FAST AND ROBUST LEVEL-SET SEGMENTATION OF DEFORMABLE STRUCTURES

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ABSTRACT

Level-sets provide powerful methods for the segmentation of deformable structures. They are able to handle protrusions and specific topological effects. In this work a particle system formulation of level-sets is introduced. It keeps all the advantages of the level-set approach for the segmentation of deformable structures, while it overcomes some of its drawbacks. In this approach the level-sets are controlled by particles, which is of particular interest for interactive control. The particle system records the internal energy of the level-set, while the external force field comes from image data. The energy minimization process is fast, stable and robust. The use of skeleton techniques provide a reliable intialization of the particles, and it is coherent with simple affine motion. The paper is illustrated by examples coming from real image sequences.

1. INTRODUCTION

Level-sets segmentation methods have drawn specific attention these past few years ([5, 7]). Level-sets are active contours particularily designed to handle the segmentation of deformable structures. They display interesting elastic behaviours, and can handle topological changes. In their classical formulation, they are computed by solving second-order partial differential equations using sophisticated numerical resolution procedures ([5]). Classical snake methods use spline curves to model the boundary of an object ([3, 2, 1]). In the level-set formulation however, the boundary of an object is modelled by a deformable curve front whose propagation speed is a function of curvature. In the level-set framework, the curve is the iso-contour of a potential function.

In this study we are interested in solution methods that can be incorporated in an operational context. In such a context, interactivity is an important matter, and the data flow can be considerable. A typical example is a meteorological monitoring system, where the results of the segmentation must be easily manipulated by an operator, and the method of segmentation must be fast and robust. In this case the accuracy of the segmentation should be supervised by the user, and it is an important matter that the segmentation process can be driven and adjusted by an operator.

Taking into account these requirements, a new method for minimizing and operating with level-sets is presented. In this study, shapes are approximated by particle systems controlling a level-set. In the classical level-set formulation, curvature is used to control the evolution of a curve. In the particle system approach presented here, geometric and physical characteristics are incorporated in the particle system which is then responsible for the evolution of the level-set. The physical properties of the level-set come from assignements on the internal and external energies of the particle system. This results in fast and robust approximations, with adjustable accuracy, since the minimization is performed over a finite set of particles, instead of computing a minimum in an infinite dimensional space of functions. Interactive control is achieved through this particle system formulation, as an operator can use directly the particle system to control the level-set. Most importantly, specific image-dependent requirements are easily assigned on the internal and external energies. That permits the use of specific internal energies for rigid-objects, or visco-elastic energies in the case of deformable structures. The shape approximation process is accomplished by minimizing energy fonctionals. Hence no partial differential equation is solved, and the shape approximation process is very robust.

This paper is organized as follows. In section 2 the particle system formulation of level-set is introduced. In section 3 we discuss the energy formulation, where internal and external energies are described. Section 4 focuses on contour extraction and initialization, where skeleton techiques are used to provide a stable initialization. In section 5 results are presented. Lastly, the paper ends with conclusion and perspectives.

2. LEVEL-SETS CONTROLLED BY PARTICLE SYSTEMS

Level-sets objects are used in computer graphics to represent visco-elastic behaviours in modelling and animation ([8]). Obviously, the use of level-sets described only in the form $\varphi^{-1}(c)$ (where φ represents the potential function and c the iso-value) would be of very limited practical use, since most interesting objects cannot be described in such a “global” way, i.e. with a single potential function. Instead, it seems fitting to introduce here the same kind of local and interactive control as one is encountered in the theory of splines.

For that matter, a particle system is used to describe a shape. The particle system is written down in the form of a finite set of points in the plane:

$$Y = \{P_1, ..., P_n\}$$

each point P_i having a radius of influence r_i. The set of particles Y is usually written as a disjoint union

$$Y = Y^+ \cup Y^-$$

where Y^+ is the set of positive control points, and Y^- the set of negative control points. Negative control points are introduced for the modelling of concave parts of an object, and also to reduce the amount of encoding data. The implicit function φ is written as

$$\varphi = \sum_{i \in Y^+} \varphi_i - \sum_{i \in Y^-} \varphi_i$$

where each implicit function φ_i is positive. It is possible to provide different kinds of potential functions φ_i. Also, it is desirable to allow the possibility of narrow corners. To achieve this, function φ_i is often written in the form

$$\varphi_i = \psi_i \circ d$$

where $d : X \to I\!R$ is a distance function (in the sense of the classical theory of metric spaces) and $\psi_i : I\!R \to I\!R$ is a potential function. In the soft objects formulation, which is the kind of function ψ_i used in this study, one writes:

$$\psi_i(d) = \mathbb{1}_{\{d^2<1\}}(1 - \frac{22}{9}d^2 + \frac{17}{9}d^4 - \frac{4}{9}d^6).$$

$\mathbb{1}_{\{d^2<1\}}$ being the characteristic function of the set $\{d^2 < 1\}$. ([8]). In the next section, we define internal and external energies for the level-sets by assigning simple and easily computable energies on the corresponding particle system.

3. ENERGY FORMULATION

In this section, we introduce an internal energy responsible for the mutual interaction between the particles, and external energies coming from a set of extracted pixels.

3.1. The internal energy

The internal potential energy is responsible for the physical behaviour of the particle system whenever it is under the influence of the external force field. Here one clearly needs a visco-elastic energy, in such a way that the level-set both maintains its connectivity wherever there is no topological change, and is flexible enough so that its shape matches that of the structure's boundary. The generalized coordinates of our particle system are:

- the (x_i, y_i) cartesian coordinates of each control point (or particle),
- the radius of influence r_i.

The internal energy of the particle system is

$$\mathcal{U} = \frac{1}{2} \sum_{i \neq j} U_{ij}$$

where U_{ij} is the potential responsible of the mutual interaction between particles P_i and P_j. A generalized Lennard-Jones potential

$$U_{ij} = \frac{(r_i + r_j)^2}{8d_{ij}^4} - \frac{1}{d_{ij}^2}$$

is repulsive at short distances, attractive at far distances, and possesses an equilibrium position in-between. Such an internal energy is quite satisfactory for the structures encountered in the real images used in this study for experimentation.

3.2. External energies

An external energy is sought out in order to attract the level-set towards extracted pixels in an image. A two-term external energy is introduced.

3.2.1. Contour energy

Minimization of the following contour energy:

$$E_{contour} = \sum_{\omega \in \mathcal{P}} (\varphi(\omega) - c)^2$$

where $\mathcal{P}$ is the set of extracted pixels results in a level-set approximating a maximum number of extracted pixels, but it does not guarantee the approximation those extracted pixels only. Indeed, the level-set could also approximate many other features in an image. To avoid an iso-contour approximating undesirable features in an image, a regularizing term must be introduced. It is called the "collar" energy, and is presented in the next subsection.

3.2.2. Collar energy

Masking positive values of $\varphi(P) - c$ makes it possible to contemplate region-based approaches; a simple measure of the level-set proximity can be formulated this way:

$$\chi_\sigma(P) = \exp - \frac{(\varphi(P) - c)^2}{\sigma^2} \qquad (1)$$

$\chi_\sigma(P)$ is maximal (equal to 1) on the iso-contour and decreases toward zero more or less quickly, as tuned by σ.
As for snakes methods, it can be envisaged to make extrema of χ_σ close to the extrema of the image spatial gradient. This would yet suffer from the same limitations encoutered with snakes: a close initialization is essential since gradient tends to be uniformally zero within uniform areas. Using distance maps, as suggested by [6, 2], overcomes this problem: distance maps are computed after an initial contour detection. Each location P is assigned the distance to the nearest contour point. This is of course appropriate if a good quality contour detection can be carried out, and thus prevents the analysis of textured images. The main advantage is that the distance map gradient always points toward contour points, even within uniform areas. As a matter of fact, the product $D(P)\chi_\sigma(P)$ (where D is the distance map) is minimal at:

- locations far from the level-set (small values of χ_σ)
- locations close to the level-set (other values of χ_σ) and close to the image contours ($D(P)$ small).

The following external energy, defined on an image I

$$E_{collar}(..., x_i, y_i, r_i, ...) = \int\int_I D(P)\chi_\sigma(P)d(P)$$

is therefore minimal if the level-set fits the image contours. The parameter σ within the function χ_σ can be viewed as a tolerance parameter: it is used to produce a tubular neighbourhood around the level-set $\{\varphi = c\}$, as small values of σ causes the proximity mask to be a narrow area around the iso-contour, and thus the minimum of E_{collar} corresponds to a faithfull representation of contour points. On the contrary, more tolerant approximations are obtained using higher values of σ. See figure 1. This can be helpful if the noise on the image generates many false contours. The definition of the external energy is yet insufficient to achieve an operational tracking method. Later sections are devoted to the actual implementation of the implicit framework on image data. Refer to the table at the end of section 4 for the values of the various parameters used in the computation of the images.

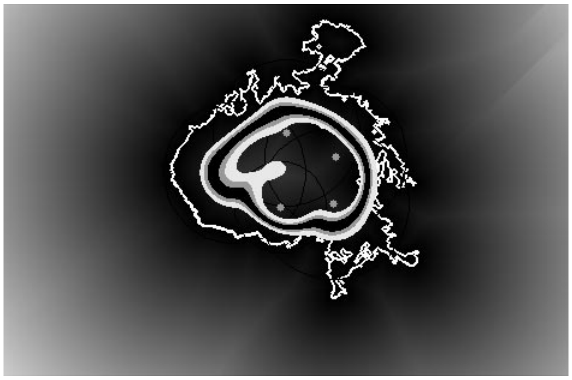

Figure 1: Plot of χ_σ for $\sigma = 0.2$. The tubular regions corrspond to pixels where χ_σ is grater to 0.8, 0.5 and 0.2 respectively. Background: distance map. Some particles are visible, and the irregular contour is the result of contour extraction on a cloud image (see section 4).

3.2.3. *Total energy*

The total energy is the sum of the internal and external energies:

$$E = \alpha E_{int} + \beta E_{contour} + \gamma E_{collar}$$

α, β and γ being weighing parameters. Since that total energy is a simple function of the geometrical attributes of the particle system -the control points locations x_i, y_i, and the radii of influence r_i- a simple and robust minimization procedure consists in using a conjugate gradient method, because the partial derivatives are explicitely computed. Note that the minimization process is performed over the finite set of particles.

4. CONTOUR EXTRACTION AND INITIALIZATION

4.1. Contour extraction

During the contour extraction preprocessing step, sets of pixels are extracted. They are used for the contour energy and for the distance map information used in the collar energy. Since operational feedback is an important matter in our applicative domain (mainly meteorological image sequences), we expect to maximize the detection of true edges, and minimize false edge detection. Some true edges may not be detected, and pixels corresponding to parasitic edges may also be kept by the contour extraction process. One expects the collar energy to be useful for these “false” pixels. Moreover contour extraction should be fast and robust, and user interaction should ideally be minimized during the preprocessing step.

As already mentionned, meteorological image sequences serve as the main applicative domain on which this study has been tested. Hence we use extensively some properties of clouds in the preprocessing step: altitude is highly correlated to grey level values. As a matter of fact, a simple thresholding of the image yields a set of locations very likely to be clouds and a first and rather good approximation of clouds’ shape. This has been tested on a 24 hours Meteosat sequence (48 images) provided by the Laboratoire de Meteorologie Dynamique (LMD): clouds are always detected by selecting low radiance pixels, i.e. pixels with gray level above 0.7 on a scale ranging from 0 to 1. Some small unwanted structures are also detected, which are discarded using a size criterion: areas with contour length greater than 100 pixels are kept, the others are discarded. Once some clouds points have been selected, a standard region growing algorithm is performed to finally obtain the clouds’ contours.

4.2. Initialization

The initialization process is a key component in the overall implicit particle system approximation, because any proper initialization of the first particles (and their radii of influence) drives markedly the quality of the convergence towards the boundary of the structure. To set up a robust initialization process, one must rely on easily computable features in the image data.
For that matter, we use the skeleton of the distance map. By skeleton we mean here the extrema of the distance map. (See figure 2). The implementation of the distance map skeleton is the one described in [4]). This choice is dictated by the fact that the distance map plays an important role in the external force field, and because any (interior) skeleton’s complex features give a fine indication of the structure’s complexity. For instance, terminal points located at the branches’ extremities indicate protrusions. Consequently we put positive control points located at the skeleton’s branches’ extremities, with a radius equal (to a pre-assigned threshold) to its distance from the contour.

In figure 2 is shown the result of contour extraction and the associated skeleton.

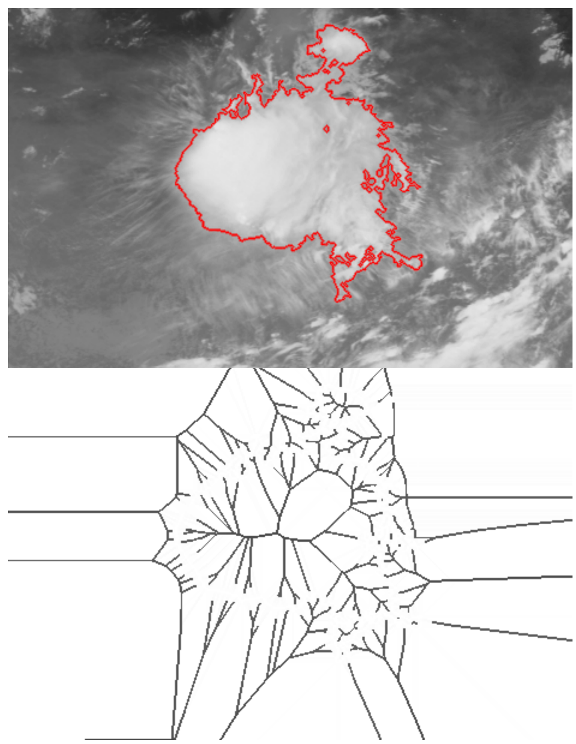

Figure 2: Frames 28 of the sequence, contour extraction (top), associated distance map skeleton (bottom).

This section is ended by the following table in which the reader will find the value of some key parameters used in the minimization process for the images displayed so far.

Indicative parameters values		
parameter	description	value
α	internal energy weight	10^{-3}
β, γ	external energy weight	1.0
σ parameter in χ_σ	tolerance factor	10^{-2}

5. EXPERIMENTS

The techniques described herein are applied on a meteoroloical real image sequence provided by LMD. It is an image sequence of clouds over Eastern Africa. Initialization is performed on the first image, then minimization is applied, and the result of the minimization processed is given as an initialization for the next image. Results are shown in figure 3. One can see that topological effects such as merging are correctly handled with this method. Also, as it is visible in figure 3, the conjugate gradient algorithm makes it possible to automatically add particles in the vicinity of a control point for which the contour energy is the strongest. To do so, the contributions of each particle to the contour energy are recorded separately. A new particle is added to the particle having the highest contribution: that particle is added in the direction of the gradient of the energy at that point. This permits the use of a small particle system, as new particles are added if necessary.

As a matter of fact, experimentation shows that the initialization scheme presented in the previous section is quite robust w.r.t. simple synthetic motion. We are currently using particle systems and level sets to perform analysis of motion.

6. CONCLUSION

The proposed method can be considered as an application driven level-set approach: it preserves the advantages of the classical formulation (handling complex shapes, topology changes, etc...) and has more flexibility to be used in an operational context. This adaptation faculty is a consequence of the formulation as a particle system: it makes it possible to define various internal energies, adapted to different types of motion (rigidity, viscosity, etc...); just as the external energy can be adapted to image data: region-based or contour based approaches are easily implementable.

In a work in progress, the model is modified in order to permit hierarchical refinement, and automatic addition or deletion of particles during the minimization process. We are also using the particle system to analyze motion in an image sequence.

(a)
(b)
(c)

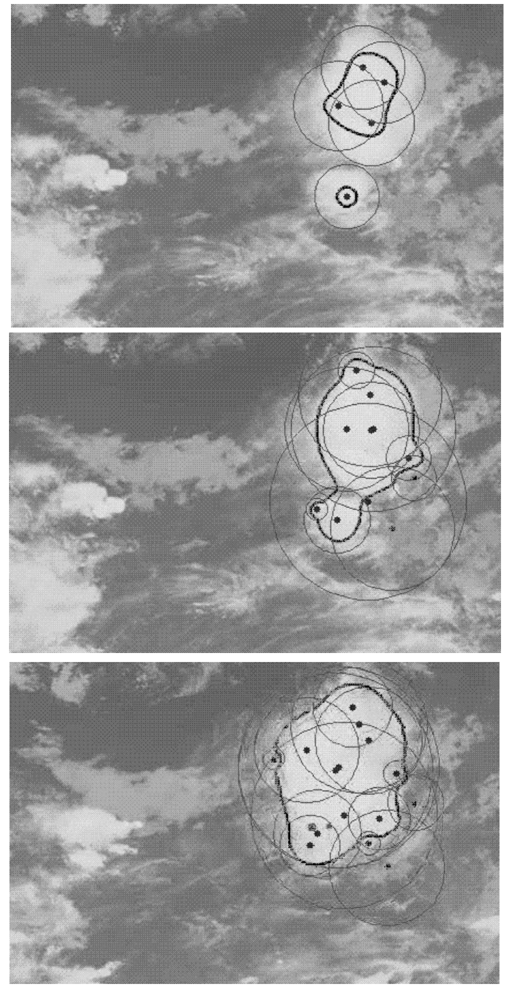

Figure 3: Level-sets structures and particle system are in dark: (a) Initialization on the first image of the sequence, (b) Result after minimization, (c) Result on the next image of the sequence.

7. REFERENCES

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