Exact order based feature descriptor for illumination robust image matching

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A R T I C L E   I N F O

Article history:
Received 28 October 2012
Received in revised form 12 March 2013
Accepted 23 April 2013
Available online 1 May 2013

Keywords:
Feature descriptor
Local order descriptor
Global order descriptor

A B S T R A C T

We present a novel method for a feature descriptor called an exact order based descriptor (EOD). The proposed method consists of three steps. First, to resolve ordering ambiguity for pixels of the same intensity, an exact order image is created by changing the discrete intensity into a k-dimensional continuous value. Second, exact order based features are generated globally and locally. Finally, the EOD is constructed by combining the global and local exact order features using the discrete cosine transform. Experimental results show that the proposed method outperforms other state-of-the-art descriptors over a number of images.

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1. Introduction

Local image features have recently received a lot of attention in the field of computer vision. They have become popular for applications in image matching, object recognition, and object representation, and their usefulness has been well demonstrated [1–3]. Since a local feature extracts image properties from a local image region, it is robust to geometric variations such as viewpoint change and occlusion. For this reason, many local feature methods using image properties such as intensity, color, texture, and edge have been proposed. Generally, local feature construction consists of two steps: interest region detection and computation of interest region descriptor. For interest region extraction, the Harris–Affine, Hessian–Affine [4], and maximally stable extremal regions (MSER) [5] detectors are widely used. Once interest regions have been extracted, their feature descriptors are computed in order to distinguish them from each other. Since we focus in this study on the problem of designing descriptors for local interest regions, we refer the interested reader to [4] for more details about interest region detectors.

As with the interest region detectors, many feature descriptors have been proposed in the literature, and it is well known that the distribution-based descriptors, which use histogram to represent the interest region, perform significantly better than descriptors based on other features, such as shape context [6], steerable filters [7], and spin image [8]. The most popular distribution-based descriptor is the scale invariant feature transform (SIFT) descriptor that uses the distribution of gradients [9]. The SIFT descriptor is a gradient orientation histogram on 4 × 4 location cells. The gradient angle is quantized into 8 orientations, leading to a SIFT descriptor with a (4 × 4 × 8 = 128) 128-dimensional descriptor. Contributions to the gradient orientations are weighted by the gradient magnitude and a Gaussian window overlaid over the region. Finally, the SIFT descriptor is normalized to enhance invariance to illumination changes. Encouraged by the success of the SIFT descriptor, many SIFT-like local features such as gradient location and orientation histogram (GLOH) which speeded up robust feature (SURF) have been proposed. For example, Mikolajczyk et al. [10] proposed the GLOH descriptor, which is designed to increase the robustness and distinctiveness of the SIFT descriptor. The GLOH descriptor can be obtained by computing the SIFT descriptor for a log-polar location grid with three radii and eight angles. The gradient orientations are quantized into 16 parts, leading to a 272-dimensional descriptor. Finally, the dimension feature is reduced into 128 dimensions by principal component analysis (PCA). Bay et al. [11] proposed the SURF descriptor, which reduces the computation time significantly by employing an integral image. The SURF descriptor calculates the Haar wavelet responses on 4 × 4 cells. In each cell, the Haar wavelet responses are extracted at regularly spaced sample points. The wavelet responses in the horizontal and vertical directions are summed over each cell. Recently, a design was proposed that incorporates global context information with the local feature descriptor to aid discrimination of local features that have similar local appearances [12].

While the above methods are robust to rotation, scale, and occlusion, they are not invariant to illumination changes. In order to deal with illumination changes, many local features based on

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http://dx.doi.org/10.1016/j.patcog.2013.04.015
intensity order rather than raw intensity have been proposed, because the intensity order of pixels in an image is invariant to monotonic changes of intensity. Ojala et al. [13] proposed the local binary pattern (LBP) operator, which creates an order based feature for each pixel by comparing each pixel's intensity value with that of its neighboring pixels. The LBP has shown promise for various computer vision problems such as face recognition and texture classification. While the LBP has the advantage of tolerance of illumination changes and computational simplicity, it produces a rather higher dimensional feature, and it is sensitive to Gaussian noise on flat regions. Thus, some dimensionality reduction methods for the LBP have been proposed. Ojala et al. [14] proposed a uniform LBP, observing that most of the texture information is contained in a small subset of the LBP. These patterns, called uniform patterns, contain at most two bitwise zero-to-one or one-to-zero transitions in the circular binary code. For $p$ neighboring pixels, this leads to a feature with $p \times (p-1)+3$ dimensions. Heikkila et al. [15] proposed the center-symmetric local binary pattern (CS-LBP) for dimensionality reduction. To generate the binary code, they compared center-symmetric pairs of pixels instead of comparing neighboring pixels with the center pixel. For $p$ neighboring pixels, this leads to a feature with $2p^2$ dimensions. In another variation, Gupta et al. [16] presented the center-symmetric local ternary pattern (CS-LTP) based on the CS-LBP. They compared only the diagonal pairs to generate binary code for a given pixel. CS-LTP produces a feature with 8 dimensions. Another recent approach has been to use intensity order distribution as an illumination-invariant feature. Tang et al. [17] proposed the ordinal spatial intensity distribution (OSID), which is constructed by rasterizing a 2-D histogram where the pixels intensities are grouped in the ordinal space as well as in the spatial space. Gupta et al. [16] proposed HRI, which is based on the relative position of each intensity with respect to the entire patch.

In this paper, we present a novel method for the local feature descriptor called the exact order based descriptor (EOD) which adopts an exact ordering method for removal of order ambiguity for same-intensity values. Based on the exact order, the global exact order feature (GEOF) and local exact order feature (LEOF) are generated, and they are combined using the discrete cosine transform (DCT) method to achieve dimensionality reduction. Our experimental results demonstrate that the proposed method outperforms many state-of-the-art descriptors under various image transformation conditions. This paper is organized as follows: Section 2 reviews order based descriptors, Section 3 introduces the proposed method in detail, the experimental results are presented in Section 4, and finally, the paper’s conclusions are provided in Section 5.

2. Related works

In this section, we briefly review order based descriptors. Order based descriptors are generally classified into two categories. One approach looks at the global distribution of orders in the patch and creates a feature based on the overall distribution of orders such as OSID and HRI. The other approach looks at the local order of pixels, creating a feature from a given pixel by comparing it with its neighboring pixels such as LBP, CS-LBP, and CS-LTP.

2.1. Global order based descriptor

Tang et al. [17] proposed the local feature descriptor called OSID which is constructed by rasterizing a 2-D histogram in which the pixel intensities are grouped in the ordinal space as well as in the spatial space. For ordinal distribution, the pixels in the patch are first smoothed with a Gaussian filter to remove noise. Then, the pixels in the patch are sorted and grouped into $n$ bins, where each bin has pixels with similar ordinal pixel intensities. Gupta et al. [16] proposed HRI, which is based on the relative position of each intensity with respect to the entire patch. In their method, they first determined the range of the intensity values in order to normalize the intensities, and they grouped the pixels in the patch into $n$ bins by dividing this range into $n$ equal intervals. The HRI descriptor is generated by incorporating the framework of SIFT. At each spatial bin, a histogram with $n$ bins generated in which the $m$th bin stores the number of pixels which have intensities in the $m$th interval. Note that OSID forms intervals based on relative orders, and HRI forms intervals based on relative intensities. For global order based descriptors, the pixels in the patch have to be grouped by some criterion. The OSID method groups the pixels based on orders which are induced from the smoothed intensity value (continuous value). However, orders induced only from the smoothed intensity value may not be consistent with the normal ordering (order induced from raw intensity value). For two pixels $p$ and $q$ ($p < q$), the order of the smoothed intensity of $p$ can be higher than that of $q$ if the surrounding pixels of $p$ are brighter than those of $q$. The HRI method groups the pixels based on the relative histogram of intensity, with the assumption that a variation of illumination results in a linear intensity change. However, a variation of illumination results in non-linear intensity change, and this may lead to large error in determining the intervals. Although an adaptive normalization scheme is applied to handle this problem, it is still somewhat unstable.

2.2. Local order based descriptor

The LBP operator proposed by Ojala et al. [13] encodes the ordering relationship by comparing neighboring pixels with the center pixel. For each neighboring pixel, the binary value is set to one if its intensity is higher than or equal to the intensity of the center pixel; otherwise, it is zero. The LBP is defined as follows:

$$\text{LBP}_{r}(x, y) = \sum_{i=0}^{N-1} s((n_{i} - n_{c})/C_{26})^2, \quad s(x) = \begin{cases} 1 & x \geq 0 \\ 0 & \text{otherwise} \end{cases}$$

where $n_{c}$ corresponds to the intensity of the center pixel of a local neighborhood, and $n_{i}$ represents the gray-levels of $N$ equally spaced pixels on a circle of radius $R$. The final LBP descriptor is a histogram of the LBP over the interest region. For an $8$-neighborhood (see Fig. 1), LBP generates an 8-bit code (256 feature dimensions). The CS-LBP is a modified version of LBP for dimensionality reduction. Unlike the LBP, the CS-LBP operator compares gray-level differences of center-symmetric pairs. The definition of the CS-LBP is given as follows:

$$\text{CS - LBP}_{r,N,T}(x, y) = \sum_{i=0}^{N/2-1} s_{r}(n_{i} - n_{c} + N/2)2^i, \quad s_{r}(x) = \begin{cases} 1 & x \geq T \\ 0 & \text{otherwise} \end{cases}$$

![Fig. 1. LBP, CS-LBP, and CS-LTP features.](image-url)
where \( n_i \) and \( n_{i+1/N} \) correspond to the gray level of the center-symmetric pixels of \( N \) equally spaced pixels on a circle of radius \( R \). This is a small positive value for robustness in a flat region. Since only 4 comparisons are made for an 8-neighborhood (see Fig. 1), CS-LBP generates a 4-bit code (16 feature dimensions), making CS-LBP more effective for the region descriptor than the original LBP. The final CS-LBP descriptor is obtained by incorporating the framework of SIFT. The center-symmetric local ternary pattern was introduced in [16].

In order to reduce the feature dimensionality, only the diagonal comparisons are used to generate the CS-LTP code for a given pixel. The CS-LTP at a \( D (D=2) \) neighboring distance is given as

\[
CS - LTP_{D,T}(x,y) = f(n_{8} - n_{11}) + f(n_{9} - n_{10}) \times 3,
\]

\[
f(x) = \begin{cases} 2, & x > T \\ 0, & x < T \\ 1, & \text{else} \end{cases}
\]

For \( D=2 \) (see Fig. 1), CS-LTP produces a feature with 8 dimensions for each pixel. (The code “4” receives zero weight, i.e., homogeneous regions are totally neglected.) The CS-LTP descriptor is a histogram of CS-LTP accumulated over spatial cells, similar to SIFT.

While the local order based methods such as LBP, CS-LBP, and CS-LTP have shown good performance, they are sensitive to Gaussian noise on flat regions, i.e., small variations in the center pixel may cause the descriptor to vary significantly. To demonstrate the effect of Gaussian noise for the local order based method, we conduct experiments in which we synthesize noise sequence images by adding Gaussian noise to the Leuven image (zero mean and uniform sampling of the interval sigma value [0.001, 0.005] with 5 samples). To analyze the robustness to Gaussian noise for each local descriptor, we apply each descriptor operator on the original image and noise sequence images. We then compare the feature histogram of the original image with those of the noise sequence images using the histogram intersection method [18] for each descriptor. If the local order based method is robust to noise, the value of the histogram intersection is close to one; otherwise, it is close to zero. The results of the histogram intersection for overall descriptors are shown in Fig. 2. As can be observed, ordering based on pixel-by-pixel operators such as LBP, CS-LBP, and CS-LTP are sensitive to Gaussian noise. However, it will be explained in Section 3.2 that the LEOF usually shows a consistent value regardless of increasing Gaussian noise, because the LEOF descriptor is generated based on the ordering derived from a block-by-block operator.

3. Exact order based feature descriptor

3.1. Global exact order feature

To be robust to illumination changes, we use intensity order rather than raw intensity value. When we use global order distribution as local feature descriptor, we first order pixels in the local patch, then sort and group the pixels into \( n \) bins by dividing the order number into \( n \) equal intervals. If pixel intensity values in the patch are different from each other, then ordering by pixel intensity may yield exact ordering. However, since each pixel has a discrete value within the range of 0–255, pixels may have the same intensity value, resulting in ordering ambiguity. Some intensity values which are different ordering numbers may be merged together under illumination changes and ordering by pixel intensity allocates same ordering number to these pixels. As shown in Fig. 15, ordering by discrete intensity yields quite different order distributions under illumination changes which cause non-linear intensity changes. To handle this situation, an exact ordering method can be adopted which changes a discrete intensity value into a \( k \)-dimensional continuous value. Coltuc et al. [19] proposed a method to assign exact orders for pixels with the same intensity by using auxiliary information. This approach is based on the fact that, for two pixels \( p \) and \( q \) with the same intensity value, humans perceives \( p \) to be brighter than \( q \) if the surrounding pixels of \( p \) are brighter than those of \( q \). For the auxiliary information, we use a set of average values which are extracted by a set of averaging filters defined for various neighborhood sizes. In [19], a set of averaging filters is designed, starting with \( \Phi_1 \), a one-pixel-sized support, and then enlarging while maintaining symmetry, with minimum increases of the filter supports. For example, the first three filters can be written

\[
\Phi_1 = [1], \quad \Phi_2 = \begin{bmatrix} 0 & 1 & 0 \\ 1 & 1 & 1 \\ 0 & 1 & 0 \end{bmatrix}, \quad \Phi_3 = \begin{bmatrix} 1 & 1 & 1 \\ 1 & 1 & 1 \\ 1 & 1 & 1 \end{bmatrix}
\]

The development of the filter family can continue for \( \Phi_4, \Phi_5, \ldots \), and so on, while continuing to maintain symmetry and minimum increases between filter supports. Let the image have a gray level \( L \), then \( f(x,y) : [0,N] \times [0,M] \rightarrow [0,L-1] \). By using a set of averaging filters, a discrete scalar pixel value is transformed into a \( k \)-dimensional continuous vector as follows:

\[
f(x,y) = \Phi_k(f(x,y)) = [\Phi_1(f(x,y)), \Phi_2(f(x,y)), \ldots, \Phi_k(f(x,y))]
\]

The order defined by the lexicographical ordering induces an exact order on these \( k \)-dimensional vectors in the patch. Finally, the ordering induced on \( \Phi_k(f(x,y)) \) can be induced also on \( f(x,y) \) as follows:

\[
f(x_1,y_1) < f(x_2,y_2) \Leftrightarrow \Phi_k(f(x_1,y_1)) < \Phi_k(f(x_2,y_2))
\]

However, extracting the order based feature directly from the exact order image patch is not appropriate, because the number of the order is too large. For simplicity and robustness, therefore, we sort and group the pixels in the patch into \( n \) bins by dividing the exact order number into \( n \) equal intervals. In this paper, we transfer the discrete intensity value into a 3-dimensional vector and group the pixels into 8-bins.

Fig. 2. Sensitivity to Gaussian noise. (a) Original image, (b) Noise image, (c) Histogram intersection.
3.2. Local exact order feature

To solve the problem of local order based methods such as LBP, CS-LBP, and CS-LTP, we use a Haar-like compact local binary pattern (HC-LBP) [20] on the exact order image patch for local order feature extraction. We briefly describe the HC-LBP, which is robust to Gaussian noise and which has small dimensionality of features due to its modification of the LBP method.

The HC-LBP is generated as follows. First, the edge class of the block with a neighboring distance $D$ is decided by comparing the average order values of the Left, Right, Up, and Down sub-blocks, as shown in Fig. 3. The edge class of the block is determined according to the sub-block with the largest average order value. Note that although diagonal edges seem to be omitted, they will be determined implicitly in the next step. After deciding the edge class of the block, the binary Haar-like feature [21] is applied according to the class of the edge. In the cases of the Left and Right edge classes, we compare the average order values of the Up and Down sub-blocks by applying the horizontal binary Haar-like feature. In the cases of the Up and Down edge classes, we compare the average order values of the Left and Right blocks by applying the vertical binary Haar-like feature. Finally, the HC-LBP at a neighboring distance $D (D = 2)$ is given as follows:

$$HC - LBP_D = 2(x, y) = \begin{cases} 
1, & \text{in case of Left edge} & \text{& BH}_{\text{vertical}}(x, y) = 0 \\
2, & \text{in case of Left edge} & \text{& BH}_{\text{vertical}}(x, y) = 1 \\
3, & \text{in case of Right edge} & \text{& BH}_{\text{vertical}}(x, y) = 0 \\
4, & \text{in case of Right edge} & \text{& BH}_{\text{vertical}}(x, y) = 1 \\
5, & \text{in case of Up edge} & \text{& BH}_{\text{horizontal}}(x, y) = 0 \\
6, & \text{in case of Up edge} & \text{& BH}_{\text{horizontal}}(x, y) = 1 \\
7, & \text{in case of Down edge} & \text{& BH}_{\text{horizontal}}(x, y) = 0 \\
8, & \text{in case of Down edge} & \text{& BH}_{\text{horizontal}}(x, y) = 1 
\end{cases}$$

(7)

where BH is the binary Haar-like feature operator, defined as follows:

$$BH_{\text{vertical}}(x, y) = \begin{cases} 
0, & \text{Ave.(Left)} > \text{Ave.(Right)} \\
1, & \text{otherwise} 
\end{cases}$$

$$BH_{\text{horizontal}}(x, y) = \begin{cases} 
0, & \text{Ave.(Up)} > \text{Ave.(Down)} \\
1, & \text{otherwise} 
\end{cases}$$

(8)

By combining the edge class and the binary Haar-like feature, we significantly reduce feature dimensions and increase the discriminative power of the feature.

3.3. Combination of local and global order features

The EOD is constructed by combining the GEOF and LEOF efficiently using the DCT method for dimensionality reduction. DCT is a standard method for dimensionality reduction of data. In contrast to PCA-SIFT [22] that requires pre-computed eigenvectors to be acquired from training data, computing DCT is not data-dependent, and it is more computationally efficient than PCA. For dimensionality reduction, combined GEOF and LEOF descriptors are transformed into the DCT space, and dimensionality is reduced by discarding the transform coefficients corresponding to the highest frequencies. The overall construction process of the EOD is illustrated in Fig. 4. First, the interest region is detected by an interest region detector such as the Harris–Affine or the Hessian–Affine detector. In this paper, we used the Hessian–Affine region detector [10]. Since the interest region detected by Hessian–Affine detector is an elliptic region with varying size dependent on the detection scale, we normalized this elliptic region to a $41 \times 41$ circular region to obtain scale and affine invariance. Rotation invariance was obtained by rotating the normalized region in the direction of the dominant gradient orientation. Then, an exact order image patch was generated with the exact ordering method, followed by sorting and grouping into 8 groups. In order to incorporate spatial information, the exact order image patch was divided equally into $4 \times 4$ spatial cells in a manner similar to the method in SIFT. In each spatial cell, two histograms with 8-bins were created. The first stored the number of occurrence of $m$th order at the $m$th bin, and the second stores the number of occurrence of the $m$th HC-LBP code at the $m$th bin. Then, these two histograms are concatenated, resulting in a 16-bin histogram. Finally, we reduced the concatenated histogram length using the DCT method by discarding the transform coefficients corresponding to the highest 8 frequencies. We thus had an EOD with $4 \times 4 \times 8 = 128$ dimensions. Finally, corresponding features were decided based on the Euclidean distance of the EOD. The contributions of the EOD were weighted by a Gaussian window overlaid over the region.

4. Experimental results

To evaluate the performance of the EOD, we compare the proposed descriptor with SIFT, CS-LBP, CS-LTP, OSID and HRI descriptors on the standard dataset widely used for performance evaluation of local descriptors. We followed the evaluation procedure proposed by Mikolajczyk [10]. The test dataset consisted of image sets with different geometric and photometric transformations (view point...
change, scale change, image rotation, image blur, illumination change, and JPEG compression) and with different scene types (structured and textured scenes). Fig. 5 shows the test dataset. In the cases of illumination change, the light changes are introduced by varying the camera aperture. Each image set contains 6 images with a gradual geometric or photometric distortion and the first image and the remaining 5 images were compared. In order to evaluate the descriptors under Gaussian noise, we augmented the Leuven–Gaussian noise images synthesized at Sections 2.2.

The ground-truth matches were also provided. To evaluate the descriptors, we used an evaluation metric which is based on the number of correctly and falsely matched regions between a pair of images [10]. We consider two regions of interest to be matched if the Euclidean distance between their descriptors is below a threshold. The number of correct matches is defined by the overlap error. If the overlap error is smaller than 0.5, we assume that the match is correct. The results are presented as recall versus a 1-precision curve

\[
\text{recall} = \frac{\text{# correct matches}}{\text{# correspondences}} \quad 1\text{-precision} = \frac{\text{# false matches}}{\text{# all matches}} \quad (9)
\]

where # correspondences refers to the number of matching regions between image pairs. By changing the distance threshold, we can obtain the recall versus the 1-precision curve.
For the interest region detector, we used the codes available on the website (http://www.robots.ox.ac.uk/vgg/research/affine). The interest regions were detected by a Hessian-Affine detector, and all regions were normalized to be invariant to scale, affinity, and rotation. The size of the normalized region was fixed at a 41 × 41 circular region. Then, the proposed method and other five local features are extracted as previously explained in Sections 3.3 and 2. Finally, local feature descriptors are generated in a manner similar to the method in SIFT.

First, we demonstrate the performance improvement achieved by combining GEOF with LEOF descriptor with DCT method. Figs. 6 and 7 show the results for the EOD, GEOF, and LEOF. As can be observed, the EOD gives better results than the GEOF and LEOF descriptors while keeping the feature dimensionality small. The EOD’s good performance can be attributed to the efficient combination of both local and global order features. Due to space limitations, only the performance of the Leuven and Boat image sets are shown. Similar behaviors were found for the other image sets.

In Figs. 8–14, the performance results for EOD and all other descriptors (SIFT, CS-LBP, CS-LTP, OSID, and HRI descriptors) are shown. In each figures (a) and (b) show the performance results of first-second image pair and first-forth image pair, respectively. The image degradation is much higher in the first-forth image pair than in the first-second image pair. As can be observed, the EOD outperforms all other descriptors for all the image sets. Moreover, performance degradation of the EOD with respect to image degradation is much smaller than for all other descriptors. In particular, we can see that the EOD outperforms all the other feature descriptors by a large margin in cases of illumination change and Gaussian noise, as shown in Figs. 8 and 9. This good performance is achieved because the EOD uses not only global order relationships in the overall distribution of orders but also local order relationships to improve discriminative ability.

By using the exact ordering method, the GEOF is substantially stable under non-linear intensity changes caused by illumination changes. Figs. 15–17 show three global order distributions induced from ordering by discrete intensity, relative ordering (HRI) and exact ordering under illumination changes. As shown in the Fig. 15, illumination change causes non-linear intensity changes. Under this non-linear intensity changes, ordering by discrete intensity yields very different global order distributions as shown in Fig. 15 because it cannot be separated among equal intensity level pixels. If illumination changes cause linear intensity changes, relative ordering method will yield same global order distributions. However, illumination changes cause non-linear intensity changes and relative ordering method shows unstable result as shown in Fig. 16, even though there is no error in determining the intervals. Especially, it shows very poor performance when saturated pixels exist. The exact ordering method defines exact orders which range 1 to number of pixels in the patch with auxiliary information. Thus, we can find exact order among pixels having the same
Fig. 8. Comparison of SIFT, CS-LBP, CS-LTP, HRI, OSID, and EOD for “Leuven” images (illumination change) (a) 1–2 and (b) 1–4 from the dataset. The image degradation is much higher in the 1–4 pair than in the 1–2 pair.

Fig. 9. Comparison of SIFT, CS-LBP, CS-LTP, HRI, OSID and EOD for “Leuven-noise” images (noise change) (a) 1–2 and (b) 1–4 from the dataset. The image degradation is much higher in the 1–4 pair than in the 1–2 pair.

Fig. 10. Comparison of SIFT, CS-LBP, CS-LTP, HRI, OSID, and EOD for “Boat” images (rotation change) (a) 1–2 and (b) 1–4 from the dataset. The image degradation is much higher in the 1–4 pair than in the 1–2 pair.
Fig. 11. Comparison of SIFT, CS-LBP, CS-LTP, HRI, OSID, and EOD for "Graffiti" images (affine change) (a) 1–2 and (b) 1–4 from the dataset. The image degradation is much higher in the 1–4 pair than in the 1–2 pair.

Fig. 12. Comparison of SIFT, CS-LBP, CS-LTP, HRI, OSID and EOD for "Wall" images (affine change) (a) 1–2 and (b) 1–4 from the dataset. The image degradation is much higher in the 1–4 pair than in the 1–2 pair.

Fig. 13. Comparison of SIFT, CS-LBP, CS-LTP, HRI, OSID, and EOD for "Bike" images (blur change) (a) 1–2 and (b) 1–4 from the dataset. The image degradation is much higher in the 1–4 pair than in the 1–2 pair.
Fig. 14. Comparison of SIFT, CS-LBP, CS-LTP, HRI, OSID, and EOD for “UBC” images (JPEG change) (a) 1–2 and (b) 1–4 from the dataset. The image degradation is much higher in the 1–4 pair than in the 1–2 pair.

Fig. 15. Intensity order distributions under illumination changes.

Fig. 16. Relative order distributions under illumination changes.
intensity value, but different auxiliary information. These exact orders are preserved under non-linear intensity changes and it results in almost same global order distributions as shown in Fig. 17.

In addition, the HC-LBP method makes the LEOF robust to Gaussian noise and illumination changes. The LBP and LBP-like descriptors are generated by a pixel-by-pixel order operator, which seems to be unstable with illumination change and Gaussian noise. However, the HC-LBP method uses a block-based order instead of a pixel-based order, which seems to alleviate this problem. Moreover, the combination of local and global exact order features using the DCT method increases the discriminating power of the EOD while keeping the feature dimensionality small. The running time of the proposed method and five other methods are summarized in Table 1. Since running time depends on number of interest region, we divide whole running time by number of interest region. The platform to execute the algorithms is Intel(R) Core(TM) 2 Quad CPU Q6600 at 2.40 GHz. As shown in Table 1, HRI is the fastest descriptor and the EOD is the slowest descriptor. The running time of the EOD is rather slower than five other descriptors because of sorting step. However, it can be improved by using fast sorting method.

5. Conclusions

In this paper, we propose an exact order based descriptor that is robust to illumination changes. To resolve the ambiguity of ordering for pixels of the same intensity value, the exact ordering method is adopted which changes discrete pixel values into k-dimensional vector values. With the exact ordered image patch, order based features are generated locally and globally, representing the local and global characteristics of the image patch respectively. The global order based feature looks at the global distribution of orders in the patch, and the local order based feature looks at the order relationship of the center pixel by comparing it with its neighboring pixels. With an efficient combination of local and global exact order features, the proposed descriptor has good properties for feature matching including small feature dimensionality, tolerance to illumination change, and robustness to Gaussian noise. Experimental results indicate that the proposed descriptor outperforms many state-of-the-art methods for various image transformations.

Conflict of interest

None declared.

Acknowledgments

This research was supported by a grant from the R&D Program (Industrial Strategic Technology Development) funded by the Ministry of Knowledge Economy (MKE), Republic of Korea. Also, The authors are deeply thankful to all interested persons of MKE and Korea Evaluation Institute of Industrial Technology (10040018, Development of 3D Montage Creation and Age-specific Facial Prediction System).

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