Color Image Enhancement Based on Adaptive Nonlinear Curves of Luminance Features

Hosang Cho¹, Geun-Jun Kim¹, Kyounghoon Jang¹, Sungmok Lee², and Bongsoon Kang¹

Abstract—This paper proposes an image-dependent color image enhancement method that uses adaptive luminance enhancement and color emphasis. It effectively enhances details of low-light regions while maintaining well-balanced luminance and color information. To compare the structure similarity and naturalness, we used the tone mapped image quality index (TMQI). The proposed method maintained better structure similarity in the enhanced image than did the space-variant luminance map (SVLM) method or the adaptive and integrated neighborhood dependent approach for nonlinear enhancement (AINDANE). The proposed method required the smallest computation time among the three algorithms. The proposed method can be easily implemented using the field-programmable gate array (FPGA), with low hardware resources and with better performance in terms of similarity.

Index Terms—Luminance enhancement, color emphasis, tone mapped image quality index (TMQI), FPGA implementation

I. INTRODUCTION

Due to recent advances in display technology, devices with ultrahigh definition image quality have been released [1]. Although high performance image sensors have a wide dynamic range of brightness, most video devices have narrow expression ranges, smaller than that of color negative film. The transfer-function design, which increases visual perception, is of key importance to high-quality image enhancement. When images are acquired that have backlighting, the bright and dark regions of the images are generally extremely distributed. As a result, the images have low visual quality, and it is sometimes impossible to identify objects in the displayed images. In order to solve this kind of problem, algorithms to improve image quality in dark regions have been widely studied [2-4].

Improving visibility using histogram equalization and nonlinear curves such as gamma correction curve has a comparative advantage in high-speed operation [5, 6]. However, this process requires additional processing to correct colors distorted during the improvement. In order to combine the gamma correction with the local characteristics of the image, the SVLM was developed; this method is based on a bilateral filter [7]. Using a single Gaussian filtering, the SVLM is calculated with the local average luminance in the rescaled image. Due to the significant computational complexity of the filtering, the SVLM may not be appropriate for real-time applications. In addition, color correction must be considered because of the color distortion caused by contrast enhancement in luminance space.

The AINDANE method was developed for low and non-uniform luminance conditions [8]. It is composed of adaptive luminance enhancement, local contrast enhancement, and color restoration. The luminance enhancement improves the brightness of the dark areas of the image while the local enhancement corrects the contrast caused by the adaptive luminance enhancement.
Thus, the AINDANE method can improve image quality by increasing the brightness contrast. However, the visibility of the uncorrected bright region is reduced since the transfer function of the enhancement lacks local characteristics, as well as lacking the ability to improve the bright region.

Most luminance enhancing algorithms change local intensity and contrast. Thus, the structural similarity (SSIM) in [9] was inappropriate for comparative methods because the algorithms changed the local intensity and contrast. Therefore, a measure of tone mapped image quality index (TMQI) was suggested in [10] to compare the numerical performance data in order to successfully improve luminance.

This paper is organized as follows. Section II presents the proposed algorithm including ideas on luminance enhancement and color emphasis. Section III discusses a series of simulation results, evaluating the TMQI using input/output brightness changes. Section IV describes the system complexity of the proposed algorithm based on computational times and hardware implementation. Section V presents concluding remarks.

II. PROPOSED ALGORITHM

In this section, we present a method of image enhancement based on nonlinear curves of the luminance features of an input image. The distribution of luminance values is used to characterize to increase the luminance contrast in the low-light region. The color distribution is expanded along with the luminance enhancement. The following presents more details of the process.

1. Luminance Enhancement

Luminance enhancement uses the probability density function (PDF) of the luminance value \( L(x,y) \) to achieve the cumulative distribution function (CDF). Eq. (1) defines the \( \text{cdf} \) for 8bit luminance values with an index \( k \). The \( \text{pdf} \) represents the normalized PDF of the input histogram.

\[
cdf(k) = \sum_{j=0}^{k} \text{pdf}(j), \quad \text{for } k = 0,1,\ldots,255 \tag{1}
\]

In this study, for luminance values whose visibility is sufficiently secured, luminance enhancement is proposed to improve the image contrast in low-light regions while preserving the contrast in high-light regions. This study also adopts an adaptive limit point (ALP) that depends on the luminance mean and the CDF of the input. The ALP is determined from a CDF index equation of \( ax + b \). ‘a’ is the slope, which is +0.02/255 when the luminance mean is greater than 128 or -0.02/255 otherwise. ‘b’ is the offset value of 0.04. ‘x’ represents the differentiation between luminance values corresponding to the CDF values of 0.9 and 0.1. Then, the luminance value corresponding to the calculated CDF index is selected for the ALP. These values are chosen to maximize the TMQI through experimental tests. The average luminance values change in every image. Thus, the ALP was used to determine the starting value for the emphasis of the luminance regions in each image.

Fig. 1 shows the proposed steps. Fig. 1(a) provides a non-uniform image that has a luminance mean of 63.7. Fig. 1(b) shows the pdf and Fig. 1(c) depicts the cdf in (1). The ALP, determined from Fig. 1(a), is 6.0; this is also depicted in Fig. 1(c).

In order to provide higher gains for smaller luminance values in the input image, the proposed method uses nonlinear weights of \( P(x,y) \) with the ALP and an alpha (\( \alpha \)) factor as

\[
P(x,y) = \left( 1 - \frac{L(x,y) - \text{ALP}}{255} \right)^{\alpha} \times 255 \tag{2}
\]

where \( x \) and \( y \) are the number of pixel locations in the X and Y axes, respectively. The alpha is calculated using an equation of \( ax - b \) and is limited to the range of 0 to 2. ‘a’ is the slope of 1.5/(luminance mean – luminance value at CDF=0.1). ‘b’ is the offset value of 0.55. ‘x’ represents the differentiation between luminance values corresponding to the CDF values of 0.4 and 0.1. These values are also chosen to maximize the TMQI. In general, the weight varies in proportion to the luminance mean.

Additional square weights of \( P_s(x,y) \) are used to emphasize the low-light region in the image as

\[
P_s(x,y) = \left( \frac{L(x,y)}{255} \right)^2 \tag{3}
\]

We can now achieve a luminance gain of \( LG(x,y) \) in (4) by multiplying \( P_s(x,y) \) by \( L(x,y) \). 2\(^{21}\) is used as the normalization factor for scaling \( L(x,y) \) between 0 and
1.17. This is depicted in Fig. 2. The green lines, for example, depict the luminance gains for the factors of 0.5, 1.0, and 2.0. The factor used for Fig. 1(a) is 0.

Fig. 2 also depicts a case with a red line. In the figure, we can see that the luminance values in the low-light region can change with different alpha factors.

\[ LG(x,y) = \frac{P_s(x,y) \times L(x,y)}{2^{21}} \]  
(4)

We now adopt an equation of the luminance weight of \( LW(x,y) \) to multiply by the gain as

\[ LW(x,y) = \left( \frac{S_i}{256} \times L(x,y) + Y_L \right) \]  
(5)

The second term of the multiplication is the luminance enhancement achieved by the proposed method. In the case shown in Fig. 1(a), the \( S_i \) is -22.7 and \( Y_L \) is 80.8. Fig. 3 shows the results for the four cases in Fig. 2 with green and red lines. From the figure, we can see that the low-light luminance values are emphasized while the luminance below ALP is unchanged.

2. Color Emphasis

When luminance enhancement is performed, the luminance contrast can be increased in the low-light region, as in (6). However, the overall image quality worsens because the color distribution in the chromaticity coordinates becomes smaller [11]. Thus,
color components $CC(x,y)$ of Cb and Cr should be emphasized according to the desired degree of the enhancement to maintain natural colors. For this purpose, we use the color gain of $CG(x,y)$ as

$$CG(x,y) = CC(x,y) \times r(x,y)$$  \hspace{1cm} (7)$$

where $r(x,y)$ represents the ratio multiplied by color components. For simplicity, we subtract 128 from Cb and Cr in order to obtain the components. Let us now define the ratio between the enhanced luminance $EL(x,y)$ in (6) and the input luminance $L(x,y)$ as

$$r(x,y) = \frac{EL(x,y)}{L(x,y)}$$  \hspace{1cm} (8)$$

We now adopt an equation of the color weight of $CW(x,y)$ to multiply by the color gain as

$$CW(x,y) = \begin{cases} 0.7 & \text{if } L(x,y) < L_{th1} \\ \frac{L(x,y) - L_{th1}}{L_{th2} - L_{th1}} + 0.7 & \text{else if } L(x,y) \leq L_{th2} \\ 0.44 & \text{otherwise} \end{cases}$$  \hspace{1cm} (9)$$

where $L_{th1}$ and $L_{th2}$ are the number of luminance thresholds to generate the weight. Eq. (9) shows the color weight. The values of 0.7 and 0.44 are chosen to maximize the TMQI. The $L_{th1}$ is the luminance threshold value of the CDF, which exceeds 0.1. The $L_{th2}$ is the upper threshold value for the color weight. The number 128 is one of the threshold values and is selected for the 8bit luminance values with our color emphasis. The enhanced color of $EC(x,y)$ is then obtained by adding the color component $CC(x,y)$ to the multiplication of $CG(x,y)$ and $CW(x,y)$ as

$$EC(x,y) = CC(x,y) + CG(x,y) \times CW(x,y) + 128$$  \hspace{1cm} (10)$$

The second term of the multiplication indicates the color emphasis achieved by the proposed method.

Fig. 4 shows the emphasis results for Fig. 1(a) on the CIE1931 chromaticity coordinates. The triangular region represents the RGB-color gamut. Cyan dots show the distribution of original colors and Blue dots are the distribution of the enhanced colors. From the figure, we can see that the distribution is expanded by the color emphasis in (10).

III. SIMULATION RESULTS

In this section, we discuss the performance of the proposed method by comparing the results with those obtained using AINDANE and SVLM. For this purpose, we use the retinex images of twenty-five pictures taken under various circumstances in [12].

The TMQI is shown as an objective measure for evaluating the structure similarity and naturalness between the reference and processed images [10]. It is

$$Q = aS^\alpha + (1 - a)N^\beta$$  \hspace{1cm} (11)$$

where $S$ represents the structural fidelity and $N$ represents the statistical naturalness. $\alpha$ and $\beta$ determine the sensitivities of $S$ and $N$. We also use the final model parameters $\alpha = 0.8012$, $\beta = 0.3046$, and $\beta = 0.7088$ in [10] as the authors suggested. The values of $S$ and $N$ have an index range between 0 and 1. An index of 1 implies no loss of structure or naturalness in the image.

Fig. 5 shows comparison results for the reference image shown in Fig. 1. Fig. 1 is one of twenty-five pictures in [12] and is numbered “Image Number 16” for further usage. Fig. 5(a) is the input. Figs. 5(b) and (c) show output images processed using AINDANE and SVLM, respectively. Fig. 5(d) shows the resulting image obtained using the proposed method. We calculated the TMQIs in (11) to compare the objective measures for three processed images. The resulting values were 0.8580,
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We can obviously see that the proposed method performed the best.

We continued testing the remaining twenty-four images for performance comparison. The luminance means were found to change in every image. The ALP determined the starting value for the emphasis of the luminance regions in each image. The alpha was used to determine the intensity and range of the luminance gain depending on the image.

Table 1 summarizes the TMQI results. All twenty-five images are numbered from ‘1’ to ‘27’ as in [12], with two missing numbers, ‘12’ and ‘13’. The second column shows the luminance means for the images. The third column indicates the ALP. Alpha is represented in the fourth column. The TMQIs for the AINDANE are tabulated in the fifth column. The average TMQI for the twenty-five images is 0.8307. The TMQIs for the SVLM

0.8642, and 0.9305 respectively. The proposed method had the biggest TMQI among these results. We can obviously see that the proposed method performed the best.

Table 1. Summary of TMQI results

<table>
<thead>
<tr>
<th>Image Number</th>
<th>Mean</th>
<th>ALP</th>
<th>Alpha</th>
<th>AINDANE</th>
<th>SVLM</th>
<th>Proposed Method</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>88.4</td>
<td>28</td>
<td>0.09</td>
<td>0.8170</td>
<td>0.7548</td>
<td>0.8564</td>
</tr>
<tr>
<td>2</td>
<td>74.7</td>
<td>4</td>
<td>0.60</td>
<td>0.8766</td>
<td>0.8686</td>
<td>0.8794</td>
</tr>
<tr>
<td>3</td>
<td>74.0</td>
<td>6</td>
<td>0.28</td>
<td>0.8463</td>
<td>0.8317</td>
<td>0.8788</td>
</tr>
<tr>
<td>4</td>
<td>77.1</td>
<td>8</td>
<td>0.19</td>
<td>0.8294</td>
<td>0.8324</td>
<td>0.8562</td>
</tr>
<tr>
<td>5</td>
<td>90.3</td>
<td>26</td>
<td>0.45</td>
<td>0.8666</td>
<td>0.8698</td>
<td>0.8873</td>
</tr>
<tr>
<td>6</td>
<td>88.0</td>
<td>21</td>
<td>0.24</td>
<td>0.8737</td>
<td>0.8663</td>
<td>0.9047</td>
</tr>
<tr>
<td>7</td>
<td>61.4</td>
<td>11</td>
<td>0.25</td>
<td>0.8325</td>
<td>0.8014</td>
<td>0.8846</td>
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<tr>
<td>8</td>
<td>67.6</td>
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<td>0.16</td>
<td>0.8293</td>
<td>0.8042</td>
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<tr>
<td>9</td>
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<td>3</td>
<td>0</td>
<td>0.7688</td>
<td>0.7659</td>
<td>0.8101</td>
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<tr>
<td>10</td>
<td>83.1</td>
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<td>0.25</td>
<td>0.9237</td>
<td>0.9217</td>
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<tr>
<td>11</td>
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<td>0.9201</td>
<td>0.9331</td>
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<tr>
<td>14</td>
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<td>17</td>
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<td>0.8540</td>
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<tr>
<td>15</td>
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<tr>
<td>16</td>
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<td>0</td>
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<td>0.7628</td>
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<tr>
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<td>0.8163</td>
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<tr>
<td>20</td>
<td>72.2</td>
<td>7</td>
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<td>0.9080</td>
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<tr>
<td>21</td>
<td>8.0</td>
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<td>0.7352</td>
<td>0.7505</td>
<td>0.7463</td>
</tr>
<tr>
<td>22</td>
<td>56.8</td>
<td>6</td>
<td>0.29</td>
<td>0.7662</td>
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<tr>
<td>23</td>
<td>57.4</td>
<td>4</td>
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<td>0.8766</td>
<td>0.9714</td>
</tr>
<tr>
<td>24</td>
<td>42.5</td>
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<td>0.8163</td>
<td>0.7933</td>
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<tr>
<td>25</td>
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<td>143</td>
<td>1.44</td>
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<td>0.6589</td>
<td>0.6348</td>
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<tr>
<td>26</td>
<td>136.6</td>
<td>109</td>
<td>1.25</td>
<td>0.7214</td>
<td>0.7241</td>
<td>0.7286</td>
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<tr>
<td>27</td>
<td>60.3</td>
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<td>0.03</td>
<td>0.8984</td>
<td>0.8895</td>
<td>0.9808</td>
</tr>
<tr>
<td>Average</td>
<td></td>
<td></td>
<td></td>
<td>0.8307</td>
<td>0.8209</td>
<td>0.8736</td>
</tr>
</tbody>
</table>

Fig. 5. Performance comparison of the image enhancement (a) the reference image, (b) the AINDANE, (c) the SVLM, (d) the proposed method.
are also tabulated in the sixth column. The average TMQI is 0.8209. The seventh column shows the TMQIs obtained using the proposed method. The average TMQI can be seen to have increased to 0.8736, which is larger than the previous results. From these results, we can see that the proposed method can maintain detailed structures closer to those of the reference image.

IV. SYSTEM COMPLEXITY

Fig. 6 characterizes the computational complexity of the proposed systems with AINDANE and SVLM by measuring CPU running times in seconds (sec). For this purpose, we use a personal computer that has a hexa-core CPU running at 3.4 GHz and 8GB RAM. The times, averaged for AINDANE and SVLM, are 0.58 sec and 7.91 sec, respectively. The time required for the proposed system is 0.24 sec, which is the smallest time among the three.

The proposed system was also designed using Verilog with a Xilinx FPGA (xc5vlx330) used to evaluate the hardware complexity. Fig. 7 provides a block diagram of the proposed method. It is composed of five functional blocks and a 256 × 18 SPRAM. Table 2 summarizes the FPGA implementation. The slice registers and the slice look-up-tables (LUTs) represent the logical area for the implementation. The block RAMs (BRAMs) indicate the memory usage. The proposed system uses 2,784 slice registers, which is an only 1.34% utilization among the total 207,360 registers available. The system also requires 5,528 LUTs, which implies 2.67% usage. Only one BRAM was used for the system, which is a 3.12% usage. The maximum speed for hardware operation was 138.26 MHz.

V. CONCLUSIONS

Image enhancement based on nonlinear curves of luminance features was accomplished by adaptive luminance enhancement and color emphasis. The luminance enhancement increased the visual quality in the low-light region while preserving details of the

![Fig. 6. Comparison of computational times.](image)

![Fig. 7. Block diagram of the proposed system.](image)

<table>
<thead>
<tr>
<th>Table 2. Summary of the Xilinx* FPGA implementation</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Slice Logic Utilization</strong></td>
</tr>
<tr>
<td>slice Registers</td>
</tr>
<tr>
<td>207,360</td>
</tr>
<tr>
<td>slice LUTs</td>
</tr>
<tr>
<td>BRAMs</td>
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<tr>
<td>Maximum Freq. (MHz)</td>
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</table>

* The Xilinx software was provided by the IDEC, Korea
original structures. The simulation results showed that the average TMQI was 0.8736. This was the largest measure among the three algorithms tested. The proposed system required the lowest computational power, and accordingly it was easily implemented in an FPGA device with real-time operational capability. The average utilization in the device was as small as approximately 2%.

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REFERENCES


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