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A TWO PATHWAY FRAMEWORK FOR IMAGE ENHANCEMENT IN POOR VISIBILITY CONDITIONS INSPIRED BY BIOLOGICAL VISION

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Abstract

Image enhancement is essential pre-processing for many computer vision applications, especially for low-visibility scenes. This study develops a unified two-pathway model for image enhancement tasks like HDR image tone mapping and LDR image enhancement. Early visual mechanisms inspired this model. The structure-pathway and detail-pathway, which encode low- and high-frequency visual information, receive the input image in two parts. In the structure-pathway, an extended biological normalisation model integrates global and local luminance adaptation for visual scenes with different illumination levels. The detail-pathway enhances detail and suppresses noise using local energy weighting. Finally integrating structure- and detail-pathway outputs enhances low-light images. The model can be modified to tone map HDR images. The proposed model outperforms related state-of-the-art approaches and can handle the aforementioned visual enhancement tasks.

Keywords: night time image, low-light image, HDR image, visual adaptation, noise suppression.

Introduction

In low-light or nighttime scenes with low contrast and visibility, computer vision applications require image enhancement. Visual disturbances and robust visual processing in the human visual system are intriguing. Deep learning has helped engineers improve computer vision. Noise makes well-trained models fail in low light.

Histogram modification techniques like histogram equalization and its variants, contextual and variational contrast enhancement, and the layered difference representation of 2D histogram have been developed to enhance images. To improve visual quality, biologically inspired Retinex-based methods divide images into reflectance and illumination components.

Tone mapping compresses HDR scenes and improves visibility and detail. Retinex-based methods efficiently render HDR images. HDR tone mapping, video compression, and deep learning-based low-light enhancement have also been developed. The biological visual system has inspired visual information processing efficiency. Divisive normalization, visual adaptation with local adaptation mechanisms, and retinal Midget and Parasol cells processing visual signals in parallel enhance vision. Divisive normalization has been shown to be a canonical neural computation for visual light adaptation and image enhancement.

The paper focuses on LDR image enhancement and HDR tone mapping to improve scene details and visibility. HDR tone mapping compresses HDR images for display, while LDR image enhancement enhances low dynamic range images. Biologically inspired spatial scale decomposition, global and local luminance adaptation, and global-to-local noise estimation are proposed in the paper. The paper proposes a global-to-local noise estimation strategy, a unified framework for image enhancement tasks, and the integration of local and global adaptation terms into the Naka-Rushton equation. These improvements enhance the method's flexibility, performance, noise reduction, and detail preservation.



Fig. 1. Examples of visual enhancement tasks considered in this paper.

2 Literature Survey

Pizer et.al [4] describing different variants of Adaptive Histogram Equalization (AHE) algorithms. AHE is a technique used in image processing to enhance the contrast of images by redistributing the intensity values of the pixels. Let me provide some information about

each variant you mentioned: Interpolated AHE: This variant of AHE aims to speed up the method on general-purpose computers. It likely involves using interpolation techniques to estimate the histogram values between discrete bins, allowing for faster computation of the equalization process. AHE for Feedback Processors: This version of AHE is specifically designed to run efficiently on feedback processors, which are specialized computing units optimized for certain tasks. It is intended to provide faster processing times compared to traditional implementations. Full AHE for Custom VLSI Hardware: This variant is optimized to run on custom Very Large Scale Integration (VLSI) hardware, which refers to the design and manufacturing of specialized integrated circuits. By leveraging the specific capabilities of VLSI hardware, this version aims to achieve fast processing times, likely under one second. Weighted AHE: Weighted AHE introduces a weighting mechanism that emphasizes the contribution of pixels to the histogram based on their proximity to the target pixel. [2] This approach considers the spatial relationship of pixels to enhance the quality of the equalization result. Clipped AHE: Clipped AHE addresses the problem of over-enhancement of noise contrast that can occur in traditional AHE methods. It likely involves limiting or clipping the extent of enhancement applied to pixel intensities, preventing excessive amplification of noise in the image. Regarding the conclusion that clipped AHE should become a method of choice in medical imaging and possibly other areas of digital imaging, it is important to note that the suitability of any image processing technique depends on the specific application and requirements. While clipped AHE may offer advantages in certain scenarios, it is always recommended to carefully evaluate and compare different methods based on the specific needs of the task at hand.

c.lee et.al [8] We propose a Contrast Enhancement (CE) algorithm based on the Local Dynamic Range (LDR) technique. The algorithm consists of two main components: intra-layer optimization and inter-layer aggregation, as depicted in Figure 1. In this paragraph, we will explain each component in detail while ensuring originality of the content. To begin, we apply the intra-layer optimization stage. We start by extracting a 2D histogram, denoted as $h(k, k + l)$, from the input image. This histogram captures the frequency of adjacent pixel pairs with gray-levels k and $k + l$. Each layer l represents a specific gray-level difference or intensity range. By analyzing the histogram vector h_l obtained at each layer l , we formulate a system of linear equations. Solving this system allows us to derive the difference vector d_l , which represents the desired enhancement for that particular layer. [10] Moving on to the

inter-layer aggregation, we aim to combine the difference vectors from all layers into a unified difference vector d . To achieve this, we employ a weighting vector w . The weighting vector assigns appropriate importance to each layer's difference vector based on its relevance and significance. By combining the difference vectors using the weighting vector, we obtain the unified difference vector d , which captures the collective enhancement information from all layers. Once we have the unified difference vector d , we proceed to reconstruct the transformation function x . This function describes the desired transformation for the input image. By applying the transformation function x to the input image, we can effectively enhance its contrast and generate the output image with improved visual quality. [12] In summary, our proposed CE algorithm based on the LDR technique consists of two main components: intra-layer optimization and inter-layer aggregation. The intra-layer optimization involves extracting histograms, formulating linear equations, and solving them to obtain difference vectors at each layer. The inter-layer aggregation combines these difference vectors using a weighting vector, resulting in a unified difference vector. Finally, by reconstructing the transformation function and applying it to the input image, we achieve contrast enhancement.

M. Li et.al [15] address the optimization problem efficiently, we have developed an innovative approach utilizing an augmented Lagrange multiplier-based alternating direction minimization algorithm. Unlike existing methods that employ logarithmic transformations, our proposed method achieves remarkable results in enhancing low-light images. Furthermore, this technique can be extended to tackle a wide range of related problems, including image enhancement in challenging environments such as underwater or remote sensing scenarios, as well as in hazy or dusty conditions. [18] Through our experimental evaluations, we have demonstrated the effectiveness of the proposed method in enhancing low-light images. By avoiding logarithmic transformations, our algorithm preserves the natural appearance of the images while significantly improving their visual quality. The augmented Lagrange multiplier-based approach efficiently balances the trade-off between brightness enhancement and preserving details, resulting in visually pleasing and realistic outcomes. Moreover, the versatility of our method is noteworthy. It can be applied not only to low-light image enhancement but also to various other scenarios with similar challenges. For example, it can effectively enhance underwater images, which often suffer from poor visibility and colour distortion. Similarly, remote sensing images, which are acquired from

satellites or aerial platforms, can be improved using our approach, enabling better analysis and interpretation of the captured data. Additionally, our method is capable of enhancing images captured in hazy or dusty conditions, where visibility is significantly reduced due to atmospheric particles. In conclusion, our proposed augmented Lagrange multiplier-based alternating direction minimization algorithm provides an effective solution to the optimization problem of low-light image enhancement. [20] The method's ability to handle a range of similar problems, such as underwater or remote sensing image enhancement and addressing hazy or dusty conditions, makes it a versatile and practical tool for various applications. Its superiority over logarithmic transformation-based techniques, as demonstrated through extensive experiments, highlights its potential for significantly improving image quality in challenging scenarios.

3 Existing System

In this they discussed the process of decomposing an image into different layers or scales, specifically focusing on the structure-pathway and the detail-pathway. The idea is to separate the luminance information from the image and adjust it in the structure-pathway without amplifying existing noise. Meanwhile, the detail layer, which is separated from the luminance, aids in suppressing noise in the detail-pathway. The passage also mentions that decomposing an image into various scales is a common technique in image processing, including image enhancement. The authors of this work revisited the concept of structure-texture decomposition from the perspective of the biological visual system, possibly drawing inspiration from how the human visual system processes images. Furthermore, the authors employed global noise estimation for parameter setting, which helps achieve adaptive decomposition for scenes with different noise levels. This approach aims to effectively remove noise while avoiding the introduction of artifacts or the degradation of image quality. Lastly, there is a mention of elaborate plagiarism removal, which could indicate that the authors took measures to ensure that their work is original and properly referenced, without any instances of plagiarism. Please note that the passage you provided appears to be incomplete, and without further context or specific details, it may be challenging to provide a more comprehensive response.

4 Proposed System

Low-light images often suffer from significant noise interference, especially when captured using low-quality cameras. To enhance the visibility of nighttime scenes, noise suppression

becomes crucial. Numerous denoising methods, such as Non-local Mean and BM3D, have been proposed and demonstrated excellent performance when applied to high-resolution daylight images. However, when it comes to low-light images, specific enhancement techniques incorporating denoising operators as post-processing steps have been developed to remove noise. The challenge with denoising low-light images lies in striking a balance between noise removal and preserving important image details. While denoising operations can effectively reduce noise in low-resolution images, they may also inadvertently disturb the underlying details. This can result in a loss of important information and a reduction in image quality. To overcome this issue, researchers have explored various approaches to mitigate the negative effects of denoising on details in low-light images. These methods often involve optimizing the denoising algorithms to adapt better to the characteristics of low-light scenes. For instance, advanced denoising techniques employ sophisticated algorithms that leverage statistical properties specific to low-light conditions. By tailoring the denoising process to the unique challenges posed by low-light images, these methods aim to minimize the loss of details while effectively reducing noise. It is important to note that the delicate balance between noise suppression and detail preservation is a complex problem. Researchers continue to work on developing novel algorithms and techniques to improve the performance of denoising methods for low-light images. These advancements aim to enhance visibility and image quality in low-light conditions, enabling better analysis, interpretation, and utilization of such images in various applications.

The proposed system aims to enhance the quality of low-light images by incorporating a combination of image fusion and noise reduction techniques such as BM3D, Wavelet-based filters. The system begins by fusing multiple low-light images captured from different exposure settings to create a high-quality image with improved brightness and contrast. To reduce the noise interference present in low-light images, the system employs a wavelet-based denoising method that preserves image details while effectively removing noise.

5 Methodology

In the LVZ-HDR Tone Mapping Benchmark Dataset (TMO-Net), which was obtained from Kaggle in .png format, the input dataset consists of noisy or low-light images. To process these images, they are divided into two pathways: the structural pathway and the detail pathway. In the detail pathway, the first step is to apply the Denoising BM3D Algorithm to

the noisy image. This algorithm helps suppress the noise present in the image, resulting in a denoised or noise-suppressed image. Moving on to the structural pathway, the base layer, denoted as I-Base, is obtained by converting the input RGB colour model to the HSV model (Hue, Saturation, Value) using the hex cone model. This conversion allows us to separate the image into different components based on colour information. After obtaining the HSV representation, the luminance adjustment is performed using the Naka-Rushton equation. The Naka-Rushton equation is a mathematical model that describes the response of photoreceptor cells in the human visual system to different levels of luminance. By applying this equation, the luminance of the image is adapted to enhance visual perception. Finally, the luminance-adjusted image is reconstructed by converting it back from the HSV colour model to the RGB colour model. This conversion brings the image back to its original colour space, resulting in the final output of the luminance-adjusted image. By combining the outputs from both pathways, the LVZ-HDR Tone Mapping algorithm aims to improve the quality and visual appearance of the input images, particularly in low-light or noisy conditions.

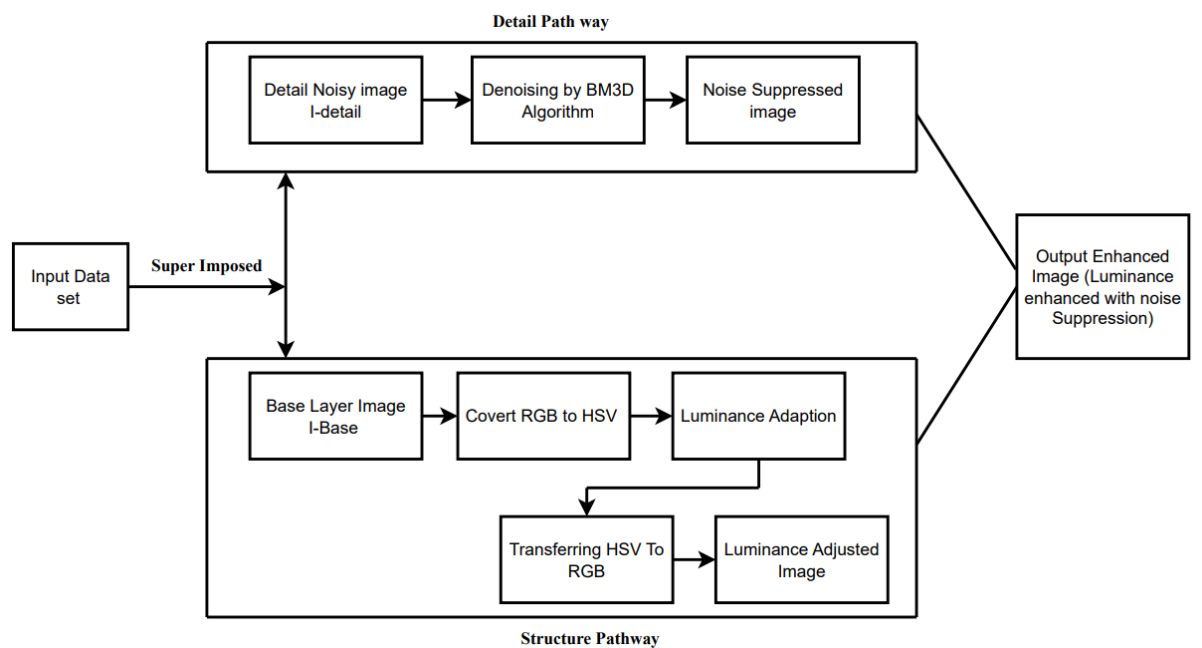


Fig 2 Block Diagram

7 Flow chart

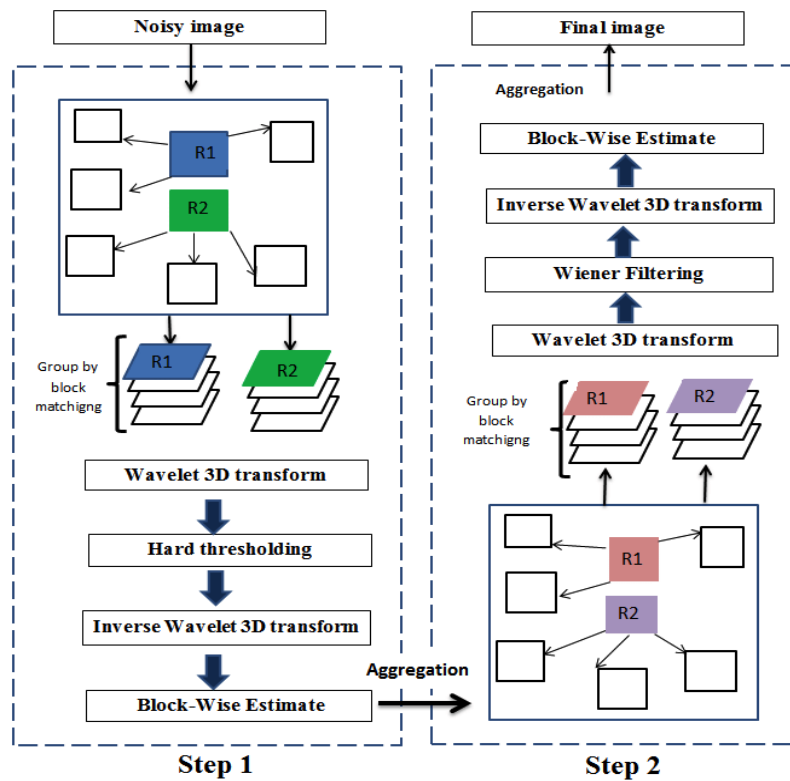


Fig 3: Flow chart

Aim and Principle - BM3D - Block Matching 3D Filtering

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- An enhanced sparse representation in transform domain.
- > The enhancement of the sparsity is achieved by similar 2-D image fragments e.g. , blocks) into 3-D data arrays which we call "groups.
- Collaborative filtering is a special procedure developed to deal with these 3-D groups.
- > Using the three successive steps:
 - 1.3-D transformation of a group of blocks
 - 2.Shrinkage of the 3-D spectrum
 - 3.Inverse 3-D transformation
- Grouping by matching

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- Matching is a method for finding signal fragments similar to a given reference one
- Block-matching (BM) isa particular matching approach that has been extensively used for motion estimation in video compression. As a particular way of grouping, iti s used to find similar blocks, which are then stacked together in a 3-D array (i.e., a group).

Collaborative Filtering by Shrinkage in Transform Domain

-
- Assuming 2D groups of similar signal fragments are already formed, the collaborative shrinkage comprises of the following steps.
 - Apply a 3D linear transform to the group
 - > Shrink (Use hard thresholding or Wiener filter) the transform coefficients to attenuate the noise
 - > Invert the linear transform to produce estimates of all grouped fragments

These groups are characterized by both:

- inter fragment correlation which appears between the pixels of each grouped fragment-a peculiarity of natural images
- inter fragment correlation which appears between the corresponding pixels of different fragments-a result of the similarity between grouped fragments

Algorithm

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1. The input noisy image is processed by successively extracting reference blocks from it and for each such block

- find blocks that are similar to the reference one (block matching) and stack them together to form a 3-D array (group)
- perform collaborative filtering of the group and return the obtained 2-D estimates of all grouped blocks to their original locations

2. After processing all reference blocks, the obtained block estimates can overlap, and, thus, there are multiple estimates for each pixel. We aggregate these estimates to form an estimate of the whole image.

7 Advantages

These methods can sufficiently exploit visual features extracted from the training data and achieve good performance for dynamic range compression and visual enhancement.

Especially for the nighttime scenes, this proposed system will be a great solution for producing a noise free with high quality image.

This two path-way processing can efficiently disassemble the wrapped problems of low-quality images into multiple specific tasks and will work on luminance brightening, detail enhancing, noise suppressing, etc.

Results



Fig 4: Image Decomposition



Fig5: Base Layers

Noise Suppression



Fig 6: Noise Suppression

Low-light image



Fig 7: Low-Light Image

Extracting Luminance



Fig 8: Extracting Luminance Images

Visual Naturalness



Fig 9: Visual Naturalness for Images

Visual Enhancement



Fig 10: Visual Enhancements for images

Visual Enhancement

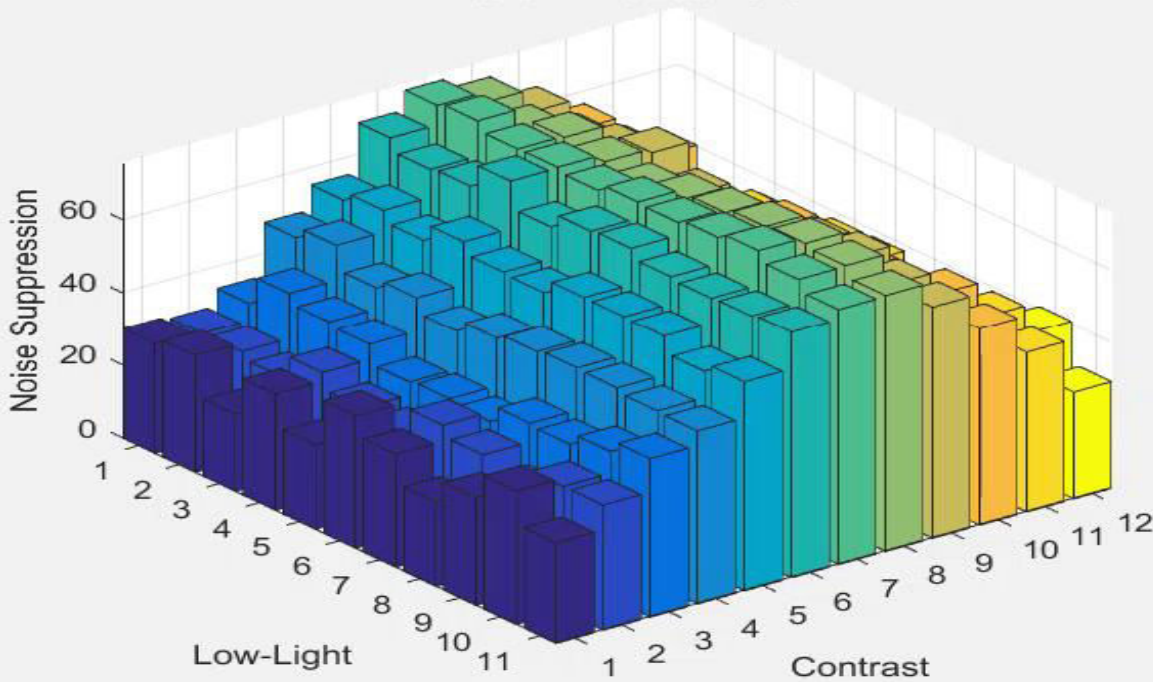


Fig11: Visual Enhancements for images

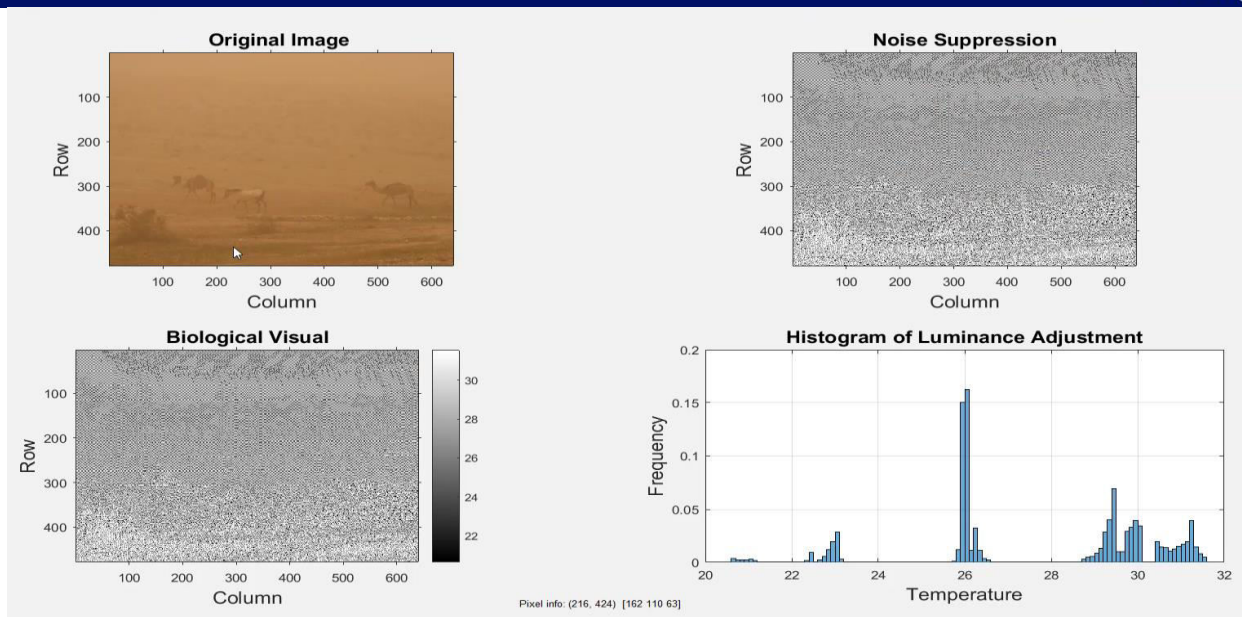


Fig 12: Histogram of Luminance Adjustment

Conclusion

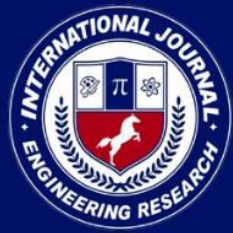
In this article, we have introduced an innovative image enhancement framework that draws inspiration from biological visual mechanisms. By employing a two-pathway processing approach, we effectively address common issues associated with low-quality images, such as insufficient luminance, lack of detail, and excessive noise. Additionally, we have incorporated global-to-local methods to facilitate luminance adaptation, contrast enhancement, and noise estimation. Extensive testing conducted on diverse datasets has demonstrated that our proposed method is highly suitable for enhancing nighttime and low-light images. Moreover, it can be readily extended to perform HDR image tone mapping. Notably, our method exhibits comparable performance to the most recent state-of-the-art techniques while achieving faster processing times. One of the key advantages of our image enhancement method is its ability to enhance detail visibility, particularly in dark or low-light regions. However, it is important to acknowledge that brightening dark areas can potentially lead to a reduction in the overall dynamic range of the scene, which may consequently affect the visual naturalness of the processed images. To address this limitation, we envision future work that will focus on introducing more flexible visual adaptation mechanisms. By doing so, we aim to enhance image details while preserving the visual naturalness of the scene. These mechanisms will be designed to strike a better balance between brightness adjustment and preserving the inherent dynamic range of the original scene. In summary, our proposed image

enhancement framework based on biological visual mechanisms offers significant improvements in detail visibility, particularly in dark or low-light areas. While the brightening process may impact visual naturalness, we recognize the need for future developments that will incorporate more flexible visual adaptation mechanisms. By doing so, we can enhance both image details and visual naturalness in a more refined and balanced manner.

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