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Research Article

A COMPARATIVE EXPERIMENTAL STUDY OF INTEREST POINT DETECTORS AND FEATURE DESCRIPTORS FOR VISUAL NAVIGATION

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A B S T R A C T

Feature detection and matching is the first important module of visual navigation system. Therefore, how to select a pair of good feature detector and descriptor is a problem that visual navigation system must face. So far, there are many kinds of feature detectors and descriptors appearing in the literature, and the methods used are quite different. Although scholars try to make up for some shortcomings of existing algorithms, each feature detector or descriptor has its own advantages and disadvantages, but there is no perfect scheme to adapt to all applications. In this case, it is of great significance to evaluate the characteristics of feature detectors and descriptors.

INTRODUCTION

Features refer to specific and meaningful structures in images. It can be a single pixel, edge and contour, or even a target in the image. Feature detection is the process of finding these meaningful structures in images. The output of feature detector used by visual navigation is usually specific positions in the image, called feature points. These features usually have strong tolerance for noise, illumination and various image transformations. In feature matching, feature points need to be represented by feature descriptors. As the basis of feature matching, feature descriptors represent a subset of the total pixels near the feature points, or other metrics generated by the feature points. Feature descriptors can make features more stable. Some feature algorithms only contain feature detector, such as Harris (Harris and Stephens, 1988), FAST (Rosten and Drummond, 2006), CENSURE (Agrawal *et al*., 2008), etc. Some feature algorithms only contain feature descriptors, such as BRIEF (Calonder *et al*., 2010), FREAK (Vandergheynst *et al*., 2012), NESTED (Byrne and Shi, 2013), etc. Some feature algorithms design feature detector and feature descriptor, such as SIFT (Lowe, 1999), SURF (Bay *et al*., 2006), ORB (Rublee *et al*., 2011), BRISK (Leutenegger *et al*., 2011), etc. Several feature algorithms to be evaluated in this paper are shown in Table 1. When choosing feature algorithms, this paper tries to select different types of feature detectors and descriptors from the aspects of methods, popularity and age.

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Table 1 The feature algorithms to be evaluated.

Algorithms	Year	Detector/Descriptor	Rotation Invariant	Scale Invariant
SIFT	1999, 2004	detector, descriptor	Yes	Yes
SURF	2006	detector, descriptor	Yes	Yes
FAST	2006	detector	Yes	Yes
CENSURE	2008	detector	Yes	Yes
BRIEF	2010	descriptor	No	No
ORB	2011	detector, descriptor	Yes	Yes
BRISK	2011	detector, descriptor	Yes	Yes
FREAK	2012	descriptor	Yes	Yes

Experimental Design

In order to evaluate the performance of various feature algorithms comprehensively and fairly, this paper designs experiments from three aspects: datasets, evaluation metrics and matching method.

Datasets

This paper chooses four existing image datasets for experiment, namely Oxford dataset (Mikolajczyk *et al*., 2005), ALOI dataset (Geusebroek *et al*., 2005), USC-SIPI and dataset provided by Heinly. These datasets cover various types of image transformation. Oxford dataset is composed of bark, bikes, boat, graf, leuven, trees, UBC and wall. Each subset contains six images and five matrices. Each subset is designed for specific image transformation. Five matrices represent the homography transformation from the original image (the first image) to other images, respectively. ALOI dataset record 1000 images of objects by systematically changing the imaging conditions such as illumination and viewpoint. Each object produces more than 1000 images, so the dataset contains a total of 110,250 images. USC-SIPI is a digital image dataset. Its first version was released in 1977, and new images have been added to it since then. The dataset is mainly used for image processing and analysis and machine vision research. Heinly datasets are mainly used to measure the pure rotation, scale and illumination changes of images. Since the above three datasets do not contain images with pure scale changes, Heinly dataset can be used as a supplementary dataset.

Considering the application environment of intelligent vehicle visual navigation, this paper mainly evaluates the performance of feature algorithm under five image transformations, including illumination, viewpoint, blur, rotation and scale transformation.

Evaluation metrics

In order to evaluate the performance of the feature algorithm, it is necessary to design reasonable performance evaluation metrics. There are many evaluation metrics for feature algorithm, such as Precision, Recall, Repeatability, Matching Score, Efficiency and Stability. Specific evaluation metrics should be selected for specific applications. This paper chooses Precision and Recall to evaluate the performance of the feature algorithm.

Precision

Precision is defined by the following formula:

$$\text{Precision} = \frac{N_p}{N_p + N_F} \tag{1}$$

Where N_p denotes the number of correct matching and N_F denotes the number of wrong matching. The criterion of correct matching pairs and mismatching pairs is whether they can be geometrically verified by the known camera position. Precision characterizes the accuracy of a pair of feature detector and feature descriptor. Precision has a significant impact on the performance of robust parameter estimation. For example, the execution time of RANSAC algorithm increases exponentially with the decrease of the proportion of inliers.

Recall

Recall is defined by the following formula:

$$\text{Recall} = \frac{N_p}{N_c} \tag{2}$$

Where N_p denotes the number of correct matching, and N_c denotes the total number of features given two images. The Recall represents the ability of descriptors to obtain correct matching pairs from a certain number of matching pairs. It can also measure the compactness between a pair of feature detector and descriptor. If a feature descriptor is more selective when combined with a feature point, the Recall will be higher. In addition, the stricter the matching criteria is set, the lower the Recall will be.

Matching Method

The search algorithm of feature matching is brute force search algorithm. The default parameter values of OpenCV are used for the parameters of various feature algorithms, and there is no special restriction on the number of feature points extracted. The matched feature points are re-projected to the original image by homography matrix (plane geometry) or three-dimensional motion matrix (non-plane geometry), and the re-projection error is calculated. In this paper, the threshold of the inliers is set to 2, that is to say, the matching with the re-projection error less than 2 is considered to be the correct matching. This is an empirical value, this value should not be too large, otherwise some mismatches will be regarded as correct matches; this value can not be too small, because measurement and re-projection will have certain errors. Finally, Euclidean distance is used as similarity criterion for SIFT and SURF descriptors, and Hamming distance is used as similarity criterion for ORB, BRIEF, BRISK and FREAK.

Experimental Results and Analysis

According to the experimental method designed above, the eight feature algorithms in the introduction are evaluated. Six of these feature algorithms include feature detectors: SIFT, SURF, FAST, CENSURE, ORB and BRISK, respectively; there are six algorithms including feature descriptors, they are SIFT, SURF, BRIEF, ORB, BRISK and FREAK. Since feature detection detectors and feature descriptors are used in pairs, this paper does not evaluate the performance of a single feature detector or feature descriptor. We evaluate the performance of the feature pairs after the combination of the two. The evaluation object is 6 x 6 = 36 feature pairs. Table 2-6 lists the experimental datas of the Precision and Recall of each feature pair in five image transformations. For the convenience of displaying in the table, the abbreviations of each feature algorithm are as follows: SIFT (ST), SURF (SF), FAST (FT), CENSURE (CN), BRIEF (BF), ORB (OB), BRISK (BK), FREAK (FK). Table 7 ranks the Precision and Recall of each feature pair based on the average data in Table 1-5.

Table 2 Illumination.

(a) Precision （%）

	BF	BK	FK	OB	ST	SF
BK	52	48	44	47	47	32
CN	39	29	48	36	47	30
FT	52	41	36	47	57	35
OB	40	42	32	52	40	41
ST	37	25	24	32	29	23
SF	33	26	29	25	29	44

(b) Recall （%）

	BF	BK	FK	OB	ST	SF
BK	38	42	30	38	32	24
CN	31	24	35	29	36	22
FT	36	34	27	35	44	26
OB	20	26	20	35	23	25
ST	24	16	17	22	23	16
SF	24	18	20	19	20	34

Table3 Viewpoint.

(a) Precision （%）

	BF	BK	FK	OB	ST	SF
BK	41	43	47	42	39	35
CN	41	36	36	37	45	36
FT	51	38	43	44	47	26
OB	41	47	48	47	36	39
ST	39	36	36	34	38	26
SF	35	33	36	32	29	43

(b) Recall （%）

	BF	BK	FK	OB	ST	SF
BK	31	36	33	31	28	26
CN	32	27	27	29	33	20
FT	36	32	33	34	36	21
OB	25	32	32	36	24	26
ST	26	24	24	26	29	19
SF	27	25	27	24	21	35

Table 4 Rotation.

(a) Precision （%）

	BF	BK	FK	OB	ST	SF
BK	40	75	81	32	35	60
CN	40	82	78	32	38	42
FT	42	80	78	33	38	39
OB	36	83	83	82	73	67
ST	34	86	80	86	88	47
SF	33	69	71	65	60	70

(b) Recall （%）

	BF	BK	FK	OB	ST	SF
BK	21	61	59	17	19	46
CN	31	72	64	25	26	38
FT	22	71	67	19	22	29
OB	22	66	67	67	57	49
ST	20	66	61	73	76	32
SF	17	54	54	50	45	55

Table 5 Blur.

(a) Precision（%）

	BF	BK	FK	OB	ST	SF
BK	55	42	46	52	44	31
CN	67	51	51	65	66	33
FT	74	57	55	75	75	19
OB	67	55	52	60	52	53
ST	67	49	55	55	62	24
SF	73	65	66	56	60	61

(b) Recall（%）

	BF	BK	FK	OB	ST	SF
BK	46	38	36	43	36	27
CN	58	43	42	56	56	27
FT	64	52	50	68	69	17
OB	38	40	38	46	37	36
ST	45	33	36	41	46	18
SF	61	53	55	46	46	50

Table 6 Scale.

(a) Precision（%）

	BF	BK	FK	OB	ST	SF
BK	66	59	58	35	50	51
CN	48	50	45	53	64	31
FT	60	38	68	43	66	34
OB	71	76	56	39	71	68
ST	41	40	50	35	62	43
SF	39	52	50	43	45	60

(b) Recall（%）

	BF	BK	FK	OB	ST	SF
BK	43	43	37	25	31	34
CN	36	35	32	40	45	23
FT	41	29	48	33	49	25
OB	41	54	38	35	45	44
ST	28	26	32	27	43	27
SF	28	35	35	30	29	44

Table 7 Average rank.

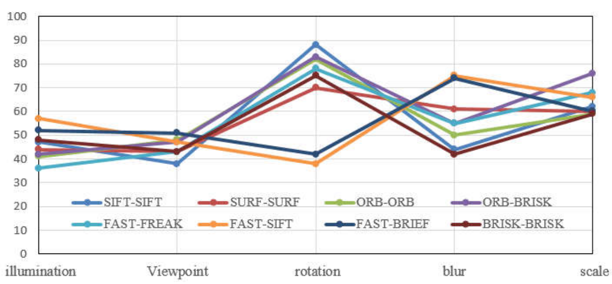
(a) Precision（%）

	BF	BK	FK	OB	ST	SF
BK	50.8	53.4	55.2	41.6	43	41.8
CN	47	49.6	51.6	44.6	52	34.4
FT	55.8	50.8	56	48.4	56.6	30.6
OB	51	60.6	54.2	56	54.4	53.6
ST	43.6	47.2	49	48.4	55.8	32.6
SF	42.6	49	50.4	44.2	44.6	55.6

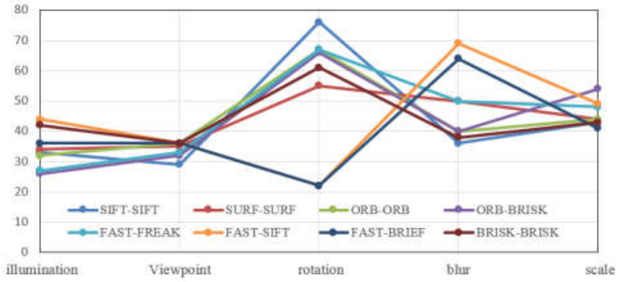
(b) Recall（%）

	BF	BK	FK	OB	ST	SF
BK	35.8	44	39	30.8	29.2	31.4
CN	37.6	40.2	40	35.8	39.2	26
FT	39.8	43.6	45	37.8	44	23.6
OB	29.2	43.6	39	43.8	37.2	36
ST	28.6	33	34	37.8	43.4	22.4
SF	31.4	37	38.2	33.8	32.2	43.6

A good feature pair needs both high Precision and Recall. Therefore, eight feature pairs with the highest Precision and Recall are selected as candidate feature pairs of the system. They are SIFT-SIFT (5, 8), SURF-SURF (7, 5), ORB-ORB (3, 4), ORB-BRISK (1, 5), FAST-FREAK (3, 1), FAST-SIFT (2, 2), FAST-BRIEF (5, 11), BRISK-BRISK (12, 2). Figure 1 shows the score curves of the Precision and Recall obtained from the above eight feature pairs in five image transformations. From the figure we can see that some curves are relatively flat (SURF-SURF), which shows that these features are relatively stable in various image transformations. Some curves fluctuate sharply (FAST-BRIEF), which shows that the performance of these features in various image transformations is quite different. Because the five kinds of image transformation are often encountered in intelligent vehicle vision odometry system, we select feature pairs with stable characteristics as far as possible.



(a) Precision



(b) Recall

Figure 1 Score curves of Precision and Recall.

In order to facilitate further analysis, the performance of feature pairs is divided into three grade: good, medium and bad. For an image transformation, three "good" feature pairs are usually selected, but it can be seen from the curve that FAST-SIFT and FAST-BRIEF perform better than other feature pairs when the image is blur. In this case, only two "good" feature pairs are selected. For an image transformation, two "bad" feature pairs are usually selected. The feature pairs that are neither "good" nor "bad" are classified as "medium". Table 8 lists the grade of the eight features for five image transformations.

From the table we can see that SIFT-SIFT, FAST-FREAK, FAST-BRIEF and BRISK-BRISK have obtained two "bad" feature pairs. Among them, SIFT-SIFT, FAST-FREAK and BRISK-BRISK all performed the same, and obtained two "bad", two "medium" and one "good". FAST-BRIEF obtains two "bad" and three "good", which again shows that the performance of the feature varies greatly under five image transformations. The remaining four feature pairs SURF-SURF, ORB-ORB, ORB-BRISK and FAST-SIFT obtained at most one "bad". Therefore, these feature pairs can be used to construct a visual navigation system.

Table 8 The grade of the features for five image transformations.

	ST-ST	SF-SF	OB-OB	OB-BK	FT-FK	FT-ST	FT-BF	BK-BK
illumination	medium	medium	medium	bad	bad	good	good	good
viewpoint	bad	medium	good	medium	bad	good	good	medium
rotation	good	medium	good	good	medium	bad	bad	medium
blur	bad	medium	medium	medium	medium	good	good	bad
scale	medium	medium	medium	good	good	good	bad	bad

DISCUSSION AND CONCLUSIONS

In this paper, 36 feature pairs consisting of eight feature algorithms are evaluated using a variety of datasets. Precision and Recall are used as evaluation metrics. The robustness of the 36 features to illumination, viewpoint, rotation, blur and scale is tested. Finally, four best feature pairs for visual navigation system are selected.

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