FILTERING IN THE SEGMENTATION SPACE

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ABSTRACT

In this paper, we introduce a method aiming at improving the segmentation results obtained with complex natural images. It is based on the integration of a set of image segmentation maps. This technique allows the redundancy between some primary segmentations to be extracted.

Our approach is mainly region-oriented. It is based on a fuzzy description of the segmentation by means of a mechanism associating regions of different maps. Introducing a dissimilarity measurement allows a so-called segmentation filtering to be performed. This approach turns out to be very efficient in the case of natural complex images. It can be regarded as an extension of nonlinear filtering techniques.

keywords: image segmentation, nonlinear filtering, dissimilarity measurement, fuzzy regions.

INTRODUCTION

In the task of segmentation of some complex pictures, it is often difficult to obtain good results using only one image segmentation method. The tendency toward the integration of several techniques seems to be the best solution. In most cases, a cooperation between region growing or split and merge processes and edge detection processes is introduced [1]. Edge detection can be performed by classical operators [2] or by means of active contour (snakes) [3].

Unlike the method proposed in [4], our approach is mainly region-oriented. It is based on a fuzzy description of the segmentation by means of a mechanism associating regions of different maps. Introducing a dissimilarity measurement allows a so-called segmentation filtering to be performed. This approach turns out to be very efficient in the case of natural complex images. It can be regarded as an extension of nonlinear filtering techniques.
Though it is presented in the case of grey level images, this technique can be applied to color images and multispectral images.

The paper is composed of three parts:
- Building up fuzzy regions
- Principle of the segmentation filtering
- Experimental results

BUILDING UP FUZZY REGIONS

At the starting point, *n* segmentation maps of the same image are available. They are obtained either by different techniques applied to the same image or by the same technique with different parameter values or by different techniques applied to the components of a multispectral image.

Let X be the system of reference.
Let $x \in X$ be a pixel.
Let **S1**, .. **Sn** be the set of primary segmentations of X.

Let $R1, \ldots, Rn \subset X$ with $Rk \in Sk$ or $Rk = \emptyset$, be a set of regions associated to the same physical region R in the scene.

Region R can be regarded as a fuzzy region characterized by the membership function μ_R defined by: [5]

$$\forall x \in X \qquad \mu_R(x) = \sum_{x \in Rk} w(Rk) \tag{1}$$

with

$$w(Rk) = w_k \geq 0, \text{ and } \sum_{k=1}^{n} w_k = 1$$

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association process

Let r_k^i be the i^{th} region of segmentation **Sk**.

Let Nk be the number of regions in Sk.
We have:

$$S1 = \{r_1^1, ..., r_1^i, ..., r_1^{N1}\}$$
$$.........$$
$$Sk = \{r_k^1, ..., r_k^i, ..., r_k^{nk}\} \quad (2)$$
$$........$$
$$Sn = \{r_n^1, ..., r_n^i, ..., r_n^{Nn}\}$$

Let $NT = \sum_{k=1}^{n} Nk$ be the total number of regions.

Regions r_k^i are ordered according to their area (in decreasing order).

Let $(R_{(1)}, ..., R_{(NT)})$ be the ordered list of regions.
Let $R_{(1)}$ belong to segmentation Sk1.

At the first step, we search the list for the region having the maximum overlap with $R_{(1)}$.
Let $R_{(i)} \in Ski$ be this region.

We then seek for the region $R_{(j)}$ such that:

$$R_{(j)} \notin Sk1, R_{(j)} \notin Ski$$

and $\text{area}\left(R_{(1)} \cap R_{(j)}\right)$ is maximum.
and so on, until the end of the list is reached. Regions $R_{(1)}$, $R_{(i)}$, $R_{(j)}$, ... are associated together.
Each selected region is withdrawn from the list. Then, the list is scanned again starting from the greatest region. The process continues until the list of regions is empty.

PRINCIPLE OF THE SEGMENTATION FILTERING

Given a set of fuzzy regions, a crisp segmentation is classically obtained by maximizing the membership function at each pixel x of X.

By tuning the weighting coefficients w_k, it is possible to emphasize the influence of a given segmentation map with respect to the others.
Our experience is that if a region is produced only by noise, its shape is generally not stable as parameter values are modified. Hence, measuring the dissimilarity between the different segmentations provides us with information about the overall quality of these segmentations.
Therefore, by setting coefficients w_k as a function of the dissimilarity measurement, it is possible to decrease the weight of the less relevant segmentations.

dissimilarity measurement
We propose to use a dissimilarity measurement based on the Baddeley metric defined for binary images [6]

Let $S = \{R1, ..., Ri\}$ and $U = \{T1, ..., Tj\}$ be two segmentations of image X.

Let $d(x, R) = \min\{d(x, r)\}$, $r \in R$, be the distance between pixel x and region R.
Let $d_c(x, R) = \min(c, d(x,R))$.

Let card(X) denote the number of pixels in X.

The dissimilarity measure between S and U is given by:

$$\Delta(S, U) = \left(\frac{1}{\text{card}(X)} \cdot \sum_{x \in X} |f(x)|^p\right)^{\frac{1}{p}} \quad (2)$$

with
$c > 1, p \geq 1$

$$f(x) = \sum_{l=1}^{i} d_c(x, R_l) - \sum_{m=1}^{j} d_c(x, T_m) - (i-j)c$$

This measure takes into account not only the number of misclassified pixels [7][8] but also their relative location (localization error).

cost function and weighting coefficients
Given a dissimilarity measure and a set {**S1**, ... **Sn**} of segmentations, we can define a cost function ε by:

$\forall S \in \{S1, ..., Sn\}$

$$\varepsilon(S) = \sum_{k=1}^{n} \Delta(S, Sk) \quad (4)$$

In a way similar to the approach used in [9] for filtering multispectral images, we propose to define the weighting coefficients as:

$$w_k = \frac{\varepsilon^r(Sk)}{\sum_{j=1}^{n} \varepsilon^r(Sj)} \quad (5)$$

with $r \leq 0$

If we set r = 0, we obtain $w_1 = w_2 = ...= w_n = \frac{1}{n}$.
The resulting segmentation can be regarded as the 'average' of the primary segmentations.

Let, for instance, S_m be the segmentation minimizing the cost function.
By setting w_m=1 and w_k=0 for $k \neq m$, the resulting segmentation can be regarded as the 'median' of the primary segmentations. This is obtained from equation (5) if $r \rightarrow -\infty$.

To some extent, this filtering technique can be regarded as an extension of vector filtering [10]

postprocessing

It is possible to obtain improved results by performing a relaxation procedure [11] controlled by an entropy parameter. Further improvements can be achieved by taking into account some geometrical information (region size, shape)

EXPERIMENTAL RESULTS

In this section, we present experimental results obtained on both synthetic and real images.

In the example of Figure 1, four primary segmentations are produced by a simple region growing process, with the same threshold and four different directions of image scanning (Top-Left-Bottom-Right, Top-Right-Bottom-Left, etc.). The regularization effect of the filtering procedure can be observed on images 1g and 1h.

In the example of Figure 2, twenty primary segmentations are obtained by varying the aggregation threshold (5) and the scanning direction (4) of a region growing process. Five primary segmentations are displayed (2b-2f). The parameters values are p=2, c=10.

The assessment of the segmentation of natural images is a difficult task. Nevertheless, by considering the number of false regions and the location of edges, the improvement obtained by the filtering procedure can be noticed.

CONCLUSION

In this paper, we propose a method aiming at combining the results obtained by different segmentation techniques. It was experienced that this approach, which can be regarded as filtering in the segmentation space, improves the segmentation results.

The quality of the final result obviously depends on the input data. Satisfactory results are obtained if over-segmented and under-segmented data are available.This problem is similar to that caused by asymmetrical noise distributions in signal smoothing. It can be solved by an appropriate choice of coefficient r.
The mechanism introduced in this paper is an extension of scalar and vector signal filtering. Other filters similar to trimmed mean filtering [12] can easily be implemented.

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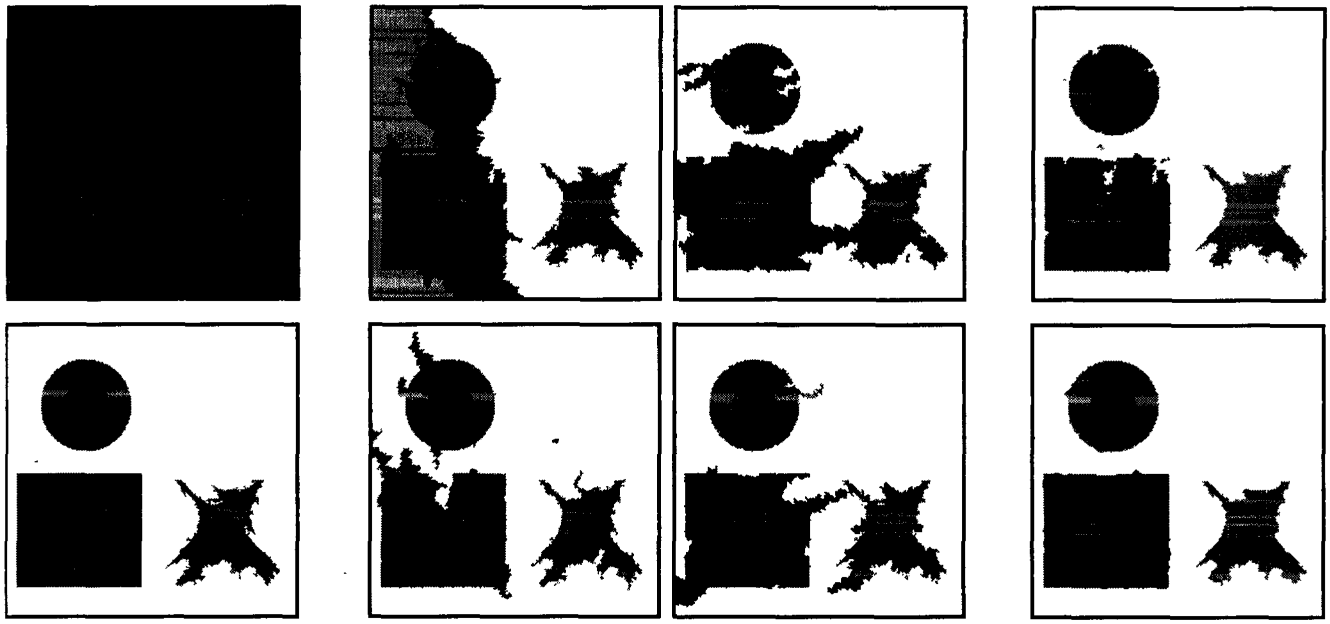
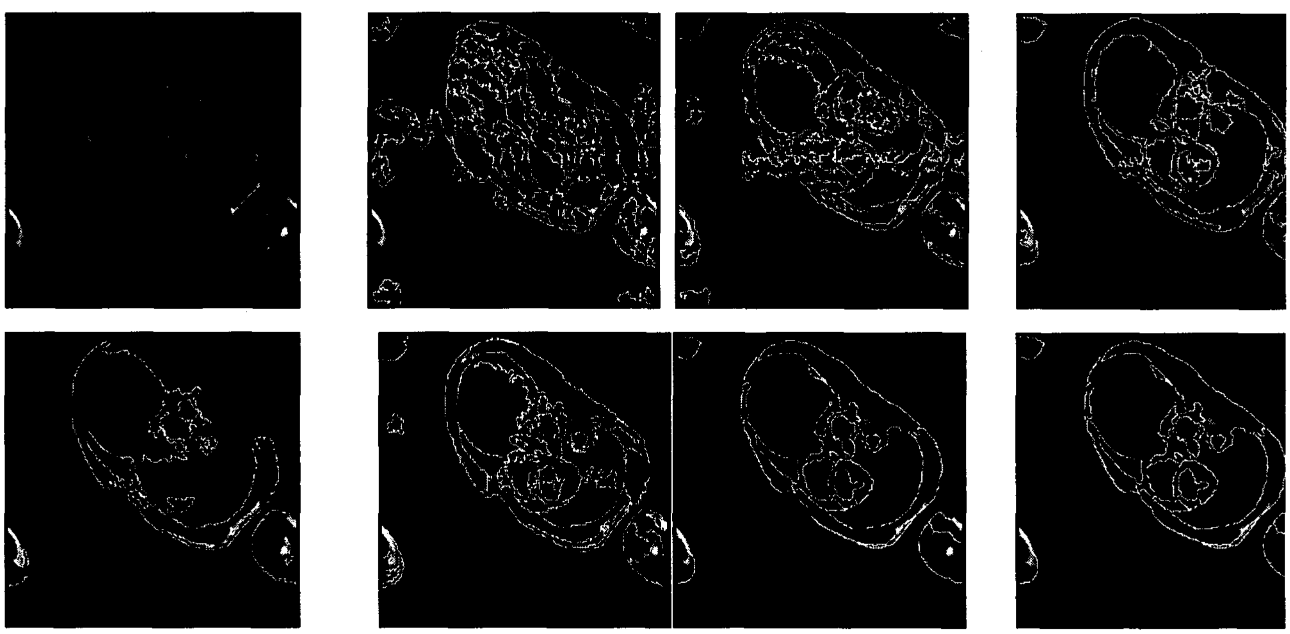


a/ original image (bruit2.gdr)
b/ true segmentation
c-f/ primary segmentations

g/ 'average' segmentation
h/ 'average' post-processed by relaxation

a	c	e	g
b	d	f	h

Fig.1 - Synthetic Image



a/ original image (irm.gdr)
b-e/ primary segmentations
f/ 'median' segmentation ($r = -\infty$)

g/ 'average' segmentation (r=0)
h/ filtered segmentation (r=-2)

a	c	e	g
b	d	f	h

Fig.2 - Natural Image - MRI