RESEARCH ON HIGHLIGHT RESTORATION ALGORITHM FOR SEA SURFACE OIL SPILL IMAGES

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Abstract. With the advancement of digital image processing technology, the restoration of highlight images has become a significant research direction. In the case of oil spill monitoring systems for close monitoring of the sea surface, improper camera shooting positions and the presence of sunlight at a small incident angle can result in highlight areas in the captured images. These highlight regions significantly impact the quality of oil images which also reduces and the detection accuracy of oil spills. Since traditional highlight removal methods cannot be applied to water scenes, this paper proposes a Criminisi-PM highlight restoration algorithm for image enhancement. Firstly, for the improvement of the priority calculation formula, the multiplicative relation between the confidence item and the data item is changed to the addition relation. In this way, even if the confidence term is zero, the impact of data items still exists, which avoids the impact on priority when the confidence is zero, and improves the stability and accuracy of the algorithm. The introduction of the brightness term of the image in the priority calculation formula can focus more on the restoration of pixel points with larger brightness values. Secondly, for the improvement of the matching formula of the best matching block, the pixel gradient and Euclidean distance information are added to consider the features of the image more comprehensively, which makes the matching process more robust, especially in the processing of images with complex texture structures. The proposed algorithm can effectively improve the quality of visible oil spill image by eliminating the influence of the highlight region in the image. Experiments show that the method has a strong anti-interference ability and after removal the image is more natural.

Keywords: highlighted images, Criminisi, priority calculation, best-matching block, matching formula.

Introduction

With the advancement of the digital image processing technology, the restoration of highlighted images has become a significant research direction. Fuchs et al. applied the higher-order TV restoration model to the field of image restoration, introducing a new method to the discipline [1]. Getreuer et al. employed the split Bregman algorithm to compute total variation (TV) for image restoration, introducing a new concept – fractional-order variation to describe the characteristics of pixel value distribution changes in local areas under a non-Gaussian noise background [2]. Highlight phenomena, such as overexposure, frequently occur in images. Currently, the restoration of highlighted images can be broadly classified into two categories: traditional methods and deep learning methods. Traditional methods are primarily based on specific algorithms, while deep learning methods leverage deep neural networks for automatic analysis and processing.

Based on traditional methods: Wang et al. proposed a method for removing specular reflections in ocean surface images captured by unmanned aerial vehicles. They initially employed an intensity ratio-based approach to identify highlighted areas in ocean surface images. Subsequently, the FMM (Fast Marching Method) algorithm was utilized to rapidly restore highlighted regions, achieving high-quality ocean surface images [3]. To address the issue of information loss in highlighted regions in real-world scenarios, Xin et al. introduced a highlight image enhancement algorithm based on the dark channel prior. Initially, the dark channel prior algorithm was used, estimating the global illumination component through a moving window minimum filter. Subsequently, a weighted function based on local pixel colour differences was introduced to mitigate halo and pseudo-shadow artifacts in the image. Then, an improved guided filtering algorithm was applied to optimize the transmission rate, enhancing the algorithm computational efficiency. Finally, the Contrast Limited Adaptive Histogram Equalization (CLAHE) algorithm was employed to adjust image brightness and enhance local details [4].

Deep learning-based methods include: Zhang et al. introduced a method for removing highlighted regions in endoscopic imaging using a partial convolutional network. They utilized a brightness threshold with illumination compensation to classify the image into highlighted and non-highlighted areas. Subsequently, a partial attention network was employed to restore highlighted region pixels [5]. Yuan et al. presented a deep learning model based on dual-mask guidance to remove highlighted regions in images of industrial product surfaces while preserving defect areas [6]. Guo et al. introduced a fast highlight elimination method combining U2-Net and LaMa. In the first stage, U2-Net was used to detect partially reflected highlights in the input image and generate a highlight region mask image. In the second stage, the input image and the mask image were fed into the LaMa network, leveraging LaMa's image restoration capability to eliminate highlight regions [7]. Kang et al. proposed a novel highlight image restoration algorithm. By defining a classification table to detect pixels corresponding to highlighted regions in the HIS colour space, they rapidly identified highlight areas. Subsequently, image restoration was achieved using GMCNN (Generative Multi-column Convolution Neural Networks) [8]. Lin et al proposed a method based on multi-baseline stereo and colour analysis, which uses a sequence of captured images to achieve separation of highlight areas [9]. Ghorai et al. applied the problem of image restoration using the Markov Random Field (MRF) framework, mapping the information of image blocks into a Markov random field space. Utilizing the properties of Markov, they modeled the known pixel information to derive a probabilistic equation about the image. Then, by solving this equation, they obtained the final restored image. [10]. The unknown pixels in an image are primarily restored by this algorithm using the neighbourhood information of pixels. This algorithm primarily uses the neighbourhood information of pixels to restore unknown pixels in an image. However, the definition of the repair sequence in this algorithm is relatively vague, and as the algorithm progresses, an effect of edge blurring may occur [11].

This paper investigates the Criminisi-PM highlight restoration algorithm, which holds significant importance for enhancing highlight-overexposed oil spill images. The main contributions are summarized as follows:

(1) Improvement in the Priority Calculation Formula: The modification involves changing the multiplication relationship between the confidence term and data term to an addition relationship. This adjustment ensures that even if the confidence term is zero, the impact of the data term persists, mitigating the influence of zero confidence on priority. This enhancement contributes to improved stability and accuracy of the algorithm.

(2) Improvement in the Matching Formula for the Best-Matching Block: The enhancement involves incorporating pixel gradients and Euclidean distance information into the matching formula. This comprehensive consideration of image features improves the robustness of the matching process, particularly enhancing accuracy when dealing with images featuring complex texture structures.

Materials and methods

Utilizing the Criminisi algorithm in conjunction with the SLIC (Simple Linear Iterative Clustering) superpixel algorithm [12], pixels in the original image are clustered into regions with similar features, treating each pixel block as an individual pixel. The SLIC superpixel algorithm achieves this by merging similar pixels to form larger regions, reducing the complexity of the image while preserving its structural information. These resulting regions are referred to as superpixel blocks, and in subsequent processing, they can be treated as individual pixels to simplify the representation and analysis of the image. This approach aids in reducing the dimensionality of the image while maintaining visual consistency.

After superpixel clustering, the brightness average of all pixels within each superpixel block is computed. Using a thresholding method, superpixel blocks with high brightness are selected, indicating regions where glare phenomena and information loss may occur in the image. The brightness average of the superpixel blocks is as follows:

$$M = \frac{\sum_{i=1}^{N} V_i}{N}, \tag{1}$$

where V_i – brightness of each pixel within the superpixel block;
N – total number of pixels in the hyperpixel block.

In RGB images, the expression for pixel brightness is given by:

$$V_i = 0.299 \times R_i + 0.587 \times G_i + 0.114 \times B_i, \tag{2}$$

where R_i – colour values of the pixel in the red channel;
G_i – colour values of the pixel in the green channel;
B_i – colour values of the pixel in the blue channel.

To select superpixel blocks with high brightness using a thresholding method, the expression is as follows:

$$\begin{cases} 255, & M \geq T \\ 0, & M < T \end{cases}, \tag{3}$$

If the brightness is higher than the threshold, the respective superpixel block is labelled as a region requiring restoration (assigned a value of 1); conversely, it is marked as background (assigned a value of 0). In the experiment, the brightness threshold is denoted as ‘T’, with a value of 245, and the number of superpixels is set to 300. Figure 1 shows the identification of the area to be repaired.

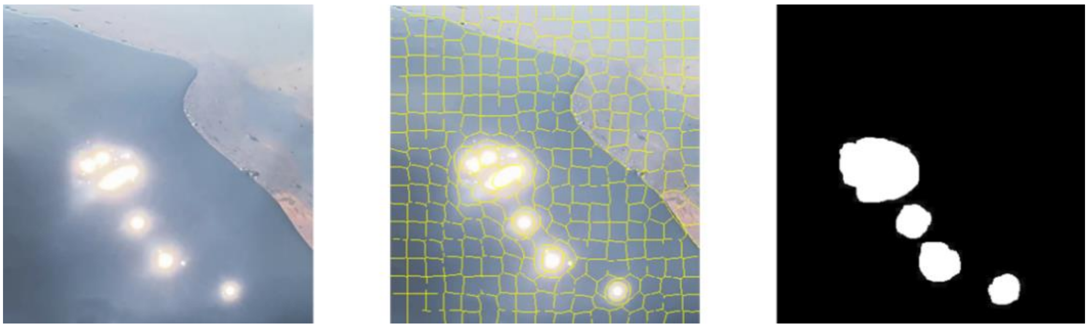


Fig. 1. **Determination of regions requiring restoration:** a – original image; b – superpixel processing result; c – region to be restored

In the Criminisi algorithm, when computing the priority, if the confidence term $C(p)$ is zero, the priority $P(p)$ becomes zero as well. This can lead to the algorithm behaving randomly when repairing sample blocks. To address this issue, this paper proposes several improvement methods, and a key modification is changing the multiplication relationship between the confidence term and data term to an addition relationship. This adjustment ensures that even if the confidence term is zero, the influence of the data term persists, avoiding the impact on priority when confidence is zero. This enhances the stability and accuracy of the algorithm.

Glare is caused by significant changes in brightness. Considering this, it is beneficial to prioritize the handling of pixels with higher brightness values during the restoration process. To achieve this goal, this paper introduces a brightness term into the priority calculation formula. By incorporating brightness information into the calculation, the algorithm can focus more on restoring pixels with higher brightness values. This adjustment directs more attention to regions with richer texture information during the restoration process, thereby elevating the priority of boundary restoration in glare areas and further improving the restoration outcome. This ensures that the restored area aligns well with its surrounding environment, making the restoration result more natural and accurate.

This paper introduces improvements to the priority calculation formula, as shown below:

$$P'(p) = \alpha C(p) + \beta(D(p) + V(p)), \tag{4}$$

where $C(p)$ – confidence term;
$D(p)$ – data term;
$V(p) = 0.299 \times R_p + 0.587 \times G_p + 0.114 \times B_p$ – brightness term representing.
α and β – weighting factors, satisfying $\alpha + \beta = 1$ $\alpha + \beta = 1$.

In this paper, $\alpha = 0.3$, $\beta = 0.7$ β. The purpose of having $\alpha < \beta$ is to prioritize the restoration of regions where structural information is more pronounced.

In addition, in the Criminisi algorithm, for the sample block to be matched, the smallest target block is usually selected as the optimal matching block by calculating the sum of squared differences between the target block and its known pixels. This method mainly considers the relationship between sample blocks and target block pixels, but does not take into account other factors related to the two matching blocks. The problem with this method is that the calculated features are too single, which may perform well for images with simple texture structures, but for images with complex texture structures, there is a high possibility of incorrect matching. Therefore, we propose a new matching criterion that incorporates pixel gradient and Euclidean distance information on the existing basis to more comprehensively consider the features of the image. This new criterion incorporates pixel gradient information and Euclidean distance between pixels, making the matching process more robust, especially in processing images with complex texture structures, which can improve the accuracy of matching. This matching method that considers multiple factors comprehensively helps improve adaptability to the complexity of image texture structure, and enhances the robustness and performance of the algorithm.

The expression for the improved similarity C between pixel blocks A and B is as follows:

$$d'(\psi_p,\psi_q)=[d_1(\psi_p,\psi_q)+d_2(\psi_p,\psi_q)]*e^{d_3(p,q)}, \tag{5}$$

where $d_1(\psi_p,\psi_q)=\sum_{i=1}^{m}\sum_{j=1}^{n}[(p_{i,j}^R-q_{i,j}^R)^2+(p_{i,j}^G-q_{i,j}^G)^2+(p_{i,j}^B-q_{i,j}^B)^2]$ – represent the sum of squared differences in colours across the three channels in an RGB image;

$d_2(\psi_p,\psi_q)=\sum_{i=1}^{m}(|\nabla\psi_{pi}|-|\nabla\psi_{qi}|)$ – represent the sum of squared differences in colour gradients in an RGB image;

$V(p) = 0.299\times R_p + 0.587\times G_p + 0.114\times B_p$ – represent the brightness term;

$d_3(p,q)=\sqrt{(p_x-q_x)^2+(p_y-q_y)^2}$ – represent the Euclidean distance between points $p(p_x,p_y)$ and $q(q_x,q_y)$.

The formula for calculating the best-matching block is as follows:

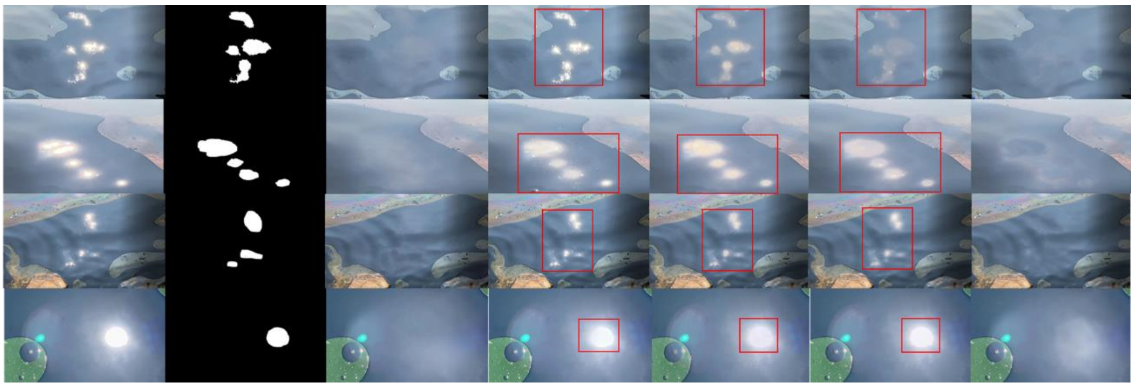
$$\psi_q' = \arg\min d'(\psi_p,\psi_q) \tag{6}$$

Results and discussion

In this experiment, restoration experiments are performed by restoring 106 sea surface oil spill highlight images collected from different scenes. This section conducts highlight removal experiments on ocean surface images using references from [13], the CDD model, the Criminisi algorithm, and the Criminisi-PM algorithm to demonstrate the effectiveness of the proposed algorithm in this paper.

The comparative experiment for the elimination of highlight regions on the ocean surface is shown in Fig 2. Despite restoration efforts using references from [13] and the CDD model, the results are still heavily impacted by a significant amount of highlight regions, yielding unsatisfactory restoration outcomes. Although the Criminisi algorithm can partially reduce the brightness in the central area of the highlight region, it fails to meet the requirements due to substantial colour differences between the central region and the surrounding unrepaired area, accompanied by the appearance of halos. The Criminisi-PM algorithm visually better fulfils the requirements for the restoration of highlight regions, thereby enhancing the overall quality of restoration. The proposed algorithm effectively eliminates the halo effect around the restored region, resulting in a visually better integration of the restored area with the surrounding environment. As indicated in Table 1 and Table 2, the improved Criminisi-PM algorithm achieves optimal PSNR and SSIM metrics, demonstrating the effectiveness of the proposed algorithm in this paper.

a)
b)
c)
d)



Original Image mask Ground True Reference [13] CDD Criminisi Ours

Fig. 2. **Comparison of sea surface highlight area elimination experiment**

Table 1

Comparison of PSNR performance for image highlight removal

Model	**Reference [13]**	**CDD**	**Criminisi**	**Ours**
Fig. 2 a	24.179	26.542	27.569	29.364
Fig. 2 b	24.030	24.921	25.353	26.398
Fig. 2 c	26.396	26.309	27.901	29.502
Fig. 2 d	18.622	19.291	19.495	23.003

Table 2

Comparison of SSIM performance for image highlight removal

Model	Reference [13]	CDD	Criminisi	Ours
Fig. 2 a	0.891	0.924	0.945	0.957
Fig. 2 b	0.910	0.915	0.922	0.961
Fig. 2 c	0.882	0.902	0.909	0.943
Fig. 2 d	0.859	0.860	0.865	0.907

Conclusions

Considering the potential interference of highlight regions in visible light images on oil spill detection, we introduced a Criminisi-PM highlight restoration algorithm for image enhancement. The refinement of the priority calculation formula, by changing the multiplication relationship between the confidence term and data term to an addition relationship, has enhanced the stability and accuracy of the algorithm. The improvement of the best-matching block matching formula, incorporating pixel gradients and Euclidean distance information, enhances matching accuracy, particularly in images with complex texture structures. The Criminisi-PM algorithm improves PSNR by 6% and SSIM by 4% over the original Criminisi algorithm. By eliminating the influence of highlight regions, the proposed algorithm effectively enhances the quality of visible light images. This provides a more reliable input for subsequent oil spill detection tasks.

Author contributions

Conceptualization, W.Y.; methodology, W.Y. and Y.Q.C.; software, Y.I.; validation, W.Y., S.T.Z. and Q.C.Z.; data curation, W.Y., S.T.Z. and Q.C.Z.; writing – original draft preparation, W.Y.; writing – review and editing, W.Y. and Y.Q.C.; visualization, S.T.Z., Q.C.Z.;

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