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KEYPOINTS ON THE IMAGES: COMPARISON OF DETECTION BY DIFFERENT METHODS

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This paper investigates the effectiveness of image description using detectors and keypoint descriptors for image similarity evaluation. SIFT, SURF, ORB, and BRISK methods are compared for detection and matching procedures. Similarity coefficients are computed for each image pair, and corresponding similarity coefficient matrices are constructed for image similarity analysis. An evaluation of the speed of keypoint detection and description for each of the methods was conducted. It was found that SIFT yielded the he SURF method performed better in recognizing similar images compared to BRISK and ORB, but was significantly slower. The research results can be useful in the field of visual search and image identification.

Keywords: SIFT, SURF, ORB, BRISK, detection, description, keypoints.

Introduction.

In today's world, where we are surrounded by a large number of images, there is a need for the development of efficient algorithms for digital image processing. Various methods based on computer vision have been developed to solve this problem. Detection and description of image features have been an active research area for decades due to their promising productivity [1-3].

Methods that use keypoints as sets of features in images have found applications in many fields. For example, in medical imaging for organ recognition and disease diagnosis [4-6], for registration and recognition of images taken by unmanned aerial vehicles [7-9], for studying fruit conditions in agriculture [10-11], and others. One of the main tasks of computer vision and image processing is to search for and match features in a set of images that may belong to different groups. However, comparing images by their appearance is a challenging task due to various aspects such as lighting, perspective, displacement, scaling, and other factors that can affect their appearance. To effectively compare images, methods for assessing the degree of similarity between them are necessary. In this context, keypoints and their descriptors are important tools for image processing. However, the question arises as to which algorithms should be used to achieve the best accuracy and speed.

In this paper, several of the most widely used methods for keypoint detection and description - SIFT (Scale-Invariant Feature Transform), SURF (Speeded-Up Robust Features), ORB (Oriented FAST and Rotated BRIEF), and BRISK (Binary Robust Independent Elementary Features) [12-15] - are compared. The aim of the study is to compare the effectiveness of the listed methods for detecting similar images. The results obtained can be useful in creating programs for processing a large number of images, taking into account the accuracy of matching and recognition speed.

Results and discussion.

The paper analyzes the effectiveness of comparing images based on keypoint detectors and descriptors for assessing image similarity. The dataset consists of 25 images of crisps packages, each with identical dimensions of 832*828 pixels and in PNG format (Fig. 1). They are divided into 5 groups, according to the packaging groups. To compare the methods for detecting and describing keypoints discussed in the article, programs were created in Python using the OpenCV library [16].

Fig. 1 The set of investigated images.

The described methods show different results depending on the parameter that sets the number of keypoints for detection. For the SIFT and ORB methods, this parameter is *nfeatures* [17], which allows setting the required number of feature points. Considering the sizes and characteristics of the images, the value of *nfeatures* was chosen to be 300.

In the SURF algorithm, the restriction is controlled by the parameter *hessianThreshold* [17], which is set to 2700, allowing to obtain roughly the same number of key points as in the SIFT and ORB methods. The selection of the correct value for *hessianThreshold* may depend on the specific application and image properties. Typically, a high threshold value allows selecting only the most salient and robust key points, but some smaller key points or image areas may be missed. On the other hand, a low threshold value enables finding more key points, but some of them may not be robust to changes in the image or ambiguous for further processing.

For the BRISK method, the threshold parameter *tresh* was set to 65 [17]. This parameter selects the most significant points of the image, i.e., those with the most distinct properties among the other points. Increasing the threshold value selects fewer keypoints, while decreasing it selects more.

Table 1. Comparison of detection and description speed.

Methods	Parameters	Number of keypoints	Time, sec
Sift	nfeatures = 300	300	2.15
SURF	hessianThreshold = 2700	~ 445	0.87
ORB	nfeatures = 300	300	0.18
BRISK	thresh = 65	~ 430	0.29

The detection and description speed of the key points are presented in Table 1. The results show that the ORB method is the fastest among the investigated methods. This is due to the use of the FAST [18] method for detection and the BRIEF [19] algorithm for describing key points. The slowest method is SIFT, which may have negative consequences when used in real-time mode. The SURF method is an improved version of SIFT [20], which also affects the processing time: from the table, it can be seen that it works almost twice as fast. The BRISK detector and descriptor have similar results to ORB and can be used to solve real-time tasks.

Comparison of image similarity was performed using the Brute Force algorithm with the *knnMatch* method [21-22] and a parameter k=2. In this case, the method returns the two best matches for each descriptor. For distance comparison in the SIFT and SURF methods, the Euclidean distance (NORM_L2) was applied in the OpenCV implementation [17]. For distance comparison in the binary descriptors ORB and BRISK, the Hamming distance (NORM_HAMMING) was used [17]. It measures the number of positions in which two binary strings differ. This means that the Hamming distance is equal to the number of bits that need to be changed to transform one string into another. The Hamming distance significantly reduces computational complexity for binary descriptors compared to standard metrics such as NORM_L1 or NORM_L2. The program uses Lowe's ratio test, which compares the two closest neighbors for each local feature and discards matches where the first distance is significantly smaller than the second, multiplied by a coefficient of 0.75 [12]. Thus, this procedure can increase the accuracy of matching key points and reduce the number of false positives.

To evaluate the effectiveness of the obtained sets of key points, a comparison of the similarity detection performance using SIFT, SURF, ORB, and BRISK methods was conducted. For each pair of images, a similarity coefficient was found, which shows the percentage of matching key points between two images relative to the total number of key points on them. In the case of SURF and BRISK methods, due to the different number of points, the minimum value was chosen to calculate the similarity between a pair of images. This is due to the fact that the implementation of these algorithms in OpenCV does not provide a clear limit on the number of points based on the specified parameter, as is done in SIFT and ORB. For each of the algorithms, a heat map matrix of 25*25 was created, corresponding to the number of images. They contain similarity coefficients, which can range from 0 to 100 and are represented by the appropriate color for better visual understanding. The diagonal elements represent the similarity of the image to itself and are always equal to 100%.

Table 2. Comparison of similarity coefficients.

Methods	average value of similarity coefficient for similar images, %	maximum value of similarity coefficient for similar images, %	average value of similarity coefficient for dissimilar images, %	maximum value of similarity coefficient for dissimilar images, %
Sift	46.92	65.7	1.49	8
SURF	41.04	61.68	2.63	9.92
ORB	38.67	48.33	3.95	11.66
BRISK	32.53	50.91	0.57	3.98

Table 2 presents the results of the analysis of obtained similarity coefficients between images. To assess recognition effectiveness, the average similarity coefficient values were calculated for images of products from the same and different packaging groups. Additionally, the corresponding maximum values of coefficients were determined for the investigated set of images.

Comparing the obtained data, it can be said that for the SIFT method (Fig. 2), the values of the similarity coefficient are higher compared to other methods for most pairs of similar images (Table 2).

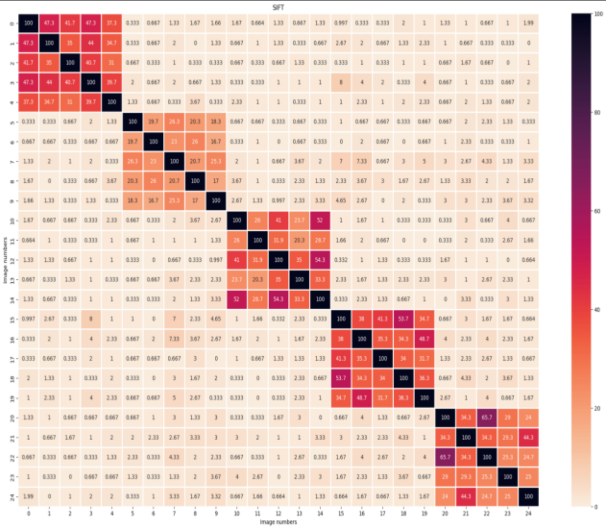

Fig 2. The similarity matrix for the set of keypoints generated using the SIFT method.

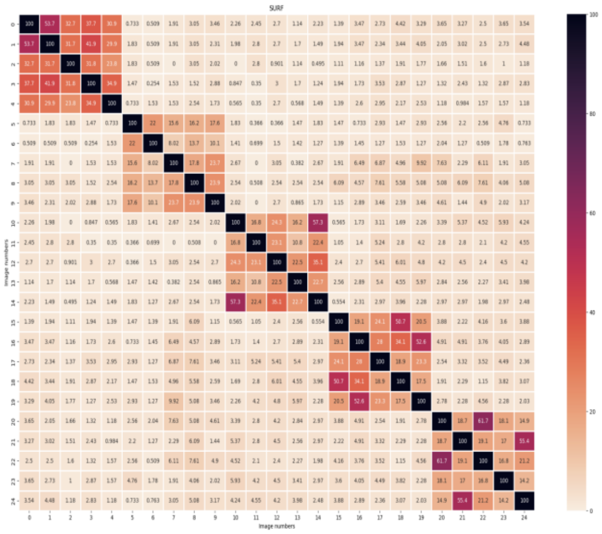

Fig.3 The similarity matrix for the set of keypoints generated using the SURF method.

The results (see Table 2) indicate that the SURF algorithm (Fig. 3) is less accurate than the SIFT method (Fig. 1) in terms of similarity coefficient values, but it is almost three times faster (see Table 1). Therefore, SURF can be used in systems where both accuracy and speed are important criteria.

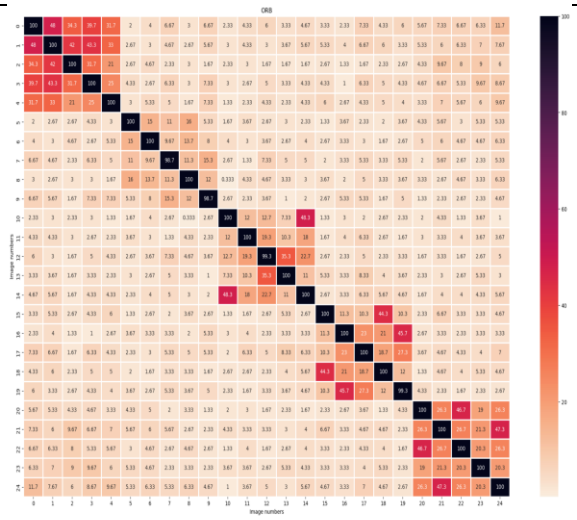

Fig.4 The similarity matrix for the set of keypoints generated using the ORB method.

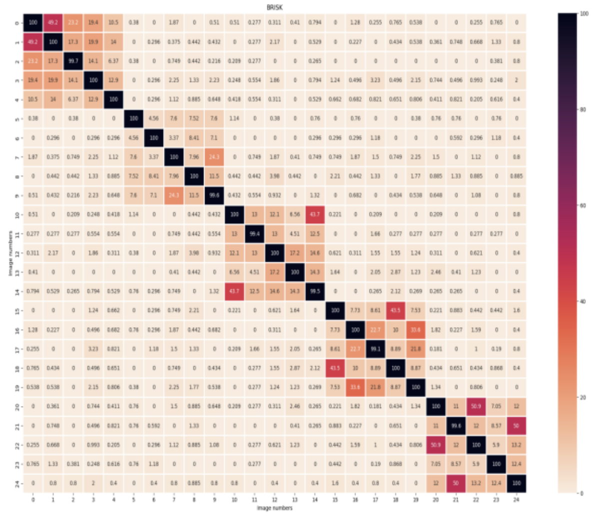

Fig. 5 The similarity matrix for the set of keypoints generated using the BRISK method.

When analyzing the similarity matrix (Fig. 4) for ORB, it can be observed that the method yields significantly lower similarity coefficient values for similar image pairs, whereas in the case of different images, ORB has a higher similarity coefficient than other methods (see Table 2). This can be a challenge for programs that rely on a low threshold value of this coefficient for image recognition. However, the algorithm works the fastest, making it a better option for real-time applications. ORB is useful in tasks with large datasets for quick image recognition, where accuracy is not a critical parameter.

The BRISK method (Fig. 5) has noticeably lower accuracy in finding correspondences between images compared to other investigated methods. However, it is comparable in speed to ORB, which can be explained by its binary approach to forming a description of the area around key points (see Table 1). Thus, BRISK can be applied for making quick decisions where recognition accuracy has lower priority than speed, but it remains important. From the results (Table 2), it can be seen that BRISK performs better in situations where images are not similar to each other. In the case of BRISK, the average value of the similarity coefficient between different images is approximately three times lower than that of the SIFT method and almost eight times lower than that of ORB.

Conclusions.

This article examines image descriptions generated by sets of key points formed by the SIFT, SURF, ORB, and BRISK methods for evaluating image similarity. To estimate the similarity coefficient between a set of images, a similarity matrix was used, which reflects the ratio of the number of matches to the number of keypoints between all pairs of images. In addition, to further evaluate the effectiveness of each method, an analysis of detection and description speed was performed.

The research has shown that SIFT is the most effective method for finding similar images. Although this algorithm is significantly slower than other methods, it is the best choice for systems that require high accuracy. SURF is slightly faster than SIFT but has lower accuracy.

ORB and BRISK, which use binary descriptors, are less accurate in recognizing the set of images. ORB is the fastest among the methods, which allows it to be used for real-time tasks. The BRISK method showed the lowest coefficient of similarity for cases when the images are different. In terms of accuracy, BRISK is inferior to SURF, but has better speed.

Overall, the choice of method for finding similarity between images should depend on the specific task and requirements for accuracy and speed. The results of this study can be useful in parameters optimization of keypoint detection methods for image recognition tasks.

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ОСОБЛИВІ ТОЧКИ НА ЗОБРАЖЕННЯХ: ПОРІВНЯННЯ РЕЗУЛЬТАТІВ ВИЯВЛЕННЯ РІЗНИМИ МЕТОДАМИ

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Ключові точки активно застосовуються в області комп'ютерного зору та обробки зображень. Актуальність використання цього підходу пояснюється характерною здатністю ключових точок до виявлення та опису унікальних особливостей зображень, що дозволяє здійснювати ідентифікацію, порівняння та пошук.

У роботі досліджено ефективність опису зображень за допомогою детекторів та дескрипторів ключових точок для оцінки схожості зображень. Розглянуто чотири методи, а саме SIFT, SURF, ORB та BRISK, для яких описано процедури знаходження та відбору співпадінь.

Оцінка якості виявлення та опису точок проведена таким чином: для кожної пари зображень обчислено коефіцієнт подібності, що відображає частку співпадінь ключових точок у порівнянні з загальною кількістю точок на зображеннях. За допомогою цих коефіцієнтів побудовані матриці схожості, які є мірою подібності зображень. Крім того, для кожного з методів здійснена оцінка швидкості знаходження та опису ключових точок.

В результаті дослідження встановлено, що при використанні методу SIFT отримано найвище значення коефіцієнта схожості у порівнянні з іншими методами, але час детекції та дескрипції виявився найповільнішим. За часом виконання виділяється метод ORB, що дозволяє найшвидше знаходити та описувати ключові точки, хоча результати точності є помітно гіршими порівняно з SIFT. Застосування методу SURF виявилося кращим у завданнях розпізнавання подібних зображень у порівнянні з BRISK та ORB, але швидкість виявлення та дескрипції ключових точок є меншою. Результати, отримані при використанні методу BRISK показують певний компроміс між точністю та швидкістю.

Результати дослідження мають цінність для застосування в області візуального пошуку та ідентифікації зображень. Вони можуть бути корисними у завданнях детекції та дескрипції ключових точок у системах розпізнавання зображень, а також для вдосконалення вже існуючих алгоритмів та методик.

Ключові слова: SIFT, SURF, ORB, BRISK, детекція, дескрипція, ключові точки.

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