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Multi-Exposure Fusion Method for Space Target Images Based on Multi-Feature Weights

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Abstract. Aiming at the characteristics of low brightness of space target image, low contrast with space background and uneven image exposure, a multi-exposure fusion method of space target image based on multi-feature weight was proposed. In this method, contrast features, adaptive optimal brightness features and salience features are used as the basic weights of image fusion weights, and the final weights of image fusion are calculated from these three weights. At the same time, aiming at the low brightness of space target image, local color correction technology is further used to improve the overall brightness of fused image. The experimental results show that compared with the four commonly used multi-exposure fusion methods, the proposed method can achieve better multi-exposure fusion effect on space target images, and the information entropy, spatial frequency and average gradient indexes are improved by 103.8%, 7.69% and 33.72%, singly. IL-Niqe, PIQE and BRISQUE had an increase of 33.99%, 13.57% and 19.07%, respectively.

Keywords. multi-exposure fusion; space target image; pyramid fusion; color correction

1. Introduction

Space non-cooperative satellites are different from shooting common natural environment objects on the ground. The environment of space targets is a vacuum, and the light is irradiated at a single angle due to the lack of atmospheric diffuse reflection. The performance is that the light spots in the texture of the direct light source area are unrecognizable, and most of the inner area is dark; this further leads to the low overall brightness of space objects and low contrast with the background. Aiming at the problem of poor lighting conditions of space targets, a better solution is to obtain images of different exposure levels of the target object in a short period of time, and then fuse these images with different exposure levels to obtain a target object with good exposure, high contrast, and details. Clear and high dynamic range remote sensing images of space targets.

In terms of multi-exposure image fusion, Mertens et al. [1] proposed a multi-resolution-based Laplacian pyramid fusion method. After decomposing the original images with different exposure levels into Laplacian pyramids, the weights combined by

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contrast, saturation and good exposure are weighted, and finally the fusion result with high dynamic range is obtained by fusion means. This method can achieve remarkable results in multi-image fusion problems, but the details in the brightest and darkest regions of the image are still missing. On this basis, Paris et al. proposed an image fusion method based on local Laplacian filters to achieve smooth edges of fused images or small-scale detail enhancement [2]. The advantage of this method is that it is simple in calculation and only relies on It is based on simple point-wise nonlinearity and small Gaussian convolution, rather than complicated optimization process. Zhong Qu, Xu Huang et al. proposed an improved multi-exposure fusion method for detail enhancement, which uses good exposure evaluation function, color information evaluation function and local detail preservation function to measure the weight map [3]. To further enhance the details, they proposed an improved multi-exposure fusion framework based on pyramid decomposition and achieved good experimental results. Li et al. proposed an image fusion method based on guided filtering. This method divides the input image into base layer and detail layer, and uses guided filtering to construct a weight map, which can well preserve local detail information [4]. Ma et al. proposed a multi-exposure fusion method based on structural patch decomposition [5], which can maintain good global contrast, but halo artifacts appear in regions with large differences in intensity values. Fei Kou et al. proposed an edge-preserving smooth pyramid fusion algorithm for multi-scale exposure fusion. In addition, Ye Tao et al. [6] proposed an effective and robust underwater image enhancement method using multi-exposure fusion technology, which outperforms previous underwater dehazing algorithms in both subjective and objective evaluations.

Existing multi-exposure image fusion methods can achieve good fusion visual effects for ordinary image sets. However, because the imaging environment of space images is very different from that of natural images, the background of the image is completely black, and the brightness and contrast of the target object are low. The current mainstream multi-exposure image fusion method is difficult to apply to images of space region images with such characteristics. According to the characteristics of space images, this paper improves the Laplacian image fusion pyramid model proposed by Mertens et al.: Adaptive optimal brightness, contrast features and salient features are used as the basic weights of image fusion weights, and the final weight is obtained from these three weights. The image fusion weight of the pyramid model is used to fuse and then the local color correction technology [7] is used to improve the shortcomings of the space image.

2. Multi-Exposure Fusion Method

The main steps of the multi-exposure fusion method proposed in this paper are shown in Figure 1. Based on the Laplacian pyramid multi-exposure image fusion framework in [1], combined with the characteristics of satellite images of space targets, this method uses three different feature indicators as the weights of multi-exposure image fusion to weight the input image fusion. Get the initial fusion result. Finally, brightness enhancement processing is performed on the initial fusion result to eliminate the influence of the environment and improve the overall brightness effect of the fusion image.

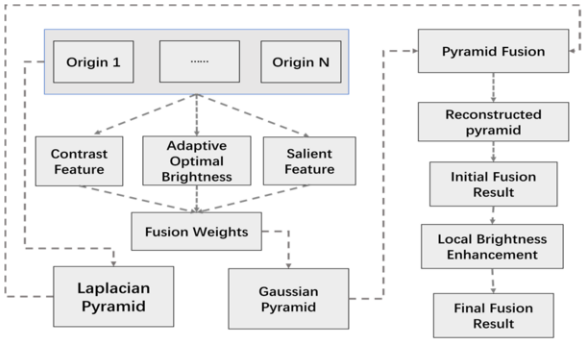


Figure 1. Process diagram of the method in this paper

2.1. *Weight Design*

According to the characteristics of remote sensing images of space targets, this paper uses the contrast feature of the input original image as the first weight and uses the adaptive optimal brightness and its saliency features as the fusion weights two and three respectively, to enhance the target of the fusion image. The contrast between the object and the space background. Through the design of these three weights, the contrast information between the space target and the space environment and the overall brightness information of the space target can be effectively improved and enhanced.

2.1.1.Contrast Feature

Contrast is one of the important indicators for measuring the level of detail in an image. A higher value of the contrast feature indicates that the image details are more clearly presented. In this paper, the calculation of the image contrast feature is described by Eq. (1), which allows for the computation of the contrast feature while ensuring that it does not negatively impact the image quality.

$$C = Igray + LPF(Igray) \tag{1}$$

Where C represents the contrast of the image. $Igray$ is the grayscale image of the input image. $LPF(Igray)$ means that the grayscale image of the input image is convoluted using the Laplacian filter. In this paper, Laplacian filtering is performed on the grayscale image of the input image, and on this basis, according to the principle of image sharpening, the original image and the Laplacian filter are superimposed to sharpen the image and restore other images information.

2.1.2. Adaptive Optimal Brightness

In terms of exposure evaluation index, literature [1] uses the Gaussian function model to calculate the best exposure point for each position according to the characteristics that the pixels in different channels of each image can reflect the pixel exposure intensity. After pixel normalization, 0.5 is taken as the best exposure point. Pixels with a pixel value less than 0.5 are listed as low-exposure pixels, and pixels with a pixel value greater than 0.5 are listed as high-exposure pixels. On this basis, this paper uses the brightness layer of the input image sequence as the extraction input of the optimal brightness value, and the specific process is shown in formula (2).

$$E = guided\left(exp\left(-\frac{[hsii-(1-\omega)]^2}{2\sigma_{hsii}^2}\right)\right) \tag{2}$$

Where E represents the calculated optimal brightness value, $hsii$ is the brightness layer of the input image sequence, ω is the brightness mean of $hsii$, and σ is the standard deviation of $hsii$. In this paper, according to the low-brightness characteristics of space target images, (1-ω) is used as the expected value of the Gaussian model to extract the brightness information of each image to the greatest extent, and G represents the guided filtering operation.

2.1.3. Salient Feature

In this paper, a larger weight is given to image fusion through the brightness saliency feature. According to the pixel value of the input image, the saliency of the input image sequence is calculated [8], and then the original image is compared with the saliency feature map, and the position weight of the pixel value in the original image is not less than the saliency value is set to 1, and other are set to 0 to obtain the initial saliency weight map. In the case of multiple input images, the same brightness value of the same pixel position between different images leads to the problem that the fused image is out of bounds. This problem can be solved by normalizing the initial saliency weight.

2.2. Fusion Weights

Based on Eq. (1), Eq. (2), and the saliency calculation method, the three weight features of the original image, namely contrast feature, adaptive optimal brightness feature, and saliency feature, can be obtained. Using these three weight features, this paper calculates the initial weights of the fusion image as shown in Eq. (3).

$$W_k = [C_k] * [E_k] * [S_k] \tag{3}$$

Where W_k represents the initial fusion weight of the k-th image in the input image sequence. C_k is the local contrast feature of the k-th image, E_k is the adaptive optimal brightness of the k-th image, and S_k is the saliency feature of the k-th image in the input sequence. The * operator denotes the multiplication operation among these three weight features.

Then normalize the initial weights, as shown in Eq. (4).

$$\widehat{W_k} = [\textstyle\sum_k^N W_k]^{-1} * W_k \tag{4}$$

Then, the obtained image fusion weights, W_k, and the original image sequence are combined using a pyramid fusion model, as shown in Eq. (5).

$$L\{R\}^l = \textstyle\sum_k^N G\{\widehat{W}\}_k^l * L\{I\}_k^l \tag{5}$$

Where l represents the pyramid model has l layers, $L\{I\}_k^l$ represents the Laplacian pyramid transformation applied to the k-th original image, and $G\{\widehat{W}\}_k^l$

represents the Gaussian pyramid transformation applied to the fusion weights of the k-th original image. The initial fusion result is obtained by inverse construction of the fusion pyramid.

2.3. Local Brightness Enhancement

To enhance the overall brightness of space image fusion, a non-linear mask-based local color correction method is used in this paper, as shown in Eq. (6).

$$Output = 255 * \left(\frac{Input}{255}\right)^{\left(\frac{128-Mask}{128}\right)} \tag{6}$$

Where $Mask$ represents the mask for the input image, and $Output$ represents the corrected result.

There are two core steps in this method: one is to blur the input image to generate a mask, and the other is to use gamma correction on the input image to obtain the correction result. According to the mask generation method proposed by Moroney [9], Gaussian blur is used to process the input image. Gaussian convolution will blur the edge information of some details, and the use of mean filter processing has a better effect on retaining edge details. And to reduce the degree of loss of detail information in the filtering process.

$$\gamma = \frac{L'}{L} \tag{7}$$

$$\begin{bmatrix} R' \\ G' \\ B' \end{bmatrix} = \gamma * \begin{bmatrix} R \\ G \\ B \end{bmatrix} \tag{8}$$

In Eq. (7), L is the initial brightness of the fused image, L' is the brightness after performing local brightness correction on L. The brightness conversion ratio is calculated using Eq. (7). Then, in Eq. (8), the initial fused image in the RGB color space is transformed using the same conversion ratio, resulting in the final fused image represented by R', which contains the RGB color space values.

3. Experiment and Analysis

3.1 Experimental Data Introduction

This article conducted experimental verification using a sequence of images captured by remote sensing satellites in space. The sequence consists of 5 images with different exposure levels. The exposure times for the images are 6.4ms, 9.05ms, 9.8ms, 12.8ms, and 18.7ms, respectively. Each image has a size of 1024 x 1024 pixels and is composed of three-color channels: R, G, and B. The images have a bit depth of 8 bits. As shown in Figure 2.

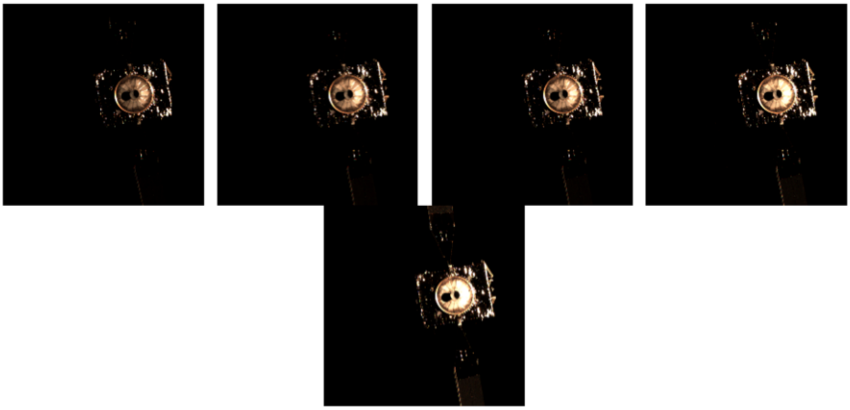


Figure 2. Sequence of different exposure levels of space satellite images

3.2 Weight Validity Analysis

3.2.1 Contrast Feature Analysis

To verify the validity of the contrast feature proposed in this paper, this paper uses the model in literature [1] as the original model for comparison and verification and changes the Laplacian filter extraction contrast method in the original model to the contrast feature extraction method proposed in this paper. The calculation of contrast features has been elaborated in Section 1.1.1 of this paper. Keeping the other methods in the literature [1] unchanged, the satellite image sequence is processed separately to obtain the fusion result, as shown in Table 1, [1] is the image index of the result obtained by the original model, Ours1 is the image index added to the contrast feature result of this paper ; The effect of this paper and the effect of the fusion of the local contrast proposed in the original model have been improved to a certain extent in the objective evaluation indicators of information entropy, average gradient, spatial frequency, mean and standard deviation.

Table 1. A single indicator of the original model and the fusion result of adding contrast features

	Entropy	AG	SF	Mean	SD
[1]	1.9728	1.4633	14.5058	7.8493	34.1144
Ours1	2.0915	1.5333	15.1452	8.2224	35.0162

3.2.2 Adaptive optimal brightness analysis

In order to verify the feasibility of the adaptive optimal brightness weight method in this paper, this paper uses the model in the literature [1] as the original model of the comparative test, and replaces the original model with the adaptive optimal brightness calculation method in the original model to extract the exposure weight. The specific process has been elaborated in Section 1.1.2 of this paper. After conducting guided filtering on the initially extracted optimal brightness, this paper uses the Structural Similarity (SSIM) objective evaluation index to show the influence of the adaptive optimal brightness on the fusion result. The results are shown in Table 2: Adding the feature weight After that, the fusion result improves the SSIM score of the original model by 1.17%.

Table 2. Comparison of SSIM scores comparing fusion results

	Original Model	After adding adaptive optimal brightness
SSIM	0.8147	0.8264

3.2.3 Salient feature analysis

To verify that the multiple exposure fusion methods are added to the effectiveness of the fusion results, this article is based on the model of the literature [1]. The method in the literature [1] as the original model, remove the saturation weight of the original model, add the significant characteristics of the design of this article, and maintain other methods of the original model. The calculation, this article has been explained in detail in section 1.1.3.

It can be seen from Table 3 that the results of OURS2 added significant features in the original model of the literature [1], and the value of the five objective evaluation indicators of information entropy, average gradient, spatial frequency, average, and standard deviation has improved. Adding significant features in the fusion rights can increase the amount of information of the fusion image results.

Table 3. The original model and the single indicator of the fusion result of adding significant features

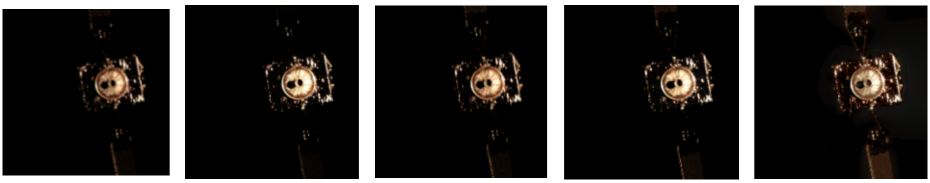
	Entropy	AG	SF	Mean	SD
[1]	1.9728	1.4633	14.5058	7.8493	34.1144
Ours2	2.4596	1.5197	15.3408	9.3455	38.8195

3.3 Image Fusion Comparative Analysis

To verify the effectiveness of this method, the experimental verification was completed using the Matlab-R2021A software on the Windows 10 platform. A comparative analysis was made to compare the method and commonly exposed image fusion methods of this method with common images. The comparison methods include Mertens's classic pyramid exposure fusion, Lee [10] self -adaptal value fusion method, Wang [11] yuv color space the details of the details and the calculation method of the improvement weight calculation of Karakaya [12] and others. The experimental results are shown in Table 4.

Table 4. Various objective evaluation indicators of different methods

	Entropy	SF	AG	IL-Niqe	PIQE	BRISQUE
Mertens	1.472	13.831	1.371	72.478	64.232	86.269
Lee	1.556	13.668	1.224	68.477	71.646	94.051
Wang	1.387	14.108	1.397	76.673	63.705	85.168
Karakaya	1.616	13.040	1.262	79.40	65.933	87.460
Proposed	**3.294**	**15.493**	**1.868**	**45.204**	**55.06**	**68.923**



(a)Mertens (b)Lee (c)Wang (d)Karakaya (e)Proposed

Figure 3. Results of different multi-exposure fusion methods

It can be seen from Table 4 that in the multi-exposure fusion of remote sensing images of space targets, the currently commonly used multi-exposure fusion methods are all the same in the three objective evaluation indicators of the degree of information contained in the image, namely, information entropy, spatial frequency, and average gradient. The index value is not as high as the multi-exposure fusion method proposed in this paper. The reason should be that the image data for common fusion methods are mostly ordinary scenes, and the particularity of space environment images is not considered. Figure 3 shows the multi-exposure fusion results obtained by different methods. (a), (b), (c), and (d) are the results obtained by the four comparison methods in this paper, and (e) is the fusion result obtained by the method in this paper. In the figure, the main part of the satellite is darker in (a) and (c), so the information entropy, SF and AG of the image are lower than those of the other three; in the two sailing parts of the satellite, the first four images visually the effects are not obvious, but in the results obtained by the method in this paper, the sailboard part can be clearly seen. Therefore, in general, the method in this paper is far superior to the other four methods in the three indicators of image information entropy, SF and AG. In order to verify the quality of fusion results from multiple aspects, this paper also uses three different no-reference model evaluation indicators, namely naturalness image quality evaluation (IL-Niqe)[13], no-reference image spatial quality evaluation (BRISQUE)[14] and perceptual-based image quality evaluation (PIQE) for statistical evaluation, the lower the value of these three indicators, the better the image effect, that is, the more natural the processed image looks; as can be seen from Table 4, The method in this paper has the lowest value among the three no-reference model evaluation indicators, and the results are better than the other four methods..

4. Conclusion

In response to the characteristics of the space -sensing image of space targets, this article proposes a multi -exposed fusion method based on multi -characteristic weights. Based on adaptive optimal brightness, contrast characteristics and significant characteristics as the fusion weight, use the pyramid model to carry out multi -scale integration of weights and satellite image sequences. Finally Enhanced high -dynamic HDR satellite image. The experimental results show that the method of multiple exposure images obtained on space remote sensing images with low background and target objects with low contrast and target objects is better than the commonly used fusion method.

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