DETECTING EDGES IN COLOUR IMAGES USING DICHROMATIC DIFFERENCES

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Many computer vision techniques need the detection of edges in the image as a first step of an image understanding process. In some cases, a grey-level edge detector is not rich enough to describe changes that are present in the image and the use of colour information and colour edges is a valuable tool for some problems.

In this paper, we propose a distance function in the colour space to measure the perceived difference between two colour vectors. This function is further used combined with some concepts of the Canny edge detector to define a novel approach to colour edge detection. The experiments carried out show that the proposed method for colour edge detection provides satisfactory results both in synthetic and real colour images.

INTRODUCTION

Edge detection is an important subject in the computer vision literature. Usually, the edge detection process serves to simplify the analysis of digital images by drastically reducing the amount of data to be processed, while at the same time preserving useful structural information about object boundaries.

Edges can be defined as a discontinuity in some image attributes, usually the brightness for grey-scale images. There exists an extensive literature about edge detection applied to grey level images. In 1975, Davis [3] published "*A Survey of Edge Detection Techniques*". Examples of edge detection methods are the well-known Roberts gradient, the Sobel gradient, and the Laplacian operator [8]. Later, Canny published in 1986 *"A computational Approach to Edge Detection"* [2] which is a basic reference in this subject.

In colour image processing, the colour of a pixel is usually given as three values corresponding to the tri-stimuli of red, green and blue. A lot of literature [13] has been developed to transform the colour coordinate system for different purposes of colour image processing, but they still use a set of tristimulus values to specify a colour. For colour images, an edge can be said to exist if and only if the luminance field contains and edge. This definition ignores discontinuities in hue and saturation that occur in regions of constant luminance. Another way to define a colour edge [13] is to check if an edge exists in any of its constituent tristimulus components. A third definition is based on forming the sum of gradients of the tristimulus values or some linear or non-linear colour components. In this case, an edge exists if the sum of gradients exceeds a threshold.

The edge detection problem applied to colour images has not had as much attention as in the grey level case. Most of the solutions proposed consist of transforming from the RGB colour space to other different colour spaces, where colour differences can be easier quantified. Machuca and Phillips [9] treated colour images as vector fields and transformed the colour space from the RGB model into the YIQ model and detected edges in the hue plane. Also, the LUV colour space has been used to quantify colour differences [12]. However, the non-linear transformation needed makes this space very sensible to the presence of noise in the image. Di Zenzo [4] extended the gradient based edge detection technique to multispectral images and combined the three colour component results by taking the root mean square, or the sum, or the maximum of their absolute values. Gershon [7] developed a mathematical model to represent the physiological knowledge of colour edge detection based on concentric opponent units (e.g. R+/G-) and double-opponent units (e.g. R+G-/R-G+). Using this models, Forsyth developed a system for finding changes in colour [5] which obtains good results for synthetics images.

More recently, some methods for colour space dimensionality reduction have been developed. The idea is to find an axis onto which all colour component values are projected to produce a new image with a single spectral band. The methods differ on the axe onto which the colour vectors are projected. Some approaches are the Karhunen-Loève expansion [6], the vector median [1] and the vector obtained as the difference between two centroids obtained by moment-preserving thresholding [17]. By this way of reducing the 3-dimensional colour space to one dimension, edge detection methods for grey-scale images become applicable to colour images.

We present here a novel approach to colour edge detection based on a colour distance definition that is combined with a modified version of the Canny edge detector algorithm. Section 2 introduces some concepts of colour representation, and based on the Dichromatic model we justify the use of spherical coordinates instead of Cartesian coordinates. In section 3, we define a colour distance function and then combine this definition with a modified version of the Canny edge detector to obtain a colour edge detector algorithm. Finally, in section 4, some experiments are carried out using both synthetic and real images, and compare the results obtained using the algorithm proposed with the results obtained using the Canny edge detector over the corresponding grey level images, and with the results of the Canny edge detector over the images obtained applying the method described in [17] for reduction of colour space dimensionality.

COLOUR REPRESENTATION

According with the dichromatic reflection model proposed by Shafer [15], the light L reflected from an object point can be view as a composition of the light reflected at the material surface L_s and the light reflected from the material body L_b:

$$L(\lambda,i,e,g)= L_s(\lambda,i,e,g) + L_b(\lambda,i,e,g)$$

where λ is the wavelength of the light spectrum, i is the incidence angle between the illumination direction and the surface normal, e is the exitance angle between the surface normal and the viewing direction, and finally, g is the phase angle between the incidence angle and the viewing angle. Usually, it can be assumed that any point of an object surface exhibits the same spectrum of surface reflection, so L_s can be modelled as the product of the spectral power distribution $c_s(\lambda)$ and a geometric factor $m_s(i,e,g)$. Similarly, the body light refection L_b is modelled as the product of the spectral power distribution $c_b(\lambda)$, and a geometric factor $m_b(i,e,g)$. Therefore:

$$L(\lambda,i,e,g)= c_s(\lambda)\, m_s(i,e,g) + c_b(\lambda)\, m_b(i,e,g)$$

The Dichromatic Reflection Model describes light reflection using a physically precise representation, the continuous spectrum. Light sensing devices use a set of sample measurements to describe the spectrum which are obtained by filtering the light spectrum and integrating over the filtered spectrum. The sensing device integrates the amount of incoming light $L(\lambda,i,e,g)$, weighted by the spectral transmittance $\tau_f(\lambda)$ of the respective filter and the spectral responsivity of the camera $s(\lambda)$, over all wavelengths λ:

$$C_f = \int L(\lambda,i,e,g)\, \tau_f(\lambda)\, s(\lambda)\, d\lambda$$

The red, green and blue filters τ_r, τ_g, τ_b of a camera are used for the spectral integration. The spectrum of an incoming light beam at position (x,y) is represented by a vector $C(x,y)= (C_r,C_g,C_b)$, where x and y are determined by angles i,e and g, and by the position of the object relative to the camera.

Spectral integration from the infinite-dimensional vector space of spectral power distributions $L(\lambda,i,e,g)$ to a three-dimensional colour space $C= (C_r,C_g,C_b)$ is a linear transformation [14]. Thus, if a light beam $L(\lambda)$ is a linear combination of $c_s(\lambda)$ and $c_b(\lambda)$ then the colour vector C, resulting from spectral integration on $L(\lambda)$ is the same linear combination of the colour vectors C_s and C_b that result from spectral integration on $c_s(\lambda)$ and $c_b(\lambda)$.The dichromatic reflection model for the three dimensional colour space is obtained as:

$$C(x,y)= m_b(i,e,g)\, C_b + m_s(i,e,g)\, C_s$$

Let us suppose now any two different points from the same object surface. For these two points, the spectral power distributions of ambient light and the direct illumination are proportional in the ideal case [7]. Thus, the spectral power distribution of the light in those two points may be modelled as:

$$E_1(\lambda)= k\, E_2(\lambda)$$

On the other hand, if a point is illuminated by a light source with power spectral distribution $E(\lambda)$, fixed the geometry of the problem i, e and g, then the surface and body reflections $c_s(\lambda)$ and $c_b(\lambda)$ can be defined as $c_s(\lambda)= E(\lambda)S(\lambda)$, where $S(\lambda)$ is the surface spectral reflectance, and $c_b(\lambda)= E(\lambda)B(\lambda)$ where $B(\lambda)$ is the body spectral reflectance [16]. Thus, two lights L_1 and L_2 incoming from two points of the same object surface where the geometric factor m_s and m_b are the same, can be expressed as:

$$L_1= m_s\, E_1(\lambda)\, S(\lambda) + m_b\, E_1(\lambda)\, B(\lambda)$$

$$L_2= m_s\, E_2(\lambda)\, S(\lambda) + m_b\, E_2(\lambda)\, B(\lambda)$$

and using the relation $E_1(\lambda)= kE_2(\lambda)$ between the spectral power distributions of the illumination, we obtain:

$$L_1= k\, [m_s\, E_2(\lambda)\, S(\lambda) + m_b\, E_2(\lambda)\, B(\lambda)] = k\, L_2$$

By the spectral integration process, the corresponding colour vectors C_1 and C_2 of L_1 and L_2 will also be proportional, that is $C_1= kC_2$. This means that the two colour vectors lie in the same direction in the RGB colour space [11].

Let $C(x,y)= (C_r,C_g,C_b)$ be a point in the RGB space, and let (r,ϑ,φ) be the spherical coordinates corresponding to the point $C(x,y)$ taking the coordinates (C_r,C_g,C_b) as the Cartesian coordinates. Then, two colour vectors from the same colour object surface with the same geometry factors $C_1= (r_1,\vartheta_1,\varphi_1)$ and $C_2= (r_2,\vartheta_2,\varphi_2)$ lie in the same direction and therefore they have the same angular coordinates, $\vartheta_1=\vartheta_2$ and $\varphi_1=\varphi_2$, and only their r components are different.

COLOUR DISTANCE AND COLOUR EDGE DETECTION

The concept of distance between two points in a colour space is usually needed in a large variety of image understanding applications. If we are working with grey level images, the distance or difference function between two points in the grey scale, G1 and G2, can be obtained as the module of the difference between the two values |G1-G2|.

If we want to work with colour images, we need to define a valid colour distance in the colour space. This definition is not immediate. For example, the Euclidean distance between two points in the RGB colour space is not a good function to quantify the perceived colour difference. In some cases, small differences in the colour space lead to important differences in colour and, on the other hand, there are cases where larger differences in the RGB space do not mean a significant change in the perceived colour.

Let us assume that two points from the same colour surface are close enough in such a way that we can consider these points approximately have the same geometrical factors, that is, these two points will be also neighbours in the corresponding image. According with the reasoning of the previous section, these two points will lie in the same direction in the RGB colour space, i.e., if they are represented using spherical coordinates they will have the same values of the ϑ and φ angles, and r will differ up to a proportional

factor. Similarly, two neighbouring points in the image with different values in the ϑ and φ components will indicate the presence of a colour change in the image, that is, a colour edge. Therefore, given a point $C=(r,\vartheta,\varphi)$ in the RGB colour space, minor changes in neighbour points the ϑ and φ components will also produce small differences in the colour perceived, and the difference of the perceived colour will become bigger when changes in the ϑ and φ angles increase.
Thus, let us define a distance function D in the colour space in such a way that if two distances $d_1=D(C_1,C_2)$ and $d_2=D(C_3,C_4)$ have similar magnitudes, that is, $d_1 \approx d_2$, then the perceived visual differences should be similar.

Let D be a function distance between two colours C_1 and C_2 in the RGB colour space expressed as:

$$D(C_1,C_2)= \alpha(C_1,C_2)$$

where $\alpha(C_1,C_2)$ represents the angle between the RGB vectors C_1 and C_2, that is

$$\cos\alpha = \frac{C_1 \cdot C_2}{|C_1||C_2|}$$

This distance function satisfies the previously exposed requirements, i.e., if two colours have similar values of their spherical components ϑ and φ, the distance obtained will be small, and the distance obtained will increase as the difference in the ϑ and φ components become bigger.

This distance function defined in the colour space may be used as a criterion to find colour edges in an image combining it with the principles of most of the edge detection methods developed for grey level images [5][10], like the Directional Differentiation, the Roberts gradient, the Canny edge detector, etc.

Lets us focus on the Canny edge detector method and try to combine it with the above introduced colour distance measure to define a colour edge detector. Canny [2] found the first derivative of a Gaussian to be a good approximation of the optimal edge detector filter. Also the first derivative of Gaussian operator can be computed with much less effort in the two dimensional case. In this case, an edge also has an orientation defined as the direction of the tangent to the contour that the edge defines. If we wish to detect edges of a particular orientation, we should create a two-dimensional mask for this orientation by convolving a linear edge detection function aligned normal to the edge direction. This can be done by convolving the image with a symmetric two-dimensional Gaussian and then differentiating normal to the edge direction. Furthermore, we do not have to do this in every direction because the slope of a smooth surface in every direction can be determined from its slope in two directions. If we wish to convolve the image with operator G_n which is the first derivative of a two-dimensional Gaussian G in some direction n, we have:

$$G_n = \frac{\partial G}{\partial n} = n \nabla G$$

Ideally, n should be oriented to the direction of an edge to be detected, which is not known a priori. However, we can obtain a good estimate of it from the smoothed gradient direction

$$n = \frac{\nabla(G*I)}{|\nabla(G*I)|}$$

where * denotes the convolution operator. An edge point is defined to be a local maximum of G_n*I, that is, $\frac{\partial}{\partial n} G*I$. At such a point, the edge strength will be the magnitude of $|G_n*I| = |\nabla(G*I)|$.

Canny concludes that we can first convolve with a symmetric Gaussian G, then compute directional first derivative maxima to locate edges, and use the magnitude of the gradient to estimate edge strength.

The modification of this edge detection method to be applied to colour images will require the definition (or a substitute) of the concept of derivative of a colour image in directions x and y. We can do this using the distance function in the colour space previously defined, that is, we define

$$\frac{\partial}{\partial x} I(x,y) = D(I(x+1,y), I(x-1,y))$$

$$\frac{\partial}{\partial y} I(x,y) = D(I(x,y+1), I(x,y-1))$$

Using this definition and the concept of non-maximal suppression used in the Canny edge detector we will have an edge detector method that could be used with RGB colour images.

To summarise the previous discussion, we can express the colour edge detector algorithm as follows:

- Let the colour image be $I(x,y)$, where each colour component of the image is $I_r(x,y)$, $I_\vartheta(x,y)$ and $I_\varphi(x,y)$.
- Define a Gaussian filter with parameter σ as G_σ. The smoothed image $I'(x,y)$ is obtained computing for each colour component i $I_i'(x,y) = G_\sigma * I_i(x,y)$, where * stands for convolution.
- Compute $\nabla I'$ defined as $(Grad_x, Grad_y)$, where
  $Grad_x(x,y) = D(I'(x+1,y), I'(x-1,y))$, and
  $Grad_y(x,y) = D(I'(x,y+1), I'(x,y-1))$.
- For each point (x,y) in the image,
  If $|\nabla I'(x,y)|$ > Threshold then
  If $|\nabla I'(x,y)|$ is a local maximum in the direction of the gradient vector $\nabla I'(x,y)$, mark this point as an edge.

The defined colour gradient operator has got a direction (such as the original grey level gradient), but in this case it has no sign, in other words, it is always positive.

EXPERIMENTAL RESULTS

To check the accuracy of the new colour edge detection method proposed, some experiments have been carried out using both synthetic and real images. The images used in all the experiments are 256x256 pixels in RGB format, with 8 bits per colour plane.

Synthetic images

A colour chessboard with 8 x 8 cells has been built. Each cell in the chessboard has been assigned a random colour (r, ϑ, φ), using the following criteria:

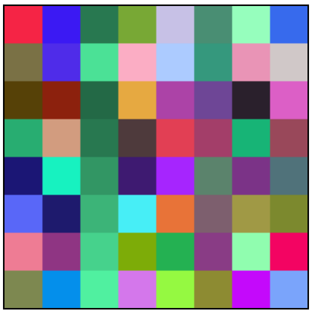
The cells in the third column have the same values for the ϑ and φ components, and a random value for the r component.

For the cells in the sixth column, the value of the r component has been fixed, and the values of the ϑ and φ component have been obtained randomly.

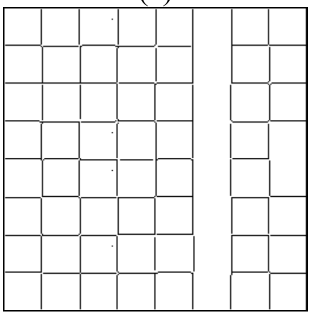
The rest cells in the chessboard have been assigned random values for the three components, r, ϑ and φ.

Figure 1 (a) shows the random colour chessboard obtained. In the colour image, all the cells of the third column are perceived as "green" cells, though having different tones. However, the cells of the sixth column can be described as blue, pink, black, green, brown, etc. The results of the Canny edge detector method over the grey level image are shown in figure 1 (b). The results of the colour edge detector algorithm proposed are shown figure 1 (c).

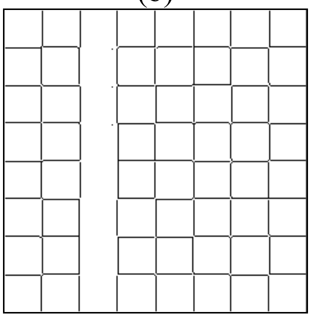
As it can be expected, the colour edge detector cannot find the edges between cells in the third column, due to they have the same values for the ϑ and φ colour components. Similarly, the grey level edge detector fails to detect the edges between cells in the sixth column, i.e., those having the same value of the r component. The edge in the middle of the last column of the grey level detector is missed due to the fact that the random process of colour assignment gave two colours with the same value of r for these two contiguous cells.



(a)



(b)



(c)

Fig. 1.- Random Colour Chessboard. (a) Original image. (b) Result of the Canny edge detector over the grey level image. (c) Result of the proposed colour edge detector.

From these results we can conclude that a combination of these two methods should perform well as a general edge detector for some application dependent problems. Further, we can assign different weights to the colour and grey level components of the edge to adjust the method to a particular problem.

Real images.

We have tested the proposed colour edge detector algorithm using four colour images. Three of them (house, lena, and peppers) are well-known in the computer vision literature. The fourth image represents an orange with some skin defects over a blue background, and is related with one of our research projects. Our goal is to segment this sort of images to locate the stem and the possible defects on its surface. The segmentation process uses the information of the edge detector as an input.

In figure 2 we show, beside each original image, the results obtained using:

1. the Canny edge detector over the corresponding grey level image,
2. the proposed colour edge detector, and
3. the Canny edge detector applied to the image obtained after reducing the colour space dimensionality as described in [17]. For this method, we have used overlapping windows of 9x9 pixels to find the projection axe. After each pixels has been projected onto this axe, the Canny edges of a central area of 7x7 pixels are obtained.

In all cases, we have tried with several threshold values. The results we show here correspond with the best one obtained in each case.

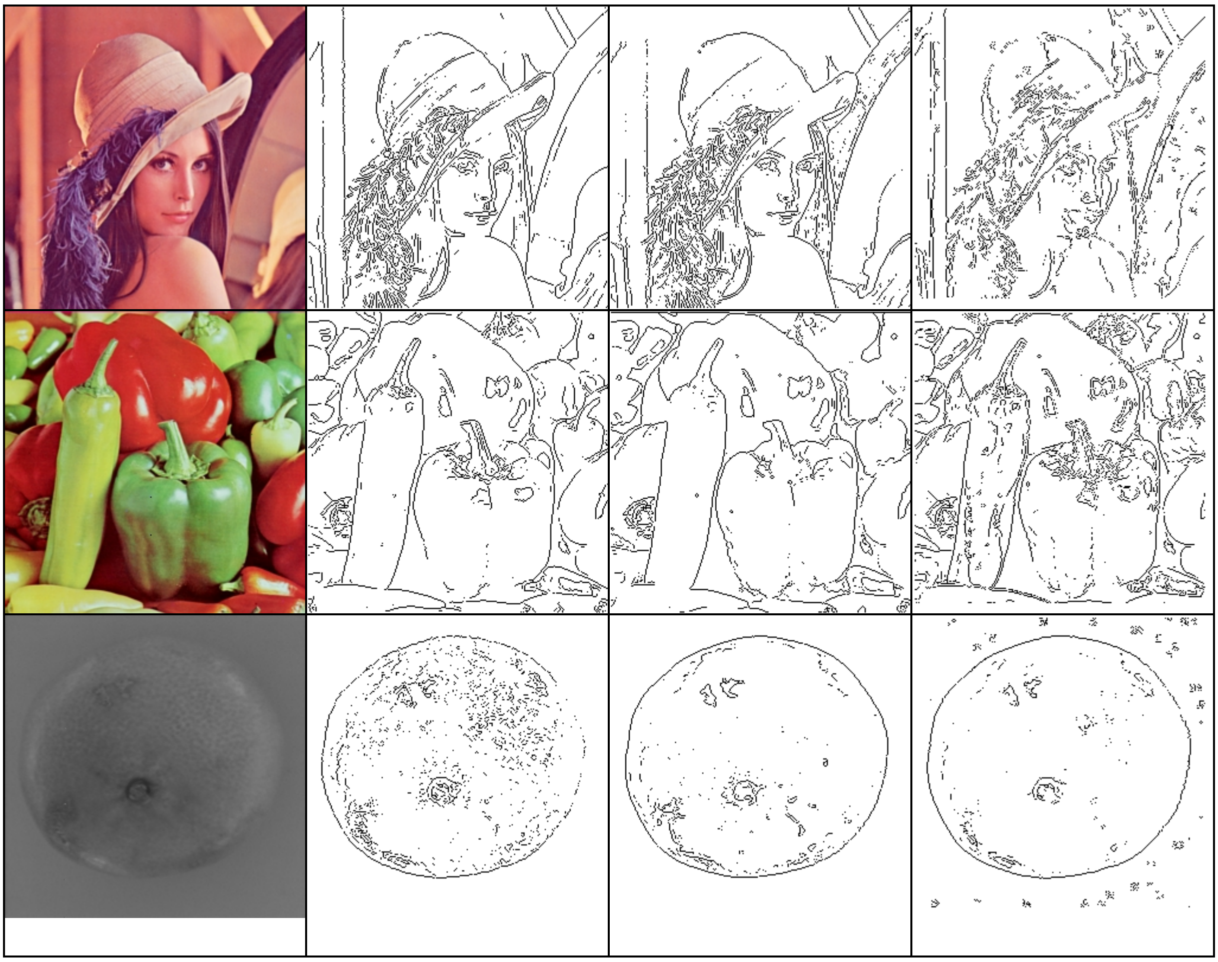


Fig. 2.-Colour images.

First row: House. **Second row:** Lena. **Third row:** Peppers. **Fourth row:** Orange.

First column: Original images. **Second column:** Results of the Canny edge detector over the gray level image. **Third column:** Results of the proposed colour edge detector. **Fourth column:** Results after reduction of colour dimensionality and the Canny edge detector.

In the first image *(house)*, let us focus on the area of the tiled wall which is shadowed by the roof. Note that the Canny detector applied to grey level image and to the reduced colour space image find an edge in the change between the lighted and the shadowed areas. However, the proposed method does not consider and edge in this case. This is due to the fact that our method consider the two areas have the same colour (in fact they both belong to the same surface) and they only differ because they received different amounts of light. Thus, this can be considered as a brightness edge but not as a colour edge.

For the second and third images, that is, *Lena* and *peppers,* the results are similar in both cases. The reduction of the colour space dimensionality gives a quite noisy result, while the grey level and the colour edge detectors perform similarly. Also in the image of peppers, we can notice that the colour edge detector suppress the weak highlights on the pepper in the foreground, but not the stronger ones on the pepper in the background.

In the last image (*orange*), note that the contour of the stem is clearer in the proposed colour edges image than in the other ones. We can see in the proposed colour edges image two clear contours in the area which is located at the top-left of the stem. These contours correspond to two defects (stains) in the orange surface. On the contrary, these contours appear very diffuse in the grey level result image, and not well defined in the reduced colour image. Another stain located at the bottom-left margin of the orange, is better outlined by the colour edge detector than by the other methods. Also the main contour of the orange is better delimited. Finally, it can be seen that the result images obtained using the grey level edge detector and the reduced colour space have much more noisy edges than the one obtained using the colour edge detector due to the presence of some texture in the orange surface.

In general, we can say that edge detection after the reduction of the colour space produce quite noisy results due to the local scope of this method. For example, it finds some noise in the background of the *orange* image. The Canny edge detector performs well when applied to grey level images in which the difference between colour also imply a difference in brightness. However, the results obtained for the chessboard image and for the orange image clearly show that this method itself is not enough for colour images in general. On the other hand, the proposed method, though it does not give always the best results, performs quite well in general for all the images we have tried.

CONCLUSIONS AND FUTURE WORK

A new colour edge detector based on a distance function in the RGB space have been introduced. This distance definition assumes difference zero for two points of a same surface which are illuminated by light sources with proportional power spectral distributions. Most of the usual edge detector methods for grey level images are based on the difference of grey level between some pixels of the image. The new colour distance definition can be combined with some of this methods, so they can be adapted to be used for colour edge detection. In particular, the Canny edge detector has been studied, showing the modifications needed to be used in colour images. The experiments carried out both in synthetic and real colour images show that, in general, the colour edge detector proposed gives better results than Canny edge detector applied to the corresponding grey level image or to the image obtained after colour space dimensionality reduction.

The present algorithm for edge detection may be extended to work both with colour and grey level edges simultaneously, assuming that an edge is present whether there is a colour edge or a grey level edge, or some combination of them. The use of either colour or grey level information, or both simultaneously, may depend on the particular application problem.

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