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Research Article

PERFORMANCE EVALUATION OF WELL-KNOWN FEATURE DETECTORS AND DESCRIPTORS

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ABSTRACT

The detection and matching of feature points is an important part in many computer vision applications. In this paper, we explore the performance of six state-of-the-art detectors and descriptors which are SIFT with SIFT, SURF with SURF, BRISK with FREAK, BRISK with BRISK, ORB with ORB and FAST with BRISK. We conduct comparisons of invariance against image transformations such as rotation, illumination, blur and viewpoint in terms of Precision and Matching Ratio. We find that the combination of SIFT with SIFT is most robust to rotation, blur and viewpoint changes. We also find that ORB algorithm performs best under various changes in all binary algorithms.

INTRODUCTION

The detection and matching of feature points is a fundamental problem in visual correspondence, object matching, and many other vision applications (Benseddik *et al.*, 2014). In the past decades, a number of feature detectors and descriptors have been proposed in the literature. Feature detection identifies a set of image locations presenting meaningful structures in an image, such as corners and blobs. The feature descriptor is represented by a subset of the total pixels in the neighborhood of the detected feature point. In the image matching, a first issue is robustness with respect to image transformations, such as image rotation, illumination and viewpoint changes and so on. It can get good matching results by selecting appropriate matching algorithm for different image transformations (Moreels and Perona, 2006). Mikolajczyk and Schmid (2005) explored several early feature algorithms using the evaluation criterion of $P_{correct}$ and P_{false}. Ferrarini *et al.* (2015) evaluated the performance of several feature algorithms in a specific scene. Chien *et al.* (2016) associated feature algorithms with specific applications and only considered the performance of several feature algorithms in monocular visual odometry. They did not consider the relationship between image transformations and feature algorithms. In this paper, the evaluation criteria of Precision and Matching Ratio are used to reasonably evaluate the performance of several feature algorithms under various image transformations, including binary features such as FREAK, BRISK, and ORB. The Precision value means that how relevant the matched features to each other. The Matching Ratio can be evaluated as a metric measuring the pairing strength between a detector and a descriptor.

FEATURE DETECTORS AND DESCRIPTORS

SIFT

The SIFT algorithm was proposed in 1999 and summarized in 2004 (Lowe, 1999; Lowe, 2004). The detected feature points have high invariance to rotation and viewpoint changes. In the method, interest points are extracted from the image in two steps. In the first stage, the image is scanned over location and scale in order to determine potential interest points that are invariant to scale and orientation. The initial detection of the keypoints is accomplished through the comparison of the two adjacent Difference of Gaussian (DoG) images in the same group. The point in the middle is not only compared with the 8 adjacent points on the same scale layer, but also compared with the 26 points corresponding to the upper and lower adjacent scale layers to ensure that the extreme points are detected in both the scale space and the image space. The above method

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detects extreme points in discrete space, and is probably not accurate. Therefore, it is necessary to further accurately locate the extreme points. The points that have a low contrast are rejected with respect to a predefined hreshold. In addition to the low contrast points in the image, the edge of the image is easily disturbed by the noise. The relationship between the principal curvature and the eigenvalue can be used to further remove these unstable points. It is assumed that the distribution on an edge region should give larger eigenvalues and the distribution on a non-edge region should give small eigenvalues.

SURF

Bay *et al.* (2006) proposed a robust local feature detection algorithm known as SURF. It uses the approximate Hessian matrix to detect feature points, and the integral image is employed to reduce the amount of computation greatly. Instead of the DoG operators, the SURF algorithm employs a box-filter-approximated second-order differential operator to locate extrema in the scale space. The efficiency improvement from SIFT to SURF is large due to the use of integral image. For a given image I and pixel (x, y), the integral image at the point refers to the sum of the pixel values of all pixels in the rectangular region from the image origin to the pixel (x, y). Once an image is converted into an integral image, the sum of the pixels within a rectangular region can be calculated by three addition and subtraction operations. This method effectively improves the efficiency because the area of the rectangle does not affect the amount of computation. To ensure that the detected feature points have rotation and scale invariance, it is necessary to determine the orientation of the feature points. Haar wavelet plays an important role in the construction of the orientation for SURF feature points. The advantage of using Haar wavelet is that only 6 operations are required to obtain the X and Y gradients.

FAST

FAST algorithm (Rosten and Drummond, 2006) is an accelerated segment test algorithm based on machine learning. The feature points are extracted by segmenting the distribution of gray values in the neighborhood of the detected points. It mainly consists of three steps for determining whether pixel m is a feature point. The first step is to perform a segmentation test on a circle with the pixel m as the center and a radius of 3 pixels, removing a large number of points. The second step is the detection of feature points based on classification, using a machine learning ID3 greedy algorithm to build a decision tree. The last step is to use non-maximal suppression after detecting the candidate corner points. This is done by obtaining the sum of the absolute difference between the pixels, then the values of two adjacent interest points are compared and the lower one is discarded.

BRISK

Leutenegger *et al.* (2011) proposed a new binary detector and descriptor BRISK (Binary Robust Invariant Scalable Keypoints) with scale invariance and rotation invariance. The key steps of the BRISK algorithm are feature point extraction, binary feature description and feature matching. The first stage is to construct a scale-space pyramid structure, and then use an AGAST (adaptive and generic accelerated segment test) algorithm (Mair *et al.*, 2010) to extract local extreme points in continuous scale space. The image pyramid built by the BRISK algorithm contains 4 common layers and 4 middle layers. The essence of AGAST is the improvement of FAST algorithm. AGAST algorithm is applied to detect the feature points in all layers of the image. In order to eliminate the feature points with lower accuracy, the non-maximum suppression method is adopted. When interpolation is used to estimate parameters, high accuracy feature points can be obtained in continuous scale space. The second stage is to create a binary feature descriptor for the local image, and the last stage is to use the Hamming distance for matching.

ORB

The ORB (Oriented FAST and Rotated BRIEF) algorithm (Rublee *et al.*, 2011) combines an enhanced FAST feature point with a direction-normalised BRIEF (Binary Robust Independent Elementary Features) descriptor (Calonder *et al.*, 2010; Calonder *et al.*, 2012). The FAST algorithm mainly considers the gray level change of pixels. The candidate point is selected as a feature point if the difference between the measured point and its neighborhood is large enough. It can reduce the amount of computation. However, FAST algorithm does not have the scale and rotation invariance. In view of the above two disadvantages, ORB algorithm modifies the FAST detector. To achieve scale invariance, it uses pyramid to build a multi-scale space, allowing FAST algorithm to detect feature corners in different scale spaces. In order to achieve rotation invariance, the ORB algorithm uses an intensity centroid to add the local orientation to the feature points. The intensity centroid assumes that a corner's intensity is offset from its center, and this vector may be used to impute an orientation.

FREAK

FREAK (Fast Retina Key-point) algorithm (Vandergheynst *et al.*, 2012) was inspired by the retina. The region where light influences the response of a ganglion cell is the receptive field. They are segmented into four areas: foveal, fovea, parafoveal and perifoveal. When the object is identified, the central mainly identifies the details, and the surrounding area mainly identifies the outline information. The FREAK descriptor just simulates the structure of obtaining information in this subregion. It constructs a series of concentric rings centered on the feature points, typically a seven-layer circle. Each circle of the ring is taken six sampling points at equal intervals, for a total of 43 sampling points including the feature point. The rotation of the feature points is computed by the sum of the local gradients over selected pairs which are symmetric to each other.

DATASETS

The image databases used for evluation are introduced in this section. We prefer the wellknown Oxford dataset (Mikolajczyk *et al.*, 2005). We also include the ALOI dataset (Geusebroek *et al.*, 2005) and the database from USC-SIPI (2012). These datasets contain a very large variety of image transformations from real-world scenes.

The Oxford dataset (Fig 1) is used on purpose to test the robustness of image blurring, rotation, illumination and viewpoint. The ALOI dataset (Fig 2) is used for evaluating the illumination variation and viewpoint changes. The USC-SIPI dataset (Fig 3) is used for evaluating the rotation variation of textures.

Figure 1 The images of Oxford dataset.

Figure 2 The images of ALOI dataset.

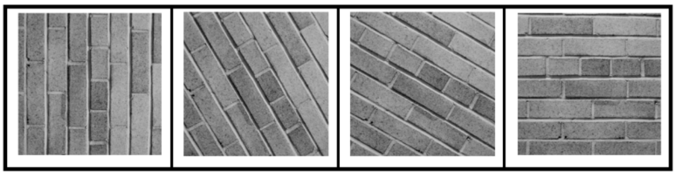

Figure 3 The images of USC-SIPI dataset.

EVALUATION METRICS

Precision=number of correct matches/number of total positive matches: we use the criterion proposed in (Mikolajczyk and Schmid, 2002) to verify the correct matches based on a known camera position. The Precision value means that how relevant the matched features to each other. It also represents the matching accuracy of a detector–descriptor pair, i.e., high Precision indicates a better pair.

Matching Ratio=number of correct matches/number of features: It represents how the descriptor has performed in extracting correct matches from initially detected features. This can also be evaluated as a metric measuring the pairing strength between a detector and a descriptor.

RESULTS

Comparison of robustness for rotation Variation

When the image rotates, the pixels will rotate around the rotation center. The gradient of the pixels around the feature points and the direction information of the feature points will change. The rotated images were matched with the original image, and the number of feature point pairs that can be correctly matched was compared. The comparison results are shown in Table 1.

Table 1 Precision and Matching Ratio values for rotation variation（ST: SIFT, SF: SURF, BK: BRISK, OB: ORB, FK: FREAK, FT: FAST.

Evaluation Metrics	ST-ST	SF-SF	BK-FK	BK-BK	OB-OB	FT-BK
Precision	0.42	0.39	0.21	0.26	0.36	0.19
Matching Ratio	0.26	0.17	0.15	0.18	0.20	0.13

Comparison of robustness for illumination Variation

To analyze the performance of methods under increasing level of illumination, an experiment was conducted on Oxford and ALOI datasets. For this purpose, the brightness of the same image was gradually reduced, and the changed image was matched with the original image. The comparison results are shown in Table 2.

Table 2 Precision and Matching Ratio values for illumination variation (ST: SIFT, SF: SURF, BK: BRISK, OB: ORB, FK: FREAK, FT: FAST).

Evaluation Metrics	ST-ST	SF-SF	BK-FK	BK-BK	OB-OB	FT-BK
Precision	0.26	0.25	0.27	0.32	0.36	0.27
Matching Ratio	0.18	0.15	0.20	0.26	0.24	0.22

Comparison of robustness for Blur Variation

The experiment was conducted on bikes and trees images of Oxford datasets. The resolution decreases after the images blurred. The images have a minimum resolution. For the resolution in excess of minimum, the performance is improved steadily with the increase of the resolution. The comparison results are shown in Table 3.

Table 3 Precision and Matching Ratio values for blur variation (ST: SIFT, SF: SURF, BK: BRISK, OB: ORB, FK: FREAK, FT: FAST).

Evaluation Metrics	ST-ST	SF-SF	BK-FK	BK-BK	OB-OB	FT-BK
Precision	0.44	0.35	0.30	0.24	0.43	0.45
Matching Ratio	0.34	0.21	0.25	0.21	0.27	0.40

Comparison of robustness for Viewpoint Variation

The experiment was conducted on viewpoints change datasets, i.e., wall and graffiti of Oxford datasets and ALOI datasets. The changes in the viewpoint will cause some feature points to fall on the edge or outside of the original image. The larger the viewpoint changes, the less the original features can be retained. The original scene was rotated in a certain angle, and the images from different viewpoint were matched with the original image. The comparison results are shown in Table 4.

Table 4 Precision and Matching Ratio values for viewpoint variation（ST: SIFT, SF: SURF, BK: BRISK, OB: ORB, FK: FREAK, FT: FAST）.

Evaluation Metrics	ST-ST	SF-SF	BK-FK	BK-BK	OB-OB	FT-BK
Precision	0.42	0.31	0.31	0.26	0.34	0.26
Matching Ratio	0.30	0.16	0.22	0.17	0.25	0.19

DISCUSSION AND CONCLUSIONS

It is an important research content for the robustness in different image transformations. This paper introduced several popular feature algorithms, and compared the robustness of the algorithms in four commnon image transformations. We conducted comparisons of invariance against rotation, illumination, blur and viewpoint variation in terms of Precision and Matching Ratio. In all tests except for illumination variation, SIFT detectors and descriptors obtained better results than the other combinations. SURF detection operator and descriptor have a good Precision. However, the Matching Ratio is poor, which indicates that the pairing strength between the detector and the descriptor is weak. We also find that ORB algorithm performs best under various changes in all binary algorithms. The above conclusions can provide a reference for image matching. How to design a more scientific performance metrics is the future work.

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