A Fuzzy Colour Image Segmentation Applied to Robot Vision

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Abstract

In this paper, a new growing region algorithm to segment colour images is proposed. A region is defined as a fuzzy subset of connected pixels and it is constructed using topographic and colour information. To guide the growing region process, a distance defined in the HSI colour space is proposed. This distance is used both to select the pixels which will be linked in each step of the algorithm, and to calculate membership degree of each point to each region. The proposed technique is applied to vision-guided robot navigation with the aim of detecting doors in indoor environments.

Keyword: Colour image segmentation, fuzzy segmentation, colour distance, robot vision.

1 Introduction

The image segmentation, view as the process of dividing the image into significant regions, is one of the most widely used step in image processing. Usually, this operation allows to arrange the image in order to make it more understandable for higher levels of the analysis (for example, in image database retrieval [4], motion estimation [10] or robot navigation [2, 8]).

Many types of segmentation techniques have been proposed in the literature. They can be grouped into three main categories corresponding to three different definitions of regions: the methods in the first group, called pixel based segmentation methods, define a region as a set of pixels satisfying a class membership function. In this category are included the histogram based techniques [5] and the segmentation by clustering algorithms [12]. The methods in the second group, corresponding to the area based segmentation techniques, consider a region like a set of connected pixels satisfying a uniformity condition. The growing region techniques [7] and the split and merge algorithms [1] are two examples of this group. The last type of segmentation methods corresponds to the edge based algorithms, where a region is defined as a set of pixels bounded by a colour contour [11].

In real images, the separation between regions is usually imprecise. This is one of the main problems of the crisp segmentation techniques, where each pixel have to belong to an unique region. To solve this problem, some approaches propose the definition of *region* as a fuzzy subset of pixels, in such a way that every pixel of the image has a membership degree to that region [3]. In this sense, many algorithms have been developed to segment grey scale images, but the fuzzy segmentation of colour images has been paid less attention.

Other important aspect to take into account is the colour information processing. The most common solutions in the literature are (i) combining the information of each band into a single value before processing (for example, the gradient), or (ii) analyzing each band separately and then combining the results (for example, histogram analysis of each band and subsequent combination). Apart from the difficulty to choose an adequate criterion to pool the data, the main problem of these approaches is the application of the same combination rule to the whole image, without considering the particularities that appear in the comparison of two colours. That problem is most significant in methods, like those based on growing region, where the decision in each step depends on the difference between pixels.

In this paper, a new growing region algorithm to segment colour images is proposed. In our approach, a region is defined as a fuzzy subset of connected pixels and it is constructed using topographic and colour information, i.e., two

pixels will be assigned to the same region if they are connected through a path of similar colours. To process the colour information, a distance defined in the HSI colour space is proposed. This distance is used in the growth of a region both (i) to select the pixels which will be linked in each step of the algorithm, and (ii) to calculate the membership degree of each point to each region.

Although the proposed algorithm is a multipurpose segmentation technique, in this paper it has been applied to vision-guided robot navigation in indoor environments. Concretely, it has been used to detect doors with the aim of moving a robot to the exit of the room.

2 Colour space

Many colour spaces may be used in image processing: RGB, YIQ, HSI, HSV, etc. [9]. Although the RGB is the most used model to acquire digital images, it is well known that it is not adequate for colour image segmentation. Instead, other colour spaces based on human perception (HSI, HSV or HLS) seem to be a better choice for this purpose [9]. In these systems, hue (H) represents the colour tone (for example, red or blue), saturation (S) is the amount of colour that is present (for example, bright red or pale red) and the third component (called intensity, value or lightness) is the amount of light (it allows the distinction between a dark colour and a light colour).

In this paper, the HSI colour space will be used. This model separate the colour information in ways that correspond to the human visual system. Moreover, it offers many advantages in a segmentation process (for example, the use of hue avoids the shading effects). Geometrically, this colour space is represented as a cone, in which the axis of the cone is the grey scale progression from black to white, distance from the central axis is the saturation, and the direction is the hue (figure 1).

Since we use a digital camera to acquire images in RGB coordinates, it is necessary to define a relationship between RGB and HSI systems. In this paper, the following transform is applied [9]:

$$\begin{aligned} H &= \arctan\left(\frac{\sqrt{3}(G+B)}{2R-G-B}\right) \\ S &= 1 - \min\{R,G,B\}/I \\ I &= (R+G+B)/3 \end{aligned} \tag{1}$$

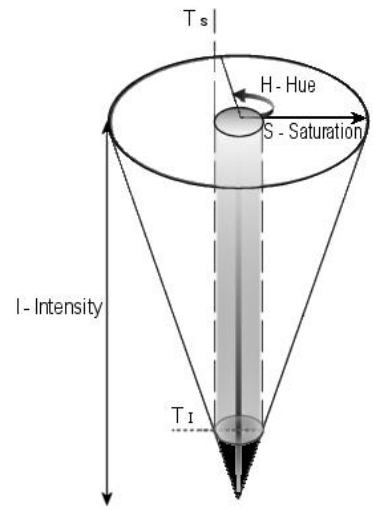

Figure 1: HSI colour space

2.1 Distance between colours

Once the colour space is selected, a distance between two colour points $p_i = [H_i, S_i, I_i]$ and $p_j = [H_j, S_j, I_j]$ is defined. For this purpose, we first define the differences between components as:

$$\begin{aligned} d_H &= \begin{cases} |H_i - H_j| & if\, |H_i - H_j| \leq \pi \\ 2\pi - |H_i - H_j| & otherwise \end{cases} \\ d_S &= |S_i - S_j| \\ d_I &= |I_i - I_j| \end{aligned} \tag{2}$$

with d_H, d_S and d_I being the distances between hue, saturation and intensity respectively. Based on the previous distances, the following equation will be used to measure the difference between colours:

$$d_C(p_i, p_j) = \left[\left((d_1)^2 + (d_2)^2\right)\Big/ 2\right]^{1/2} \tag{3}$$

where d_1 is the normalized difference between intensities given by $d_1 = d_I / MAXI$ with $MAXI$ being a constant equals to the maximum level of intensity (usually 255), and d_2 is defined as

$$d_2(p_i, p_j) = \begin{cases} 0 & if\, p_i\, or\, p_j\, are\, achromatic \\ d_{HS} & if\, p_i\, and\, p_j\, are\, chromatic \\ d_S & otherwise \end{cases} \tag{4}$$

with $d_{HS} = \sqrt{\left((d_S)^2 + (d_H/\pi)^2\right)/2}$ being a distance which combines information about hue and saturation. Notice that $d_C(p_i, p_j) \in [0, 1]$.

In the previous equation we introduce the notions of chromaticity/achromacitiy to manage two well known problems of the HSI representation: the imprecision of the hue when the intensity or the saturation are small, and the non-representativity of saturation under low levels of intensity. An often practical solution to solve this problem is to perform a partition of the colour space based on the chromaticity degree of each point. In equation (4), we propose to split the HSI space into three regions: *chromatic*, *semi-chromatic* and *achromatic* (figure 1). This partition is defined on the basis of two thresholds T_I and T_S : the first one, T_I, correspond to the level of intensity under which both hue and saturation are imprecise; the second one, T_s, defines the value of saturation under which the hue is imprecise (but not the intensity). Therefore, a point $p_i = [H_i, S_i, I_i]$ will be *achromatic* if $I_i \leq T_I$ (black zone in figure 1), *semi-chromatic* if $I_i > T_I$ and $S_i \leq T_S$ (grey zone in figure 1), and *chromatic* if $I_i > T_I$ and $S_i > T_S$ (white zone in figure 1). In this paper, the thresholds have been fixed empirically to $T_I = MAXI/5$ and $T_s = 1/5$.

3 Segmentation method

Our approach will segment the colour image in two steps:

1. Firstly, a set of "*seed points*", noted as $\Theta = \{s_1, s_2, \ldots, s_q\}$, will be calculated.

2. Secondly, a collection of fuzzy sets, noted as $\widetilde{\Theta} = \left\{\widetilde{S}_1, \widetilde{S}_2, \ldots, \widetilde{S}_q\right\}$, will be defined from Θ. For this purpose, a method to calculate the membership degree of a given pixel to a fuzzy set $\widetilde{S}_k$ will be proposed based on topographic an colour information.

In the following sections, the previous stages will be analyzed in detail.

3.1 Seed points

In the growing region methods, the selection of seeds that hopefully may correspond to structural units is a critical step. Due to this paper is focused in a particular application, i.e., the localization of doors in indoor environments, a seed point selection is proposed for this specific case.

Figure 2: Example of seed points selection

In our approach, we have considered that a door have at least one corner point in its frame. Based on the previous assumption, the seed selection is performed in two steps. In the first one, corner points are detected in the intensity band using the Harris method [6]. Afterwards, a couple of seeds are put at a distance D from each corner in the direction of its gradient (one per each way). In this paper, D has been fixed to 7 pixels. Figure 2 shows an example where twelve seed points have been marked corresponding to six corner points (they are showed with green crosses and red points respectively).

It would be desirable for each door to contain a single seed, but this is not often the case. Indeed, it is usual to find several seeds into the same door (which implies several regions). To solve this problem, the proposed algorithm will discard seeds during the segmentation process. This point will be explained in detail in section 3.3.

Although the previous seed selection method has been designed for a particular case, a general one could be considered in order to give more generality to the technique (for example, seed regions could be located in the local minima calculated over the gradient of the image). This will be an object of future research.

3.2 Fuzzy regions

In this section, a method to fuzzify a set of "seed points" $\Theta = \{s_1, s_2, \ldots, s_q\}$ is proposed. For this purpose, a membership function for fuzzy regions is defined (section 3.2.2) based on a distance between pixels (section 3.2.1).

Algorithm 1 Algorithm to calculate d_P

Input:
Image I of size $N \times M$
Seed point s_v

Notation:
$Contour(L)$: Pixels in the contour of a region L
$Neighbor(p_i)$: 8-neighborhood of p_i

1.-Initialization
$d_P(s_v, s_v) = 0$
$L = \{s_v\}$

2.- While $Card(L) \neq N \times M$

$$(p_{in}, p_{out}) = \underset{(p_i, p_j)}{argmin} \; \{d_C(p_i, p_j) \,/\, p_i \in Contour(L) \,,\, p_j \in Neighbor(p_i) \setminus L\}$$

$$d_P(p_{out}, s_v) = max\,[d_P(p_{in}, s_s), d_C(p_{in}, p_{out})] \quad (1)$$

$$L = L \cup \{p_{out}\}$$

3.2.1 Distance between pixels

Let $\prod_{ij}$ be the set of possibles paths linking the pixels p_i and p_j through pixels of the image I. Given a path $\pi_{ij} \in \prod_{ij}$, its cost is defined as the greatest distance between two consecutive points on the path:

$$cost(\pi_{ij}) = max\,\{d_C(p_r, p_{r+1}) \,/\, p_r, p_{r+1} \in \pi_{ij}\} \tag{5}$$

where p_r and p_{r+1} are two consecutive points of π_{ij}, and $d_C(p_r, p_s)$ is defined in equation (3) and measures the distance between colours. Let $\pi^*_{ij} \in \prod_{ij}$ be the optimum path between p_i and p_j defined as the path that link both points with minimum cost:

$$\pi^*_{ij} = \underset{\pi_{i,j} \in \Pi_{i,j}}{argmin} \; \{cost(\pi_{i,j})\} \tag{6}$$

Based on the previous definition, the distance between two pixels p_i and p_j is defined as the cost of the optimum path from p_i to p_j:

$$d_P(p_i, p_j) = cost(\pi^*_{ij}) \tag{7}$$

Let us remark that the distance defined in (7) make use of topographic information (paths linking the pixels) and distances between colours. In addition, it is sensitive to the presence of edges in the following sense: if the optimum path linking two points p_i and p_j pass through an edge (that is, a point which separate two regions), its cost, and consequently the distance between p_i and p_j, will be high. That is because of the fact that there are consecutive points, in the portion of the path that cross over the edge, with a high distance between them.

3.2.2 Membership function for fuzzy regions

The membership degree $\mu_{\widetilde{S_v}}(p_i)$ of a pixel p_i to a fuzzy region $\widetilde{S_v}$ is defined as

$$\mu_{\widetilde{S_v}}(p_i) = \frac{1 - d^*_P(p_i, s_v)}{\sum_{k=1}^{q}(1 - d^*_P(p_i, s_k))} \tag{8}$$

where $s_v \in \Theta$ is the seed point of $\widetilde{S_v}$, and $d^*_P(p_i, s_v)$ is defined as

$$d^*_P(p_i, s_v) = \begin{cases} 1 & if\; p_i \in \Theta \,,\, p_i \neq s_v \\ d_P(p_i, s_v) & otherwise \end{cases}$$

Let us remark that $\sum_{v=1}^{q} \mu_{\widetilde{S_v}}(p_i) = 1$. Using the equation (8) we can calculate the membership degree of every point $p_i \in I$ to each seed $s_v \in \Theta$. That allows us to obtain the set of fuzzy regions $\widetilde{\Theta} = \left\{\widetilde{S}_1, \widetilde{S}_2, \ldots, \widetilde{S}_q\right\}$ from the set of seed points $\Theta = \{s_1, s_2, \ldots, s_q\}$.

[1] Notice that $d_P(p_{in}, s_v)$ has been calculated in a previous step

3.3 Algorithm

Given a set of seed points $\Theta = \{s_1, s_2, \ldots, s_q\}$, a growing region algorithm is applied to each $s_v \in \Theta$ in order to obtain the set of fuzzy regions $\widetilde{\Theta} = \left\{\widetilde{S}_1, \widetilde{S}_2, \ldots, \widetilde{S}_q\right\}$. For each $s_v \in \Theta$, the membership degree $\mu_{\widetilde{S}_v}(p_i)$ is obtained for every point of the image using the equation (8). For this purpose, it is necessary to calculate the distance $d_P(p_i, s_v)$ given by equation (7). The algorithm 1 calculates that distance for all the points p_i of an image I with respect to a given seed point $s_v \in \Theta$. Its computational complexity is $O(nK)$, where $n = N \cdot M$ is the number of pixels of the image, and K is defined as $K = \max\{N, M\}$ (notice that the maximum size of a contour is $4(N + M)$). Due to the algorithm have to be applied for each seed point of Θ, the overall process has a complexity of $O(qnK)$, where q is the number of seeds.

As we mentioned in section 3.1, it is usual to find several seeds into the same region. To overcome this problem, given a seed point $s_v \in \Theta$, all the seeds of the subset $\{s_u\}_{u=1..K}$ verifying $d_P(s_v, s_u) < C$ will be eliminated. This new step may be introduced in the algorithm 1 without increase its complexity. In this paper, the constant C has been fixed to 0.01.

4 Results

The proposed segmentation method has been applied to different colour images. To acquire these images, a SONY EVI-401 colour camera connected to the mobile robot Nomad 200 has been used (figure 3).

Six of the images used for testing our methodology are showed in figure 4(A-F). To show the results, the segmentation has been "defuzzified" allocating each pixel to the region for which it has the highest membership degree. The examples 4(A-D) show images with a single closed door. In all the cases, the proposed algorithm generates a fuzzy region corresponding to the door (the associated crisp region is showed in blue colour in figure 4(G-J)). The number of regions obtained are 5, 10, 4 and 3 respectively, although the number of seeds detected in each case was 12, 34, 14 and 12 respectively. That reveals the goodness of the method proposed to discard seeds during the segmentation process

The examples 4(E-F) correspond to images with two doors. Whereas in the first case both of them are closed, in the second one there are an open door in the foreground and a close one behind it. In both cases, our approach obtains one fuzzy region for each door (figure 4(K-L)). On the image 4(E), the algorithm generates four regions: one of them corresponds to the background, another one is associated to a label, and the last two regions correspond to the doors. On the example 4(F) our technique obtains eight fuzzy regions, four of them corresponding to the two doors and its frames (figure 4(L)). The number of seeds was 9 and 30 respectively.

Figure 3: Mobile robot Nomad 200

Although in all the examples there are a degradation in the luminance and zones with different brightness (see the door in image B), the results show that our methodology detect the doors without split them in several regions. That reveals that the use of a distance which consider both colour and topographic information improves the results.

5 Conclusions

A new fuzzy methodology to segment colour images has been presented. The technique is based on the growth of regions which are treated as fuzzy subsets. To manage the colour information, a distance between pixels has been defined in the HSI colour space. Using that distance and topographic information, the membership degree of each point to each region has been calculated. Our experiments suggest the combination of the proposed colour distance and the growing region process improve the results obtained with the classical segmentation techniques.

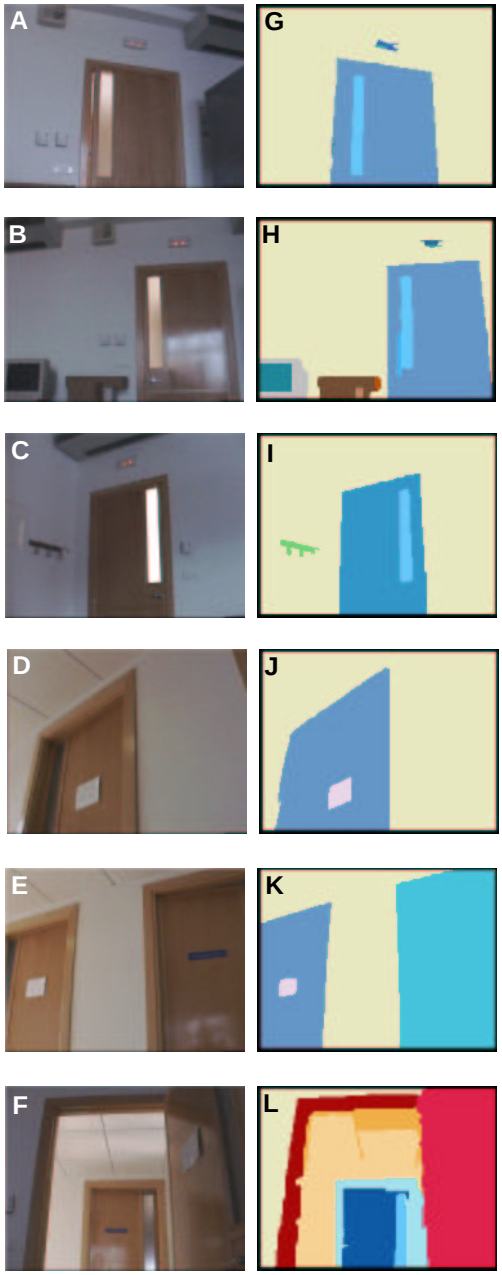

Figure 4 : Segmentation results

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