AN EFFECTIVE METHOD FOR IMAGE MATCHING BASED ON MODIFIED LBP AND SIFT

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Abstract: Scale Invariant Feature Transform (SIFT) is a very powerful and popular descriptor for image registration, which is commonly used in feature matching. However, there is still a need for improvement with respect to the matching accuracy of SIFT. In this paper, we present a combination of modified LBP and SIFT method for more reliable feature matching. The main idea of the proposed method is to extract spatially enhanced image features with modified Local Binary Pattern (LBP) from the images before implementation Difference-of-Gaussian (DoG) in SIFT. The proposed method is also robust to illumination changes, rotation and scaling of images. Experimental results show significant improvement over original SIFT.

1 INTRODUCTION

The image matching, an important component in image processing, is widely used in numerous applications that range from object recognition, building panoramas guidance, automatic surveillance, navigation, robot vision and mapping sciences, and so forth. For image matching, the technology based on Lowe's descriptor (Lowe, 1993; Lowe, 1991; Lowe, 2004) has merits of selecting stable features in a scale space, which is named Scale Invariant Feature Transform (SIFT). Recently, improvement techniques developed for SIFT are mostly foucsed on minimization of the reduction of computational time (H. Bay, 2006; G. Michael, 2006; Y. Ke, 2004).

Local Binary Pattern (LBP) is a powerful descriptor for texture feature analysis (T. Ojala and Maenpaa, 2002). In this paper, we propose a combination of modified LBP and SIFT method for more reliable feature matching. The proposed method helps emphasize some features, such as edges, in original images and then improves performance of image matching. The proposed method also carries on the good properties of LBP and SIFT, so that it is robust to gray scale, illumination, rotation and scaling variation.

By combining SIFT operator and Local Binary Pattern, it is shown to be a robust and effective approach for feature matching. In some cases, we got results of 100% correct matching . The advantages of our method is illustrated in the following part.

The rest of the paper is organized as follows. In Section 2, we first briefly describe the original SIFT and LBP. Sections 3 gives details for the proposed approach. Experiment results with the proposed method, and comparisons between our method and the SITF are shown in Section 4. The conclusion is given in the last section.

2 SIFT AND LBP METHODS

Before presenting in detail about our method, we give a brief review of the SIFT and LBP methods that form the basis of our work.

2.1 Scale Invariant Feature Transform

The scale invariant feature transform algorithm (Lowe, 2004) is an algorithm for image features generation which is invariant to image translation, rotation, scaling, illumination changes and partially affine projection. SIFT first searches over all scales and locations of the original image. It is implemented efficiently by using a Difference-of-Gaussian (DoG) function to identify potential interesting points.

Then for each candidate interesting location, a detailed model is fit to determine location and scale. Key-points are selected based on measures of their stability. After the key-point location, one or more orientations are assigned to each key-point location

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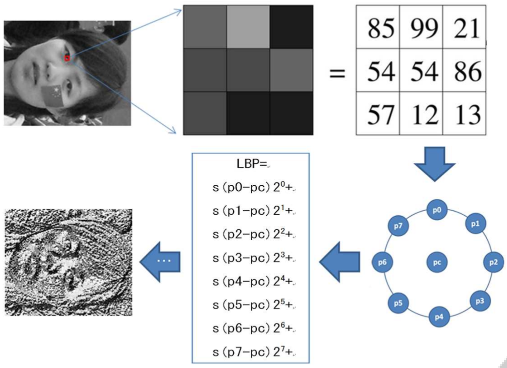

Figure 1: LBP features for a neighborhood of 8 pixels.

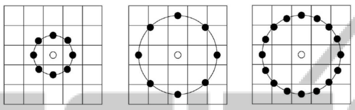

Figure 2: The circular model (8,1), (8,2), and (16,2) neighborhoods.

based on local image gradient directions. All further operations are performed on the features which are assigned orientation, scale, and location, thereby providing invariance to these transformations.

2.2 Local Binary Pattern

The LBP operator was originally designed for texture description. The operator assigns a label to every pixel of an image by thresholding the neighborhood of each pixel in comparison with the center pixel value and transforms the pixel to a binary number (Fig. 1).

To be able to deal with textures in different scales, the LBP operator was later extended to use neighborhoods with different sizes (T. Ahonen and Pietikainen, 2004). Defining the local neighborhood as a set of sampling points evenly spaced on a circle centered at a pixel with radius in any length and sampling points in any number, bilinear interpolation is used when a sampling point does not fall in the center of a pixel. The notation (P,R) stands for pixel neighborhoods with P sampling points on a circle with radius of R (Fig. 2). If the graylevel of a pixel on the circle is equal to or greater than that of the central pixel, its value is set to be one, otherwise zero. The descriptor shows the results over the neighborhood

as a binary number (binary pattern):

$$LBP_{R,P}(x,y) = \sum_{i=0}^{P-1} s(p_i - p_c)2^i, s(x) = \begin{cases} 0, x<0 \\ 1, x\geq 0 \end{cases} \tag{1}$$

where p_c corresponds to the graylevel of the center pixel of a local neighborhood, and p_i to the graylevels of P equally spaced pixels on the circle of radius R.

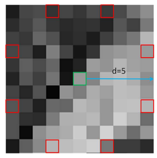

Figure 3: A sample of modified LBP model.

Since correlation between pixels decreases with distance, most texture information can be obtained from local neighborhoods, thus R is usually kept small. In practice, Eq. (1) means that the signs of the differences in a neighborhood are interpreted as a P-bit binary number, resulting in 2^P distinct values for the binary pattern.

3 THE COMBINATION OF MODIFIED LBP AND SIFT

The main objective of SIFT is to identify locations and key-points in an image. The SIFT generates key-points through finding the extrema of (DoG) function in an image. After a key-point candidate is found in comparison with its neighbors, detailed fit to the nearby data for location, scale, and ratio of principal curvatures is performed. These information allows pixels that have low contrast or are poorly localized along an edge to be rejected. The corresponding edges are discarded because they are sensitive to noise. However, this process is overly simplified, because it completely ignores the geometric information among descriptors. Some useful key-points are also discarded with eliminating edge responses. In order to improve the performance of describing an enhanced texture features image for SIFT-matching, we extracted spatially enhanced texture feature with LBP from images before the implementation of DoG in SIFT. Local Binary Pattern descriptor is used to help achieve finding more correct features. Unlike the original LBP, we used the points (the red ones in Fig. 3) distributed uniformly on the frame of the window, sized $D_8 = 2d$, where D_8 is a chessboard distance, and d is a user-settable parameter. The points used in LBP instead of interpolation value, also helps reduce the computational cost. Through experiments, this modified method has outstanding performance to emphasize features such as edges in the image, and based on which SIFT can find more correct features (Fig. 4).

In case of processing rotated images (Fig. 11), the LBP value changes after an image is rotated. We record the sequence of the binary pattern which forms the original LBP. For example, the pattern is

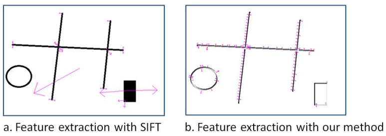

Figure 4: Results of feature extraction in comparison with SIFT method and our method.

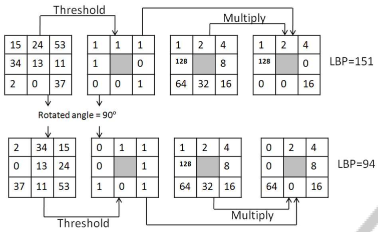

Figure 5: Comparison of LBP operator between the original image and the rotated image.

11101001 and the LBP value is 151 for the original image. The pattern changes to be 01111010 and the LBP value becomes 94 (Fig. 5) after the rotation of the image. Finally, we get two completely different LBP. During this transformation, SIFT cannot find correct features and match them.

In order to solve this problem, we also modify the LBP descriptor as:

$$LBP_{R,P}(x,y) = \sum_{i=0}^{P-1} s(p_i - p_c)256/P, s(x) = \begin{cases} 0, x<0 \\ 1, x \geq 0 \end{cases} \quad (2)$$

We used average value 256 /P instead of 2^i shown in Eq. (2).

Based on this simple modification, the LBP value keeps the same after rotation (Fig. 6), and SIFT can find the corresponding features correctly.

4 EXPERIMENTAL EVALUATION

In this section, a performance evaluation of the proposed method is presented. Our proposed method is assessed on the feature matching problem. The implementation of our proposal is based on the open source work from Lowe's SIFT detector (link-a). To ensure the reproducibility of the tests, the publicly available image data set (link-b) was utilized to test the performance of the proposed method. The test data contains images with different geometric and photometric transformations. Different transformations evaluated in this study are scale change, image rotation, image blur and illumination change. In the test we chose two different sets (illumination changed images are shown in Fig. 9, and blurred images are shown in Fig. 10) of the test data. And in order to study in more detail for

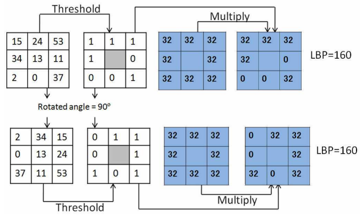

Figure 6: Comparison of the modified LBP operator between the original image and the rotated image.

Figure 7: Random face matching results of original SIFT and the proposed method.

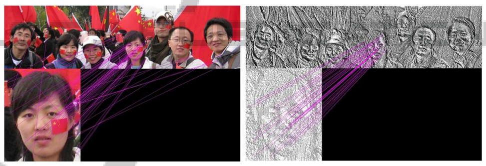

Figure 8: Enlarged random face matching results of original SIFT and the proposed method.

the tolerance of our descriptor, we took another 4 sets of photos (shown in Fig. 7, Fig. 8, Fig. 11 and Fig. 12). We also present the advantages of our proposed method compared to original SIFT (shown in Table. 1) through all the experiments.

First, we introduce two experiments which has very high accuracy of matching: we took photos of faces, and randomly cut one face from them. Then, original SIFT and our proposed method were used to find corresponding features between the two images (Fig. 7). As the results, we got 100% of correct positive match, 174 correct matches and 0 false match (Table. 1). On the other hand, we enlarged the size of the cut face, to compare our proposal with original SIFT method. We also got excellent results: 100% of correct positive match, 54 correct matches and 0 false matches (Table. 1).

Furthermore, the proposed method outperformed original SIFT on both illumination changed (Fig. 9) and blured images (Fig. 10). The advantages of our proposed method compared to original SIFT were shown in Table. 1.

To test matching of image rotation, we took photos of the same type projectors in different rooms. The level of illumination is not the same in the two rooms,

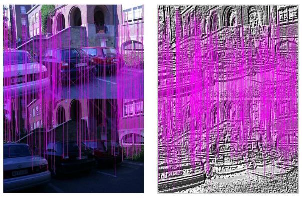

Figure 9: Illumination changed image matching results of original SIFT and the proposed method.

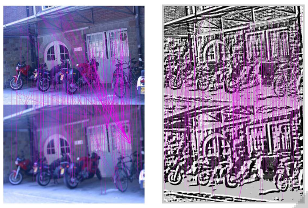

Figure 10: Image blur matching results of original SIFT and the proposed method.

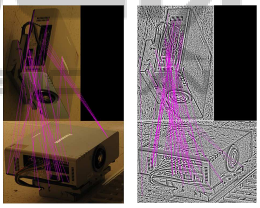

Figure 11: Image rotation (90^o) matching results of original SIFT and the proposed method.

Table 1: Comparison of the accuracy between the proposed method and original SIFT.

The proposed method			Original SIFT	
Test image	Correct	False	Correct	False
Fig. 7 (d=1; P=8)	174	0	71	34
Fig. 8 (d=1; P=8)	54	0	48	16
Fig. 9 (d=4; P=8)	897	9	384	17
Fig. 10 (d=11; P=8)	236	37	135	103
Fig. 11 (d=4; P=8)	55	0	24	7

that one photo is in normal direction, the other one is rotated 90^o (Fig. 11). As the result, we got 100% of correct match, 55 correct matches and 0 false match (Table. 1). Through all the experiments, our method showed outstanding performance comparing to original SIFT.

5 CONCLUSIONS

In this paper we presented a combination of modified LBP and SIFT method with more reliable feature matching performance. We adopted the idea that the appearance of image edges can be well characterized and emphasized by local features. To combine the strengths of SIFT and LBP, we modified LBP as a feature enhance descriptor for SIFT. The performance of the proposed method was compared to SIFT on feature matching in several different cases. For all of the test images, our proposed method gave outstanding performance compared to original SIFT. The proposed method can get more correct matches with less error. In the future work, an adaptation of our proposed method to more challenging image transformation is going to be carried out.

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