Saturation and Value-Based Luminance Enhancement Model

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Abstract — This paper presents a saturation and value-based Luminance Enhancement Model (LEM) for colored images. The LEM was modified to addresses the issue of noise amplification associated with the use of a Laplacian filter in image enhancement. The images which were originally in RGB format were converted to HSV format to ensure a more stable performance of the model. A mathematical model was developed and applied to the formatted HSV image. The result obtained from the developed model is presented and benchmarked against the existing methods of color enhancement using the HSV color space. Simulations of the developed model were achieved using MATLAB. A Structural Similarity Index (SSIM) and Peak-to-Signal Noise Ratio (PSNR) of 67.9 and 0.8901 respectively were obtained using the developed model. The obtained results showed significant improvement over existing models.

Keywords — color image, CLAHE, Laplacian Filter, Enhancement

I. INTRODUCTION

Image enhancement techniques as a tool are used to manipulate digital image constituent to make the resulting output improved as compared to the original [1] – [4]. The image can be enhanced in its natural format as in spatial domain techniques or transform to another domain before enhancement as in transform domain techniques [5], [6]. RGB and HSV color model is used in image enhancement. But, the HSV color model is mostly used because of the fact that color manipulations perform better in HSV color space than in RGB color space. Fig. 1. depicts the HSV color space model.

Image enhancement is an aspect of image processing research that has caught the attention of researchers due to its areas of applications such as medicine and satellite technology. However, enhancing the images in these domains requires techniques that are dependent on the type of images used. This necessitates the need to develop an improved enhancement technique that can achieve a reasonable result in a wide variety of images [4].

The domains of image enhancement are the spatial and frequency domains. Nonetheless, for real-time applications, spatial domain enhancement has been proven to be efficient and reliable. Therefore, the spatial domain enhancement technique is the focus of this paper. Sobel, Prewitt, Roberts, Cann, Laplacian amongst others are the typically used spatial domain filters. But, the peculiarity of the Laplacian filter is that it can determine sharp changes in pixels values. This makes it mostly the choice of many candidate’s researchers as against others. However, the use of the Laplacian filter is limited by noise amplification.

Therefore, the paper proposes the development of saturation and value-based enhancement model that will reduce noise amplification with the use of the Laplacian filter to the barest minimum.
II. RELATED WORKS

Pertinent related works are reviewed as follows: The work of [7] proposed a local based spatial processing technique for color image enhancement. This technique used the luminance component of the image, thereby enhancing the contrast based on neighborhood dependency. The overall tone of the enhanced image is then enhanced using local gamma correction, although their approach displays significant improvement based on colorfulness and proportion of the number of saturated pixels as related with existing techniques like Dualistic sub-image Histogram Equalization (DSIHE), Histogram Equalization (HE) and Brightness preserving Bi-Histogram Equalization (BBHE). But it is only effective for images with non-uniform luminance.

Authors in [8] combined the histogram equalization with the magnitude compression procedure, color stretching process, and saturation maximization for color image enhancement. The approach showed a reduced artifact with improved contrast and colorfulness. However, the details in the image are not effectively enhanced. This was due to the inconsideration of edge preservation in the image.

This was also the case of the work of [9] where the sigmoid function was first used to enhance satellite images, after which the gamma correction employed for intensity preservation and multi-objective particle swarm optimization (PSO) was used to control over-enhancement and artifacts. The authors in [10] Illuminated each pixel by first estimating and individually determining the optimal value of the RGB channels that will provide Low-light image enhancement. The final map was generated using the illumination map through structure refinement. Though this method has lower lightness order error as compared with HE, Adaptive Histogram Equalization (AHE), GC, and CVC it involves a lot of weighting value and approximation analysis that make it unsuitable for practical application.

A knee transfer and gamma correction are applied to dark satellite images for enhancement as proposed by [11]. The dark low contrast satellite image acquired as test data were decomposed into four quadrants which are LL, LH, HL, and HH with a view to estimating the singular value matrix. Inverse DWT is applied to these quadrants separately and then combined to obtain the enhanced image. In comparison with conventional methods like gamma correction, BPFDHE, and GHE, the contrast and local details are better improved by the proposed technique. However, it results in an exaggeration of image inherent noise towards the edges which may lead to loss of useful information.

[12] presented an iterative mean filter for image denoising with a view to improving the image quality. The presented model addressed a salt and pepper type of noise that degrades the quality of an image. Fixed-size of the window was used to justify the effectiveness of the algorithm. Using a fixed-size window increases accuracy and processing speed but inadequately removes noise.

A cascade filter was presented by [13] that was capable of removing salt and pepper noise of high-density in colored images. The developed algorithm made use of a clipped median filter based on pixel values for image restoration. Nonetheless, the use of the median filter for saturation and value-based enhancement is not efficient in the RGB space model.

Nonetheless, past research works in image processing have presented an enhancement model as in equation (1) and (2). This equation tunes the Saturation (A) and Value (B) component of an image in the HSV model. This is intending to improve the image quality and reduce the problem of the existing techniques to the barest minimum [14], [15].

\[
\rho(g,h) = \frac{1}{\sqrt{\sigma_A^2(g,h),\sigma_B^2(g,h)}}\sum_{A} [B(g,h)\cdot B_{a}(g,h)]\cdot [A(g,h) - A_{a}(g,h)]
\]

\[
B_{enh} = B(g,h) + K_{1}[B(g,h) - B_{a}(g,h)] - K_{2}[A(g,h) - A_{a}(g,h)] \cdot X\cdot \rho(g,h)
\]

However, this paper seeks to readdress the model developed and presents an improved model with a view to achieving a better-enhanced image.

III. PROPOSED TECHNIQUE

The proposed enhancement model is discussed as follows:

**Step I: Image Manipulation**
Input: Load RGB Image and convert into HSV and the A and B component will be filtered using the Laplacian filter to give A_s and B_s as presented by the work of [16] and [17]. The A_s and B_s are input to the modified processing block.

**Step II: Modified Enhanced Processing Block**
The variance and correlation are calculated and this is used to enhance the Laplacian filtered B_s using equations (3) and (4).

\[
B_{variance} = \sigma_B^2(g,h) = \sum_{B(i,j)} [B(i,j) - B_{a}(i,j)]^2
\]

\[
A_{variance} = \sigma_A^2(g,h) = \sum_{A(i,j)} [A(i,j) - A_{a}(i,j)]^2
\]

Both A and B variance serves as the input to the correlation and final enhancement. The equations for correlation and enhancement are presented in equation (5) and (6).

\[
\rho(g,h) = \frac{1}{\sqrt{\sigma_B^2(g,h),\sigma_A^2(g,h)}}\sum_{B} [B(g,h) - B_{a}(g,h)]\cdot [A(g,h) - A_{a}(g,h)]
\]

\[
B_{enh} = B(g,h) + K_{1}[B(g,h) - B_{a}(g,h)] - K_{2}[A(g,h) - A_{a}(g,h)] \cdot X\cdot \rho(g,h)
\]

The modification is done in the correlation phase and final B enhancement where the B_s and A_s is replaced with B_{variance} and A_{variance} respectively.

**Step III: Contrast enhancement:**
The output of contrast after subjecting it to the Laplacian filter is enhanced using a fixed value of gamma 0.77 [14].
\[ A_{\text{enh}} = A^{0.77} \]  
(7)

Enhanced luminance \( B_{\text{enh}} \) and contrast \( A_{\text{enh}} \) is added to Hue and converted to RGB to get the final enhanced image. Table 1 presents the pseudocode for the proposed Luminance Enhancement Model (LEM).

**TABLE 1: PROPOSED LEM ALGORITHM.**

**Algorithm: Luminance Enhancement**

<table>
<thead>
<tr>
<th>Start</th>
</tr>
</thead>
<tbody>
<tr>
<td>Input: Input Original Color Image</td>
</tr>
<tr>
<td>RGB [\rightarrow] HSV: Convert RGB to HSV</td>
</tr>
<tr>
<td>Laplacian filter: compute S and V component of Processing Block:</td>
</tr>
<tr>
<td>Use Equations 3 and 4 to find ( B_{\text{variance}} ) and ( A_{\text{variance}} )</td>
</tr>
<tr>
<td>Compute the Correlation and Luminance Enhancement using equations 5 and 6</td>
</tr>
<tr>
<td>Colour Enhancement:</td>
</tr>
<tr>
<td>Enhance overall saturation component using equation (7)</td>
</tr>
<tr>
<td>end</td>
</tr>
</tbody>
</table>

IV. EXPERIMENTAL RESULT AND ANALYSIS

Standard test images were used to test the developed luminance enhancement model. These test images were retrieved from standard databases [18]. The Structural Similarity Index (SSIM) and Peak Signal-to-Noise Ratio (PSNR) as shown in equations (8) and (9) was used to determine the performance of the luminance enhancement model.

\[
\text{SSIM} = \frac{(2M_p M_i + C_i)(2C V_{0i} + C_2)}{(M_0^2 + M_i^2 + C_1)(S D_0^2 + S D_i^2 + C_2)} 
\]  
(8)

Where,
- \( M_p, M_i \): is the mean of the input and output image
- \( C V_{0i} \): is the cross co-variance for both images
- \( S D_0 \): is the standard deviation of the output image
- \( S D_i \): is the standard deviation of the input image

\[
\text{PSNR} = 10 \log \left[ \frac{255^2}{\text{MSE}} \right] 
\]  
(9)

Where MSE is given by [12]

\[
\text{MSE} = \frac{\sum_{r,b} (I_o(r,b) - I_p(r,b))^2}{rb} 
\]  
(10)

Where,
- \( r \) and \( b \) are the number row and column in the image respectively
- \( I_o(r,b) \) is the output image
- \( I_p(r,b) \) is the input image.

The test images are presented in Fig. 2 (a-h)
Table 2 presented the comparison of LEM with the Laplacian-CLAHE enhancement model. To further ascertain the efficiency of LEM it was compared with other enhancement models by various researchers on an average PSNR of 67.9. While Gang Song et al [19] achieved PSNR of 32.3 and Hanumantharaju et al [15] achieved a PSNR of 32.5.

VI. VISUAL ANALYSIS

Since the paper implemented a luminance enhancement model, the efficiency of the model was tested on the standard dataset presented in Fig. 2 (a-h). The images were fed directly as input to the model and visual output generated enhancement images using LEM are presented in Fig. 3 (a-h)

<table>
<thead>
<tr>
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</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>butterfly</td>
<td>66.5140</td>
<td>0.8901</td>
<td>28.3227</td>
<td>0.6636</td>
</tr>
<tr>
<td>2</td>
<td>Clinmill</td>
<td>72.1548</td>
<td>0.8811</td>
<td>29.5946</td>
<td>0.6311</td>
</tr>
<tr>
<td>3</td>
<td>flower</td>
<td>84.8484</td>
<td>0.9174</td>
<td>29.6242</td>
<td>0.5466</td>
</tr>
<tr>
<td>4</td>
<td>voit</td>
<td>57.4388</td>
<td>0.9383</td>
<td>28.3812</td>
<td>0.7245</td>
</tr>
<tr>
<td>5</td>
<td>Tulips</td>
<td>57.6491</td>
<td>0.8414</td>
<td>27.5110</td>
<td>0.4976</td>
</tr>
<tr>
<td>6</td>
<td>peppers</td>
<td>62.4335</td>
<td>0.9011</td>
<td>29.9763</td>
<td>0.7261</td>
</tr>
<tr>
<td>7</td>
<td>Barnfall</td>
<td>76.2424</td>
<td>0.8337</td>
<td>29.6223</td>
<td>0.5219</td>
</tr>
<tr>
<td>8</td>
<td>bodie</td>
<td>66.1341</td>
<td>0.8886</td>
<td>30.7823</td>
<td>0.5677</td>
</tr>
</tbody>
</table>

Fig.2 Test Images

V. PERFORMANCE ANALYSIS

The performance of the Luminance Enhancement Model was determined using the standard test images of Fig. 2 (a-h) which are of poor quality using PSNR and SSIM as presented in Table 1. From the generated results and as presented in Fig. 3 (a-h), it is evident that the LEM outperformed the existing models that used the HSV color space. However, the plate number in output in Fig. 3 (d) had cracked characters which imply that the model cannot perform effectively on images with numbers. But, nonetheless, the general image was adequately enhanced.
This paper proposes the development of a saturation and value-based enhancement model that will reduce noise amplification with the use of the Laplacian filter to the barest minimum. Most of the enhancement models are based on the RGB color space. However, color manipulations are not adequately achieved in this space. Thus, leading to difficulty in image enhancement. As such, based on the HSV color model, an improved luminance enhancement model is presented in this paper. The result obtained showed that the proposed LEM performed effectively on most of the images except for the image that has number plate were the characters in the plate was cracked. Further work will consider the use of metaheuristics to optimize the filter as well as improving the LEM to support character enhancement.

**REFERENCES**


