

Visible Edges Thresholding: a HVS based Approach

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Abstract

This paper presents a technique, which determines whether an edge is visible for a human eye or not. First, a threshold function is built according to the optical characteristics of the sensor and a contrast sensitivity function (CSF). Then, the DCT coefficients of each 8×8 block are computed. For each one, the computed spectrum is compared with the previous threshold function, which enables to conclude about the presence of visible picture elements. Finally, this information is applied to edges detection using a binarization technique. Results are given on images grabbed onboard a moving vehicle.

1. Introduction

Edge detection is a classical problem in computer vision. Different reviews of work on edge detection are for a long time available in the literature [11, 14]. Gradient magnitude [12], optimality criteria [4], zero-crossing [7] are among the most used techniques. However, a problem faced by edge detectors is the choice of relevant threshold values, which are often empirically chosen. In order to automatically find the best threshold, standardizations of gradient magnitudes according to the surrounding pixels have been proposed. In this aim, statistical approaches have been developed [13]. Otherwise, approaches inspired by the human visual system (HVS) characteristics have been tested [1, 10]. Actually, our method belongs to this family.

In this paper, we propose a technique based on the contrast sensitivity function (CSF) of a human eye [2] to automatically find visible edges in images. In this aim, we compute the angular resolution of the device used to grab the pictures using its optical characteristics. Then, a contrast threshold function is built by taking into account the angular resolution of the sensor and a classical model of CSF. We compute the algebraic area between the previous threshold function and the DCT coefficients of each 8×8 block of pixels to determine whether it is visible or not. This information is finally applied to edges detection in outdoor

images. The use of a CSF has been earlier proposed for in-vehicle visibility evaluation [16]. However, this approach does not take the optical characteristics of the sensor into account, which is problematic.

2 Angular Resolution of a Camera

In this section, we compute the angular resolution of a CCD camera, which will be expressed in cycles per degree (cpd). This unit is used to measure how well details of an object can be seen separately without being blurry. This is the number of lines that can be distinguished in a degree of a visual field. The first section presents a geometric model of the camera. The second section presents the link between the aperture of the camera and its resolution.

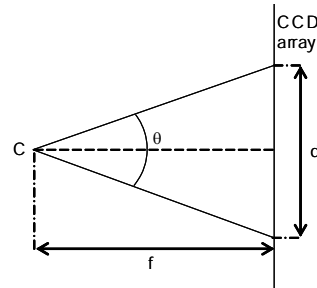


Figure 1. Geometric camera model to compute its angular resolution. Parameters : f focal length, C optical center.

2.1 Geometrical optics based model

With the notations of Fig. 1, the length d for a visual field θ of one degree is expressed by $d = 2f \tan \frac{\theta}{2}$. To obtain the maximum angular resolution of the camera r_{cpd}^* , it is enough to divide d by the size t_{pix} of two pixels (black and white alternation) of the CCD array:

$$r_{cpd}^* = \frac{f}{t_{pix}} \tan \frac{\theta}{2} \quad (1)$$

2.2 Wave optics based model

2.2.1 Diffraction and Airy spot

We now model the camera by the set (camera objective and sensor) described on Fig. 2. The objective is composed of both a lens of focal f and a diaphragm of diameter D . If we consider an object placed at the infinite, its image is projected on the focal plane of the objective.

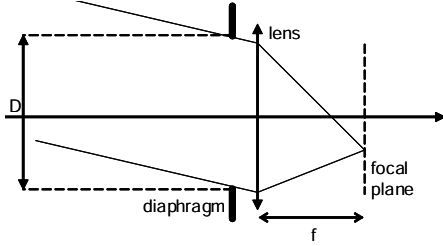


Figure 2. Simplified optical model of a camera

However, the consequence of the undulatory nature of light is the diffraction phenomena [8], that is to say the image of a point by a perfect optical system is not a point but an Airy spot of diameter ε , expressed by:

$$\varepsilon = 2,44 \times \frac{\lambda f}{D} \quad (2)$$

where λ is the wavelength of the light. Generally, objectives are characterized by their aperture number N , expressed by:

$$N = \frac{f}{D} \quad (3)$$

Consequently, ε can be written as:

$$\varepsilon = 2.44 \times \lambda.N \quad (4)$$

2.2.2 Effects on the camera resolution

On a CCD array, where the size of the pixels is t_{pix} , two situations can arise:

1. $\varepsilon \leq t_{pix}$. The Airy spot is smaller than the pixels. The resolution of the camera is r_{cpd}^* , given on Eq. 1.
2. $\varepsilon > t_{pix}$. The resolution of the camera is now:

$$r_{cpd} = \frac{f}{\varepsilon} \tan \frac{\theta}{2} = \frac{t_{pix}}{2.44\lambda N} r_{cpd}^* \quad (5)$$

2.3 Application to our camera

Our camera is a CCD 1/2" ($t_{pix} = 8.3 \mu m$) equipped with an auto-iris objective 8.5 mm allowing $N \in [1.3, 360]$. On Fig. 3, we plot its resolution with respect to the aperture

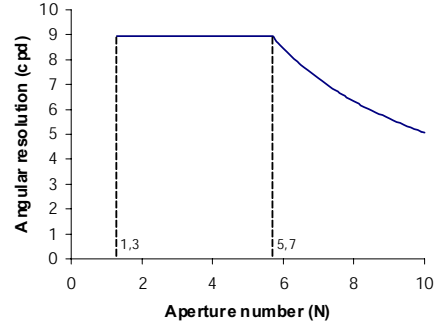


Figure 3. Evolution of the angular resolution (cpd) of our camera according to its aperture number N .

number. For this figure, we consider a wavelength λ centered in the visible spectrum [$0.4 \mu m$, $0.8 \mu m$], that is to say $0.6 \mu m$.

In this section, we modeled the angular resolution of the camera according to its geometric model and the diffraction phenomena. A more complete model could also take into account the noise and the depth of field.

3 Human Vision System Modeling

In the previous section, we studied the angular resolution of a CCD camera. Let's now study some characteristics of the Human Visual System (HVS).

It is remarkable that our ability to discern low contrast patterns varies with the size of the pattern, that is to say its spatial frequency, which is often expressed in cycle per degrees (cpd). The Contrast Threshold Function (CTF) is a measure of the minimum contrast needed for an object to become visible. This CTF is defined as $1/CSF$, where CSF is a Contrast Sensitivity Function. Several CSF models have been proposed in the literature. We chose the widely accepted CSF of Mannos [6], plotted on Fig. 4 and expressed by:

$$CSF(f) = 2.6(0.0192 + 0.114f)e^{-(0.114f)^{1.1}} \quad (6)$$

4 Design of a Visibility Criteria

4.1 DCT transform

In this section, we design a method, which decides if a block of pixels contains some "visible" edges for a human eye. In this aim, we compare the spectrum of each block with the minimum required to be visible by a human eye.

We use the discrete cosinus transform (DCT) to transform the image from the spatial domain to the frequency

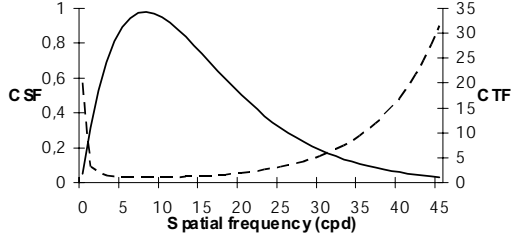


Figure 4. CSF (—) and CTF (--) of the Human Visual System, proposed by Mannos [6].

domain. We denote $A = \{a_{ij}\}$, a block of the original image and $B = \{b_{ij}\}$, the corresponding block in the transformed image. With these notations, the b_{ij} coefficients are expressed by:

$$b_{ij} = \frac{2}{n} c_i c_j \sum_{k=0}^{n-1} \sum_{l=0}^{n-1} \cos \left[\frac{(2k+1)i\pi}{2n} \right] \cos \left[\frac{(2l+1)j\pi}{2n} \right] a_{kl} \quad (7)$$

where $c_0 = 1/\sqrt{2}$, $c_i = 1$ for $i = 1 \dots n-1$ and n denotes the block size. Like for JPEG format [15], we have chosen $n = 8$.

Then, to convert the DCT coefficients in cycles per degrees, we simply consider that the maximum frequency of the DCT transform, i.e. a spatial period of two pixels, is obtained for the maximum resolution of the sensor, that is to say r_{cpd}^* . Thus, with (7) and (1), we have:

$$2t_{pix} = \frac{4n}{2n-1} \quad (8)$$

$$r_{cpd}^* = \frac{2(2n-1)}{4n} f \tan \frac{\theta}{2} \quad (9)$$

Thanks to (9), we are now able to convert the DCT coefficients $\{b_{ij}\}$ of a block B to cycles per degree and then to plot the DCT coefficients of a block with respect to the corresponding values of the CTF.

4.2 Visibility criteria

To decide whether a block is visible or not, we propose to compute the algebraic area \bar{A} between the spectra of the block and the CTF given in section 3. However, the sensor is not always able to reproduce all the frequencies of the CTF model. Consequently, the CTF must be restricted to the angular resolution of the sensor, that is to say r_{cpd} . Thus, the proposed criteria is:

$$\bar{A} = \int_{\mathbb{R}_+} \left(B|_{f < r_{cpd}} - CTF|_{f < r_{cpd}} \right) df \quad (10)$$

$$= \sum_{\substack{(i,j) \neq (0,0) \\ (i,j) \in \mathbb{R}_+^{(n^*-1, n^*-1)}}} (b_{ij} - CTF_{ij}) \quad (11)$$



Figure 5. Illustration of the proposed visibility criteria. When the block is visible, the gray level of the block is proportionnal to \bar{A} .

where $n^* = \left\lfloor \frac{1}{2} \left[(2n-1) \frac{r_{cpd}}{r_{cpd}^*} - 1 \right] \right\rfloor$ is obtained thanks to (7) and (9). We denote $\lfloor x \rfloor$ the integer part of x .

Finally, if \bar{A} is positive, the block is considered to be visible. In the contrary case, the block is supposed to contain no visible information. We applied this criteria on sample images on Fig. 5. If \bar{A} is positive, the gray level of the blocks is directly proportional to this value.

5 Application to Edges Detection

Once we know in which blocks there is some visible picture elements, we can detect the visible edges. However, this must be achieved without adding an arbitrary threshold, for example on the magnitude of the gradient. That's why we propose to find the border which maximizes the contrast between two parts of a block, without adding a threshold on this contrast value. The edges will then be the pixels on this border.

We proposed to use Köhler's approach [5], which is quite efficient and relies on spatial information. Let I be a gray level image. A couple of pixels (x, x_1) is said to be separated by the threshold s if two conditions are met. First, $x_1 \in V_4(x)$. Secondly, the condition (12) is respected:

$$\min(I(x), I(x_1)) \leq s < \max(I(x), I(x_1)) \quad (12)$$

Let $F(s)$ be the set of all couples (x, x_1) separated by s . With these definitions, for every value of s belonging to $[0, 255]$, $F(s)$ is built. For every couple belonging to $F(s)$, the contrast $C_{x, x_1}(s)$ is computed:

$$C_{x, x_1}(s) = \min(|s - I(x)|, |s - I(x_1)|) \quad (13)$$

The mean contrast (14) associated to $F(s)$ is then performed:

$$C(s) = \frac{1}{\text{card}(F(s))} \sum_{(x,x_1) \in F(s)} C_{x,x_1}(s) \quad (14)$$

The best threshold s_0 verifies the following condition:

$$s_0 = \underset{s \in [0,255]}{\text{argmax}} C(s) \quad (15)$$

s_0 is the threshold which has the best mean contrast along the associated border $F(s_0)$, which becomes the set of visible edges. This algorithm can be directly applied to the visible blocks. Examples of such edges detection are given on Fig. 6.



Figure 6. Edges detected on our sample images using Köhler's technique on the visible blocks.

6 Discussion

The results obtained with the method are quite good. However, some improvements are possible. Firstly, by thresholding the 8×8 blocks by Köhler's method, we implicitly assume that there is only one object in the block. One could recursively implement the method in each block. Secondly, the size 8×8 of the blocks can be increased to 16×16 to improve the sensitivity of the method. However, these improvements have a high computational cost.

In addition, other models of CSF could be used, like the ones proposed in [9] or [3].

7 Conclusion

In this paper, we have proposed a method to detect the visible edges in a digital image. We have first built a model of the resolution of a CCD camera by taking into account its geometric model and the effect of light diffusion. Knowing the ability of this sensor to reproduce some given spatial frequencies, the spectrum of blocks of our image are compared with the required minimum for a human eye to be visible. In this way, we have obtained visibility maps, where all visible blocks are highlighted. Finally, from this information the visible edges are deduced by using a efficient binarization technique.

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