Analyzing the effect to discriminative power of adding color information to local descriptors

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***Abstract*—Local descriptors are utilized for image matching tasks, which constitute the fundamental technique in computer vision systems. The grayscale image is often used as the input for many of these tasks due to its simplicity in calculations. However, the omission of color content can result in the loss of interest points and a decrease in matching performance. In this paper, two methods based on the image gradient and intensity are discussed as a solution to these issues. An intensity-based method was then implemented, which involved adding offset to color and exposedness of the image, and the performances of various detecting and description algorithms were analyzed and evaluated for their improvements over the regular grayscale method. Assessments were conducted based on overall performance time, number of detected and matched points, and matching ratio. Consequently, the proposed method was demonstrated to enhance feature detection and description in challenging outdoor environments for many navigation systems, such as autonomous lawnmowers. Furthermore, the drawbacks of intensity altering were illustrated.**

Keywords: *Local detectors, local descriptors, grayscale, color and exposedness offset, detected points, matched points, inliers, performance time, FAST, Harris, SURF, KAZE, BRISK, ORB, Minimum eigenvalue method, FREAK.*

I. Introduction

Local features efficiently represent the scene captured by a camera in various forms such as edge (line), corner, and blob. By detecting them in two or more images of a certain object or scenes from different viewpoints, common points can be found by using the local descriptors. This technique is widely used in computer vision applications such as 3D reconstruction, object recognition, detection, tracking, image and video retrieval, and texture classification.

Local descriptors commonly use grayscale images to describe the shape features of local features, as it reduces complexity in calculations. However, color images provide more information that can result in better performance for both feature descriptors and detectors. Nonetheless, using color information presents certain challenges. This paper discusses the main challenges of using color information and proposes solutions to overcome them. The paper is organized as follows:

- Section II introduces the tools used for detection and description of features of the image for both grayscale and color image approaches.
- Section III is dedicated to the papers related to the topic where main challenges and proposed solutions for adding color information were discussed with the techniques of local feature detection and description.
- Section IV explains the details about the proposed approach step by step and discusses the idea behind each of them.
- In section V, different local feature detectors and descriptors were tested for different scenarios of the input image.
- Last section presents the conclusion for the entire work with advantages and disadvantages of the proposed approach. In addition, it was estimated the best couple of detector-descriptors within the further improvements.

II. Preliminaries and Tools

The proposed approaches were fully implemented in MATLAB. For detecting interest points and matching features, it has been used built-in functions of MATLAB Computer Vision Toolbox.

III. Related work

A review of existing literature on the use of color information in keypoint detection and description approaches reveals that grayscale images are preferred due to their simplicity and faster implementation. However, combining features obtained from different channels, such as red, blue, and green channels, presents challenges for color images. Two main types of features for images are "gradient-based" and "intensity-based".

*A. **Gradient based approach***

According to Gevers, Weijer, and Stokman [1], the primary challenge of using color images in local descriptors is the difference in directions of channel derivatives (R, G, B). This creates opposing vectors on edges where the signal decreases for one channel while it increases for another. Consequently, the simple addition of channels reduces the total strength of derivatives by causing them to cancel each other out, even for evident structures. This issue will be discussed in Section IV.

Author states red and blue channels of an image have opposing directions, but the same orientations. In that case, it is better to implement tensor mathematics since tensors describe the local orientation instead of direction. For instance, the tensor of a vector and the tensor of the same vector rotated to 180 are the same. Accordingly the following method is the solution for that.

1. **Tensor based gradient**.

The earliest solution for opposing vectors is the use of Color Tensor, which was proposed by S. D. Zenzo [2]. This method is suitable for combining the first-order derivatives of color image channels in order to reinforce each other.

The structure tensor is given by:

$$G = \begin{pmatrix} \overline{f_x^2} & \overline{f_x f_y} \\ \overline{f_x f_y} & \overline{f_y^2} \end{pmatrix} \tag{1}$$

where subscripts are spatial derivatives and the bar specifies convolution with a gaussian filter. For color information $f = (R, G, B)^T$ where T is transpose [1].

Correspondingly, its color structure tensor:

$$G = \begin{pmatrix} \overline{R_x^2 + G_x^2 + B_x^2} & \overline{R_x R_y + G_x G_y + B_x B_y} \\ \overline{R_x R_y + G_x G_y + B_x B_y} & \overline{R_x^2 + G_x^2 + B_x^2} \end{pmatrix} \tag{2}$$

Resulted eigenvalues of the certain point in an image:

$$\begin{aligned} \lambda_1 &= \tfrac{1}{2}\left(\overline{f_x^T f_x} + \overline{f_y^T f_y} + \sqrt{\left(\overline{f_x^T f_x} - \overline{f_y^T f_y}\right)^2 + \left(2 * \overline{f_x^T f_y}\right)^2}\right) \\ \lambda_2 &= \tfrac{1}{2}\left(\overline{f_x^T f_x} + \overline{f_y^T f_y} - \sqrt{\left(\overline{f_x^T f_x} - \overline{f_y^T f_y}\right)^2 + \left(2 * \overline{f_x^T f_y}\right)^2}\right) \end{aligned} \tag{3}$$

The λ-s can be unified to give the following local descriptors:

- Total local derivative energy: $\lambda_1 + \lambda_2$;
- Derivative energy in the most prominent direction: λ_1;
- "Line" energy, when λ_1 is corrected for noise by λ_2: $\lambda_1 - \lambda_2$;
- The derivative energy which is orthogonal to the prominent local orientation (it is good for tracking[4]): λ_2;

The use of color information in Harris Corner Detector is a common practice, as indicated by Th. Gevers, J. Weijer, and H. Stokman [1]. If we assign image as f and color Harris operator of an image will be computed as following:

$$Hf = \overline{f_x^T f_x}\; \overline{f_y^T f_y} - \overline{f_x^T f_y}^2 - k\left(\overline{f_x^T f_x} + \overline{f_y^T f_y}\right) \tag{4}$$

2. **Oriented patterns**.

It is a similar approach to [6] found by Kass and Witkin. In this case, they considered the orientation patterns of an image which are patterns with dominant orientation everywhere. In this method, local structures are described by lines (roof edge).

Its structure tensor:

$$G = \begin{pmatrix} \overline{(f_{x,y}u_1)^T (f_{x,y}u_1)} & \overline{(f_{x,y}u_1)^T (f_{x,y}u_2)} \\ \overline{(f_{x,y}u_1)^T (f_{x,y}u_2)} & \overline{(f_{x,y}u_2)^T (f_{x,y}u_2)} \end{pmatrix} \tag{5}$$

where, $u_1 = (1\ \ 0)^T$ and $u_2 = (0\ \ 1)^T$ are derivative energies on the axes. This method is suitable to extract features from the structures like circle, spiral and star.

Accordingly its eigenvalues :

$$\begin{aligned} \lambda_1 &= \overline{x^2 f_x^T f_x} + \overline{2xy f_x^T f_y} + \overline{y^2 f_y^T f_y} \\ \lambda_2 &= x^2 f_y^T f_y - 2xy f_x^T f_y + y^2 f_x^T f_x \end{aligned} \tag{6}$$

where, λ_1 - derivative energy of circular structures, λ_2 - derivative energy of star-like structures.

B. *Intensity based approach*

Most local descriptors use grayscale images in the input in order to reduce the complexity. However, as [7] shows color neglecting can lead to wrong and missing matching results. The reason for that is that some regions with different colors can have similar grayscale levels. Accordingly, it would be taken by the descriptor as the same region. Example is shown in Fig. 1.

Fig. 1: Object distinction issue caused because of neglecting color content [7]

1. Color and exposedness offset

The researchers from Jilin University, School of Communication Engineering [8] proposed a solution to the issue of Fig.1. They stated that even regions with similar grayscale levels have different hue levels. Based on this observation, they implemented a method for SIFT that added an offset value to the color (Eq. 8) and exposedness (Eq. 9) of the image by converting them to different color spaces such as CIELAB, CIELUV, YIQ, YC_BC_R.

In the paper, YC_BC_R color space was chosen, where Y-luminance , C_B - bluish chrominance, C_R - reddish chrominance components. They are characterised by RGB channel as following:

$$\begin{aligned} Y &= 0.299\ R + 0.587\ G + 0.114\ B; \\ C_B &= -0.169\ R - 0.331\ G + 0.500\ B + 128; \\ C_R &= 0.500\ R - 0.419\ G + 0.081\ B + 128; \end{aligned} \tag{7}$$

Color offset Y_C:

$$Y_C = k\ sgn(m_R - m_B)\ sgn(C_R - C_B) \times |C_R - C_B|^{\alpha} \tag{8}$$

where $k \in$ [1,4] - contrast parameter; $\alpha \in$ [0.4, 0.6] - range parameter; m_R, m_B - mean of C_R, C_B .

Exposure offset Y_C:

$$Y_E = (128 - m_p) \exp\left[\frac{-(i - 0.5)^2}{2\sigma^2}\right] \tag{9}$$

Final grayscale value W of the proposed method:

$$W = Y + Y_C + Y_E \tag{10}$$

C. *Local feature detectors and descriptors*

FAST algorithm, proposed by Rosten and Drummond [10], is a robust corner and blob detection algorithm known for its real-time performance and computational efficiency. The algorithm selects a pixel and considers a surrounding 16-pixel circle. If the values of the circle are higher or lower than the set threshold value, the pixel is detected as an interest point. However, it has limitations. For instance, when N is less than 12, it detects too many interest points. The algorithm's speed depends on the order of pixel querying, and it is not scale-invariant.

Harris, an improved version of Moravec's detector, was introduced by Chris Harris and Mark Stephens [11] as a corner and blob detector. Its advantage is that it takes into account the directions of channel derivatives. If the Harris detector is applied to a gray-scale image [3], it will result in a high percentage of corner detection and it can differentiate between true corners and false corners using some filters. However, its main disadvantage is that it is time-consuming. In the case of the Harris detector for color images [5], logical operations such as AND and OR are used to combine the corners obtained from different channels (R, G, B). This approach improves the performance speed of the algorithm, but it can sometimes lead to the detection of unwanted corners (noise).

SURF is both detector and descriptor proposed by Herbert Bay, Andreas Ess, Tinne Tuytelaars, and Luc Van Gool [12] in 2006. Its detecting algorithm is based on the Hessian matrix where local minima detects saddle points and local maxima image blobs (both dark and bright uniform regions). Its advantages is performance speed (several times faster than SIFT). Nevertheless, it has following disadvantages: not stable to rotations and doesn't work well with illumination changes.

KAZE like SURF is both detector and descriptor algorithm, published by Pablo F. Alcantrilla, Adrian Bartoli, Andrew J.Davison in 2012 [13]. The working principle is also similar to SURF (using Hessian detector). The major difference is that it describes the local features in nonlinear scale space which allows it to detect features with less outliers. Moreover, it is scale invariant. Its disadvantages: it is computationally expensive compared with SURF.

BRISK is a local feature point detection and description method introduced by Leutenegger S., Chli M., Siegwart R.Y in 2011 [14]. Its working principle is based on comparing the intensity values of pixels in a circular pattern. Consequently it has following advantages: invariance to scaling and rotation; faster comparatively with traditional methods. Disadvantages: consumes more time in keypoint detection.

Minimum eigenvalue is a corner detection algorithm developed by Shi and Tomasi in 1994 [4]. According to the paper, two small eigenvalues represent the region with constant intensity; small and large eigenvalues show the unidirectional pattern of texture; two large eigenvalues correspond to the corners. It is not scale invariant.

ORB is both detector and descriptor introduced by E. Rublee in 2011 as an improvement to the FAST algorithm [15]. It is computationally efficient and able to detect features in real-time. Moreover, it is invariant to scaling, rotation and limited affine variations. Nevertheless, it is not robust to noise and has shortcomings in matching performance.

FREAK is a descriptor developed by Alahi, Alexandre, Raphael Ortiz, and Pierre Vandergheynst in 2012 [16]. Similar to BRISK it uses a circular pattern but with more densely located points close to the center. It has advantages in viewpoint changing, rotation, zooming than ORB, BRISK. However, it has worse performance in intensity changings.

IV. Proposed approach

Before implementing the proposed method, the difference between the original grayscale method and the simple addition of color channels (R, G, B), as well as normalized RGB (Fig. 2) were analyzed using SURF+SURF couple prior to implementing the proposed method.

SURF+SURF	Grayscale	Normalzied RGB
Detected points	1104	1986
Matched points	352	260
Inliers	332	222
Matching ratio, %	94.3	85.4
Detecting time, sec	0,065	0,089
Matching time, sec	0,33	0,061
All time, sec	0,395	0,15

Fig. 2: Comparison of original grayscale and simple addition of color channels (R, G, B)

As can be seen from the table, simple addition of channels detects more points than grayscale. In fact, it is the total number of detected interest points in all 3 channels which has even less amount of matched points than grayscale which is the case of different direction of channel derivatives. However, it is still faster than the grayscale method, but not an optimal solution for the given task.

In order to improve the results of the grayscale method following steps have been done (Fig. 3).

The **proposed method** utilized an approach of color and exposure offset, as proposed in [**9**]. The main idea of this method is to reduce the color dimension of an image and increase the contrast between image pixels. Parameters such as α, k, and σ are tuned depending on the local feature detector to detect more keypoints. Additionally, the computational time of detection was taken into consideration, and the fastest detector with the most improvement was selected.

In the **keypoint detection** stage, various corner detector methods, including FAST, Harris, SURF, KAZE, BRISK, Min. eigenvalue algorithm, and ORB discussed in Section III, were evaluated. In addition to SIFT, we experimented with these detectors to identify the best performer. The selected detector was then utilized in the next stage, description

In **keypoint description**, following methods were used to extract features for keypoint matching: SURF, KAZE, FREAK, BRISK, ORB.

In **keypoint matching**, the locations of corresponding points from 2 images were retrieved according to the features extracted by local descriptors in the previous stage.

In **common keypoint selection**, the outliers (wrong matchings) were eliminated, after that we obtained the correct quantity and location of inliers (correctly matched points).

Last stage, **comparison**, the best couple of detector and descriptor were defined based on following criterias: performance time, matched points, matching ratio and improvement percentage comparatively than grayscale method.

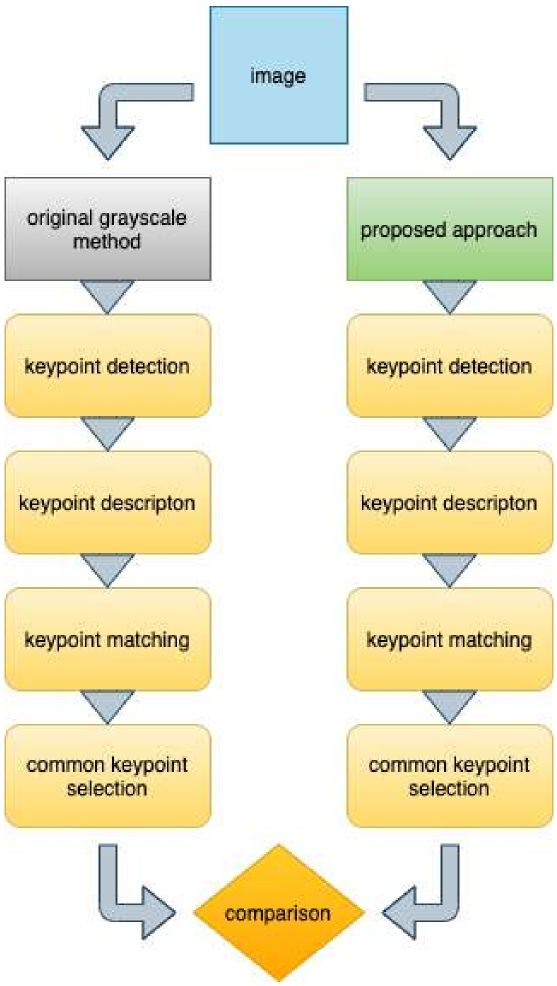

Fig. 3: Flowchart of the approach

V. Experimental study

In this section the task is to compare the results of the original grayscale and proposed method. We will select that couple of descriptor-detectors where it is possible to obtain the best improvement for the grayscale method.

A. Experiment description

First, demonstrative experiment was shown by proving the effect of color and exposedness offset method.

In Fig. 4, the original image depicts buildings with their reflections on the lake, containing various color shades and textures. Fig. 5 displays the grayscale result of the original image, while Fig. 6 shows the grayscale result of the proposed method discussed in Section III. The proposed method result enhances pixel contrast and edges, as evident from the clear structure. A zoomed example in Fig. 9 further demonstrates the difference between the grayscale methods. Based on the results, the SURF algorithm detects more points in the proposed method's image (Fig. 7 and 8) compared to the original grayscale method. The proposed approach aims to detect as many robust points as possible to improve the matching performance accordingly.

Fig. 4: Original color image

Fig. 5: Original grayscale image

Fig. 6: Grayscale image from the proposed method

According to A. Hoffman [9], a high number of outliers can be observed in outdoor environments for the navigation systems of autonomous lawn-mowers when using grayscale

Fig. 7: Original grayscale results: **2652 keypoints**

Fig. 8: Proposod method results: **2942 keypoints**

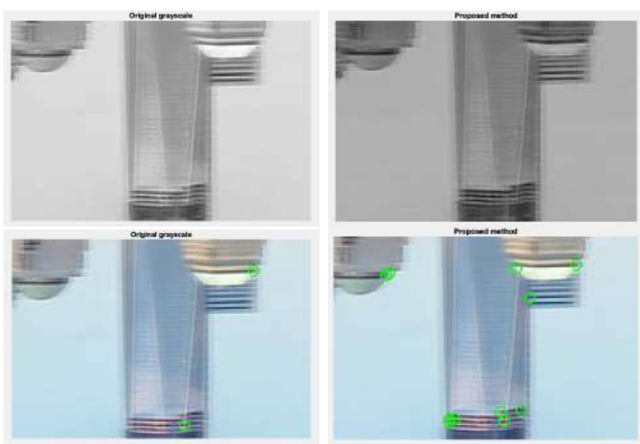

Fig. 9: Feature points obtained by SURF. First column shows grayscale results, and the second column displays the result of the proposed method.

methods in feature matching. To imitate the outdoor environment, two images (Fig. 10) of the courtyard were taken with some angle difference in the horizontal plane. The images contain complex textures with more green and brown color shades, such as leaves with reflections and bricks of the wall, which makes the detecting-descripting tasks complicated. The original images were downscaled by 1/4 times in order to reduce the computational cost.

Fig. 10: Courtyard images

B. *Local feature detectors*

To discover the best matching performance, the descriptor with the best improvement was found by comparative analysis.

1) BRISK:

- keypoint detection improvement for 68%.
- detection time is almost the same (Fig. 11)

BRISK	Grayscale	Proposed method
Detected points	4182	7040
Detecting time, sec	0,374	0.42

Fig. 11: BRISK detector. Parameters of proposed method: α = 1.2, σ = 0.2, k = 4

2) SURF:

- keypoint detection was improved by 43%.
- detection time is almost the same (Fig. 12)

SURF	Grayscale	Proposed method
Detected points	1104	1623
Detecting time, sec	0,065	0,089

Fig. 12: SURF detector. Parameters of proposed method: α = 1.2, σ = 0.2, k = 4

3) Harris:

- keypoint detection was improved by 3.8%.
- proposed method's detection performance is 7 times faster (Fig. 13)

Harris	Grayscale	Proposed method
Detected points	1933	2007
Detecting time, sec	0,779	0,11

Fig. 13: Harris detector. Parameters of proposed method: α = 0.5, σ = 0.2, k = 4

FAST	Grayscale	Proposed method
Detected points	2967	3143
Detecting time, sec	0,077	0,094

Fig. 14: FAST detector. Parameters of proposed method: α = 0.7, σ = 0.2, k = 4

4) FAST:

- keypoint detection was improved by 6%.
- detection time is almost the same (Fig. 14)

5) ORB:

- keypoint detection improvemed for 11%.
- detection time is almost the same (Fig. 15)

ORB	Grayscale	Proposed method
Detected points	17631	19568
Detecting time, sec	0,101	0.12

Fig. 15: ORB detector. Parameters of proposed method: α = 1.2, σ = 0.1, k = 4

6) Min. eigenvalue:

- keypoint detection was improved by 2.7%.
- detection time is almost the same (Fig. 16)

Min. eigenvalue	Grayscale	Proposed method
Detected points	4001	4109
Detecting time, sec	0,163	0,135

Fig. 16: Minimum eigenvalue detector. Parameters of proposed method: α = 0.1, σ = 0.6, k = 3

7) KAZE:

- keypoint detection was improved by 3%.
- detection time is almost the same (Fig. 17)

KAZE	Grayscale	Proposed method
Detected points	4855	5004
Detecting time, sec	0,42	0.4

Fig. 17: KAZE detector. Parameters of proposed method: α = 0.8, σ = 0.2, k = 4

C. Local feature descriptors

In descripting part, detector with best improvement in detected points and detecting time was selected (SURF).

1) KAZE: It is 2 times faster with proposed method than original grayscale method. Matching performance was improved by 18.7% (Fig. 18).

2) SURF: It is 3.3 times faster with proposed method than original grayscale method. Matching performance was improved by 69% (Fig. 19).

3) FREAK: It is 2.4 times faster with proposed method than original grayscale method. Matching performance was improved by 9% (Fig. 20).

SURF + **KAZE**	Grayscale	Proposed method
Detected points	1104	1623
Matched points	230	273
Inliers	229	272
Matching ratio, %	99.5	99.6
Detecting time, sec	0.31	0.33
Matching time, sec	0,4	0.02
All time, sec	0,71	0.35

Fig. 18: Comparison of original grayscale and proposed method for KAZE descriptor. Parameters of proposed method: α = 1.2, σ = 0.2, k = 4

SURF + **SURF**	Grayscale	Proposed method
Detected points	1104	1623
Matched points	352	582
Inliers	332	561
Matching ratio, %	94.3	96.3
Detecting time, sec	0.065	0.089
Matching time, sec	0,33	0.031
All time, sec	0,395	0.12

Fig. 19: Comparison of original grayscale and proposed method for KAZE descriptor. Parameters of proposed method: α = 1.2, σ = 0.2, k = 4

SURF + **FREAK**	Grayscale	Proposed method
Detected points	1104	1623
Matched points	220	240
Inliers	219	238
Matching ratio, %	99.5	99.1
Detecting time, sec	0.1	0.13
Matching time, sec	0,5	0.02
All time, sec	0,6	0.25

Fig. 20: Comparison of original grayscale and proposed method for KAZE descriptor. Parameters of proposed method: α = 1.2, σ = 0.2, k = 4

4) BRISK: It is 1.5 times faster with proposed method than original grayscale method. Matching performance was improved by 18.7% (Fig. 21).

SURF + **BRISK**	Grayscale	Proposed method
Detected points	1104	1623
Matched points	230	273
Inliers	224	270
Matching ratio, %	97.3	98.9
Detecting time, sec	0.33	0.36
Matching time, sec	0.44	0.025
All time, sec	0,6	0.385

Fig. 21: Comparison of original grayscale and proposed method for KAZE descriptor. Parameters of proposed method: α = 1.2, σ = 0.2, k = 4

5) ORB: It is 3.1 times faster with proposed method than original grayscale method. Matching performance was improved by 40% (Fig. 22).

SURF + **ORB**	Grayscale	Proposed method
Detected points	1104	1623
Matched points	275	384
Inliers	265	371
Matching ratio, %	96.3	96.6
Detecting time, sec	0.11	0.13
Matching time, sec	0.39	0.028
All time, sec	0,5	0.158

Fig. 22: Comparison of original grayscale and proposed method for KAZE descriptor. Parameters of proposed method: $\alpha = 1.2$, $\sigma = 0.2$, $k = 4$

D. Matching point methods

Comparison of fundamental matrix computation methods in order to calculate the inliers (correct matched points) is shown in Fig. 23-24 in terms of computation time and matching ratio.

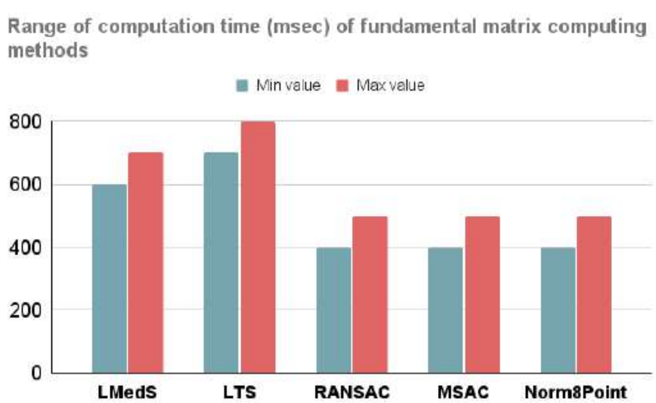

Fig. 23: Computation time range

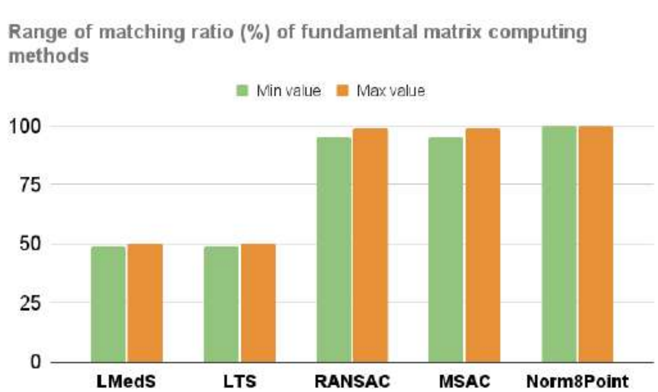

Fig. 24: Matching ratio range

E. Testing descriptor for various images

To check the matching performance of the local descriptor, two images of the same object from different viewpoints were taken. Changes were made to the colors in RGB color space, as shown in Fig. 25-27. In the second part, changes were made to the color temperature (chromacity) and tint using the Adobe Lightroom application.

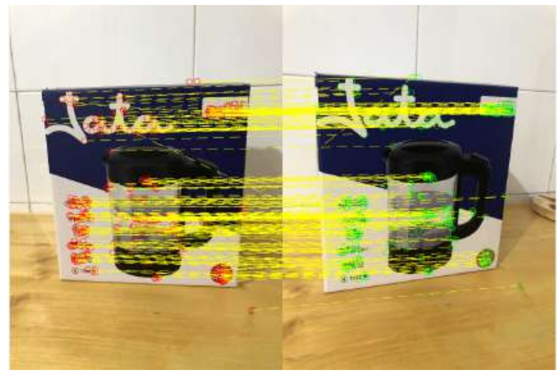

Fig. 25: Original images. Correctly matched points: **240**

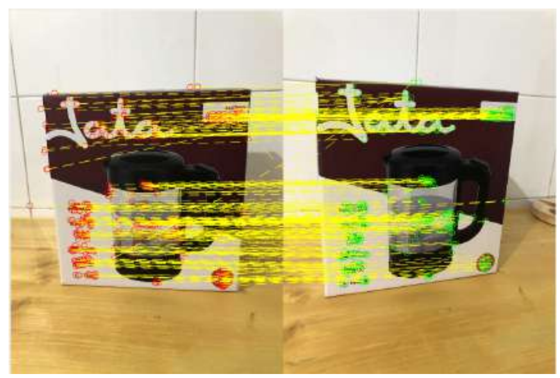

Fig. 26: Blue color of the box was substituted by brownish color. Correctly matched points: **241**

Fig. 27: Blue color was substituted by greenish color. Correctly matched points: **252**

1) Color changes: As we can see from Fig. 25-27, simple color change in RGB space more or less doesn't affect the matching performance of the descriptor descpite the fact SURF isn't invariant to illumination changes. In the case of complex scene (outdoor environment), using Harris detector is efficient.

Fig. 28: Original images. Correctly matched points: **330**

Fig. 29: Temperature = -100; Tint = +50. Correctly matched points: **437**

Fig. 30: Temperature = +100; Tint = +100. Correctly matched points: **15**

2) Intensity changes: Fig. 28-30 demonstrate that changing intensity of the image significantly affects the matching performance of the proposed method of adding color information.

There are even cases when the proposed approach isn't able to match any keypoints in the images. Examples are shown in Fig. 31-32.

Two metal keys were captured from a close distance with the camera flash. The non-uniform surface of the keys caused differences in light reflection in both images, making matching tasks complicated, including keypoint detection. It is worth noting that parameter tuning of the proposed method as discussed in Section V did not lead to any improvements in the descriptor performance in this case.

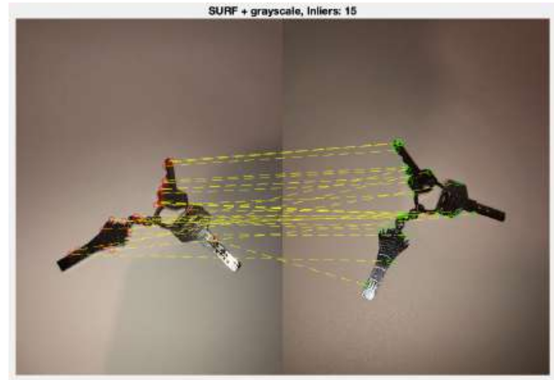

Fig. 31: Original grayscale approach. Correctly matched points: **15**

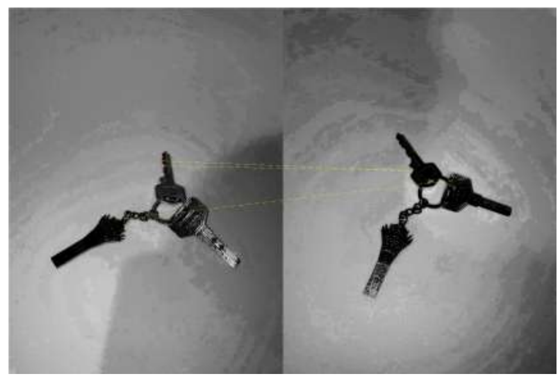

Fig. 32: Proposed method. Correctly matched points: **0**.

F. Discussion

The proposed method showed improvement in the number of detected keypoints for all detectors. It was observed that almost all of the detectors were slower in detecting keypoints using the proposed approach, except for Harris, which was 7 times faster. However, BRISK was the slowest detector, despite having the highest detection improvement. When comparing all the results, it was found that SURF was the optimal choice due to its speed and a detection improvement of 43%.

Improvement was observed in all descriptors in terms of performance time and correctly matched points, with the best result achieved by the SURF-SURF couple with a 69% improvement in matching points.

Color changes can be handled by using different descriptors depending on the nature of the environment and by tuning the parameters of the proposed method (α, k, σ). However, limitations in intensity changes exist for the proposed method.

VI. Conclusions

In comparing all detection and description methods, the SURF-SURF pair was found to give the best improvement for

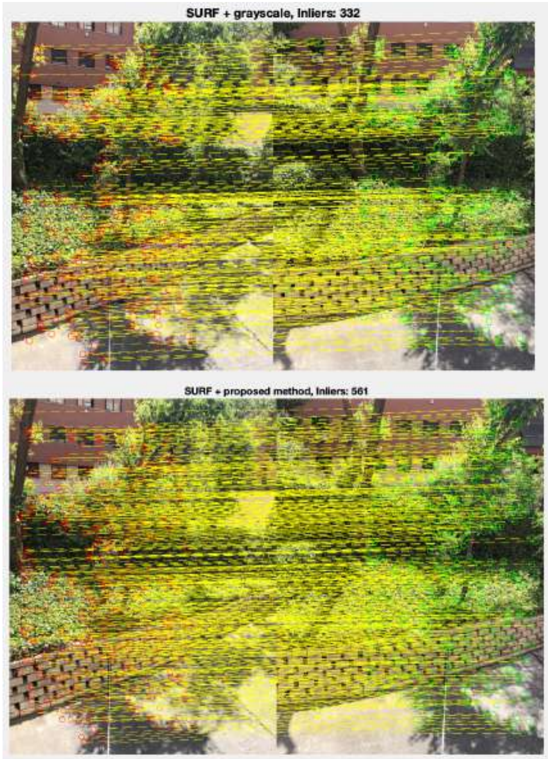

Fig. 33: SURF+SURF

the complex image of an outdoor environment. It was also observed that using grayscale images in descriptors was straightforward, but color images can significantly improve performance results. The experiments showed that color changes can be addressed by using different descriptors depending on the nature of the environment and by tuning the parameters of the proposed method (α, k, σ), but there are limitations in handling intensity changes.

- 3.3 times faster;
- keypoint detection was improved by 43%;
- matching performance was improved by 69%;
- matching ratio was improved by 3.2%

Almost all descriptors showed enhanced results between 9% and 70%. Need to note, different descriptor-detector pairs can be chosen depending on the nature of the task. For instance, for scaling and rotation BRISK descriptor; for illumination changes Harris algorithm is appropriate. However, the algorithm also has some drawbacks.

- It is not stable. The parameters of offset values should be tuned depending on the color and intensity of an image to have better performance than the grayscale method.
- it is not able to match keypoints in too bright image with complex (reflecting) object (Fig. 32)

Further improvement can be achieved by incorporating a state-of-the-art gradient-based approach. In Fig. 9, clear edges in the region were not detected by the proposed method. Additionally, using different algorithms in parallel is suggested to achieve more robust performance.

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