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Visual object detection by an active region model

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Abstract: In this paper, we propose an unsupervised image segmentation which integrates perceptual informations of regions in an image from colour and texture properties in order to perform image segmentation. This proposed segmentation algorithm is based on a active region model.
To correctly take semantic object (region and boundary information) into account , a mixture of Gaussians is used to model pixels of the background image and those of the semantic object. The model minimizes a modified Chan–Vese functional over each component of the colour image, and improves appreciably the chan-vese algorithm and is fast and robust with respect to noise. The results for segmenting objects in an sequence of images are demonstrated.
Key words: Active contour, energy minimization, object detection , color image , segmentation

1 Introduction

The goal of the image segmentation is to detect and extract the important areas in an image contrary to the classification problem where the identification of the regions is not required. The literature is full with a great whole of proposals which try to segment the image, but one can distinguished two basic approaches: Approaches based on areas and those based on contours. The execution of any active model of segmentation requires the minimization of a function which describes the energy of cutting. This functional energy has two components typically internal energy which is characterized by the control of the regularity of the curve, and external energy which makes it possible to attract contour towards the strong gradients or the strong ones contrasts of luminosity of the image.

Classical active contours which were proposed for the first time by Kass and others [1.2], which were used to segment the medical images. The mean idea is based on deforming an initial contour towards the boundary of the semantic object to be detected. This model was to confront with several challenges, such as the detection of one alone contour starting from only one curve initial, and the dependence of the function of energy to the parameterization of the curve what is constraining. Caselles et al. [4] and later Malladi et al. [5] proposed an implicit geometric active contour model which includes geometrical considerations similar to Sethian work [6].

The geodesic active contour model [7,8] was introduced as a geometric alternative for snakes in order to overcome some of their limitations, their main advantages over classical explicit snakes are implicit handling of topological changes, numerical stability and independence of parameterization. However, their main drawback is the additional computational complexity, in their simplest implementation. Most approaches are based on an explicit or forward Euler scheme which demands very small time steps .This model was efficiently used to implement level set propagations[3,10] , and was also usefully used in [11,12]. Some algorithms which combine the techniques of active contour models and the regions growing were developed [13].

The remainder of this paper is organized as follows: Section 2: introduces our active region model which presents a prolongation of the model by Chan-Vese in the context of the color images. Section 3: describes an implementation of our model. We present results and computation times for different images segmentation in the next section, and finally we finish paper by a section of short conclusion.

2 Colour object detection:

The proposed method of segmentation uses at the same time the model based area that enables us to take account of the information of area and the model based contour in order to segment the whole image. This method integrates perceptual informations of the color and texture properties in order to better detect the object has to be segmented. The most models use the gradient of a smoother version of the image u0, to detect edges [14]. Mumford and Shah studied [16] functionals which measure the degree of match between an image u and a segmentation. First, they defined a general functional E :

$$F_{MS}(u,C) = \mu \cdot length(C) + \lambda \int_{\Omega} |u_0 - u|^2 dx + \int_{\Omega \backslash C} |\nabla u|^2 dx$$
$$\mu, \lambda > 0$$

In contrast, the Chan-Vese active contour model without edges proposed in [15,16] does not use the stopping edge function to find the boundary. This model detects edges both with and without gradient ; it gives a partition of the image in to two regions, one formed by the set of detected regions, while the second one gives the background. T.F. Chan and L.A. Vese proposed an active contour model using the energy minimization technique given by:

$$F(C,c_1,c_2) = \mu \cdot (length(C))^p + \nu \cdot area(insideC)$$
$$+ \int_{inside(C)} \frac{1}{N} \sum_{i=1}^{N} \lambda_{1,i} |u_{0,i} - c_{1,i}|^2 dx$$
$$+ \int_{outside(C)} \frac{1}{N} \sum_{i=1}^{N} \lambda_{2,i} |u_{0,i} - c_{2,i}|^2 dx$$

$$\mu, \nu \geq 0, \lambda_{1,i}, \lambda_{2,i} > 0, p = 1, 2, \frac{M}{M-1}$$

where $u_{0,i}$ is the initial image de ith channel, C is any variable curve, c_1 and c_2 are constants vectors depending on C and representing the “average” value of $u_{0,i}$ inside and outside the curve in ith channel of an image, respectively. Minimizing F(c_1, c_2 ,C) , the object to be detected will be given by one the regions , and the curve C will be the boundary of the object. The additional terms such as length and area are used like regularizing terms, and have a scaling role.
C is represented by the zero level set of a Lipschitz function such that:

$$inside(C) = \{x \in \Re^N : \phi(x) > 0\}$$
$$outside(C) = \{x \in \Re^N : \phi(x) < 0\}$$
$$\phi : \Re^N \to \Re$$

In this paper, we use an extended approach of this Chan-Vese model in order to take account of colour and texture properties in image. The input image is composed of homogeneous regions which We assume that are modeled by a Gaussian distribution.

where P_k: a priory probability of a connected component k. Hence, in the gray image the probability

$$p(x) = \sum_{k=1} P_k \, p_k(x)$$

of a pixel j of belonging to a region R_i modeled by (μ_i, σ_i) is:

$$P_{R_i}(j/(\mu_i,\sigma_i)) = \frac{1}{\sqrt{2\pi}\sigma_i} e^{-\frac{(I_j-\mu_i)^2}{2\sigma_i^2}}$$

where Ij is the intensity of the pixel j, µi is the mean intensity of region Ri and its standard deviation. The global energy is defined with two basic terms. The boundary term measures the probability that boundary pixels are really edge pixels. The probability of a given pixel j being at the real boundary is measured by P outside(j). Meanwhile, the region term measures the homogeneity of the regions in the interior by the probability that these pixels belong each corresponding region. The energy function is defined as:

$$E = \alpha - \int_{inside(C)} \log(P_R(u_0 - c_1)) dx + \int_{outside(C)} \log(P_R(u_0 - c_2)) dx$$

where α is a model parameter weighting the region homogeneity used as regularizing term.

In many cases, the basic RGB components may provide very valuable information about the environment. However, the perceptual models, such as HSV or HIS, are more intuitive and therefore enable the extraction of characteristics according to the model of human perception. In our context, CIE Lab color space is the most appropriate. Our goal is to partition the image into homogeneous regions with color or texture properties in its interior, we consider each region modeled by a three-variant Gaussian distribution . So the mean vector and the covariance matrix characterizes the color region behavior and the probability of a pixel j of belonging to a region Ri is given by:

$$P_{R_i}(j) = \frac{1}{\sqrt{(2\pi)^3 |\Sigma_i|}} e^{-\frac{1}{2}(\vec{I}j - \vec{\mu}_i)^T \Sigma_i^{-1} (\vec{I}j - \vec{\mu}_i)}$$

where $\vec{I}_j$ is the pixel color vector, $\vec{\mu}_i$ is the color mean vector of the region i and $\sum_i$ its covariance matrix.
Then the energy function is defined as:

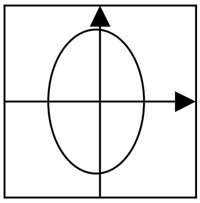
$$
\begin{aligned}
E = {} & \mu \cdot (length(C))^p \\
& + \int_{inside(C)} \sum_{i=1}^{N} \log(P_R(u_{0,i} - c_{1,i}))dx \\
& + \int_{outside(C)} \sum_{i=1}^{N} \log(P_R(u_{0,i} - c_{2,i}))dx
\end{aligned}
$$

$$\mu \geq 0, N = 3, p = 1, 2, \frac{M}{M-1}$$

where C is any variable curve, c_1 and c_2 are constants vectors depending on C and representing the “average” value of $u_{0,i}$ inside and outside the curve in ith channel of an image, respectively.

3. The proposed algorithm:

The initial curve is automatically defined in function of the center of the image as follows:



Step I : Initialization

- Initialize the actual curve with the initial curve C
- Compute the PR(p) ,μR and σ_R for inside and outside the initial curve C

Step II : Updating and evolution of the initial curve

For each pixel p of the original image Do
Compute the Gaussian function gR for inside and outside the curve C : g_{in} and g_{out}
Energy = Regularizing terms + gout - gin
IF p in outside of the initial curve then
IF Energy > 0.0 AND there is a similar pixel near inside in the initial curve THEN
- Update the actual curve by changing the state of the pixel: p changes from inside to outside pixel;
ENDIF
ELSE
IF Energy <= 0.0 AND there is a similar pixel near outside in the initial curve THEN
- Update the curve by changing the state of the pixel: p changes from outside to inside pixel;
ENDIF
Memorize the position of the pixel p in a pile.
ENDIF

Step III : Update the means, and variances values and display the intermediate step of the curve

IF pile. length # 0 THEN
- Update means and variances values inside and outside of the curve
- GO to step II.
ENDIF

Step IV : The output image is the actual curve

4. Experimental results:

All experiments, illustrations have been made using the active contour approach developed in the C++ language and based on the Linux platform on a PII 350 MHz. The algorithm was tested on different images, and we compare results of the general model based on means and the model which uses the function of the Gaussian.

The first test consists of segmenting three images in grey (Fig.1, Fig.2-a, and Fig.3-a) and color space (Fig2 .b, and Fig.3-b). Our algorithm extends the general model with Gaussian function to segment a visual objects in an image. The experimentation of our algorithm shows that the general model does not have to give satisfactory results because the homogeneous areas of object to detect have the same mean . The model propose to employ it average to distinguish the homogeneous area. The means change during the evolution of the curve which delimits the areas. While the use of the Gaussian function made it possible to have better results because of their covariance matrix which may be different.

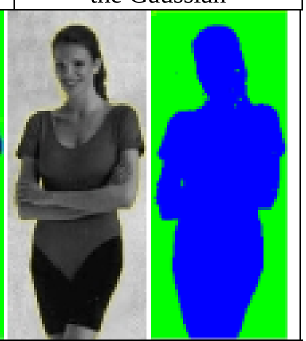
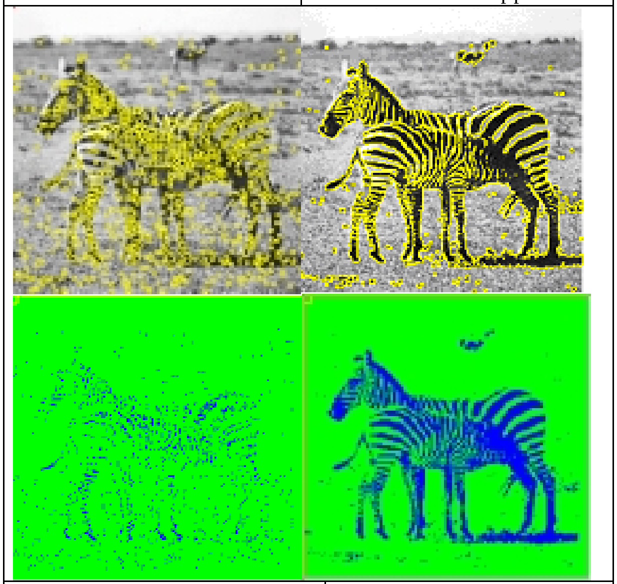
General model based on the means	The approach which use the Gaussian
	
cpu = 1,326 s.	cpu = 0,583s.

Figure 1: Perceptual information with respect to the different regions for the woman image segmented image

GRAY (a)

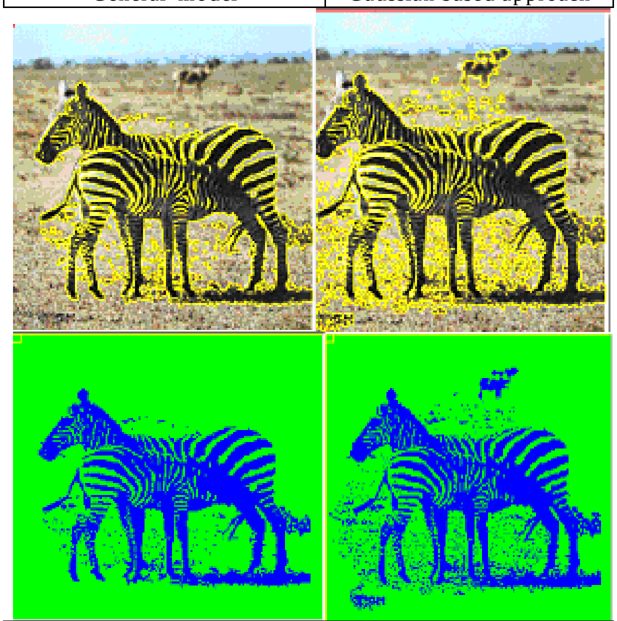
General model	Gaussian based approach



cpu = 0,110 s.	cpu = 0,20s

COLOR (b)

General model	Gaussian based approach



cpu = 1,680s.	cpu = 1,980s

Figure 2: Perceptual information with respect to the different regions for the zebra image (a) Segmented image (gray), (b) Segmented image (color)

Conclusion and perspectives

In this paper, we present an approach which use perceptual informations in order to perform colour image segmentation assuming Gaussian distributions to model each region by minimizing an energy function. This method detect the homogeneous visual objects in an image. The semantic objects are still not easily detectable in images of video documents. For that we apply an algorithm which take account of perceptual informations of regions and not depends only of means of objects. A combination of the various methods which integrates other descriptors such as the shape and the motion, will improve the segmentation stage and allow a more effective detection. Our approach is successfully applied in object tracking where the initial object is segmented and its detected contour is used as an initial curve in the next frame.

In future work, we will extend our model to take into account the moments in the characterization of the areas such as the Krawtchouk moments.

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