HISTO-BINARY COMBINED CORNER ENHANCEMENT (HBCCE) IMPROVED ALGORITHM FOR IMAGE PROCESSING CORNER DETECTION

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Abstract - *A novel algorithm, Histo-Binary Combined Corner Enhancement (HBCCE), for enhancing corner detection is discussed. The main goal is to enhance the repeatability for the corner by corner sharpening using a preprocessing filtering strategy. We are particularly interested in corner points because they are defined locally, usually in very small neighborhoods. The quality of the corners and the efficiency of the detection methods are both very important aspects that can greatly impact the accuracy, robustness and real-time performance of the corresponding corner-based vision system. There are many variant of corner detectors, but, no precise corner detector exists. The most used corner detectors our days are, Harris corner detector [1], Sh-Tomasi detector [2], SUSAN detector [3], CSS detector [4], FAST detector [5] and AGAST detector [6].*

In the present paper, we propose a new strategy to enhance the corner detectors by adding a preprocessing stack prior to any detection step, as mentioned previously the final goal is to sharpen the corners so they can be easily detected. Our approach is based on an efficient combination of filters. We verify the performance of the proposed method by measuring the repeatability rate under various JPEG compressions, rotation, scale, blur and illumination changes using a standard dataset [7].

Keywords: binary features, enhance corner detector, preprocessing, AGAST, ORB, BRISK

1 Introduction

Corners, also known as junctions, key points or interesting points, are used in many image applications such as image registration, shape analysis, object recognition/tracking, motion analysis, scene analysis, stereo matching, etc. Therefore, when working on two-dimensional features, a particular interest is given to corner detection [1] [2] [15] [16]. Because of the growing interest of using corner based features, many researches investigate on finding a nonlinear operator able to remove texture and noise, while preserving edges and corners [5] [6] [7] [8] [14]. The leading operators are based on median filtering [9], bilateral filtering [10], mean shift [11], total variation [12] and the most popular anisotropic diffusion [13]. The last one is not computationally efficient and has been subject of many improvements in last year's [14].

The purpose of these techniques is to process an image so that the final image gives more visual information than the original one, but none of these algorithms can give good results for all types of applications.

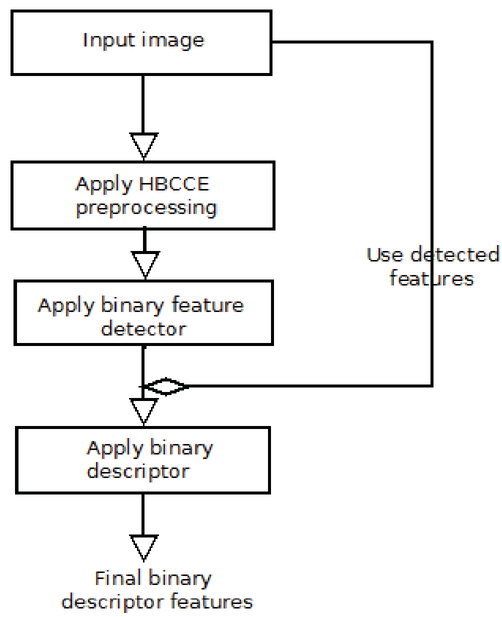

Fig. 1: How to integrate the HBCCE stack with any binary detector/ descriptor approach.

In this paper we propose a new preprocessing stack enhancing corner detection while removing noise, blur and minimizing the effect of illumination changes (Figure1). The purpose is to come out with a new model for building a more accurate local binary features detector based on a very efficient preprocessing stack. Our method proceeds as follows (Figure. 2):

First, the original image is converted to a 16-bit grayscale image.

Second, we apply a contrast-wise version of Contrast Limited Adaptive Histogram Equalization to reduce the illumination effects.

Third, we use Unmask Sharpening, the purpose is to reduce the noise with a Gaussian blurring operator and then subtract the blurred version from the original one.

Fourth, we apply Laplacian Filter for shapes sharpening, in our case we work directly on the resulting image after Laplacian Filtering without subtracting the filtered image from the original one.

Finally, we convert the final enhanced image matrix to 8-bit grayscale, representing the final HBCCE enhanced image. The first aim of this paper is to set out a concise overview of the proposed HBCCE method and demonstrate its efficiency under numerous image changes. In the next section we describe the steps used in our approach.

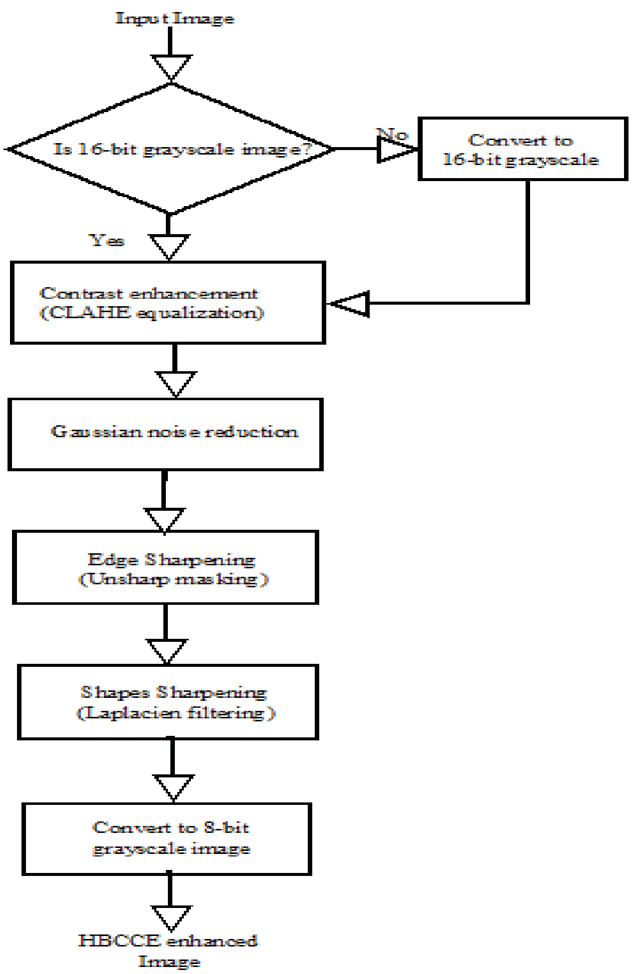

Figure 2: a – Diagram of different steps involved in HBCCE preprocessing algorithm.

2 CLAHE: Contrast-Limited Adaptive Histogram Equalization

The first step in our preprocessing stack is to improve the contrast of the overall objects presents in the processed image. For that raison, we will use CLAHE [18][32] as a powerful contrast enhancement.

Contrast enhancement methods are not intended to increase or supplement the intrinsic structural information in an image but rather to improve the image contrast and hypothetically to enhance particular characteristics. The input images are 8-bit grayscale images. We can process these images directly. But there is a slight problem with that. Black-to-White transition is taken as Positive slope (it has a positive value) while White-to-Black transition is taken as a Negative slope (It has negative value). So when we convert data, all negative slopes are made zero. And then we miss some edges. To bypass this problem, we convert data type to some higher forms like 16-bit, 64-bit etc (we use 16-bit grayscale images), process it and then convert back to original 8-bit

2.1 CLAHE concept:

Initially developed for medical images, CLAHE has demonstrated to be successful for enhancement of low-contrast images such as portal films [32]. CLAHE is an adaptive contrast enhancement method based on Adaptive Histogram Equalization (AHE) [17]. AHE proceed as follows: The histogram is calculated for the contextual region of a pixel. The resulting pixel's intensity is transformed to a value within the display range proportional to the pixel intensity‘s rank in the local intensity histogram but this process can over amplify the noise in the initial image.

Basically, developed to prevent the over amplification of noise that AHE can give rise to [18] [19], CLAHE refine AHE by imposing a user specified maximum, ie, Clip Limit, to, the height of the local histogram, and thus on the maximum contrast enhancement factor. The enhancement is thereby reduced in very uniform areas of the image “tiles”. The resulting neighboring tiles are then stitched back seamlessly using bilinear interpolation, which prevent over enhancement of noise and reduce the edge-shadowing effect of unlimited AHE (Figure 3). Thus, CLAHE can limit the noise whereas enhancing the contrast [18] [32].

In our case we use a Uniform distribution with a clip limit equal to 0.1. (Figure 3) shows an example of the produced enhanced grayscale image by applying the CLAHE enhancement.

The clip limit can be obtained by: ß [19].

$$\beta = \frac{M}{N}\left(1 + \frac{\alpha}{100}(S_{max} - 1)\right) \quad (1)$$

Where α is clip limit factor, M region size, and N is grayscale value. The maximum clip limit is obtained for α=100.

The uniform CLAHE equalization is obtained by (2)

$$I = (I_{max} - I_{min}) * P(f) + I_{min} \quad (2)$$

Where:

I : computed pixel value

I_{max} : Maximum pixel value

I_{min} : Minimum pixel value

P(f) : Cumulative probability distribution

2.2 CLAHE Testing Results:

Testing CLAHE (Figure 3) on the image datasets proposed

by Mikolajczyk and Schmid [20] and available on[1], shows that the downsides of CLAHE equalization are:
Amplify image noise for flat regions.
Introduce ring artifacts for strong edges.
To reduce the noise introduced by the contrast enhancement, we apply Gaussian smoothing basically used for Gaussian noise reduction.

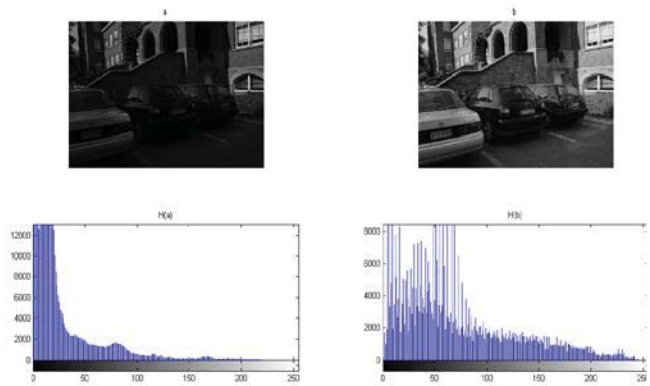

Fig. 3: a - original grayscale image (leveun-6), b - grayscale enhanced image with CLAHE (Distribution = unifrom , clipLimit=0.1,tileSize=(2,2)), H(a)- classical histogram image for original grayscale image and H(b)- CLAHE histogram for the transformed image.

3 Noise reduction: Gaussian blurring

Many attempts have been trying to construct digital filters which have the qualities of noise attenuation and detail preservation. One of the best known filters when dealing with impulsive noise is the median filter [23].
Median filter is less efficient in presence of Gaussian noise. Several researchers have attempted to generalize the standard median filter for removing Gaussian noise with more or less success. In our case we use Gaussian blurring for noise reduction.

3.1 Gaussian Blurring Concept:

Blurring filters generally follows the equation (3):

$$J(i,j) = \sum_{k,l} I(i+k, j+l) * G(k,l) \tag{3}$$

Where:
$J(i,j)$ is the blurred image
$I(i+k, j+l)$ is the input pixel values.
$G(k,l)$ is the kernel (the coefficient of the filter).

The Gaussian Blur effect is a filter that blends a specific number of pixels incrementally, following a bell-shaped curve. The blurring is dense in the center and feathers at the edge [28]. For Gaussian blurring, we replace in (3), $G(k,l)$ by the Gaussian kernel; which is given by (4):

$$G(k,l) = \frac{1}{2\pi\sigma^2} e^{-\frac{k^2+l^2}{2\sigma^2}} \tag{4}$$

To produce a discrete approximation of the Gaussian filter, we use the property that, the distribution approximate zero at about three standard deviations from the mean. 99% of the distribution falls within 3 standard deviations. Gaussian filter, is probably the most useful, simple and frequently used filter for noise reduction (but not the fastest). It's implemented by convolving each point in the input image with a Gaussian kernel and summing them to output the final blurred image. Gaussian filtering is more effective at smoothing images. It has been proven that neurons in the human visual perception system create a similar filter when processing visual images [29]. Gaussian smoothing is commonly the first step in edge and corner detection. It has the following characteristics [28]:

The Gaussian filter is a non-uniform low pass filter.

The kernel coefficients diminish with increasing distance from the kernel's centre.

Central pixels have a higher weighting than those on the periphery.

Larger values of σ produce a wider peak (greater blurring).

Kernel size must increase with increasing σ to maintain the Gaussian nature of the filter.

Gaussian kernel coefficients depend on the value of σ.

At the edge of the mask, coefficients must be close to 0.

The kernel is rotationally symmetric with no directional bias.

Gaussian kernel is separable which allows fast computation.

Gaussian filters might not preserve image brightness.

Figure 4: left: the CLAHE enhanced image, Right: the resulting image after CLAHE enhancement and Gaussian Blurring with σ=5

3.2 Gaussian Blurring Limitations:

Gaussian filtering is very useful for noise and detail removing (figure 4). But, contrary to median filter, Gaussian filter is not effective at salt and pepper noise removing [23].

The resulting image is a smoothed image. In next step we will sharpen this image to improve the clarity of details in the image

4 Unsharp Masking

Sharpness describes the clarity of detail in a photo, and can be a valuable creative tool for emphasizing texture.

We use Unsharp masking (UM) to emphasize texture and Detail [21].
Unsharp masking filter, also known as edge enhancement filter, is a simple operator to enhance the appearance of detail by increasing small-scale acutance without creating additional detail. The name was given because this operator improves details and other high frequency components in edge area via a process by subtracting a blurred version of the original image from the first one.

[1]http://www.robots.ox.ac.uk/~vgg/data/data-aff.html

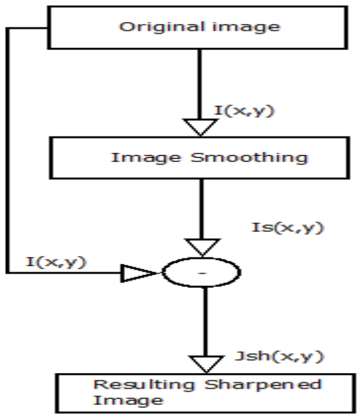

Fig. 5: Block diagram of the classical Unsharp masking

4.1 UM Concept:

Sharpening is a simple spacial filtering concept that produces an enhanced image J by increasing the contrast of the given image I along edges, without adding too much noise within homogeneous regions in the image.

The principle of UM is quite simple [21] [22]:

First a blurred version of the original image is created (we use a Gaussian blurring filter in our case).

Then, this one is subtracted from the original image to detect the presence of edges, creating the unsharp mask.

Finally this created mask is used to selectively increase the contrast of theses edges (fig. 5).

Mathematically this is represented by (5):

$$J_{sh}(x,y) = I(x,y) - I_s(x,y) \tag{5}$$

Where $J_{sh}(x,y)$ is the sharpened resulting image

$I(x,y)$ is the original image

$I_s(x,y)$ is the smoothed version of $f(x,y)$ obtained by

$$I_s(x,y) = I(x,y) - \{I(x,y) * HPF\} \tag{6}$$

Where HPF is a height pass filter.

4.2 UM Limitations:

Unsharp masking is a very powerful method to sharpen images (fig. 6). But, too much sharpening can also introduce undesirable effects such as "halo artifacts". These are visible as light/dark outlines or halos near edges. Halos artifacts become a problem when the light and dark over and undershoots become so large that they are clearly visible at the intended viewing distance.

Here we are addressing only the gray level images. The sharpened image may contain some introduced noise. To reduce this probably introduced noise we will apply a Laplacian filter to a smoothed version of the previously sharpened image.

Fig. 6: left: the CLAHE enhanced and Gaussian Blurred image, Right: the resulting image after Clahe enhancement and Gaussian Blurring and Unsharp Masking

5 Laplacian Filtering

Sharpening filters are used in order to highlight fine details within an image. They are based on first and second order derivates. First order derivatives are used to produce thicker edges in an image and are usually used for edge extraction.

Second order derivatives on the other hand, have a stronger response to fine detail and are usually better for image enhancement than the first order derivatives.

5.1 Laplacian Filtering Concept:

Laplacian filter is a second order or second derivative filter of enhancement. It is used to find areas of rapid change (edges) in images. Any feature with a sharp discontinuity (like noise) is enhanced by a Laplacian filter [30].

Since derivative filters are very sensitive to noise, it is common to smooth the image (e.g., using median filter, Gaussian filter…) before applying the Laplacian. If the Laplacian filter is used with a Gaussian filter, this process is called the Laplcaian of Gaussian (LoG).

The Laplacian is a linear operator; it forms an isotropic filter and is one of the simplest sharpening filters. In order to get a sharpened image, typically, the resulting Laplacian filtered image is added to the original image [31].

The Laplacian is given by (7)

$$L(x,y) = \nabla^2 f(x,y) = \frac{\partial^2 f(x,y)}{\partial x^2} + \frac{\partial^2 f(x,y)}{\partial y^2} \tag{7}$$

Where the partial 1st order derivative in the x direction is defined as follows (an approximation):

$$\frac{\partial^2 f}{\partial^2 x} = f(x+1,y) + f(x-1,y) - 2f(x,y) \tag{8}$$

and in the y direction as follows:

$$\frac{\partial^2 f}{\partial^2 y} = f(x,y+1) + f(x,y-1) - 2f(x,y) \tag{9}$$

Replacing (8) and (9) in (7) give the final approximation of the Laplacian filter:

$$\nabla^2 f(x,y) = [f(x+1,y) + f(x-1,y) + f(x,y+1) + f(x,y-1)] - 4f(x,y) \tag{10}$$

Finally (10) can be represented with the following matrix that's used to implement the digital Laplacian:

$$\begin{bmatrix} 0 & 1 & 0 \\ 0 & -4 & 1 \\ 0 & 1 & 0 \end{bmatrix} \tag{11}$$

There are other slightly different versions of Laplacian implementation [31].

Applying the kernel shown in (11) give the result showed in (Figure 7)

5.2 Laplacian Filtering Limitations:

Laplacian is a second derivative operator, which make it very sensitive to noise. Thus, it has the effect of enhancing noise as well as the structure. Therefore, it should be applied only in areas which have low noise, or areas which have been subjected to noise reduction operator (such as image smoothing).

Fig. 7: left: the resulting image after Clahe enhancement, Gaussian Blurring and Unsharp Masking, Right: the resulting image after Clahe enhancement, Gaussian Blurring, Unsharp Masking and Laplacian filtering.

Fig. 8: left: The resulting image after Clahe enhancement, Gaussian Blurring, Unsharp Masking and Laplacian filtering, Right: the resulting image after subtracting the left image from the CLAHE enhancement image.

The filtered image should be subtracted from the original one to get the final sharpened image (Figure 8).

6 Performance evaluation

To prove the efficiency of our HBCCE approach on enhancing the features detection, we test our approach extensively following the evaluation method and datasets proposed by Mikolajczyk and Schmid [14]. We use the same dataset used in [14] and available online[2].

In this paper, the Open Computer Vision (OpenCV)[3] is used as the implementation framework for BRISK detector [4] (we use the last stable available version 2.4.9). HBCCE is implemented using C++ language.

We test our approach on a PC with CPU: INTEL(R) PENTIUM(R) 2.13 GHZ dual core, RAM: 3GO and windows 7 Ultimate Edition (32 bits) as an operating system.

Each of the datasets contains a sequence of six images presenting an increasing amount of transformation.

Our proposed method is evaluated against six image transformations: scale changes, view changes (Graffiti and Wall), zoom and rotation changes (Bark and Boat), illumination changes (Leuven), image blur (Bikes and Trees) and JPEG compression (Ubc).

6.1 Repeatability enhancement:

(Figure 11) shows the result of applying HBCCE stack effect on enhancing the repeatability of the BRISK [4] detector. As defined in [20], the repeatability is the ratio between the corresponding keypoints and the minimum total number of keypoints visible in both images.

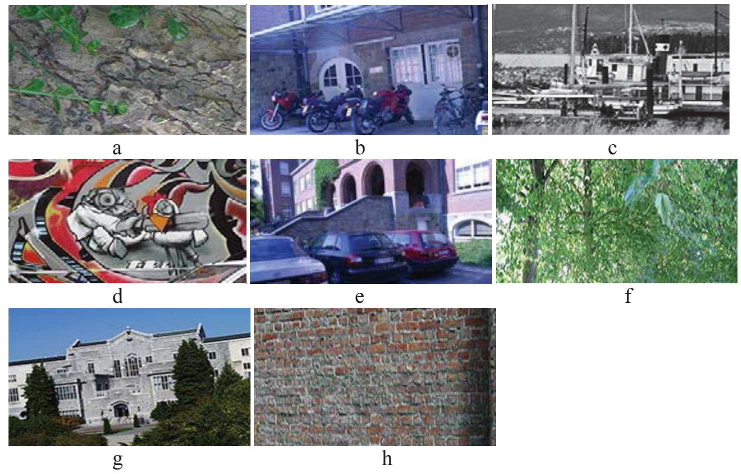

Fig. 9: Examples of images used for the evaluation: viewpoint change (Graffiti (d) and Wall (h)), zoom and rotation (Bark (a) and Boat (c)), JPEG compression (Ubc (e)), brightness change (Leuven (g)), and blur (Bikes (b) and Trees (f)).

As we can see in (fig. 11), the HBCCE stack drastically enhance the repeatability of the BRISK [4] detector.
We have also tested HBCEE on AGAST [2] and FAST [1] with similarly great success.

6.2 Results:

Results show that the proposed algorithm, Histo-Binary Combined Corner Enhancement (HBCCE), improves drastically the quality of the features detected while delivering comparable computation time. (Figure 10) illustrates the quality image enhancement introduced by the algorithm. HBCCE corrected the lighting effect, enhanced the appearance of details by increasing small-scale acutance, reduced the Gaussian noise and highlighted the fine details with second order spatial derivative to produce the final enhanced image. (Figure 11) shows the repeatability scores for 50% overlap error of the BRISK [4] and the BRISK-HBCCE detector. It is clearly shown that the proposed algorithm enhances the repeatability of the detector from 10% to 40%.

Figure 10: Left: The original image taken from dataset proposed in [20], Right: The resulting image after applying the HBCCE enhancement method.

[2]http://www.robots.ox.ac.uk/~vgg/data/data-aff.html
[3]http://docs.opencv.org/index.html

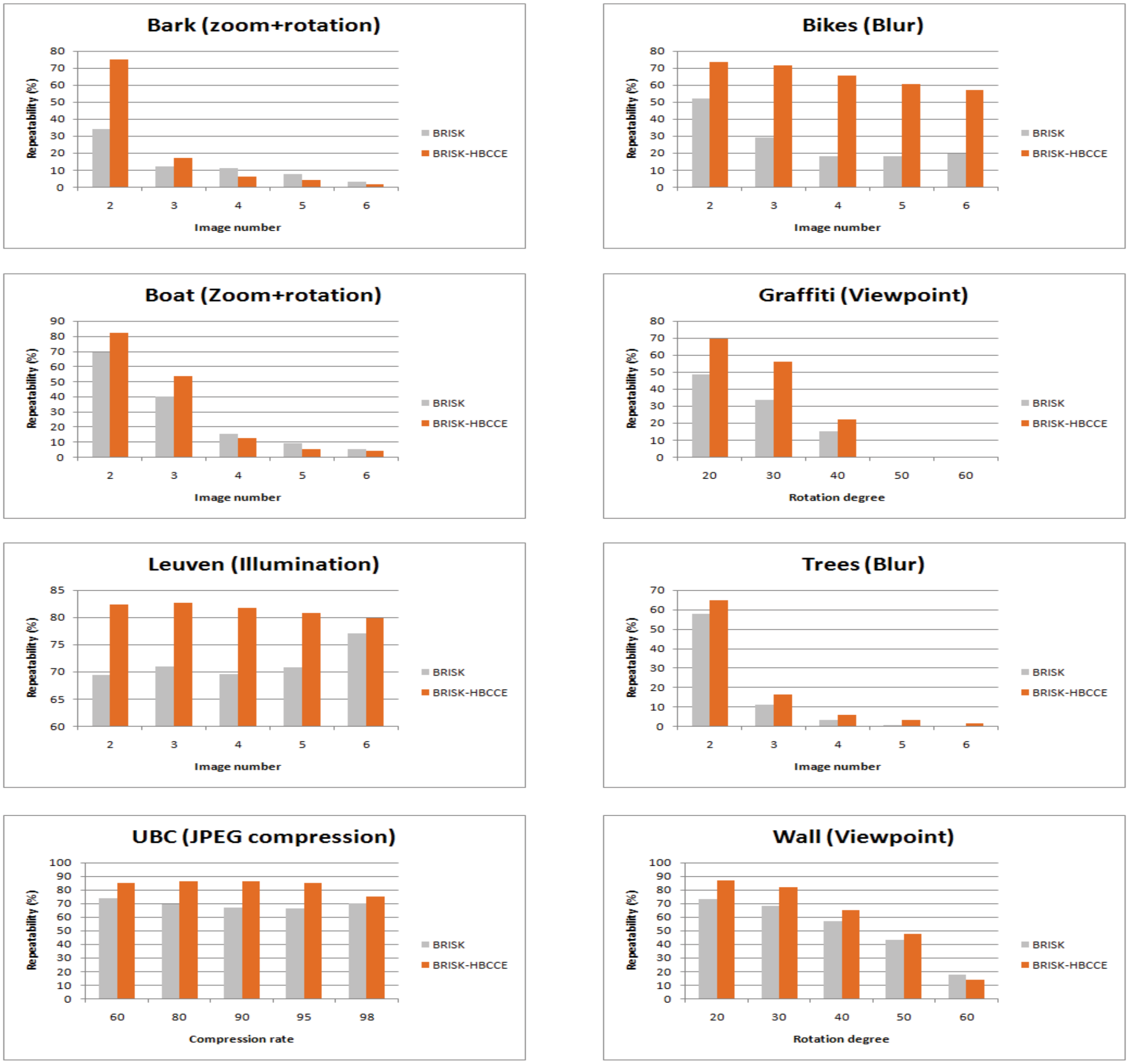

Fig. 11: Repeatability scores for 50% overlap error of the BRISK and the BRISK-HBCCE detector

7 Conclusions:

We have presented a novel approach named HBCCE, which Effectively combines different preprocessing algorithms to produce a very efficient preprocessing stack.
We have demonstrated the efficiency of our approach by exhaustively testing it on a standards dataset, and shown the improvement introduced by the proposed method on detectors repeatability.

8 Acknowledgements

This research was supported by the INVENTIVE Technologies laboratory[4] , a part of the Creargie MediaScan[5] in CASABLANCA Morocco and the TT&MIA (Télédétection spatiale-Traitement signal/image & Maths appliquées-Informatique-Aide à la decision) from university Abdelmalek Essaâdi. We are grateful to Mr. Dominique Schwartz the CEO of INVENTIVE Technologies and Creargie MediaScan for his valuable inputs, as well as to many other colleagues at TT&MIA and INVENTIVE Technologies laboratory for very helpful discussions.

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