Improving Image Visual Quality on a Dimmed Display

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***Abstract*—Decreasing the brightness of digital displays results in reduced power consumption and improved battery life. However, decreasing the brightness of an image reduces the image contrast and negatively affects the overall image quality. We propose a method to improve the visual quality of dimmed displays, without changing the overall brightness and power consumption. Our method consists of two steps: image enhancement and brightness reduction. We propose two possible image enhancement techniques: human contrast sensitivity and intensity saturation. We use just noticeable differences to reduce the brightness of our images after enhancement, constraining the final image brightness to be no more than the original image brightness so as to not increase power consumption. We evaluate our approach through subjective testing. Our results suggest that the intensity saturation method does not improve the original image by a large margin at higher brightnesses, but at lower brightnesses it does. The human contrast sensitivity method outperforms the intensity saturation method and improves the original image by a significant margin. Therefore by comparison, the human contrast sensitivity method is the better way to improve the image quality without increasing the brightness.**

Keywords—image quality, display, power consumption, image enhancement, just noticeable difference

I. BACKGROUND

Reducing the brightness on displays such as smartphones or tablets is a common practice among users. Bright displays can lead to eye strain and discomfort, especially during extended use. A reduced brightness level can make it easier to use devices for longer periods. However, most commonly users decrease the brightness of their screens to extend the battery life of their device because brighter displays consume more power.

However, reducing the brightness of a display can negatively impact the overall quality of an image. When the brightness of an image is reduced, both the light and dark areas of the image become less distinguishable, leading to a reduction in contrast. This can make it difficult to see the details in the image, and can result in a loss of color accuracy. The reduced brightness can also make it more difficult to display fine details in the image, as the reduced light output can result in increased visual noise, such as graininess or color artifacts. All of these factors come together to produce a significantly inferior image.

There are many existing image enhancement methods to improve image quality. However, most of these enhancement techniques result in increases to the overall luminance, leading to greater power consumption. However, higher power consumption is not acceptable in many scenarios (e.g. a situation where the user has limited battery without easy charging access). Hence, we would like to develop a strategy to improve image quality without increasing power consumption. We leverage knowledge of the human visual system (HVS), namely the contrast sensitivity function (CSF) and just noticeable differences (JND) to accomplish this task.

The CSF refers to the ability to detect and discriminate between different levels of contrast in an image. Figure 1 shows the shape of a typical CSF curve for a human. The gratings in the area under the curve are visible to the human eye, while the gratings in the area above the curve are indistinguishable.

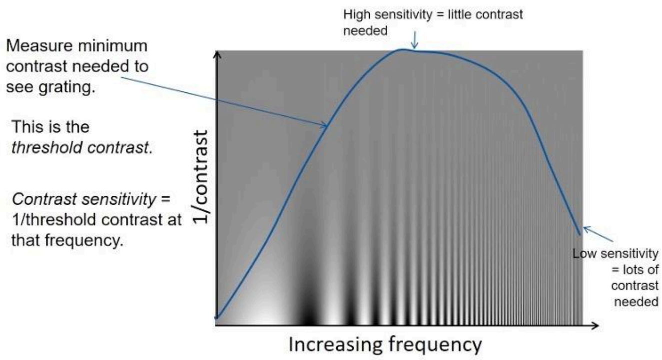

Figure 1. Contrast Sensitivity Function

JND refers to the smallest difference in pixel intensity that can be detected by a human observer [1]. It defines a minimum threshold beyond which changes in intensity, frequency, or duration can no longer be perceived by the HVS [1]. JND depends on the CSF, luminance adaptation, and contrast masking [1]. In our method, we use JND to adjust the pixel intensity after image enhancement to keep the overall luminance unchanged.

We propose a two-step technique to improve the quality of dimmed images, first enhancing the image using an image enhancement technique, then using a JND threshold map to constrain the overall image brightness so as to not increase power consumption.

II. Method

We consider two different existing approaches for image enhancement. One method leverages knowledge of the HVS and relies on human contrast sensitivity, and the other relies on saturating the intensity of pixel values in the image. After the image is enhanced through one of the two methods, we constrain the overall brightness of the image using our JND-based algorithm, such that the final image brightness is not greater than the original image brightness. In the following sections we describe the details of our two image enhancement methods, our brightness reduction module, and the subjective testing we use to compare the performance of the two approaches.

A. Human Contrast Sensitivity

The first image enhancement method we consider follows the paper by Aditi Majumder and Sandy Irani [2], which focuses on a method to enhance the contrast of images based on the human visual system's contrast sensitivity and the CSF. It describes the approach in two steps: (a) it determines critical points of the image to enhance where they are determined by a contrast threshold parameter. In these regions, people would be more sensitive to the image. (b) Then at the critical points, it checks the gradient magnitude and orientation to determine how to change the pixel intensities at the regions. The paper proposes to maximize the objective function:

$$f(\Omega) = \frac{1}{4|\Omega|} \sum_{p\in\Omega} \sum_{q\in N_4(p)} \frac{I'(p) - I'(q)}{I(p) - I(q)} \quad (1)$$

subject to a perceptual constraint

$$1 \leq \frac{I'(p) - I'(q)}{I(p) - I(q)} \leq 1 + \tau \quad (2)$$

and a saturation constraint

$$L \leq I'(p) \leq U \quad (3)$$

where scalar functions $I(p)$ and $I'(p)$ represent the gray values at pixel p of the input and output images respectively, Ω denotes sets of pixels that makes up the image, $|\Omega|$ denotes the cardinality of Ω, $N_4(p)$ denotes the set of four neighbors of p, L and U are the lower and upper bounds of the gray values (e.g. $L = 0$ and $U = 255$ for images that have gray values between 0 and 255), and $\tau > 0$ is the single parameter that controls the amount of enhancement achieved [2].

Their objective function was derived using knowledge of human contrast sensitivity at suprathreshold levels (i.e. above the minimum threshold to detect contrast differences). For every pixel p in the image, it maximizes the change in image intensity between pixel p and its four neighboring pixels (denoted by q) in the horizontal and vertical direction, up to a maximum change of $1 + \tau$ from the original image, where τ is a hyperparameter that constrains the maximum change that can be applied to the image, derived using suprathreshold contrast sensitivity and the Weber law.

To solve this optimization problem, they use an iterative greedy algorithm that attempts to change each pixel difference by the maximum possible amount (i.e. $1 + \tau$) so long as the saturation constraint is not violated. At each iteration, they generate graphs based on a threshold, compute connected components (which they call hillocks) and attempt to stretch the pixels in these hillocks as much as possible without violating constraints. The threshold is then increased by Δ at each iteration, which is a hyperparameter that determines the runtime of their algorithm. Two sweeps of threshold values from L to U are performed, first stretching the peaks of the hillocks, followed by inverting the image and stretching the valleys, and finally inverting the image again to obtain the final enhanced image. They extend their results to color images by converting RGB to the CIE XYZ color space and operating their enhancement algorithm on the luminance channel [2].

Figure 2 shows an example of the human contrast sensitivity image enhancement method. After enhancement, the contrast on the flower is improved, showing more details.

Figure 2. Original image (left) and enhanced image (right) generated through the human contrast sensitivity enhancement method.

B. Intensity Saturation

Another approach we consider for image enhancement is intensity saturation. Saturation is a measure of the intensity of a color. It indicates how much a color differs from a neutral gray of the same brightness. A fully saturated color is vivid and intense, while a desaturated color comes across as muted.

In MATLAB, we use the imadjust(I) function to perform the intensity saturation, where I is the input grayscale image. This function saturates the bottom 1% and top 1% of all pixel values, stretching the histogram distribution to cover the full range of possible pixel values. After adjustment, we get an output image with more details and better contrast as shown in Figure 3.

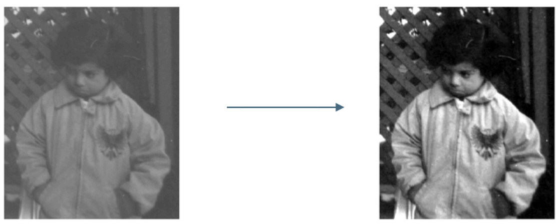

Figure 3. Original image (left) and enhanced image (right) generated through the intensity saturation method

To implement the intensity saturation method for an RGB color image, we follow the workflow in Figure 4. First, we convert the image colorspace from RGB to YCbCr, where we separate its luminance from the chroma components. Then we extract the luminance channel which we perform the intensity saturation on. Finally, we change the enhanced image back to RGB to generate our enhanced image.

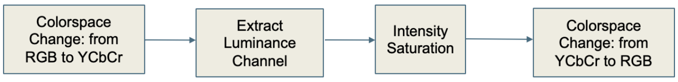

Figure 4. Workflow of Intensity Saturation

Figure 5 shows an example of an image generated through our intensity saturation method. After the adjustment, the tower and the road have better contrast.

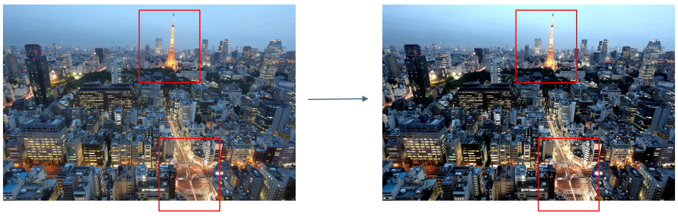

Figure 5. Original image (left) and enhanced image (right) generated through our intensity saturation approach on a color image

C. *Just Noticeable Differences for Brightness Reduction*

Our prior image enhancement techniques on a dimmed image typically produce an output image with higher mean brightness than the original dimmed input image. However, we would like to constrain the brightness of the enhanced image to be no more than the brightness of the original dimmed image to not increase the power consumption (which is directly proportional to the image brightness). To accomplish this, we propose to use a JND threshold map, which can be computed at a pixel level to identify regions of the image that can be altered without being noticed by the human visual system. We use the work by Yang et al. [3] to compute this pixel-level threshold map. The key idea is, if we interpret the JND threshold map as a relative weighting of the importance of each pixel compared to its neighbors, we can use the JND threshold map to make spatially variant modifications to the image based on pixel importance. Humans are more sensitive to regions of the image with a lower JND threshold (i.e. a small change is enough for us to notice a difference), meaning these regions should be changed less compared to regions with a higher JND threshold. We operate on the L channel (which represents the perceptual lightness) in the Lab color space to compute the JND thresholds and adjustments to the image.

Mathematically, we formulate the problem as follows: given the L channel (in the Lab color space) of a dimmed input image I_{in} with mean brightness $\mu(I_{in})$, we want to enhance the image using an image enhancement technique E to produce an enhanced image $I_{enh} = E(I_{orig})$. Here, E represents the transformation applied by either the human contrast sensitivity or intensity saturation method. This enhanced image has a mean brightness $\mu(I_{enh})$. Typically, the image enhancement method increases the mean brightness of the image, hence we have $\mu(I_{enh}) > \mu(I_{in})$, where $\mu(I)$ denotes the mean brightness of image I. We want to develop a technique to reduce the brightness of the enhanced image to produce a final output image I_{out} with a mean brightness that is less than or equal to the original image brightness, i.e. we want $\mu(I_{out}) \leq \mu(I_{in})$. We propose to use JND thresholds for this purpose.

Let $J(I_{enh})$ represent the JND thresholds computed at a pixel-level for the enhanced image I_{enh}. $J(I_{enh})$ is a matrix with the same dimensions as the image I_{enh}, with each element representing the JND threshold for that pixel. We want to find a transformation $f(J(I_{enh}))$ that can be applied to I_{enh} such that $I_{out}=f(J(I_{enh}))\odot I_{enh}$ where $\odot$ denotes elementwise matrix multiplication. We compute $f(J(I_{enh}))$ using the following algorithm:

We start by inverting the JND thresholds by taking the additive inverse of matrix J. We do this because a high JND threshold represents a lower significance and a low JND threshold represents a higher significance to the HVS. Hence, we want to modify the pixels with higher JND thresholds more, which is equivalent to multiplying by a smaller value.

$J \leftarrow -J(I_{enh})$

We then normalize the JND thresholds to have a mean of 0 and a standard deviation of 1, where σ denotes the standard deviation computed across all elements of J.

$J \leftarrow (J - \mu(J)) / \sigma$

We clip any values in the JND matrix that are more than σ away from the mean to remove outliers.

$J_{ij} \leftarrow \sigma \ \forall \ J_{ij} > \sigma$ and $J_{ij} \leftarrow -\sigma \ \forall \ J_{ij} < -\sigma$

This helps to remove drastic modifications to the image by constraining the range of modifications. We then shift the values in the JND matrix to be in the range [1-α, 1], where α is a hyperparameter we introduce to control the extent of differences across the image compared to a uniform adjustment to reduce brightness. For example, a lower α would correspond to a smaller difference between the smallest and largest adjustments applied to the image pixels. We use a fixed α = 0.3, which we empirically determine as a global optimum that generally works well for most of our sample reference images.

$J \leftarrow \alpha(J + \sigma) / (2\sigma) + (1 - \alpha)$

Note that this is just a direct application of the linear scaling formula:

$$\frac{x - r_{min}}{r_{max} - r_{min}}(t_{max} - t_{min}) + t_{min}$$

used to convert a variable x in the range $[r_{min}, r_{max}]$ to the range $[t_{min}, t_{max}]$, with $r_{min} = -\sigma$ and $r_{max} = \sigma$ (from our clipping step) and our new target bounds as $t_{min}=1-\alpha$ and $t_{max}=1$.

We then iteratively identify how much the enhanced image brightness needs to reduced by to arrive at an output image that that has the same mean brightness as our original image:

$\beta=1$, $s=0.01$

while $\mu(I_{in}) \leq \mu(\beta J \odot I_{enh})$: $\beta \leftarrow \beta(1 - s)$

where s denotes the step size to decrement by in each iteration. We use s=0.01, where the image intensity is changed by 1% at each iteration. Hence, we have our transformation matrix as $f(J_{enh}) = \beta J$.

Once we have identified the desired β value, we can simply apply the adjustment as follows:

$I_{out} = (\beta J) I_{enh}$

which gives us the output image (enhanced with our enhancement method and constrained to have the same brightness as the input image using JND techniques).

We visualize this process in Figure 6. $J(I_{enh})$ contains the pixel-level JND thresholds of our enhanced image (computed using the algorithm proposed by Yang et al. [3]) which may be arbitrary values between 0-100 (which are the limits of the L channel in the Lab color space). Our transformation $f(J(I_{enh}))$ contains values between 0-1 and can be directly multiplied with the L channel of the enhanced image I_{enh} through element-wise multiplication to generate the L channel of our output image I_{out}. Note that larger values in $f(J(I_{enh}))$ (i.e. the castle walls) represent pixels with lower JND thresholds (which we interpret as regions of greater importance), and hence these pixels will be changed less in the brightness reduction (i.e. they will retain more of their brightness). We then convert the enhanced image from Lab back into the RGB color space.

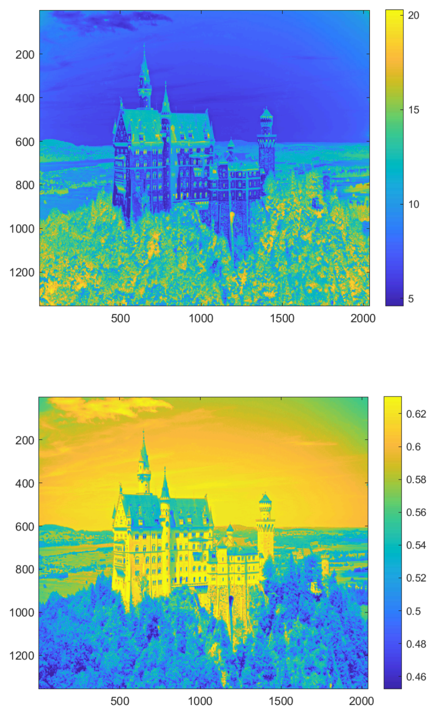

Figure 6. The original JND threshold matrix $J(I_{enh})$ (top) and the computed transformation $f(J(I_{enh}))$ (bottom) following our proposed algorithm.

D. Subjective Testing Setup

We use subjective tests to evaluate the performance of our approaches. Subjective tests rely on the opinions and perceptions of individuals to evaluate the image quality, brightness, and overall visual experience. We compare the performance of two image enhancement methods in our subjective tests: (i) method 1: enhancing the image with human contrast sensitivity and (ii) method 2: enhancing the image with intensity saturation. We use the same JND brightness reduction module for both methods to constrain the brightness of the enhanced image. We evaluate our algorithm on images at 3 different brightness levels: 40%, 60%, and 80% to simulate dimming the display. We do this since our algorithms currently operate in the image domain, modifying the pixel values themselves, though it shouldn't be difficult to extend them to read the display brightness and operate in that domain instead in the future.

We evaluate 3 test configurations, using binary comparisons between (a) the dimmed input image vs. output of method 1, (b) the dimmed input image vs. output of method 2, and (c) the outputs of method 1 vs. method 2. For each test configuration, we use 18 representative comparisons for a total of 54 comparisons displayed to the participant in a full subjective testing session. For each test configuration, we used the following distribution of dimmed images at 40%/60%/80% brightness: (a) 8/4/6 (b) 6/7/5 (c) 3/8/7, as we had focused on selecting representative images instead of balancing the distributions. To prepare images for subjective testing, we crop them and place them side-by-side horizontally on a gray background for a 4K display. We randomize the placement of each image (i.e. left or right) and add unique identifiers to keep track of which images are being displayed and the image brightness levels in a log file.

Prior to the subjective tests, we screen each participant for visual acuity and color blindness. We perform the tests on a 4K display with at most 3 participants at a time. The participants are seated away from the screen at a distance 1.5x the width of the display. During the test, each image comparison is preceded by an identifier number for 2 seconds, then the image comparison is displayed for 10 seconds, and after each image is displayed, participants are given a 6 second window to mark down which image they prefer (from 3 choices: left > right, left < right, left = right). During this time, a gray slide with text prompting participants to vote is displayed. We provide participants with a 2-minute break between each test configuration to rest their eyes.

III. Results

E. Qualitative Results

We show 3 representative outputs from our methods in Figure 7. The contrast is improved in both of our proposed methods, with the most noticeable difference in the dark image of Singapore. We see that the intensity saturation method (method 2) seems to alter the image more drastically compared to the human contrast sensitivity-based enhancement method (method 1), especially for darker images.

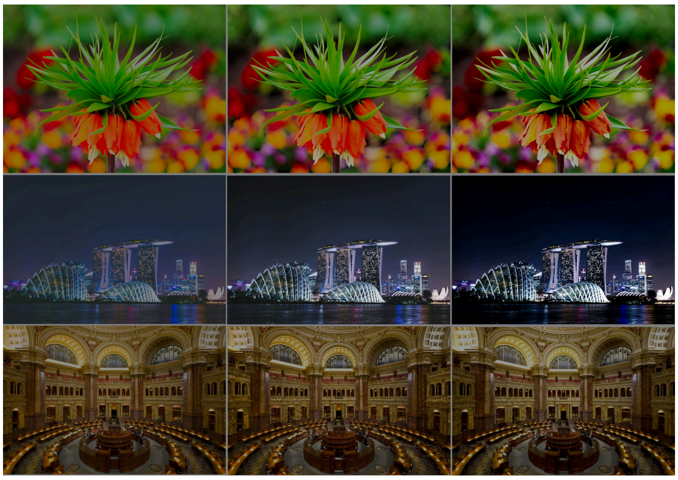

Figure 7. Example images using our proposed method at 60% brightness. The left column is the original dimmed image. The center and right columns correspond to the outputs of method 1 and method 2 respectively.

F. *Subjective Testing Results*

We evaluated the performance of our approaches using the subjective testing setup discussed in Section D with 7 participants. One data point from test configuration 2 and one data point from test configuration 3 were discarded because the intent of the subject was unclear. Figures 8-10 show the results from the seven participants.

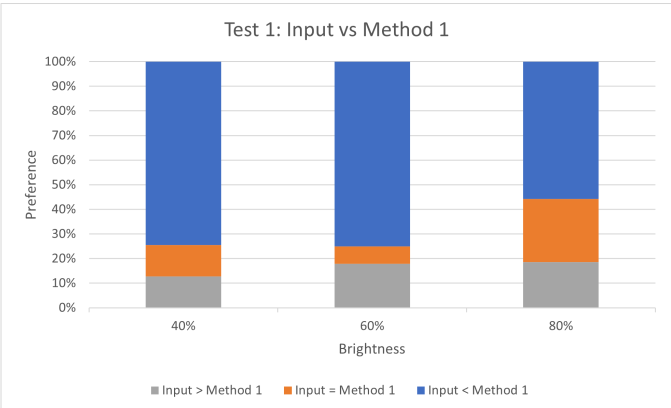

Figure 8. Subjective test results for the input image vs the human contrast sensitivity method. The blue bar represents the percentage of times the participants thought the modified image was better than the input. The orange bar represents the percentage of times participants felt the images were equal. The gray bar represents the percentage of times they felt the input was better than the modified image.

Looking at Figure 8, we can see that the participants found the modified image better for all three levels of brightness. However for the 80% brightness images, the participants found a greater number of image pairs to be of similar quality. This shows that the human contrast sensitivity function enhances images at low brightness, and at higher brightness it will either improve the image or keep it at the same level of quality.

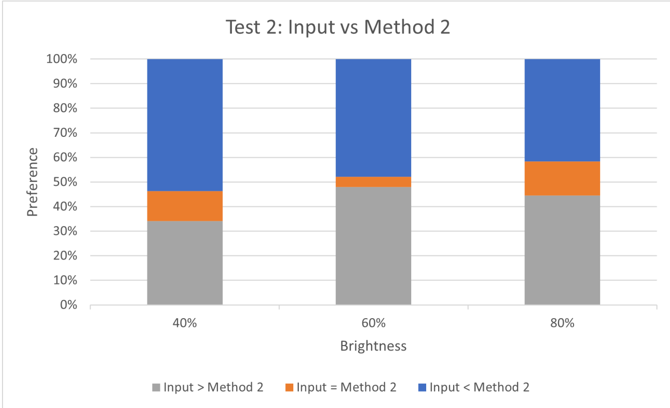

Figure 9. Subjective test results for the input image vs the intensity saturation image enhancement method. The bars have the same representation as Figure 8 except now the input image is being compared to method 2 (intensity saturation).

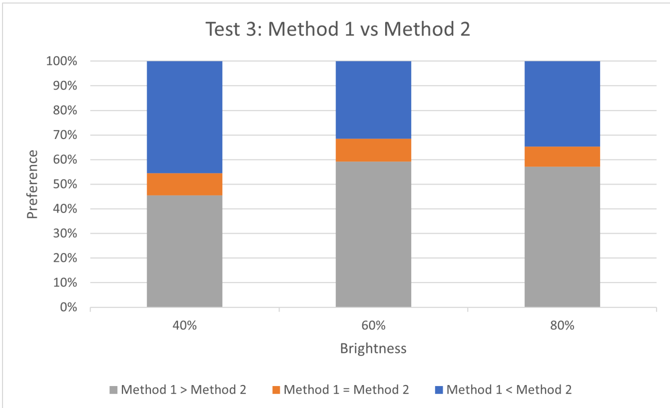

Figure 10. Subjective test results for an image modified by the human contrast sensitivity method vs the intensity saturation method. The blue bar represents the percentage of times the participants found the image modified by the intensity saturation method better. The orange bar represents the percentage of times the participants found both modified images to be equal. The gray bar represents the number of times participants found the image modified by the human contrast sensitivity method better.

Based on the results in Figure 9, it is evident that the intensity saturation method does not improve the image quality by a significant amount, especially when compared to method 1. Both at 60% and 80% brightness there is a similar distribution between whether the participants preferred the input image or the modified image. The only difference in results at 60% and 80% brightness is that the participants felt more of the image pairs were similar in quality at 80% brightness. However, at 40% brightness, the participants felt more of the images modified by intensity saturation were better. This was still not as high as the results from the human contrast sensitivity method though.

From Figure 10, we can see that the participants preferred the human contrast sensitivity method over the intensity saturation method for all three brightness levels. At 40% brightness, there is a smaller gap between the two. This could potentially mean as the brightness gets lower, the two methods perform similarly. Other possible reasons could be that the images are too dark to tell a difference, it was an anomaly, or the performance might vary at lower brightness levels. More testing is required to determine the root cause.

Looking at all three graphs, we can conclude that the human contrast sensitivity method produces images that are better than the original at the same brightness level. Meanwhile, the images produced by the intensity saturation method were not significantly better than the original images at higher brightnesses. But at lower brightness levels, the intensity saturation method does perform better. Overall, 68% of votes preferred the output of the human contrast sensitivity method over the dimmed input image and 56% of votes preferred the human contrast sensitivity method over the intensity saturation method across all 3 brightness levels. Therefore, we conclude that the human contrast sensitivity image enhancement method performs better than the intensity saturation method.

IV. Conclusion

We develop and compare two potential approaches to improve image quality on dimmed displays. Using subjective testing, we determine the human contrast sensitivity-based image enhancement technique that leverages knowledge of the human visual system to be superior over an intensity saturation approach.

In designing our image enhancement approaches, there were hyperparameters that needed to be selected. We make no claims that our hyperparameters are optimal, though we did experiment with some different possible values. For example, in our intensity saturation method, we had used the default configuration of saturating the top and bottom 1% of pixels as this seemed to work well for most images. However, instead of selecting a fixed value for our hyperparameters, it may be worthwhile to design an approach to identify the optimal parameters for a given input image, depending on the original image's features (e.g. brightness, contrast, etc.).

Ultimately, we would like to generalize our approach to video applications, performing real-time video quality improvement on dimmed displays. However, our current algorithm runtime is not optimal, as there are many iterative steps involved (e.g. enhancing the image, computing JND thresholds, determining how much to dim the enhanced image), hence it would be helpful to investigate further optimizations to improve the runtime of method as well. Specifically, the human contrast sensitivity method can take tens of seconds to run for a larger image.

Lastly, while we simulate dimming the display in our experiments by modifying the image pixel values directly, ultimately, we would like to apply our approach to dimmed displays instead of simulated dimmed images. Hence, future work would also involve designing an approach to translate pixel brightnesses on a display screen to a map/image that can be input into our algorithms to be processed.

V. References

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