Gradient domain weighted guided image filtering

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Abstract
Guided image filter is a well-known local filter in image processing. However, the presence of halo artifacts is a common issue associated with this type of filter. This paper proposes an algorithm that utilizes gradient information to accurately identify the edges of an image. Furthermore, the algorithm uses weighted information to distinguish flat areas from edge areas, resulting in sharper edges and reduced blur in flat areas. This approach mitigates the excessive blurring near edges that often leads to halo artifacts. Experimental results demonstrate that the proposed algorithm significantly suppresses halo artifacts at the edges, making it highly effective for both image denoising and detail enhancement.

Keywords Edge-preserving filtering · Average strategy · Detail enhancement · Image denoising · Halo artifact

1 Introduction
Edge preservation is a widely employed technique in various fields, including image processing, computer vision, and camera measurement. One such application of edge preservation is image smoothing [1], which typically results in the blurring of edges. However, if an image can be smoothed while preserving its edges, the resulting image quality can be significantly improved.

A variety of edge-preserving image denoising algorithms can be broadly categorized into two categories: global optimization algorithms and local filtering algorithms. The former category includes algorithms such as total variation (TV) [2, 3], weighted least squares [4, 5], and L0 parametric gradient minimization method [6]. These algorithms combine different regularization and fidelity terms into an optimization problem that is solved through multiple iterations. However, global edge-preserving algorithms typically suffer from slow runtime, excessive memory consumption, and gradient inversion. The latter category of algorithms includes faster and more memory-efficient methods such as guided image filtering (GIF) [7]. The guided filter (GIF) [7] is a linear filter that can avoid gradient inversion. However, GIF tends to produce halo artifacts in the edge region. To address this problem, researchers have proposed a series of improved algorithms. For instance, Li et al. [8] proposed the weighted guided image filter (WGIF), which introduces an edge-aware weighting operator in the guided filter to improve its edge protection property. Kou et al. [9] proposed the gradient-domain guided image filter (GDGIF), which combines the first-order edge-aware constraint to further improve the edge protection property of the guided filter. Xie et al. [10] proposed an improved guided filter algorithm incorporating gradient information, which can adaptively distinguish and emphasize the edges using exponential function framework to design weights that control the smoothing multiplier in different image regions. Chen proposed a weighted aggregated guided filtering (WAGIF) [11] that can obtain sharp edges and avoid halo artifacts using a mean-value strategy for handling overlapping windows. Sun et al. proposed guided filtering with steering kernel (SKWGIF) [12], which can adaptively learn the directional information of edges and obtain high-quality images while mitigating edge artifacts. While the edge-aware operator proposed by WGIF [8] and Xie et al. [10] lacks explicit edge constraints and is prone to edge blurring, GDGIF [9] has limited protection for tiny edges, and WAGIF [11] only improves the guided filtering weighting strategy without explicit edge protection.

This paper proposes a novel gradient-weighted guided filtering algorithm to address the limitations of existing
The guided image filter and its derived versions, namely GIF, WGIF, GDGIF, Xie and WAGIF. The proposed algorithm combines gradient information and weighted information and introduces edge-aware and edge-preserving operators, as well as pixel weight distribution, to address halo artifacts, excessive image smoothing, and enhance image edge preservation. Unlike GDGIF, the edge-aware operator in the proposed algorithm utilizes gradient and edge change information to accurately distinguish edge regions from flat regions. Furthermore, the proposed edge protection operator uses fast gradient calculation to protect the edge pixels while maintaining computation speed. Additionally, a new overlap window computation strategy is introduced in this algorithm in order to improve its edge-preserving property, which uses accurate image weight distribution. Experimental evaluations of the proposed algorithm for image detail enhancement and image denoising show that it outperforms existing methods, including GIF, WGIF, GDGIF, Xie, and WAGIF, demonstrating the efficacy of the proposed approach.

The rest of this paper is organized as follows. GIF, edge-preserving and smoothing properties are summarized in Sect. 2. Section 3 describes the details of GWGIF. The GWGIF algorithm is analyzed and experimentally verified in Sect. 4. Two applications of GWGIF are given in Sect. 5. Section 6 provides concluding remarks.

2 Related works

2.1 Guided image filtering

The guided filter is closely related to the matting Laplacian matrix [13]. The initial model of GIF is a linear model with input data consisting of an input image X and a guide image G. Assume that the output image Z is a phenomenal transformation of the guide image G in the window \( \Omega_{\xi 1} \) [13, 14]:

\[
Z_{(p)} = a_p G_{(p)} + b_p', \quad \forall p \in \Omega_{\xi 1}(p')
\]

(1)

where \( Z_{(p)} \) denotes the output image, \( G_{(p)} \) denotes the input guide image, \( p' \) represents the current pixel and \( p \) represents the pixel in the window corresponding to the current pixel point \( p' \). \( a_p' \) and \( b_p' \) sourced from linear ridge regression model:

\[
E = \sum_{p \in \Omega_{\xi 1}(p')} \left[ (a_p' G_{(p)} + b_p' - X(p))^2 + \lambda a_p'^2 \right]
\]

(2)

the objective is to find the value that minimizes the gap between the output image and the desired filtered image while satisfying the linear model \( a_p' \) and \( b_p' \). \( \lambda \) is the regularization parameter of the penalty term \( a_p' \). The final values of \( a_p' \) and \( b_p' \) are as follows:

\[
a_p' = \frac{\mu_G \circ X_{, \xi 1}(p') - \mu_{G, \xi 1}(p') \mu_{X, \xi 1}(p')}{\sigma_{G, \xi 1}^2(p') + \lambda}
\]

(3)

\[
b_p' = \mu_{X, \xi 1}(p') - a_p' \mu_{G, \xi 1}(p')
\]

(4)

where \( \circ \) denotes the multiplication of two matrix elements. \( \xi 1 \) denotes the size of the window radius. \( \mu_{G, \xi 1}(p') \) and \( \mu_{X, \xi 1}(p') \) denotes the means of the matrix \( GX \) in \( G \) and \( X \) in the window \( \Omega_{\xi 1}(p') \). \( \sigma_{G, \xi 1}^2(p') \) represents the variance of the matrix \( G \) in the window \( \Omega_{\xi 1}(p') \).

The values within the overlap window need to be normalized. GIF uses the mean value strategy: average over all a and b. The final output is

\[
Z_{(p)} = \bar{a}_p G_{(p)} + \bar{b}_p'
\]

(5)

where \( \bar{a}_p' = \frac{1}{|\Omega_{\xi 1}(p')|} \sum_{p \in \Omega_{\xi 1}(p')} a_p' \) and \( \bar{b}_p' = \frac{1}{|\Omega_{\xi 1}(p')|} \sum_{p \in \Omega_{\xi 1}(p')} b_p' \). \( |\Omega_{\xi 1}(p)| \) is the normalization factor of \( \Omega_{\xi 1}(p) \) to avoid data overflow.

2.2 Edge preservation analysis

Analyzing Eq. (1), the value of \( a_p' \) determines the pixel distribution at the edge of the image and the value of \( b_p' \) determines the pixel distribution in the flat region. Calculate the gradients on both sides of Eq. (1).

\[
\nabla Z_{(p)} = a_p' \nabla G_{(p)}
\]

(6)

The value of \( a \) determines the edge-preserving nature of the GIF. The major method for eliminating edge halo artifacts is to provide a more accurate description of the edge information of the image. However, due to the fixed value of the regularization parameter \( \lambda \), the consistent \( \lambda \) norm intensity tends to cause some edges to be over-smoothed and produce halo artifacts when dealing with edges in different areas. An adaptive guided filtering has been proposed in [13] to solve this problem by replacing Eq. (2) with the following equation.

\[
E = \sum_{p \in \Omega_{\xi 1}(p')} \left[ (a_p' G_{(p)} + b_p' - X(p))^2 + \frac{\lambda}{\Gamma_G(p')} a_p'^2 \right]
\]

(7)

where \( \Gamma_G(p') \) is defined as an edge-aware constraint consisting of the variance of the local 3x3 window domain.

\[
\Gamma_G(p') = \frac{1}{N} \sum_{j=1}^{N} \frac{\sigma_{G, \xi 1}^2(p') + \varepsilon}{\sigma_{G, \xi 1}^2(p) + \varepsilon}
\]

(8)
$\sigma_{G,1}^2(p')$ is the variance within the window $\Omega_{\xi 1}(p)$. $\varepsilon$ is a smaller positive constant defined as $(0.0001 * L)^2$. $L$ is defined as the dynamic range of the input image. The role of $\Gamma_G(p')$ is to constrain the regularization parameter $\lambda$ in Eq. (3).

3 Gradient domain weighted guided filtering

In this paper, we propose a gradient-domain guided filtering combined with weight distribution, including edge-aware constraint, explicit first-order edge protection constraint and weighted-mean strategy.

The flow chart of the algorithm in this paper is shown in Fig. 1.

3.1 Edge-aware constraints

Compared with WGIF [8] and GDGIF [9], the proposed edge-aware constraint combines the coefficient of variation and gradient information to more accurately represent the fine edge information of an image. The edge perception constraint is determined by the coefficient of variation within the 3*3 window of the gradient domain image, the coefficient of variation of the input image within the $(2*\xi 1+1)$ window and the gradient image. The formula is defined as follows.

$$\Gamma_G(p') = \frac{1}{N} \sum_{p=1}^{N} \xi(p') + \varepsilon$$

where $\xi(p') = \varphi_{G,3} \varphi_{G,\xi 1} G$

$$\varphi_{G,3} = \frac{\sigma_{G,3}(g,p')}{{\text{mean}}_{G,3}}$$

and $\varphi_{G,\xi 1} = \frac{\sigma_{G,\xi 1}(p')}{{\text{mean}}_{G,\xi 1}}$ denote the coefficients of variation of the gradient information corresponding to a window radius of 3 at pixel $p'$. $\varphi_{G,\xi 1}$ denotes the coefficient of variation at pixel $p'$ with radius $\xi 1$. $G$ denotes the gradient image obtained from the gradient calculation of the guide image, which can reflect the edge information of the image to a certain extent. The formula is shown below.

$$g_x = \frac{\partial f(x, y)}{\partial x} = f(x + 1, y) - f(x, y)$$

$$g_y = \frac{\partial f(x, y)}{\partial y} = f(x, y + 1) - f(x, y)$$

$$g(x, y) = sqrt\left(g_x^2 + g_y^2\right)$$

In the context of gradient information computation, relying solely on horizontal and vertical gradient calculations may result in a considerable loss of relevant information.

To accurately obtain gradient information while maintaining algorithmic efficiency, gradient calculation in all four directions is utilized. This paper adopts a global-based fast gradient computation approach in all four directions. Specifically, the entire image is subjected to row- and column-based difference operations, obviating the need for template operation traversal and reducing algorithmic complexity. The final gradient computation proceeds as follows.

$$g(x, y) = sqrt\left(g_0^2 + g_1^2 + \ldots + g_3^2\right)$$

where $g(x, y)$ is the gradient at the pixel point $(x, y)$, the $g_0$, $g_1$, $g_2$ and $g_3$ are the gradient information in the upper, lower, left and right directions, respectively.

3.2 Edge protection constraints

Based on the analysis in Sect. 2 for edge-preserving properties, combined with the edge-aware constraint operator proposed in (1), substituting the operator into Eq. (3) yields

$$a_{p'} = \frac{\mu_G \bigcirc_{\xi 1}(p') - \mu_{G,\xi 1}(p')\mu_{X,\xi 1}(p')}{\sigma^2_{G,\xi 1}(p') + \frac{1}{\Gamma_G(p')}}$$

(15)

Let $\mu_G \bigcirc_{\xi 1}(p') - \mu_{G,\xi 1}(p')\mu_{X,\xi 1}(p') = \sigma^2_{G,X,\xi 1}(p')$ Substitute into Eq. (14).

$$a_{p'} = \frac{\sigma^2_{G,X,\xi 1}(p')}{\sigma^2_{G,\xi 1}(p') + \frac{1}{\Gamma_G(p')}}$$

(16)

When the input guide image $X$ is equal to the input image $G$, $\sigma^2_{G,X,\xi 1}(p') = \sigma^2_{G,\xi 1}(p')$, the value of $a_{p'}$ is given by the regularization parameter $\lambda$ and $\Gamma_G(p')$. Due to the edge-awareness constraint $\Gamma_G(p')$, the effect of $\frac{1}{\Gamma_G(p')}$ on $a_{p'}$ is smaller than the effect of the regularization parameter $\lambda$ on $a_{p'}$. When the pixel is in the edge region but the effect still exists, which results in $a_{p'}$ in the edge region being only close to 1 but not equal to 1. Therefore, to further reduce the effect of the regularization term parameter $\lambda$ on the edge pixels, the gap between the numerator denominators of $a_{p'}$ is reduced as much as possible by making the following changes to $a_{p'}$.

$$a_{p'} = \frac{\sigma^2_{G,X,\xi 1}(p') + \frac{\lambda}{\Gamma_G(p')}}{\sigma^2_{G,\xi 1}(p') + \frac{\lambda}{\Gamma_G(p')}}$$

(17)

at this point, the $a_{p'}$ of the pixels in the edge region is equal to 1. Since the $a_{p'}$ of the pixels in the flat region should converge to 0, a first-order edge protection constraint $\eta$ is introduced in order to distinguish the edge region from the flat region.

$$a_{p'} = \frac{\sigma^2_{G,X,\xi 1}(p') + \frac{\lambda}{\Gamma_G(p') + \eta_{p'}}}{\sigma^2_{G,\xi 1}(p') + \frac{\lambda}{\Gamma_G(p') + \eta_{p'}}}$$

(18)
η is defined as follows.

\[
\eta(x, y) = \begin{cases} 
1 & g(x, y) > 1.7 \text{mean}(g) \\
0 & \text{else}
\end{cases}
\]

(19)

where \( g \) is the gradient image obtained from the edge-aware constraint, which is already computed in the edge-aware constraint. Therefore, \( g \) does not need additional computation. 1.7 is the threshold parameter that works best after experimental validation.

### 3.3 Weighted average strategy

Based on the analysis of the strategy for handling overlapping windows in Sect. 2, a fast weighted mean strategy is proposed in this paper.

First, the template of \( (2k + 1) \times (2k + 1) \) is constructed and the absolute difference of the neighborhood sum of the center pixel in the template is calculated. Then, traverse the image and set a threshold, the image is reconstructed according to the threshold. Finally, obtain uniform and non-uniform regions, which are the weight distribution of the images. The calculation formula is as follows.

\[
\mu_s = \begin{cases} 
1 - \frac{s\text{var}_{i,j}(n)}{Th_{\text{var}}}, & s\text{var}_{i,j}(n) \leq Th_{\text{var}} \\
\tau, & s\text{var}_{i,j}(n) > Th_{\text{var}}
\end{cases}
\]

(20)

where \( s\text{var}_{i,j}(n) \) is the absolute difference of the neighborhood summation of the current center pixel. \( Th_{\text{var}} \) is the set absolute difference threshold.

When \( s\text{var}_{i,j}(n) \) is less than the threshold value, it is regarded as a uniform region, and the value of this region is set to an adjustable parameter \( \tau \). When \( s\text{var}_{i,j}(n) \) value greater than the threshold value, this region is considered as a non-uniform area.

After getting \( \mu_s \). After that, it is considered as the weight distribution of the input image, and the weighted image is obtained by doing inner product with the input image, and finally, the weighted image is normalized separately to obtain the final weighted mean output with the following formula.

\[
Z(p) = \frac{1}{|\Omega_1|} \sum_{p^r \in \Omega_1} \mu_s(a_{p'}G(p) + b_{p'})
\]

(21)

where \( |\Omega_1| = \sum_{p \in \Omega_1} \mu_s \) is the normalized coefficient of the weight distribution \( \mu_s \). Consequently, the Eq. (21) can be written as

\[
Z(p) = \tilde{a}_{p'}G(p) + \tilde{b}_{p'}
\]

(22)

where \( \tilde{a}_{p'} = \sum_{p \in \Omega_1} \mu_s1 a_{p'} \), \( \tilde{b}_{p'} = \sum_{p \in \Omega_1} \mu_s2 b_{p'} \). \( \mu_s1 \) and \( \mu_s2 \) are the weights of \( a \) and \( b \) the pixel \( p' \).

After calculating each pixel point’s \( a_{p'} \) and \( b_{p'} \), the weighted averaging [15] strategy proposed is used for processing: as shown in Fig. 2, \( G \) is the input guide image, denotes the inner product, \( \mu \) denotes the weight distribution map. Figure 2 illustrates that the central pixel is concurrently calculated and assigned in different windows (1, 2, 3). The left side of the figure presents the normalization coefficients,
Fig. 2 Weighted average strategy

Fig. 3 Processing effects of different guided filtering algorithms $r = 16, \lambda = 1$; a GIF; b Xie; c WAGIF; d WIGF; e GDGIF; f Proposed

Fig. 4 Comparison of the 1D data illustrations in Fig. 6. $r = 16$, and $\lambda = 1$; the input image is derived from the red channel of the original input image in Fig. 3a
while the right side depicts the weight output. Dividing them yields the final weighted mean output.

The proposed strategy calculates the weight distribution map through global calculation while computing pixel weights. Next, it directly derives the weighted output from the inner product of the weight distribution map and the original map, avoiding the need to traverse all image windows to assign values. Finally, the output is rapidly computed using the boxfilter presented in [7]. The complexity of this strategy is $O(N)$ for images with $N$ pixels, which is consistent with GIF [7] owing to the boxfilter used. Consequently, this strategy has a shorter running time and effectively enhances image quality.

### 4 Validation

Figure 3 provides one-dimensional data illustrations and objective evaluation index data of the proposed algorithm and other algorithms to verify the validity of the above analysis.

Figure 3 shows the comparison of the processing effect between the proposed algorithm and other algorithms, and we set the parameters to be consistent for fairness ($r = 16$, $\lambda = 1$). Both subjective perception and objective data show that the proposed algorithm has sharper edges in detail regions and higher overall image quality, which can bring better visual experience. Table 1 reveals that the proposed algorithm yields the highest objective evaluation index among the compared algorithms.

Figure 4 demonstrates that, in comparison to the GIF, Xie, WAGIF, GDGIF, and WGIF algorithms, the proposed algorithm more closely aligns with the original input image in the edge region, whereas the corresponding positions’ pixel distribution of other algorithms is notably distant from the original input image. Further, when considering zoomed-in details, the proposed algorithm is the most aligned with the input image. In other words, the edges of the image processed by this algorithm are close to the edges of the input image.

|Fig. 3| Comparison of detail enhancement results, $r = 16$, $\lambda = 0.4$, a GIF, b GDGIF, c WGIF, d Xie, e WAGIF, f Proposed |
|---|---|---|---|---|---|---|
|Table 1 Quantitative evaluation of different edge-preserving smoothing algorithms|
|  | GIF | Xie | WAGIF | WGIF | GDGIF | Proposed |
|PSNR | 25.42 | 25.76 | 25.95 | 28.78 | 35.00 | 37.93 |
|SSIM | 0.9794 | 0.9807 | 0.9820 | 0.9899 | 0.9976 | 0.9982 |
|Table 2 Quantitative evaluation of different algorithms for image enhancement|
|  | GIF | WAGIF | Xie | WGIF | GDGIF | Proposed |
|BIQI | 37.5353 | 41.4550 | 53.9159 | 66.4462 | 69.8050 | 71.6857 |
image. The value of $a^p_1$ is closer to 1 in the edge region. This means that the edge of the algorithm proposed is closer to the input image and the edge protection effect of this algorithm is better. In summary, the algorithm proposed (GWGIF) can effectively maintain the edge sharpness and avoid the appearance of over-smoothing and halo artifacts, which verifies the superiority and reasonableness of this algorithm in edge protection.

5 Application of the new filter

5.1 Image detail enhancement

According to the analysis in Sect. 2, the consistency of the regularization parameter $\lambda$ causes the GIF to have certain defects at the edges: the anisotropy of the pixel distribution is ignored when representing the edges, and the edge information cannot be extracted accurately. Linear scaling further amplifies the deficiency in edge information, as evidenced by black edges and edge distortion caused by excessive brightening [7]. Although perceived visual improvements may suggest that the image contrast has been enhanced [16, 17], it is essential to acknowledge that image quality is a multifaceted concept that cannot be solely evaluated based on contrast. Therefore, to ensure a comprehensive and objective evaluation, we employed the Blind Image Quality Index (BIQI) metric, which has been previously utilized in studies [5, 9, 10]. A higher score on the BIQI indicates a superior image quality, and we employed this metric to compare and contrast the efficacy of different algorithms.

Figure 5 illustrates the superimposition of the detail layer into the input image, where the first row of the figure presents the comparison of different algorithms in terms of detail enhancement, while the second row shows the corresponding local enhancement of the detail layer image. Notably, despite the overall similarity in the enhancement effect of all algorithms, a greater emphasis is placed on the local edge regions, which exhibit more significant gaps. For instance, in the petal edge regions of the GIF and WAGIF images, the algorithms severely sharpened the images, resulting in a more pronounced black edge effect. In contrast, our algorithm contains fewer but sharper edge details, leading to enhanced sharpness in the edge regions. Thus, the proposed approach avoids linear enhancement that incorporates excessive information at the edge, thereby enhancing the image quality and preventing the degradation of image quality caused by sharpening and artifacts. As supported by the data presented in Table 2, our algorithm achieved the highest index score, thereby indicating that it provides the most effective image enhancement.

According to the previous analysis: the larger the value of $\lambda$, the lower the image quality and the more serious the halo artifacts. As shown in the Fig. 6, the comparison experiment of algorithm enhancement effect with different parameters $\lambda$ is shown. As $\lambda$ increases, the image quality index (BIQI) of all algorithms in the Table 3 decreases, among which, the index of GIF algorithm decreases the most and the index of this algorithm decreases the least. It is proved that: as the regularization parameter $\lambda$ increases, the algorithm proposed in this paper is less affected and has obvious optimization of the regularization parameter $\lambda$. According to the previous analysis: the edge artifact phenomenon of the guided filtering algorithm mainly comes from the consistency of the regularization parameter $\lambda$. In summary, the proposed algorithm makes the edge artifact phenomenon better suppressed and outperforms the GIF in [7], the WAGIF in [11], Xie et al. [10], the GDGIF in [9] and the WGIF in [8] algorithms in image detail enhancement.

5.2 Image denoising

Given that the GIF algorithm exhibits edge-preserving properties, it has the ability to eliminate noise while preserving edge information. To assess the effectiveness of the proposed algorithm, we performed a grayscale image denoising experiment using the grayscale image of Lena.

To be fair, we set the experimental parameters to be consistent ($r = 9$, $\lambda = 0.1$), and superimposed a Gaussian noise with a standard deviation of 25 on the experimental images. Figure 7 demonstrates that the proposed algorithm achieved the most optimal output when tested on noisy images, and the objective evaluation metrics, including peak signal-to-noise ratio and structural similarity, also yielded the best results. This indicates that, compared to other algorithms, our proposed approach can effectively remove noise while preserving image quality.
Table 3 Quantitative evaluation of image enhancement by different algorithms with different $\lambda$

|          | 0.04$^2$ | 0.05$^2$ | 1/128  | 0.01   | 0.04   |
|----------|----------|----------|--------|--------|--------|
| GIF      | 67.6986  | 66.8689  | 52.9433| 47.7353| 37.5353|
| WAGIF    | 67.4945  | 67.1120  | 53.1729| 49.0460| 41.4550|
| Xie      | 73.7712  | 72.5683  | 68.6918| 67.2269| 53.9159|
| WGIF     | 73.0985  | 71.9041  | 70.7354| 70.5101| 66.4462|
| GDGIF    | 74.1637  | 72.2886  | 70.2363| 69.7229| 69.8050|
| Proposed | 79.3267  | 76.2469  | 71.5277| 70.8845| 71.6857|

Fig. 7 Denoising effect of different algorithms. $r = 9$, $\lambda = 0.1$. a GIF, b WAGIF, c Xie, d GDGIF, e WAGIF, f proposed

Table 4 Quantitative evaluation of different algorithms for image denoising

|          | NOISE | Xie   | WAGIF | GIF   | GDGIF | WGIF | Proposed |
|----------|-------|-------|-------|-------|-------|-------|----------|
| PSNR     | 18.86 | 20.67 | 22.10 | 22.20 | 22.34 | 22.43 | 22.65    |
| SSIM     | 0.8731| 0.9193| 0.9475| 0.9447| 0.9434| 0.9456| 0.9481   |

In processing noisy images, the application of the mean value strategy in GIF often leads to the generation of excessively blurred images, as depicted in Fig. 7a. By incorporating the fast weighted averaging strategy and the edge retention operator, the proposed algorithm demonstrated remarkable preservation of pixels in edge regions, as evidenced in Fig. 7. Notably, the algorithm significantly enhances imaging quality in flat regions. The effectiveness of the proposed approach is further corroborated by the superior performance revealed by objective evaluation indices presented in Table 4.

6 Conclusion

To address the limitation of the guided filtering algorithm in preserving edges, this study proposes a novel approach called GWGIF. GWGIF is a guided filtering algorithm that combines gradient and weight information in the edge constraint to accurately preserve the sharp edges of the image. Unlike previous guided filters, such as GDGIF and WGIF, which only introduce either gradient or weight information, the proposed approach incorporates both, leading to more precise edge preservation. Moreover, to enhance the accuracy of edge detection, we propose a new image weight assignment strategy and edge constraint operator. The proposed
weight assignment strategy enables accurate identification of edge regions in the image, while the edge constraint operator helps to smooth the pixels in flat regions reasonably. Our experiments on image detail enhancement and image noise removal demonstrate that the images generated by the GWGIF filter have better visual perception and image quality than those produced by other guided filter-based algorithms. Given the superior performance of guided filters, we anticipate that the GWGIF algorithm can be applied to a wide range of fields, such as image defogging [18], fusion of differently exposed images, joint upsampling [19], and tone mapping of HDR images [15], among others. In the future, we will continue to investigate related issues to further enhance the accuracy and effectiveness of the proposed method in various image processing applications.

Authors’ contributions BW performed the experimental validation and wrote the major manuscript. YW reviewed and revised the manuscript. All authors reviewed the manuscript.

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Availability of data and materials The datasets used or analyzed during the current study are available from the corresponding author on reasonable request.

Declarations

Competing interests The authors declare that they have no known competing financial interests or personal relationships that could have influenced the work reported in this paper.

Ethical approval This declaration is not applicable.

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