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Interest Points Detection in Color Images

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Abstract

This paper presents a new interest point detector for color images. It is based on a non linear filtering of the image which preserves edges, and on the use of a color point detector based on the Harris detector. We present how does interest points detectors work to justify the use of this filtering. We compare it with the Harris detector under the criteria of repeatibility, information content and localization accuracy.

1 Introduction

Tasks like camera calibration, environment modelling or robot absolute localization involve 3D accurate reconstruction of specific scene points. Such a reconstruction may be achieved by using 3D vision or dynamic vision. This reconstruction involves the matching of interest points extracted from gray level or color images. Several approaches to detect features like corners have been reported. The Harris detector[1] is one of them and recent studies have analyzed its performance[5]. Compared with several intensity based detectors, the Harris detector for gray level images gives better results in terms of localization accuracy and robustness with respect to variations of viewing conditions (view point, luminosity). Some extensions to color have been proposed [15]. However, the detector expression is issued from differential geometry and no study has been made to verify the suitability of such a scalar operator to color case. Moreover, the Harris detector presents some drawbacks for localisation and stability[9]. They can be reduced by an a priori smoothing step able to preserve edges. Classical smoothing methods make use of linear filters which are applied separately to the three channel of the color image. This separate smoothing induces unexpected color combinations close to edges[16]. So, we propose to use a nonlinear filter which takes into account not only the spatial distance between two pixels, but also their similarity in the chromatic space. A similar approach has been used by C.Tomasi with the so called bilateral filter[16]. Our method differs from the previous one in the sense that the smoothing function is applied iteratively to a smaller neighborhood. This smoothing step is coupled with a new expression of the detector.

This paper presents in a first part an overview of some works on interest point detection for gray level images and extension to color. We also present non linear filtering methods for smoothing and preserving edge informations. Finally, we combine the smooth step with a modified expression of color Harris detector and present results.

2 Overview of interest point detectors

For intensity based approaches, a corner is a discontinuity or a high curvature of the signal. Lot of works used this property to develop interest points detectors. Beaudet[14] is at the origine of those based on the principal curvatures of the intensity[12][3][17]. These methods use the determinant of the Hessian matrix which is related to the product of the principal curvatures $k_{\min}, k_{\max}$ (the Gaussian curvature) as follows [13] [2]:

$$k_{\min}.k_{\max} = \frac{\det\begin{bmatrix} I_{xx} & I_{xy} \\ I_{xy} & I_{yy} \end{bmatrix}}{\left(1 + I_x^2 + I_y^2\right)^2} \tag{1}$$

Where I_i and I_{ij} are the first and the second derivatives of the intensity surface in the direction of i and j.

Nagel[11] has shown that this approach is equivalent to a method proposed by Kitchen and Rosenfeld [3] who study the directions of the gradient vector. Plessey[6] and Harris gave similar operators based only on the first derivative of the signal. Harris detector uses autocorrelation of gradient[1]:

$$R = \det(H) - k \times trace^2(H) \tag{2}$$

with $H = grad(I).grad(I)^t$. and $k = 0.04$.

Many of these detectors had a localization drawback. Deriche and Giraudon [9] show that these operators locate the corner on the bissector line depending on the value of its angle. Schmid [5] proposes an improved version of the Harris detector by computing the matrix H with Gaussian masks. The localization problem is reduced, the detector is robust with respect to the camera point of view and to the illumination variations, but it became sensitive to noise. She had to use a Gaussian smoothing to stabilize the result.

$$H = grad_\sigma\left(\widetilde{I}\right).grad_\sigma\left(\widetilde{I}\right)^t \tag{3}$$

Where $\widetilde{I}$ decribes the convolution of the image I by a Gaussian smoothing filter (dimension $\widetilde{\sigma}$).

Gouet[19] extended the improved version of the Harris detector to multispectral images by using the Di Zenzo gradient [20]. The definition of a Rieman metric of identity type permits to define the new gradient's autocorrelation function:

$$grad_\sigma\left(\tilde{I}\right)\cdot grad_\sigma\left(\tilde{I}\right)^t=\left[\begin{array}{cc} a_{11} & a_{12} \\ a_{21} & a_{22}\end{array}\right]$$

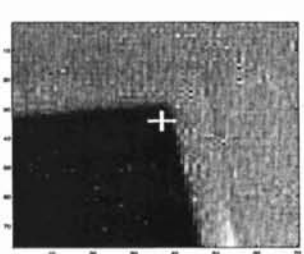
$$a_{11}=\left(\widetilde{R}_x^2+\widetilde{G}_x^2+\widetilde{B}_x^2\right)_\sigma$$

$$a_{22}=\left(\widetilde{R}_y^2+\widetilde{G}_y^2+\widetilde{B}_y^2\right)_\sigma$$

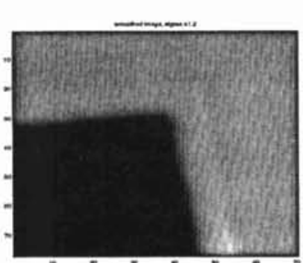
$$a_{12}=a_{21}=\left(\widetilde{R}_x\widetilde{R}_y+\widetilde{G}_x\widetilde{G}_y+\widetilde{B}_x\widetilde{B}_y\right)_\sigma$$

Where $(R_x)_\sigma$ is the convolution of the R image component by the first derivative of a Gaussian filter (dimension σ) in the direction x.

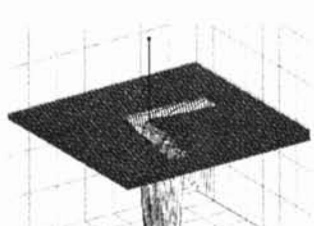
Smoothing the image is still necessary, but a marginal method needs a larger mask in order to avoid multiple maxima for the R function (eq. 2). This multiplicity is due to the presence of 3 colors components. A smoothing filter applied on a wide neighborhood presents the advantage to preserve the most significant features (particularly edges) since the topology of the signal is preserved. Nevertheless this property is not true in case of corners since high discontinuities are reduced. As we can see in Figure 1, increasing parameter σ preserves the detector response along edges, but the local maximum at the corner is smoothed.



(a)



(b)



(c)

Figure 1: (a) Position of the corner on the original color image. (b)Gaussian smoothed image ($\sigma = 0.9$). (c) Harris detector response ($\widetilde{\sigma} = 1$)

We show on Figure 1 an exemple of corner detection on a color image by using a Gaussian smoothing filter and the Harris detector given by equation 2

The *determinant* and *trace* operators applied on matrix H allow us to evaluate product and sum of the eigen-values of autocorrelation gradient without computing them. In the next section, we propose to use a smoothing operation which preserves discontinuities near of corners.

3 Color image smoothing

Many efforts have been made in order to reduce edge diffusion when smoothing color images[18][7][10][4]. For exemple, the bilateral filter proposed by Tomasi[16] takes into account not only the spatial distance between two pixels, but also their similarity in the chromatic space. The idea is to weight the coefficients of a Gaussian filter by the chromatic distance of the involved pixels. The general expression for the convolution of the image I with filter g is:

$$I_g(x)=k_g(x)\,.\int_{\xi_x=-\infty}^{+\infty}\int_{\xi_y=-\infty}^{+\infty} I(\xi)\,g(\xi,x)\,d\xi \quad (4)$$

where x and ξ are position vectors, $g(\xi,x)$ expresses the weight applied to pixel $I(\xi)$. It is normalized by the scalar function k_g . Weights depend on the Euclidian distance between pixels. In a Gaussian filter, this measure of proximity is expressed by:

$$g(\xi,x)=e^{-\frac{(\xi-x)^t.(\xi-x)}{2}} \text{ and } k_g^{-1}=\int\int g(\xi,x)\,d\xi \quad (5)$$

By using the same mathematical scheme, a similarity function is defined. It takes into account the chromatic distance betwen pixels. The convolution result is given by:

$$I_s(x)=k_s(x)\,.\int\int_{-\infty}^{+\infty} I(\xi)\,s\left(I(\xi),I(x)\right)d\xi \quad (6)$$

k_s permits normalization of s with the condition :

$$k_s(x)\,.\int\int_{-\infty}^{+\infty} s\left(I(\xi),I(x)\right)d\xi=1 \quad (7)$$

k_s can be evaluated during the calculation of I_s. In order to keep coherence with the chromatic distance measure which appears in the color Harris detector, the similarity fonction makes use of the Euclidian distance:

$$s(c_1,c_2)=e^{-\frac{(c_1-c_2)^t.(c_1-c_2)}{\sigma_s^2}} \quad (8)$$

Then, the final expression of the smothing operator is :

$$I_g(x)=k(x)\,.\int\int_{-\infty}^{+\infty} I(\xi)\,.g(\xi,x)\,.s\left(I(\xi),I(x)\right)d\xi \quad (9)$$

with normalization:

$$k(x)\,.\int\int_{-\infty}^{+\infty} g(\xi,x)\,.s\left(I(\xi),I(x)\right)d\xi=1 \quad (10)$$

We have improved the performance of smoothing by using an iterative filter applied to a 8-neighbourhood. It is based on the $d_{\alpha\beta}$ filter described in [8]. This statistical iterative filter extracts main modes of the local color distribution. Each pixel is equivalent to an element of the chromatic space which interacts with its 8-neighbourhood. Pixels color is modified according to:

$$\vec{c}_{k+1} = \vec{c}_k + \sum_{c_v \in V(c_k)} \left(\frac{K_{kv}}{[d_c(c_k, c_v)]^{\alpha}} \right)^{\beta} \frac{\vec{c}_v - \vec{c}_k}{\|\vec{c}_v - \vec{c}_k\|} \tag{11}$$

where c_k is the chromatic vector associated to pixel k, $V(c_k)$ is the neighbourhood of c_k and $d_c(c_k, c_v)$ is a distance measure between the chromatic vectors c_k and c_v associated respectively to pixels k and v. K_{kv} is a gain which depends on the relative position of pixels k and v.

This filter provides an efficient image smoothing but its iterative aspect increases considerably computation time.

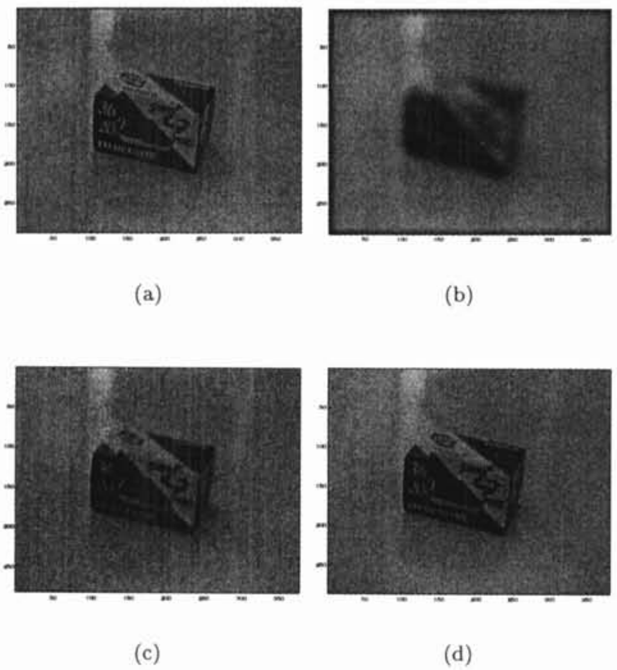


Figure 2: (a)original color image (b) image after Gaussian filtering ($\sigma = 2$) (c) image after bilateral filtering ($\sigma = 2$). (d) image after our iterative filter.

Figure 2 allows us to compare the performance of this bilateral filter (c) with that of the Gaussian filter (b). We can see that best results have been obtained with our iterative filter (d).

4 Color interest point detector

The Harris detector expression is issued from differential geometry and is generally used in a gray level context. The determinant of the matrix H (eq.2) is linked to the expression of the shape operator [2][9] (or Weingarten map) which permits to determine the Gaussian curvature of the intensity surface. For colored images, we assume that H doesn't describe a surface, nevertheless, eigenvalues of H characterize chromatic variations in the image main directions. Sum of these eigenvalues increases strongly on edges and corners whereas their product takes a high value only on corners. So, we have modified the form of the operator R (eq.2) as follows:

$$R' = (\det(H) - k \times trace(H))^2 \tag{12}$$

We have compared our detector given by equation (12) and bilateral filtering, with the classical one based on equation (2) and Gaussian filtering. The image sequences we used have been obtained by different 3D camera motions. We have selected a constant number of detected points. The evaluation of robustness is based on the number of points pairs which are preserved in the sequences compaired with the number of detected points. The results difference between the two methods is about 6% depending on the displacement type. We have considerably increased distinctivness of corners. Since classical Harris detector preserves image topology, the bilateral smoothing preserves discontinuities near edges. It permits to extract more significant values on corners (fig.3), comparatively with results shown on Figure 1. Nevertheless, the smoothing step stretchs out computation times (particulary the iterative smoothing) and some bad points can be detected due to aliasing.

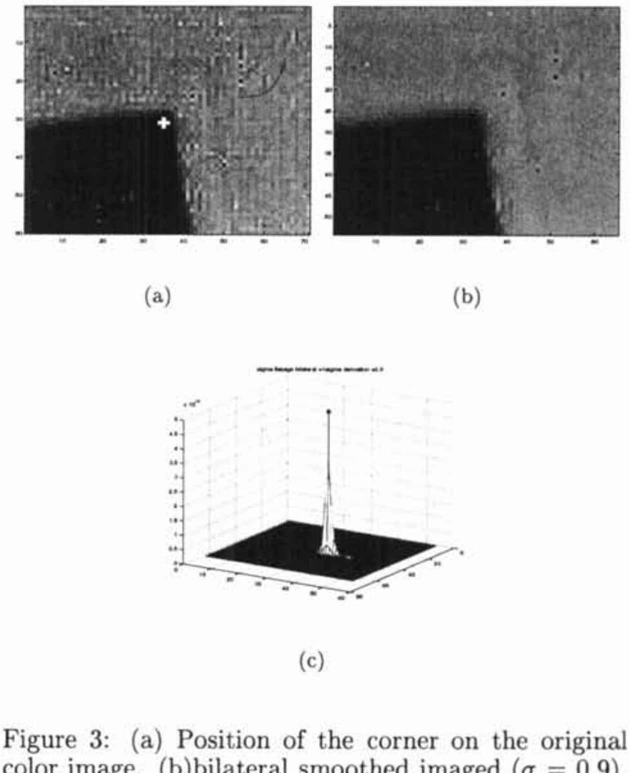


Figure 3: (a) Position of the corner on the original color image. (b)bilateral smoothed imaged ($\sigma = 0.9$). (c) Modified Harris detector response ($\widetilde{\sigma} = 1$)

5 Conclusion

In order to ensure stability and repeatability, traditionnal implementations of Harris detector extract a large set of characteristic points. Generally, a Gaussian filter is used to obtain more stable results (i.e. noise reduction). Nevertheless, this solution tends to delocalize detected points and to reduce the level of detector response. In this paper, we have proposed two methods for smoothing color images while avoiding the delocalization drawback. The first one is based on the bilateral filter. It takes into account proximity and similarity of pixels to determine the coefficients of a convolution mask. The second one is based on the same concept. Its iterative form improves the smoothing, but it stretchs out the computation time.

Then, we have increased the distinctivness of the detector response with a new formulation of its expression. Stabilization of this operator allows us to keep a smaller set of extracted points. They will be used for the computation of chromatics invariants for matching purposes. Our further research will consist in a more complete experimental evaluation of this detector.

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