Improved SURF in color difference scale space for color image matching

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Abstract—This paper presents an improved SURF (Speeded Up Robust Features) for image matching which considers color information. Firstly, a new color difference scale space is constructed based on color information to detect feature point. Then we extracted a 192-dimensional vector to describe feature point, which includes a 64-dimensional vector representing the brightness information and a 128-dimensional vector representing the color information in a color image. Finally, in the process images matching, a new weighted Murkovski distance is used to measure the distance between two descriptors. From the experiment results, we can know that, compared the other methods, the feature points detection method proposed is more robust. The matching scores and precision of our method are dominant among different methods of color image matching. Compared with SURF, the number of feature points detected by the proposed method increases by 163%, the average matching scores and matching precision increase by 16% and 15.81% respectively.

Keywords—Color image matching, color difference space, 192-dimensional descriptors, weighted Murkovski distance.

I. INTRODUCTION

Image matching is a fundamental aspect of many problems in computer vision, including object or scene recognition, Image retrieval, 3D reconstruction [1]. Existing image matching methods of color images are commonly grey-value-based [2-5] or feature-based [6-17], and the most widely used method is feature-based image matching for better robustness. Typical features of images include point features, line features, and region features. Line features focus on general lines, contours, and edges of images [6-8]; region features include closed boundary regions with high contrast and the most commonly used operators are MSER (Maximally Stable Extremal Regions), EBR (Edge-based Regions), affine Hessian, among others [9-11]; point features comprise the corners, spots or T-junctions of images. They are applied according to different uses of researches. In this study, we propose to match images based on point features.

Image matching can be divided into three steps: feature points detection, descriptor of feature point, and matching images based on descriptors. In the first step of searching for discrete image points, three main steps are listed as follows [12]: First, interest points are selected at distinctive locations in the image, such as corners, blobs, and T-junctions. The most valuable property of an interest point detector is its repeatability. The repeatability expresses the reliability of a detector for finding the same physical interest points under different viewing conditions. Second, the neighborhood of every interest point is represented by a feature vector, named descriptor of the feature point. This descriptor has to be distinctive and at the same time robust to noise, detection displacements and geometric and photometric deformations. Third, the descriptor vectors are matched between different images. The matching is based on the distance between the vectors. At present, image matching algorithms based on point features mainly include FAST (Features from Accelerated Segment Test), Harris, SIFT (Scale-invariant feature transform) and SURF (Speeded up robust features) [12-18]. In FAST and Harris, feature points are extracted directly from grey-value images [13-14], while in SIFT and SURF, image pyramids are built to detect feature points also from grey-value images [15-18]. In the second step of image matching, descriptors are established based on the feature points. Descriptors are vectors that describe the features points and reflect the information of the neighborhood of the feature points. In the establishing of descriptors, both Harris and SIFT algorithms use gradient direction histograms to obtain 128-dimensional descriptors [15-16]. In the SURF algorithm, the dimension of descriptors decreases to 64 by the use of the Haar wavelet, which increases efficiency [17-18]. The third step of image matching is calculating the similarity of corresponding feature points of two images. The criterion of testing the matching degree of two feature points is usually proposed by Euclidean distance [15-18].

In color image matching, it is important to add color

information especially when we match images with similar structure but much different in color, or images with distinct color information. However, the above introduced traditional image matching methods only focused on the grey value of images. To solve this problem, color image matching methods have been proposed. Some methods extract feature points based on color invariants, such as G-SIFT, C-SIFT and A-SIFT [19-20], but the descriptors are obtained only using the grey value information of the image. In [21], based on SIFT, descriptors that represent color information are extracted in several color spaces. In [22], feature points are obtained from complex-valued images, which are more independent than real-valued images and decrease mutual information. In [23], 67-dimensional descriptors which include three-dimensional descriptors of R, G, and B are proposed, but the feature points are extracted based on grey value. These methods fail to make use of color information in the whole image matching process.

To fully use the color information of images, we propose to match images based on CIELab color space. First, we proposed a new color difference scale space based on color information to detect feature points based on SURF, and then construct a 192-dimensional feature point descriptor, which includes a 64-dimentional vector representing the brightness information of an image and a 128-dimentional vector representing color information of an image. Finally, the descriptor vectors are matched by the new weighted Murkowski distance between different images. The perceptual sensitivity of the eye to different colors is not equal in RGB color space, but CIELab space was designed to be perceptually uniform with respect to human color vision [24]. It is important to add color information in feature point detection for color images, and brightness information is also important to represent image information, so we need to find a proper color space where the color and brightness can be separated, and CIELab space can separate brightness information from color information.

The contributions of our method are summarized as follows:

(1) We propose to construct multi-scale color difference space in CIELab color space, which is different from the existing image matching method that uses RGB color space.

(2) We propose to improve SURF algorithm by adding color information in both feature point detection and descriptor building. Based on the 192-demensional descriptors we proposed, we measure the similarity of feature points based on weighed Murkovski distance, which has not been used to our best knowledge.

(3) In the experiments, we compare the proposed method with images matching with different dimensions of descriptors, different similarity measurement methods, and different color spaces. The results verify the effectiveness of our method.

The second part of this paper gives a detailed description of our novel images matching method, which includes feature points detection based on the proposed color difference space, the establishment of novel 192-dimensional descriptors, feature points matching by the nearest neighbour method using weighted Murkovski distance. The third part of this paper is the

experimental results and analysis. The fourth part is the conclusion of this paper.

II. METHOD

Since image matching based on the grey value will lead to the loss of important color information, a color image matching method based on SURF in color difference space is proposed. The specific process is shown in Figure 1.
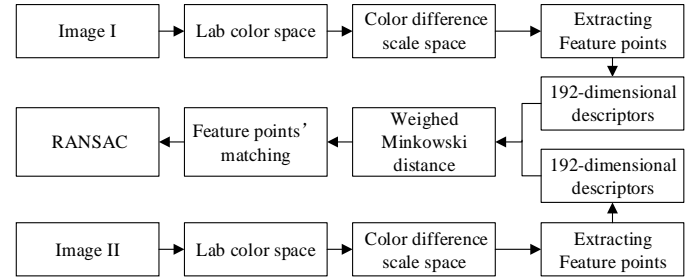

Figure 1. Process of the proposed method

A. Feature points detection based on color difference scale space

To add color information in the process of feature points' detection, color images are first transformed from RGB color space into XYZ as an intermediate mode, then into CIELab color space [25-26]. In our paper, CIELab color space is abbreviated as Lab color space. L denotes brightness, a channel represents the red-green channel, and the b channel is the yellow-blue channel. In Lab space, the color difference is defined as follows:

$$\Delta E = \sqrt{(\Delta L)^2 + (\Delta a)^2 + (\Delta b)^2} \tag{1}$$

where Δg is the difference value of the image, and defined as follows:

$$\Delta L = \frac{1}{2}(L_h^{(i+1,j)} - L_h^{(i,j)}) + \frac{1}{2}(L_v^{(i,j+1)} - L_v^{(i,j)}) \tag{2}$$

$$\Delta a = \frac{1}{2}(a_h^{(i+1,j)} - a_h^{(i,j)}) + \frac{1}{2}(a_v^{(i,j+1)} - a_v^{(i,j)}) \tag{3}$$

$$\Delta b = \frac{1}{2}(b_h^{(i+1,j)} - b_h^{(i,j)}) + \frac{1}{2}(b_v^{(i,j+1)} - b_v^{(i,j)}) \tag{4}$$

In (2), $L_h^\bullet$ and $L_v^\bullet$ are the horizontal and vertical pixel value in the L channel, (i, j) is the location of points, which is similar to (3) and (4) in a channel and b channel.

In SURF [12], scale space is obtained by using the same grey value image convolved with filters in different sizes, and the scale of each layer σ is calculated in (5), in which N is the size of each box-filter [12].

$$\sigma_{surf} = 1.2 \frac{N}{9} \tag{5}$$

In our method, because of the existence of degradation as the filter size increases, we use only the first five octaves, each of which has 4 layers. Since we use L2-norm of ΔL, Δa and

Δb when establishing the color difference scale space, the value of scale is defined in (6), for the sake of the full coverage of scale space, a control parameter $\kappa < 1$ is set, and empirically, in our method, $\kappa = 0.75$. The details of establishment of color difference scale space is shown as Algorithm 1.

$$\sigma = \kappa \sqrt{3 \times (1.2 \frac{N}{9})^2} = 1.299 \sigma_{surf} = 1.56 \frac{N}{9} \qquad (6)$$

Algorithm 1: Establishment of color difference scale space

1. Transform color image from RGB color space to Lab color space.
2. Build SURF scale space using image matrix in L channel.
3. Build SURF scale space using image matrix in a channel.
4. Build SURF scale space using image matrix in b channel.
5. Calculate the scale spaces of ΔL, Δa and Δb by (2)-(4).
6. Establish the proposed color difference scales space based on (1).

The proposed new scale space reflects the color difference information of the neighborhood. A larger value represents a stronger color difference. Thus, coarse feature points are extracted by non-maximum suppression. First, the maximum values of the eight neighborhoods in each scale space are computed, then the maximum values in 3D color difference scale space are extracted by comparing with the two adjacent scale spaces. Finally is the process of feature points' elimination and accurately located by 3D interpolation [27-28].

B. Descriptor of feature point

In [12], the first step of describing the feature point is to identify the feature points' domination orientation, which is related to Haar-wavelet responses and determined by the gray value of feature point. Then we can construct a 20s×20s square region centered the feature point, where s is the scale in the corresponding layer, and orient along the domination orientation. The square area is divided into smaller 4 × 4 square sub-region. For each sub-region, we can calculate Haar wavelet responses. Σdx is the sum of horizontal Haar responses and Σdy is the sum of vertical Haar responses. Their absolute value Σ|dx| and Σ|dy| are respectively obtained. Finally a 4×16=64-dimensional descriptor can be obtained.

In our method, because of the consistency of dominant orientation in each channel in the Lab color space, we use the L channel to determine the orientation. In the process of feature points' description, we want the square area size to be the same as the traditional method, but the scale of our novel method is 1.299 times bigger than that in traditional SURF, so we choose 16s×16s square area. We use SURF to build 64-dimensional descriptors in each channel of Lab space, which are called basic descriptors, each basic is all added in our proposed descriptors, arranged end to end, as shown in (7):

$$V = [V_L, V_a, V_b] \qquad (7)$$

where $V_{\bullet}$ represents the descriptors in one of the color channels, consisting of vectors in 16 sub-regions, marked as $V_{\bullet\_subn}, n = 1, 2...16$.

$$V_{\bullet} = (V_{\bullet\_sub1}, V_{\bullet\_sub2}, ..., V_{\bullet\_sub16}) \qquad (8)$$

$$V_{\bullet\_subn} = (\sum dx, \sum |dx|, \sum dy, \sum |dy|) \qquad (9)$$

C. Descriptor matching

Euclidean distance is widely used in similarity measurement, (10) is the definition of Euclidean distance, where $V(x)$ and $V(y)$ are vector spaces of the feature points from the two images. $V(x_i)$ and $V(y_i)$ are the descriptors of two images in vector space, i refers to a positive integer value from 1 to n, n is the dimensionality of descriptors.

$$E(x, y) = |V(x) - V(y)| = \left(\sum_{i=1}^{n} |V(x_i) - V(y_i)|^2 \right)^{\frac{1}{2}} \qquad (10)$$

However, Euclidean distance has been proven to be always useful for high dimensional vectors, we introduce a new method of image matching based on weighted Murkovski distance [29-30]. Murkovski distance is shown as follows:

$$D(x, y) = |V(x) - V(y)| = \left(\sum_{i=1}^{n} |V(x_i) - V(y_i)|^p \right)^{\frac{1}{p}} \qquad (11)$$

where p is the Murkovski factor.

In our method, the weighted Murkovski distance in the proposed method is shown in (12), the details of it is shown as Algorithm 2. We have investigated the performance of different values of p and the weight, in our paper, p=0.2 is chosen to measure the similarity of descriptors for its better performance. Since the human eye is quite insensitive to blue than green and red [24], the weight of the red-green channel is set to be larger. We do several experiments on image matching when the weights change, and finally the value of $\alpha=0.25$, $\beta=0.5$ and $\gamma=0.25$ are defined in our method.

$$D(x, y) = \left(\sum_{i=1}^{n} \begin{array}{c} \alpha |V_L(x_i) - V_L(y_i)|^p \\ + \beta |V_a(x_i) - V_a(y_i)|^p \\ + \gamma |V_b(x_i) - V_b(y_i)|^p \end{array} \right)^{\frac{1}{p}} \qquad (12)$$

Algorithm 2: Descriptors matching method

1. Descriptors of feature points in image 1: $X^1, X^2...X^n$;
   Descriptors of feature points in image 2: $Y^1, Y^2...Y^m$.
2. **for** i=1:n
3.   **for** j=1:m
4.   Calculate the weighed Murkovski distance based on (12): $D(j) = |X^i - Y^j|$.
5.   **end**
6. $[d_{n1}, j^*] = \min D(j)$; $d_{n2} = \min D(j)$, $j \neq j^*$
7.   **if** $d_{n1} / d_{n2} < 0.6$
8. X^i and Y^{j^*} are set as a pair of matching points

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9.   **else** continue
10.   end
11. end

The process of color image matching is shown in the Algorithm 2. Firstly, detect feature points from two images and extract their descriptors. Then calculate the distance between two descriptors from different images. When the distance meet some requirements, the two feature points are matched.To achieve higher matching precision, we then use RANSAC (Random Sample Consensus) to obtain the final matching points[31-32].

III.   Results And Discussion

We evaluate the performance of our method on a number of images. Some are from the images in the ALOI (Amsterdam Library of Object Images) dataset [33], others are real-world images captured in a different scene among campus, illumination and view. The resolution ratios of our test images are different as well. The computer for the work is Intel I7, 16G RAM, 320G hard disk, the Matlab 2007 is taken as the calculation tool.

A.   *Evaluation of the ability of feature points detection*

Firstly, we test the feature points number detected by the proposed method and other state-of-the-art methods, such as SURF [12], SIFT [15], Harris [14], and FAST [13]. In addition, we add SURF-RGB, which uses the same process with our method in feature points' detection applied in RGB color space.

The images that we choose are shown in Figure 2, which include different scenes and illumination, the resolution ratios of the first six images are 768×576, others are 863×640, 863×640, 200×112, 863×640, 625×463, 200×237, 256×143, 170×85, 350×174. There are 15 images in total. Figure 3 shows

the number of feature points detected by the proposed method and other methods.

From Figure 3, SIFT extracts more feature points than other algorithms, and FAST detects fewer points than other methods, the feature points detected by the proposed method are 163% averagely more than by SURF. Although the proposed feature points' detection method detects fewer feature points than by SIFT, experimental results show that our method has better robustness than other methods.

Then, we test the ability of feature point detection for images in different light sources and view points. We change the illuminati(reducing the illumination), light source(point light and parallel light) and view point(view angles are 15°,30°,45° respectively named view 15°,30°,45°) of images shown in Figure 2. Figure 4 shows the changes of feature points of the second image in Figure 2, and we can see that the proposed method performs well in different conditions of images. The increasing trend or decrease trend of the proposed method changes fewer than other methods. The results of the other images in Figure 2 are nearly the same as the second image.

We further test 100 more images in the ALOI dataset, result is given in Table 1, the indices include the feature points' number, the robustness to illumination and view point. The robustness is calculated by the absolute value of the change rate between the number of original feature point and the number after different changes.

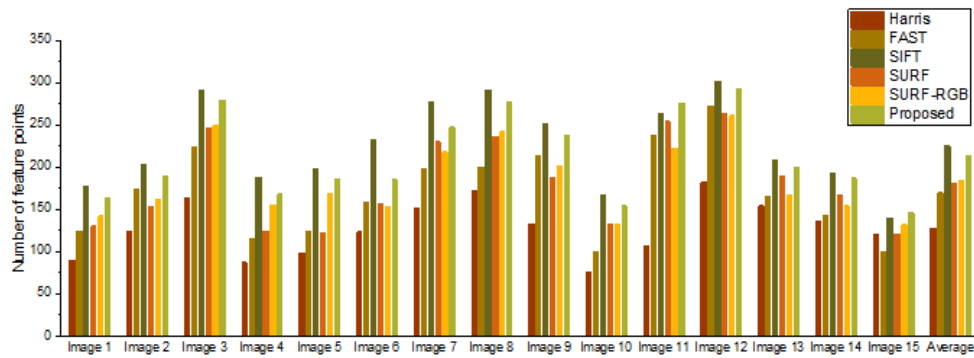Figure 2. Test images in feature points dection

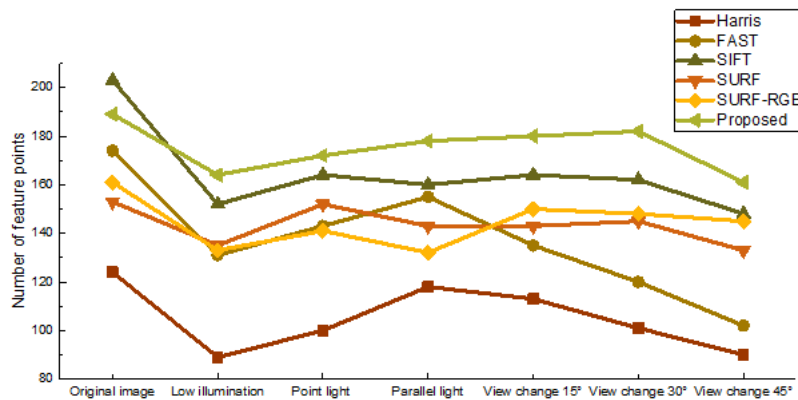Figure 3. Number of feature points detected from the test images.

Figure 4. Feature points' number in different conditions. Change the illuminati(reducing the illumination), light source(point light and parallel light) and view point(view angles are 15°,30°,45° respectively named view 15°,30°,45°) of the second image shown in Figure 2

Table 1. The comparison for 100 images from ALOI

		Harris	FAST	SIFT	SURF	S-RGB	S-Lab
'Feature points' number	Average	154	161	175	131	142	151
	Largest	225	196	272	211	259	265
	Lowest	49	73	106	93	94	102
Robustness to illumination	Average	38.02%	47.68%	37.83%	36.18%	36.06%	31.61%
	Best	26.11%	29.36%	25.61%	22.62%	23.13%	20.01%
	Worst	63.42%	68.05%	57.49%	40.61%	39.06%	31.29%
Robustness to view point	Average	32.76%	39.89%	30.28%	30.12%	32.16%	28.87%
	Best	22.24%	23.42%	21.13%	24.48%	25.34%	20.18%
	Worst	38.21%	42.03%	36.87%	38.25%	37.75%	33.98%

B. Performance of image matching

In our method, matching scores and matching precision [34] are the indices of the performance evaluation of image matching. Matching scores represent the ratio of correct matching points' number to the number of feature points detected in the two images. Matching scores represent the discrimination of feature points' detection. Matching precision reflects the accuracy of image matching, which is obtained by the ratio of correct matching points' number to the number of all matching points, it is a significant index for evaluating the matching results in the case of strict matching requirements.

Ten pairs of images in Figure 5 are used to test the performance of image matching of the protsposed method and others , the resolution ratios of the images are respectively 130×192, 90×113, 192×144 (the third to the seventh), 768×576, 640×480, 800×640. Then we further tested 100 pairs of images in the ALOI dataset and compare the matching scores and matching precision with other methods.

The proposed method in this paper is identified as S-Lab192.

The comparison methods are marked as follows:

1) To verify the effectiveness of weighted Murkovski distance, we add comparison methods, the methods named S-Lab192(E) and S- Lab192(M) use Euclidean distance

and Murkovski distance respectively according to Formula (10) and (11). S-Lab192 (D) uses DeltaE 2000[22] instead of other distances.

2) To verify the effectiveness of 192-dimensional descriptors, we test the effect of methods with a different dimension of descriptors. The method is marked as S-Lab64 which has the same feature point detection as the proposed method and a 64-dimensional descriptor same as SURF based on grey information of the image. The method is marked as S-Lab80 which has the same feature point detection as the proposed method and obtains 16-dimensional descriptors from color difference scale space and a 64-dimensional

descriptor same as SURF based on grey information of the image. The 16-dimensional descriptors in S-Lab80 are obtained by calculating the mean value of the color difference in each sub-regions introduced in section 2.2. The method is marked as S-Lab128 which has the same feature point detection as the proposed method and obtain 64-dimensional descriptor same as SURF based on grey information of the image and other 64-dimensional descriptors are obtained by calculating the L2-norm of basic 64-dimensional descriptors in (7). The distances of the descriptor vectors in method S-Lab64, S-Lab80 and S-Lab128 are Murkovski distances as Formula (11).
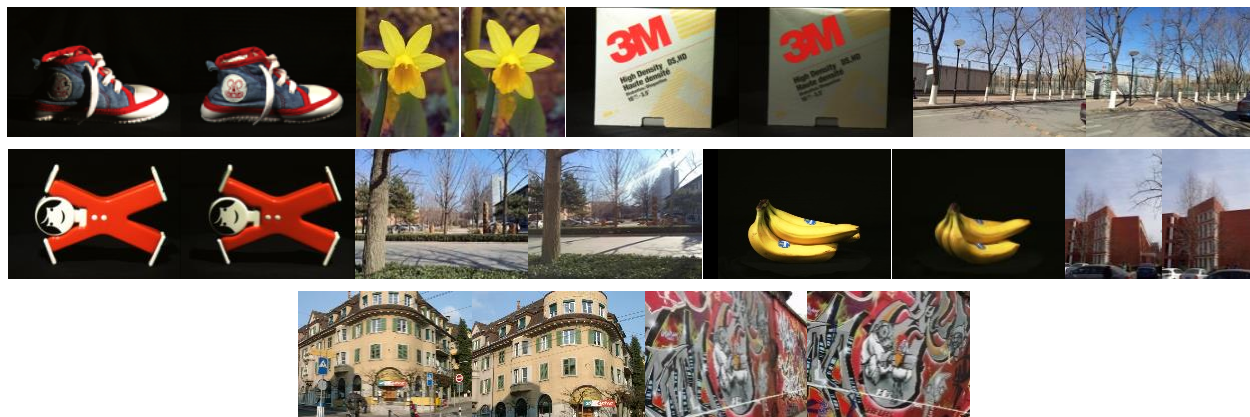

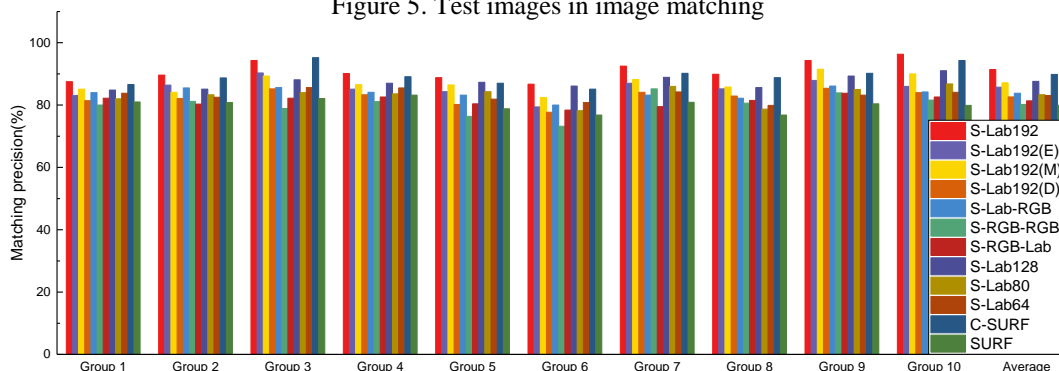Figure 5. Test images in image matching

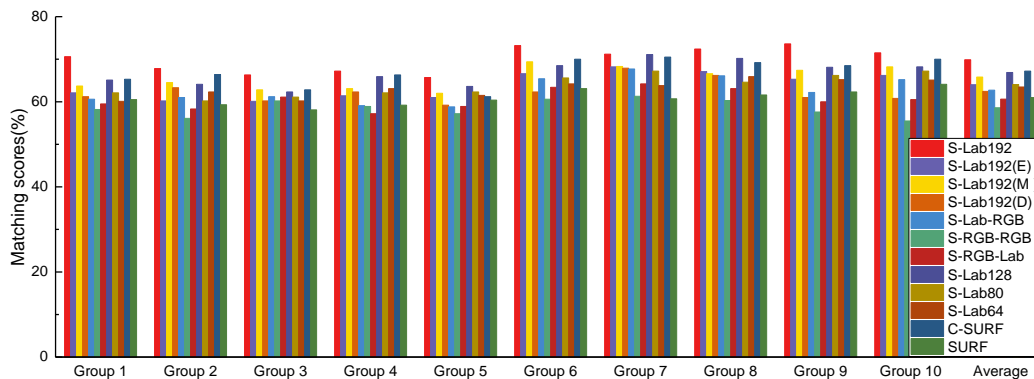

Figure 6. Matching scores for different images

Figure 7. Matching precision for different images

Table 2. The comparison for 100 pairs of images from ALOI

Method	Feature points' extract	Descriptors' obtaining	Dimension of descriptor	Distance	Average Matching score	Average Matching precision
S-Lab192	Lab	Lab	192	Weighted Murkovski	**75.12%**	**74.28%**
S-Lab192(E)	Lab	Lab	192	Euclidean	67.25%	66.52%
S-Lab192(M)	Lab	Lab	192	Murkovski	74.72%	73.91%
S-Lab192(D)	Lab	Lab	192	DeltaE 2000	61.56%	61.23%
S-Lab-RGB	Lab	RGB	192	Weighted Murkovski	62.43%	61.17%
S-RGB-RGB	RGB	RGB	192	Weighted Murkovski	50.21%	49.56%
S-RGB-Lab	RGB	Lab	192	Weighted Murkovski	57.29%	56.69%
S-Lab128	Lab	Lab	128	Weighted Murkovski	71.56%	70.40%
S-Lab80	Lab	Lab	80	Weighted Murkovski	63.21%	62.20%
S-Lab64	Lab	Grey	64	Weighted Murkovski	70.11%	69.34%
C-SURF	Grey	RGB	67	Euclidean	72.28%	70.12%
SURF	Grey	Grey	64	Euclidean	59.12%	58.47%

3) To verify the advantages of Lab color space, we add other image matching methods when RGB color spaces are used instead of Lab. The method is marked as S-Lab-RGB which extracts feature points in Lab color space and the descriptors are obtained by substituting Lab into RGB. S-RGB-Lab and S-RGB-RGB are similar to it.

4) We also compare the performance of the proposed method with SURF, C-SURF[23].

Results of matching scores and matching precision for 10 pairs of images are respectively shown in Figure 6 and 7. From Figure 6 and 7, the matching scores and matching precision of

the proposed method are dominant among the algorithms we tested. Table 2 gives the summary of these methods and the average matching score and matching precision for 100 pairs of images in the ALOI dataset. We compare the space used in feature points' detection and descriptors' obtained, the dimension of the descriptor and the distance used in similarity measurement, from the average matching score and precision, the proposed method effectively improve the performance of image matching, the distributions of weighted Murkovski distance, Lab color space and 192-dimensional descriptors are verified.
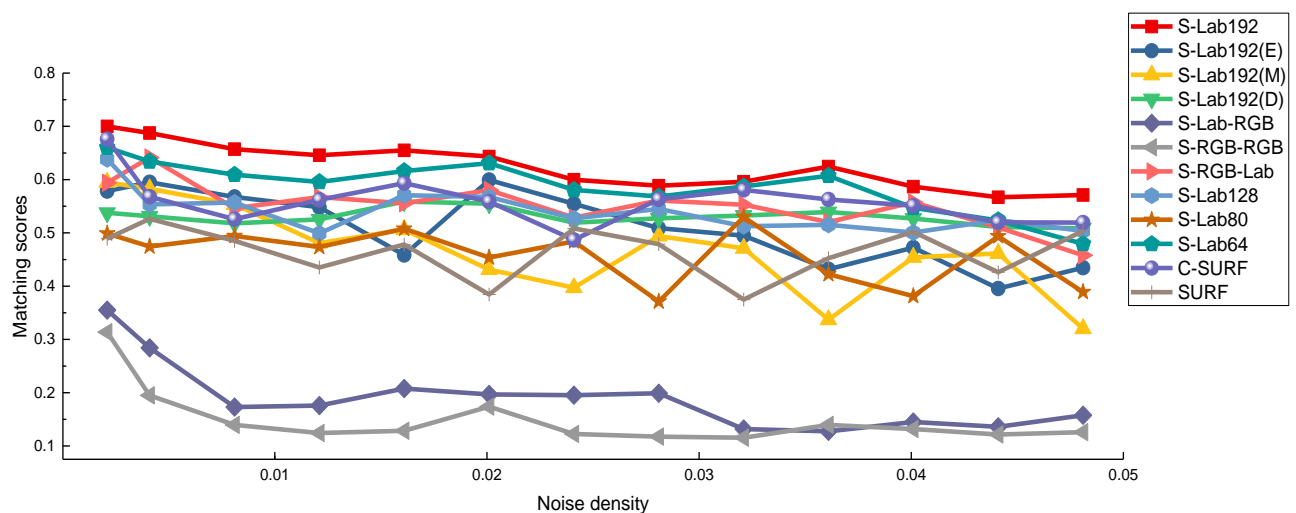

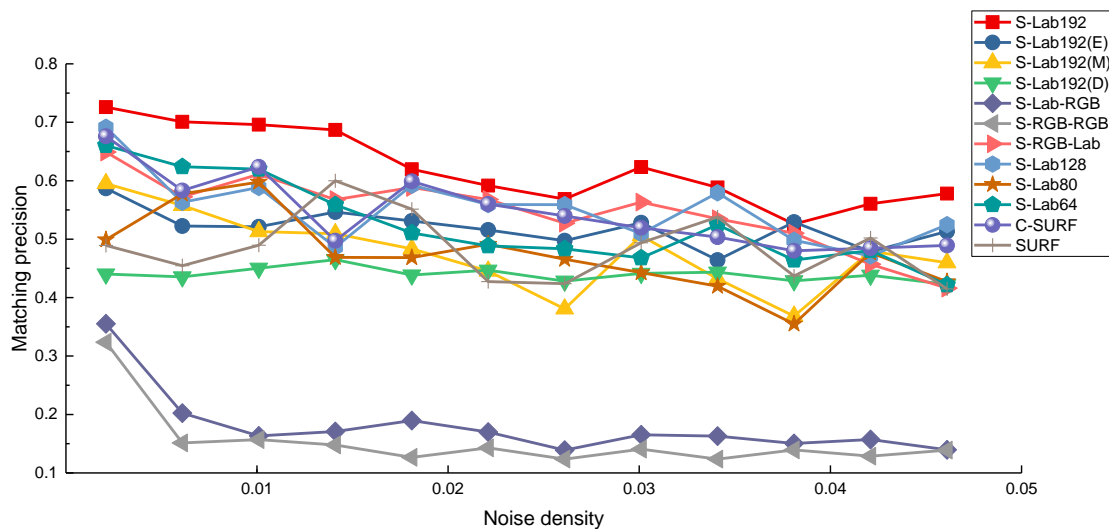Figure 8. Average matching scores in different densities of salt&pepper noise

Figure 9. Average matching precision in different densities of salt&pepper noise

C. Robustness to noise

To evaluate the robustness of the proposed method to noise, we tested the synthetic images obtained by adding salt&pepper noise to the images in Fig.5. There are 10 pairs images in total. Noise density is the percentage of image regions with noise, when the noise density increases, the image quality becomes worse. When the noise density ranges from 0.001 to 0.005, the average matching scores and precision are shown in Fıgure 8 and 9.

We can see from Figure 8 that the matching scores remain higher than other methods when noise density increases. As shown in Figure 9, when the noise density is less than 0.002, the image matching precision of the proposed method remains higher than 80%. Other methods are not superior when compared with the proposed method. Thus, S-Lab192 is robust to noise in a wide range and has a stronger ability to resist noise.

IV. CONCLUSION

In this paper, we proposed a method of image matching in color difference scale space based on SURF. First, the color difference scale spaces are built in Lab color space, and feature points are detected from the proposed scale space. Then, 192-dimensional descriptors of feature point that contain both grey value information and color information are calculated. Finally, the feature points are matched by the nearest neighbor method using weighted Murkovski distance, and RANSAC is used to eliminate the wrongly matching points.

The experimental results show that the feature points' number extracted by the proposed method increases by 163% compared with SURF based on grey value, and the robustness of feature points' detection in the proposed method is better than those of other state-of-the-art methods. The performance of image matching outperforms those of other state-of-the-art methods. The robustness to noise of the proposed method is further verified from the comparison of the degradation trend when noise density increase.

There exist some deficiencies in the algorithm. Although the 192-dimensional descriptors contain more complete information, the amount of computation is increased. How to establish lower dimensional descriptors is a problem we will further explore.

REFERENCES

[1] Dou, J. , Q. Qin , and Z. Tu . "Robust image matching based on the information of SIFT." Optik 171(2018):850-861.

[2] Shahhosseini S, Rezaie B. Pattern Matching Using Partial Fourier Spectrum. IEEE Transactions on Circuits and Systems for Video Technology. 2016;26(7):1229-40.

[3] Strickland M, Stephens T, Liu J, Tjandra N. Exploiting image registration for automated resonance assignment in NMR. Journal of Biomolecular Nmr. 2015;62(2):143-56.

[4] Aqel MOA, Marhaban MH, Saripan MI, Ismail NB. Adaptive-search template matching technique based on vehicle acceleration for monocular visual odometry system. IEEJ Transactions on Electrical and Electronic Engineering. 2016;11(6):739-52.

[5] Debayle J, Presles B. Rigid image registration by General Adaptive Neighborhood matching. Pattern Recognition. 2016;55:45-57.

[6] Liu H, Liang Z, Hu W, Mo J, Wang S. Measurement of Deformation and Force for Microcantilevers Based on Feature Point Matching and Digital Image Correlation. Sensors and Materials. 2015;27(2):143-63.

[7] Cui X, Kan J, Li W. A new line matching method based on color invariants in the rgb orthogonal color space. Journal of Computational Information Systems. 2015;11(9):3265-73.

[8] Zhang Y , Qu H . Rotation invariant feature lines transform for image matching[J]. Journal of Electronic Imaging, 2014.

[9] Sedaghat A, Ebadi H. Accurate Affine Invariant Image Matching Using Oriented Least Square. Photogrammetric Engineering and Remote Sensing. 2015;81(9):733-43.

[10] Hietanen A, Lankinen J, Kamarainen J-K, Buch AG, Kruger N. A comparison of feature detectors and descriptors for object class matching. Neurocomputing. 2016;184:3-12.

[11] Cui X, Kan J, Li W. Region matching based on colour invariants in rgb orthogonal space. Iet Computer Vision. 2016;10(6):545-50.

[12] Bay H, Ess A, Tuytelaars T, Van Gool L. Speeded-Up Robust Features (SURF). Computer Vision and Image Understanding. 2008;110(3):346-59.

[13] Rosten E, Drummond T. Machine learning for high-speed corner detection. In: Leonardis A, Bischof H, Pinz A, editors. Computer Vision - Eccv 2006 , Pt 1, Proceedings. Lecture Notes in Computer Science. 39512006. p. 430-43.

[14] Zhu M, Wang W, Liu B, Huang J. Efficient Video Panoramic Image Stitching Based on an Improved Selection of Harris Corners and a Multiple-Constraint Corner Matching. Plos One. 2013;8(12).

[15] Lowe DG. Distinctive image features from scale-invariant keypoints. International Journal of Computer Vision. 2004;60(2):91-110.

[16] Mentzer N, Paya-Vaya G, Blume H. Analyzing the Performance-Hardware Trade-off of an ASIP-based SIFT Feature Extraction. Journal of Signal Processing Systems for Signal Image and Video Technology. 2016;85(1):83-99.

[17] Yoon K, 서정진. Modified Speeded Up Robust Features(SURF) for Performance Enhancement of Mobile Visual Search System. Journal of Broadcast Engineering. 2012;17(2):388-99.

[18] Zhang N. Computing Optimised Parallel Speeded-Up Robust Features (P-SURF) on Multi-Core Processors. International Journal of Parallel Programming. 2010;38(2):138-58.

[19] Wu J, Cui Z, Sheng VS, Zhao P, Su D, Gong S. A Comparative Study of SIFT and its Variants. Measurement Science Review. 2013;13(3):122-31.

[20] Kobayashi M, Kameyama K. A Composite Illumination Invariant Color Feature and Its Application to Partial Image Matching. Ieice Transactions on Information and Systems. 2012;E95D(10):2522-32.

[21] Chen J, Li Q, Peng Q, Wong KH. CSIFT based locality-constrained linear coding for image classification. Pattern Analysis and Applications. 2015;18(2):441-50.

[22] Bradley PE, Jutzi B. Improved Feature Detection in Fused Intensity-Range Images with Complex SIFT (CSIFT). Remote Sensing. 2011;3(9):2076-88.

[23] Huang L, Chen C, Shen H, He B. Adaptive registration algorithm of color images based on SURF. Measurement. 2015;66:118-24.

[24] Kovesi P. Good Colour Maps: How to Design Them. arXiv e-prints. 2015.

[25] Wuebbeler G, Campos Acosta J, Elster C. Evaluation of uncertainties for CIELAB color coordinates. Color Research and Application. 2017;42(5):564-70.

[26] He L, Gao X, Lu W, Li X, Tao D. Image quality assessment based on S-CIELAB model. Signal Image and Video Processing. 2011;5(3):283-90.

[27] Kowalewski M, Larsson E, Heryudono A. An adaptive interpolation scheme for molecular potential energy surfaces. Journal of Chemical Physics. 2016;145(8).

[28] Shivanian E. On the convergence analysis, stability, and implementation of meshless local radial point interpolation on a class of three-dimensional wave equations. International Journal for Numerical Methods in Engineering. 2016;105(2):83-110.

[29] Li BT, Chang E, Wu Y. Discovery of a perceptual distance function for measuring image similarity. Multimedia Systems. 2003;8(6):512-22.

[30] Gijsenij A, Gevers T, Lucassen MP. A perceptual comparison of distance measures for color constancy algorithms. 10th European Conference on Computer Vision, ECCV 2008, October 12, 2008 - October 18, 2008; 2008; Marseille, France: Springer Verlag.

[31] Vourvoulakis J, Kalomiros J, Lygouras J. FPGA accelerator for real-time SIFT matching with RANSAC support. Microprocessors and Microsystems. 2017;49:105-16.

[32] Wu J, Li K, Zhang Q, An W, Jiang Y, Ping X, et al. Iterative RANSAC based adaptive birth intensity estimation in GM-PHD filter for multi-target tracking. Signal Processing. 2017;131:412-21.

[33] Geusebroek JM, Burghouts GJ, Smeulders AWM. The Amsterdam Library of Object Images. International Journal of Computer Vision. 2005;61(1):103-12.

[34] Mikolajczyk K, Schmid C. A performance evaluation of local descriptors. IEEE Transactions on Pattern Analysis and Machine Intelligence. 2005;27(10):1615-30.

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