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COMPARATIVE ANALYSIS OF BRISK AND ORB METHODS FOR LOCAL FEATURE DETECTION IN SATELLITE IMAGERY

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Abstract**—***Binary local feature detection, which is very important for the satellite image processing of object recognition and image matching, was studied in this paper. In this examination, the BRISK and ORB methods, now used extensively for detecting features for the satellite image processing purpose, have been evaluated. The objective of this paper is investigation of the methods in respect of their ability to detect keypoints and their robustness against transformation and identify their strengths and weaknesses. As an example, an experimental comparison is put forward in the MATLAB environment for images from Vatican City and one of its buildings. This evaluation will help researchers in choosing the most appropriate method depending on their applications.*

Keywords—Computer vision; binary local feature detection; BRISK; ORB; satellite imagery; object recognition; image matching.

I. INTRODUCTION

Satellite imagery plays a significant role in decision-making, environmental monitoring and other researches because of the latest advances in remote sensing technology, high-resolution images of the Earth's surface and creation of powerful algorithms which are used for analysis. They include monitoring climate change, land-use determination, foreseeing natural disasters before their severity increase and agricultural purposes. These images are also required for the improvement of forest conservation, urbanization, military activities and GPS accuracy as human dependence on land resources data increases and as a result demand on more refined and effective techniques for managing and analysing such images appeared.

The identification and classification of objects are primary issues in the analysis carried out through satellite images. The data acquired through satellites is complex because of variations in illumination, atmospheric interference and diverse topography, conventional analysis will not work for this [1]. However, local feature detection is widely accepted to accommodate such difficulties.

This paper will provide a comparative analysis between BRISK (Binary Robust Invariant Scalable Keypoints) and ORB (Oriented FAST and Rotated BRIEF), two of the widest used algorithms for local feature detection. Both are efficient and robust in handling processes on a large scale with satellite imagery. The criterion of evaluation will include repeatability of features, computational speed and transformation robustness. The purpose of analysis would serve to prove the practical application of BRISK and ORB in remote sensing for researchers in selection for feature detection options regarding satellite imaging project applications.

This study's experiment tests have been conducted within the MATLAB environment. Using the Image Processing Toolbox, the experiment will implement and analyse feature detection methods. By comparison, the research aims to bring about a better understanding of local feature extraction techniques for satellite image analysis and aid practitioners in devising their methodology for remote sensing applications.

II. DESCRIPTION OF BINARY LOCAL FEATURE DETECTORS

Feature descriptors are mostly used to help in the entire procedure of computer vision by encoding features so they could be used in such activities like object or image matching and even scene reconstruction. With various types of descriptors, binary image descriptors have been increasingly applied due to the computation overhead and robustness. Unlike the conventional vector representation of descriptors in high-dimensional floating-point vector form, binary descriptors represent features in compact binary bit strings. This difference qualifies binary descriptors as most useful to applications where real-time usage combined with efficient storage and very rapid feature matching is needed, such as a satellite image analysis [2].

The binary descriptors have different fundamental characteristics which increase their efficiency. Features are encoded as binary strings of 128–512 bits, compared to conventional vectors descriptors this is compact representation which minimize the storage requirements. Fast matching is enabled with the Hamming distance measure via a simple bitwise comparison, a procedure which far outperforms the time taken to calculate the vector distance by Euclidean distance measures for the vector descriptors [3]. Illumination and rotation variations show maximum resilience to the various binary descriptors incorporated with orientation normalization and intensity encoding schemes.

The operation of the binary descriptor revolves around systematic extraction and encoding of features. First, keypoints can be detected with corner or blob detectors, when these keypoints are processed by the predefined sampling pattern around each keypoint, this algorithm is used to extract intensity information. Pair comparisons on the intensity of pixels within this sampling pattern form the descriptor. If one pixel's intensity is greater than another's a bit '1' is assigned, else a '0'. In this way, a unique binary string that representing the local feature is created. Mathematically, the descriptor D is computed as:

$$D = \sum_{i=1}^{N} \delta\left(I(\rho_i) - I(q_i)\right) 2^{(i-1)}, \tag{1}$$

where $I(\rho_i)$ and $I(q_i)$ represent the intensity values of two sampled pixels; $\delta(x)=1$ if $x>0$ and $\delta(x)=0$ otherwise, and N is the total number of sampled pairs, determining the descriptor length [4].

Binary descriptors differ mainly in their sampling patterns, keypoint detection strategies and descriptor lengths [5].

Binary robust invariant scalable keypoints (BRISK) is a binary descriptor that is used for detecting keypoints using a circular pattern. It is the best suited for real time applications which require a considerable scale and rotation invariance. The ORB (Oriented FAST and Rotated BRIEF) represents high speed, relative safety from rotation and great efficiency in computational processing by its appropriate combination between the FAST keypoint detector and modified BRIEF descriptor. Fast Retina Keypoint (FREAK) which mimics the sampling pattern of the human retina, thus providing greater robustness to noise and light illuminations changes while being computationally cheap. Accelerated-KAZE (AKAZE) employs nonlinear scale space detection with a binary descriptor that is robust against scale and illumination changes yet is extremely fast [6].

III. The Operational Algorithms of BRISK and ORB

Following methods for local feature-based object detection are stated in the paper: the BRISK and ORB algorithms. An analysis of the algorithms will show their advantages, disadvantages and applicability. Such an inquiry allows for even deeper comprehension of these techniques for all computer vision practitioners.

Keypoint detection in BRISK uses the scale-space pyramid approach, progressively downsampling the image into multiple octaves and intra-octaves in order to capture keypoints at different scales. This type of detection is based on features from accelerated segment test (FAST), which efficiently indicates corner structures.

Given an input image $I(x,y)$, BRISK generates a set of scaled images $I_\sigma(x,y)$, where each scale level σ is computed as:

$$I_\sigma(x,y) = I(x,y) G_\sigma(x,y), \tag{2}$$

where $G_\sigma(x,y)$ is a Gaussian function that smooths the image at level σ. Depending on the scale-space representation, it can be applied to detect keypoints in images for various resolutions, as with satellite imagery, where images may be taken with different zoom levels [7].

Binary robust invariant scalable keypoints has implemented the FAST corner detector at all levels of scale for detecting keypoints. A pixel p can be considered a keypoint if its intensity is significantly dissimilar to that of the surrounding pixels in a circular neighborhood. The FAST test compares the intensity $I(p)$ of a pixel to 16 other pixel intensities surrounding it in a circular circumference. If a cluster of contiguous pixels appears brighter or darker than $I(p)$, then p will be designated as a corner point. The next step will be interpolation of the keypoint in order to improve accuracy in localization.

Rotation invariance is achieved by BRISK by assigning an orientation to each detected keypoint. The orientation is established through intensity comparisons in a circular pattern of sampling.

This ensures that the descriptor remains consistent under rotational transformations. The BRISK descriptor calculates pairs of intensity comparisons among sampling points in an organized and circular manner (Fig. 1). The sampling pattern includes N points placed along the concentric circles around the keypoint. Since the descriptor size is usually equal to 512 bits (256 intensity comparisons), it is stored compactly and matches very efficiently. Algorithm uses short and long-distance comparing approaches: short-distance comparisons computing the local gradient direction needed for orientation assignment and the long-distance comparisons build the final binary descriptor.

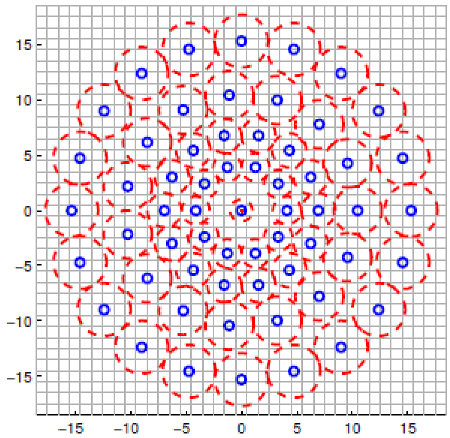

Fig. 1. BRISK sampling pattern

After computing the binary descriptors, BRISK perform feature matching between two images by calculating the Hamming distance between the descriptors. The Hamming distance $H(D_1, D_2)$ between two binary descriptors D_1 and D_2 is counted as:

$$H\left(D_1, D_2\right) = \sum_{i=1}^{N}\left(D_1[i] \oplus D_2[i]\right), \quad (3)$$

where $\oplus$ is the *XOR* operation and N is the length of the descriptor. The lower the Hamming distance, the higher the similarity between keypoints [8].

Oriented FAST and Rotated BRIEF (ORB) is an algorithm developed for local feature detection and description which is faster than SIFT and SURF while being, in general, almost as robust. It combines the FAST and BRIEF algorithms. FAST and BRIEF is known for its computational efficiency and speediness in performance. It not only provides a much lower computational cost than SIFT and SURF but also offers similar robustness as both algorithms [9]. The technique uses FAST for the interest point, BRIEF for the feature vector and a very efficient implementation of two algorithms used in combination.

As BRISK does, keypoint detection in ORB is based on the FAST corner detection algorithm. However, the feature detection techniques used in FAST do not address the problem of stability of the algorithm. Consequently, approaches like this lead the feature-based target selection to ORB, which uses the Harris corner response to sort features and enhance their detection capabilities. The ranking of such features via Harris corner guarantees the selection of only the stable and distinctive features which improves the performance of feature-based target selection depending on the acquired imagery [10].

FAST does not compute an orientation for keypoints to attain rotation invariance, which is a critical property of keypoints. In essence, ORB takes advantage of the intensity centroid approach to achieving this, which comes up with an orientation for a keypoint-the average orientation. In other words, first-order image moments are transformed into:

$$m_{p,q} = \sum_{x,y} x^p y^q I(x, y), \quad (4)$$

The centroid of the intensity distribution is then obtained as:

$$C_x = \frac{m_{10}}{m_{00}}, \; C_y = \frac{m_{01}}{m_{00}}, \quad (5)$$

where m_{00} represents the total image intensity in the local region. The dominant orientation θ of the keypoint is computed as:

$$\theta = \tan^{-1}\frac{m_{10}}{m_{00}}, \quad (6)$$

This orientation is used to rotate the sampling pattern for descriptor computation, ensuring rotation invariance.

Upon detection of keypoints and assignment of orientation, a binary descriptor is computed using a variant of BRIEF. BRIEF basically makes up a binary output string by comparing some random luminance around the feature with that around a number of randomly picked keypoints [11]. Some applications of standard BRIEF cannot be practicable in some situations that involve image rotation, particularly in the case of changing perspectives. In order to overcome this problem, the ORB algorithm provides an additional amount of information that is called rotated BRIEF (rBRIEF), in which the distribution of the sampling patterns for the descriptor computation matches the main orientation of the keypoint. rBRIEF was proposed to eliminate the effects of a distorted pattern and maintain the descriptor's performance in the presence of rotation. The usage of rBRIEF enables ORB to be operational under large distance remote sensing scenarios with the ability to resist geometric obstacles.

After the descriptors of image are extracted, the matching of characteristics will be done by using Hamming distance. Also, ORB uses a k-nearest neighbor (*k-NN*) search with a ratio test, as a result only the strong correspondences are left for further analysis. This filtering process greatly reduces the possibility of identifying falling matches and the improved accuracy of keypoint correspondences [12].

IV. Methods Comparison and Evaluation

This section will provide an experimental evaluation of BRISK and ORB binary local feature detection methods. The experiment includes 50 satellite images and analysed in MATLAB environment in order to detect the objects in the image. The steps would involve pre-processing the image, detecting keypoints, extracting features, matching features and go to identification. In all instances, the images will have to be converted to grayscale if found necessary to ensure uniform image processing. ORB and BRISK algorithms will have to be applied to extract keypoints and obtain descriptors for capturing the distinctive pattern within the satellite imagery. The experimental results of the study would estimate the effectiveness of BRISK and ORB algorithms in detecting objects under conditions such as different lighting, scaling and rotation. The Image Processing Toolbox in MATLAB will form the basic framework for implementing all features for object detection based on features [13].

Fig. 2. Vatican City satellite image

The choice of the Vatican City satellite image (Fig. 2) as a detection example, with a resolution of 3000x3000, is justified by the diversity and intensity of objects on it. The area of the city is likely to cover numerous geometric patterns, sharp edges and contrasting textures; hence, this could be a good data set for analysis. The complexity of the scene within the city will exploit the nearest real-life scenarios for objects detection.

This experiment was mainly aimed at the detection of the building shown in Fig. 3.

The results of detection showed on the Fig. 4.

BRISK and ORB efficiency evaluation was performed by calculation of keypoints detected in 50 satellite images which have the same resolution, weather, brightness conditions etc. This study can help in understanding how binary local feature detectors work when dealing with a very complex environment [14]. An average result of detected keypoints is showed on Fig. 5.

Fig. 3. Image of building that need to be detected

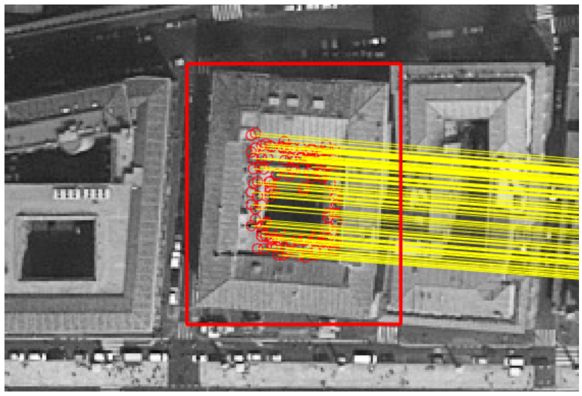

Fig. 4. Detected required object

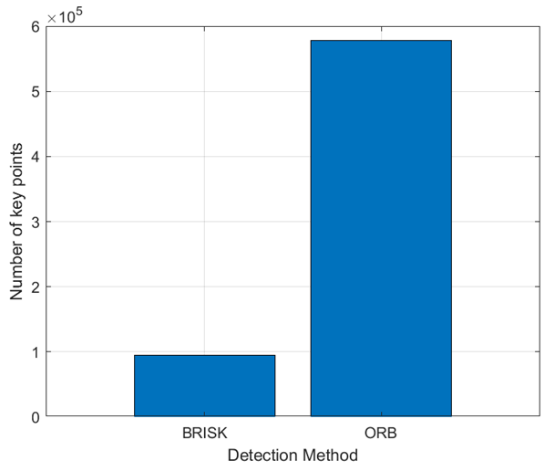

Fig. 5. Average number of keypoints in researched satellite images depend on detection method

The higher number of keypoints found for ORB than for BRISK across the satellite image indicates that ORB appears to identify more distinctive features. This is because ORB employs FAST corner detections and Rotated BRIEF descriptor which are optimized for high-contrast regions and edges that lead to increase distributions of keypoints. BRISK has a sampling pattern that is predefined which limits the number of keypoints in output.

The analysis of the number of keypoints on the reference image as a function of rotation is helpful to measure the rotation invariance of both the BRISK and ORB methods as most satellite images are subjected to geometric transformations due to changes in perspective or in sensor orientation.

As seen in the results (Fig. 6), ORB is able to detect a greater number of keypoints compared to BRISK. It was noticed that at some angles BRISK showed better results, so it proves that it can be efficiently used at certain conditions. These fluctuations indicate that both methods are under the influence of rotational transformations, however, ORB proves to be more stable. Also, both methods do not show periodic dependence compared with SIFT and SURF vector descriptors.

In the next step it is necessary to investigate the number of matched points depending of detection method and rotation of searched image.

From this observation (Fig. 7), it can be conferred that ORB seems to detect more matching keypoints when compared to BRISK, claiming to be better at rotation. The periodic peaks indicate that at certain rotation angles both algorithms perform moderately better in feature alignment [15].

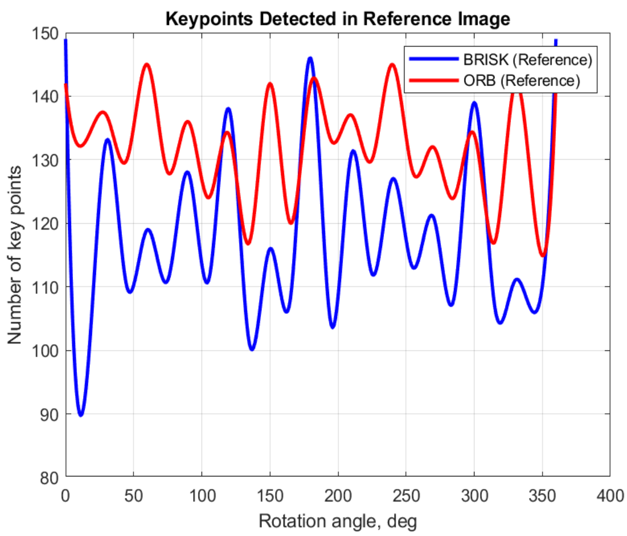

Fig. 6. Number of building image keypoints depending on detection method and rotation angle

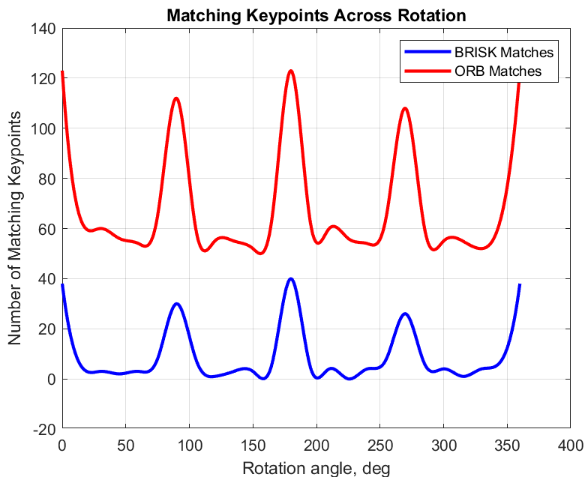

Fig. 7. Number of matched points depending on detection method and rotation angle

V. CONCLUSIONS

The study found that ORB detects more keypoints compared with BRISK as ORB is more sensitive to features in the images. Interrogation on the matching performance showed that also that the number of matched keypoints between the satellite image and rotated image that need to be detected followed in a periodic way. ORB always showed the highest number of matched keypoints compared with BRISK, which means that it is better in matching capability under rotational transformations.

Take into account structural and textural differences, which are generally seen in satellite images, ORB is a good candidate for feature extraction and matching. Thus, this adds understanding on the performance of BRISK and ORB in analysing satellite images while also being relevant to the applications that these methods could find in the real world.

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А. В. Рябко, В. Ю. Грішненко. Порівняльний аналіз методів BRISK та ORB для виявлення локальних ознак на супутникових знімках

У роботі досліджено бінарні методи локального виявлення ознак, які відіграють важливу роль у супутниковій обробці зображень для розпізнавання об'єктів. Розглянуто методи BRISK та ORB, які широко використовуються для виявлення особливостей у супутникових зображеннях. Метою роботи є оцінка цих методів щодо їхньої здатності визначати ключові точки, стійкості до трансформацій, а також виявлення їхніх переваг і недоліків. Як приклад проведено експериментальне порівняння в середовищі MATLAB для зображень Ватикану та однієї з його будівель. Це дослідження допоможе науковцям обрати найбільш відповідний метод залежно від їхніх завдань.

Ключові слова: комп'ютерний зір; бінарне локальне виявлення ознак; BRISK; ORB; супутникові зображення; розпізнавання об'єктів; порівняння зображень.

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