Feature extraction for an image retrieving scheme

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Abstract

In this paper we present two basic modules within the designed scheme for retrieving images of a database from the object colour and shape in the scenes. On the one hand, we design a new method to detect edges in colour images. We offer a new approach to the perceptual space (H,S,I) (an Uniform Chromatic Scale space) about which we describe its properties as well as the metrics to work in it. On the other hand, we develop an information simplifying process to form a graphic structure in which the image pixels join in similar colour areas. For this, we describe a region growing mechanism with the gradient information given by the edge detector module, together with their division module.

Key Words: Color image segmentation, color spaces, image retrieving.

1 Introduction.

The study of the techniques to access large databases of graphic documents and images through key images is one of the most developed topic in recent years[5][13][19]. The key image design by means of a simplification of the searched image, using the present information in one or several characteristics such as shape, colour, texture, etc. is one of the most interesting points, since it lets us study, at the same time, the quantity of necessary information to recover images in an efficient way.

In this paper, we have developed a part of a complete storage scheme and recovering of information about an image database. In it, colour or shape are the elements to be used in the interaction process with the database. Figure 1 shows the general scheme corresponding to an image retrieving model. This piece of work pays attention only to the characteristic extraction module.

Figure 1: General scheme of image retrieving from a database.

The extraction of characteristics, which are based on the image content in the creative part and in the database retrieving, works from colour images. When checking the present objects in the scene, the detection, simplification and hierarchical structuring of colour information in the image pixels
make their segmentation easier. Those are exactly the items to be dealt with in this communication. Image division in homogeneous areas - being homogeneity the uniformity of any characteristic, as intensity, colour or texture - is one of the first processes to be applied to an image in its analytic or understanding stage. It's applied directly to the image pixels and we obtain, as a result, a series of primitives (regions, shapes, ...) that increase the abstraction level on our knowledge about the image content, and that are normally used by later recognition or interpretation processes to model a scene description.

The colour in one scene is a quite discriminant attribute in order to delimit the regions for the human eye. Perceptual experiments demonstrate that any person can distinguish differences in colour easily even if the image intensity is uniform. Then, it seems certain to include, somehow, the pure chromatic information of a scene and to put it together with the intensity component, so that the results get better in detecting edges. However, traditionally speaking, colour information has been ignored in many occasions, not only to simplify calculation but also to reduce the storage space necessary for the images. Recent essays have an increasing interest in the use of colour as an attribute for the segmentation of images [3] [4] [17], as well as for their use in image recovering in large databases [18] [9].

In order to adapt as much as possible to the way in which the human eye perceives colours, the so-called perceptual colour spaces were developed (Uniform Chromacity Scale Spaces), these try to describe colour information in the most similar way that human perception does. So the intensity information is separated totally from the pure chromatic one, so that, for a constant value in the first one, we could have grouped all the colors in the spectrum that have such intensity in an only level. Spaces of this kind are, among others, \([L^*, a^*, b^*]\), \([L^*, u^*, v^*]\) and \((H, S, I)\).

Traditional approaches that have been applied to the segmentation of regions in images (colour or not) are based on three different mechanisms: a) shape detection [8][12], b) segmentation through grouping of pixels (clustering)[2] [21] [22] [15], and c) segmentation through region growth [15] [20] as split-and-merge [14] techniques are.

Among the three above mentioned approaches, the one used in this article is that of shape or edge-detection followed by a region growth from them. To be able to search local variations in image colour, it will be necessary to define distance and order within the chosen colour space. Starting from them, we shall determine some operators that will allow us to reckon the gradient vector in each pixel of a colour image.

In section 2, we deal with colour and introduce the Uniform Chromacity Scale Spaces. Sections 3 and 4 explain a new approach to the space \((H,S,I)\) (conversion from \((R,G,B)\), metrics, order and distinction between chromatic and achromatic zones) and the extension of an algorithm of edge detection that are traditionally used with monochromatic images. Section 5 describes the mechanism of simplification and hierarchical structuring of the information. In section 6 we present the experiments made, and in section 7 we explain the conclusions.

## 2 Perceptual Colour Spaces.

Colour is a psychological attribute, perceptual spaces usually describe colours according to its hue, intensity and saturation. Intensity \(I\) is a measure of the total amount of energy reflected in the visible region of the spectrum, that is, the achromatic component of colour. In fact, a monochromatic image has only the intensity values of the total image. Hue \(H\) is a perceptual attribute of colour, such as red, yellow, green, blue and so on. These colour are organized in circle
at each level of uniform intensity, so that our hue measure will be an angle. Saturation S is used to
describe the purity of a concrete colour, so a completely non-saturated colour will be grey, while a
complete saturated colour will be bright and brilliant.

Geometrically, saturation S will be the distance of the grey line in which the colour at issue is.
In figure 2, we can appreciate the geometric interpretation of these three components within a
cylindrical representation.

![Geometric interpretation of the coordinates (H,S,I) in the cylindrical space in which they are inscribed.](image)

**Figure 2:** Geometric interpretation of the coordinates (H,S,I) in the cylindrical space in which they are inscribed.

### 3 Approach to the space (H,S,I).

The colour space (H,S,I) is a tricolour system that formalizes the colour system developed by
Munsell [10] [10]. Its design reflects the way in which humans see colour, so that it offers numerous
advantages in image processing. In this paper, we have preferred to develop our own approach for
this space which satisfies all our requirements.

In the space (H,S,I), component I indicates the total intensity of pixel brightness, forming circular
levels of constant intensity. Component H or hue component, represents the color hue used and it
is shown as an angle in which 0° stands for red, 120° for green, and 240° for blue. Between 240°
and 360° we can find the non-spectral colours that the human eye sees (purple line in the space
chromacity diagram). The saturation component represents the distance from the colour to the
centre of the circle.

Geometrically speaking, it seems to us a cylindrical space, in which in a base chromacity plane
there is black, meanwhile white appears in the opposite base. We must remark that black and
white are individual colours, that, instead of represented in points, will fulfill each base in the
cylinder, and, as a consequence, destabilizing greatly the calculations (in fact, black could have
a finite distance with itself more than zero). For this reason, we have chosen a geometric form
slightly different to represent the colour space.

As for the approach made to the space (H,S,I), here we have borne in mind a geometric form of
two cones joined at their bases by a cylinder (fig. 3.c). Pure black and white would be set at the top
of each cone. As we move along the intensity axis to the pure white or black, the appearance of this
geometric form is due basically to the lack of sense in considering hue and saturation information.

Black has intensity zero and white has the maximum intensity, there is neither a black or white
colour more or less saturated nor with a colour hue, though.
3.1 Conversion between (R,G,B) and (H,S,I).

The conversion from the space (R,G,B) into a space (H,S,I) as it is designed in the previous section, can be carried out as the following:

As the cube diagonal (R,G,B) from (0,0,0) to (1,1,1) is the grey line, (fig. 3.a), the first step is to rotate the cube RGB so that this diagonal is lined up to one of the axes (fig. 3.b). In this way, we separate the chromatic information (axes X and Y) from the corresponding to luminosity (axis Z):

\[ x = \frac{1}{\sqrt{6}} [2R - G - B] \]
\[ y = \frac{1}{\sqrt{2}} [G - B] \]
\[ z = \frac{1}{\sqrt{3}} [R + G + B] \]

(1)

Later, we transform to cylindrical coordinates by means of the next equations:

\[ \rho = \sqrt{x^2 + y^2} \quad \phi = \arctan(\frac{y}{x}) \]

(2)

These coordinates (\( \phi, \rho, z \)) correspond to the values (H,S,I). However, our space still has a cube shape. In order to transform the central part in a cylinder an the superior and inferior ends in cones, we shall divide S by the maximum value that \( \rho \) can have for the \( \phi \) and \( z \) values given, and we shall also multiply by the maximum radius corresponding to the I value.

This transformation is as follows:

\[ \phi_1 = \phi + k \frac{2\pi}{3} \quad \text{, where } \phi_1 \in \left[ -\frac{\pi}{3}, \frac{\pi}{3} \right] \]

\[ \phi_2 = \phi - \frac{\pi}{3} + k \frac{2\pi}{3} \quad \text{, where } \phi_2 \in \left[ -\frac{\pi}{3}, \frac{\pi}{3} \right] \]

\[ m_1 = \frac{\sqrt{\pi - 1}}{\sqrt{2} \cos \phi_1} \quad m_2 = \frac{1}{\sqrt{2} \cos \phi_2} \]

(3)

\[ S = \left\{ \begin{array}{ll}
\frac{\rho \left[ 1 - 2 \left( \frac{1}{\sqrt{3}} - \frac{1}{2} \right) \right] \sqrt{3}}{\min(m_1, m_2)}, & \text{if } I \not\in \left[ \frac{1}{\sqrt{3}}, \frac{2}{\sqrt{3}} \right] \\
\frac{2\rho}{\sqrt{6 \min(m_1, m_2)}}, & \text{if } I \in \left[ \frac{1}{\sqrt{3}}, \frac{2}{\sqrt{3}} \right]
\end{array} \right. \]

The result is formed by the minimum cones and cylinder that, having as an axis the main diagonal of the original cube (R,G,B), wraps this cube, all that in the inner part of the cylindrical space that will later be employed to define the metrics used (fig. 3.c) I stays in the rank \([0, \sqrt{3}]\), H in \([0, 2\pi]\) and S in \([0, \frac{2\pi}{\sqrt{3}}]\).

In figure 4 is shown this space from a sectional view, in the same way as a chromatic level on which red, green, and blue are.

3.2 Chromatic and achromatic zones in the space (H,S,I).

Previous investigations [15] [23] prove that the hue component is generally the most discriminating character of the space (H,S,I). Any effective method for detecting edges about colour images must bear in mind their use in chromatic information regions. Black, grey, and white are achromatic colours, only characterized by their intensity component value. Whenever a scene is matched under bad conditions of illumination achromatic regions come to the image. So, for instance, weak illumination makes the object have dark aspect in which we cannot distinguish any colour. In contrast, bright illumination produces a saturation in the sensors (not to be confused with
the saturation component $S$ of a colour) and colour distortion that will give a decreasing in the saturation value.

Under such conditions, the hue character $H$ is less important, becoming the intensity $I$ the only discriminant factor in the achromatic region segmentation. In order to optimize the segmentation algorithm is necessary to define a mechanism useful to allow the classification of the pixels depending on their belonging to chromatic or achromatic zones, as to measure distances in the most satisfactory way.

In our approach, we have split the defined space $(H,S,I)$ in two delimited areas by means of a paraboloid centered in the intensity axis (fig.5), in a way that we consider achromatic all the space colours which are within this paraboloid and chromatic colour those which are out of it. For the distance, bearing in mind that all the points in the disc within the parametrized paraboloid located in each level of intensity have a saturation level the same as those is in all its border. Let’s remember that in these zones the human eye is supposed to distinguish only grey, in that case all those points must be considered to be equivalent independently from their $H$ and $S$ values.

In order to parametrize correctly the paraboloid, we have carried out an experiment in which ten people thought of chromatic and achromatic colours from a series of colours chosen at random in all the space. Once we have represented those points, and taking into account that chromacity or achromacity of a colour does not depend on its hue value ($H$), we have come to the following 2nd-degree polynomial which shows a reasonable approximation to the experimental results:

$$\Omega_1 = 0.15 + 0.2 \left( I - \frac{\sqrt{3}}{2} \right)^2$$  \hspace{1cm} (4)
where $\Omega_1$ means the minimum saturation value that a colour must have to be considered chromatic, for a given intensity value $I$.

![Diagram](image)

**Figure 5:** Representation of the chromatic and achromatic zones.

In the next sections we describe order and metrics in $(H,S,I)$. As we shall see further, we have preferred to define them in a way that they can be applied homogenically to chromatic and achromatic pixels. In this way, we do not need to distinguish explicitly chromatic or achromatic zones in the image, as other methods do, but we shall deal with them all in the same form.

### 3.3 Definition of metrics in the space $(H,S,I)$.

For analyzing colour images is very important to have metrics which allow us to qualify the difference (or distance) between two colours. As our space $(H,S,I)$ is within a cylinder, we shall explain the distance between any two points $P_1 = (H_1, S_1, I_1), P_2 = (H_2, S_2, I_2)$

$$d = ((d_I)^2 + (d_C)^2)^{1/2}$$

(5)

where

$$d_I = |I_1 - I_2|$$

(6)

and

$$d_C = \begin{cases} ((S_1)^2 + (S_2)^2 - 2S_1S_2 \cos \phi)^{1/2} & , \text{if } P_1 \text{ and } P_2 \text{ are chromatic} \\ 0 & , \text{if } P_1 \text{ and } P_2 \text{ are achromatic} \\ S_1 - \Omega_{I_2} & , \text{if } P_1 \text{ is chromatic and } P_2 \text{ is achromatic} \end{cases}$$

(7)

being

$$\Omega_{I_2} = \text{Chromaticity threshold for } I_2$$

(8)

$$\phi = \begin{cases} |H_1 - H_2| & , \text{if } |H_1 - H_2| < \pi \\ 2\pi - |H_1 - H_2| & , \text{if } |H_1 - H_2| > \pi \end{cases}$$

(9)

d_I value is the difference of intensity between the two points, $d_C$ is the distance between the projections of the points in a chromaticity level, and $\phi$ is the minor angle that separates $H_1$ and
$H_2$. In figure 6 we can see the geometric interpretation of these metrics. If these two points were achromatic, the distance would only obey to the difference of intensities. If, on the contrary, only one of them were achromatic, we consider the point of the equivalence class of the nearest colour to that one with which we want to measure distance, which will be that having the same value as $H$ and an $S$ value the same as the chromacity threshold. $d_c$ is then calculated subtracting from the saturation value of the chromatic point the chromacity threshold for the intensity level of the non-chromatic point.

![Diagram of distance between points A and B in a cylindrical space.](image)

**Figure 6:** Graphic representation of the distance between points A and B in a cylindrical space, being $d_i$ difference in intensity, an $d_c$ distance from B to the projection on its chromatic level.

3.4 **Specifying order in the space (H,S,I).**

In order to complete our algorithm, as it can be seen later, we shall need to define order within the space $(H,S,I)$ that will allow us, given two points, to decide which of them both is bigger.

As there is not a natural form universally accepted to order colours, we shall determine our order arbitrarily. A simple technique, which even produces good results, practically speaking, will evaluate one of the components in the two elements to be ordered, and will choose the biggest element that which possesses bigger value in that component. If equality is the result, we shall go to the next component and so on.

In our case, given two pixels $(H_1, S_1, I_1)$ and $(H_2, S_2, I_2)$ we compare the $I$ values at first, then those of $S$ and finally $H$. To compare this latter component the employed criterion is as follows: if the minor module angle to come from $H_1$ to $H_2$ is positive, we choose $(H_2, S_2, I_2)$ as greater element, and, on the contrary, we have $(H_1, S_1, I_1)$.

In case those two points we want to order were achromatic, we will only pay attention to their intensity differences. If only one was achromatic in the same conditions in intensity, the chromatic point is considered greater (which has necessarily greater saturation).

4 **Edge detection in colour images.**

The segmentation focus based on detecting shapes is supported by the so-called differential operators, which serve to detect discontinuities or local changes in the pixels values.

In this point, we will generalize the edge detection techniques for monochromatic images to those defined in our colour space. The obtaining of the gradient estimation in colour spaces will be made
from the distance and order defined for the above-mentioned space.

4.1 Gradient vector estimation in colour images.

Being \( f(x, y) \) a scaling function defined about \( \mathbb{R}^2 \), as for example, a monochromatic image, we explain the \( f \) gradient, noted as \( \nabla f \), as follows:

\[
\nabla f = \begin{pmatrix}
\frac{\partial f}{\partial x} \\
\frac{\partial f}{\partial y}
\end{pmatrix}
\]  

(10)

From this definition we deduce that the \( f \) gradient is an \( \mathbb{R}^2 \) vector, oriented in the direction where the \( f \) variation is maximum. The module of the said vector is the \( f \) derivative magnitude in the direction of this vector itself.

The previous definition of the gradient concept is not applied directly to multiband images, yet there is not the concept of partial derivative of a function whose values are in \( \mathbb{R}^2 \). Trying to solve this problem, there come different approaches of estimation of what is called *multispectral gradient* [16].

Many of these approaches are based on the combination of the individual gradients of each image band. If \( P(x, y) \) is the point colour \((x, y)\) and \((P_1, P_2, P_3)\) are its components in the colour space, then:

\[
\nabla C = F(\nabla P_1, \nabla P_2, \nabla P_3)
\]  

(11)

where \( \nabla C \) is the gradient in the point \((x, y)\), \( F \) means any function and \( \nabla P_1, \nabla P_2, \nabla P_3 \) are the individual gradients in \((x, y)\) of each of the \( P \) components. That is, image is treated as if it were three monochromatic ones, and once we have obtained the gradients for each image, we look for a way of combining them. The problem of this method is exactly the skill in that combination.

Other techniques try to estimate the component module of the gradient vector according to any distance defined about the colour space. Since the derivative in one direction can be explained as the difference between a pixel and the next in the same direction, then we can use the distance in a colour space to estimate the module of the said difference:

\[
|\nabla C_2| = \left\| \frac{\partial P}{\partial x} \right\| \simeq d(P_{x,y}, P_{x+1,y}) \\
|\nabla C_2| = \left\| \frac{\partial P}{\partial y} \right\| \simeq d(P_{x,y}, P_{x,y+1})
\]  

(12)

In the present paper, we have preferred to develop a similar approach, expressing the image value derivative as a distance, but the new development as been the concept of order, which will allow us to estimate not only the component model of the gradient vector, but also its direction. Thus, we will point the component obtained from the gradient vector towards the greatest pixel value according to the order we have defined.

As for order itself, it is enough to say that, although arbitrary, it is still inline with the natural order in the grey scale, so that, in practice, it does not produce detectable instabilities, showing excellent experimental results.

4.2 Extension of the Canny Filter to colour images.

The information about the gradient vector (magnitude an direction) which gives us the operator of the first order used is fundamental in edge interpretation. In this section, we shall extend the mask
used of the first order based on the Gaussian, as the Canny’s filter does [1], from monochromatic images to colour ones.

The convolution of a grey level image with the first partial derivative of Gaussian can be carried out convolving successively the image with two perpendicular, unidimensional masks, being the first one the derivative of the Gaussian and the second one the Gaussian itself. As this first convolution outcome would be real numbers (positive or negative depending on the gradient vector direction), our problem is reduced then to an only dimension, but with arbitrary length masks. In order to explain this, we shall use the following property:

\[
\frac{\partial G(x, y)}{\partial x} = -\frac{\partial G(-x, y)}{\partial x}
\]  

(13)

Then, in the discrete case, the action of applying a mask of partial derivatives in x of a Gaussian can be expressed as follows:

\[
\sum_k m_k x_{i+k} - m_k x_{i-k}
\]

(14)

where the \(m_k\) values stand for the mask coefficients and \((x_{i+k}, x_{i-k})\) for the image coefficients.

At this stage, it seems logical to think that we can group the pixels having the same weight (affected by the same coefficient). Grouping then the terms and matching the correspondent to pixels equidistant from the point where the mask is centered, we come to the next statement:

\[
\sum_k m_k (x_{i+k} - x_{i-k}) = \sum_k m_k e(x_{i+k}, x_{i-k}) d(x_{i+k}, x_{i-k})
\]

(15)

being \(d(x_i, x_j)\) the distance between the colours of \(x_i\) and \(x_j\) pixels and

\[
e(x_i, x_j) = \begin{cases} 
1 & \text{if } x_i > x_j \\
-1 & \text{if } x_i \leq x_j
\end{cases}
\]

(16)

an order function as the one defined above.

As it can be appreciated, it is enough to define metrics and order in the colour space to be able to convolve the image with the partial derivative in one direction, and later convolve perpendicularly the result (let’s remember that they are already real numbers) with a Gaussian mask. From this point, the rest of the steps in Canny’s algorithm are employed, that is, the non-maximal suppression and the hysteresis step to finally isolate the most promising edge points.

With this result, we have generalized the Canny’s filter of edge detection to the case of colour images. Moreover, it can be observed that, apart from the use of intensity as information to detect edges, we are using information coming from the colour and saturation level. It is easy to perceive, even, that this filter applied to grey-level images is equivalent to the Canny’s filter, taking for granted the same result.

5 Image segmentation.

Image segmentation is, in signal processing, one of the first processes of information condensation. It is directly applied to the image pixels and it produces their grouping with any criterion for the formation of shapes, regions, etc. These primitives describe and model the image and are generally used by the later processes of identification/interpretation of scenes.
Generally speaking, as we have previously treated in the introduction, the image segmentation algorithm (whatever the kind of image: colour, monochrome, ...) can be classified in three categories, depending on their acting.

One of the main objections to the use of region growing techniques comes from the necessity of an image pixel selection method, the seed, around which the region will grow. In the approach presented in this paper, we have chosen a region growing technique from the gradient information obtained in edge detection.

5.1 Region growth.

5.1.1 Sowing with seeds.

As we mentioned before, the first step when carrying out a region growing technique is the election of the seed points from which we will spread the different regions within the image. This growing technique tries to profit from the gradient and edge information of the image we already possess, making the resultant regions not exceed the edges obtained in the previous step, and also making them grow according to the image colour gradient calculated before. Following this technique we make the edges themselves act, on the one hand, as if containing wall of the flood process and, on the other, being them, more concretely the obtained gradient information, those which give the similarity criterion in the pixel gathering process to the different seeds.

In order to avoid the regions to surpass the already calculated edges, we shall sow two different seeds for each edge segment all along its distance covered, one seed on the right and the other on the left (coinciding with this edge). So, the first thing to define is a series of points as union of the different regions, coincidental with the already calculated edges in previous steps.

Having the purpose of eliminating inconsistencies in the sowing field and simplifying the algorithm, we shall remove all the threefold points in the edge map, in a way that all the segments remaining lack of ramifications. A threefold point (see fig. 7.b) is that which has three neighbours (let’s remember that after the process of thinning, the value 1 points can only have 0, 1, 2 or 3 neighbours to 1). Finally, we shall mark as seeds all the remaining points just on the right and left of the edge segment, using a label for those on the right and another one for those on the left. In figure 7.a we explain the said sowing process along an edge detected segment.

\vspace{1cm}

\begin{figure}[h]
\centering
\includegraphics[width=0.5\textwidth]{image.png}
\caption{a) Sowing process with two different labels, on one side and on the frontier, b) an example of a threefold point.}
\end{figure}

On the one hand, this approach guarantees that the resultant regions will not invade each other, and on the other, it allows the non-connected segments in the frontier detection process which define one form to be sowed by different seeds. This will give rise to a form covering according to
characteristic regions (as colour) very similar among themselves (see fig. 8), which make us group those regions in only one, paying attention to the neighbouring information we have.

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**Figure 8**: a) Generated regions after the initial sowing and their growth, b) obtained form through "A" grouping.

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### 5.1.2 Region Growth.

Our region growing algorithm is based on a controlled descent along the gradient image pitch. If we remember our seeds were set precisely in the image frontiers which correspond to the maxima (or the crests) that the gradient image shows.

The propagation algorithm is simple: for each pixel we observe the non-labeled neighbours and we label with the same value of the original pixel that which has a gradient magnitude value nearer to the one which the pixel possessed originally. This growing mechanism is, by itself, insufficient, because it makes the regions grow in a homogeneous way, independently from the real differences in the gradient magnitude. Then, a region presenting a marked pitch in the gradient magnitude image will grow the same as another one with smaller or no pitch. To avoid this, we limit the minimum value $M$ of gradient magnitude that can have a pixel for the edge to be spread. When the propagation step does not make any change, we decrease the $M$ value and it is still propagated. The growth algorithm is, then, as follows:

\[
\begin{align*}
G(x,y) &: \text{Gradient magnitude image} \\
E(x,y) &: \text{Label image} \\
M &= \max(G) \\
m &= \min(G) \\
K &= M \\
\text{Repeat while } K \geq m \\
&\quad \text{Repeat while there are changes in } E(x,y) \\
&\quad \quad \text{For every } E(x,y) \text{ be } E(x',y') \text{ a non-labeled neighbour} \\
&\quad \quad \quad E(x',y') = E(x,y) \text{ if } |G(x,y)-G(x',y')| \text{ is minimum and } G(x',y') \geq K \\
&\quad \quad \end{align*}
\]

End For

End Repeat

$K = K - dK$

End Repeat

where $dK$ stands for an increment of the used gradient magnitude.
5.1.3 Region interpolation.

Once we have our regions spread out we can interpolate the values \((H,S,I)\) in a simple way, action which gives us a better display of the information contextual dependencies of the regions calculated.

As to carry out the interpolation, we shall calculate the value \((H,S,I)\) average of the original image in the whole region. The mechanism used to calculate the above-mentioned average is the following:

\[
x = \frac{1}{n} \sum_{i=1}^{n} S_i \cos(H_i) \quad y = \frac{1}{n} \sum_{i=1}^{n} S_i \sin(H_i)
\]

\[
\tilde{R} = \arctan \left( \frac{y}{x} \right) \quad \mathcal{S} = \sqrt{x^2 + y^2} \quad \bar{I} = \frac{1}{n} \sum_{i=1}^{n} I_i
\]

(17)

(18)

5.2 Final division of the regions.

As our initial sowing started from the edge segment calculated originally, and as these segments can be incomplete, there exists the risk of any region spread out through any gap in the edges, invading what would correspond to another region (see fig. 9.a.a). It is also likely that we have an edge segment which delimits on one side for one or more different regions, then we would be committing an error in the sowing (see fig.9.b)

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Figure 9: Error cases which can occur in the region growth.

So that we can solve these possible problems some regions get parted. The criterion used to determine whether a region must be parted or not attends to that the average of the distances \((H,S,I)\) between the interpolated values and the original pixels values exceeds or does not the given threshold.

The designed partition mechanism divides the regions in its narrowest part, searching the two shape points whose quotient between euclidean distance and the shortest distance along the shape is minimum, under the restriction of which the segment joining them belongs to the region.

6 Experiments realized.

In order to carry out these experiments we have selected 256x256 pixel images, with a byte for each band and pixel. Some of them have been synthesized just to remark the situations in which the canny's filter can give problems.

The implementation in all the filters and necessary operations for the experiments has been made under khoros 2.2. With this purpose we have designed a toolbox with the different transformations
Figure 10: The segment A presents a minimum, but it is not inner to the region. The cut will be at B.

among colour spaces, and the libraries necessary to calculate the distances within the space (H,S,I), to develop all the steps in each filter and the region growth from the detected edge segments.

6.1 Results obtained.

Content of the resulting figures:

1. In (a) we show original images.
2. In (b) the result of the application of region growing process with their later division and interpolation.
3. In (c) the result of the application of the Canny’s filter to the arithmetic mean of the three colour bands with following parameters: $\sigma = 1$, higher threshold of hysteresis $h = 0.9$, and lower threshold $l = 0.5$.
4. In (d) the result obtained after applying the Canny’s colours filter to each image, with the same parameters $\sigma$, $h$ and $l$. The paraboloid used to delimit chromatic and achromatic zones is the revolution of the parabola given in (4).

All the result images have been treated by a process of thinning for the edges appearing in the images have a pixel thick.

Figure 11 corresponds to a synthetic image that represents a house. Most of the colours which have been selected possess the same grey hue when having the three band average. That is the reason why the Canny’s filter is unable to find these edges, while the filter based on the distance (H,S,I) detect the colour difference among regions without any difficulty.

In figure 12, corresponding to the scorpion image, we see an important characteristic: the scorpion cefalotorax has a longitudinal drawing which goes totally unnoticed for Canny.

Figure 13, representing a green frog on a red leaf, has strong contrast for us, the one which is reduced when we paint it grey. That is why the Canny’s filter is unable to get all the frog shape. On the right bottom, we can see how the texture presenting the image is treated by the Canny’s filter in a more coherent way.

Figure 14, showing a toucan, states a similar phenomenon. On the beak base we appreciate a different colour from yellow to blue, while in the grey image we have two very similar hues. The Canny’s filter does not detect this edge.

In all then we have observed that the regions interpolations shows visually how all the objects and important information features for the interpretation of the scene have been collected.
Figure 11: a) Original image, b) image of interpolated regions, c) Canny segmentation on grey levels, d) Canny segmentation on (H,S,I).

Figure 12: a) Original image, b) image of interpolated regions, c) Canny segmentation on grey levels, d) Canny segmentation on (H,S,I).
Figure 13: a) Original image, b) image of interpolated regions, c) Canny segmentation on grey levels, d) Canny segmentation on \((H,S,I)\).

Figure 14: a) Original image, b) image of interpolated regions, c) Canny segmentation on grey levels, d) Canny segmentation on \((H,S,I)\).
7 Conclusion.

It has been stated the interest and the great utility of using colour spaces of the Uniform Chromaticity Scale when detecting edges of a image, instead of reducing it to grey levels (loss of strong perceptual approach to the colour space \(H,S,I\), with its own metrics and a mechanism to separate the chromatic and the achromatic zones from the space.

In general terms, we can assert about the designed methods that:

- We separate in a natural way the intensity information from the strictly chromatic one.
- The colour specification in this kind of spaces is nearer to that which gives human intuition.
- The perceptual differences among colours can be represented directly with the space metrics.
- Whthin the general scheme of image recovering in a database is inserted a module of region covering capable of structuring their information in a superior relation order which makes possible, with the adequate techniques now being developed, the presence of the component forms in the scenes to be analyzed.

Using the given metrics and order definition for this \(H,S,I\) space, we have developed an extension of the Canny multiscale operator, getting as a result a quite strong technique for the detection of edges in colour images, and clearing a way for the application of multiresolution techniques in a direct way for multiband images.

One of the most interesting results, which is deduced from this piece of work, is that we can apply operators of gradient-kind (it is said here gradient-kink because the gradient concept as it is does not exist in representation spaces of more one dimension) to multiband images using only the definition of order and metrics in the representation space.

The greatest inconvenient may be the necessity of definition of this order, yet it does not exist one universally accepted in these spaces. The natural order in \(R\) is evident, but it is not as simple in \(R^2\) and higher order spaces. This takes us to our necessity of definition of our order arbitrarily, risking ourselves in that it can cause problems when applying the operator.

Four fundamental contributions have been revealed in this paper:

- The use of the perceptual information that colour give in the edge detection scheme designed.
- The extension of the algorithm of Canny’s edge detector to colour images.
- The growing of image covering regions from the gradient information given by the edge detector algorithm.
- The adaptation of region information composing the image with regard to a hierarchical structure of neighbourhood dependency among themselves.

References


