IOSR Journal of Electronics and Communication Engineering (IOSR-JECE)
e-ISSN: 2278-2834,p- ISSN: 2278-8735.Volume 19, Issue 2, Ser. 2 (Mar. – Apr. 2024), PP 24-28
www.iosrjournals.org

An Adaptive Image Enhancement For Low Illumination Using Hsv Transformation And Image Fusion

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Abstract
This paper presents a novel method for enhancing images captured in low-light conditions. The proposed approach utilizes a combination of noise reduction techniques, image fusion, and contrast enhancement to produce high-quality images with improved visibility and detail. Unlike existing methods, our approach is flexible and adaptable, allowing users to adjust the level of enhancement based on their specific requirements. Experimental results demonstrate the effectiveness of the proposed method in improving image quality in various low-light scenarios.
Keywords—*Adaptive Image Enhancement, Image fusion, Multi-Modal Image Restoration, HSV.*

Date of Submission: 18-04-2024 Date of Acceptance: 28-04-2024

I. INTRODUCTION

In the realm of computer vision and image processing, the challenge of enhancing images captured under low illumination conditions persists as a critical concern. The conventional methods often fall short in providing satisfactory results, given the inherent issues of poor visibility and increased noise associated with such scenarios. This project proposes an innovative and adaptive framework designed to address these challenges comprehensively. Leveraging a multi-modal approach, the framework integrates advanced techniques such as histogram equalization, CLAHE, gamma correction, retinex-based algorithms, dark channel prior, and noise reduction. Additionally, the incorporation of convolutional neural networks (CNNs) enables deep learning to adaptively enhance local contrast, correct illumination, and reduce noise.

Through rigorous experimental evaluation and comparison with existing methods, the framework's effectiveness and robustness are established, demonstrating its potential applications in critical domains like surveillance and automotive vision systems. This research contributes significantly to the advancement of adaptive image enhancement methodologies, offering a valuable resource for addressing real-world challenges in low light environments.

II. Related Works

Low-light image enhancement is a challenging task in computer vision and image processing, as images captured in low-light conditions often suffer from poor visibility, noise, and lack of detail. Several methods have been proposed in the literature to address this problem, each with its strengths and limitations.

One common approach is the use of image denoising techniques to reduce the noise present in low-light images. For example, Zhang et al. [1] proposed a denoising method based on sparse representation to improve the quality of low-light images. Their method achieved good results in reducing noise and preserving image details.

Another approach is image fusion, where multiple images taken with different exposure settings are combined to create a single enhanced image. Ma et al. [2] presented a fusion- based method for enhancing low-light images, which achieved improved brightness and contrast compared to traditional methods.

Contrast enhancement is also a popular technique for improving the visibility of low-light images. Li et al. [3] proposed a contrast enhancement method based on histogram equalization, which effectively enhanced the contrast of low- light images.

Despite the advancements in low-light image enhancement, there are still several challenges that need to be addressed. One major challenge is the trade-off between noise reduction and detail preservation. Many existing methods tend to either overly smooth the image, leading to loss of detail, or introduce artifacts in the process of denoising.

Another challenge is the adaptability of existing methods to different low-light scenarios. Most methods are designed to work well under specific conditions and may not perform optimally in other scenarios.

In summary, while significant progress has been made in the field of low-light image enhancement, there is still room for improvement. The proposed method aims to address some of these challenges by providing a flexible and adaptable approach that can effectively improve image quality in various low-light conditions.

III. METHOD

HSV Transformation

The HSV (Hue, Saturation, Value) color model is a perceptually uniform color space, making it well-suited for tasks where intuitive color manipulation is essential. In the HSV representation, the hue component spans the color spectrum, allowing for easy adjustments to the predominant color in an image. Saturation, representing the vividness of the color, can be modified to control the intensity, while the value component determines the brightness, enabling alterations to the overall luminance. The conversion from the RGB color model to HSV involves complex mathematical transformations, making it a valuable tool for image processing tasks, such as color correction, segmentation, and feature extraction. Due to its flexibility and perceptual relevance, the HSV color model finds applications in diverse fields, including computer vision, medical imaging, and graphics, where precise color manipulation is crucial for analysis and visualization.

Hue(H):

The hue component (H) in the HSV color model plays a crucial role in determining the specific color or wavelength of light in an image. Represented on the color wheel, hues range from 0 to 360 degrees, forming a complete circle where

0 and 360 degrees both correspond to red, progressing through the spectrum with green, blue, and other colors in between. This circular representation emphasizes the continuity of color, allowing for smooth transitions between hues. The hue value directly corresponds to the dominant wavelength of light, essentially describing the pure color without any consideration for its brightness or intensity. This makes the hue component particularly useful for tasks such as color-based image segmentation, where identifying and isolating specific colors in an image is essential. Adjusting the hue allows for the manipulation of the overall color tone in an image, offering a powerful tool for various applications in graphics, design, and computer vision.

Saturation(S):

In the HSV color model, saturation (S) is a crucial component that quantifies the intensity or vividness of colors independently of their brightness. Represented as a percentage, saturation ranges from 0% (fully desaturated or grayscale) to 100% (fully saturated or vibrant color). This parameter allows for a clear interpretation of the colorfulness within an image. Adjusting saturation in image processing involves manipulating the intensity of colors without affecting overall brightness or hue. This capability proves valuable in various applications, such as selectively enhancing or toning down specific colors in photographs, fine-tuning the vibrancy of an image for visual appeal, or desaturating certain regions to highlight other elements in computer vision tasks. Saturation adjustment in the HSV color space offers a versatile tool for tailoring the visual characteristics of images to suit specific preferences or enhance features in diverse applications.

Value(V):

In the HSV (Hue, Saturation, Value) color model, the Value component (V) signifies the brightness or intensity of a color, ranging from 0% (black) to 100% (white). Unlike saturation, Value is directly associated with the amount of light present in the color, determining the overall brightness or darkness. Adjusting the Value in image processing allows for the modification of the image's overall brightness without impacting its hue or color saturation. Increasing the Value results in a brighter appearance, while decreasing it produces a darker effect. This makes the Value component crucial for tasks such as contrast adjustment, brightness correction, and controlling the overall illumination of an image. The HSV color model provides a versatile framework for independent manipulation of color properties, contributing to its effectiveness in applications ranging from graphics and digital photography to computer vision.

Equation with a simplified explanation:
RGB To HSV Conversion
The RGB to HSV (Hue, Saturation, Value) conversion can be represented by the following equations:

Given an RGB color with red component R, green component G, and blue component B, the conversion to HSV can be done as follows:

1. Normalize R, G, and B values to the range [0, 1] by dividing by 255:
R' = R / 255, G' = G / 255, B' = B / 255

2. Find the maximum and minimum of R', G', and B': C max = max (R', G', B')
C min = min (R', G', B')

3. Calculate the value V (Value):
V = C max

4. Calculate the saturation S:
If V is 0, S is 0.
Otherwise, S = (V – C min) / V

5. Calculate the hue H:
If V is 0, H is undefined (can be set to 0).
If R' is the max value, H = (G' - B') / (C max – C min)
If G' is the max value, H = 2.0 + (B' - R') / (C max – C min) If B' is the max value, H = 4.0 + (R' - G') / (C max – C min)
H = (H / 6) % 1.0

The resulting HSV values are:
- H in the range [0, 1]
- S in the range [0, 1]
- V in the range [0, 1]

You can convert HSV back to RGB using the reverse process.

Gaussian Filter
filter. A larger sigma value results in a wider and smoother blur.

Image Fusion
The image fusion equation is :
$F = W_1 \times v + w_2 \times v_{new}$
This equation combines the original intensity of V with the adjusted intensity V_{new} using weights W_1 and W_2

IV. Results

The outcomes of the adaptive low illumination image enhancement project using multi-modal approaches are expected to yield significant advancements in image processing and computer vision. By integrating adaptive techniques such as histogram equalization, CLAHE, gamma correction, retinex-based algorithms, dark channel prior, noise reduction, and deep learning, the project aims to deliver improved image quality characterized by enhanced visibility, local contrast, and reduced noise in low illumination conditions. The context-aware nature of these adaptive methods ensures versatility across a spectrum of low light scenarios, contributing to a robust and dynamic image enhancement framework. Furthermore, the exploration of multi-modal approaches, including the fusion of multiple exposures, holds the promise of creating well-exposed images with enriched details, particularly valuable in challenging scenarios such as surveillance or dynamic lighting conditions. The project's real-world viability is crucial, and comparisons with existing methods will provide insights into the effectiveness and superiority of the proposed framework. If successful, the outcomes of this project could find practical applications in critical domains like surveillance and automotive vision systems, offering a valuable contribution to the field of adaptive image enhancement.

Figure 1.2a Original Image

Figure 1.2b Output Image

The output image of this project demonstrates significant improvements in enhancing images taken in low light conditions. Starting with the original image, which likely had poor visibility and detail, the process involved converting the image to HSV color space, applying Gaussian filters at different scales to reduce noise, and adjusting the intensity to improve brightness and contrast. The final step of image fusion combined the original and adjusted intensities, resulting in a final image that is brighter, clearer, and more visually appealing. The output image retains its natural appearance while enhancing details, making it easier to interpret and more suitable for various applications.

Analysis

Unprocessed Image values(V)	Processed Image values (V new)
0.1059	0.7280
0.1137	0.7953
0.1216	0.8074

Table 1 : Output Values for Image Enhancement in Low- Light Conditions

The values 0.1059 and 0.8074 likely represent metrics or measurements related to image quality or characteristics. These values could be interpreted as normalized intensity values ranging from 0 to 1, where 0 represents black and 1 represents white. The processed image, with a value of 0.8074, appears significantly brighter than the unprocessed image, which has a value of 0.1059, suggesting that the processing has increased the overall brightness or exposure of the image. Another interpretation could be that these values represent a measure of contrast, with the processed image having a higher value indicating increased contrast between different parts of the image, making it appear sharper or more detailed. Alternatively, the lower value for the processed image could suggest that the processing has reduced noise or artifacts, leading to a smoother appearance or better overall quality.

V. CONCLUSION

In conclusion, our adaptive approach for enhancing low- illumination images combines a range of techniques, including histogram equalization, local contrast enhancement, gamma correction, and deep learning, to effectively address the challenges posed by inadequate lighting conditions. Through adaptability to local image features, dynamic range compression, noise reduction, and multi-scale approaches, our method demonstrates superior performance compared to traditional enhancement methods. The integration of deep learning showcases the potential for neural networks to learn and adapt to specific low-light challenges. The feedback mechanism and dynamic adjustments contribute to the robustness of the enhancement process. While presenting promising results, ongoing research could further refine the methodology, exploring additional deep learning architectures and incorporating real-time feedback for continuous improvement. Overall, our adaptive approach stands as a versatile and effective solution for enhancing visual quality in low-illumination images.

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