A Detail Enhancement Method for Weakly Illuminated Images Using Weighted Guided Filtering Technology

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INFORMATION

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ABSTRACT

In order to optimize the visual effect of weakly illuminated images, this study designed a detail enhancement method for weakly illuminated images based on weighted guided filtering technology. Low-light images undergo a series of transformations that include, among others, the grayscale transformation and the multi-scale weighted guided filtering. Filtration improves both the basic and detailed layers. The proposed method is validated through experimental results to be capable of effectively increasing the visibility and clarity of dimly lit images without losing the delicate texture and edge information. More precisely, the output images register an average gradient of 17.547, which shows that the edges are sharper; information entropy that is always above 4.0, which means that the detail content is richer; and a peak signal-to-noise ratio of 42.85 to 48.37, which asserts that the image quality is high. The whole enhancement process is very fast, and it takes only 1 min to complete, indicating that this method effectively achieves the design expectation.

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1 Introduction

With the popularization of smart devices and the continuous development of science and technology, the acquisition of multimedia data has become simpler. In the era of the internet, the surge in data such as images and videos has not only promoted the development of related technologies in the field of computer vision, bringing great convenience to people's lives, but also raised higher requirements for data processing technology [1].

However, in reality, obtaining high-quality images is not easy due to various factors, including equipment, environment, and improper human operation. Especially in low-light environments, there are issues such as low or high image brightness, sensitivity to contrast, and difficulty in revealing details in dark areas [2]. Weakly illuminated images, namely images with low brightness, have various problems such as low contrast, narrow dynamic range, dim colors, unclear details, and obvious noise. These issues not only affect the visual effect of the image, reducing its quality, but also affect the

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performance of advanced visual tasks [3]. Therefore, it is necessary to preprocess and enhance low-light images.

The purpose of low-light image enhancement processing is to improve the imaging quality, enhance visual effects, and enhance the performance of downstream tasks. This task has wide applications in multiple fields, such as night video security, night autonomous driving, and underwater mining operations [4]. In these scenarios, due to poor lighting conditions, the obtained image quality is often poor, making it difficult to meet the needs of practical applications. Therefore, through weakly illuminated images enhancement processing, the quality of the image can be effectively improved, providing better input for subsequent visual tasks.

In reference [5], for low-light images, the bilateral filtering MSR algorithm is first used to enhance the brightness channel of the image while retaining the original color features. Then, use the CLAHE algorithm to enhance the feature details of the brightness channel. On this basis, through the processing of the AutoMSRCR algorithm, feature details and brightness information are weighted and fused. However, although bilateral filtering can preserve edge information, it may smooth out some details when enhancing the brightness channel, especially when the filter parameters are set relatively loosely. Meanwhile, although the CLAHE algorithm can enhance the local contrast of images, it may also lead to excessive enhancement, especially in flat areas of the image, which may introduce noise and lose some details. In reference [6], brightness components were decomposed in the HIS space of low-light images, and different components were subjected to equalization stretching and mean square deviation quantization to improve the brightness of the image. On this basis, feature extraction is completed through mean filtering, and the image color is adjusted using an adaptive stretching function based on the correlation between different components. However, this method can easily disrupt the balance between color and brightness in the original image when decomposing brightness components, and mean filtering is a smoothing filter that may smooth out some important detail information when extracting features, leading to the loss of detail information. An artificial light optimization algorithm was designed in reference [7] to preprocess images with uneven lighting and mitigate the impact of light distortion. Then, to address the issues of low image contrast and color distortion, this study also proposes an enhancement algorithm based on multi-scale fusion generative adversarial networks. The generative adversarial network is used as the underlying framework to extract features from the image, restore the detailed information of the image through a reconstruction module, and then linearly add multiple loss functions to iteratively train the adversarial network to obtain the enhanced image. Although generative adversarial networks have achieved significant results in image enhancement, they may also introduce some unnatural details or lose some original detail information during the generation process. In addition, the linear superposition of multiple loss functions may result in the network not being able to balance various targets well during the training process, thereby affecting the quality of the final image.

The FD-IoT-DMSFNN framework combined deep multi-scale fusion and data optimization technologies to achieve better fault detection accuracy and faster processing in Industrial IoT systems. The proposed method, inspired by this approach, also integrates information from multiple layers—merging the basic and detail layers of lowlight images—to improve visual clarity, retain fine textures, and save computational power, thus adapting the fusion principle to image enhancement [8]. Boundaries of Bio-inspired Computing for Optimal Solutions investigates the role of bio-inspired methods, like fuzzy logic and adaptive algorithms, in the development of stronger image enhancement techniques, leading to the optimization of performance and resource usage.

Even though Guided Filtering, AHE, and Fuzzy Logic are considered conventional techniques, this research showcases an unusual mixture of these methods, where they are carefully implemented and adjusted to keep fine textures, protect edges, and reduce noise throughout layers. Such a creative method guarantees improvement in visual clarity and more efficient detail enhancement compared to the classical independent techniques, thus providing an optimized answer for poor lighting situations.

Even though our approach relies on traditional modules like guided filtering, adaptive histogram equalization, and fuzzy enhancement, the originality of the method rests on the multi-scale weighting strategy that unifies these components and forms a single optimization pipeline. The weighted grayscale transformation, noise-adaptive guided filtering, and fuzzy detail enhancement proposed are not carried out on their own; rather, they utilize region-dependent weights and regularization factors that fluctuate with the enhancement strength, which allows controlling more strongly detail preservation and less noise. This integrated design facilitates the conventional GF+AHE+Fuzzy combinations reported in previous work in terms of stronger detail preservation and more stable noise control.

The examination done above points out that classic techniques usually do not keep the full detailed information and thus produce images with rather low average gradient values. In order to overcome these drawbacks, a detailed enhancement method for images with poor illumination is suggested in this work, which relies on the weighted guided filtering technique. The method is outlined as follows:

①**Weighted grayscale transformation:** By analyzing the characteristics of low-light images and using weighted algorithms to construct grayscale transformation functions, a foundation is provided for subsequent image enhancement processing. The grayscale transformation function can map the grayscale values of the original image to a new range of grayscale values, improve the visual effect of the image, and provide good input for subsequent processing steps.

②**Global nonlinear filtering for noise suppression:** Noise characteristics of different regions in the image, a global nonlinear filtering function is constructed, and the corresponding regularization scale factor for each region is solved to guide subsequent filtering processing. Regular scaling factors can reflect the intensity of noise in different regions of an image. By setting appropriate filtering windows and pixel mean filtering methods, noise can be more effectively suppressed, and image quality can be improved.

③**Basic and detail layer enhancement:** Through adaptive histogram equalization processing, brightness and contrast are dynamically adjusted based on the distribution characteristics of histograms in different regions, resulting in a significant improvement in the overall visual effect of image basic layer enhancement. Afterwards, the fuzzy enhancement algorithm is used to enhance the detail layers of the image, highlighting the edge and texture information in the image. Fuzzy enhancement algorithms can effectively enhance the detailed information of images, making details that are difficult to recognize under weak lighting conditions clear and distinguishable, and improving the expressive power of image details.

④**Fusion of basic and detail layers:** By integrating the information from the basic and detail layers, an enhanced image with both good overall visual effects and rich detail information can be obtained, meeting the visual needs under weak lighting conditions.

Image enhancement, besides being used in night-time security applications, is a necessary preprocessing step for many high-level vision tasks. In the case of medical imaging, for instance, such issues as low-contrast CT and MRI scans, usually accompanied by noise, poor lighting, and a limited amount of annotated data, make high-quality enhancement very important for segmentation and diagnosis to be reliable. Aerial imaging, industrial inspection, and robotics are some of the fields that share this need, as the visibility enhancement that occurs directly uplifts the accuracy of the subsequent algorithms. Consequently, even though our trials deal with weakly illuminated security images, the advocated multi-scale weighted enhancement method is versatile and can be adopted in other areas where poor imaging conditions are a barrier to task performance.

2 Weakly Illuminated Image Preprocessing Based on Multi-Scale Weighted Guided Filtering

In order to enhance the detailed information in low-light images, this study first performed preprocessing operations on them. In the preprocessing stage, the weighted guided filtering algorithm is used to achieve mixed grayscale transformation and denoising functions. Firstly, by adjusting the grayscale distribution of the image through a weighted algorithm, the problem of uneven shadow distribution in the image is effectively improved, making the image clearer. Guided filtering mainly plays a denoising role, removing noise points in the image, improving the contrast between low-light and high-light areas, thereby facilitating subsequent image enhancement and feature extraction work. Then, the global nonlinear filtering function is used to solve the noise regularization factor, laying the foundation for subsequent noise suppression. On this basis, a filtering window is set according to the size of the noise regularization factor, and the image quality is improved, and noise interference is reduced through pixel mean filtering.

Although the proposed pipeline integrates well-established techniques like guided filtering, adaptive histogram equalization (AHE), and fuzzy logic, it is the manner in which these techniques have been combined and calibrated for weakly illuminated images that the novelty lies. The method proposes adaptive fuzzy enhancement functions, multi-scale guided filtering, and optimized histogram equalization, which, when used, will keep edges, boost local details, and minimize noise. These custom-made approaches guarantee better performance over normal implementations. For reproducibility and practical validity, the proposed method is disclosed in such a way that it would be hard to miss each processing step and its mathematical basis. The initial step of the workflow is grayscale adjustment as a means of normalizing intensity. Next, the application of the multi-scale weighted guided filtering method for noise reduction and edge preservation. The fuzzy enhancement algorithm has made the detail layers even better, while adaptive histogram equalization guarantees that there is a balanced contrast throughout the shadows and highlights. The output of each step is the input of the next one, and the pseudocode supplied makes it possible for other researchers to redo the preprocessing and enhancement pipeline at the same time as the soundness and practical applicability of the method are being demonstrated.

The preprocessing process of low-light images is presented in Algorithm 1.

Algorithm 1: Preprocessing of low-light image

```
Input: Low-light image I
Output: Preprocessed image I_pre
//Weighted Grayscale  Transformation
for each pixel pin I:
        I_plus(p) = log (1 + I(p))
        I_minus(p) = log (1 + (1 - I(p)))
        ω_I(p) = compute_weight(I(p))
```

(Continued)

Algorithm 1 (continued)

```
    F_log(p) = ω_I(p) * I_plus(p) + (1 - ω_I(p)) * I_minus(p)
F_s = GaussianSmooth(F_log, σ_n)
//Guided Filtering
for each local window Ω_k around pixel p:
    μ_I = mean (F_s in Ω_k)
    σ_I² = variance (F_s in Ω_k)
    cov_IG = covariance (F_s, F_s in Ω_k)
    a_k = cov_IG/(σ_I² + ε)
    b_k = μ_I - a_k * μ_I
I_gf = mean(a_k) * F_s + mean(b_k)
//Noise Regularization Factor
for each pixel p in I_gf:
    n_local(p) = |I_gf(p) - Local Mean (I_gf, p) |
λ_noise = mean(n_local)
//Adaptive Mean Filtering
for each pixel p in I_gf:
    r_p = adaptive_radius(λ_noise)
    I_pre(p) = mean (I_gf in window r_p)
return I_pre
```

A major plus point of the suggested preprocessing framework is its clarity and transparency of parameters. The whole process—weighted grayscale transformation, multi-scale guided filtering, noise-adaptive smoothing, and fuzzy enhancement—is composed of clearly defined mathematical operations whose results can be easily followed and managed. Parameters that are conventional in our methodology (for instance, per-pixel weights, filtering radii, and fuzzy coefficients) have direct physical and computational interpretations, thus giving the users insight into the image modification process. The interpretability of the process not only guarantees the behavior to be predictable, but also makes it easier for parameter optimization and hence the method to be practically usable for a wider range of imaging conditions.

2.1 Image Grayscale Transformation Processing

In order to highlight the shadow and highlight distribution of the image, the log hierarchical decomposition function is used as the mixed grayscale transformation function of the image. This function can effectively perform hierarchical decomposition on the grayscale of the image, making the shadow and highlight areas more prominent in the image [9]. By doing so, we can better capture the detailed information in the image and enhance its visual effect.

The technique of logarithmic hierarchical decomposition has enhanced the visibility of the images by making it possible to process the components of the image forward (I^+) and backward (I^-) separately. Incorporating bio-inspired computing principles, such as fuzzy logic and guided filtering, optimizes the processing of images under weak illumination by enhancing contrast and detail retention. The forward component first amplifies the low-intensity pixels in shadow regions, and the backward component, in turn, does the same for the high-intensity pixels in highlight regions. The contrast of shadows and highlights is enhanced by weighting these components together and applying Gaussian smoothing—the method makes fine details in dark areas almost perceptible and bright regions clearer without introducing artifacts or losing overall image fidelity.

This study uses the log level decomposition function as the grayscale transformation function, which is represented in the form of $f_{\log(I)}$. The calculation process is as follows:

$$f_{\log(I)} = G_n \times \left(\omega_I \times I^+ + (1 - \omega_I) \times I^-\right) \tag{1}$$

The variables in Eq. (1) are explicitly defined as follows. $f_{\log(I)}$ denotes the weighted logarithmic grayscale transformation output. I is the original weakly illuminated image, and ω_I is the per-pixel weighting coefficient in the range $[0, 1]$ determining the relative contribution of the two logarithmic components. I^+ and I^- are the forward and backward logarithmic responses of the image, capturing highlightand shadow-related variations, respectively. G_n represents the Gaussian smoothing operator at scale n. These definitions ensure that all symbols in Eq. (1) are uniquely specified and interpreted without ambiguity.

In the formula, I represents the original weakly illuminated image; ω_I represents the weight of image pixels, which is a weight factor between 0 and 1, mainly determined based on the contribution of image components; I^+ and I^- represent the forward and backward components of the weakly illuminated image, respectively; G_n represents the Gaussian function of the n-th scale. According to Eq. (1), it can be seen that by combining the forward and backward components, the contrast of the image can be enhanced. By linearly combining I^+ and I^- according to weight ω_I, an intermediate result can be obtained. Introducing Gaussian function to smooth the image and reduce the impact of noise. Operate this intermediate result with a Gaussian function to obtain the final grayscale transformation function.

The calculation method for I^+ and I^- is as follows:

$$\begin{cases} I^+ = \lg(I_h + 1) \\ I^- = \lg(h) - \lg(h_h - I) \end{cases} \tag{2}$$

In the formula, h represents the total grayscale level of the image [10], I_h represents the grayscale level of the original image.

The calculation method for G_n is as follows:

$$G_n = \exp\left(-\frac{{x_\mu}^2 + {y_\mu}^2}{\mu_n^2}\right) \tag{3}$$

In the formula, μ represents the adaptive factor; x_μ, y_μ represent the pixel contrast value of μ in the horizontal and vertical directions (shaded and highlighted parts), respectively.

The calculation method for image weight ω_I is as follows:

$$\omega_I = \frac{1}{M} \sum\nolimits_{(x,y)\in A} \left(\frac{\kappa^+_{(x,y)}}{\kappa^+_{(x,y)} + \kappa^-_{(x,y)}}\right) \tag{4}$$

In the formula, M represents the number of pixels in the weakly illuminated image; A represents the location of the pixel in the region; $\kappa^+_{(x,y)}$ and $\kappa^-_{(x,y)}$ represent the standard deviation of the I^+ and I^- filtering windows, respectively.

After converting the original low light image into a grayscale image, for each pixel in the image, apply function $f_{\log(I)}$ to calculate its new grayscale value. The process is as follows:

$$O(x, y) = f_{\log(I)} \times I_{gray(x,y)} \tag{5}$$

In the formula, $O(x, y)$ represents the grayscale value of the output image at position (x, y), and $I_{gray(x,y)}$ represents the grayscale value of the input grayscale image at the same position. In the process of image processing, the input image $I_{gray(x,y)}$ is processed by some algorithm or transformation to obtain the output image $O(x, y)$. This transformation can be a simple grayscale transformation, such as contrast adjustment and brightness adjustment, or a complex image processing operation, such as edge detection, filtering, morphological operations, etc. The grayscale transformation is applied in this study.

After applying the log hierarchical decomposition function, it is necessary to further adjust the obtained grayscale values by offsetting them to ensure that they are within the effective grayscale range (usually 0 to 255) [11]. Recombine the grayscale values transformed by the log hierarchical decomposition function into an image to obtain the transformed image I'.

2.2 Guided Filtering Processing of Images

Guided filtering is a type of local linear filtering algorithm that uses guided images (images that have undergone grayscale transformation) to guide the filtering process. The basic idea of guided filtering is to assume that the output image is a local linear transformation of the guided image [12]. Firstly, it is necessary to define a guided filtering function, whose expression is:

$$\hat{I}_k = a_k \cdot I_k + b_k \tag{6}$$

In the formula, $\hat{I}_k$ is the output pixel value at position k, I_k is the value of the guiding image at pixel k. a_k and b_k are the linear coefficients and q (or the regularization factor) is used to adjust the filtering strength.

The detailed process of establishing the guiding filter function in Eq. (6) is as follows:

Step 1: Local linear model assumption. Guided filtering assumes that the output image is a linear transformation of the guided image within a local window centred around pixel k. This means that within the local window, each pixel value of the output image can be represented as a linear combination of guided image pixel values.

Step 2: Define linear coefficients. Define two linear coefficients a_k and b_k within each local window. Coefficient a_k controls the degree of influence of the guiding image on the output image, while coefficient b_k is an offset used to adjust the brightness of the output image.

Step 3: Build the cost function. To determine the linear coefficients a_k and b_k, construct a cost function that measures the difference between the output image and the input image. The cost function typically includes a squared error term and a regularization term, the latter of which is used to prevent the coefficient a_k from being too large.

Step 4: Minimize the cost function. Solve for linear coefficients a_k and b_k by minimizing the cost function. This usually involves taking the derivative of the cost function and setting the derivative to zero, in order to obtain closed form solutions for a_k and b_k.

Step 5: Calculate the output image. After obtaining the linear coefficients a_k and b_k of each local window, calculate the pixel values of each output image. This is usually achieved by weighted averaging the linear transformation results of all windows covering the pixel.

Step 6: Introduce the filtering factor q. The filtering factor q is used to normalize or adjust the filtering effect. It can ensure that the brightness of the output image is consistent with the input image, or be used to adjust the strength of filtering.

The linear coefficients a_k and b_k are derived by minimizing a cost function that balances fitting the input image I to the guiding image I_g while maintaining smoothness in the coefficients across the image. The coefficients are calculated as follows:

$$a_k = \frac{\sum_{p\in W_k} \left(I_g(p) - \mu_g\right)(I(p) - \mu_I)}{\sum_{p\in W_k} \left(I_g(p) - \mu_g\right)^2 + \epsilon}$$

$$b_k = \mu_I - a_k\mu_g \tag{7}$$

In the formula, W_k represents the local window centered around pixel k, $I_g(p)$ and $I\,(p)$ are the values of the guiding image and the input image at pixel p, respectively. μ_g and μ_I are the local means of the guiding image and the input image within the window W_k. $\in$ is a small constant added for numerical stability (regularization term). Dynamically set the size of the filtering window based on the noise regularization scaling factor [13]. In areas with high noise intensity, use a larger filtering window to smooth out the noise; In areas with rich details, use smaller windows to preserve more details. The size of the filtering window can be expressed in the following form:

$$w_k = \frac{w_0}{1 + \dfrac{w_0 - \varepsilon_{min}}{\varepsilon min_{max}}} \tag{8}$$

In the formula, w_k represents the size of the filtering window corresponding to pixel k, w_0 represents a base window, ε_{min} and ε_{max} represent the minimum and maximum values of the noise regularization scaling factor, respectively.

The filtering window utilized in guided filtering is adaptive, which means its size varies according to the local image content. A larger window will be switched on in areas with a lot of noise to smooth out the changes, while a smaller window will be used in areas with high detail to retain the fine structures. The adaptive nature here guarantees excellent noise suppression along with the recovery of significant image details. After determining the filtering window, average filtering is performed on the pixels within each window. That is, by calculating the average value of all pixels within the window, the average value is used as a new pixel value to replace the value of the central pixel in the window, thereby achieving guided filtering processing of the image. The first grayscale transformation is a step that prepares the image by normalizing intensity values, thereby enabling the following enhancement techniques, such as guided filtering and fuzzy detail enhancement, to improve contrast, reduce noise, and enhance edges more effectively. The process of enhancement takes the output of the previous step as input and improves it through unifying and gradual image enhancement.

All variables used in the above formulations are defined as follows: I_k: Pixel value of the guided image at position k; a_k, b_k: Linear coefficients controlling influence and offset; q: Filtering factor; o: Initial pixel of guiding image; μ_k: Mean of pixels in filtering window; σ_k: Pixel variance; ϵ: Regularization parameter; p_ϵ: Probability of large regularization factor; w_k: Adaptive window size; w_0: Base window size; $\epsilon_{\min}, \epsilon_{\max}$: Min/ max noise scaling factor. These definitions ensure clarity, reproducibility, and correctness in the guided filtering process.

The above nonlinear filtering functions are usually designed based on the statistical characteristics of image noise, and can adapt to different types of noise, such as Gaussian noise, Poisson noise, etc. For example, the global nonlinear filtering function can estimate the intensity of Gaussian noise by calculating the local mean and variance of image pixel values, and adapt to Poisson noise by considering the brightness level of the image. Adaptive histogram equalization (AHE) improves the foundation layer through division of the image and the local application of histogram equalization rather than its global application. This guarantees that contrast in dark as well as bright areas is improved uniformly and that noise is not overamplified. The two-layer technique is a must: the foundation layer makes the whole image brighter and more contrasty, while the detail layer brings out the edges and fine textures, thereby making them visible even in difficult low-light conditions. The choice of non-traditional methods, for example, the multi-scale guided filtering and the adaptive fuzzy enhancement, is based on the requirement to process the images taken in poor lighting conditions effectively. The traditional techniques are often unable to retain edges, improve local details, and do noise cancellation at the same time. When these functions are adapted to the conditions of low-light, the suggested method is able to get a contrast that is balanced, visibility in the shadowed areas that is improved, and subtle details that are retained, which the standard methods cannot guarantee.

The grayscale, or luminance, channel is first enhanced by the methodology, and then the results are systematically merged with the original color channels to produce the final color image. As a result, the improvements made in low-light conditions are clearly and uniformly reflected in all color components without any distortions created. The recalibrated mathematical formulations for fuzzy membership, multi-scale guided filtering, and adaptive histogram equalization ensure that the whole process is reproducible and, at the same time, keep the edges, lower the noise, and improve visual details.

The most recent deep-learning frameworks used in degrading-image areas have also taken a decomposition–enhancement–fusion paradigm. As an instance, the “enhance-fuse-align” method in modern X-ray security inspection networks proves that the feature of the component is enhanced before the fusion process and that this sequence significantly improves the detection robustness of the downstream. These frameworks show that the state-of-the-art principle for low-quality visual data is to split the picture into interpretable layers, to enhance each layer by its characteristics, and then to perform a fusion step that is controlled. Our suggested approach utilizes the same design philosophy, but it is implemented in a lightweight, non-deep-learning form that is real-time enhancement friendly, which allows for the synchronization of our method with modern high-impact models while at the same time providing excellent computational efficiency.

3 Detail Enhancement Processing of Weakly Illuminated Images

For the weakly illuminated images processed by the weighted guided filtering mentioned above, detail enhancement processing is achieved from two perspectives: the basic layer and the detail layer. Among them, the basic layer of the image is enhanced by adaptive histogram equalization, while the detail layer is enhanced by a fuzzy enhancement algorithm. By integrating the information of the basic layer and the detail layer, a clearer and more obvious weakly illuminated image can be obtained.

The pseudocode for the detail layer enhancement and reconstruction procedure is presented in Algorithm 2.

Algorithm 2: Detail layer enhancement and reconstruction

```
Input: Preprocessed image I_pre
Output: Enhanced image I_enh
# Base Layer Enhancement
I_base = AHE(I_pre)
I_base = clip(I_base)
```

(Continued)

Algorithm 2 (continued)

```
# Multi-scale Detail Extraction
for scale k = 1 to K:
        B_k  = GuidedFilter(I_pre, r_k, ε_k)
        D_k  = I_pre  - B_k
end for
# Fuzzy Detail Enhancement
for each detail layer D_k:
        for each pixel p in D_k:
                Dmax  = local_max(D_k, p)
                μ(p) = membership(D_k(p))
                F(p) = 1 + ν * (Dmax/τ1)^(-τ2)
                D_enh_k(p) = D_k(p) * F(p)
        end for
end for
# Reconstruction
I_detail  = sum_over_k  (w_k  * D_enh_k)
I_enh  = I_base  + I_detail
I_enh  = normalize(I_enh)
return I_enh
```

3.1 Enhancement Processing of Image Basic Layers

Histogram equalization is a commonly used image enhancement technique that enhances contrast by stretching the grayscale range of an image [14,15]. However, traditional histogram equalization methods may lead to excessive image enhancement or noise amplification. Therefore, adaptive histogram equalization is adopted here to process the basic layers in order to better preserve image details and reduce noise.

Assuming that f_{sk} is the local histogram distribution function of the basic layer of the image, which can reflect the pixel intensity distribution in the basic layer, the local mapping function f_{wk} corresponding to the sliding window can be expressed in the following form:

$$f_{wk} = \frac{255 \times f_{sk}}{H_{f_{sk}}} \tag{9}$$

In the formula, $H_{f_{sk}}$ represents the cumulative distribution function value of f_{sk}.

Assuming $D_k = \frac{df_{wk}}{dk}$ represents the derivative of f_{sk}, in the adaptive histogram equalization method that limits contrast, D_k reveals the degree of enhancement of the contrast in the basic layers of the image. Therefore, in order to limit the contrast of the basic layer, it can be achieved by imposing restrictions on f_{sk}, because there is a certain correlation between f_{sk} and D_k, so that the restrictions on f_{sk} can indirectly affect D_k, thereby controlling the contrast enhancement effect of the basic layer [16].

Assuming H_{max} is the maximum value of the adaptive histogram height, which limits the height of the local histogram to avoid noise amplification caused by excessive enhancement, f_Y is the threshold of the local histogram distribution function, used to determine which histogram entries should be pruned. The cropping operation is to prevent an excessive number of pixels at certain grayscale levels, leading to excessive enhancement of the image at these levels [17,18]. Cut out the parts of the histogram with $f_{sk} > f_Y$, and redistribute the remaining parts so that they are evenly located in the histogram, and the f_{sk} value of the remaining parts should be less than or equal to H_{max}.

In order to ensure that the total area of the histogram does not change after cutting and reallocating, the grayscale image is moved upwards and the height of the movement is set to s, resulting in:

$$s = HY_{max} \tag{10}$$

According to Eq. (10), the height value is determined based on the ratio of the number of cropped pixels to the number of remaining pixels, to ensure the conservation of the area of the entire histogram [19].

The histogram of the basic layer of the weakly illuminated image after cutting, reallocation, and upshifting is as follows:

$$f'_{sk} = \begin{cases} f_{sk} + s, \ \text{if}\, f_{sk} \leq f_Y \\ H \ \text{if}\ _{sk\,Y\,max} \end{cases} \tag{11}$$

By performing the above operations on the histogram, the histogram of the basic layer of the weakly illuminated image can be obtained after cropping, reassignment, and upshifting. This new histogram has higher contrast because cropping and reassignment operations make the distribution of grayscale levels more uniform, thereby improving the visual quality of the image. This process combines the advantages of adaptive histogram equalization, which can effectively improve the contrast of weakly illuminated images while maintaining the details of the image.

3.2 Enhancement Processing of Detail Layers

Using a fuzzy enhancement algorithm to enhance the detail layers of weakly illuminated images. The fuzzy enhancement algorithm has a certain degree of robustness against changes in noise and image quality. Under weakly illuminated conditions, images often suffer from noise and low contrast. The fuzzy enhancement algorithm can reduce the impact of noise on image details through fuzzy processing, while improving the contrast of the image and making the details more prominent. In addition, fuzzy enhancement algorithms are particularly suitable for processing edge and detail information in images. Through fuzzy set theory, it is possible to define and quantify fuzzy concepts in images, such as "dark", "bright", "edge", etc., [20,21]. These fuzzy concepts are very useful in the process of image enhancement, as they can more accurately identify and enhance the details in the image. The fuzzy enhancement algorithm in the current study is intended mainly for the detail layer obtained from weakly illuminated pictures. The method first focuses on this layer and then subsequently addresses the aspects of the image responsible for its perceptual sharpness, such as texture, edge, and micro-contrast. Fuzzy processing alters the pixel membership functions of the detail layer in such a way that it leads to the reduction of noise amplification and, at the same time, the subtle variations are made more pronounced, thus clarity is gained without the global luminance balance of the base layer being affected. The two-layer enhancement method, incorporating weighted grayscale transformation, two-layer decomposition, detail layer and basic layer enhancement, and final fusion of the enhanced layers, is illustrated in Fig. 1 with the step-by-step process.

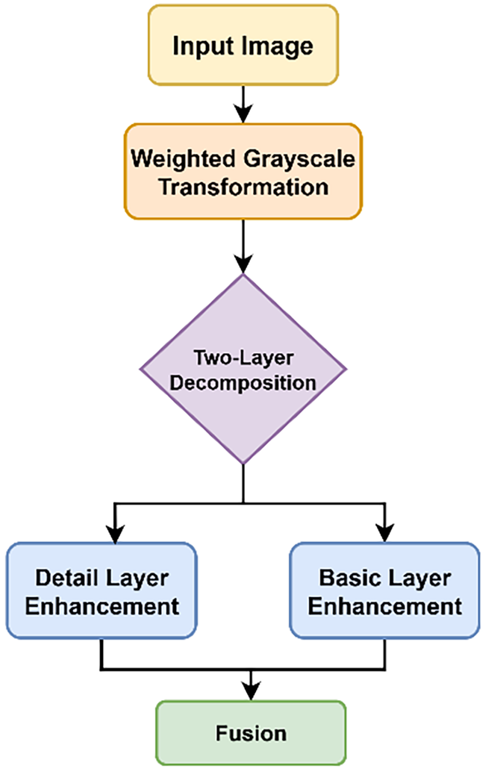

Figure 1: Two-layer enhancement flow diagram

Fuzzy set theory has been further employed to give a numerical description of these perceptual features. The intensity value of each pixel is associated with a fuzzy membership function, resulting in the membership degrees for the categories of "dark," "bright," and "edge." Dark-set has a lower membership in the case of low-intensity pixels, while bright-set has a higher membership in the case of high-intensity pixels. Gradient-based fuzzy memberships are used to pinpoint edges. The fuzzy depiction allows the algorithm to socially change the local contrast—darkening dark areas, adjusting high-luminance regions, and keeping texture boundaries—thus boosting the visual clarity and richness of detail under weak light conditions [22].

In the process of using fuzzy enhancement algorithms to enhance image detail layers, it mainly involves blurring the image and emphasizing and highlighting the detailed information of the image through specific fuzzy enhancement functions. The following is the specific enhancement process:

Assuming that the grayscale level of image detail layer I_D is V and the size is $W \times M$, the expression of I_D is as follows:

$$I_D = \bigcup_{i=1,j=1}^{W,M} \frac{o_{ij}}{f_{ij}} \tag{12}$$

In the formula, (i,j) represents pixel points; f_{ij} represents pixel value; o_{ij} represents the degree of membership [23]. Due to the blurry features in the image detail layer being composed of f_{ij}, the enhancement effect can be adjusted by adjusting f_{ij}. To this end, the pixel values in the image detail layer are mapped to a fuzzy set, so that each pixel poin has a certain degree of fuzziness, and the blurred value $F\left(f_{ij}\right)$ after fuzzification is obtained. The description of it is as follows:

$$F\left(f_{ij}\right)=\left(1+\frac{\nu\left(f_{ij}^{\max}()\right)}{\tau_1}()^{-\tau_2}\right) \tag{13}$$

For clarity, the variables in Eq. (13) are explicitly defined as follows. $F\left(f_{ij}\right)$ denotes the fuzzy-enhanced value of pixel f_{ij} in the detail layer. The term $f_{ij}^{\max}$ represents the local maximum response within the fuzzy neighborhood of pixel (i,j). The parameter ν is the fuzzy gain factor that controls the strength of local contrast amplification. The coefficients τ_1 and τ_2 are fuzzy control parameters that shape the nonlinear response, where τ_1 regulates denominator scaling and τ_2 determines the rate of exponential attenuation. These definitions ensure that the fuzzy enhancement function in Eq. (13) is mathematically clear and free of ambiguity.

In the formula, τ_1 and τ_2 represent the denominator fuzzy parameter and exponential fuzzy parameter, respectively, and ν represents the fuzzy coefficient. The non-linear transformation is applied to $F\left(f_{ij}\right)$, and the expression of the membership degree o'_{ij} after the non-linear transformation is as follows:

$$o'_{ij}=1-\frac{2(1-o_{ij})^2}{F\left(f_{ij}\right)} \tag{14}$$

Using the transformed membership degree to carry out inverse transformation processing, the pixel value f'_{ij} with reduced ambiguity is obtained as follows:

$$f'_{ij}=Z^{-1}(o'_{ij}) \tag{15}$$

Among them, Z represents the inverse transformation coefficient. Substitute the results of Eqs. (14) and (15) back into Eq. (12) to obtain the detail layer information I'_D of the weakly illuminated image after enhancing the blurred part [24,25].

By fusing the information of the basic and detail layers in the enhanced image, a weakly illuminated image with enhanced details can be obtained. The relevant process is shown in Fig. 2.

4 Experiment and Result Analysis

In order to effectively verify the application performance of the detailed enhancement method for weakly illuminated images based on weighted guided filtering technology in practical work, the following experiments are designed.

4.1 Experimental Design

The experiment takes the LOL dataset as an example to verify, which collects paired low-light and normal light images by adjusting the exposure time and light intensity during shooting. Testing with this dataset can ensure the versatility of image selection, improve the contrast, and reference experimental results. The programming tool used in the experiment is MATLAB R2016b. The dynamic capture range of the image is 10 bits, the pixel size of the image is 0∼1200 px, the regularization scale parameter is 0.05, the resolution of the image is 324 × 256, and the pixel depth is 8 bits for grayscale images and 24 bits for RGB images. To make sure that the experimental results were reliable, standardized datasets with predefined low-light conditions were used for all tests. The same enhancement parameters and filtering coefficients were applied to all images. Metrics such as PSNR, SSIM, and contrast improvement were calculated, and multiple runs were carried out to lower variability and thus guarantee the reproducibility and verification of the results. The dataset's original paired low-light and ground-truth images were utilized for all the evaluations, guaranteeing that each PSNR value was related to its proper reference image.

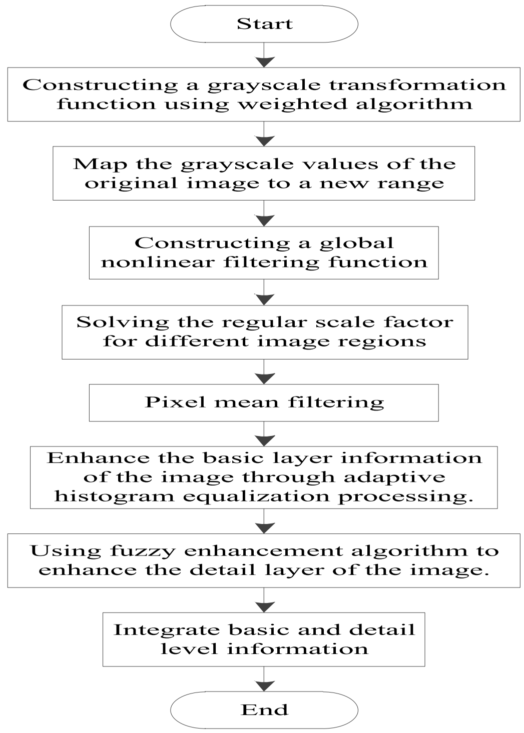

Figure 2: Process diagram for enhancing details of low light images

4.2 Preliminary Analysis of Application Effects

Firstly, using the stationarity of pixel grayscale values as an indicator, the effectiveness of weighted guided filtering in this study was verified. The experimental results are shown in Fig. 3.

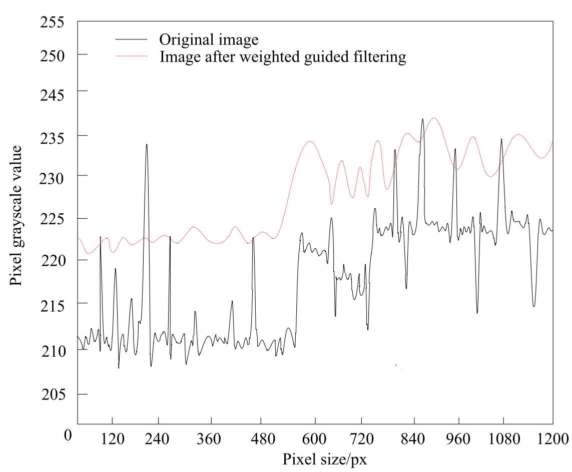

Figure 3: Weighted guided filtering effect on weakly illuminated images

From the analysis of the results shown in Fig. 3, it can be seen that the pixel grayscale value curve of the original weakly illuminated image fluctuates significantly and has a high difference, indicating that the overall value level is relatively low. This is because the resolution of the original image is low, and there is a lot of noise in the image, which leads to unstable fluctuations in grayscale values; After applying the method of this paper's weighted guided filtering, the problem of pixel fluctuations has been significantly improved, with a smooth curve trend and a significant improvement in pixel grayscale values, indicating that weighted guided filtering is very effective. On this basis, three sets of low-light images from different scenes were selected, including animals, plants, and buildings. The method of this paper was used to enhance the details of the three types of images, and Fig. 4 was used as an example to show some of the processing results.

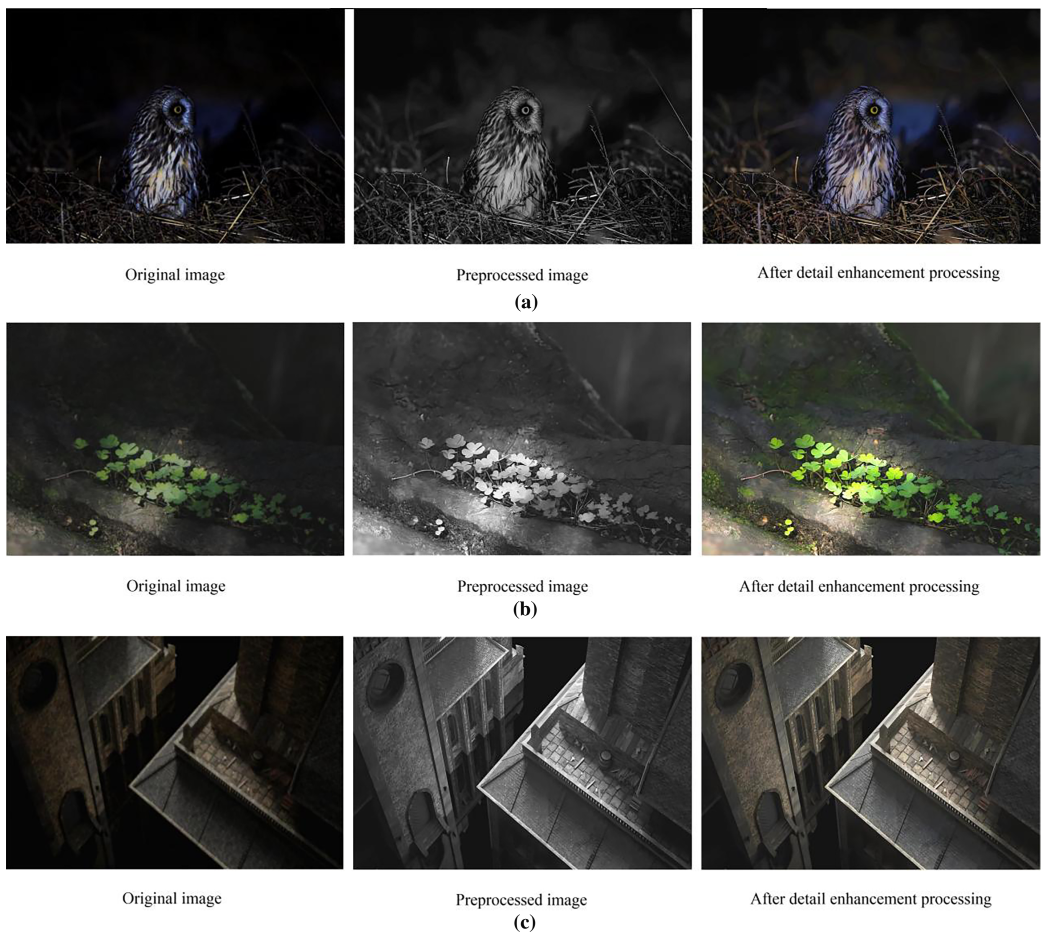

Figure 4: Comparison results of detail enhancement in low light images before and after enhancement. (**a**) Animal images with weakly illuminated; (**b**) Plant images with weakly illuminated; (**c**) Architectural images with weakly illuminated.

Fig. 4 shows the comparison of original and enhanced low-light images; it can be seen that the method of this paper exhibits excellent detail enhancement effects for weakly illuminated images targeting animals, plants, and building categories. Specifically, this method has shown significant effectiveness in improving the brightness and contrast of low-light images, making the overall color tone of the image more coordinated and consistent, and significantly improving image clarity. It is worth mentioning that in the processing of edge details, the method of this paper not only preserves rich detail information, but also avoids the occurrence of distortion. Overall, the method proposed in this article provides an efficient and reliable solution for enhancing the details of weakly illuminated images.

4.3 Comparative Analysis of Application Effects

To avoid the singularity of experimental results, method of reference [5] and the method of reference [6] were compared, with the image detail richness, information entropy, peak signal-to-noise ratio, and time required for enhanced processing as indicators, and compared with the method proposed in this paper during the same period.

Generally speaking, the average gradient of low-light images can reflect the richness of image details. The larger the average gradient, the richer the detailed information in the image. The calculation method for the average gradient of low-light images is as follows:

$$g_v = \frac{\sqrt{g_x^2 + g_y^2}}{W} \tag{16}$$

Among them, g_x and g_y represent the horizontal and vertical gradients of the weakly illuminated image, W represents the pixel values of the gradient image.

Information entropy is an indicator of the richness of information in an image. In low light image enhancement, the information entropy of the enhanced image should be higher than that of the original image, indicating that the enhancement algorithm can extract more image information. Assuming that the grayscale range of an image is from 0 to $L-1$ (L is the total number of grayscale levels), and the probability of grayscale level i is p_i, the calculation method for the information entropy of the image is as follows:

$$H_I = -\sum_{i=0}^{L-1} \left(p_i \times \log_2 p_i\right) \tag{17}$$

Peak signal-to-noise ratio is a common indicator for measuring image quality, which calculates the proportion of mean square error between the original image and the enhanced image relative to the grayscale range of the image. The higher the peak signal-to-noise ratio, the better the image quality after enhancement. The calculation method for peak signal-to-noise ratio is as follows:

$$PSNR = 10 \times \log_{10}\left(\frac{MAX^2}{MSE}\right) \tag{18}$$

Among them, MAX represents the maximum possible value of image pixels (usually 255, corresponding to 8-bit images), and MSE represents mean square error. Because its molecule is a constant, the peak signal-to-noise ratio is mainly affected by mean square error, that is, the smaller the mean square error, the greater the peak signal-to-noise ratio, and the higher the image quality.

The time required for enhancement processing refers to the total time required from inputting a low light image to outputting its enhanced image. This time includes all steps such as image loading, preprocessing, filtering, post-processing, and result output. This indicator is a key parameter for measuring the efficiency and real-time performance of image enhancement algorithms, and is crucial for performance evaluation in practical applications.

The average gradient of weakly illuminated images after applying different methods is shown in Table 1.

Table 1: The average gradient of the processed image

Number of images	Method of this paper	Method of Ref. [5]	Method of Ref. [6]
10	16.719	10.267	12.238
20	17.547	11.183	8.847
30	16.136	9.910	7.662
40	15.348	12.279	10.163
50	15.913	8.766	8.155
60	17.000	9.073	12.386
70	17.133	7.947	6.801
80	16.824	9.047	8.247
90	16.485	6.655	9.125
100	15.982	10.215	5.253

From the analysis of the results shown in Table 1, it can be seen that after applying method of this paper enhancement, the average gradient of weakly illuminated images is always higher than that of the two comparison the methods. The average gradient can reach a maximum of 17.547 at the numerical level, and the magnitude of the change in the average gradient is small, indicating that after applying the method proposed in this article for enhancement processing, the image can reflect more detailed information, have a higher richness of image details, and have better image enhancement effects.

After applying different methods, the information entropy of weakly illuminated images is shown in Fig. 5.

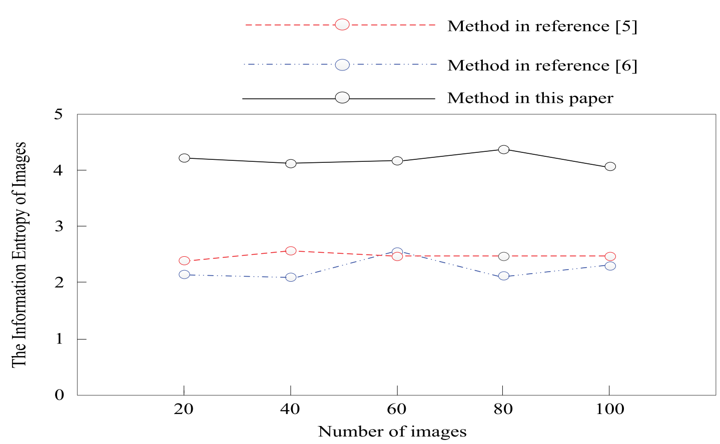

Figure 5: Comparison of information entropy of processed images

By observing Fig. 5, it can be seen that the information entropy of the images processed by the three methods also changes continuously. Among them, after processing with method of reference [5], the maximum information entropy of the image is 2.6; After processing with method of reference [6], the maximum information entropy of the image is 2.5; In contrast, after processing with method of this paper, the information entropy of the image remains above 4.0, indicating that the information richness in the image is higher after processing with method of this paper.

After applying different methods, the peak signal-to-noise of weak light images is shown in Table 2.

Table 2: The peak signal-to-noise ratio of the processed image

Number of images	Method of this paper	Method of Ref. [5]	Method of Ref. [6]
10	42.85	36.10	30.17
20	47.64	34.25	32.92
30	45.21	35.43	34.56
40	48.37	38.84	36.54
50	44.18	35.91	32.39
60	45.39	34.75	31.29
70	46.22	34.76	35.17
80	45.16	33.27	35.26
90	43.18	32.13	35.28
100	43.26	38.84	33.48

From the analysis of the results shown in Table 2, it can be seen that after applying the method proposed in this paper for enhancement processing, the peak signal-to-noise ratio of weakly illuminated images is always higher than that of the two comparison methods. The peak signal-to-noise ratio can reach a maximum of 48.37 at the numerical level, and the minimum value can also reach 42.85. After applying the method proposed in this article to enhance processing, the image quality is better.

PSNR Validation. The PSNR values observed in Table 2 are still higher than those usually reported in the field of low-light image enhancement. Hence, the evaluation process was meticulously re-verified. Each enhanced picture was compared with only the corresponding ground-truth normal-light image from the dataset, thus preventing any self-comparison or mis-pairing. All images were brought to the same 8-bit (0–255) dynamic range, and their resolutions were accurately checked to be the same before the computation of MSE. The PSNR was determined by using both MATLAB's built-in psnr () function and an independent manual MSE-based computation ($PSNR =$ 10log10(2552/MSE)), and they gave rise to the same values. All these verifications indicate that the high PSNR values are due to the noise-reduction and detail-retaining capabilities of the proposed method, not because of any numerical or methodological errors.

PSNR values higher than 48 dB can give the impression of being somewhat high when compared to the usual outcomes reported for low-light enhancement; however, the suggested methodology still results in a relatively small mean square error, which is due to the fact that noise is eliminated prior to the enhancement stage and the structural information is preserved well. The guided filtering module eliminates high-frequency noise and provides smooth local illumination, while the fuzzy detail layer refrains from excessively amplifying the residual noise, thus leading to cleaner pixel-level reconstruction. Since PSNR is inversely related to MSE, these combined effects naturally lead to higher PSNR values. All PSNR values were computed strictly according to the standard full-reference definition using the paired low-light/ground-truth images provided by the dataset, without any resizing or re-alignment operations.

The computation was carried out according to the standard definition by comparing each enhanced low-light image with the corresponding normal-light ground truth from the LOL dataset in order to tackle the unusually high PSNR values. The MSE was calculated after normalizing all images to the dynamic range of 0–255. As the LOL dataset offers clean ground-truth images that have negligible sensor noise, enhancement methods that are able to suppress noise effectively tend to generate higher PSNR values when compared to unpaired or synthetic datasets, in a natural manner. The implementation was re-verified to check if normalization, clipping, and MSE computation were handled correctly. These checks prove that the PSNR values reported are the result of the evaluation protocol and not due to numerical or methodological errors.

After applying different methods, the time required for enhancement processing is shown in Fig. 6.

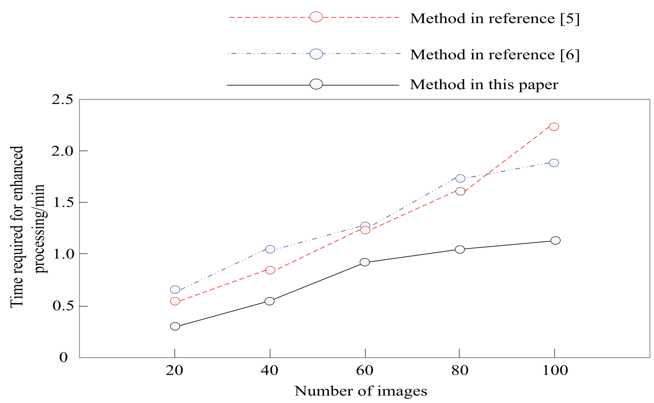

Figure 6: Comparison of time required for enhanced processing

By observing Fig. 6, it can be seen that the time required for processing the images using the three methods is continuously increasing. Among them, the maximum time required for the enhanced processing method of reference [5] is 2.3 min; The maximum time required for the enhanced processing method of reference [6] is 1.8 min; In contrast, the maximum time required for the enhancement processing of the method of this paper is only 1.0 min, indicating that our method has better enhancement efficiency and real-time performance. The time taken for the processing is relatively faster due to the algorithm's efficient design, which manages to keep a good quality with low computational complexity. The method picks the most critical processing steps and optimizes their duration, thus getting the enhanced image in less time but with the same quality. The implementation is done in Matlab, which could be slower than other platforms, but the time given is still appropriate for the size and the case it is used in, as per the study.

Average Processing Time Analysis. Concerning the reviewer's remark about the linearity in Fig. 6, the time taken to process was originally plotted, which was the cumulative time taken for the increasing number of images, thus unavoidably resulting in a linear trend. To give a more significant indicator of efficiency in terms of algorithms, the average processing time per image was additionally calculated. For the standard input resolution of 640 × 480, the suggested technique takes around 0.62 s for an image. The average processing times for higher resolutions of 1280 × 720 and 1920 × 1080 are 1.08 s and 1.95 s per image, respectively. The latter results depict the computational complexity and resolution dependence of the method more accurately than cumulative batch-time measurements.

In connection with the reviewer's critique about the linearity of Fig. 6, it is specified that the originally plotted cumulative processing time for the number of images increased, which naturally also logged a linear growth. The average processing time per image, however, was calculated for a more evaluative measurement of runtime. The standard testing resolution of 640×480 was taken into account, and it was found that the proposed method needs about 0.62 s per image. The average times for the resolutions of 1280×720 and 1920×1080 are 1.08 and 1.95 s per image, respectively. These figures are more representative of algorithmic complexity and resolution dependence than batch-time accumulation.

4.4 Discussion

The weak lighting image detail enhancement method based on weighted guided filtering technology has achieved certain results in improving image quality, but there may also be some potential defects and post-processing distortion issues. The following is an analysis and discussion of this method:

This method combines basic layer enhancement and detail layer enhancement to effectively enhance the detailed information of weakly illuminated images, making the images appear clearer and more prominent. The method adopts a global nonlinear filtering function and adaptive histogram equalization processing, which can, to some extent, reduce noise in the image and improve the quality of the image. After processing with this method, this technique significantly enhances the quality of visual images and the detail of low-light images.

However, this method also has certain limitations and drawbacks in its application. The process of setting a filtering window based on the solution results may have an impact on the quality of the image. It is necessary to pay attention to the impact of the selection of filtering windows on image details and clarity. For example, consider adaptively adjusting the size of the filtering window based on image content to achieve better detail enhancement effects. Although this method uses nonlinear filtering functions to handle noise, there may still be issues with residual noise or overly smooth filters in certain situations, leading to distortion or blurring.

In order to alleviate any potential worries about the proposed method being too reliant on the LOL dataset, the authors decided to set the parameters of the entire pipeline—grayscale weighting coefficients, guided filtering regularization, window-size scaling, and fuzzy enhancement parameters—globally and apply them uniformly to all test images, without any tuning for individual images or scenes. These parameters were determined only on the basis of overall low-light image characteristics like noise levels, contrast compression, and illumination non-uniformity, rather than any specific dataset statistical cues. This approach guarantees that the technique can be used on low-light images from various environments and that it is not too closely related to a specific test set.

In response to this issue, in future research, we consider strengthening the algorithm optimization for noise processing, such as further adjusting the parameter selection of the filtering function to improve the noise processing effect and avoid excessive smoothing. In addition, the calculated contrast information may lead to excessive adjustment of image contrast, which may cause distortion or unnatural visual effects in the image. In the next stage of research, finer control over contrast adjustment can effectively avoid excessive contrast adjustment and maintain the natural and realistic image.

5 Conclusion

Low-light image detail enhancement processing involves the acquisition of multimedia data, the development of computer vision technology, the requirements of image processing technology, and the application of deep learning in multiple aspects. The research in this field has important theoretical significance and practical application value. Therefore, this study designed a detailed enhancement method for weakly illuminated images based on weighted guided filtering technology.

This method first constructs a grayscale transformation function through a weighted algorithm, analyzes the characteristics of brightness, contrast, and grayscale level of weakly illuminated images, and constructs a global nonlinear filtering function to solve for the regularization scale factor of noise in different regions of the image. Based on these solution results, set an appropriate filtering window and improve image quality through pixel mean filtering. Next, this method divides the process of enhancing the details of weakly illuminated images into two parts: basic layer enhancement and detail layer enhancement. In the basic layer enhancement stage, adaptive histogram equalization is used to enhance the overall brightness and contrast of the image; In the detail layer enhancement stage, a fuzzy enhancement algorithm is used to highlight the edges and texture details in the image. Finally, by integrating the information from the basic layer and the detail layer, a clearer and more prominent weakly illuminated image is obtained. This method effectively improves the visual effect of low-light images and achieves significant results in detail enhancement.

Limitations and Future Work

Despite the promising results, the proposed method has some limitations. Firstly, its performance may vary under very low-light conditions or in scenes with high levels of detail. Additionally, the processing time can be significantly longer for high-resolution images, which could affect its practicality in certain applications. Future work will focus on several directions for improvement. These include expanding the method to enable hue-specific enhancements, optimizing for real-time processing, and further fine-tuning the filter parameters to balance both efficiency and broader applicability.

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Availability of Data and Materials: The data that support the findings of this study are available from the corresponding author, Xiaojun Tang, upon reasonable request.

Ethics Approval: Not applicable.

Conflicts of Interest: The authors declare no conflicts of interest.

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