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A Robust method for constructing rotational invariant descriptors



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ABSTRACT

Unlike most existing descriptors that only encode the spatial information of one neighborhood for each sampling point, this paper proposed two novel local descriptors which encodes more than one local feature for each sampling point. These two local descriptors are named as MIOP (Multi-neighborhood Intensity Order Pattern) and MIROP (Multi-neighborhood Intensity Relative Order Pattern), respectively. Thanks to the rotation invariant coordinate system, the proposed descriptors can achieve the rotation invariance without reference orientation estimation. In order to evaluate the performance of the proposed descriptors and other tested local descriptors (e.g., SIFT, LIOP, DAISY, HRI-CSLTP, MROGH), image matching experiments were carried out on three datasets which are Oxford dataset, additional image pairs with complex illumination changes, and image sequences with different noises, respectively. To further investigate the discriminative ability of the proposed descriptors, a simple object recognition experiment was conducted on three public datasets. The experimental results show that the proposed local descriptors exhibit better performance and robustness than other evaluated descriptors.

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1. Introduction

Local feature descriptors have a great impact on the performance of computer vision system. Therefore, many local descriptors are proposed by researchers in recent decade and have been successfully used in computer vision applications, such as structure from motion [1–4], object recognition [5], classification [6], texture recognition [7], and image stitching [8]. Local features mainly include interest points and interest regions. The computation of interest points detection is simpler than that of interest regions detection. Many different approaches for the interest points detection have been proposed in literatures [9,10], and some local descriptors [11,12] also contain feature points detector. However, the vision system using interest points shows poor performance under the condition of large viewpoint changes. To alleviate this problem, various methods for interest regions detection were proposed by researchers [13,14].

A good local feature descriptor should have high discriminative and rotation invariant ability so that the detected local feature can be easily distinguished from other features. To achieve this goal, various descriptors [12,13,15–19] have been proposed by researchers in recent decade. These descriptors usually estimated a reference orientation for the local descriptor to achieve its rotation invariance. However, the orientation estimation is an error-prone process and the estimation error might

result in the mismatch of the correct corresponding features, which have been proven in Refs. [18,20]. To avoid calculating the reference orientation, many inherently rotation invariant local descriptors have been developed in the past decade [18,20–23]. In general, the local descriptors without reference orientation show poorer performance than those with reference orientation. However, the rotation invariant local descriptors are said to possess better performance [18,20–23].

Usually, the more spatial information of support region a local descriptor encodes, the better discrimination ability it shows. Hence, we proposed a novel method to encode more than one local feature for each sampling point in the image patch. And then two local descriptors named as MIOP and MIROP are proposed in this paper.

The rest of the paper is organized as follows: a brief overview of some related work is presented in Section 2; Section 3 illustrate the details of the MIOP and MIROP descriptor, respectively; the experimental results and performance evaluation are given in Section 4; Section 5 summarizes the conclusion.

2. Related work

In this section, we briefly introduce the well-known local feature detection methods and local descriptors.

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2.1. Local interest features

Local interest features detection is a first step in most computer vision tasks. Local interest features mainly include interest point and interest region. Harris corner points [10] and FAST (Features from Accelerated Segment Test) points [9] are widely used in computer vision system. The Harris point detector moves a small window in all directions. If the grayscale intensity of pixels in this window shows a large change, that means there is a corner point in the window. FAST compares the intensities of 16 pixels around the central pixel. If the intensity of more than 12 pixels is significantly different from that of the central pixel, the central pixel should be classified as an interest point. One problem of FAST is that it does not have scale invariance. Harris point has certain affine invariance, but its detection speed is slower than FAST. In addition, some famous local descriptors [11,12] also include interest points detector. For example, SIFT (Scale Invariant Feature Transform) [11] descriptor detects interest points by searching local extrema in the DoG (Difference of Gaussian) scale space. The DoG interest point shows better scale invariance and affine invariance than Harris points and FAST, but its detection speed is lower than FAST and Harris. The vision system using local interest points shows good performance in most application scenarios, except the scene with large viewpoint changes. To alleviate this problem, many affine invariant region detectors are proposed in Refs. [13,14,24,25]. These affine regions such as Hessian-affine regions and Harris-affine regions are invariant to affine image transformations and can work well in the case of large viewpoint changes. The main drawback of these local interest regions is that the calculation process is more complex than that of interest points detection. To fairly evaluate the performance of local descriptors, we adopted the same evaluation procedure and evaluation criterion proposed by Mikolajczyk [19], and chose the Hessian-affine regions and Harris regions for the image matching experiments.

2.2. Local feature descriptors

Meanwhile, local descriptors have been paid more and more attention in the computer vision community. Many local descriptors were proposed by researchers in the past decade. SIFT (Scale Invariant Feature Transform) developed by Lowe [11] is probably the most famous local feature descriptor. It is a 3D histogram of gradient location and orientation where the contribution to the location and orientation bin is weighted by the gradient magnitude. Inspired by SIFT, many variants of it were proposed by researchers. Ke and Sukthankar [26] applied PCA (Principal Component Analysis) method to reduce the dimension of the SIFT, and proposed the PCA-SIFT descriptor which was said to be more compact and distinctive than SIFT. The GLOH (Gradient Location and Orientation Histogram) [19] descriptor replaced the Cartesian location grid in SIFT with the log-polar location grid, and applied PCA method to reduce the size of the descriptor. The SURF (Speed Up Robust Feature) descriptor [12] used a Hessian matrix-based measure for local feature detection and Haar Wavelet responses for the descriptor. Its construction time is significantly reduced by using integral image instead of image convolutions. Tola et al. [27] developed a fast descriptor on circular regions around the key point for dense matching, namely DAISY. Winder and Brown [28] proposed a framework to learn local descriptors with different combinations of local features and feature pooling schemes.

These descriptors mentioned above are usually time-consuming and much more complex. To reduce the dimension and complexity, many local binary descriptors were proposed by researchers in recent years [20,29–32]. For example, Ethan Rublee et al. [29] developed a binary descriptor ORB which combines the FAST interest points operator and the BRIEF descriptor, and it has a better performance than SIFT in many conditions, including light changes, image blur, and perspective distortion. However, these binary descriptors usually need to be trained by large sample data. Thus, their performance and robustness are significantly affected by the sample data.

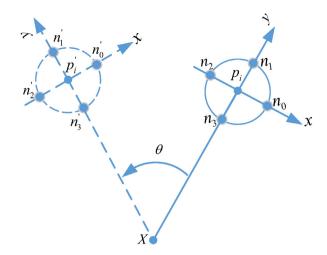


Fig. 1. Rotation invariant coordinate system.

Recently, many intensity ordinal information based local descriptors were presented by researchers. Gupta et al. [15] presented a new feature descriptor HRI-CSLTP by combining the CS-LTP and relative intensities. Tang et al. [33] calculated a 2D histogram which encodes both the spatial distribution and the ordinal distribution to deal with complex brightness changes. Heikkila et al. [34] proposed a CS-LBP descriptor combined the strength of the SIFT descriptor and LBP texture operator, and the obtained descriptor was reported to have better performance than SIFT. Goswami et al. [35] presented another descriptor based on LBP method which computed pairwise ordinal information from adjacent circular neighborhoods.

The above-mentioned local descriptors usually require an estimated reference orientation to achieve their rotation invariance. However, the error estimation of orientation might cause the mismatch between corresponding features. This fact has been proven in Refs. [18,20]. To avoid estimating reference orientation, some methods have been proposed by researchers. For example, Ojara et al. [21] rotated image patch to obtain the smallest output of LBP. In this way, the local descriptor achieves the rotation invariance without calculating the reference orientation. Wang et al. [22,23] presented a rotation invariant coordinate system and built a rotation invariant local descriptor LIOP which shows better performance than SIFT, especially in the condition of drastic illumination changes. As shown in Fig. 1, suppose X is the center pixel in the image patch, p_i is a pixel in the image patch, n_i are the neighboring points of p_i . The local rotation invariant coordinate system for p_i can be established by setting $\overrightarrow{X}\overrightarrow{p_i}$ as the positive y-axis. The pixel p_i is moved to p_i' as image patch is rotated by the angle θ . It is obviously that, the relative position between the pixel p_i and its neighboring points n_i is unchangeable. Thus, the local feature calculated on this coordinate system does not change whether the image is rotated or not. Therefore, local descriptor built on this coordinate system achieves rotation invariance without reference orientation.

Bin fan et al. [18] proposed a method to build a local descriptor, namely MROGH, by using the gradient information of the neighboring points around one sampling point, in which multi-support regions technology was adopted in the construction of local descriptor to further enhance its robustness. After the above description, a simple comparison between different local descriptor is given in Table 1. The legends in the first row of Table 1 represent the comparison items. For example, the caption "reference orientation" denotes whether the local descriptor needs to estimate the reference orientation. The captions such as image blur, affine changes, light changes and scale changes represent the performance of local descriptor under these test scenarios. The local descriptor gets higher rank means it shows better performance than others in this test condition. The last caption "computing time"

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