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

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***Abstract*—Local descriptors are used in image matching tasks which is the basic technique in computer vision systems. Many of them use the grayscale image at the input because of simplicity in calculations. However, ignoring color contents can lead to loss of interest points and drop of matching performance. As a solution to these issues, in the paper it was discussed 2 methods based on ”gradient” and ”intensity” of the image. Then by using an intensity-based method where I implemented adding offset to color and exposedness of the image, it was analyzed performances of different detecting, description algorithms and evaluated their improvements over the regular gray-scale method. Assessments were executed according to the following outcomes: overall performance time; number of detected and matched points; matching ratio. Hence, I showed that the proposed method can improve the feature detection and description in an outdoor environment which is counted as a challenging task for many navigation systems. For example: autonomous lawn-mowers. Moreover, it was shown its drawbacks in intensity altering.**

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 are efficient tools in representing the scene captured by a camera. They can be in different forms such as edge (line), corner, blob. By detecting them in two or more images of a certain object or scenes from different viewpoints, it is possible to find common points by using the local descriptors. Based on this, we use it in a vast amount of computer vision applications such as 3D reconstruction; object recognition, detection, tracking; image and video retrieval; texture classification and many others.

According to the nature of local features it is common to describe them regarding their shape features. This is why most local descriptors use grayscale images to decrease the complexity in calculations. However, color images contain more information which can provide better performance for both feature descriptors and detectors. Nevertheless, it has some difficulties. Based on that, in this paper, it was discussed the main challenges of using color information and solutions for them. It 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

Studying the works related with using color information in keypoint detection and description approaches show that using grayscale images is simple and faster to implement while color information has some challenges in combining the features obtained from different channels. For example: red, blue, green channels. As it was studied, there are two main features of image: ”gradient” and ”intensity” based features.

A. Gradient based approach

As Th. Gevers, J. Weijer, H. Stokman [1] state, the main challenge in using color images in local descriptors is different directions of channel derivatives (R, G, B). In fact, opposing vectors occur on edges where for one channel the signal decreases while for another the signal increases. Hence, simple addition of channels reduces total strength of derivatives by leading to cancellation of each other, even the evident structures. It 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 using Color Tensor proposed by S. D. Zenzo [2]. It is suited to combine first order derivatives of color image channels to let them 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;

As Th. Gevers, J. Weijer, H. Stokman[1] indicates, it is commonly used in Harris Corner Detector. 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 :

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

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 state even regions which have similar grayscale levels consist of different hue levels. Based on this, they implemented a method to SIFT where they added 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, it was chosen a YC_BC_R color space 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 is a robust corner and blob detection algorithm proposed by Rosten and Drummond [10]. Its main advantages are working in real time and computational efficiency. The working principle: it selects the pixel and takes a surrounding 16 pixel circle. If the values of the circle are higher or less than the set threshold value, then the pixel will be detected as an interest point which is the noise. Its limitations: when N is less than 12, it detects too many interest points; the speed depends on the order of pixel querying; not scale invariant.

Harris is corner and blob detector (improved version of Moravec's detector) firstly introduced by Chris Harris and Mark Stephens [11]. Its advantages is taking into account the directions of channel derivatives. If we consider the Harris detector with a gray-scale image [3], it will give a high percentage of corner detection, finding the difference between the true corner and false corners with some filters. However, the main disadvantage of it is consuming a lot of time. In the case of Harris detector for color image [5], it was used AND, OR logical operations to combine the corners obtained from different channels (R, G, B). The performance speed of the algorithm was solved and now it is faster, but it sometimes leads to 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, I analyzed the difference between with the original grayscale method and simple addition of color channels (R, G, B), normalized RGB (Fig. 2) by using SURF+SURF couple.

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).

In the **proposed method**, it was used an approach of color and exposure offset [**9**]. The main idea of the method to reduce the color dimension of an image and make contrast between image pixels. To do so, we tune parameters (α, k, σ) depending on the local feature detector to detect more keypoints. Need to mention, the computing time of detection is also targeted which means we need to select the fastest detector with more improvement.

In **keypoint detection**, authors implemented only SIFT [8]. I decided to experiment with other corner detector methods discussed in Section III. They are: FAST, Harris, SURF, KAZE, BRISK, Min. eigenvalue algorithm, ORB. Once finding the detector with best performance, we deliver it to 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.

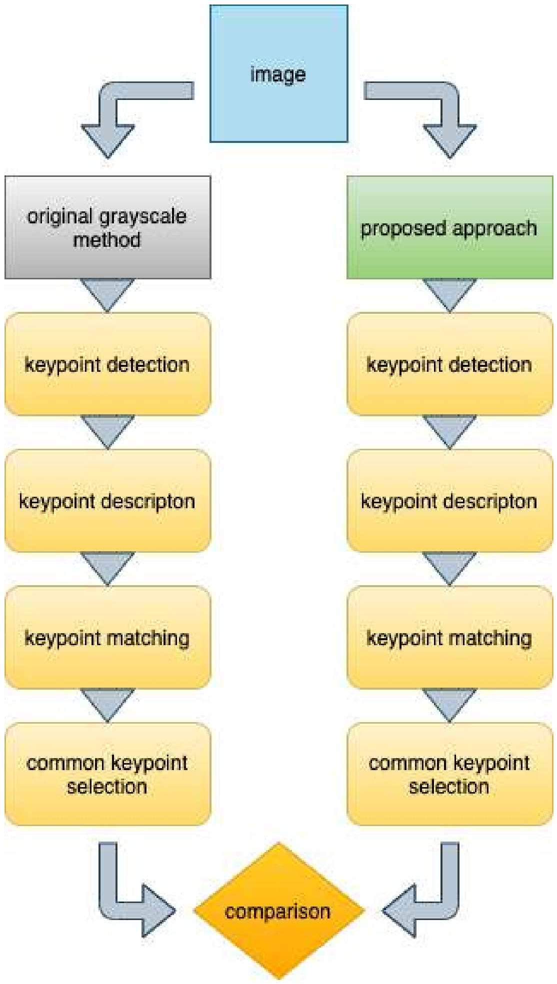

Fig. 3: Flowchart of the approach

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, I start from a demonstrative experiment of proving the effect of color and exposedness offset method.

In Fig. 4, the original image is depicted. There are buildings with their reflections on the lake. It has more color shades (blue, yellow) and textures. In Fig. 5, the result of converting the image to the grayscale is shown. Below it, in Fig. 6 we can see the grayscale result of the proposed method discussed in Section III. One can notice that the proposed method result inroduced pixel contrast and it has clear structure, edges. A zoomed example can be seen in Fig. 9. Based on that, the SURF algorithm detected more points in the image of the proposed method (Fig. 7 and 8) comparatively than the original grayscale method. Correspondingly, the main idea of the proposed approach is to detect as more robust points as possible to improve the matching performance.

Fig. 4: Original color image

Fig. 5: Original grayscale image

Fig. 6: Grayscale image from the proposed method

According to A.Hoffman[9], grayscale methods in feature matching lead to a high number of outliers in outdoor environments for the navigation systems of autonomous lawn-mowers. Related to that, it was taken 2 images (Fig. 10) of the courtyard with some angle difference in horizontal plane in order to

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

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

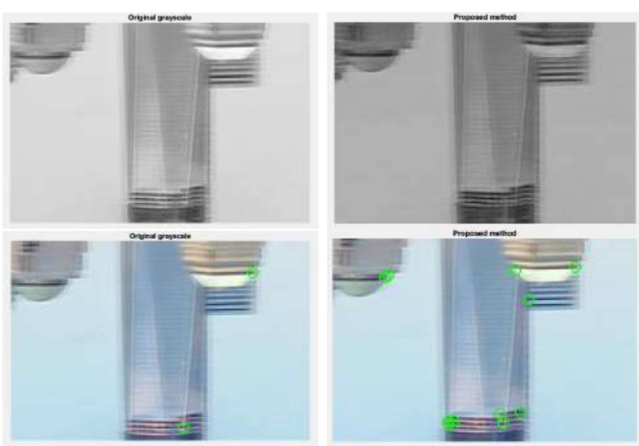

Fig. 9: Feature points obtained by SURF. First column shows grayscale results, and the second column displays the result of the proposed method.

imitate the outdoor environment. It has more green and brown color shades with complex textures (leaves with reflections, bricks of the wall) which makes detecting-descripting tasks complicated. Need to note, 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, I decided to find the descriptor with the best improvement 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

4) FAST:

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

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

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.

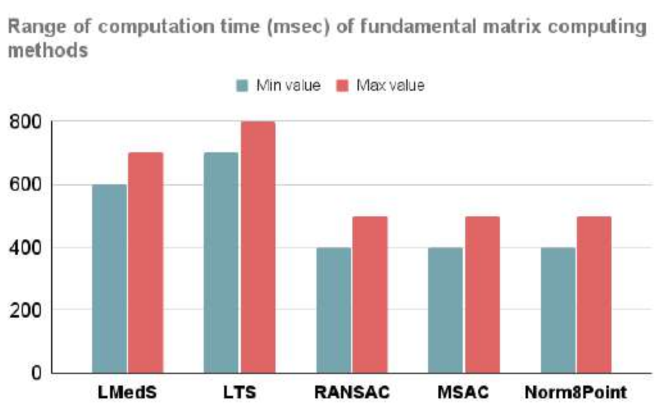

Fig. 23: Computation time range

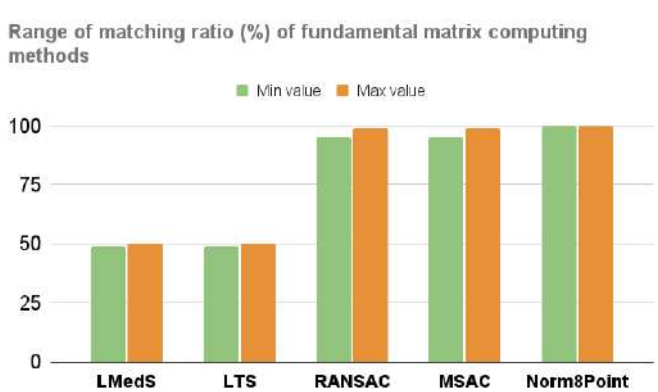

Fig. 24: Matching ratio range

E. *Testing descriptor for various images*

To check the matching performance of the local descriptor, I took 2 images of the same object from different viewpoints. Firstly, I changed colors in RGB color space (Fig. 25-27) and in the second part there are changes in color temperature (chromacity) and tint by Adobe Lightroom application.

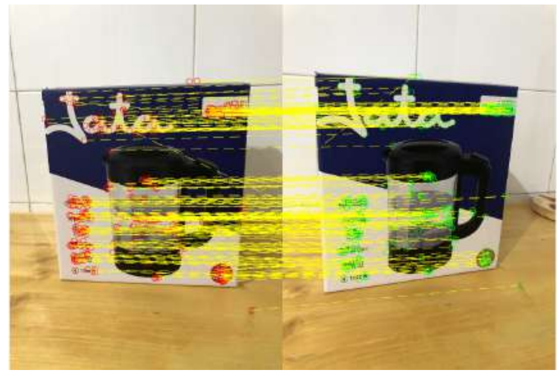

Fig. 25: Original images. Correctly matched points: **240**

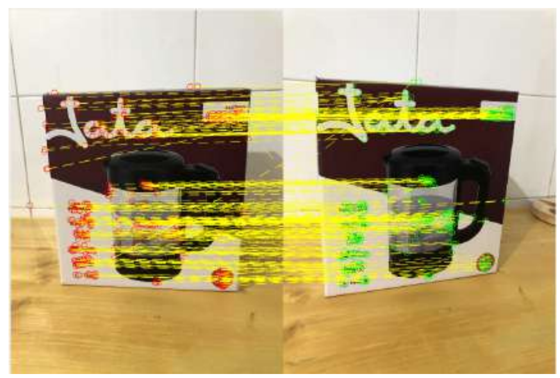

Fig. 26: Blue color of the box was substituted by brownish color. Correctly matched points: **241**

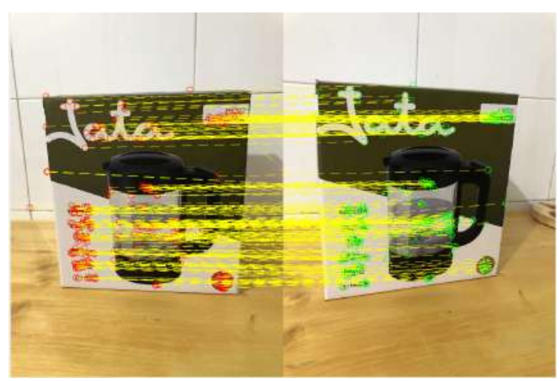

Fig. 27: Blue color was substituted by greenish color. Correctly matched points: **252**

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 taken from a close distance with the flash light of the camera. Moreover, the non-uniform surface of the keys reflect the light differently in both images which makes matching tasks complicated (even keypoint detection). Need to note, tuning of parameters of the proposed method as it was in Section V gives no improvements for the descriptor in this case.

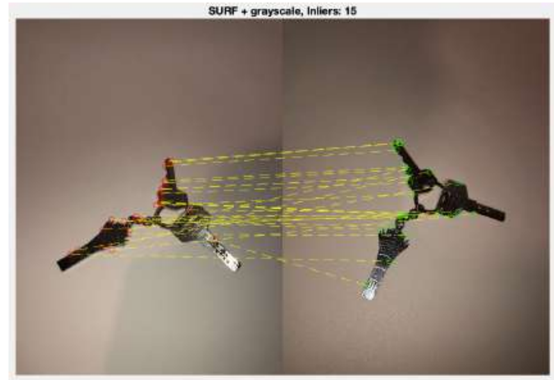

Fig. 31: Original grayscale approach. Correctly matched points: **15**

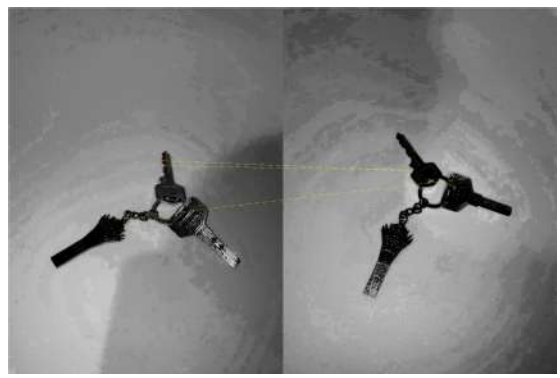

Fig. 32: Proposed method. Correctly matched points: **0**.

F. Discussion

With the proposed method, all detector showed improvement in the number of detected. Almost all of them were slower in detecting by proposed approach except the Harris (7 times faster) and BRISK was slowest detector despite the fact the detection improvement was highest. Comparing all results, the SURF is optimal choice since it is fastest detector with detection improvement of 43%.

All descriptors showed the improvement both in performance time and correctly matched points. From them, best result belongs to SURF-SURF couple with 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). Unfortunately, it has limitations in intensity changes.

VI. Conclusions

Using grayscale images in descriptors was simple to accomplish, nevertheless as experiments show, color images can boost the performance results. By comparing all detection and description methods, it was discovered that the SURF-SURF pair gives the best improvement for the complex image of an outdoor environment. In greater detail:

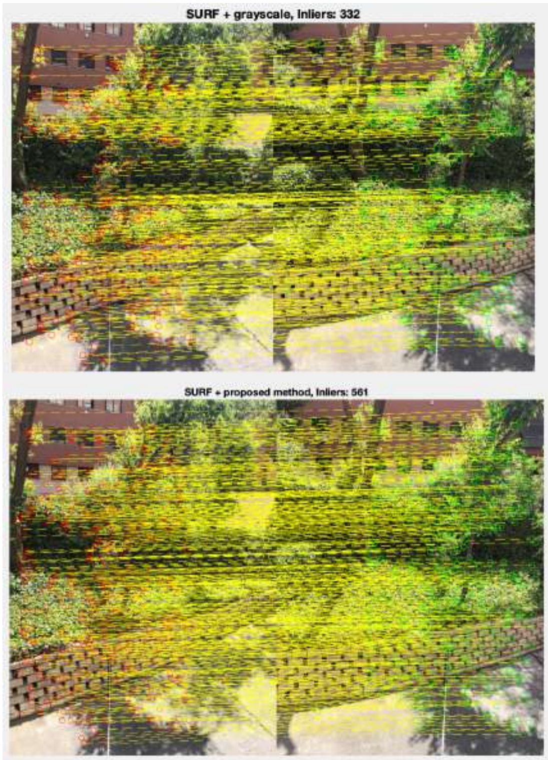

Fig. 33: SURF+SURF

- 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)

For further improvement, adding a state-of-art gradient based approach can improve the results. For instance, in Fig. 9, the proposed method didn't detect other clear edges in the region. In addition, I suggest using different algorithms in parallel to achieve robust performance.

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