Corner Detection Using Mutual Information

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Abstract

This work presents a new method of corner detection based on mutual information and invariant to image rotation. The use of mutual information, which is a universal similarity measure, has the advantage of avoiding the derivation which amplifies the effect of noise at high frequencies. In the context of our work, we use mutual information normalized by entropy. The tests are performed on grayscale images.

Keywords: Computer Vision, Corner Detection, Entropy, Mutual Information, Point of Interest.

1. INTRODUCTION

The detection of points of interest is a fundamental phase in computer vision, because it influences the treatment outcome of several applications: 3D reconstruction, robot navigation, object recognition.

A corner, which is a special case of points of interest, is a point where the direction of a contour changes abruptly. An edge is a transition zone separating two different textures in which the local statistical characteristics of the image may vary slightly [1].

In the literature, several points of interest detectors are proposed. We retain two large families: detectors based on the change of appearance: Moravec [8], SUSAN [2], FAST [3] and detectors based on operators of derivation: Harris [4], Shi and Tomasi [5], Lindeberg [6], Harris-Laplace [7].

The idea of Moravec detector is to determine the average changes in intensity in the neighborhood of each pixel when it moves in four directions: 0°, 45°, 90° and 135°. If there is a significant variation in the average intensity in all directions mentioned, then Moravec decides that the treaty point is a corner [8]. In [2], the authors propose the SUSAN detector where they use a circular mask. The points of the mask that have the same value of intensity of the center, called nucleus, form the USAN area (Univalue Segment Assimilating Nucleus). The information provided by USAN (size, barycenter) allow to detect corners and remove false detections. The final step is the removal of non-maxima. The main advantage of SUSAN is its robustness to noise. In [3], the authors were inspired from SUSAN by using a circular mask, but they only consider the points on the circle. The resulting detector (FAST) has a more isotropic response and is better on repeatability than SUSAN and Harris, but is not robust to noise and depends strongly on the thresholds [3].

Harris and Stephens are based on work of Moravec by considering the Taylor expansion of the intensity function used [4]. The result is a stable detector, invariant to rotation and has good repeatability, by cons it is not invariant to changes of scale and affine transformations and is sensitive to noise. Shi-Tomasi [5] proposed a detector based on principle of Harris detector but by directly computing the minimum of eigenvalues used by Harris.

In [6] Lindeberg proposed a detector invariant to scale changes by a process of convolution with a Gaussian kernel and using the Hessian matrix. In [7] the authors propose an improved Harris detector, invariant to changes of scale and affine transformations. The proposed detector has good repeatability.

In [9] the author proposed an algorithm that detects distinctive keypoints from images and computes a descriptor for them. The interest points extracted are invariant to image scale, rotation. SIFT features are located at maxima and minima of a difference of Gaussians (DoG) function applied in scale space. In [10] the authors propose SURF (Speeded Up Robust Features). It is a scale and rotation invariant detector and descriptor. SURF is based on the Hessian matrix and on sums of 2D Haar wavelet responses and makes an efficient use of integral images [11]. In [12] a revised version of SURF is proposed.

Recently, in [13] the authors propose imbalance oriented selections to detect interest points in weakly textured images. In [14] a new corner detector is proposed based on evolution difference of scale pace. In [15] an algorithm for corner detection based on the structure tensor of planar curve gradients is developed. The proposed detector computes the structure tensor of the gradient and seeks corners at the maxima of its determinant. In [22] the authors use a canny edge detection to present a corner detector based on the growing neural gas. In [23], the authors present a fast sequential method issued from theoretical results of discrete geometry. It relies on the geometrical structure of the studied curve obtained by considering the decomposition of the curve into maximal blurred segments for a given width.

The aim of this paper is to propose a new method of corner detection, invariant to image rotation which is based on a statistical measure that avoids the derivation in order to have better robustness to noise. Our approach is based on the mutual information. Thereafter, we present the proposed method of corner detection with the experimental results and a discussion. Finally we end with a conclusion and prospects.

2. MUTUAL INFORMATION

The mutual information (MI) between two random variables measures the amount of information that knowledge of one variable can make on another. The mutual information between two random variables X = {$x_1, x_2, \ldots, x_k$} and Y = {$y_1, y_2, \ldots, y_n$} is:

$$MI(X,Y) = H(X) - H(X/Y) \quad (1)$$

$$= H(Y) - H(Y/X) \quad (2)$$

$$= H(X) + H(Y) - H(X,Y) \quad (3)$$

Such that H is the entropy function and is equal to:

$$H(X) = E[h(x_i)] = -\sum_{i=1}^{k} p_i \log_2(p_i(x_i)) \quad (4)$$

with $p_i = P(X = x_i) / i \in \{1,2,\ldots,k\}$ and $h(x) = -\log(p(x))$.

We have:

$$MI(X,X) = H(X) \quad (5)$$

Mutual information is a positive quantity, symmetric and is cancelled if the random variables are independent.

It follows the principle of no information creation (or Data Processing Theorem):

If g_1 and g_2 are measurable functions then:

$$MI(g_1(X), g_2(Y)) \le MI(X,Y) \quad (6)$$

The inequality (6) means that no processing on raw data can reveal information.

The MI is a universal similarity measure [16][17][18] which is used in stereo matching [19], image registration[20], parameter selection[21] and other applications.
Figure 1 shows that the mutual Information detects the transition zone separating two different textures in which the local statistical characteristics may vary slightly.

FIGURE 1:a Test image

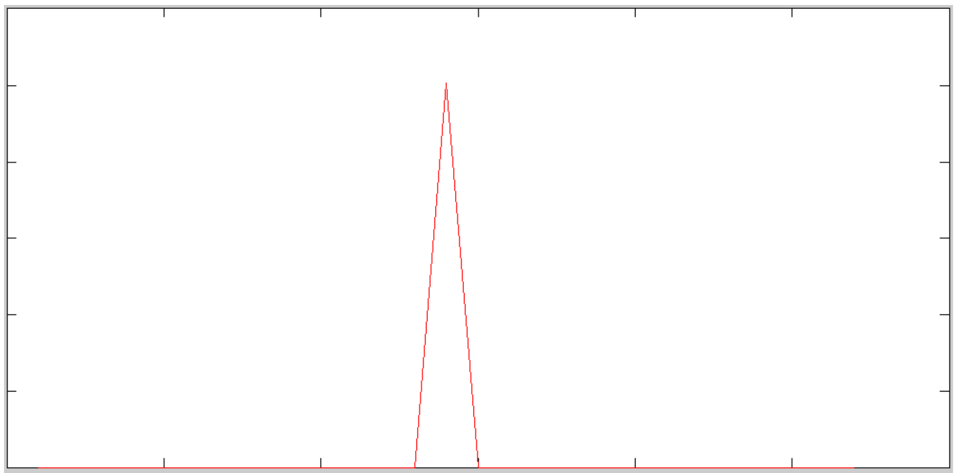


FIGURE 1:B. Values of Mutual information calculated between a window which browses the test image and its right neighbor.

3. PROPOSED METHOD
The proposed method is based on normalized mutual information. It is inspired from Moravec model [8]. Before starting treatment, the first step is the quantification of the values of image pixels in NI values.
The quantization step is crucial because it allows to homogenize the image areas whose values are relatively close. This is because the calculation of statistics is concerned with the distribution of pixels in the image and not the relative values of the pixels.
The next step is to browse the image by a large window F (Figure 2), and for each pixel in the interior, we calculate the normalized mutual information between its neighborhood W and respective shift of 0 ° , 45 °, 90 ° and 135 ° so W1, W2, W3 and W4 (Figure 3).
The mutual information used is normalized by the entropy of the neighborhood W.

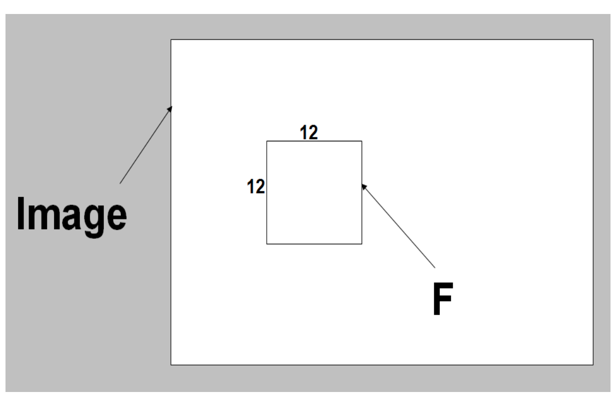


FIGURE 2: Browse the image by a large window F

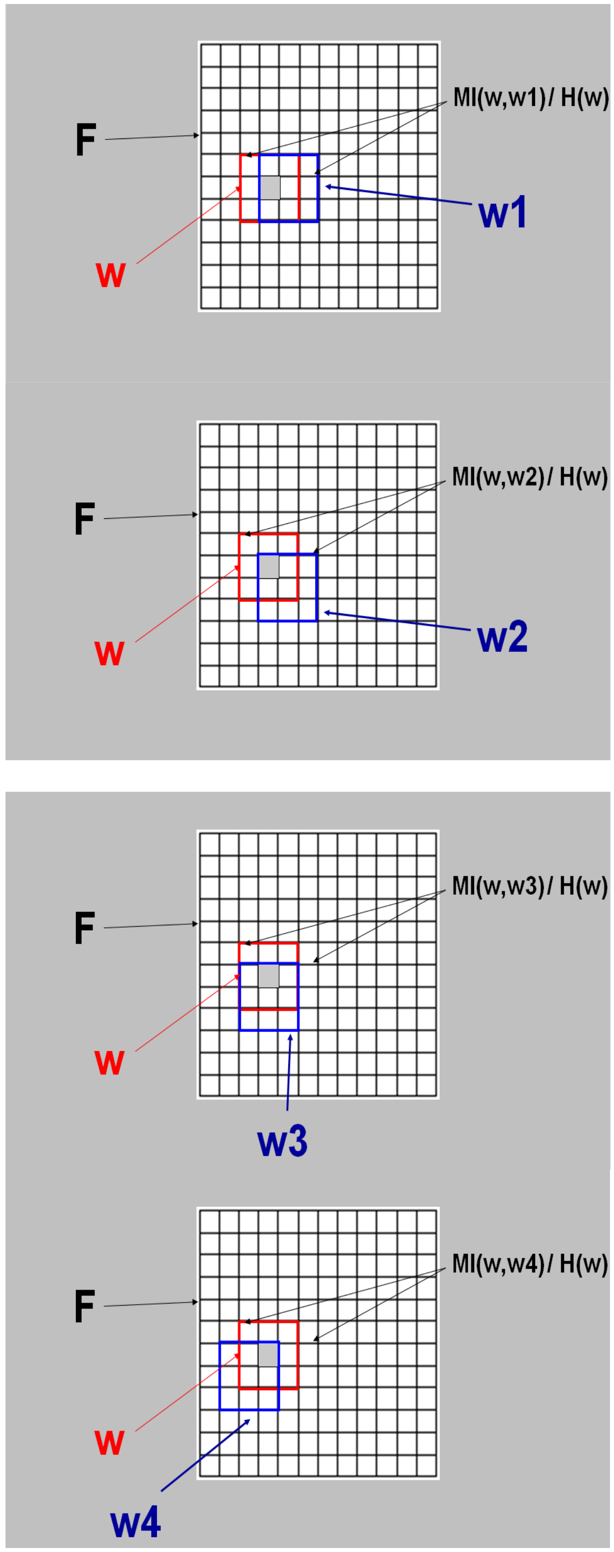


FIGURE 3: Calculation in F of normalized mutual information between w and w1, w2, w3 and w4

If measurements of the normalized mutual information between the neighborhood of the processed pixel and the four other neighborhoods are below a threshold empirically determined, the processed pixel is a corner, otherwise it is not.
Where several corners are detected within the window F, we only keep the point that minimizes the maxima of the normalized mutual information (Figure 4).

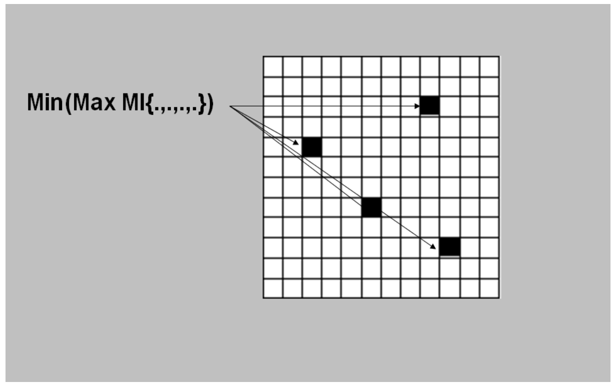


FIGURE 4: Treatment of cases where several corners are detected within the window F.

4. RESULTS AND DISCUSSION

We performed the testing on synthetic and real grayscale images. The results are shown in Figure 5 and Figure 7.

The parameters used: thresholds, window size and number of quantization depend on the image used and are chosen empirically.

In homogeneous areas, the entropy is zero, therefore we can conclude that they cannot contain corners and so we will not divide by zero entropy for normalization.

For areas not homogeneous, if a measure of normalized mutual information between neighbors exceeds the threshold, we can conclude that the processed point is not a corner.

We noisy the normalized images by Gaussian noise amplified by 10, of zero mean and standard deviation equal to 0.2. We notice the good robustness of our method to noise (Figure 6), this is because the proposed method does not use derivation operators that amplifies the effect of noise for high frequencies and are therefore sensitive noise.

In Figure 8, we applied a rotation of 45°, 60° and 90° to the original image. We note the invariance of our method to image rotation. This is due to the statistical tool we use that is invariant to position of pixels but rather to their distribution in neighborhood.

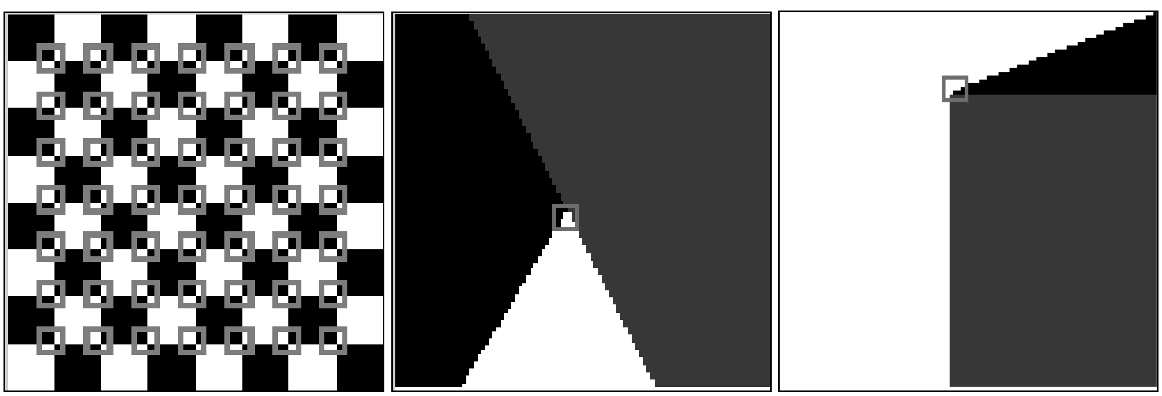


FIGURE 5 : Corner detection results on the original images

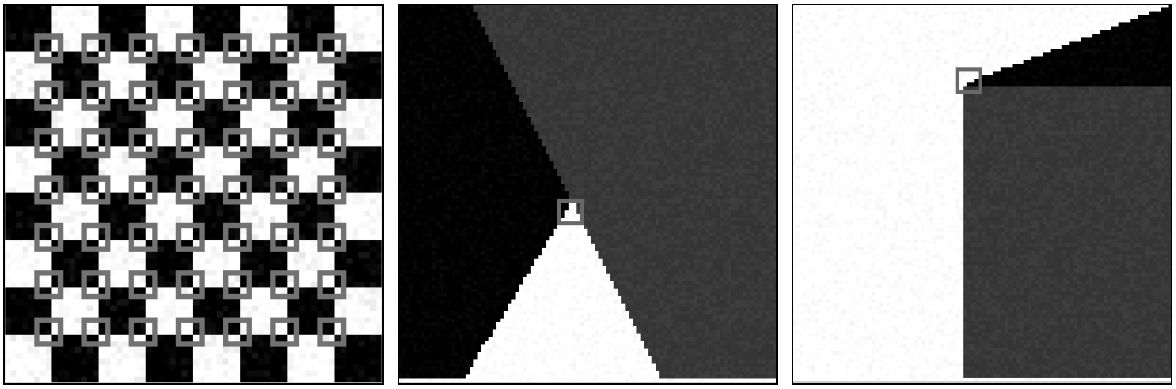
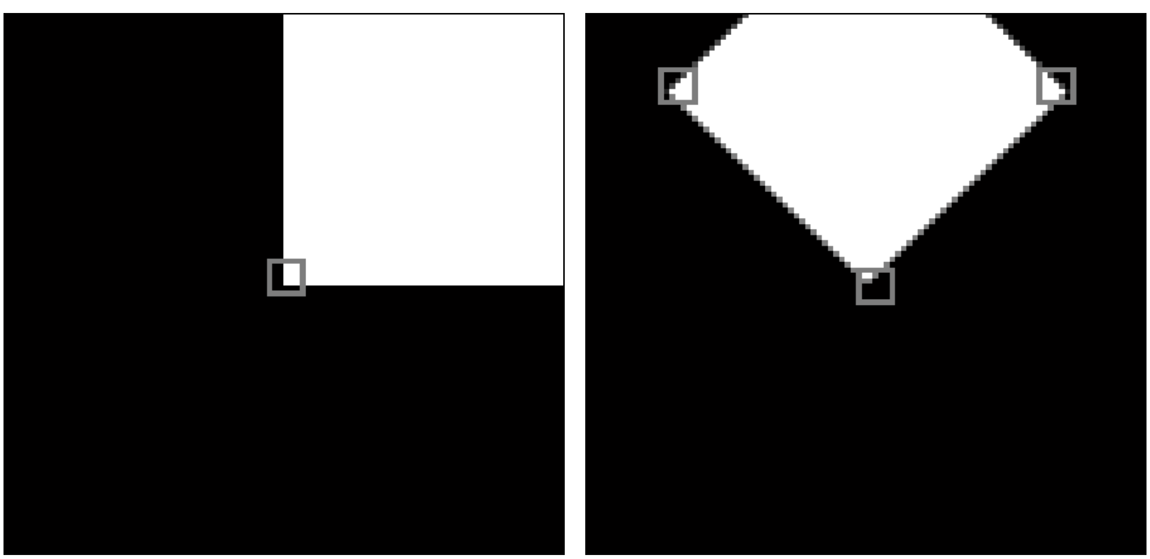
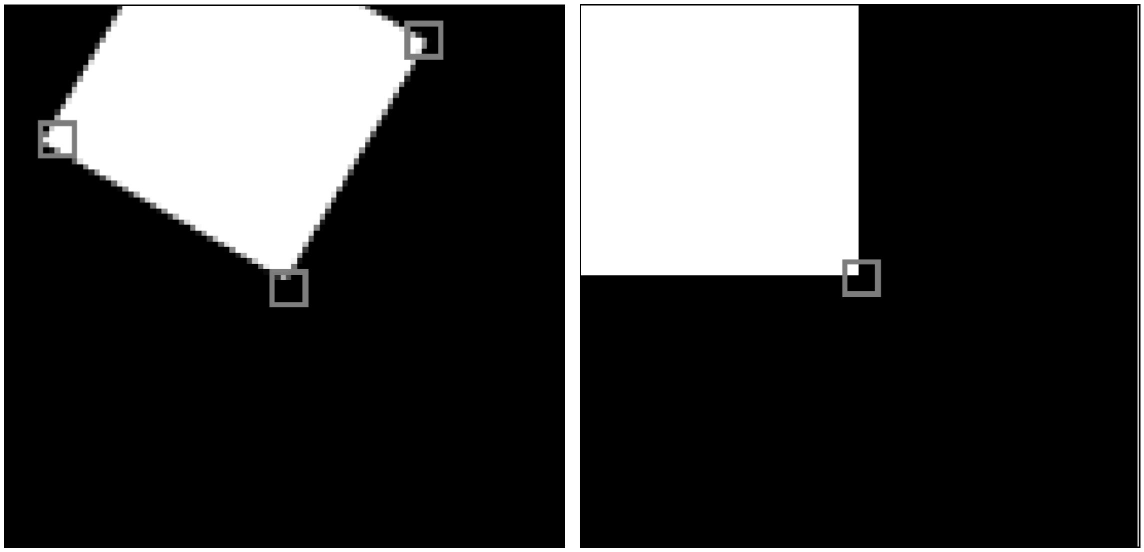


FIGURE 6: Corner detection results on the noised images

FIGURE 7: Examples of corner detection by the proposed method on real images



Original image Rotation: 45°



Rotation : 60°　　　　Rotation : 90°

FIGURE8: Invariance of the proposed method to image rotation

5. CONCLUSION

In this paper we proposed a new corner detection method invariant to image rotation, based on statistical measure which is mutual information. We noted the good performance of our method on synthetic grayscale images. We tested the good robustness of our method to noise. This is explained by the fact that the proposed method does not use derivation operators which are sensitive to noise.
The results are promising, which encourages us to apply our method to the mobile robotics knowing that a good detection of points of interest allows good localization of robot and consequently leads to a correct movement.

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