

Local Pixel Class Pattern Based on Fuzzy Reasoning for Feature Description

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Abstract: - Local features extracted from images have broad potential in varieties of computer vision applications, such as image retrieval, object recognition and scene recognition. However, many of the existing features are not robust enough due to the existence of illumination changes, which is a common occurrence in real world applications, e.g. shadowing. In this paper, a novel feature descriptor is proposed to designing more robust to illumination changes. The basic principle of the proposed method is based on the observation that although the intensity values may be changed due to illumination changes, the texture structure or pixel class in the corresponding locations still remains unchanged. Specifically, they are achieved by applying Histogram Equalization and Intensity Normalization in pre-process step, and considering overall intensity distribution properties together with local intensity difference information by introducing fuzzy reasoning rules. In order to make our descriptor more discriminative and robust, we also propose a novel gradient-based weighting scheme. Experimental results on the popular Oxford dataset have shown that our proposed descriptor outperforms many state-of-the art methods not only under complex illumination changes, but also under many other image transformations.

Key-Words: - Local feature descriptor, Illumination invariance, Histogram Equalization, Fuzzy reasoning, Local pixel class pattern

1 Introduction

Local features extracted from images have been gained tremendous importance and popularity in recent years due to their good performance in a variety of computer vision tasks, such as image retrieval [1], object recognition [2], texture recognition [3], wide baseline matching [4], and panoramic image stitching [5]. A general process usually involves the following three stages: First is detecting the interest points or interest regions that are invariant to a class of transformations, Harris corner [6], DoG (Difference of Gaussian) [2], Harris-affine/Hessian-affine [7], MSER(Maximally Stable Extremal Region) [8] and EBR (Edge-Based Region) [4] are efficient and widely used methods. Then invariant feature descriptors for each interest points or regions are built, e.g. SIFT (Scale Invariant Feature Transform) [2] and GLOH (Gradient Location-Orientation Histogram) [9]. Once the descriptors computed, we can match

interest regions between images under some similarity measure, e.g. the Euclidean distance. In this paper, we mainly focus on designing image descriptors for local interest regions.

A good local feature descriptor should be distinctive while simultaneously robust to as many image transformations as possible, such as illumination changes, perspective distortions, image rotation, image blur, image zoom, JPEG compression, and so on. Among them, illumination changes are a common occurrence in real world applications and may cause problems and challenges in many vision applications such as feature matching [4]. In this paper, we focus on designing descriptor mainly for illumination changes. The basic idea of the proposed method is based on the observation that although the intensity values may be changed due to illumination changes, the texture structure or pixel class in the corresponding locations still remains unchanged. By introducing fuzzy reasoning rules, image pixels are first divided

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into six classes which are a background class, four edge classes and a speckle edge class (a speckle is a noisy pixel). Then Local Pixel Class Pattern (LPCP) is proposed to encode the pixel class information in each patch. In order to make it more distinctive, we also combine it with another descriptor which we call Weighted Histogram of Intensities (W-HOI). The two proposed methods capture complementary properties of a feature region - one captures local intensity difference properties and the other captures the overall distribution of pixels in the patch. Both of these methods are designed to be more robust to illumination changes and found to improve upon either of the two considered separately.

The rest of this paper is organized as follows: Section 2 gives a brief overview of the related works. Then, our new descriptor is presented in Section 3. The dataset and evaluation metrics are described in Section 4. And the experimental results are carried out in Section 5. Finally, conclusions are drawn in Section 6.

2 Related Work

Recently, many methods have been proposed to handle illumination changes. Gradient-based image descriptors are one class of them. And SIFT perhaps is one of the most famous and popular descriptor among them. Inspired by the high discriminative ability and robustness of SIFT, many variant approaches are proposed. GLOH replaces the Cartesian location grid used by the SIFT with a log-polar one, and DAISY [10] creates a histogram of gradient orientations. These descriptors usually outperform other local descriptors such as shape context [12], steerable filters [13], spin images [3] and derivative-based descriptors [14]. In order to be more compact and distinctive than SIFT, Ke and Sukthankar [11] proposed the PCA-SIFT descriptor through applying PCA (Principal Component Analysis) to gradient patch of keypoint. The SURF descriptor [15] builds on the strengths of the leading existing detectors and descriptors and significantly reduces computation time by relying on integral images for image convolutions.

Although the above descriptors have been shown to be partially or fully robust to many of the variations, the performance significantly degrades when complex illumination change happens. To alleviate this problem, intensity order based methods are proposed. The Local Binary Pattern (LBP) descriptor proposed by Ojala [16] is a simple yet efficient operator to describe local image pattern, and has been highly successful for various computer vision problems such as scene recognition [17, 18],

face recognition [19]. However, LBP operator produces a rather higher dimensional histogram and is not too robust on flat image areas. Only comparing center-symmetric pairs of pixels, CS-LBP [20] descriptor was proposed by combining the strength of the SIFT descriptor. In [21], Gupta et al. extended the CS-LBP descriptor to a ternary coding style which called CS-LTP and combined with a histogram of relative intensities to build a robust feature descriptor called HRI-CSLTP. Tang et al. [22] proposed a novel descriptor called Ordinal Spatial Intensity Distribution (OSID) which uses a 2D histogram of position and intensity order to deal with monotonically increasing illumination changes. Using intensity order to encode the local ordinal information and divide subregions, a Local Intensity Order Pattern (LIOP) [23] descriptor was proposed. It is not only invariant to monotonic intensity changes but also robust to image rotation. These methods usually obtained good performance in handling illumination changes due to the observation that although the intensity values may be changed, the relative ordering of the intensity values in the corresponding locations still remains unchanged.

However, the intensity order may be noisy in the presence of Gaussian noise, especially when the nearby pixels are close in intensity just as mentioned in [21]. In [24], Liang and Looney proposed a competitive fuzzy edge detection (CFED) method. This method divides edge types into six patterns and uses fuzzy reasoning rules to determine which pattern the edge type belongs to. It is shown to be robust to Gaussian noise. Similar with CFED, Kang [25] proposed a directional median filter by using fuzzy reasoning rules. Inspired by these methods, we introduce fuzzy reasoning rules into feature descriptor and propose a novel descriptor called W-HOI-LPCP which is fundamentally different from the previous ones. The basic idea of our method is based on the observation that no matter how the illumination changes the pixel class remains unchanged or stable. We also found that the regions with more texture information usually give more contributions to the descriptor. Based on this observation, we also propose a new gradient-based weighting scheme. The experiments show improved performance over standard datasets.

3 Our Method

Our descriptor is composed of two parts. Firstly, Histogram Equalization and Normalization are applied in the pre-processing step. Then these normalized intensities are used to build a histogram

based descriptor in subregions for each patch. Next, fuzzy reasoning rules are introduced to create the LPCP descriptor. Finally, the two distinctive descriptors are concatenated together. The workflow of our method is shown in Fig 1. Detailed discussion will be presented in the following subsections.

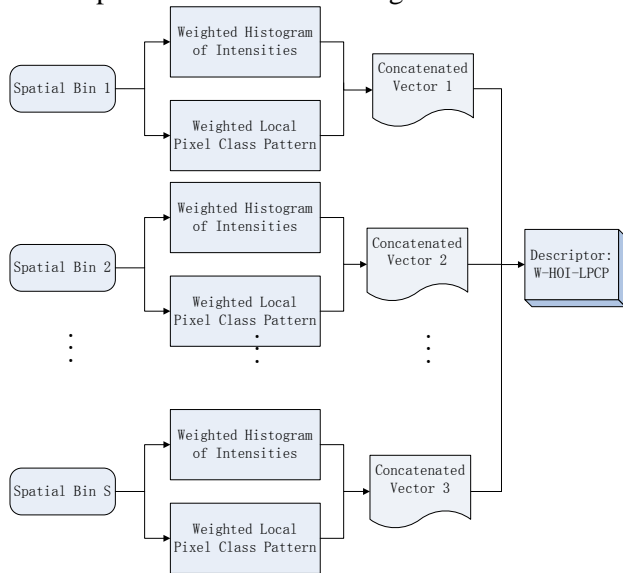


Fig.1 The workflow of our method.

3.1 Pre-processing and Region Detection

Some of the existing methods employ Gaussian filter [23] or Normalization [21] before feature region detection. However, this operation may lead to some detailed information missing. Thus, some important interest points or regions may be undetected accordingly. In our method, the original images are used to locate interest regions, and images after Gaussian filter and normalization are used to compute descriptors. The existing feature detectors such as Harris-Affine or Hessian-Affine can be used for interest region detection.

For these images to compute descriptors, we first apply Histogram Equalization to attenuate the differences that appear under illumination variations. Then a Gaussian filter with sigma σ_p is used to remove noise. After that, the range of intensities is determined which is used to normalize the intensities. In order to make it more robust to noise, the intensities below $(Lm+\epsilon)$ and above $(Hm-\epsilon)$ are set to $(Lm+\epsilon)$ and $(Hm-\epsilon)$ respectively because these values can be noisy, where Lm and Hm are the lowest and highest intensity value of image (typically ϵ is around 5), and then all the intensities are normalized to 0~1.

The detected regions need to be normalized to circular regions of a fixed diameter because the detected regions usually have varying sizes and shapes. The typical choice of the diameter is 41 but

it may vary with the image resolution and scale. In order to achieve rotation invariance, the normalized regions also need to be rotated to the local consistent orientation (e.g. the dominant gradient orientation suggested by Lowe [2]). Finally, the local patch is smoothed by a Gaussian filter with sigma σ_n to remove the noise introduced by interpolation in the normalization step.

3.2 Weighted Histogram of Intensities

At first, local patch is divided into S spatial bins in a manner similar to SIFT descriptor. This is shown diagrammatically in Fig 2. And then we create a histogram for each spatial bin. The histogram consists of k bins where the i^{th} bin stores the number of pixels have the same intensity values. Here, bilinear interpolation is needed to distribute the weight of each pixel into adjacent histogram bins just like SIFT does. Since the texture regions usually give more contributions to the descriptor than these flat regions. Furthermore, the texture regions usually have large gradient magnitudes. So these regions which have large gradient magnitudes should be given larger weights. Thus, a new weighting function for each spatial bin is proposed to improve the robustness of our descriptor, which is defined as follows:

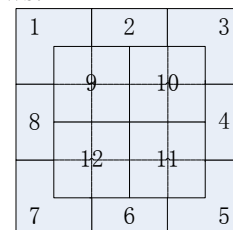


Fig.2 Region division.

$$w_s = \frac{S \times \sum_{i,j} G_s(x_{i,j})}{\sum_s \sum_{i,j} G_s(x_{i,j})} \quad (1)$$

where $G_s(x_{i,j})$ is the gradient magnitude of $x_{i,j}$ in the s^{th} spatial bin. Here, Sobel operator is used to compute gradient magnitudes. Experiments show that this weighting scheme performs better than the uniform weighting scheme and Gaussian weighting scheme (see Fig 8).

Thus, we have a descriptor of $S \times K$ bins which we call it W-HOI (Weighted Histogram of Intensities). It is noted that our region division method is different from SIFT which is equally divided into 4×4 bins. Here, our subregions are composed of eight non-overlapping regions and four partly-overlapping regions. Experiments show that this region division method reduces descriptor

dimension while simultaneously keeps the distinctive power (see Fig 9 (a)).

3.3 Local Pixel Class Pattern Descriptor

The above mentioned approach works on the overall distribution of the pixels in the patch but does not capture local intensity difference information. More recently, this information has been used for feature descriptors which achieve high performance comparable to SIFT, such as CS-LBP [20], CS-LTP [21]. They create a histogram of central symmetric local binary or ternary pattern. In this paper, local intensity difference information is used in a novel way by introducing fuzzy reasoning rules.

Before the formal definition of our fuzzy reasoning rules, the local intensity differences defined in [24] are introduced. Fig 3 shows eight local neighborhoods of pixels with a radius of R to the center pixel. The four directional intensity differences of the point x are calculated by

$$d_1(x) = |x_1 - x| + |x_2 - x| \quad (\text{Direction 1}) \quad (2-1)$$

$$d_2(x) = |x_3 - x| + |x_4 - x| \quad (\text{Direction 2}) \quad (2-2)$$

$$d_3(x) = |x_5 - x| + |x_6 - x| \quad (\text{Direction 3}) \quad (2-3)$$

$$d_4(x) = |x_7 - x| + |x_8 - x| \quad (\text{Direction 4}) \quad (2-4)$$

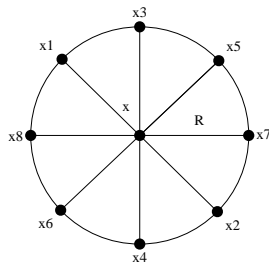


Fig.3 Eight local neighborhoods of pixels with a radius of R to the center pixel x.

An image can be segmented into two regions: flat region and texture region. Texture region can be further divided into n (n=4 in this paper) edge classes according to their directions. Based on this observation we can define six fuzzy rules to determine which class of the current pixel belongs to. The six possible classes of the current pixel are a background class, four edge classes and a speckle edge class. Four typical neighborhood situations with a radius of R=1 are shown in Fig 4.

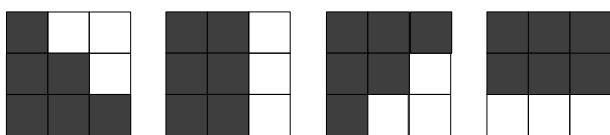


Fig.4 Four typical edge classes.

The six rules are:

- Rule-1: If d_1 is Small, d_2 is Small, d_3 is Small and d_4 is Small, then $x_{i,j}$ is possibly a background pixel.
- Rule-2: If d_1 is Small, d_2 is Big, d_3 is Big and d_4 is Big, then $x_{i,j}$ is possibly an edge pixel of direction 1.
- Rule-3: If d_1 is Big, d_2 is Small, d_3 is Big and d_4 is Big, then $x_{i,j}$ is possibly an edge pixel of direction 2.
- Rule-4: If d_1 is Big, d_2 is Big, d_3 is Small and d_4 is Big, then $x_{i,j}$ is possibly an edge pixel of direction 3.
- Rule-5: If d_1 is Big, d_2 is Big, d_3 is Big and d_4 is Small, then $x_{i,j}$ is possibly an edge pixel of direction 4.
- Rule-6: If d_1 is Big, d_2 is Big, d_3 is Big and d_4 is Big, then $x_{i,j}$ is possibly a speckle edge pixel.

Small and Big are fuzzy membership functions shown in Eq 3 and Eq 4, respectively. Both of them are trapezoid shapes and illustrated in Fig 5.

$$\text{Small}(u) = \begin{cases} 1, & u < a \\ \frac{u-a}{b-a}, & a \leq u < b \\ 0, & u \geq b \end{cases} \quad (3)$$

$$\text{Big}(u) = \begin{cases} 0, & u < a \\ \frac{u-a}{b-a}, & a \leq u < b \\ 1, & u \geq b \end{cases} \quad (4)$$

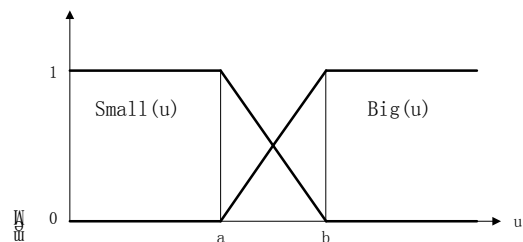


Fig.5 The fuzzy membership functions Small (u) and Big (u).

The selection of the two parameters will be discussed in Section 4. The original fuzzy rule base has 16 rules due to four inputs, d_1 - d_4 , and two fuzzy membership functions. To simplify the fuzzy rule base and reduce computational cost, only six rules are considered. Experiment results show this six pixel classes can capture most of the texture information in the image. Then let fuzzy truth value F be defined below:

$$F_1 = \text{Small}(d_1) \cdot \text{Small}(d_2) \cdot \text{Small}(d_3) \cdot \text{Small}(d_4)$$

$$F_2 = \text{Small}(d_1) \cdot \text{Big}(d_2) \cdot \text{Big}(d_3) \cdot \text{Big}(d_4)$$

$$F_3 = \text{Big}(d_1) \cdot \text{Small}(d_2) \cdot \text{Big}(d_3) \cdot \text{Big}(d_4)$$

$$F_4 = \text{Big}(d_1) \cdot \text{Big}(d_2) \cdot \text{Small}(d_3) \cdot \text{Big}(d_4)$$

$$F_5 = \text{Big}(d_1) \cdot \text{Big}(d_2) \cdot \text{Big}(d_3) \cdot \text{Small}(d_4)$$

$$F_6 = \text{Big}(d_1) \cdot \text{Big}(d_2) \cdot \text{Big}(d_3) \cdot \text{Big}(d_4)$$

Here, we use product inference engine [26] to realize the fuzzy reasoning. After all fuzzy truth values are obtained, the largest fuzzy truth is used to determine the class membership. Thus the LPCP value is defined by

Case-1: Background Class

$$\text{If } \max\{F_1, F_2, F_3, F_4, F_5, F_6\} = F_1$$

$$LPCP = \{1, 0, 0, 0, 0, 0\}$$

Case-2: Edge Class of Direction 1

$$\text{If } \max\{F_1, F_2, F_3, F_4, F_5, F_6\} = F_2$$

$$LPCP = \{0, 1, 0, 0, 0, 0\}$$

Case-3: Edge Class of Direction 2

$$\text{If } \max\{F_1, F_2, F_3, F_4, F_5, F_6\} = F_3$$

$$LPCP = \{0, 0, 1, 0, 0, 0\}$$

Case-4: Edge Class of Direction 3

$$\text{If } \max\{F_1, F_2, F_3, F_4, F_5, F_6\} = F_4$$

$$LPCP = \{0, 0, 0, 1, 0, 0\}$$

Case-5: Edge Class of Direction 4

$$\text{If } \max\{F_1, F_2, F_3, F_4, F_5, F_6\} = F_5$$

$$LPCP = \{0, 0, 0, 0, 1, 0\}$$

Case-6: Speckle Edge Class

$$\text{If } \max\{F_1, F_2, F_3, F_4, F_5, F_6\} = F_6$$

$$LPCP = \{0, 0, 0, 0, 0, 1\}$$

Finally, the descriptor is constructed by accumulating LPCPs of points in each spatial bin respectively, then by concatenating them together. Mathematically, the LPCP descriptor of the local patch is calculated as:

$$LPCP \text{ descriptor} = \{w_1 \cdot Des_1, w_2 \cdot Des_2, \dots, w_s \cdot Des_s\}$$

$$Des_s = \sum_{x \in Bin_s} LPCP_x$$

where S is the number of the spatial bins, and the dimension of the descriptor is $6 \times S$. Here, we also use the weighting function w_s described in Section 3.2 to improve the robustness of the LPCP descriptor.

The two descriptor designed by us are concatenated for improved results due to their complementary information. While one captures the overall distribution of pixels and the other captures local intensity difference properties in the patch. We call this concatenated descriptor W-HOI-LPCP.

4 Dataset and Evaluation Criterion

4.1 Dataset

To evaluate the performance of the proposed descriptor, we have tested it on the Oxford dataset which is widely used for local feature descriptors evaluation by most of researchers. This dataset can be downloaded from Oxford university website [27]. It contains real images with different photometric and geometric transformations of structured and textured scenes. The following different transformations are evaluated: illumination change, viewpoint change, scale change, image rotation, image blur, and JPEG compression. Fig 7 shows example images of our data set used for the evaluation. In order to get more detail about the performance of the proposed descriptor to complex illumination changes, we also test it on some synthesized images. We perform a square and square root operation on the 6th Leuven image which has the largest illumination changes in the Leuven dataset as [22] does. Such nonlinear transformations make images very challenging due to complex illumination changes. Fig 6 shows these two synthesized images.



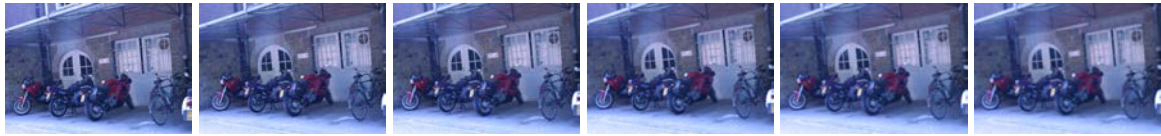
Fig.6 Synthesized images from 6th of Leuven dataset: (a) squared illumination change; (b) square root illumination change.

4.2 Detector

Since Hesaff region detector provides more interest regions than others, we use it for all descriptors in our comparison. The Hesaff detects blob-like structures and outputs elliptic regions of varying size. To make fair comparisons of the descriptors, we normalize these elliptic regions to a circular regions of a fixed diameter (diameter is set to 41) as described in Section 3.1. And then they are used to compute descriptors.



Bark: zoom + rotation



Bikes: image blur



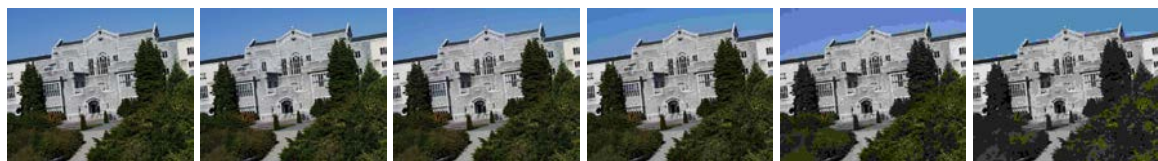
Boat: zoom + rotation



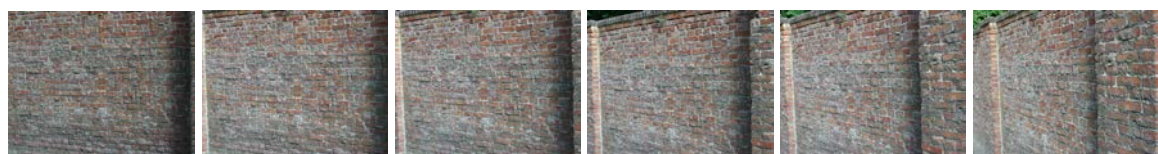
Graf: viewpoint change



Leuven: illumination change



UBC: JPEG compression



Wall: viewpoint change

Fig.7 Examples of images used for the evaluation.

4.3 Evaluation Criterion

We used the same evaluation criterion proposed by Mikolajczyk and Schmid [9] which is based on the number of correct and false matches between a pair of images. And we adopt the nearest neighbor distance ratio (NNDR) as the matching strategy, which defines a match if the distance ratio between the first and second nearest neighbors is below a threshold. The number of correct matches is determined with the “overlap error” [7]. A match is assumed to be correct if the overlap area is > 0.5 . We use this criterion for all results in our experiments. The results are presented with recall versus 1-precision where recall and 1-precision are defined as below

$$\text{recall} = \frac{\# \text{correct matches}}{\# \text{correspondences}}$$

$$1 - \text{precision} = \frac{\# \text{false matches}}{\# \text{correct matches} + \# \text{false matches}}$$

where $\# \text{correspondences}$ is the ground truth number of matches.

5 Experiments

5.1 Parameter Selection

There are seven parameters in our method: the smoothing sigma σ_p and σ_n in the pre-process step, the sampling radius R , the number of spatial bins S , the number of intensity histogram bins K , and the two parameters a and b in fuzzy membership functions. In order to study the effect of the parameters on the performance of our descriptor, we performed various simulations.

Many literatures have verified that the performance is significantly improved with smoothing prior to the descriptor computation. And best performances are obtained when setting σ_p and σ_n to 1, 1.2 respectively in our experiments. We compared the matching performance of the proposed descriptor by simply trying all combinations of these parameters in three image sequences of the Oxford dataset: Boat, Graf and Wall. Due to the space limit, only the performance of one image pairs is shown. Fig 9 (a) shows the results between the 1st and the 2nd images in Boat by varying S (12 and 16) and K (8, 10 and 16). As can be observed, the best performance obtained when $S=12$ and $K=8$. This selection also obtains smallest dimension and least computational cost. Thus, the dimension of our descriptor is $12 \times (8+6) = 168$. The performance evaluations varying a (0, 5 and 10) and b (20, 30 and 50) between the 1st and the 4th images in Wall are shown in Fig 9 (b). It is clear that both

the settings of $\{a=0, b=30\}$ and $\{a=10, b=30\}$ give good performance. Here, we select $\{a=10, b=30\}$. It is noted that all the selected parameters are unchanged in all our subsequent experiments and they are shown in Table 1.

Table.1 The selected parameters.

Parameters	σ_p	σ_n	R	S	K	a	b
Values	1.0	1.2	3	12	8	10	30

We also compared our weighting function to uniform weighting, Gaussian weighting, and without weighting. The performance evaluation results are shown in Fig 8, which we can observe that the proposed weighting function gets the best performance.

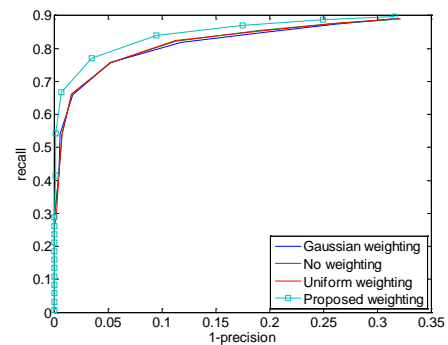


Fig.8 Performance comparison among Gaussian weighting, without weighting, uniform weighting and the proposed weighting (Eq 1).

5.2 Performance Evaluation

We have compared the proposed W-HOI-LPCP descriptor against the following existing features: SIFT [2], DAISY [11], HRI-CSLTP [21] and LIOP [23]. The binaries and Matlab codes for extracting the Hessian affine regions and computing the above descriptors are downloaded from the website [27, 28]. Note that all the subsequent tests are simulated in Matlab 7.10.0 and based on the same hardware devices (Duo CPU 2.26GHz, Memory is 4G). Due to the space limit, only the performance of two image pairs is shown.

Illumination changes: We first tested our descriptor under illumination changes in the “Leuven” dataset. Experiments are run between the first image in this dataset and the remaining five images with increasing amount of illumination change. The results are shown in Fig 9 (c)-(d). We selected the 2nd and 6th image for showing since the 2nd image has the least illumination change compared to the 1st while the 6th has the largest illumination change. From Fig 9 (c)-(d) we can see that our descriptor performs consistently better than

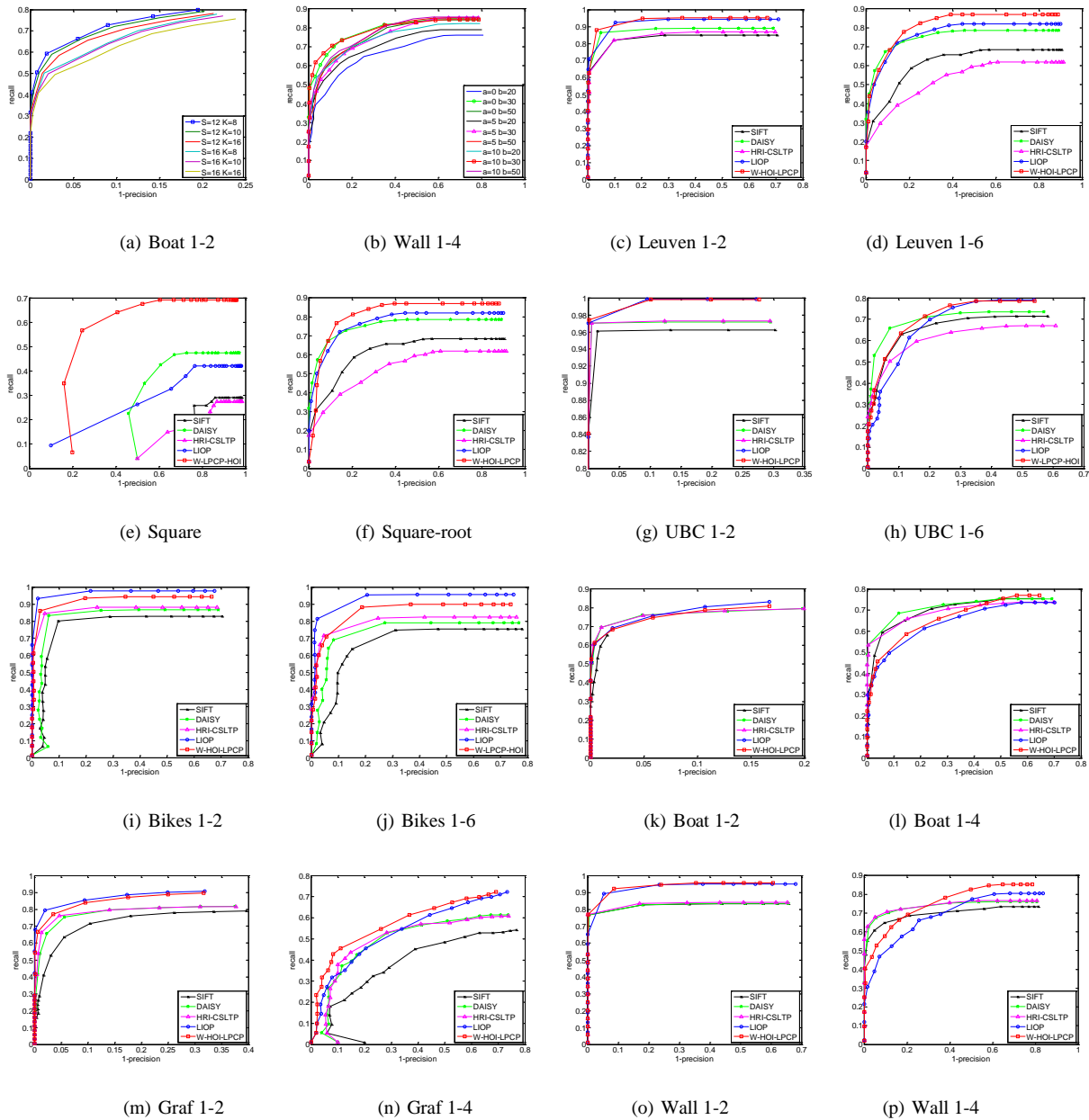


Fig.9 Experimental results: (a)-(b) performance comparison of the W-HOI-LPCP descriptor under different parameter configurations and weighting scheme. Experimental results for (i) illumination changes (c)-(f), (ii) JPEG compression (g)-(h), (iii) other transformations: image blur (i)-(j), image rotation and scale change (k)-(l), viewpoint change (m)-(p). Note that scales are different for different figures to improve the clarity of the plot.

all the other tested descriptors especially when having large illumination changes. We also evaluate the performance on the synthesized images shown in Fig 6. Our descriptor also outperforms all other tested descriptors by a wide margin especially in the case with squared illumination change.

JPEG compression: Then our descriptor is tested under JPEG compression using the “UBC” dataset. We also selected the 2nd and 6th two image pairs and the results are shown in Fig 9 (g)-(h). As

can be observed, our descriptor performs best even in the presence of significant JPEG compression in Fig 9 (g)-(h).

Other transformations: Finally, we test our descriptor for other transformations: image blur, image rotation and scale change, and viewpoint change. The results are shown in Fig 9 (i)-(p). For image blur change, it outperforms other descriptors except LIOP. For image rotation and scale change, it gets almost the same performance as the other

descriptors. For viewpoint change, our descriptor and LIOP descriptor obtain the best performance except for Wall 1-4. As can be observed, the proposed W-HOI- LPCP descriptor obtains a high discriminative and robust power not only under complex illumination change, but also under many other image transformations.

6 Conclusions

We have presented a novel feature descriptor which is combined by two different methods: Weighted Histogram of Intensities (W-HOI) and Local Pixel Class Pattern (LPCP). Both of them are designed to be more robust to complex illumination changes than the previous proposed intensity order based methods. Specifically, they are achieved by applying Histogram Equalization and Intensity Normalization in pre-processing step to attenuate the differences that appear under illumination variations before descriptors computing. Meanwhile local intensity difference information is captured in a novel way by introducing fuzzy reasoning rules to obtain illumination invariance. Furthermore, our new weighting scheme also gave improved results than Gaussian weighting scheme and uniform weighting scheme. Experimental results have shown that our descriptor obtained superior performance not only under illumination changes, but also under many other image transformations.

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