THEORY AND METHODS OF SIGNAL PROCESSING

UDC 004.932.2 (045)
DOI: 10.18372/1990-5548.55.12716

[1]M. P. Mukhina,
[2]T. A. Yeremeieva

PERFORMANCE AND SPEED COMPARISON OF SURF AND ORB DESCRIPTORS

[1,2]Aviation Computer-Integrated Complexes Department, Educational & Research Institute of Information and Diagnostic Systems, National Aviation University, Kyiv, Ukraine
E-mails: [1]mukhina@nau.edu.ua, [2]yeremeieva700@gmail.com

Abstract**—***Fast and robust image processing and matching is a very important task with various applications in computer vision and robotics. In this paper, we compare the performance of two different image matching techniques, i.e., by speed up robust features and by rotated robust independent elementary features, against different kinds of transformations and deformations such as scaling, rotation, noise, fisheye distortion, and cropping. For this purpose, we manually apply different types of transformations on original images and compute the matching evaluation parameters such as the number of key points in images, the matching rate, and the execution time required for each algorithm and we will show that which algorithm is the best more robust against each kind of distortion.*

Index Terms—Image matching; image feature; robust matching; image distortion.

I. Introduction

Over the last decades, image feature detectors and descriptors have become popular tools in the computer vision community and they are being applied widely in a large number of applications. Image representation, image classification and retrieval, object recognition and matching, 3D scene reconstruction], motion tracking, texture classification, robot localization, and biometrics systems, all rely on the presence of stable and representative features in the image. Thus, detecting and extracting the image features are vital steps for these applications.

In image processing and computer vision tasks, we need to represent the image by features extracted therefrom. The raw image is perfect for the human eye to extract all information from; however, that is not the case with computer algorithms. There are generally two methods to represent images, namely, global features and local features. In the global feature representation, the image is represented by one multidimensional feature vector, describing the information in the whole image. In other words, the global representation method produces a single vector with values that measure various aspects of the image such as color, texture or shape. Practically, a single vector from each image is extracted and then two images can be compared by comparing their feature vectors. For example, when one wants to distinguish images of a sea (blue) and a forest (green), a global descriptor of color would produce quite different vectors for each category. In this context, global features can be interpreted as a particular property of image involving all pixels. This property can be color histograms, texture, edges or even a specific descriptor extracted from some filters applied to the image. On the other hand, the main goal of local feature representation is to distinctively represent the image based on some salient regions while remaining invariant to viewpoint and illumination changes.

Feature detection is the process where we automatically examine an image to extract features, that are unique to the objects in the image, in such a manner that we are able to detect an object based on its features in different images. An ideal feature detection technique should be robust to image transformations such as rotation, scale, illumination, noise and affine transformations. In addition, ideal features must be highly distinctive, such that a single feature to be correctly matched with high probability [1], [2].

The image processing processes can be divided in to 3 overall steps.

Detection

Automatically identify interesting features, interest points this must be done robustly. The same feature should always be detected irregardless of viewpoint.

Description

Each interest point should have a unique description that does not depend on the features scale and rotation.

Matching

Given and input image, determine which objects it contains, and possibly a transformation of the object, based on predetermined interest points.

II. Feature Detectors Characteristics

Tuytelaars and Mikolajczyk [3] define a local feature as “it is an image pattern which differs from its immediate neighborhood”. Thus, they consider the purpose of local invariant features is to provide a representation that allows to efficiently match local structures between images. The following properties are important for utilizing a feature detector in computer vision applications:

– Robustness, the feature detection algorithm should be able to detect the same feature locations independent of scaling, rotation, shifting, photometric deformations, compression artifacts, and noise.

– Repeatability, the feature detection algorithm should be able to detect the same features of the same scene or object repeatedly under variety of viewing conditions.

– Accuracy, the feature detection algorithm should accurately localize the image features (same pixel locations), especially for image matching tasks, where precise correspondences are needed to estimate the epipolar geometry.

– Generality, the feature detection algorithm should be able to detect features that can be used in different applications.

– Efficiency, the feature detection algorithm should be able to detect features in new images quickly to support real-time applications.

– Quantity, the feature detection algorithm should be able to detect all or most of the features in the image. Where, the density of detected features should reflect the information content of the image for providing a compact image representation.

III. Overview Of Image Matching Techniques

A. Speed up robust feature (SURF) detector

In computer vision, SURF is a local feature detector and descriptor that can be used for tasks such as object recognition or registration or classification or 3D reconstruction. It is partly inspired by the scale-invariant feature transform (SIFT) descriptor. The standard version of SURF is several times faster than SIFT and claimed by its authors to be more robust against different image transformations than SIFT.

Speed up robust feature detector approximates Laplacian of Gaussian (LoG) with Box Filter. Below image shows a demonstration of such an approximation. One big advantage of this approximation is that, convolution with box filter can be easily calculated with the help of integral images. And it can be done in parallel for different scales. Also the SURF relies on determinant of Hessian matrix for both scale and location.

For orientation assignment, SURF uses wavelet responses in horizontal and vertical direction for a neighbourhood of size 6σ. Adequate guassian weights are also applied to it. Then they are plotted in a space as given in below image. The dominant orientation is estimated by calculating the sum of all responses within a sliding orientation window of angle 60 degrees. Interesting thing is that, wavelet response can be found out using integral images very easily at any scale. For many applications, rotation invariance is not required, so no need of finding this orientation, which speeds up the process. SURF provides such a functionality called Upright-SURF or U-SURF. It improves speed and is robust. OpenCV library supports both, depending upon the flag, upright. If it is 0, orientation is calculated. If it is 1, orientation is not calculated and it is faster.

B. Orientated robust binary (ORB) independent feature detector

Orientated robust binary (ORB) independent feature detector is a fusion of the fast keypoint detector and robust independent elementary features (BRIEF) descriptor with some modifications [9]. Initially to determine the key points, it uses FAST. Then a Harris corner measure is applied to find top N points. FAST does not compute the orientation and is rotation variant. It computes the intensity weighted centroid of the patch with located corner at center. The direction of the vector from this corner point to centroid gives the orientation. To improve the rotation invariance, moments are computed with x and y which should be in a circular region of radius r, where r is the size of the patch. Moments are computed to improve the rotation invariance. The descriptor BRIEF poorly performs if there is an in-plane rotation. In ORB, a rotation matrix is computed using the orientation of patch and then the BRIEF descriptors are steered according to the orientation.

Rotated robust independent elementary feature detector discretizes the angle to increments of $2\pi/30$ (12 degrees), and constructs a lookup table of precomputed BRIEF patterns. As long as the keypoint orientation θ is consistent across views, the correct set of points Sθ will be used to compute its descriptor.

BRIEF has an important property that each bit feature has a large variance and a mean near 0.5. But once it is oriented along keypoint direction, it loses this property and become more distributed. High variance makes a feature more discriminative, since it responds differentially to inputs. Another desirable property is to have the tests uncorrelated, since then each test will contribute to the result. To resolve all these, ORB runs a greedy search among all possible binary tests to find the ones that have both high variance and means close to 0.5, as well as being uncorrelated.

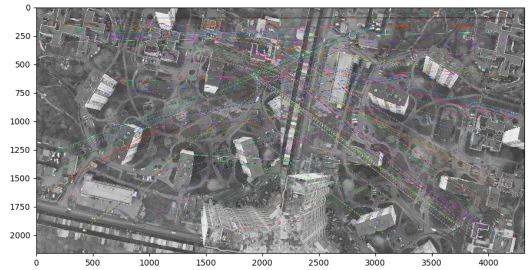
IV. Experimental Results

In this Section, we investigate the sensitivity of SURF, and ORB against each rotation, scaling, cropping, fish eye distortion, and noise.

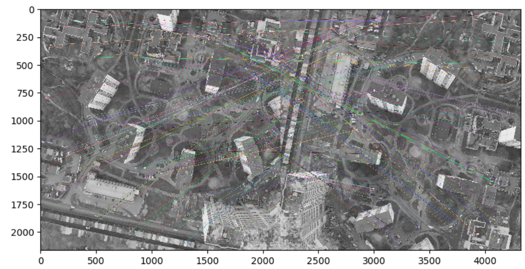
We tested ORB and SURF using Python 3.0 package and the set of images with (size 2160×2160 pixels) with different regions from UAV (unmanned aerial vehicle). These are images of real textured and structured scenes. Research was done using Python 3.0 package on images with size 2160×2160 pixels.

A. Rotation

We considered here a rotation of 90 degree to the image to be matched. The results are given in the Table 1 and Fig. 1. With rotated image, as one can see from Table I, SURF provides better match rate (76.4%), but ORB works faster.



(a)



(b)

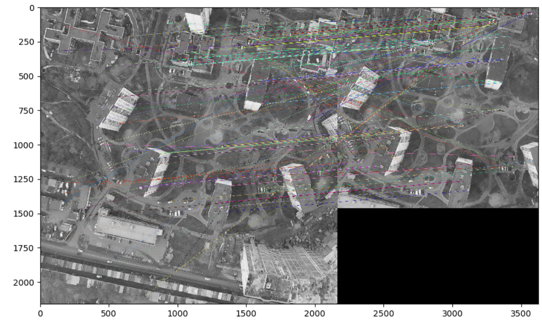
Fig. 1. The matching of 90 degrees rotated image with initial image using (a) ORB (b) SURF

TABLE I. RESULTS OF COMPARING THE IMAGE WITH ITS ROTATED IMAGE

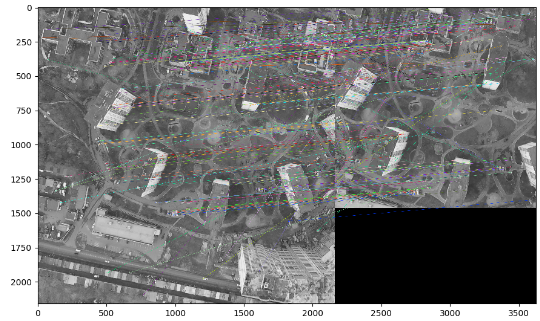
	Kpnts 1	Kpnts 2	Matches	Time (s)	Match rate (%)
ORB	510	516	314	0.000002	61.2
SURF	8192	8151	6246	0.000003	76.4

B. Cropped image

In this case, original image was cropped to see how part of image will be found in original image. SURF shows better match rate, but both algorithms has found a lot of wrong matches (Table II and Fig. 2).



(a)



(b)

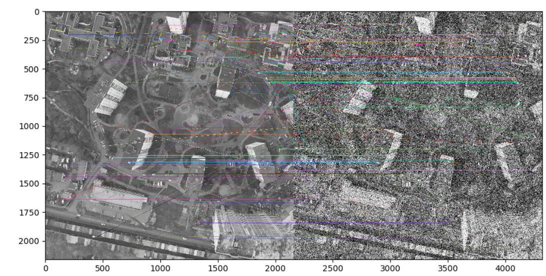
Fig. 2. The matching of cropped images using (a) ORB (b) SURF

TABLE II. RESULTS OF COMPARING THE IMAGE WITH ITS ROTATED IMAGE

	Kpnts 1	Kpnts 2	Matches	Time (s)	Match rate (%)
ORB	510	519	131	0.000002	25.5
SURF	8192	2568	1588	0.000003	29.3

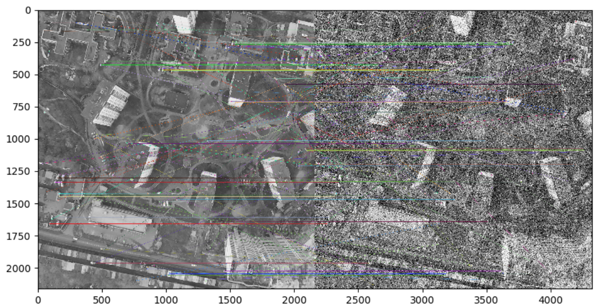
C. Noisy images

In this case, noise is added to the original image to see the effect of noise on the matching rate. From Table III and Fig. 3, one can see that ORB shows better matching rates. The added noise is randomly distributed and hence may be affecting some of the key points, but both SURF and ORB show almost equal performance.



(a)

Fig. 3. The matching of image with the image added with noise using (a) ORB and (b) SURF



(b)

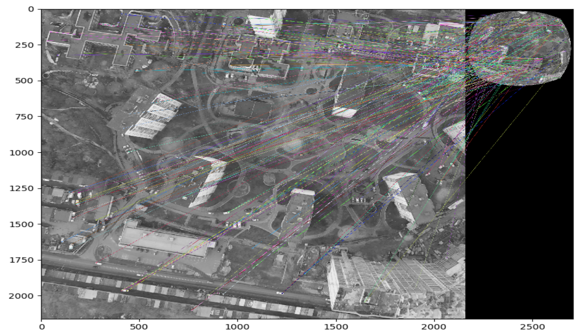
Fig. 3. Ending. (See also p. 13)

TABLE III. RESULTS OF IMAGE MATCHING WITH NOISE

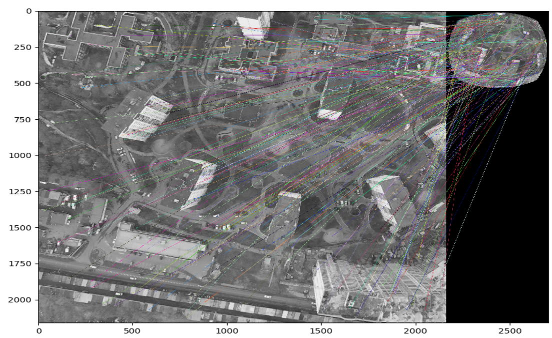
	Kpnts1	Kpnts2	Matches	Time (s)	Match rate (%)
ORB	510	518	127	0.000003	24,7
SURF	8192	32998	3899	0.000003	18.9

D. Fisheye distortion

The results are presented in Table IV and Fig. 4. From Table IV, one can see that the highest matching rate is obtained from ORB. And comparing to other scenarios SURF found less matches.



(a)



(b)

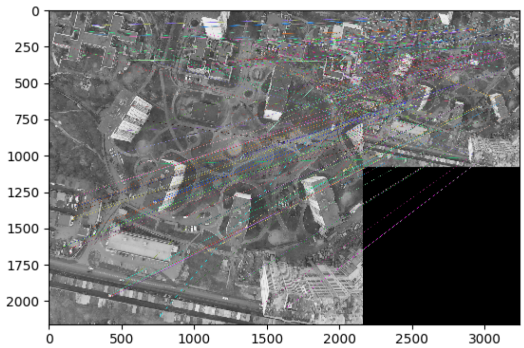
Fig. 4. The matching of an image with its fisheye distorted image using: (a) ORB (b) SURF

TABLE IV. RESULTS OF COMPARING THE IMAGE WITH ITS FISHEYE DISTORTED IMAGE

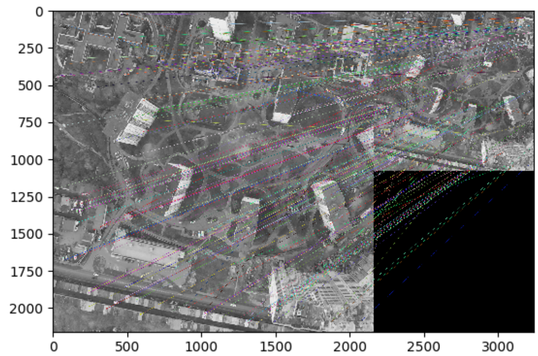
	Kpnts 1	Kpnts 2	Matches	Time (s)	Match rate (%)
ORB	510	507	127	0.0000029	24.9
SURF	637	8192	304	0.000003	6.8

E. Scaling

In this scenario, the image was scaled by 2 times to see the effect of matching with respect to scaling. Results are shown in Table V and Fig. 5. The highest matching rate is for SURF.



(a)



(b)

Fig. 5. The matching of an image with its 50% scaled image using: (a) ORB (b) SURF

TABLE V. RESULTS OF COMPARING THE IMAGE WITH ITS 50% SCALED IMAGE

	Kpnts1	Kpnts 2	Matches	Time (s)	Match rate (%)
ORB	510	512	115	0.000002	22.5
SURF	8192	2710	1425	0.000004	26.1

V. CONCLUSIONS

In this paper, we compared two different image matching techniques for different kinds of transformations and deformations such as scaling, rotation, noise, fisheye distortion, and cropping. For this purpose, we applied different types of transformations on original images and displayed the matching evaluation parameters such as the number of key points in images, the matching rate, and the execution time required for each algorithm.

We showed that ORB is in 1.5 time faster than SURF. But SURF has better match rate in the most scenarios and bigger number of useful points (41%), while ORB has only (32%). For special case with fisheye distortion and noise, ORB outperforms SURF.

REFERENCES

[1] B. Moghaddam, C. Nastar and A. Pentland, "A Bayesian similarity measure for deformable image matching," *Image and Vision Computing*, vol. 19, no. 5, pp. 235–244, 2001.

[2] B. Shan, "A Novel Image Correlation Matching Approach," *JMM*, vol. 5, no. 3, 2010.

[3] K. Mikolajczyk, T. Tuytelaars, C. Schmid, A. Zisserman, J. Matas, F. Schaffalitzky, T. Kadir, and L. Van Gool, A comparison of affine region detectors. *International Journal of Computer Vision*, 65(1/2):43–72, 2005.

[4] David G Lowe, "Distinctive Image Features from Scale-Invariant Keypoints," *International Journal of Computer Vision*, vol.50, no. 2, 2004, pp. 91–110.

[5] Herbert Bay, Tinne Tuytelaars and Luc Van Gool, "Speeded-up robust features (SURF)," *Computer vision and image understanding*, vol.110, no.3, 2008, pp. 346–359.

Received October 12, 2017

Mukhina Maryna. Doctor of Engineering Science. Professor.
Aviation Computer-Integrated Complexes Department, Educational & Research Institute of Information and Diagnostic Systems, National Aviation University, Kyiv, Ukraine.
Education: National Aviation University, Kyiv, Ukraine (2002).
Research area: images processing, navigation and control.
Publications: 60.
E-mail: m_mukhina@inbox.ru

Yeremeieva Tetiana. 6th year of study student.
Aviation Computer-Integrated Complexes Department, Educational & Research Institute of Information and Diagnostic Systems, National Aviation University, Kyiv, Ukraine.
Education: National Aviation University, Kyiv, Ukraine, Bachelor (2016).
Research interests: automation of technological processes.
Publications: 1.
E-mail: yeremeieva700@gmail.com

М. П. Мухіна, Т. А. Єремеєва. Порівняння ефективності та швидкодії детекторів характерних ознак SURF та ORB

У роботі порівнюємо ефективність двох різних методів зіставлення зображень, тобто SURF та ORB, на різного роду перетвореннях та деформаціях, таких як масштабування, обертання, шум, викривлення типу "риб'яче око" та кадрування. Для цього ми вручну застосовуємо різні типи перетворень на оригінальних зображеннях та обчислюємо відповідні параметри оцінки, такі як кількість ключових точок у зображеннях, швидкість співставлення та час виконання, необхідні для кожного алгоритму, з'ясовуючи, який алгоритм надійніший для кожного виду спотворень.

Ключові слова: зіставлення зображень; характерні особливості зображень; робасне зіставлення зображень; спотворення зображень.

Мухіна Марина Петрівна. Доктор технічних наук. Доцент.
Кафедра авіаційних комп'ютерно-інтегрованих комплексів, Навчально-науковий інститут інформаційно-діагностичних систем, Національний авіаційний університет, Київ, Україна.
Освіта: Національний авіаційний універститет, Київ, Україна, (2002).
Напрямок наукової діяльності: обробка зображень, навігація та керування.
Кількість публікацій: 60.
E-mail: mukhina@nau.edu.ua

Єремеєва Тетяна. Студентка 6-го курсу.
Кафедра авіаційних комп'ютерно-інтегрованих комплексів, Навчально-науковий інститут інформаційно-діагностичних систем, Національний авіаційний університет, Київ, Україна.

Освіта: Національний авіаційний університет, Київ, Україна, Бакалавр (2016).
Напрямок наукової діяльності: автоматизація технологічних процесів.
Кількість публікацій: 1.
E-mail: yeremeieva700@gmail.com

М. П. Мухина, Т. А. Еремеева. Сравнение эффективности и быстродействия детекторов характерных признаков SURF и ORB

В работе сравниваем эффективность двух различных методов сопоставления изображений, то есть SURF и ORB, на разного рода преобразованиях и деформациях, таких как масштабирование, вращение, шум, искажения типа "рыбий глаз" и кадрирование. Для этого мы вручную применяем различные типы преобразований на оригинальных изображениях и вычисляем соответствующие параметры оценки, такие как количество ключевых точек в изображениях, скорость сопоставления и время выполнения, необходимые для каждого алгоритма, выясняя, какой алгоритм надежнее для каждого вида искажений.

Ключевые слова: сопоставление изображений; характерные особенности изображений; робастные сопоставления изображений; искажения изображений.

Мухина Марина Петровна. Доктор технический наук, доцент.
Кафедра авиационных компьютерно-интегрированных комплексов, Учебно-научный институт информационно-диагностических систем, Национальный авиационный университет, Киев, Украина.
Образование: Национальный авиационный универститет, Киев, Украина, (2002).
Направление научной деятельности: обработка изображений, навигация и управление.
Количество публикаций: 60.
E-mail: mukhina@nau.edu.ua

Еремеева Татьяна. Студентка 6-го курса.
Кафедра авиационных компьютерно-интегрированных комплексов, Учебно-научный институт информационно-диагностических систем, Национальный авиационный университет, Киев, Украина.
Образование: Национальный авиационный университет, Киев, Украина, Бакалавр (2016).
Направление научной деятельности: автоматизация технологических процессов.
Количество публикаций: 1.
E-mail: yeremeieva700@gmail.com