Fuzzy segmentation of color images and indexing of fuzzy regions

Sylvie Philipp-Foliguet[1], Marcelo Bernardes Vieira[1 2 3], Martial Sanfourche[1]
[1] Equipe Traitement des Images et du Signal, ENSEA/UCP, 6 av. du Ponceau, 95014 Cergy Cedex, France
[2] Departamento de Ciência da Computação, Instituto de Ciências Exatas, UFMG, Av. Antônio Carlos, 6627, 31270-901, Belo Horizonte, MG, Brasil
philipp@ensea.fr bernard@dcc.ufmg.br

Abstract

This paper focuses on applications of fuzzy segmentation in region indexing and image retrieval. First, our algorithm of fuzzy segmentation is shortly explained. Some features characterizing a fuzzy region are then defined, and a distance between fuzzy regions is proposed. This distance can be used to rank regions on color and/or shape features or to perform a partial request from a image, request consisting in a set of regions.

Keywords

Fuzzy segmentation, Region indexing, Image retrieval, Partial request

1. Introduction

Image indexing rarely use regions, probably because automatic or semiautomatic segmentation is very difficult to obtain. Problem is even more difficult when indexing generalist databases where images and regions have various sizes. Nevertheless, in pre-attentive vision, our visual system perceives some zones with their average color, their coarse shape, their size, with respect to the rest of the image. To recognize objects, it is not necessary for regions to be exactly segmented or for contours to be exactly positioned. That is why we propose to perform a coarse segmentation of the image, with accurate contours when the color gradients are high, and imprecise contours elsewhere. Actually we propose to model regions as fuzzy sets.

The indexing of regions is then achieved by the way of features computed on these fuzzy regions. A set of fuzzy regions, which may overlap, constitutes a partial request on the image.

2. Fuzzy segmentation

We have proposed in [5] a definition of the fuzzy segmentation and an algorithm to achieve it. We give below the outline of this algorithm.

Let Ω be a finite referential (set of N sites). A fuzzy region is a fuzzy set of Ω defined by a mapping from Ω to [0, 1]. A fuzzy segmentation of Ω is a set of M fuzzy regions R_j whose supports are included in Ω and defined by the two following axioms :

$\mu_{Rj}(s)$ is the membership degree of site s to region R_j

(a) $\forall s \in \Omega, \forall R_j, j = 1,\dots, M, \quad \mu_{Rj}(s) \in [0, 1]$

(b) $\forall R_j, j = 1,\dots, M, \quad \sum_{s\in\Omega} \mu_{Rj}(s) \in]0, N[$.

The algorithm of fuzzy segmentation starts from an image of gradient norms obtained by Di Zenzo's algorithm [2]. It performs a region growing by simulating the flood of the image as the watershed algorithm [4] [7]. Every local minimum of the gradient norm is a seed of a basin. This leads to a very big number of basins. These basins are then merged, according to criteria of size and depth of the basins [1].

Each fuzzy region corresponds to a set of merged basins. Membership degrees to the fuzzy regions are computed from topographic distance to region's core [5].

Let f be the image of gradient norms defined on Ω and $\mu_R(x)$ be the membership degree of site x to region R.

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For each basin B
    for each site s of B
        if s ∈ core(B) then μB(s) ← 1 else μB(s) ← 0
    end for
End for
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For each basin B
  for each site s of B
    for each neighbor v (in 4-connectivity) of s
      $\mu = \mu_B(s) - \frac{1}{255}(k \cdot |f(v) - f(s)| + 1)$
      if $\mu > \mu_B(v)$ then $\mu_B(v) \leftarrow \mu$
    end for
  end for
End for

When two basins merge, a penalty is applied to all pixels of the absorbed basin, in order to maintain the highest membership degrees to core pixels of the absorbing basin. This penalty equals the difference between the bottom levels of both basins, i.e. between the gradient norms of their cores. If both cores have the same level, the penalty equals zero and the region's core is non-connected. The diffusion of the membership degrees goes on until they equal 0.

k is a scale parameter, which allows to balance gradient norms and spatial distance between sites. It has no influence on the number of regions, it has only effects on the spread of the regions. In the following examples, k always equals 2. Area and depth threshold have effect on the merging degree : the higher, the smaller the number of regions.

Figure 3b displays an example of 4 fuzzy regions, with their membership degrees. A crisp segmentation may be obtained from the fuzzy segmentation, by affecting each site to the region for which it has the highest membership degree. See [5] for more results. The advantage of this algorithm is that it provides regions, constrained by contours. Region edges are accurate when they separate areas of different colors, less accurate when transitions are slow. Impulse noise is outlined.

3. Features of fuzzy regions and region signature

Rosenfeld [6] extended the definitions of classic geometrical features to fuzzy sets. For example the area of fuzzy region R is $\sum_{s \in R} \mu(s)$, the height is $\sum_y \max_x \mu(x,y)$ and the width is $\sum_x \max_y \mu(x,y)$. The perimeter is $\sum_{\substack{i,j,k \\ i<j}} |\mu_i - \mu_j| L_{ijk}$ where L_{ijk} is the length of k^{th} edge separating levels μ_i et μ_j (μ is piecewise constant).

We also used the compactness = area/perimeter^2 and the rectangularity = area/(height×width). The first one is not bounded by $1/4\pi$ like with crisp sets. But it is invariant to changes of scale and to rotations The second one is lower or equal to 1 and is invariant to changes of scale, but not to rotations.

With the same principle, we have defined colorimetric features and a colorimetric distribution of fuzzy regions.

The colorimetric mean of feature c is :

$$mean_c = \sum_{s \in R} \mu(s) \cdot c(s) / \sum_{s \in R} \mu(s)$$

The distribution of a colorimetric feature is computed by adding the membership degrees of the pixels of the various classes of the distribution. So pixels with weak membership degrees – belonging to transitions or outliers inside a region – have little influence on the distribution shape.

To take into account both geometrical features and colorimetric features, we build a global signature composed of :

- a geometrical part with 3 features : area, rectangularity and compactness (see [6] for details),
- a colorimetric part with the color distribution in HSV space split into 162 classes based on 18 hues, 3 intensities, and 3 saturations,
- a spatial part with the position of the center of gravity, normalized by the image dimension.

The signature of a region is a vector of 167 features.

4. Distance between fuzzy regions based on geometry and color

The first application consists in extracting from an image the most similar regions to a request region designed by the user, whatever their positions in the image.

The distance between every region - or target region - and the request region takes into account the only geometric and colorimetric features.

The use of features of different kinds led us to formulate a measure of similarity using a merging operator.

Let C be a target region and $C^g=\{C_i^g, i=1, 2, 3\}$ be the set of its geometrical features (area, rectangularity, compactness). $C^c=\{C_j^c, j = 1, ..., 162\}$ is the color distribution with $\sum_{j=1}^{162} C_j^c = 1$.

Request region R is alike characterized by $\{R^c, R^g\}$.

The system separately computes a geometrical distance and a colorimetric distance. These two distances are then merged. Of course they must have similar dynamics to be merged.

The distance between color features is simple :

$$D_{col}(R,C) = \frac{1}{2}\sum_{j=1}^{162} |R_j^c - C_j^c|$$

Normalization is insured by the division by 2. This distance is maximal when both distributions contain the single value 1, positioned on two different classes.
The distance between geometrical features defined by the simple L_1 distance infers a normalization problem : a normalization with regard to a maximal measurement on the image, or a fortiori on a set of images, can create distortions.
It is better to use the ratio of geometrical features of C and R. To get a normalized value, we used the following function.

$$f(x)=\begin{cases} 1-x \text{ , if } x\in[0,1] \\ 1-\frac{1}{x} \text{ , if } x\in]1,+\infty[\end{cases}$$

The distance between geometrical features F_1 and F_2 is

$$d_g(F_1 , F_2) = f(F_1 /F_2)$$

It is easy to show that d_g is a distance .
The geometric distance between two fuzzy regions R and C is

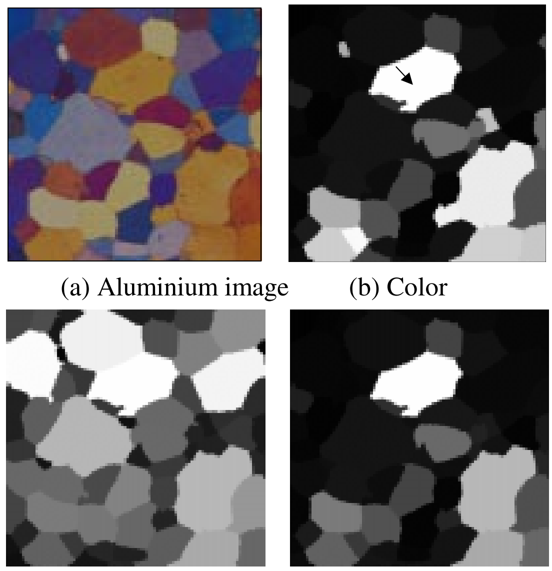
$$D_{geo}(R,G) = \sum_{i=1}^{3} \alpha_i f\left(\frac{R_i^g}{C_i^g}\right) \text{ with } \sum \alpha_i = 1$$

Weights $\{\alpha_i\}$ may be tuned by the user to refine the research criteria, by removing or increasing one of them.
To merge distances between geometrical features and colorimetric features, we have chosen the operator *max*, because it has a severe behavior. The distance between fuzzy regions R and C is then :

$$D (R,C) = \max(D_{geo} (R,C), D_{col} (R,C))$$

Let us show some results, with a retrieval of regions within an image. The user chooses a region of the image and the features on which he wishes to make his/her search. Since it is impossible to show all fuzzy regions (they overlap), system displays the basins after merging, with a gray level proportional to the distance between the current region and the request region (the brightest ones are the closest).

In Fig. 1, the request is a large dark yellow region. When using only the colorimetric features, the yellow regions are the closest, dark yellow closer than light yellow. When using amongst the geometrical features, the only area, regions are ranked by size. Merging both distances gives the large yellow regions.

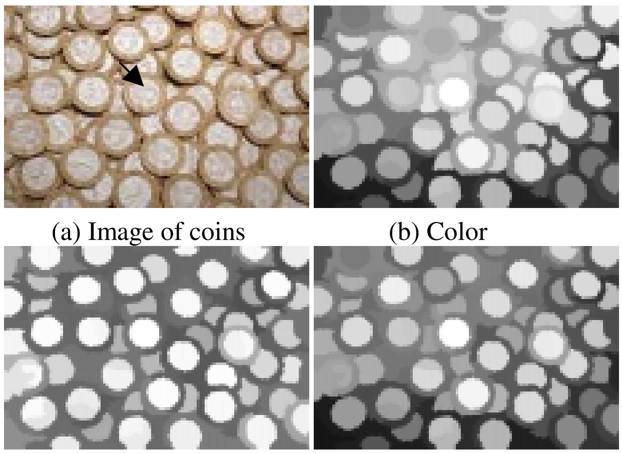


(a) Aluminium image (b) Color

(b) Area (c) Merging

Fig. 1 : Regions ranked by decreasing similarity to a request region, marked with an arrow (from white to black)

Figure 2 addresses the problem of object occlusion. In this special case of circular objects, rectangularity and color allow to retrieve partially occulted objects, even if half the object is missing.



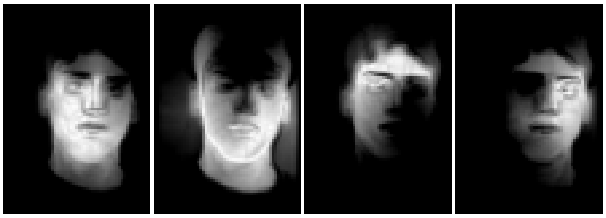
(a) Image of coins (b) Color

(c) Rectangularity (d) Merging

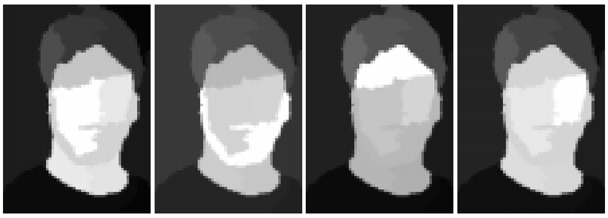
Fig. 2 : Similarity using color and rectangularity for retrieval of partially occluded objects

It is interesting to note that the result of retrieval does not much depend on request regions, if they are similar. The segmentation of a face is not an easy task. In Fig. 3, the face is split in several regions, which overlap a lot. Whatever the request region amongst these, the retrieval is the same : the whole face.

(a) original portrait



(b) 4 fuzzy regions



(c) Ranked regions,
the request is the corresponding region of (b)
Fig 3: A request with any of the 4 regions retrieves the whole face

5. Image retrieval from a single region request

A generalist database of 1200 images has been automatically segmented, with k = 2, depth threshold = 3. The area threshold is automatically tuned from an initial threshold of 5000 pixels. It is divided by 2 until the number of regions is within the interval [5, 20] (Figs. 4 and 6 first row).
The signature of each image is composed of a list of the fuzzy regions with their 167 features.
The retrieval consists in searching for each image of the database and for each region the region which best match with the request region.
The distance between spatial features is defined from the coordinates of the centers of gravity, (x_R, y_R) for the request region and (x_C, y_C) for the target region :
$D_{sp}(R,C) = \alpha_1 g(|x_R - x_C|) + \alpha_2 g(|y_R - y_C|)$,
where g is defined by :

$$g(z)=\begin{cases} 1 & \text{if } 0 \le z \le \frac{1}{3} \\ -3z+2 & \text{if } \frac{1}{3} < z < \frac{2}{3} \\ 0 & \text{if } \frac{2}{3} \le z \le 1 \end{cases}$$

The distance between fuzzy regions is then :

$$D(R,C) = \beta_1 D_{col}(R,C) + \beta_2 D_{geo}(R,C) + \beta_3 D_{sp}(R,C).$$

An example is given in Fig. 4, where the spatial position of the request region (sky) is important for the retrieval of sunset images. In this case, as in many images, the vertical position is sufficient. For example for human beings, animals, landscapes, etc., the vertical position is much more important than the horizontal one.
Features used are colorimetric features and vertical position, geometric features as well as horizontal position are of no help in that case.
The first ten images are effectively sunset images.

Fig. 5 displays the number of retrieved images which belong to class sunset (100 images in the base), versus the retrieved images. The best retrieval would give a straight line of slope 1, which is indicated in the figure. Features of color histogram alone and color histogram plus vertical position are compared. For the first retrieved images, the spatial information improves the results. After 50 images, the position of the region is no more relevant, since a sunset image does not amount to an orange region at the top !

(a) original image *(b) image of basins* *(c) request region (at the top)*

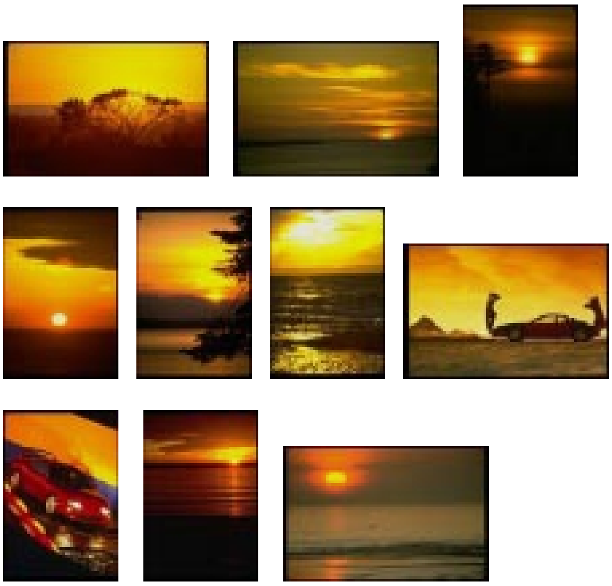


Fig. 4 : Image retrieval from one region
First ten retrieved images ranked from up to bottom, left to right
Features are the color histogram and the spatial position

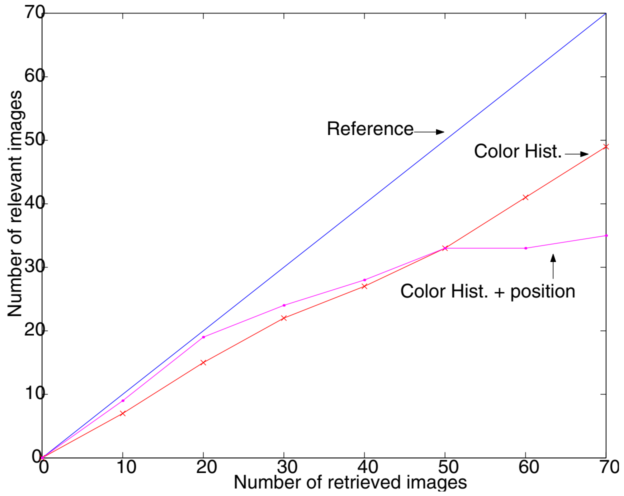


Fig. 5 : Recall : number of relevant images (belonging to the sunset class), versus number of retrieved images.

6. Partial request with multiple regions

Another important task in image retrieval is to be able to retrieve objects made of parts of different colors or different textures, or to retrieve several objects scattered in the image. The spatial relationship between fuzzy regions is stored in an adjacency matrix of regions. Two regions are adjacent if their supports have at least one common site. The adjacency matrix is symmetric and contains 1 if the regions are adjacent, and 0 if not. It could also contain more complex information, such as the fuzzy relative positions (left, above).

The request is made of several regions of an image. For each image of the database, the best set of regions is extracted : it is composed of the set of regions which are the most similar to one of the request regions. The set of regions is validated if the adjacency matrix corresponds to this of the request set. The global similarity between request image and target image is then the sum of the distance between couples of matched regions, divided by the number of regions composing the request. Two regions of the target image may match with the same request region, and vice versa.
Fig. 6 displays an example of a request with an image of flying airplane. The base includes 110 airplane images. The request is composed of two regions, the sky and one region of the plane. In Fig. 6, the only color histogram is used, with a validation with the adjacency matrix. In Fig. 7, the area and the color histogram are used. The ten best images are displayed in both cases, ranked by decreasing similarity. It is obvious that both kinds of features are needed in this case, since the sky occupies a large part of the image. Curves of recall are displayed in Fig. 8 : the feature of area obviously improves the retrieval.

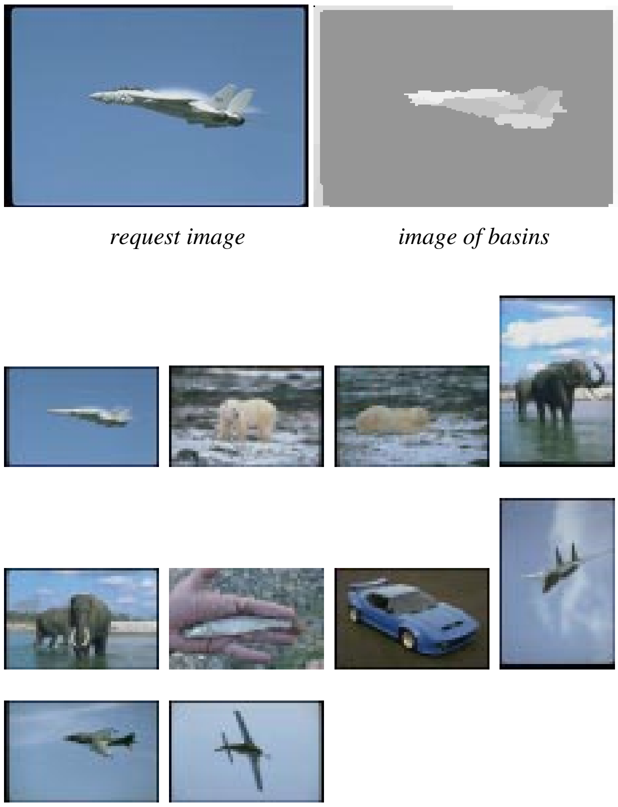


Fig. 6 : Results of image retrieval with a request composed of two regions (the sky and one region inside the plane). The only colorimetric features are used First ten images ranked from left to right and up to bottom

Fig. 7 : Same request as Fig. 6 Two features are used : color histogram and area.

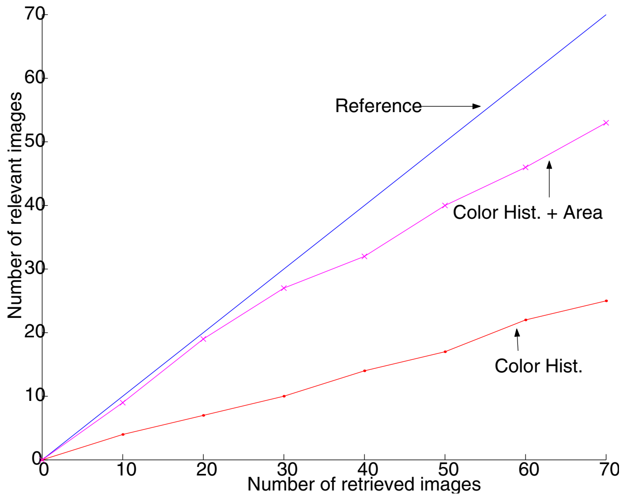


Fig. 8 : Number of pertinent images (belonging to the airplane class), versus number of retrieved images. Obviously the use of both features area and color histogram is better than the color histogram alone.

7. Conclusion and perspectives

We have proposed an algorithm of fuzzy region extraction and some applications in region or image retrieval.

This algorithm overcomes the problem of segmentation, since it does not look for accurate regions. We have shown that pattern recognition or image retrieval can be achieved even if the segmentation is not good, as soon as a degree of trust can be given to each pixel. Features of regions can be calculated and utilized for further analysis, such as region or image classification, as soon as their calculation takes into account the trust in the belonging of the site to the region, which is exactly represented by the membership degree.

Better distances would certainly improve the retrieval, as well as different criteria of merging of distances between various types of features. In the applications we have shown, the feature choice is done by the user. It can easily be automated by the way of a relevant feedback, which would also tune the weights [3].

Another important track to perform a partial request composed of several regions, is to integrate fuzzy information of spatial relation between regions into the adjacency matrix.

A color version of the paper may be found in :
http://www-etis.ensea.fr/~philipp/article/CGIV02.ps

8. References

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