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Efficient invariant interest point detector using Bilateral-Harris corner detector for object recognition application

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Abstract Interest point detection plays a significant role in computer vision applications. The most commonly used interest point detector algorithm is scale invariant feature transform (SIFT). The use of Gaussian filter in the SIFT algorithm fails to match interest points on the edge and it also causes blur annoyance in the rescaling process. To overcome this failure Bilateral-Harris Corner Detector (BHCD) has been proposed in this paper. In the proposed BHCD, a Bilateral filter preserves edges by smoothening and removing noise in an image. Accuracy in localization of interest points are improved by using the proposed dynamic blur metric calculation. The Harris corner has been added to get stable and reliable interest point detection. The proposed BHCD has been simulated for the evaluation criteria such as repeatability and matching score. Extensive experimental results show that the proposed method is more robust to illumination, scaling, rotation, compression and viewpoint changes. The experimental evaluation for BHCD has been carried for the object recognition benchmark datasets COIL-100, ZuBud, Caltech-101. The proposed BHCD achieves highest recognition rate compared to the other state-of-the-art methods.

Keywords Interest point detector · Bilateral filter · Scale invariant feature transform (SIFT) · Bilateral-Harris corner interest point

1 Introduction

Object recognition is still a challenging task in computer vision. Feature detection or interest point detection is used to extract features from an image and match the features for object

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recognition. Many object recognition techniques have been developed by researchers during the past few decades. Vision based object recognition has limitations when it comes to varied illumination, scales, viewpoint and imaging conditions [12].

Interest points have the property of repeatability and stability under both local and global perturbations and can be adapted to various transformations. The interest point should be robust to achieve repeatability [10, 13] under different viewing conditions. Commonly used interest point detectors are Harris-Laplace detector [17] and Hessian-Laplace detector [17], Maximally Stable Extremal Regions (MSER) [14], Speeded-Up Robust Features (SURF) [2], STAR [1], Binary Robust Invariant Scalable Keypoints (BRISK) [11] and KAZE [7].

Harris and Hessian Laplace detectors uses two multi scale representation. The Harris Laplace detects corners while the Hessian Laplace detects blobs. In Hessian-Laplace, interest point location has been determined by 2D Hessian determinant and normalized Laplacian has been used to select its characteristics scale [17]. The Harris Laplace uses Harris operator [8] instead of Hessian matrix. The Harris and Hessian detectors are sensitive to image scale changes and do not provide a better image matching of different sizes.

MSER is an affine-invariant method, extracts a region with respect to the image intensity level and computes feature descriptors at different scales of the detected region size. MSER proved to be better scale change, illumination change and viewpoint change detector for an image but fails in blur change image [14]. SURF approximates 2D Hessian determinant computed on each Gaussian scale-space. SURF descriptor is calculated by the sum of the Haar wavelet response. SURF has been intended to overcome the computational cost of SIFT by using integral image for image convolution [2]. STAR uses bi-level filters to approximate the Laplacian of Gaussian. STAR features are computed at the extrema of the center-surround filters. STAR gives better performance for viewpoint change images but not for others image transforms [1].

BRISK descriptor is a binary string resulting from brightness differences computed around the keypoint. Potential region of interests are identified on each scale of a Gaussian pyramid. BRISK descriptor gives less performance compared to other detectors invariant to rotation [11].KAZE features detect interest points which are the local maxima of scale normalized Hessian determinant through non linear scale space. KAZE features are computationally expensive compared to SURF, BRISK, STAR descriptors [7].

Scale Invariant Feature Transform (SIFT) is the commonly used interest point detector in computer vision applications such as object detection [22], panorama stitching [3], robot localization and mapping [20], object classification [4], object tracking [24] etc. The SIFT composed of 3 stages including scale-space extrema detection, interest point localization, orientation assignment and interest point descriptor. In the first stage, the Gaussian scale space has been constructed and extrema points are detected in DoG scale space. During the second stage, interest points are localized and low contrast or strong edge responses are eliminated. Finally in the third stage, orientation is assigned to every interest points to generate 128 feature descriptors [13].

The features extracted by SIFT are invariant in different transformative conditions like scaling, rotation, affine distortion, compression and illumination. But few interest points on the edge are easily removed after detection due to Gaussian filter [23]. The Bilateral filter retains the interest points on the edge. Huang et al. [9] used a Bilateral filter instead of Gaussian filter. Bilateral filter is known as an edge-preserving by spatial averaging and causes smoothening of images.

The corners of an image contribute significant information with the added benefit of being invariant to variations in illumination and rotation. Harris corner detector [8] finds the feature points at fixed scale with less time. The Bilateral scale space construction with Harris corner point gives significant invariance to scale changes. Thus, the proposed BHCD uses Bilateral-

Harris Corner Detector to detect the interest point in image under scaling, rotation, illumination and viewpoint changes effectively than the state-of-the-art methods.

The paper is organized as follows. Section 2 describes the proposed BHCD. The evaluation of the proposed BHCD is discussed in Section 3. Section 4 describes the experimental results on datasets for object recognition. Finally, Section 5 concludes this paper.

2 Proposed BHCD interest point detector

The proposed BHCD has three stages similar to that of SIFT algorithm [13], but gives better accuracy than SIFT algorithm. The three stages are explained below (Fig. 1).

Stage 1: Bilateral scale space construction.

To retain the edges after detection a Bilateral filter is used instead of a Gaussian filter in scale space construction [9].

The Bilateral scale space (B) of an input image I_v of size MXN is defined as,

$$B(u,\sigma_d) = \frac{1}{W_u}\sum_{v\in\Omega} I_v G_{\sigma_d} G_{\sigma_r} \tag{1}$$

where v = (u,v) is the neighborhood center pixel

$$w_u = \sum_{v\in\Omega} G_{\sigma_d} G_{\sigma_r} \tag{2}$$

where

$$G_{\sigma_d} = \exp\left(-\frac{1}{2}\left(\frac{\mathrm{d(u,v)}}{\sigma_\mathrm{d}}\right)^2\right),\quad G_{\sigma_r} = \exp\left(-\frac{1}{2}\left(\frac{\delta(\mathrm{I(u)},\mathrm{I(v)})}{\sigma_\mathrm{r}}\right)^2\right)$$

where d(u,v) is the Euclidean distance between u and v, δ(u,v) represents the intensity difference, σ_d denotes the domain parameter and σ_r denotes the range parameter. The domain and range parameter controls Gaussian shape in space and controls the influence of intensity change respectively.

Laplacian-of-Bilateral (LoB) has been computed by convolving the fixed window Laplacian filter L(u) with each Bilateral image B(u, σ_d)

$$\mathrm{LoB}(\mathrm{u},\sigma_\mathrm{d}) = \mathrm{L(u)}*\mathrm{B}(\mathrm{u},\sigma_d) \tag{3}$$

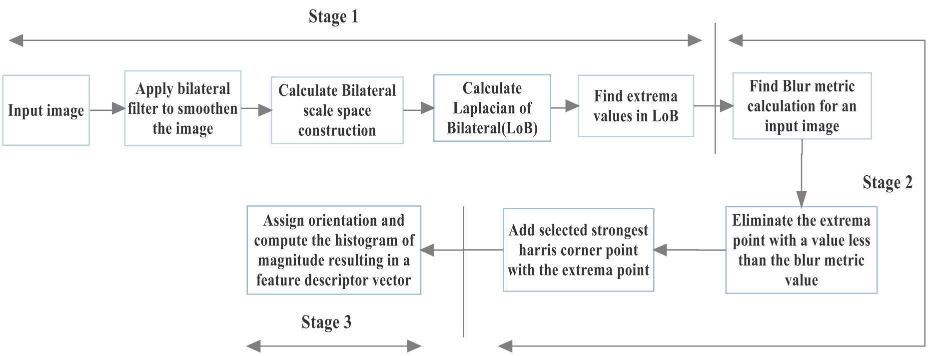

Fig. 1 Block diagram of the stages of proposed algorithm

In this experiment related parameter σ_r is fixed (σ_r = 0.04) [9]. The value of domain parameter σ_d similar to the smoothing parameter in SIFT algorithm proposed by Lowe as it controls Gaussian shape in space.

Stage 2: The low contrast and poorly localized interest points are eliminated by using the Taylor series expansion in the scale space function LoB(u,σ_d) as in SIFT algorithm. The extrema points which have a value less than 0.03 are discarded because it is an unstable low contrast extrema point and stable interest points are not extracted. Hence, a dynamic threshold has been computed for the blur metric instead of a fixed extrema value 0.03 and increases the numbers of matched interest points in the image [5].

Let 'L' be the luminance component of an image. The blur annoyance of L is estimated by blurring it in order to obtain a blurred image B. Strong horizontal (h_h) and vertical (h_v) low-pass filter have been chosen as given in Eq. 4 to model the blur effect and create B_{Ver} and B_{Hor} using Eq. 5

$$h_v = \frac{1}{9} \times [111111111]$$

$$h_h = T(h_v) = h_v{'} \tag{4}$$

$$\mathrm{B_{Ver}} = \mathrm{h_v} * \mathrm{L}$$

$$\mathrm{B_{Hor}} = \mathrm{h_h} * \mathrm{L} \tag{5}$$

The vertical (D_L_{Ver}) and horizontal (D_L_{Hor}) variations of luminance**,** blur vertical (D_B_{Ver}) and horizontal (D_B_{Hor}) are computed by using Eq. 6

$$\begin{array}{l}
\mathrm{D_L_{Ver}(i,j) = Abs(L(i,j)–L(i–1,j))\ for\ i = 1\ to\ m–1,\ j = 0\ to\ n–1} \\
\mathrm{D_L_{Hor} = Abs(L(i,j)–L(i,j–1))\ for\ j = 1\ to\ n–1,\ i = 0\ to\ m–1} \\
\mathrm{D_B_{Ver} = Abs(B_{Ver}(i,j)–B_{Ver}(i–1,j))\ for\ i = 1\ to\ m–1,\ j = 0\ to\ n–1} \\
\mathrm{D_B_{Hor} = Abs(B_{Hor}(i,j)–B_{Hor}(i,j–1))\ for\ j = 1\ to\ n–1,\ i = 0\ to\ m–1}
\end{array} \tag{6}$$

After blurring, the variation of neighboring pixels has been analyzed using Eq. 7. If the variation is high, the initial image is sharp; if it is low, the initial image has been blurred already. This variation is evaluated using the absolute differences as given below:

$$\begin{array}{l}
\mathrm{V_{Ver} = Max(0, D_L_{Ver}(i,j)–D_B_{Ver}(i,j))\ for\ i = 1\ to\ m–1,\ j = 1\ to\ n–1} \\
\mathrm{V_{Hor} = Max(0, D_L_{Hor}(i,j)–D_B_{Hor}(i,j))\ for\ i = 1\ to\ m–1,\ j = 1ton–1}
\end{array} \tag{7}$$

The variation of the initial image is compared by computing the sum of the coefficients of D_L_{Ver}, D_V_{Ver}, D_L_{Hor}, D_V_{Hor} using Eq. 8

$$\begin{array}{ll}
s_L_{Ver} = \sum_{i,j=1}^{m-1,n-1} D_L_{Ver}(i,j) & s_L_{Hor} = \sum_{i,j=1}^{m-1,n-1} D_L_{Hor}(i,j) \\
s_L_{Ver} = \sum_{i,j=1}^{m-1,n-1} D_V_{Ver}(i,j) & s_V_{Hor} = \sum_{i,j=1}^{m-1,n-1} D_V_{Hor}(i,j)
\end{array} \tag{8}$$

The result has been normalized between 0 to 1 using Eq. 9

$$b\_L_{Ver} = \frac{s\_L_{Ver} - s\_V_{Ver}}{s\_L_{Ver}} \qquad b\_L_{Hor} = \frac{s\_L_{Hor} - s\_V_{Hor}}{s\_L_{Hor}} \tag{9}$$

The maximum of the horizontal or vertical blur values is chosen the final blur value using Eq. 10

$$\mathrm{blur\_L = Max(b\_L_{Ver}, b\_L_{Hor})} \tag{10}$$

This final blur metric, blur_L value helps to find the threshold value. The threshold value is calculated from the given Eq. 11

$$\text{Threshold value} = \{0.4-(0.1*\text{blur\_L(I)})\} \tag{11}$$

where I is an input image. The values 0.4 and 0.1 are calculated based on the trial and error method. This threshold value is chosen to discard the low contrast extrema points. The Hessian matrix is used to eliminate edge response interest points [13]. The Harris corner point is further added to the extrema point to get more matched points.

Stage 3: The gradient magnitude m(x,y), and orientation (x,y) has been computed for each Bilateral smoothed image LoB(u,σ_d) by using Eqs. 12 and 13

$$m(x,y) = \sqrt{\left((L(x+1,y)-(x-1,y))^2 + (L(x,y+1)-L(x,y-1))^2\right.} \tag{12}$$

$$\theta(x,y) = \tan^{-1}((L(x,y+1)-L(x,y-1))/(L(x+1,y)-L(x-1,y))) \tag{13}$$

An orientation histogram is obtained from gradient orientations and a descriptor is formed from a vector containing the values of all the orientation histogram entries. Hence, a 128 element feature vector is formed for each interest point.

Pseudocode for BHCD algorithm

```
Input: Input digital image of M×N pixels
Output: Interest point of an output image
Parameters: Number of octave (O) = 4, Scale per octave (S) = 3, half-width of Bilateral filter (N) =2, domain
parameter σd = sigma of the Gaussian kernel, range parameter (σr) = 0.04.
// compute Bilateral scale space construction (Bss)
for (all octaves)
 {
  for (all scales)
   {
    Bss = BF(I, N, σd, σr)        \\ Smooth image using Bilateral filter
     LoB = Bss * Laplacian filter \\ Calculate Laplacian of Bilateral
    }
 }
//discarding low contrasted extrema point
extrema =  search_extrema (LoB);    \\Search each octave for stable extrema
threshold = 0.4 – 0.1 * blur_L;
for each extrema in LoB
{
    if (extrema <= threshold)
     {
       discard extrema points
     }
}
corners = Harris(I);      // detect Harris corner points
extrema = [extrema, corners];   \\add Harris corner points to the extrema points
// Assign orientation and magnitude
for (each extrema)
{
  compute gradient magnitude m(x,y) and orientation Θ(x,y)
   build the feature vector
}
```

3 Evaluation of interest point

The performance of the proposed BHCD is evaluated by using the Oxford dataset which is the most commonly used computer vision research data sets [16]. Six image transformations blur, viewpoint changes, zoom + rotation, illumination and JPEG compression are considered to evaluate the proposed BHCD. Figure 2 shows the sample image data sets for evaluation.

The interest point detectors are evaluated by measuring their repeatability and matching score [15, 19]. The main objective of the interest point detectors is to find the similarity between two similar scenes under different conditions such as different illumination, different viewpoint or different scale. The repeatability criterion is the ratio between the corresponding interest points and the minimum total number of interest points detected in both images. The repeatability evaluates the same physical location in an image under different viewing conditions. The repeatability and matching score evaluates the discriminative and descriptive qualities of the interest point detectors. Matching score is calculated as the ratio between the number of correct matches and the smaller number of detected regions in the pair of images. Matching score measures the matching ability of interest points and compares the Euclidean distance of descriptors.

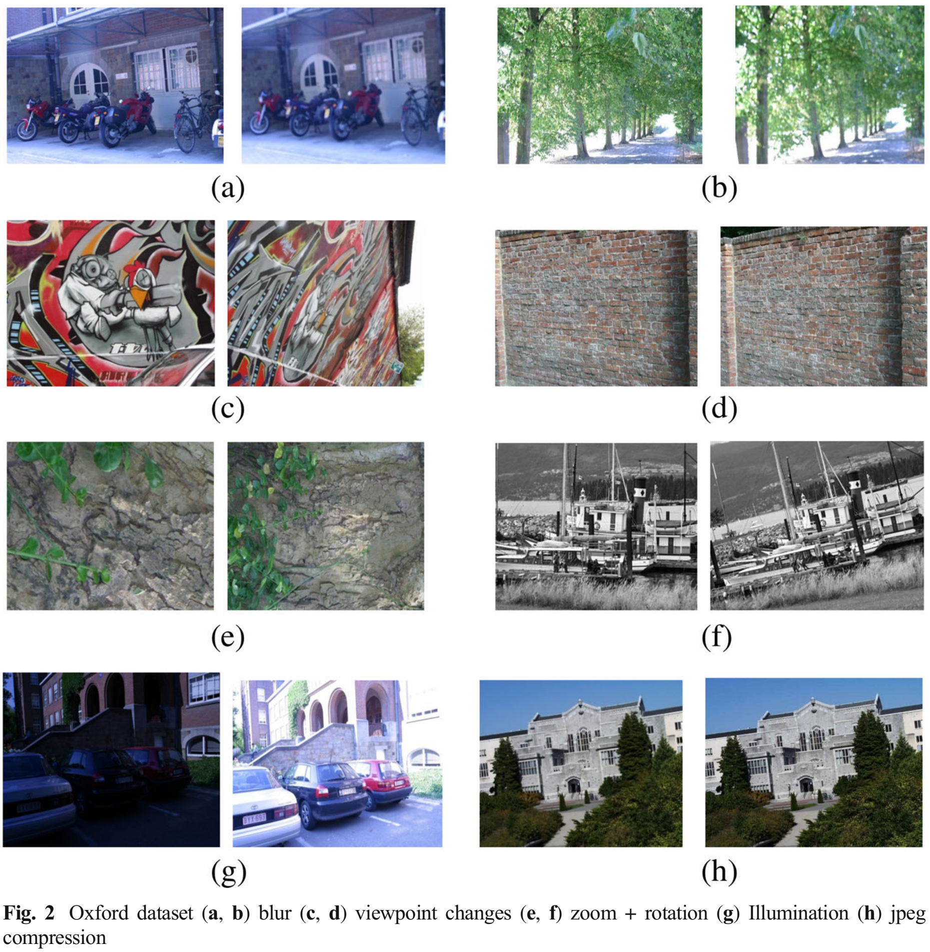

Fig. 2 Oxford dataset (**a**, **b**) blur (**c**, **d**) viewpoint changes (**e**, **f**) zoom + rotation (**g**) Illumination (**h**) jpeg compression

The performance of the proposed BHCD compared with the most popular detectors and descriptors such as Hessian-Laplace detector, Harris-Laplace detector, MSER detector, SURF, STAR, BRISK, KAZE, SIFT and Bilateral in SIFT.

3.1 Blurred image

The repeatability and matching scores of the proposed BHCD are analyzed between SIFT, Bilateral in SIFT, SURF, STAR, KAZE, MSER, BRISK, Harris Laplace and Hessian Laplace for variant blur image in the data sets. Figure 3a, b shows the repeatability performance of the SIFT, Bilateral in SIFT, Proposed BHCD, SURF, STAR, KAZE, MSER, BRISK, Harris Laplace and Hessian Laplace for the images Fig. 2a, b respectively. From Fig. 3a, b the repeatability performance for the proposed BHCD is high compared to other state-of-the-art methods due to the dynamic threshold in finding keypoint localization. Bilateral in SIFT gives better repeatability compared to SIFT and other methods, but less compared to the proposed BHCD due to the consideration of the geometric distance in the domain component and a photometric distance in the range component.

Matching score by various methods are shown in Fig. 3c, d. The proposed BHCD gives a better matching score compared to other methods for different blurred images due to the better combination of blur metric and Harris corner points.

3.2 Viewpoint change image

The repeatability score of viewpoint change images are shown in Fig. 4a, b for Fig. 2c, d test images. The results show that the proposed BHCD gives a better repeatability score compared

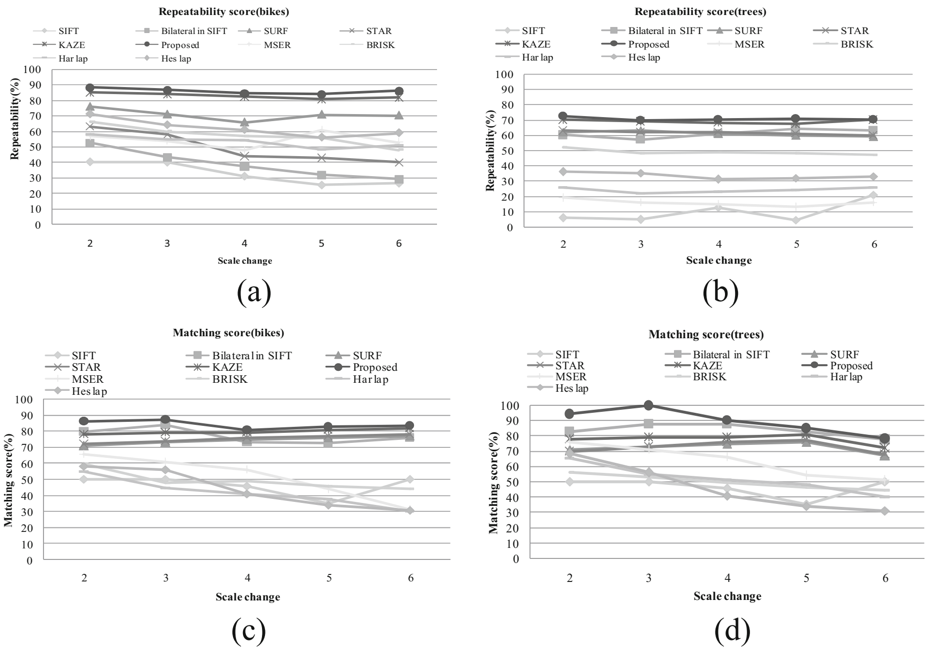

Fig. 3 **a** Repeatability score of blurred images (bikes) **b** Repeatability score of blurred images (trees) **c** Matching score (bikes) **d** Matching score (trees)

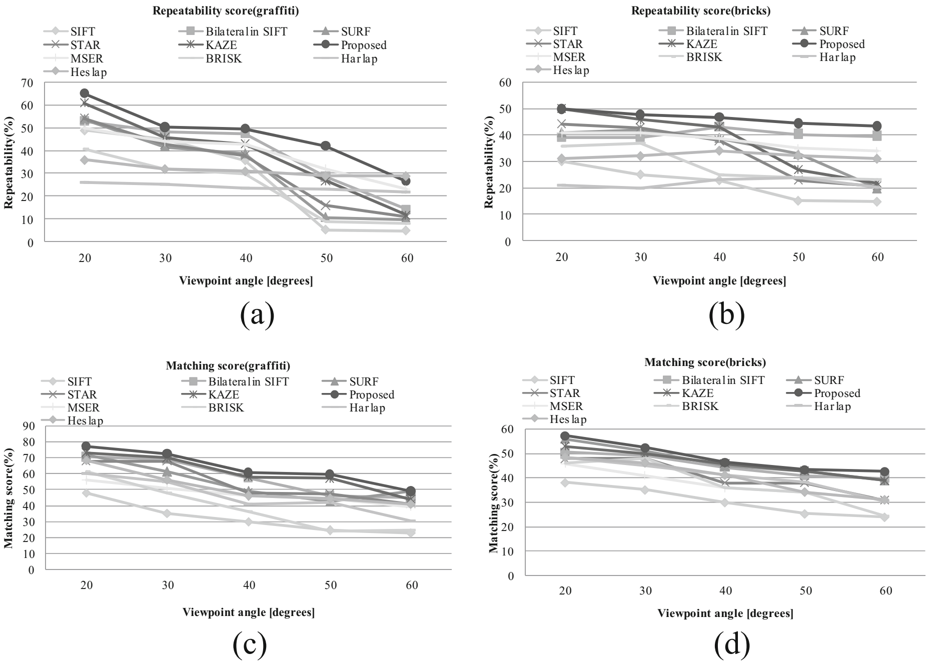

Fig. 4 **a** Repeatability score of viewpoint change images (graffiti) **b** Repeatability score of viewpoint change images(bricks) **c** Matching score (graffiti) **d** Matching score (bricks)

to other methods SIFT, Bilateral in SIFT, SURF, STAR, KAZE, MSER, BRISK, Harris Laplace and Hessian Laplace. Among all descriptors KAZE, Bilateral in SIFT and proposed outperforms. The matching score is obtained from the same images as shown in Fig. 4c, d. The proposed BHCD gives a better repeatability score and matching score as it uses the Harris corner point information and spatial averaging by Bilateral filter.

3.3 Zoom + rotation change image

The evaluations are performed for the scale changes of a factor 2–6 as shown in Fig. 2e, f of test images. Figure 5a–d shows the repeatability score and matching score of SIFT, Bilateral in SIFT, proposed method, SURF, STAR, KAZE, MSER, BRISK, Harris Laplace and Hessian Laplace. The proposed BHCD gives a highest repeatability score and matching score compared to SIFT, Bilateral in SIFT, SURF, STAR, KAZE, MSER, BRISK, Harris Laplace and Hessian Laplace due to the combination of Bilateral and Harris corner point detection.

3.4 Illumination change image

The tested sample image pairs are shown in Fig. 2g. Figure 6a, b compares the repeatability and matching score for various methods. By normalizing the intensity an illumination invariant interest points are extracted by proposed BHCD and gives higher repeatability rate and maximum matching score than other detectors such as SIFT, BRISK, MSER, SURF, STAR, KAZE, Hessian Laplace and Harris Laplace.

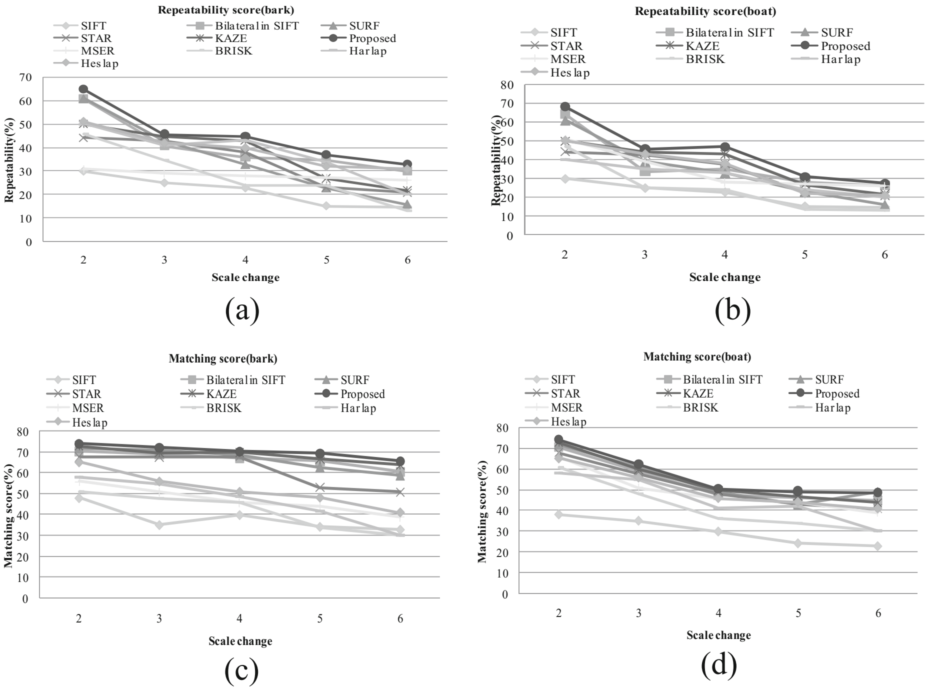

Fig. 5 **a** Repeatability score of zoom + rotation change images (bark) **b** Repeatability score of zoom + rotation change images(boat) **c** Matching score (bark) **d** Matching score (boat)

3.5 JPEG compression image

The evaluations are performed on JPEG compression images for the various test images as shown in Fig. 2h. The experimental results of repeatability score and matching score of different methods for the compressed images are shown in Fig. 7a, b. All methods are affected by JPEG artifacts, but proposed method gives a higher rate of repeatability score and matching score compared to SIFT and Bilateral in SIFT because the proposed approach extracts stable Harris corner points.

From the above experimental analysis Hessian and Harris Laplace detector gives lower repeatability and matching score for blurred images since the interest point extracted by two detectors are not scale invariant compared to SIFT and other detectors. SURF detector gives

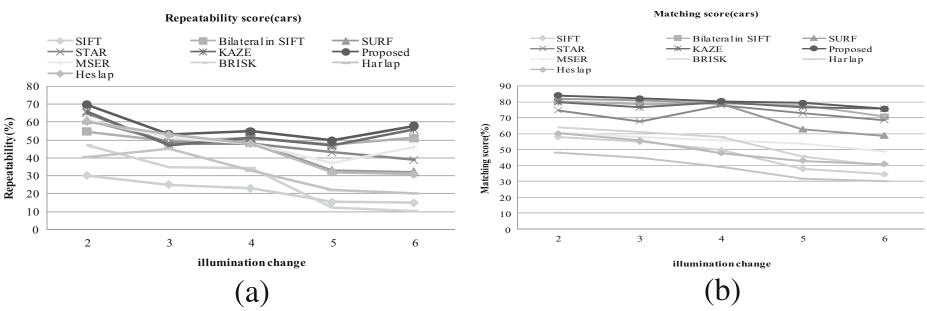

Fig. 6 **a** Repeatability score of illumination change images (cars) **b** Matching score (cars)

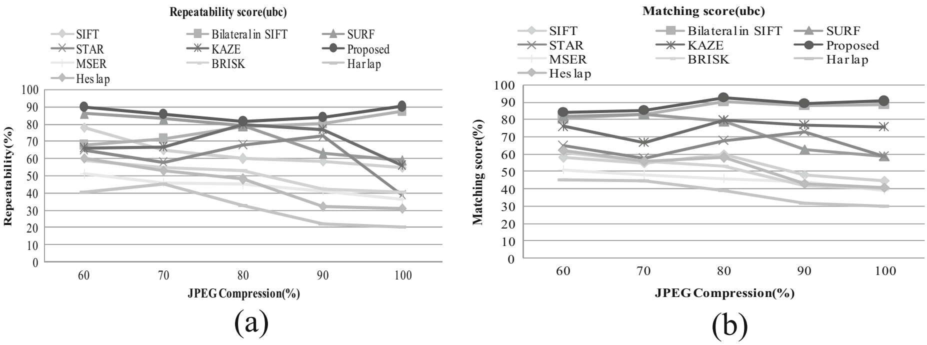

Fig. 7 **a** Repeatability score of compression images (ubc) **b** Matching score (ubc)

result nearest to SIFT detector and the speed is high compared to SIFT but the repeatability and matching score is less for all types of image conditions. BRISK, KAZE and STAR detectors also provide less performance for all types of image transformations compared to proposed BHCD. Though KAZE gives better scores than SIFT, the KAZE features are computationally more expensive. MSER gives result nearest to Bilateral in SIFT for all types of image transformations.

The proposed BHCD gives a better repeatability score and increases the number of matched interest points under different image transformation conditions. Repeatability score and matching score have been evaluated for various images under different imaging conditions. In all cases the proposed BHCD is better than other state-of-the-art detectors.

4 Application to object recognition

The task of recognizing different object types is very difficult in computer vision system due to environmental condition such as illumination, occlusion, view point and articulation. The proposed BHCD tested with publicly available object recognition benchmarks COIL-100 [18], Caltech-101 [6], ZUBUD [21]. COIL-100 contains 100 different objects, each object with 72 images at different pose intervals without background clutter, occlusion and illumination changes. Caltech-101 consists of 101 object categories, has a significant variation in colour, pose and illumination changes. ZuBuD data base contains set of images of 201 buildings with varied background and illumination changes.

The experimental results of various detectors such as Harris-Laplace detector, Hessian-Laplace detector, MSER, SURF, STAR, BRISK and KAZE are analyzed in the Section 3.

Fig. 8 COIL-100 dataset (**a**) Query image (**b**) Corresponding recognized database images of SIFT, Bilateral in SIFT and proposed BHCD (**c**) Some database images not recognized by SIFT and Bilateral in SIFT but recognized by proposed BHCD

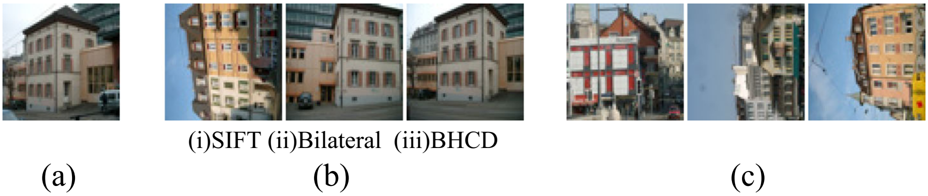

Fig. 9 ZuBud dataset (a) Query image (b) Corresponding recognized database images of SIFT, Bilateral in SIFT and proposed BHCD (c) Some database images not recognised by SIFT and Bilateral in SIFT but recognized by proposed BHCD

Hessian and Harris Laplace detector gives lower repeatability and matching score for blurred images. SURF detector gives result nearest to SIFT but the repeatability and matching score is less. BRISK, KAZE and STAR detectors also provide less performance for all types of image transformations. KAZE gives a better score, but computationally more expensive. MSER gives result nearest to Bilateral in SIFT. Due to the above mentioned drawbacks the recognition rates for these detectors were not considered. The recognition rates for SIFT, Bilateral in SIFT and the proposed BHCD have been calculated for the given datasets, as it gives a more repeatability score, matching score and more stable for image transformations.

Figure 8a, b shows the query and the corresponding recognized database images using SIFT, Bilateral in SIFT and proposed BHCD method. Figure 8c shows some of the database images that are not properly recognized by SIFT and Bilateral in SIFT but recognized by proposed BHCD.

Figure 9a, b shows the query and the corresponding database images of SIFT, Bilateral in SIFT and proposed BHCD method for ZuBud dataset. Figure 9c shows the some of the database images that are not recognized by SIFT and Bilateral in SIFT but recognized by proposed BHCD method.

Figure 10a, b shows the query images for Caltech 101 database and the corresponding resultant images by SIFT, Bilateral in SIFT and proposed BHCD method. Figure 10c shows the some of the database images that are not recognized by SIFT and Bilateral in SIFT but recognized by proposed BHCD method.

SIFT and Bilateral in SIFT are compared with the proposed BHCD for better performance in different image transformation. The recognition rates for these three methods are tabulated in Table 1. The experimental results show that the proposed BHCD gives better recognition rates for all the three datasets compared to SIFT and Bilateral in SIFT. Thus the recognition rate of the proposed BHCD confirms better object recognition in the image.

Fig. 10 Caltech 101 dataset (a) Query image (b) Corresponding recognized database images of SIFT, Bilateral in SIFT and proposed BHCD (c) Some database images not recognised by SIFT and Bilateral in SIFT but recognized by proposed BHCD

Table 1 Experimental results on different datasets

Dataset	Recognition rate		
	SIFT	Bilateral in SIFT	Proposed BHCD
COIL-100 [18]	80%	89%	97.6%
ZuBud [6]	80%	89%	98.6%
Caltech-101 [21]	88%	94%	98.9%

5 Conclusion and future work

This paper proposes the BHCD to improve interest point detection. The blur metric selects the threshold value for accurate interest point localization. Proposed BHCD substantially improves the repeatability score of detecting interest point and the number of matched interest points between two images than the state-of-the-art methods. The experimental analysis shows that the proposed BHCD is more robust to various image transformations such as zoom + rotation, blur, viewpoint, illumination and compression. The dynamic blur metric and bilateral scale space constructions make the proposed BHCD method more suitable for object recognition applications. In future the proposed BHCD is extended to object classification and tracking applications.

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