrt{(L_{i,k} - L_{j,k})^2 + (a_{i,k} - a_{j,k})^2 + (b_{i,k} - b_{j,k})^2}) \tag{3.1}$$

3.1: Distortion between 2 images. N = number of pixels, k = k^{th} pixel

Distortion computation is usefull for the real metrics we used such as the % distortion 3.1

$$\%DIST = \frac{\epsilon(image_i, image_j)}{W * H * \sqrt{(100^2 + 255^2 + 255^2)}} * 100$$

3.1.1 Workflow

The workflow we used to extract our data is consisted on:

- Create a useful transformation
- Take an image as reference and calculate the initial power contribution
- Apply the transformation on the image and calculate the power gain and distortion percentage
- If the two metrics are acceptable so apply the transformation on the dataset

3.2 Transformations

3.2.1 Hungry-red vs Hungry-blue

To start our work, we implement some simple transformations on the RGB channels. Hungry-Blue and Hungry-red reduces the value of the blue and the red channel, this will reduce the power contribution of the pixels according to the power model. We implement two type of these transformation each:

- Channel scaling: for this version a constant $k < 0$ is passed to the function as parameter, so all the channel value are scaled accordingly.
- Channel lowering: in this case a constant $k > 0$ is selected to be substracted from the channel value for all the pixels.

We chose to implement these two transformations first because of our power model, this tells us that these two channels are the most energy consuming. We applied these transformations for all of three datasets 4 times and evaluated the results obtained with different transformations parameters. For the scaling versions the used parameters are 0.60, 0.70, 0.80, 0.95, for the channel lowering instead we use multiple of 5 from 5 to 20 in order to get some impacting transformations.

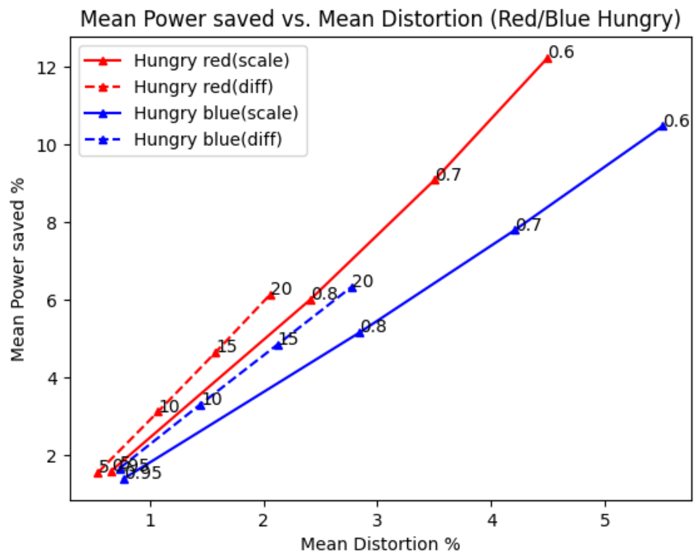

Figure 3.4: BSDS500 Dataset: Power/Distortion tradeoff Hungry-red and Hungry-blue

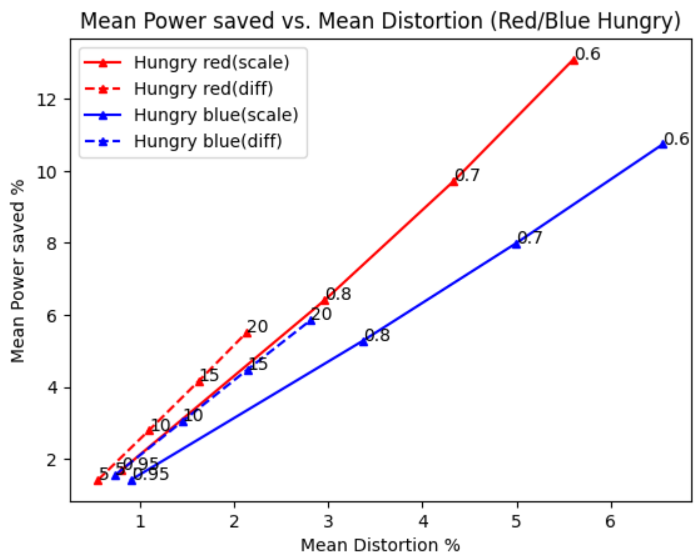

Figure 3.5: Tiff Dataset: Power/Distortion tradeoff Hungry-red and Hungry-blue

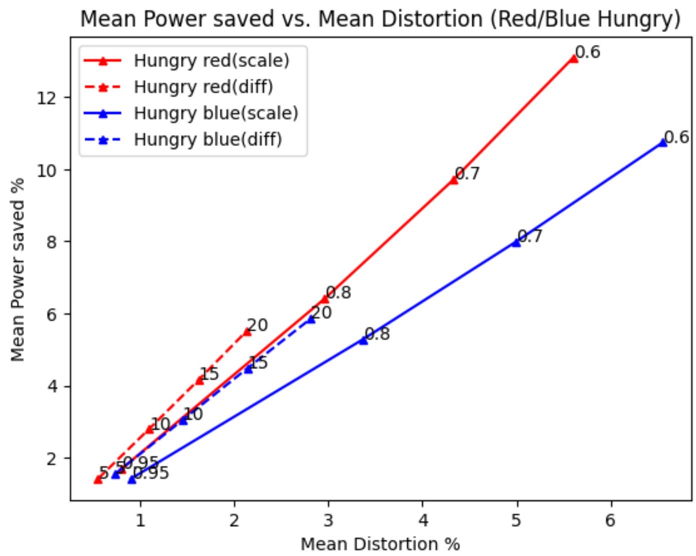

Figure 3.6: Screen Dataset: Power/Distortion tradeoff Hungry-red and Hungry-blue

Those are the graph that represent the mean Power gain percentage in function of the mean Distortion percentage. As we can see the results are all pretty the same for the three different dataset, the emerging details is that the red channel is the one that have, in mean, the most contribution in our datasets. Reading the graph is clear the fact that the most effective transformation, that gain much power consumption while keeping pretty low distortion is the Hungry-red. The distortion percentage we are interested on are the lower one 1% ,2%, 3%, and for all of the three the best transformation is always the same in this case. So we apply Hungry red(diff), with 20 as hyper parameter, to the whole set of images, to see if there are high frequency of big outliers, and poor freq in the mean region or if the transformation is effective.

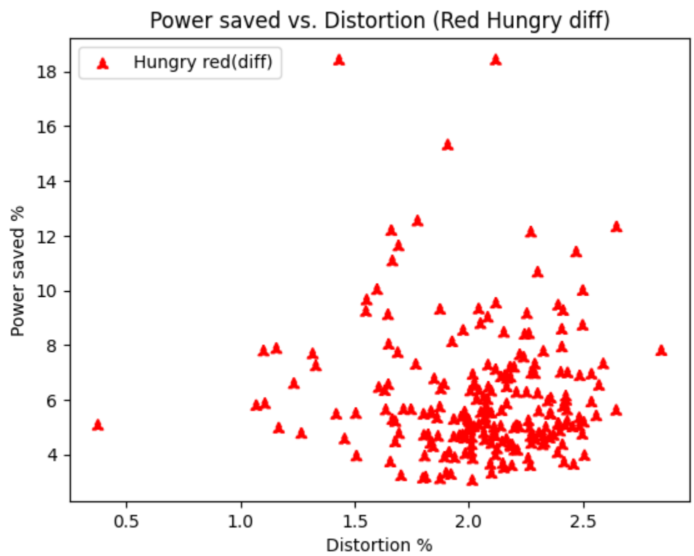

Figure 3.7: Red-Hungry diff 20 for all the test images

As show in 3.7 there are no big frequency of outliers apart from some exception, so this transformation can be useful if applied basically on all the images always remaining in the 0.5%-2% distortion range. The min-max power gain image are shown in 3.11 and 3.8 with their color graph contribution. Those data show, as expected, that the red contribution of those two images are practically one opposite of the other, the first image show a poor red contribution and as consequences low power gain and distortion percentage. All the opposite for the second image, this present an high frequency contribution of pixel with high red value that lead to huge power gain after the transformation.

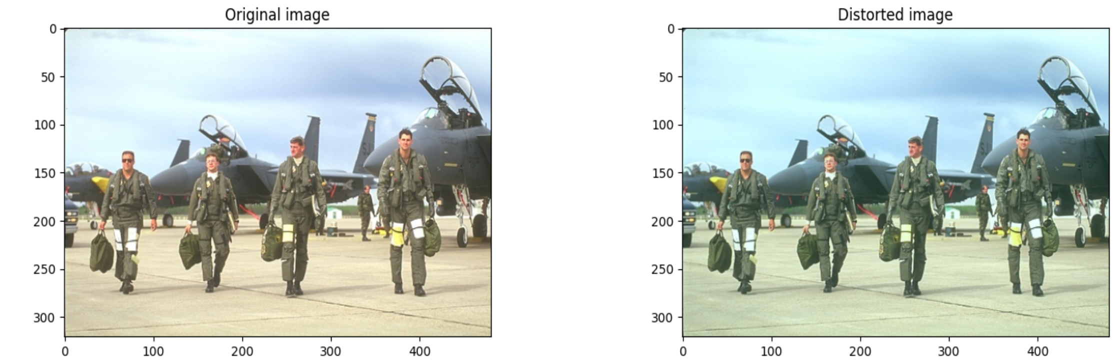

Figure 3.8: Minimum gained power percentage 3.07% distortion 2.01% image

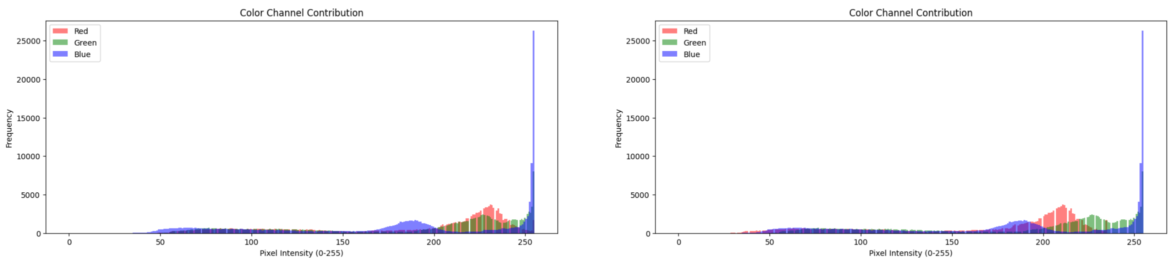

Figure 3.9: RGB channels contributions before and after the trasformation

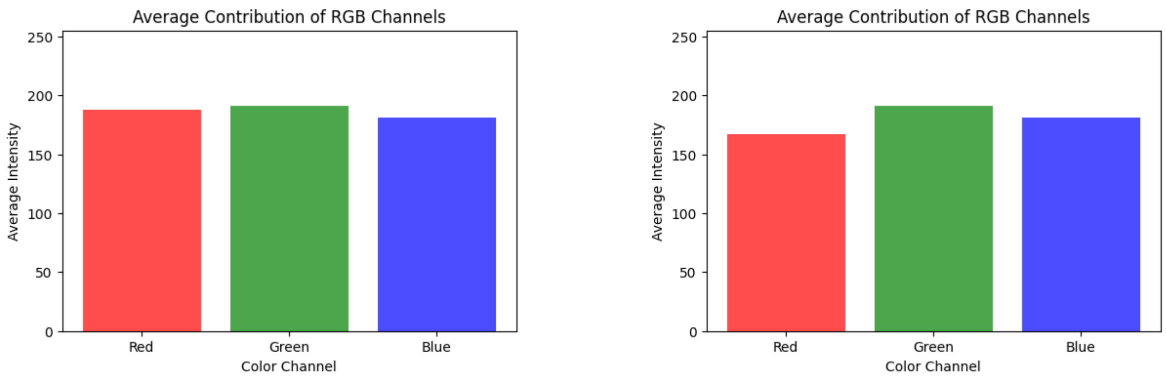

Figure 3.10: Average contribution of the three channels, red one is pretty the same as the G and B channels

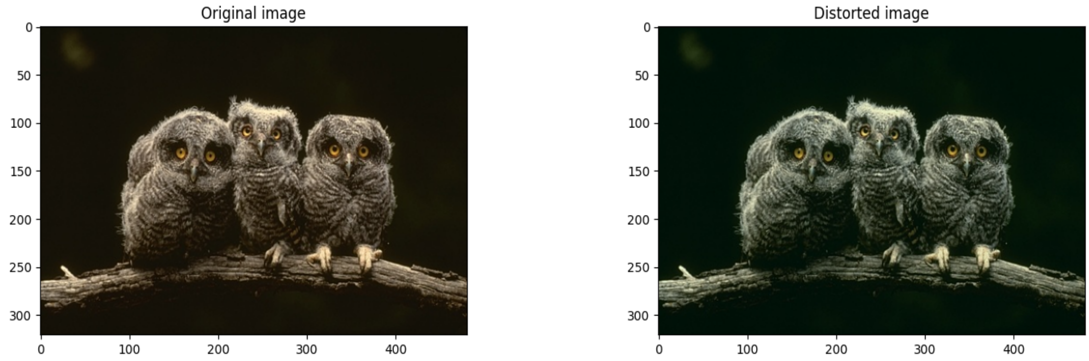

Figure 3.11: Maximum gained power percentage 18.45% distortion 2.11% image

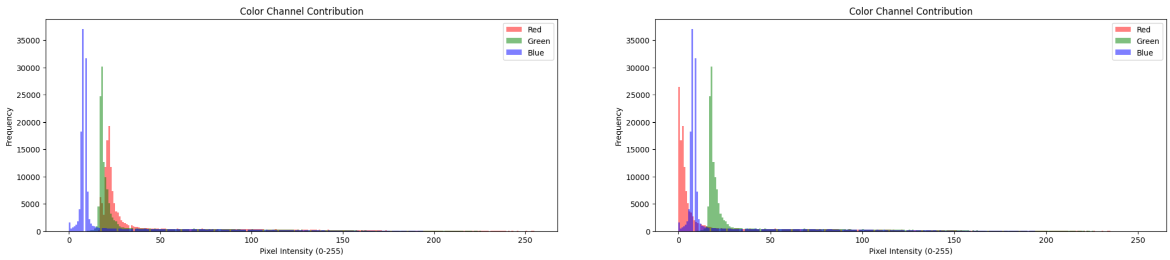

Figure 3.12: RGB channels contributions before and after the trasformation

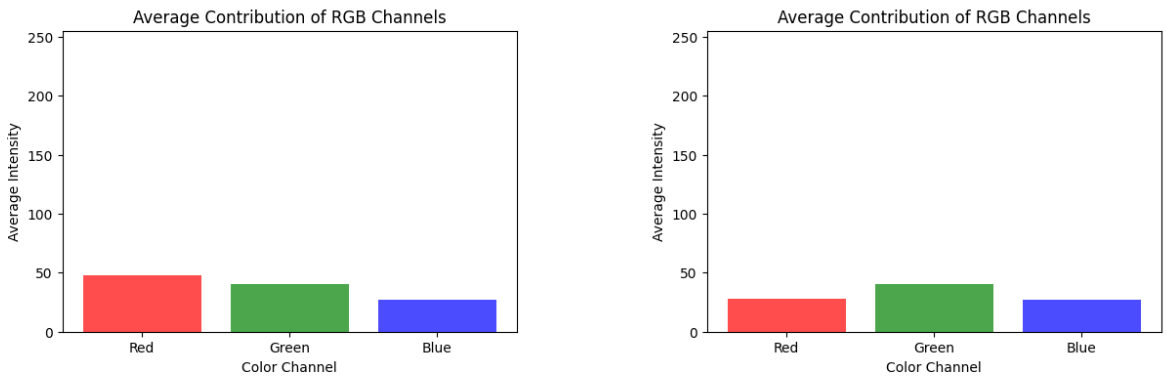

Figure 3.13: Average contribution of the three channels, red channel still has pretty same contribution as the other two so distortion is still low

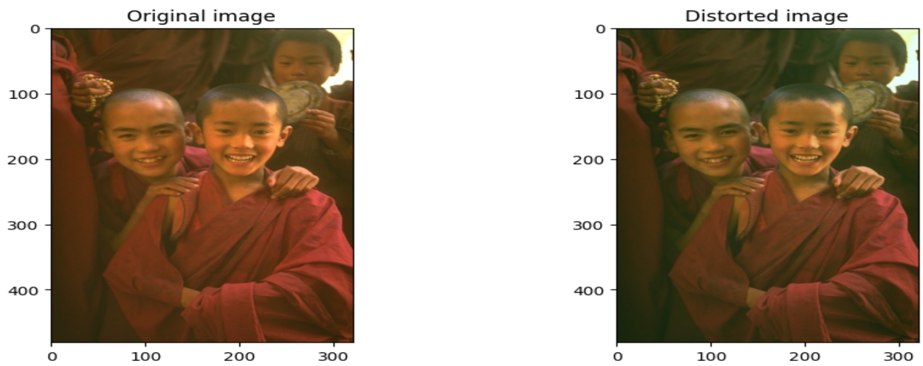

Figure 3.14: Minimum gained power percentage 7.82% distortion 2.84% image

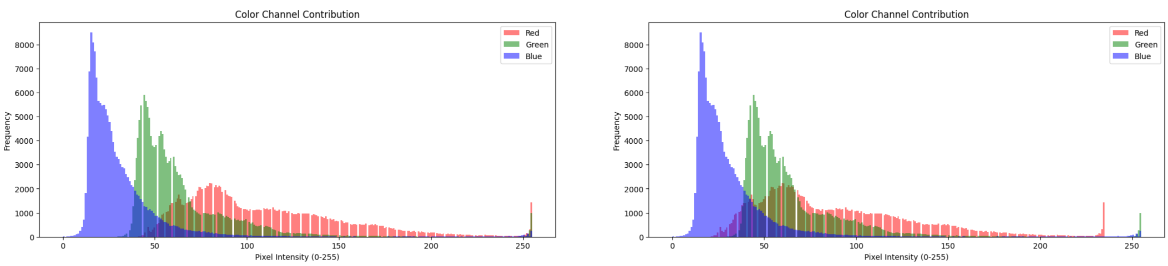

Figure 3.15: RGB channels contributions before and after the trasformation

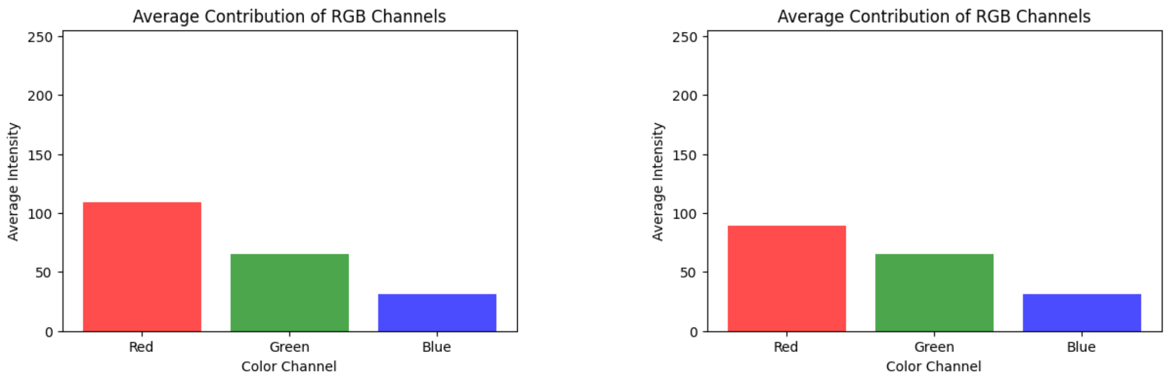

Figure 3.16: Average contribution of the three channels, red channel contribution dominates the other two so there will be a bigger distortion after the transformation

3.2.2 Histogram Equalization in the HSV Color Space

Histogram Equalization (HE) is a technique used to enhance image contrast by redistributing pixel intensities across the entire available range.

When applied to the **Value (V) channel**, HE increases overall brightness contrast, making dark regions brighter and bright regions darker, enhancing details in both shadows and highlights. This transformation can lead to excessive contrast in certain cases.

On the other hand, applying HE to the **Saturation (S) channel** modifies the intensity of colors without affecting brightness. This can make colors appear more vivid and well-distributed, preventing areas from looking washed out or oversaturated.

Here below are reported the graphs showing the results after the application of this transformations in each of the three datasets.

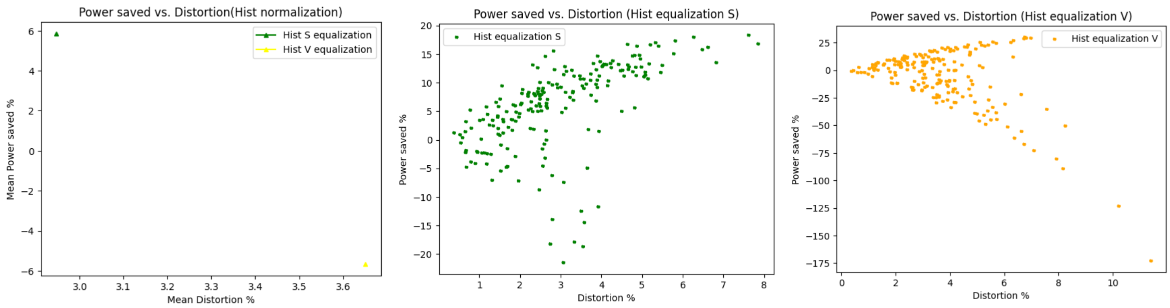

Figure 3.17: BSDS500 Dataset: mean Power/Distortion tradeoff of hist equalization on S and V channels and scatterplot of each image transformation

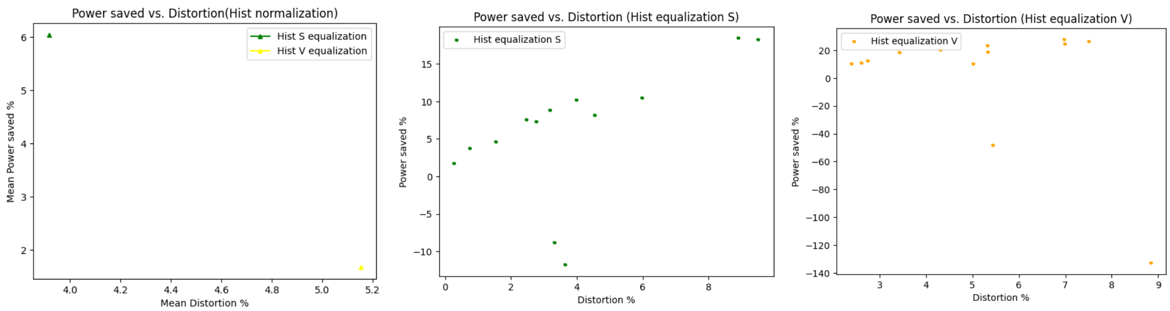

Figure 3.18: Tiff Dataset: mean Power/Distortion tradeoff of hist equalization on S and V channels and scatterplot of each image transformation

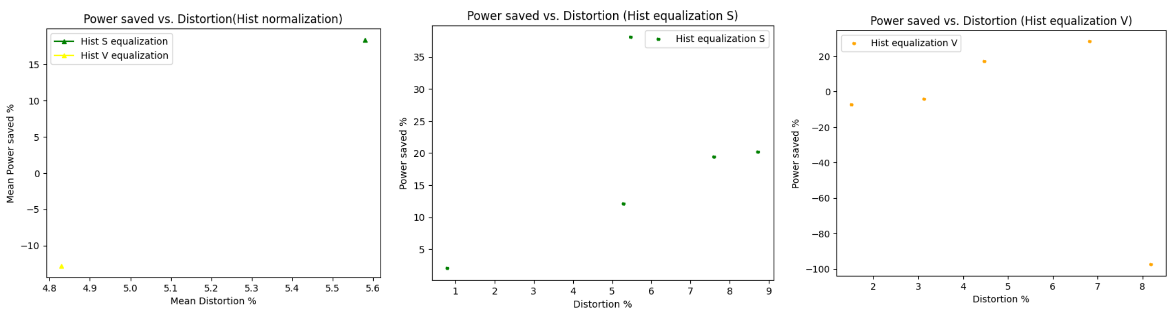

Figure 3.19: Tiff Dataset: mean Power/Distortion tradeoff of hist equalization on S and V channels and scatterplot of each image transformation

As we can see, the results given by these transformations are not very effective in general. If we look at the graphs, we can see large outliers in all three datasets, especially in the first, the largest one. Therefore, these transformations are not so effective for our images in all of the three dataset because of the inconsistency on results, this can be explained by the composition of best and worst image transformation.

By applying hist equalization on the S channel, the images with the worst power gain will all be those with an already high color saturation originally. The transformation will flatten the contribution of each pixel by decreasing the saturation of the image. As far as hist equalization on the V channel is concerned, on the other hand, the worst results will appear when the starting image is already a very dark image. The transformation will flatten the graph, increasing the contribution of high-brightness areas, thus increasing energy consumption.

Both of them will result in a high distortion value if the original image saturation or brightness contribution is not pretty uniformly distributed.

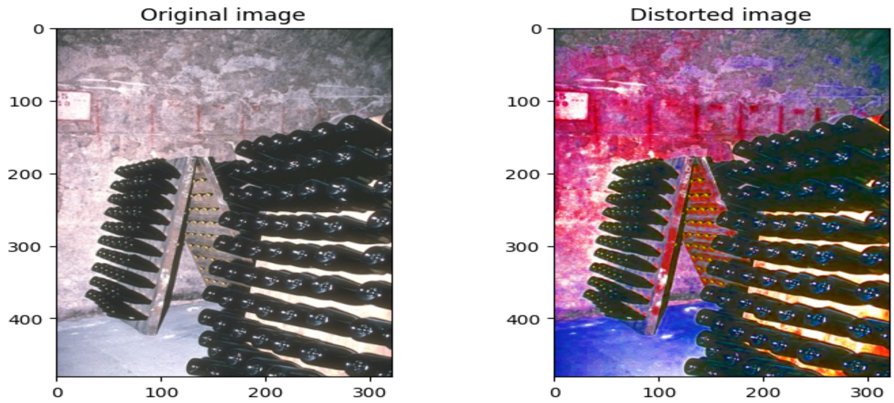

Figure 3.20: Maximum gained power percentage 18.30% but high distortion 7.62% image

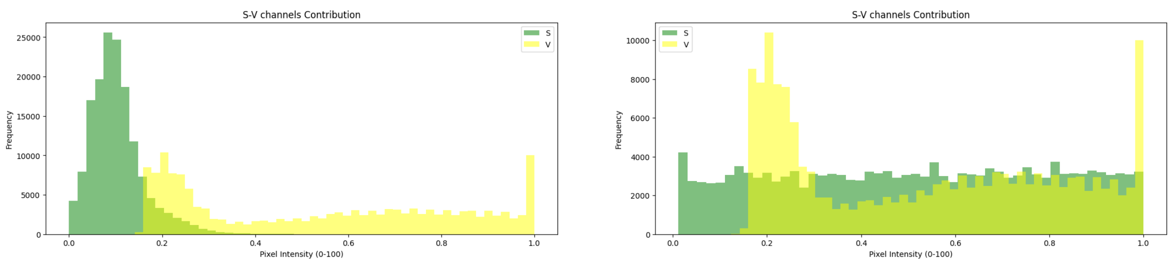

Figure 3.21: S-V graph contribution after and before S hist equalization

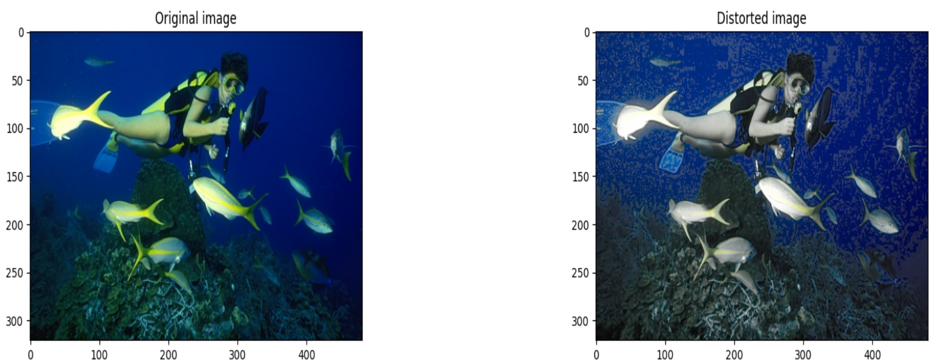

Figure 3.22: Increase power contribution by -21.48% with S hist equalization

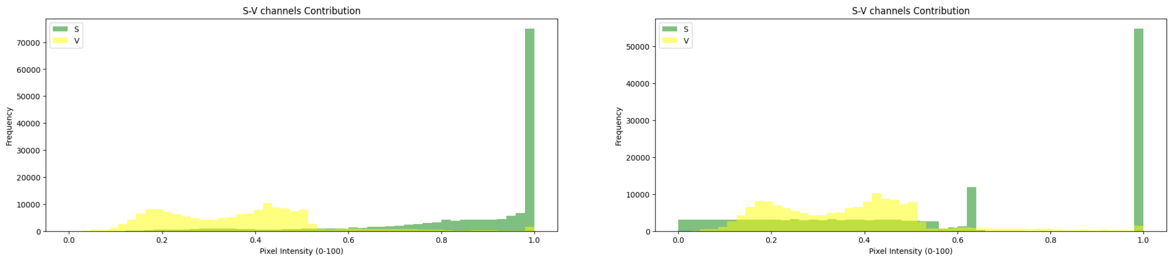

Figure 3.23: Low saturated area will be risen and the frequency of the high saturated onces are lowered

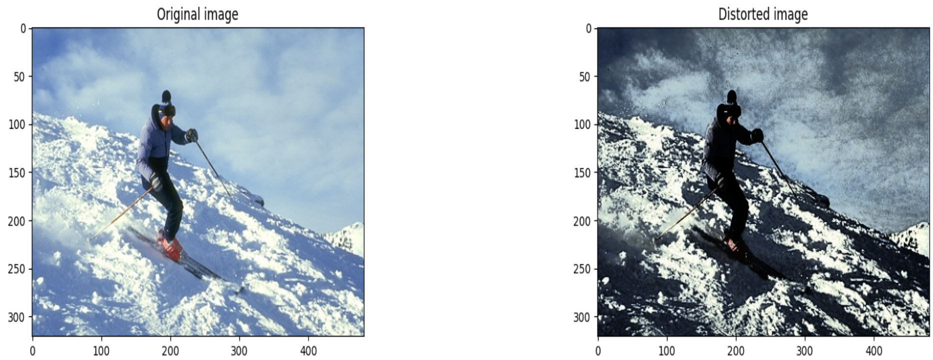

Figure 3.24: Maximum gained power percentage 30.07% but high distortion 6.76% image

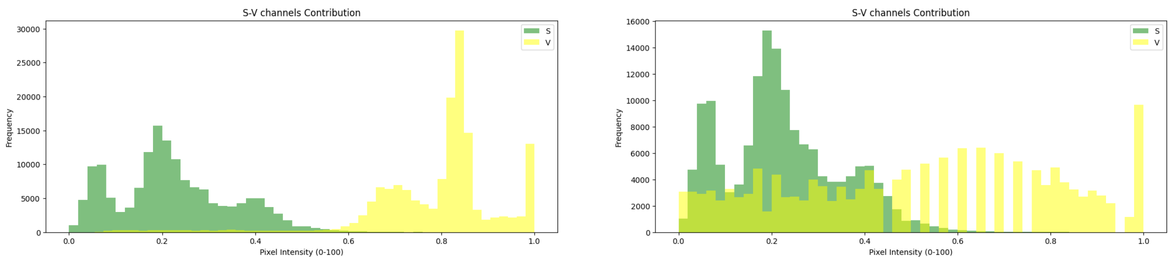

Figure 3.25: Image brightness is drastically lowered after V hist equalization

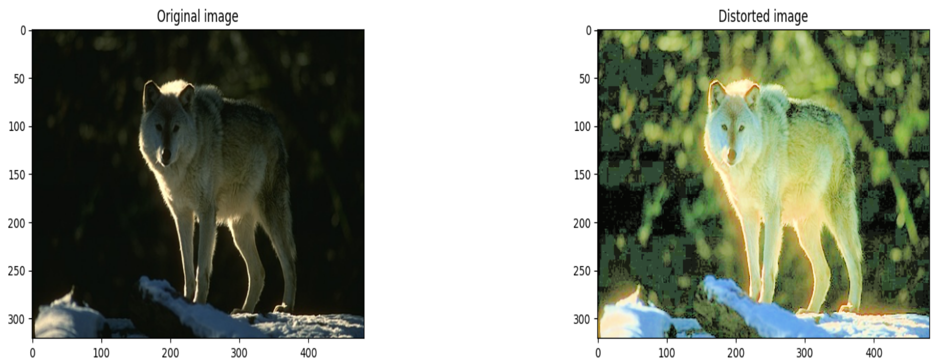

Figure 3.26: Increase power contribution by -172.97% with V hist equalization

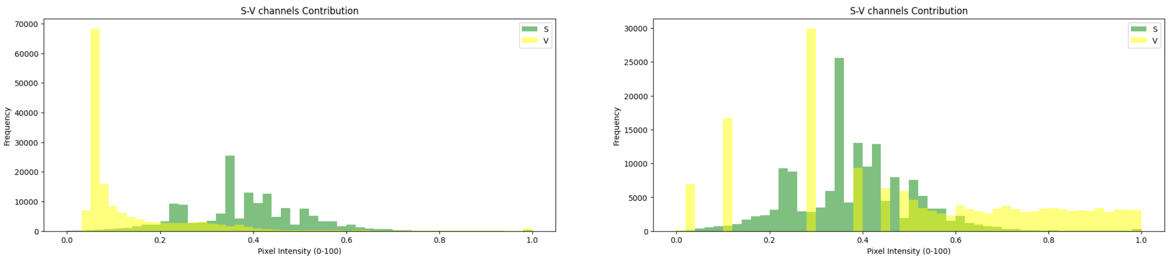

Figure 3.27: The image has already low brightness the transformation increasing it

3.2.3 HSV space transformation

Histogram equalization has shown promising results for certain images. Therefore, we will continue exploring transformations within this color space to achieve a better balance between power consumption and distortion. As discovered in the previous section, we now know that low saturation and high color brightness can make an image darker and thus save power. The goal then is to create a transformation that can adjust these two parameters, trying to improve power efficiency without creating a high image distortion. We therefore planned to apply the transformations individually, first by increasing saturation, and then separately by decreasing brightness, with various hyper parameters. The graphs below show excellent results; in fact, at all points the two transformations overperform the other two previous transformations.

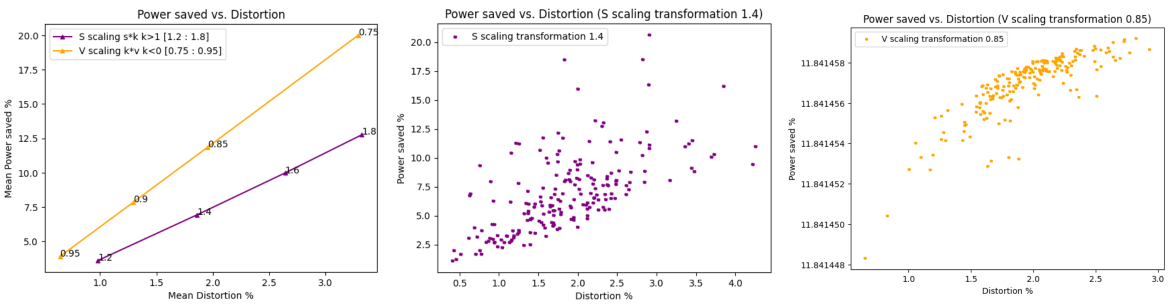

Figure 3.28: BSDS500 Dataset: mean Power/Distortion tradeoff of scaling on S and V channels and scatterplot of each image transformation in both cases

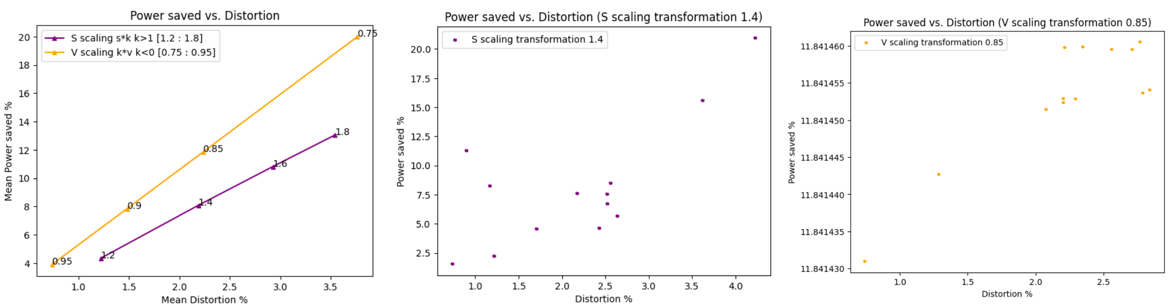

Figure 3.29: Tiff Dataset: mean Power/Distortion tradeoff of scaling on S and V channels and scatterplot of each image transformation in both cases

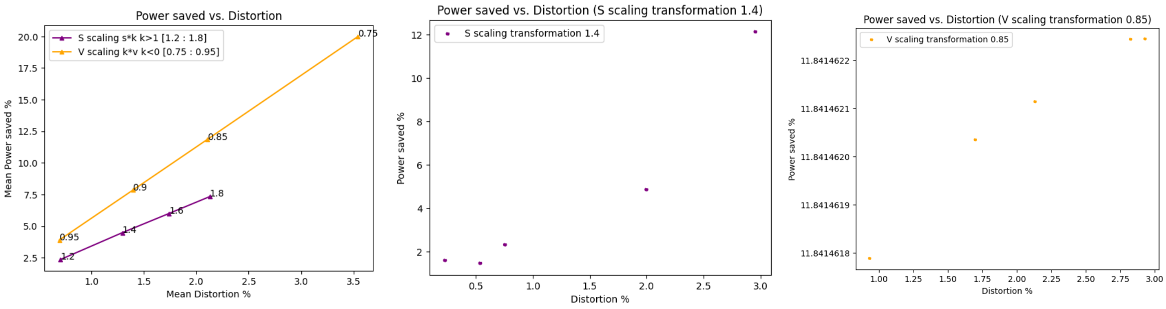

Figure 3.30: screen Dataset: mean Power/Distortion tradeoff of scaling on S and V channels and scatterplot of each image transformation in both cases

As delighted by the graph the BSDS graph, which as more image, the tranformation applied by scaling the value on the V channel is the best effective one. Also Power gain/Distortion tradeoff is more stable through the whole dataset. The last three plot, showing the results on the screen dataset, denotes an high difference between the two transformation because of the composition of the dataset.

3.2.4 Best transformation and comparison between all transformations

After the results of the last transformation it was clear for us that the best possible transformation should be a combination of the last two. So we use some combination of the previous parameters to compute the new transformation, tune it as well and reach the best possible Power gain. As shown below, this combination is outperforming the others and it result the best one for all the Distortion percentage from 1% to 3%.

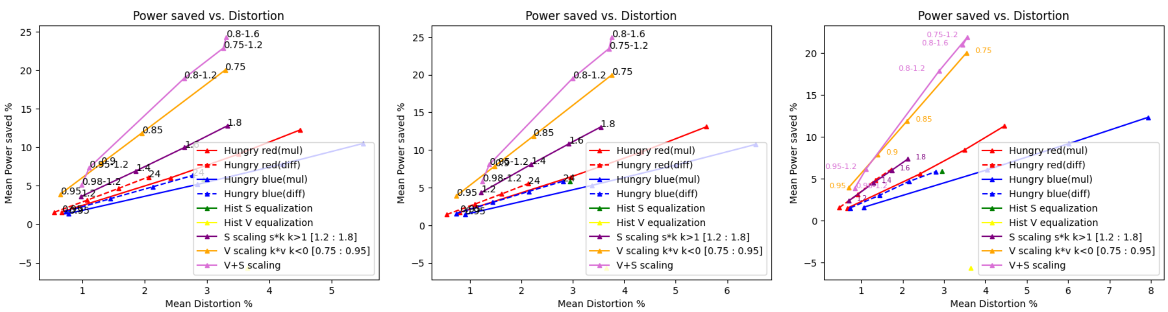

Figure 3.31: Transformation comparison for all the three datasets in exam

Pretty same result are seen in the three different dataset, so we were sure that this is the most effectiveness and general possible transformation. Here below are reported images representing best/worst gaining power and the onces with best/worst distortion percentage.

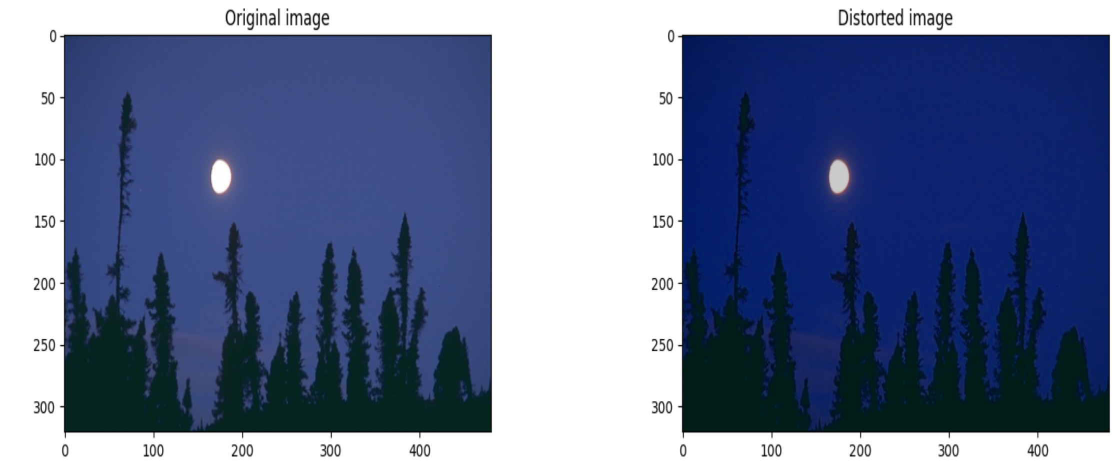

Figure 3.32: Max power gain - power gained: 36.50% distortion from original: 4.85%

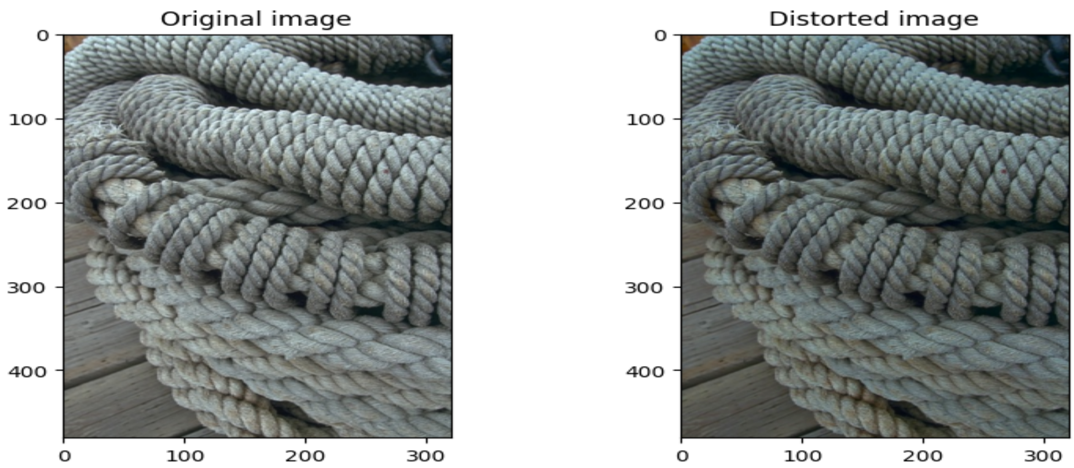

Figure 3.33: Min power gain - power gained: 17.26% distortion from original: 2.64%

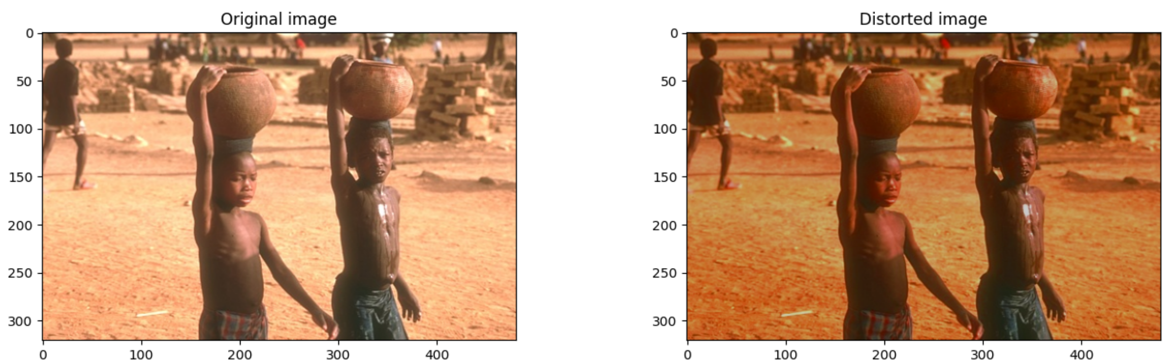

Figure 3.34: Max distortion - power gained: 30.11% distortion from original: 6.07%

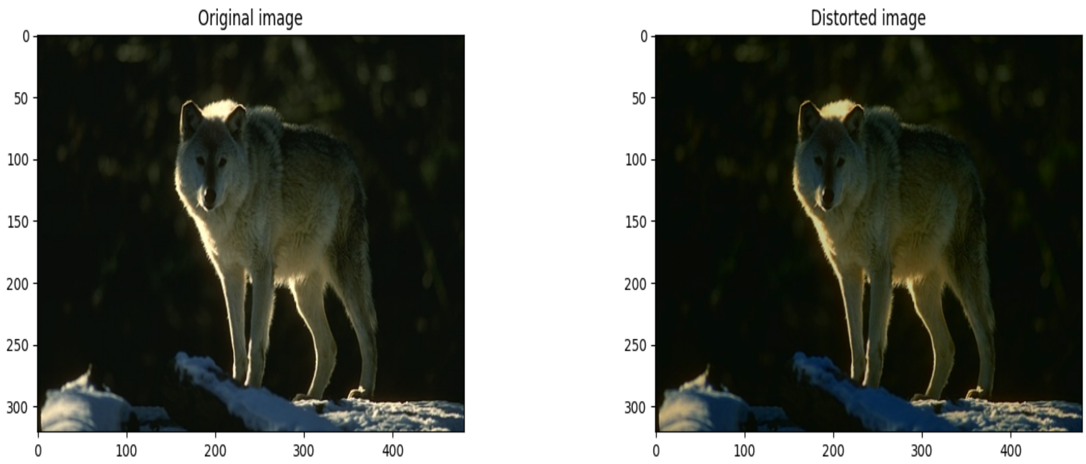

Figure 3.35: Min distortion - power gained: 24.70% distortion from original: 0.96%

CHAPTER 4

Day two - Dynamic Voltage scaling

4.1 Application of Voltage Scaling in OLED Displays

Dynamic Voltage Scaling (DVS) is a technique used to reduce power consumption in OLED displays by adjusting the supply voltage (V_{DD}). Since the voltage supply directly influences the maximum current that can flow through an OLED pixel, modifying V_{DD} affects the brightness and color representation of an image.

To simulate this effect, we use the function `displayed_image`$(I_{\text{cell}}, V_{DD})$, which takes an input image represented as a matrix of pixel currents and applies voltage scaling to determine how the image is displayed at a lower V_{DD}. The function follows these key steps:

1. **Compute the Maximum Current at the New Voltage:** The maximum possible current for a given V_{DD} is calculated using the following equation:

$$I_{\text{max}} = \frac{P_1 \cdot V_{DD}[255, 255, 255]}{255} + \frac{P_2[255, 255, 255]}{255} + P_3 \tag{4.1}$$

   where P_1, P_2, and P_3 are model parameters defining the current-voltage relationship in the OLED display.

2. **Determine the Maximum Displayable RGB Value:** The corresponding maximum RGB intensity that can be displayed without distortion is derived as:

$$RGB_{\text{max}} = \frac{I_{\text{max}} - P_3}{P_1 \cdot V_{DD} + P_2} \times 255 \tag{4.2}$$

   Any pixel whose current exceeds I_{max} will have its RGB value **clamped** to RGB_{max}, preventing colors from exceeding the display's capability at the reduced voltage.

3. **Saturation of Exceeding RGB Values:** When the calculated pixel current surpasses I_{max}, the corresponding pixel is assigned the maximum allowable RGB value, ensuring the image remains visually coherent under the new power constraints.

By applying this method to an image dataset, we can analyze the impact of voltage scaling on power savings and image fidelity. The effectiveness of this transformation is evaluated based on power reduction and distortion percentage, ensuring a balance between energy efficiency and visual quality.

4.1.1 Image compensation

Image compensation consists of various techniques aimed at adjusting the contrast and brightness of an image that has been distorted, for example, due to the application of Dynamic Voltage Scaling (DVS). The most common methods are **Brightness Scaling** and **Contrast Enhancement**, which are usually applied to the HSV color channels.

4.1.2 Contrast Enhancement

This transformation is used when it is necessary to maintain the difference between the brightest and darkest colors constant. Contrast amplification is achieved by multiplying the brightness value in the HSV space by a scaling factor b, where $b > 0$:

$$V' = V \cdot b \tag{4.3}$$

The parameter b depends on the original voltage V_{orig} and the new voltage V_{new}. To estimate b, we use the formula in Equation 4.4, since, as highlighted in Equation **??**, the maximum current (which determines the maximum RGB value) is directly dependent on the new voltage. Contrast enhancement is a multiplicative operation on pixel values, so b can be estimated as:

$$b = \frac{V_{\text{new}}}{V_{\text{old}}} \tag{4.4}$$

10V	11V	12V	13V	14V
0.67	0.73	0.8	0.86	0.93

Table 4.1: Contrast enhancement scaling factor b for different voltages.

4.1.3 Brightness Compensation

This transformation is used when it is necessary to maintain a uniform brightness level throughout the image. To achieve this, an additive operation is applied to the brightness value in the HSV space:

$$V' = V + b \tag{4.5}$$

To estimate b, we use Equation 4.6. The main idea is that voltage variation influences brightness intensity, so b can be expressed as the relative variation of the voltage with respect to the initial value:

$$b = \frac{V_{\text{new}} - V_{\text{old}}}{V_{\text{old}}} \tag{4.6}$$

10V	11V	12V	13V	14V
-0.33	-0.26	-0.2	-0.13	-0.06

Table 4.2: Brightness compensation factor b for different voltages.

4.2 Experimental Results

To evaluate the effectiveness of these techniques, we applied DVS to all images, divided by dataset, in three different ways:

1. Without any image compensation.

2. With **Brightness Compensation** after DVS.
3. With **Contrast Enhancement** after DVS.

All transformations were applied at fixed voltage values to allow a fair comparison using a valid metric.

The plots compare the three transformations applied to the three datasets separately. The samples represent voltages ranging from 14V to 10V. At first glance, it appears that all three transformations yield similar results, particularly when comparing individual samples. In fact, contrast enhancement seems nearly identical to the transformation that relies solely on DVS. However, this assumption is misleading because distortion percentage alone is not a reliable metric for evaluating image perception.

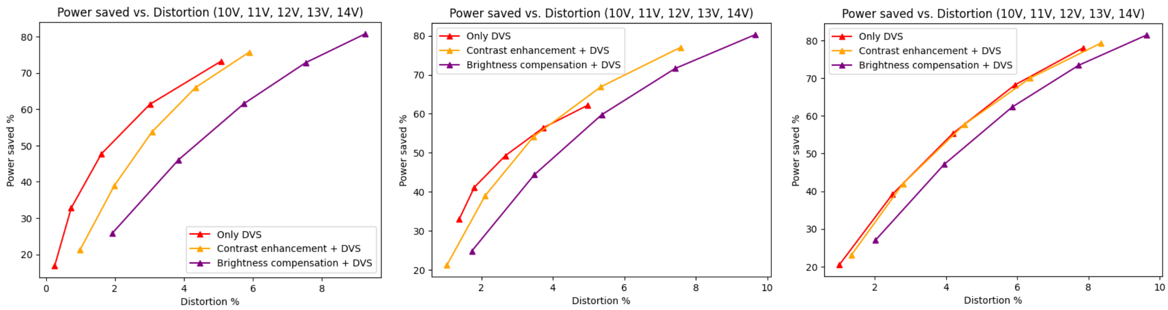

Figure 4.1: Transformation comparison for all the three datasets in exam

Instead, we analyzed the luminance of the images and its potential effects on the distorted versions. As shown in the plots, brightness compensation results in the highest power gain. However, this transformation is not always ideal, especially for images that already have a low overall luminance, as it would further darken them.

To test this hypothesis, we identified the darkest images within the largest dataset. These images tend to have lower distortion percentages, as their colors do not shift significantly. Below, we present examples of various transformations applied to selected voltage samples, illustrating the impact on different types of images.

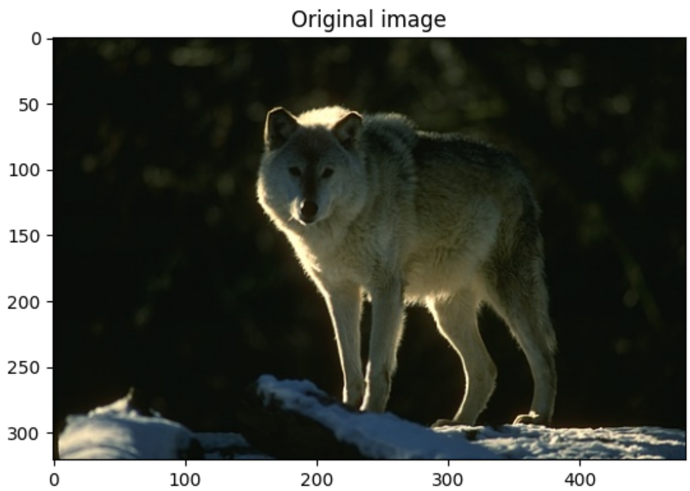

Figure 4.2: Original image

DVS only

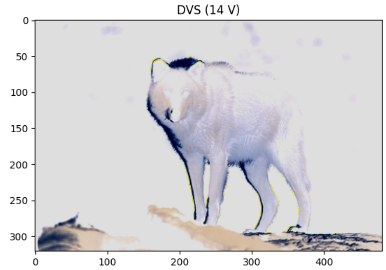

Figure 4.3: power gain = 22.06% - distortion = 20.38%

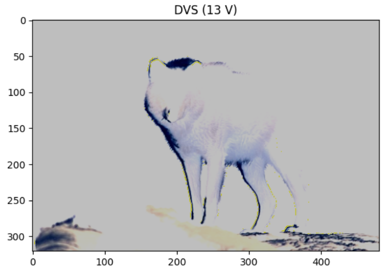

Figure 4.4: power gain = 43.81% - distortion = 17.83%

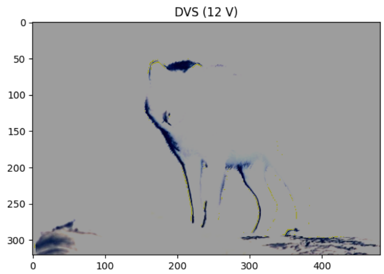

Figure 4.5: power gain = 61.63% - distortion = 14.75%

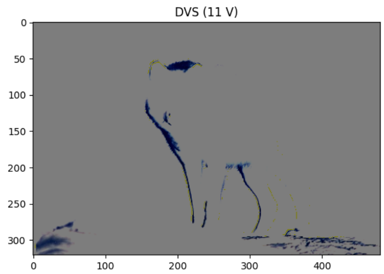

Figure 4.6: power gain = 75.17% - distortion = 11.62%

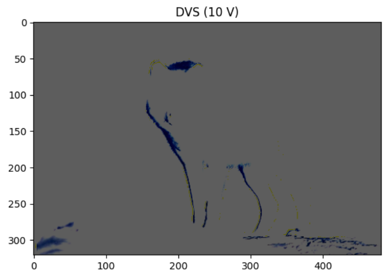

Figure 4.7: power gain = 84.74% - distortion = 8.55%

Brightness compensation + DVS

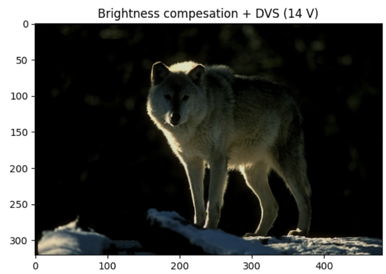

Figure 4.8: power gain = 12.05% - distortion = 1.67%

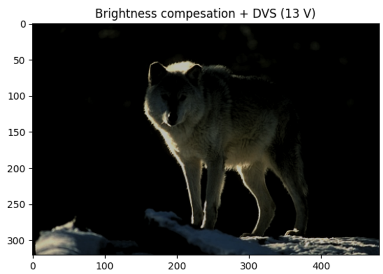

Figure 4.9: power gain = 21.54% - distortion = 2.43%

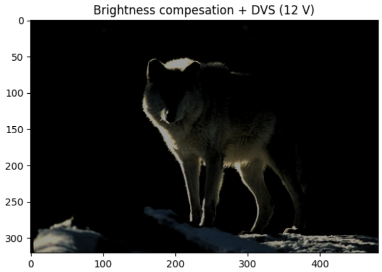

Figure 4.10: power gain = 29.14% - distortion = 2.94%

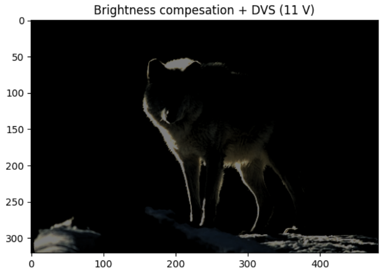

Figure 4.11: power gain = 35.39% - distortion = 3.31%

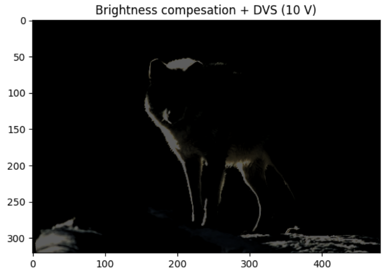

Figure 4.12: power gain = 40.97% - distortion = 3.56%

Contrast enhancement + DVS

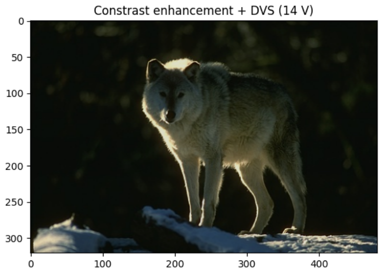

Figure 4.13: power gain = 13.35% - distortion = 0.34%

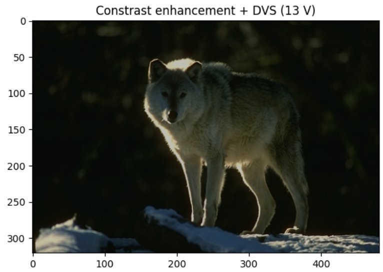

Figure 4.14: power gain = 25.35% - distortion = 0.64%

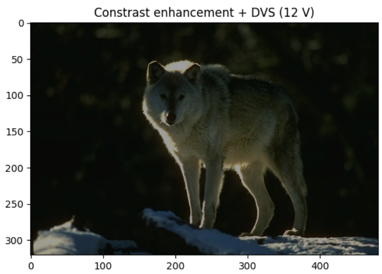

Figure 4.15: power gain = 36.11% - distortion = 0.96%

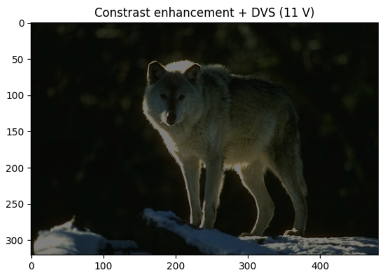

Figure 4.16: power gain = 45.55% - distortion = 1.28%

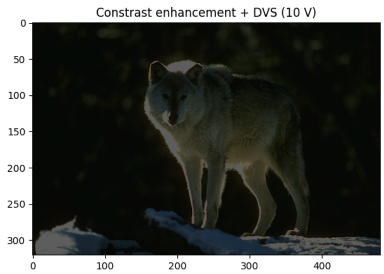

Figure 4.17: power gain = 53.83% - distortion = 1.60%

As observed, contrast enhancement is the most effective transformation for maximizing both image perception and power gain. In particular, the transformation applied at 12V provides the best balance. This is because, similar to our previous observations, if an image is already overexposed with a low overall difference in color luminance, applying an extreme voltage scaling will result in oversaturation, making the image unrecognizable.