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Research on color image matching method based on feature point compensation in dark light environment①

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Abstract

Image matching refers to the process of matching two or more images obtained at different time, different sensors or different conditions through a large number of feature points in the image. At present, image matching is widely used in target recognition and tracking, indoor positioning and navigation. Local features missing, however, often occurs in color images taken in dark light, making the extracted feature points greatly reduced in number, so as to affect image matching and even fail the target recognition. An unsharp masking (USM) based denoising model is established and a local adaptive enhancement algorithm is proposed to achieve feature point compensation by strengthening local features of the dark image in order to increase amount of image information effectively. Fast library for approximate nearest neighbors (FLANN) and random sample consensus (RANSAC) are image matching algorithms. Experimental results show that the number of effective feature points obtained by the proposed algorithm from images in dark light environment is increased, and the accuracy of image matching can be improved obviously.

Key words: dark light environment, unsharp masking(USM), denoising model, feature point compensation, fast library for approximate nearest neighbor(FLANN), random sample consensus (RANSAC)

0 Introduction

Image matching refers to the process of identifying homonymous points between two or more images by a certain matching algorithm. According to the different matching elements, image matching is divided into two types: grayscale matching and feature-based matching. The former is easily affected by color changes, while related algorithms based on local feature matching, such as scale-invariant feature transform (SIFT), have been widely used in target recognition. However, the taken images often suffer from low brightness, color distortion, noise, and other quality issues in dark light environments with illuminances below 1 lx, such as morning and evening, occluded areas, or enclosed/semi-enclosed spaces. Due to these factors, the information in the image is difficult to extract. Therefore, image matching has extremely significant research value in the dark light environment.

Feature point extraction is the most critical step in image matching. The feature points are divided into global points and local feature points. In contrast to the former, the latter is less disturbed by the environment and is widely used in image matching. For the image matching problem in the dark light environment, it is necessary to achieve feature point compensation by enhancing the dark light image before feature matching. In recent years, researchers have proposed a series of methods to achieve feature point compensation by improving the quality of the dark light image. Ref. [1] enhanced the image contrast by histogram equalization (HE), which makes up for the number of feature points to some extent and improves the accuracy of image matching. The algorithm based on Retinex[2] enhances the image information by improving the visual effect of the image. However, the presence of halo artifacts can lead to error extraction of feature points. With the development of deep learning techniques[3] and the continuous improvement of related theories, deep learning methods can be used to improve the quality of dark light images. However, their models have relatively large scales and require more running time when they process the images. Ref. [4] improved the contrast of images by separating red, green, and

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blue channels, which indirectly increases the number of extracted feature points. Ref. [5] improved the contrast and brightness of images by using Sigmoid functions instead of logarithmic functions in the multiscale Retinex algorithm. When extracting local features, this method can extract more feature points. Since the algorithm improves on the multi-scale Retinex algorithm, the halo phenomenon still exists in the processed images.

The existing methods can increase the number of feature points to a certain extent by improving the brightness and contrast of the image. However, degradation issues are not fully resolved, such as noise and color distortion in dark light images. In this paper, a denoising model based on unsharp masking (USM) is proposed, which reduces the noise influence of dark light images in some areas, and a feature point compensation algorithm based on local adaptive enhancement effectively solves the degradation problem of dark light images.

1 Acquisition and preprocessing of color dark light images

1.1 Acquisition of color dark light images

One hundred color images are selected to simulate color dark light images in different environments from an existing object detection dataset (Pattern Analysis, Statical Modeling and Computational Learning Visual Object Classes 2007, PASCAL VOC 2007). These images are processed into color dark light images with different brightness by random Gamma transform and Gaussian noise. The obtained dark light images are recorded as the dataset Newdata.

1.2 Denoising model based on unsharp mask

The image is preprocessed to eliminate interference information and restore useful information. In dark light images, the presence of noise makes the image suffer from blurred contours and unclear local details. This paper proposes a denoising model based on USM to solve this problem. The model utilizes the advantages of Gaussian low-pass filtering and the USM algorithm to solve the peculiar noise problem of dark light images.

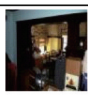
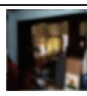
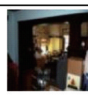
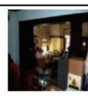
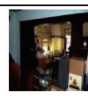
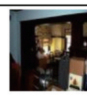
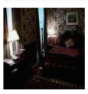
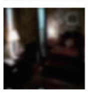
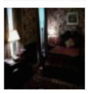
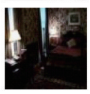
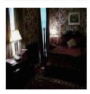
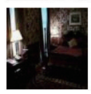
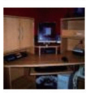
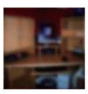
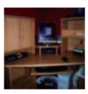
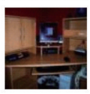
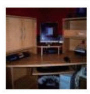
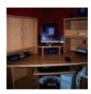
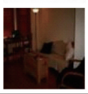
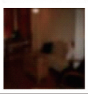
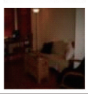
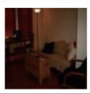
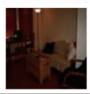
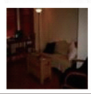
The denoising effect of the Gaussian low-pass filter depends on the value of D_0. The larger the D_0, the better the denoising effect, the more serious the loss of detailed information. The Gaussian low-pass filter is shown in Eq. (1).

$$H(u, v) = e^{-D^2(u,v)/2D_0^2} \tag{1}$$

where, D_0 is the cutoff frequency of the Gaussian low-pass filter.

The appropriate D_0 is sought by randomly selecting four images from Newdata for testing. Four sample images are processed when D_0 is selected as 10, 30, 60, 160, and 460, respectively. The results are shown in Table 1.

Table 1 Original image and Gaussian low-pass filtering image corresponding to different D_0 values

Sample images	Original image	D_0=10	D_0=30	D_0=60	D_0=160	D_0=460
Sample 1						
Sample 2						
Sample 3						
Sample 4						

From Table 1, when D_0 is 10 or 30, the image is blurred. When D_0 is 60, 160, or 460, the details of the image are richer.

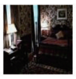
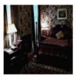
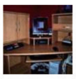
After Gaussian low-pass filtering, USM algorithm is used to sharpen the image to retain more details. The specific expression formula is shown in Eq. (2).

$$u(n, m) = g(n, m) + \lambda \cdot s(n, m) \tag{2}$$

where, $g(n, m)$ is the Gaussian low-pass filtered image, $u(n, m)$ is the sharpened image, λ is the scaling factor to control the enhancement effect, and $s(n, m)$ is the correction signal.

To further select the appropriate D_0 values for the denoising model, USM algorithm is used to sharpen the Gaussian low-pass filtering image when D_0 is 60, 160, and 460, respectively. The sharpened images are shown in Table 2.

Table 2 Denoising model images corresponding to different D_0 values

Sample images	D_0=60	D_0=160	D_0=460
Sample 1			
Sample 2			
Sample 3			
Sample 4			

From Table 2, when D_0 is 60, 160, and 460, the images processed by the denoising model do not change much in detail, and visual effect is not good.

For this reason, peak signal-to-noise ratio (PNSR) is introduced as an objective evaluation index. The larger the PNSR value, the better the image quality. The values of PNSR are shown in Table 3.

Table 3 PNSR values of denoising model with different D_0 values

Sample images	D_0 = 60	D_0 = 160	D_0 = 460
Sample 1	24.66	24.40	24.08
Sample 2	25.32	25.02	24.44
Sample 3	24.67	24.09	23.74
Sample 4	27.78	27.48	27.24

From Table 3, when D_0 is 60, the PNSR value of the image is the largest, and the image quality is the best.

For further verification, the denoising model works better when the value of D_0 is around 60. Values ranging from D_0 = 50 to D_0 = 75 are selected to test the four sample images. The results of PNSR are shown in Fig. 1.

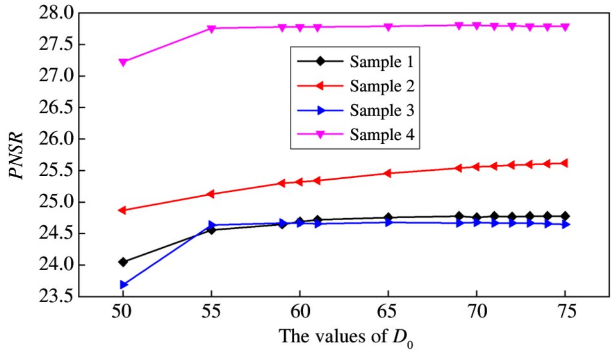


Fig. 1 Comparison of the PNSR values

By comparison, when D_0 = 60, the image denoising effect is better, and the information is more detailed. Therefore, this paper chooses the unsharp masking denoising model when D_0 is 60 to process the dark light image.

This paper selects four dark light images in the teaching building to test the effectiveness of the denoising model. These images are processed separately by using different denoising algorithms. The test results are shown in Table 4.

From Table 4, compared with the other three denoising algorithms, the image contours processed by the denoising model in this paper are clearer and the overall visual effect is better.

Table 4 Images after processing by different denoising algorithms

Test images	Original image	Gaussian filtering	Gaussian smoothing filtering	Wiener filtering	Denoising model based on unsharp masking
Test 1					
Test 2					
Test 3					
Test 4					

PNSR is used to measure the denoising effect objectively. The evaluation results are shown in Table 5.

From Table 5, compared with the other three algorithms, PNSR value of the images processed by the denoising model in this paper is the largest and contains the least amount of noise.

Table 5 PNSR values of images processed by different algorithms

Test images	Gaussian filtering	Gaussian smoothing filter	Wiener filtering	Denoising model
Image 1	27.97	28.17	26.95	28.67
Image 2	28.48	30.02	25.82	28.58
Image 3	25.88	25.03	25.57	26.94
Image 4	26.93	27.06	26.28	28.61
Mean value	27.32	27.57	26.16	28.20

1.3 Illumination compensation and multi-scale detail enhancement for the color dark light images

After the denoising model processing, the contour of the dark light image is sharper, but there are still problems of low brightness and lack of edge information. For this reason, this paper uses the brightness adaptive enhancement algorithm[6] and multi-scale detail enhancement algorithm[7] to strengthen the brightness and detail of the images.

1.4 Contrast limited adaptive histogram equalization for color dark light images

After preprocessing, the clarity of the color dark light image gets enhanced, but the overall contrast of the images is not ideal. For this problem, this paper enhances the contrast of images by using the contrast limited adaptive histogram equalization (CLAHE) algorithm. First, the image is segmented into rectangles of equal size. Then each rectangle calculates the histogram, cumulative distribution function, and corresponding transformation. Finally, the remaining pixels are obtained by the transformation function. The specific process is shown in Fig. 2.

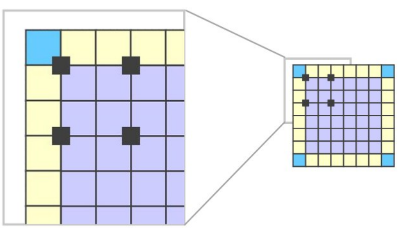


Fig. 2 Schematic diagram of CLAHE interpolation

2 Feature point compensation algorithm based on local adaptive enhancement

2.1 Adaptive local tone mapping (ALTM)

For the color distortion problem of dark light images, ALTM[8] algorithm is used to enhance the color of the equalized image. The specific steps are as follows.

The three channels of the equalized image are set to R, G, and B, respectively, and the light intensity of each pixel point is approximated as a grayscale image $W(x, y)$.

$$W(x, y) = R \times 0.299 + G \times 0.587 + B \times 0.114 \tag{3}$$

$W_o(x, y)$ is used to calculate each pixel.

$$W_o(x, y) = \ln\left(\frac{W_m(x, y)}{\overline{W}} + 1\right) / \ln\left(\frac{W_{\max}}{\overline{W}} + 1\right) \tag{4}$$

where, $W_{\max}$ is the maximum brightness value of the color image after equalization.

H_c represents the enhancement coefficient of the original color image. The expression is Eq. (5).

$$H_c = W_o(x, y) / W(x, y) \tag{5}$$

H_c[9] is used to enhance any pixel of color images.

$$W_n(x, y) = \begin{bmatrix} R_n(x, y) \\ G_n(x, y) \\ B_n(x, y) \end{bmatrix} = \begin{bmatrix} H_c \times R_p(x, y) \\ H_c \times G_p(x, y) \\ H_c \times G_p(x, y) \end{bmatrix} \tag{6}$$

2.2 Local adaptive contrast enhancement (LACE)

To further enhance the image contrast, this paper uses local adaptive contrast enhancement[10] to improve the contrast of the images.

The local adaptive contrast enhancement algorithm is described by the following equation

$$Q(i, j) = M_{i,j} + \frac{\alpha}{\sigma_{i,j}^2}[f(i, j) - M_{i,j}] \tag{7}$$

where, $Q(i, j)$ denotes the central pixel of the enhanced image, and α is the adaptive adjustment factor.

The LACE algorithm uses the maximum value $A_{\max}$ to limit the contrast gain. The calculation formula is

$$\frac{\alpha}{\sigma_{i,j}^2} \leqslant A_{\max} \tag{8}$$

For maintaining the consistency of the image color, the color of images are calculated by Eq. (9)

$$S(i, j) = \frac{I^p(i, j)}{I(i, j)} \cdot H(i, j) \tag{9}$$

where, $I(i, j)$ is the luminance component of the original image in HSI color space, $I^p(i, j)$ is the result of $I(i, j)$ processing, $H(i, j)$ is the result of converting the processed image from HSI space to RGB space. After $H(i, j)$ restores color, the result is $S(i, j)$.

3 Experimental effect analysis of feature point compensation

The proposed algorithm achieves the purpose of feature point compensation by enhancing the image information. For dark light images, the feature point compensation effect of the proposed algorithm is shown in Table 6.

From Table 6, the number of image feature points processed by the proposed algorithm is several times larger than the original image.

Table 6 Comparison of the number of feature points

Sample images	Original image	Proposed algorithm
Sample 1	376	1056
Sample 2	403	1322
Sample 3	303	1171
Sample 4	115	1174
Mean value	299.25	1180.75

In this paper, four more images are selected randomly from the Newdata dataset for testing to validate the proposed algorithm. These images are shown in Fig. 3 and the test results are shown in Table 7.

As shown in Table 7, the number of image feature points processed by the proposed algorithm is several times larger than the number of feature points in the original image. To a large extent, the proposed algorithm solves the problem of feature point loss in dark light images.

Fig. 3 Test images

Table 7 Comparison of the number of feature points

Test images	Original image	Proposed algorithm
Test 1	83	1398
Test 2	368	1390
Test 3	176	949
Test 4	208	1207
Mean value	208.75	1236.00

The specific steps of the proposed algorithm are shown in Fig. 4. For the acquired color dark light image, first, the denoising model based on the unsharp mask is used to remove noise; and the brightness adaptive enhancement algorithm is used to improve the brightness of the images; then, the multi-scale detail enhancement algorithm and CLAHE algorithm are used to enhance the edge details of the images; finally, the local features of the image are strengthened to enhance the information of images and achieve the feature point

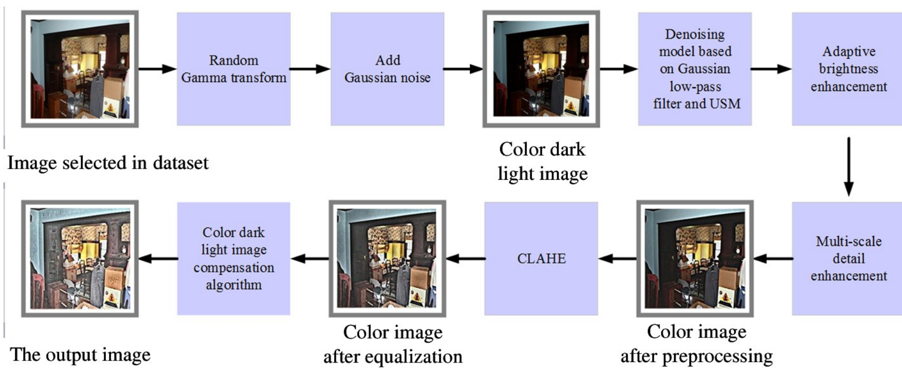


Fig. 4 Steps of the proposed algorithm

compensation by the feature point compensation algorithm based on local adaptive enhancement.

While local features are enhanced, some features of the image cannot be used in feature matching. Therefore, the feature point compensation of the proposed algorithm is evaluated objectively by using information entropy. The evaluation results are shown in Table 8.

The larger the information entropy value, the more the image information. From Table 8, the average information entropy value of the image processed by the proposed algorithm is greater than the original image and contains more information. Therefore, the proposed

Table 8 Comparison of information entropy

Image set	Original image	Proposed algorithm
Sample 1	0.056	0.057
Sample 2	0.053	0.058
Sample 3	0.057	0.056
Sample 4	0.054	0.056
Test 1	0.050	0.055
Test 2	0.053	0.058
Test 3	0.047	0.057
Test 4	0.051	0.057
Mean value	0.053	0.057

algorithm achieves the purpose of effectively compensating the feature points.

4 Image matching process

4.1 Feature points extraction

Image feature points are divided into global feature points and local feature points. This paper uses local features to extract feature points that contain more image information. Among the local feature point extraction algorithms, SIFT[11] algorithm is more robust to rotation, scale transformation, illumination, and noise. Therefore, SIFT algorithm is used to extract feature points.

4.2 Feature points matching

Two-dimensional feature matching methods are divided into brute-force-matcher (BFMatcher) and fast library for approximate nearest neighbors (FLANN). FLANN[12] algorithm is used to improve computational efficiency.

FLANN algorithm finds the closest point to the instance point by using the Euclidean distance. The calculation formula for Euclidean distance is

$$D(x, y) = \| X, Y \| = \sqrt{\sum_{i=1}^{d} (X_i - Y_i)^2} \tag{10}$$

The smaller the value of $D(x, y)$ is, the more similar the pair of feature points will be.

For FLANN algorithm, fast approximate NN matching is divided into the random k-d tree algorithm and priority search k-means tree algorithm. Due to the high requirement for matching accuracy, this paper uses the k-means tree search algorithm. The algorithm is divided into building a priority search k-means tree and searching in a priority search k-means tree[13].

4.3 Random sample consensus (RANSAC) algorithm

Since the FLANN algorithm uses proximity approximation, the accuracy is poor, and error matching may occur. For this problem, RANSAC[14] algorithm is introduced to improve the matching accuracy. The steps of RANSAC algorithm are as follows.

(1) Four sample data are selected randomly from the matched pair dataset L to calculate the transformation matrix $\boldsymbol{H}$. The resulting model is denoted as R.

(2) The error between all data in the dataset and model R is calculated by setting the threshold T_d. The set P represents the new interior point less than threshold T_d.

(3) When the size of the set P is more than some threshold T_e, the model is re-estimated with P, and the iteration ends. Otherwise, the latter sample is selected and the above steps are repeated. The set with the most internal points is selected and recomputed in the model to get the final result.

The matching process of the color dark light image processed by the proposed algorithm is shown as Fig. 5.

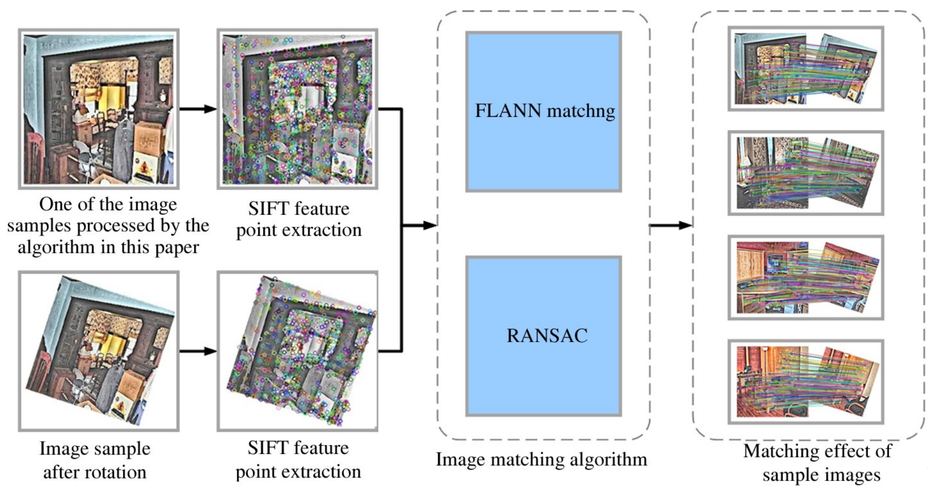


Fig. 5 Image matching process

5 Experimental analysis and simulation tests

Four images are selected randomly from Newdata for the experiment to verify the feasibility and effectiveness of the proposed algorithm. These images are processed by the multi-scale Retinex with color restore (MSRCR) algorithm, automated MSRCR algorithm, ALTM algorithm, and the proposed algorithm, respectively. The processed images use subjective and objective perspectives to compare their quality. The former uses the visual perception ability of the human eye as the evaluation index. The latter uses the number of image feature points, the average gradient, the number of feature point matching pairs, and the image matching accuracy as the evaluation indexes.

5.1 Comparison experiments of color dark light images

As shown in Fig. 6, the quality of the dark light images processed by the proposed algorithm is significantly improved. However, the color distortion of the image processed by the other three algorithms is more serious.

(a) Original image

(b) Automated MSRCR algorithm

(c) MSRCR algorithm

(d) ALTM algorithm

(e) Proposed algorithm

Fig. 6 Original image and images after processing by different algorithms

5.2 Image matching experiments

After processing using the algorithm proposed in this paper, the number of image feature points is the most, followed by the automated MSRCR algorithm. However, the number of image feature points processed by the other two algorithms is less.

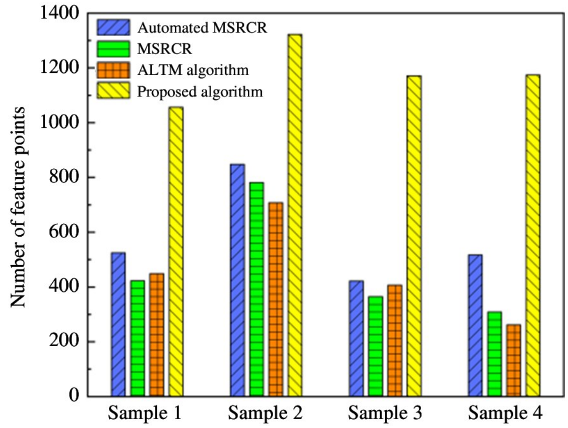


Fig. 7 Number of feature points

From Tables 9 and 10, it can be seen that the accuracy of image matching is improved after RANSAC processing. Compared with the other three algorithms, the images processed by the proposed algorithm have the largest number of matching pairs and the best matching results. However, the images processed by the other three algorithms have fewer matching pairs and poorer matching results.

The average gradient is used to objectively evaluate the color dark light images processed by the four algorithms. The larger the average gradient is, the better the image clarity is. The average gradient is calculated by

$$G = \frac{1}{M \times N} \sum_{i=1}^{M} \sum_{j=1}^{N} \sqrt{\frac{(\partial f / \partial x)^2 + (\partial f / \partial y)^2}{2}} \tag{11}$$

where, $M \times N$ is the image size, $\partial f / \partial x$ is the horizontal gradient, and $\partial f / \partial y$ is the vertical gradient.

As listed in Table 11, the image clarity after the proposed algorithm is the best. From the perspective of sample images, only in sample 2, the image clarity processed by the proposed algorithm is slightly lower than automated MSRCR algorithm. In other samples, the image clarity processed by the proposed algorithm is the highest. Among all the sample images, the image clarity processed by MSRCR algorithm is the lowest.

To further evaluate the color dark light images processed by the four algorithms, the image-matching accuracy and the number of feature point-matching pairs are used as evaluation metrics. The results are shown in Table 12.

As listed in Table 12, the number of matching pairs of image feature points processed by the proposed algorithm is the largest, the matching effect is the best, and the matching accuracy can reach at 74.78 %. Therefore, the proposed algorithm solves the problem of image matching in the dark light environment to a certain extent.

Table 9 Image matching effect without RANSAC

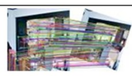
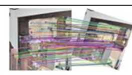
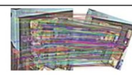
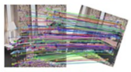
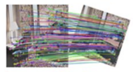
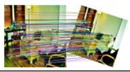
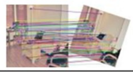
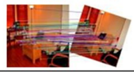
Algorithms	Sample images	Automated MSRCR	MSRCR	ALTM	Proposed algorithm
Without using the RANSAC	Sample 1				
	Sample 2				
	Sample 3				
	Sample 4				

Table 10 Image matching effect using RANSAC

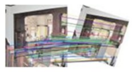
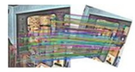
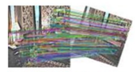
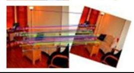
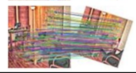
Algorithms	Sample images	Automated MSRCR	MSRCR	ALTM	Proposed algorithm
Using the RANSAC	Sample 1				
	Sample 2				
	Sample 3				
	Sample 4				

Table 11 Average gradient of images after processing by different algorithms

The sample number	Automated MSRCR	MSRCR	ALTM	Proposed algorithm
Sample 1	15.82	10.92	12.44	20.61
Sample 2	25.50	17.73	20.80	25.36
Sample 3	16.78	9.98	12.46	21.80
Sample 4	17.34	7.36	7.48	19.03
Mean value	18.86	11.50	13.30	21.70

Table 12 Number of matched pairs and matching accuracy of images processed by different algorithms

The sample number	Automated MSRCR		MSRCR		ALTM		Proposed algorithm	
	Coarse/Fine matching pairs	Matching accuracy/%	Coarse/Fine matching pairs	Matching accuracy/%	Coarse/Fine matching pairs	Matching accuracy/%	Coarse/Fine matching pairs	Matching accuracy/%
Sample 1	160/100	62.50	149/92	61.74	132/71	53.79	312/219	70.19
Sample 2	175/103	58.86	199/110	55.28	160/104	65.00	308/220	71.43
Sample 3	121/70	57.85	128/56	43.75	103/70	67.96	337/252	74.78
Sample 4	121/80	66.12	89/61	68.54	72/49	68.06	317/227	71.61

6 Conclusion

Color image matching is a key technique support for target recognition, positioning and relative applications. Aiming at the problem of local features missing of the image in dark light environment to affect or even fail the image matching, an effective feature point compensation method is proposed. Considering the special image noise property with dark light, an unsharp mask-based denoising model is established in pre-processing stage, and a feature point compensation algorithm based on local adaptive enhancement is designed to enhance the regional information of the image by strengthening the local features of the image so as to achieve the effective compensation of feature points rather than increasing the quantity simply.

The noise of the dark light image region can be eliminated by the established denoising model, and the brightness and dark details of the image can be improved adaptively by the brightness adaptive enhancement and multi-scale detail enhancement method.

Then the image is equalized by CLAHE to improve the region contrast of the image. The feature point compensation algorithm is adopted based on local adaptive enhancement to strengthen the local features of the image and enrich the image information. SIFT and FLANN algorithms are taken to realize the color dark light images matching with the assistance of the obtained point compensation. Error-matching pairs are eliminated by RANSAC to further improve the accuracy of image matching.

The experimental results show that the proposed denoising model and compensation algorithm can enhance the local features and rich the regional information obviously. The matching accuracy can be improved by 74.78%. The effect of feature points missing caused by dark light environment on color image matching is alleviated greatly. Further research will focus on the optimal parameters in the denoising model in order to explore feature points compensation limit.

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