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Robust Differential Circle Patterns based on fuzzy membership-pooling: A novel local image descriptor

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ABSTRACT

This paper presents a novel image descriptor, which is robust to a variety of photometric and geometric image transformations. Specifically, the Robust Differential Circle Patterns (RDCP) are proposed to encode the continuous intensity changes along the circular-shaped structures around each pixel. Compared to the pixel-wise feature computing schemes, RDCP is capable of describing relatively large local structures in the image. While in the descriptor constructing stage, the proposed fuzzy membership-pooling algorithm can not only capture the local structure of the interest region but also achieve rotation invariance inherently. Experimental results on three popular datasets (Oxford dataset, Patch dataset, and Ukbench dataset) demonstrate the superiority of proposed method over the state-of-the-art algorithms under various image transformations such as rotation and scaling changes, viewpoint changes, image blurring, JPEG compression, illumination changes, and image noise.

1. Introduction

A local image descriptor is a fundamental building block in computer vision community. In the last decade, it has been widely used in many visual tasks such as wide baseline stereo [1,2], object recognition [3,4], object classification [5], and texture classification [6–8].

Generally speaking, interest points or interest regions are firstly extracted by a variety of detectors (e.g. DOG (Difference of Gaussian) [3], Harris-affine [9], Hessian-affine [10], and Maximally Stable Extremal Region [11]). Then, local image descriptors of these interest points (regions) are computed to achieve various sorts of invariant properties, such as invariance to rotation, invariance to illumination change, and invariance to scale change. In this paper, we focus our works on the developing of invariant local image descriptor.

In recent years, a large number of local descriptors have been proposed and received a lot of attention. The most famous one is Scale Invariant Feature Transform (SIFT) [3]. As shown in Fig. 1(a), in order to characterize the image contents and assign dominant orientations, SIFT performed gradient computing on each sample point based on its four neighboring pixels. Thanks to the three-dimensional histogram of gradient location and orientation, SIFT achieved very good performances with both discriminative ability and robustness. After Lowe's pioneering work in this field, a number of SIFT-like local image descriptors are reported. For example, instead of using SIFTs' weighted histograms, the PCA-SIFT [12] algorithm applied Principal Components Analysis (PCA) to the normalized gradient patch, in order to be more robust to image deformations, and to be more compact than the standard SIFT representation. Another extension of SIFT is Gradient location-orientation histogram (GLOH) [13]. It changed the spatial structure of SIFT by using the log-polar location grid to accumulate the histogram and combined the PCA method to further reduce the feature dimension. To have a better computation time, DAISY [2] replaced the weighted sums of gradient norms with the convolutions of the gradients in specific directions with several Gaussian filters. It obtained promising experimental results in the case of dense wide-baseline matching. Although having different technological contributions, PCA-SIFT, GLOH, and DAISY still utilized the gradient information as the basic element to represent the local image distribution.

On the other hand, more and more ideas within different aspects of SIFT work-flow were investigated, from the interpretation of local pixel relationships to the histogram accumulating strategy. In order to improve the computational efficiency and lower the storage requirements, another family of local image descriptor is proposed, namely the so-called “Binary Feature Descriptors”. BRIEF [14], ORB [15], BRISK [16], and FREAK [17] are typical types of such binary descriptors. Generally, they share a common view that local structures can be represented by a set of

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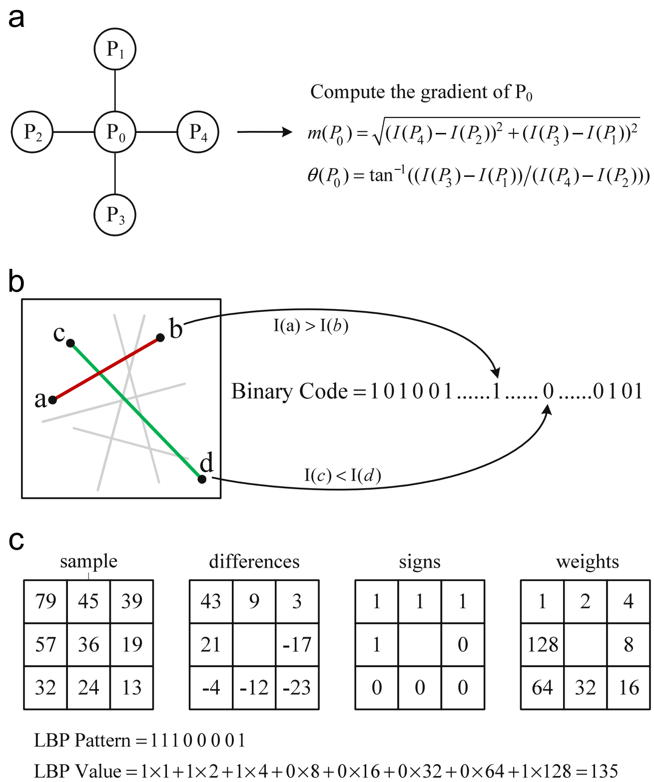

Fig. 1. Examples of local feature computing. (a) Gradient calculation in SIFT, where $I(x)$ stands for the intensity of pixel x. (b) In binary descriptors, the local features are generated by pairwise intensity comparisons. (c) One sample example of Local Binary Patterns.

pairwise intensity comparisons. Thus, in the fixed sampling pattern, each comparison was transformed into one bit of the binary strings. Moreover, the similarity between these bit vectors can be measured efficiently by computing the Hamming distance. The methodology is illustrated in Fig. 1(b). To be more comprehensive, instead of doing pairwise comparisons at a patch-level, the Local Binary Pattern (LBP) [7] and its variations (CS-LBP [18] and CLBP [8]) performed the binary test in a more local way. As shown in Fig. 1(c), the binary pattern was extracted by comparing the relative intensities between central pixel and its surroundings. Then, a LBP histogram was built to represent the whole image patch. Basically, because of the intensity comparison method, the "binary feature descriptors" and the LBPs are invariant to illumination changes, and gain great success in many tasks such as texture classification and object recognition.

As for the histogram accumulating strategy, LIOP [19], MROGH [20,21], and MRRID [21] were proposed to build feature histograms by using the intensity order pooling algorithm, which is robust to monotonic intensity changes. But in terms of local feature representations in LIOP, MROGH, and MRRID, we can find out that their basic structures are very similar to what we have introduced above [19,21]. Fundamentally, the gradient-based local feature in MROGH was extracted by computing the D_x and D_y on each pixel, which is basically identical to the method that is depicted in Fig. 1(a). Another descriptor proposed in [21] is MRRID. As mentioned in this paper, MRRID's intensity-based local feature was represented like CS-LBP. Therefore, it can be considered as an extension of the Local Binary Pattern. While in LIOP, the feature structure is a little bit different. As reported in the paper, for each pixel in the interest region, the intensities of its neighboring pixels were compared and sorted. So the local structures were interpreted by the intensity orders of these neighboring pixels.

To sum up, with respect to local feature representation, the image descriptors mentioned above are constructed based on the relationship of discrete pixels within the interest region. These pixel-wise computation schemes were successfully applied in many distribution-based descriptors because of their discriminative power. However, they have several drawbacks. Since the feature computing process is based on the sampling of individual pixels, these descriptors can be sensitive to image noise, which will eventually result in the miscalculating of local gradients or the LBP values. On the other hand, as shown in Fig. 1, the basic idea of these pixel-wise computing schemes is that the structure between two pixels can be characterized by their difference. Therefore, micro-structures in the image can be effectively extracted by gradients or local binary patterns. But because of the diversity and complexity of real world image, the uncertainty of structure between two tested pixels will increase with their spatial distance. It means that the pixel-wise feature computing is not suitable for capturing relatively larger patterns that are beneficial for image description.

In order to address these problems, we propose in this paper a novel local image descriptor based on Robust Differential Circle Patterns (RDCP). Firstly, the pre-normalized interest region will be divided into overlapped groups based on the fuzzy membership pooling algorithm. Then, the RDCP Features of each pixel in the interest region will be calculated under the polar coordinate system. To acquire the final descriptor, feature histograms that are accumulated in each group will be catenated for each multiple-sized region. The proposed descriptor is robust to many photometric and geometric transformations, such as rotation and scale changes, illumination changes, viewpoint changes, image compression, and image noise.

The rest of this paper is organized as follows. In Section 2, we present the algorithm for the computing of Robust Differential Circle Patterns. Section 3 introduces the framework of our proposed local image descriptor (RDCPD) which is formed based on the RDCP features. Section 4 then gives the experimental results to show the advantage of our proposed descriptor. Finally, conclusions are presented in Section 5.

2. The computation of Robust Differential Circle Patterns

To the best of our knowledge, many distribution based local image descriptors are built by utilizing the relationship of discrete pixels within a small region, such as gradient-based descriptors like SIFT [3], GLOH [13], MROGH [20,21], and intensity-based binary descriptors like LIOP [19], LBPs [7,18,8]. As analyzed in the introduction section, one drawback of this type of descriptors is that their description ability is usually limited to the micro-structures, so larger image contents that are beneficial for the description cannot be well characterized. Therefore, in order to investigate relatively larger patterns in the image and to examine how pixels are locally organized within these patterns, we propose in this paper the Robust Differential Circle Patterns (RDCP). In general, RDCP are designed to capture the local circular-shaped structures around each pixel and can be utilized as the basic building blocks of our local image descriptor.

As illustrated in Fig. 2, for each pixel P_i in the interest region, a circle C_i (centered at P_i) is sampled around it. The radius of C_i is set to r_i. Compared to the pixel-wise structures in common feature computing methods, circle C_i is sampled as a continuous pixel array. Thus, in order to extract adequate and useful information without breaking such a well organized structure, the coding procedure is designed to run along the circle in one particular direction. The RDCP feature of P_i is calculated as follows:

(1) Choose a starting point v_0 and then sample pixel intensities from circle C_i along the anti-clockwise direction.