Model-Based Segmentation of Cloud Structures In Satellite Image Sequences

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Abstract

Meteorological image sequences acquired with remote sensing devices contain huge amounts of available data featuring the temporal evolution of highly deformable and complex structures. In this study is presented a robust and effective model-based segmentation procedure for approximating highly deformable cloud structures. The whole image sequence may be viewed as a 3D data set, but the classical techniques for performing 3D segmentation are not meaningful here, because cloud structures are not shapes in the classical sense. The model-based segmentation presented here uses level-sets controlled by particle systems. A specific energy formulation is introduced, permitting the use of robust conjugate gradient techniques. The model is validated on a real meteorological image sequence. We outline the generalizations of the this particle system to perform image analysis tasks on truly 3D images.

1. Introduction

Since their inception, satellite image data confront image analysis specialists with particular demands. They represent huge amount of time varying data, and they often feature complex structures subject to high geometrical variations and topological changes, as it is the case in meteorological image sequences. Geostationnary satellites produce data sets which can be viewed as 3D images, or more precisely as 2D dynamic image sequences. 3D image analysis techniques could sometimes be used ([5, 8]) but the very specific nature of clouds structures (they do not possess well defined shapes) lead to some difficulties: even optical flow methods need specific supplementary assumptions to describe the inner motion of vortices, as described in [1].

In this study is presented a preliminary research on meteorological satellite image sequences which is intended to describe a model-based segmentation for time varying images displaying deformable structures. The method can be applied to 2D sections of 3D image data sets. We make the decision of focusing on level-set methods ([10]), as they feature many desirable properties in a meteorological application context. However, classical level-set methods are not sufficient to plainly fulfill the requirements of the application. They require complex numerical methods, and they do not permit interactive control on the shape. In the meteorological application framework, one does not need a complete and automatic image analysis set of tools. Instead, it is expected that image analysis helps an operator in extracting and manipulating a shape for various purposes such as data base indexing or scientific visualization queries. From that point of view, it is desirable that the shape can be manipulated with control points, and that image analysis tools are fast and robust. Taking into account these requirements, the work presented in this study comes up with a new level-set approach to deformable boundary approximation. In this study, shapes are approximated by particle systems controlling a level set. The implicit formulation presented in this work makes it possible to use the particle system formulation suitable for performing segmentation in true 3D imagery. Such generalizations are outlined here.

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, robust level-set approximations, with adjustable accuracy.

The initialization step has received particular attention by using the skeleton of an image and the distance map. It permits the design of an efficient initialization procedure, where a minimum set of particles is assigned specific geometric location in an image, resulting in a stable minimization procedure. It produces a set of particles consistent with elementary transformations such as translation and rotation, thus permitting the analysis of motion.

The presentation is organized as follows. In section 2, we describe precisely some features and characteristics of clouds in a meteorological image sequence. Section 3 focuses on level sets controlled by particle systems. In section 4 an energy formulation for the particle system is described. Section 5 focuses on contour extraction. In section 6 the use of skeletons for a robust initialization is presented. The results of the method are shown in section 7. In section 8 is we outline a generalization of the method for generating an interpolating surface between successive templates. Conclusion and perspectives are contemplated in section 9.

2. The specific characteristics of time-varying cloud image sequences

Meteorological image sensors collect images showing the apparition, evolution and motion of cloud structures. They produce data sets that help the computation of numerous parameters associated with clouds, such as wind speeds. They are a key component of any weather forecast system. Cloud structures may appear in very different shapes in these images, such as vortices, where the cloud is winding round its center, while it is also subject to global translation and rotation motion, or in more evanescent cloud structures, which can break themselves in connected components, merge or disappear. (See figure 1). It is important to notice that, in connection with 3D image analysis, the cloud segmentation itself involves specific difficulties. This is for instance the case of Sahel rain-season: the clouds have a remarkably constant altitude, and therefore a very narrow grey level variance. More complicated matters are encountered with vortex structures, which involve much more larger areas, and altitude variability. Specific analysis must be performed to extract them. (See [2] for examples).

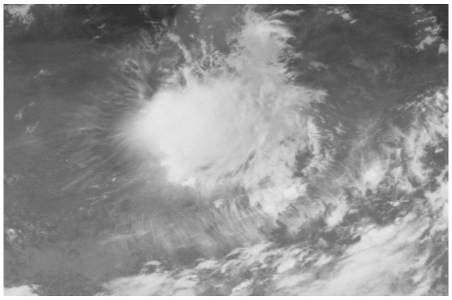

Figure 1. High altitude cloud over Sahel. Meteosat IR image provided by L.M.D.

The fundamental difficulties are related to the temporal aspect of the problem, and of course to clouds themselves. It is an important matter to not forget that clouds are not "objects" in the usual sense, as for instance buildings in airbone imagery, or organs in medical imaging. The satellite provides measures of the top (or sometimes an average) of a vertical fluid structure. The cloud is often subject to intense inner motions. It has no well-defined shape, and the presence of motion both internally and at its borders may affect the sharpening of visible edges. The most awkward consequence is that clouds do not always preserve their integrity: they interact with atmosphere and other clouds. This is in fact related to motion problems.

Cloud analysis therefore requires a model with specific characteristics:

Deformation: whether the cloud is segmented on the basis of its edges or as a region, the model must allow important and non-linear deformations of edges.

Topology: topology changes are very often encountered. The model must handle this "naturally", for instance by imposing visco-elastic behaviors.

Global vs local motion: the local (though possibly considerable) deformation of the structure is superimposed to a global translation motion. A hierarchical representation of motion is then suitable.

As mentionned in the introduction, the use of classical 3D segmentation technique is not well adapted to the analysis of these very specific cloud structures. But any cloud segmentation model can be very helpful for the analysis of 3D images, wherever a classical polygonal or voxel information is not always of primary importance. We will use a level set formalism to achieve the image segmentation on these images. These level sets are different from the classical formulation. They are introduced in the next section.

3. Implicit objects

In computer graphics, implicit objects are successfully used to model shapes and physical properties of objects that would be difficult to attain using standard spline surface models [6]. Implicit functions are used to:

- model any shape, even those with sharp corners and protrusive many-furcated ramiforms,
- glue objects together without resorting to complicated algorithms to properly handle the joints,
- control the viscosity of an object with very few parameters,
- model complex topologies.

Let $X = \mathbb{R}^2$ or $\mathbb{R}^3$. An implicit object $\mathcal{O}$ is defined by an equation

$$\mathcal{O} = \{M \in X / \varphi(M) = c\} = \varphi^{-1}(c)$$

φ being a continuous or differentiable function $\varphi : X \to \mathbb{R}$. The quantity c is called the iso-value. To allow the possibility of narrow corners, function φ is often written in the form

$$\varphi = \psi \circ d$$

where

$d : X \to \mathbb{R}$ is a distance function[1] and
$\psi : \mathbb{R} \to \mathbb{R}$ is a potential function.

Narrow corners and sharp edges are easily modelled if d is a L^∞ metric. For other parts of an object standard L^2 metrics can be used. Many types of potential function ψ have been experimented. (See [4]). For instance we use bounded support potential functions like ([13]):

$$\psi(d) = 1\!\!1_{\{d^2<1\}}(1 - \frac{22}{9}d^2 + \frac{17}{9}d^4 - \frac{4}{9}d^6). \qquad (3)$$

$1\!\!1_{\{d^2<1\}}$ being the characteristic function of the set $\{d^2 < 1\}$.

Instead of using a global function φ, which would be of little pratical use for our application, implicit functions are used with the help of particle systems.

3.1. Particle system formulation

Particle systems have already been used to model elastic surfaces [11]. A principal advantage of using particle systems in image analysis is found in their ability of describing complex dynamics with a finite set of particles. From that outlook, they capture the geometry and dynamics properties of a continuous shape with more simple assignements written over the finite set of particles. This is a very important matter which ultimately justifies their use in this work. For instance, the description of the elastic properties of an active contour is written as an integral energy in the snake framework or in the geodesic active contours. Particle systems allow the control of the dynamics properties of a shape by using much more tractable forms of internal energy, thus avoiding the resolution of cumbersome partial differential equations.

In the control point formulation of implicit functions, the particle system used to describe a shape is a written down as 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 and mathematically expressed by an expression like (3). Wherever a shape is modelled with an implicit function defined with control points, the geometric and visco-elastic properties of the shape are encoded within the particle system defined by the control points and the stiffness parameters of each local contribution φ_i. Having set up a particles system formulation for the level sets, we now define in the next section the energy formulation of that particles system.

4. 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.

4.1. 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:

[1] A distance function in the classical theory of metric spaces.

- 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. In classical Newton theory, the law of action and reaction is attained by constraining the internal potential term between two particles as being a scalar function of the mutual interdistance $d_{ij} = \|P_i - P_j\|$. A generalized Lennard-Jones potential

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

is repulsive at short distances, attractive at far distances, and possesses an equilibrium position in-between (at $(r_i + r_j)/2$.

4.2. External energies

The deformable model interacts with image data under the control of the external forces. Their definition is therefore application-dependent by nature. An external energy is sought out in order to attract the iso-contour towards extracted pixels in an image. A two-term external energy is introduced.

4.3. Contour energy

Minimization of the following contour energy:

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

where $\mathcal{P}$ is the set of extracted pixels, results in an iso-contour approximating the extracted pixels, but it does not guarantee that the iso-contour approximate those extracted pixels only. Indeed, the iso-contour could also approximate many other undesirable features in an image, leading to iso-contours displaying non acceptable small connected components. 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.

4.4. Collar energy

The implicit function framework leaves the user with a remarkable freedom of designing various external forces, adapted to different situations. This relies on a basic property of any implicit model: the simple computation[2] of the iso-surface φ at location P is enough to establish whether P is inside the iso-contour ($\varphi(P) - c > 0$), outside ($\varphi(P) - c > 0$) or right on it ($\varphi(P) - c = 0$). Thus, masking specific values of $\varphi(P) - c$ makes it possible to contemplate region-based approaches; a simple measure of the iso-contour proximity can be formulated this way:

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

$\chi_\sigma(P)$ 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 gradients. This would yet suffer from the same limitations encoutered with early snakes: a close initialization is essential since gradient tends to be uniformally zero within uniform areas. Using distance maps, as suggested by [9, 7], overcomes this problem: distance maps are computed after an initial contour detection. Each location P of the image is assigned the distance to the nearest contour point. This is of course appropriate if a good quality contour detection can be carried out. The main advantage is that the distance map gradient always points towards contour points, even within uniform areas: within homogeneous regions of an image, the gradient of intensity is zero, though the gradient of the distance map does not vanish. 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 iso-contour (small values of χ_σ)
- locations close to the iso-contour (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 iso-contour image fits the image contours. The parameter σ can be viewed as a tolerance parameter: it is used to produce a tubular neighbourhood around the iso-contour $\{\varphi = c\}$. A small value of σ causes the proximity mask to be a narrow area around the iso-contour, and thus the minimum of E_{collar} will correspond to a faithfull representation of contour points. On the contrary, more tolerant approximations are obtained using higher values of σ (see figure 2). This can be helpful if the noise on the image

[2]Computing φ in a N control points formulation requires at most N distance computations.

generates many false contours, as this masking process prevents the iso-contour of being attracted towards small undesibable features of an image.

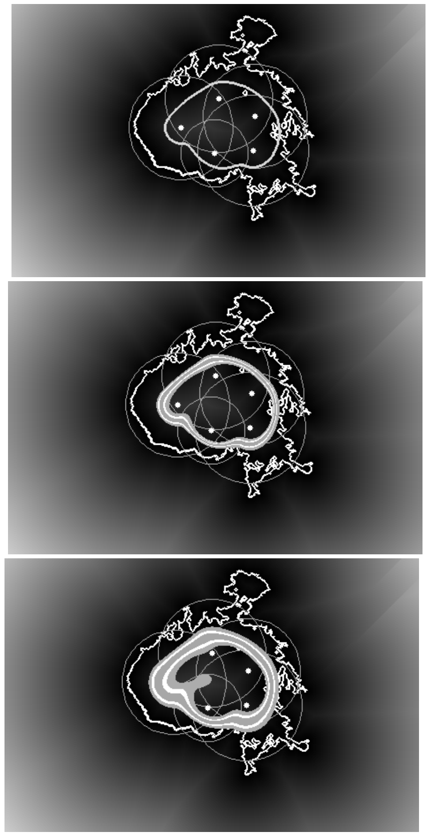

Figure 2. From Top to bottom: iso-contour, plot of χ_σ for $\sigma = 0.1$ and $\sigma = 0.2$. The various collars correspond to regions where $\chi_\sigma \geq 0.8$, $\chi_\sigma \geq 0.5$ and $\chi_\sigma \geq 0.2$. Background: distance map.

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.

4.5. 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. Refer to the table at the end of section 7 for the values of the various parameters used in the computation of the images.

5. Preprocessing step

The extraction of pixel features from the image data is an essential preprocessing step: it is used to compute distance maps, which play an important part in the definition of external forces. It serves also in the computation of $E_{contour}$. Pixel extraction is achieved using a property of clouds (see section 2): the 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): clouds are always detected by selecting low radiance pixels, i.e. pixel with grey 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. A first approximation of the shape is given by the contours of the selected areas. See figure 3. The two parameters, i.e. the cloud detection

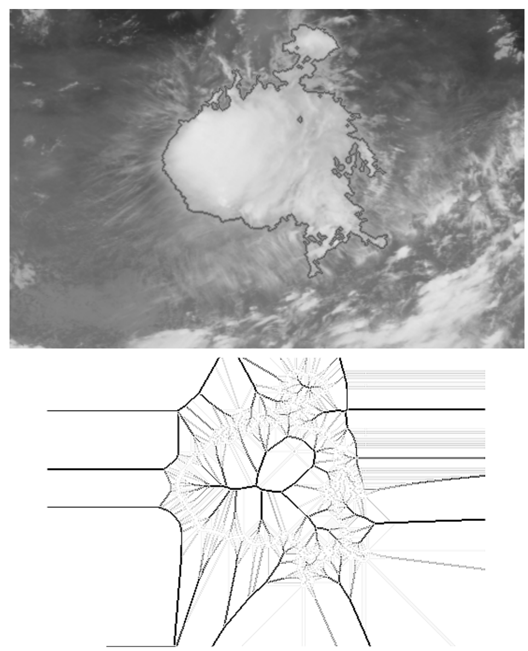

Figure 3. Frames 28 of the sequence. Top: extracted pixels form the darker boundary. Bottom: skeleton image from distance map.

threshold and the size threshold, do not need to be carefully tuned: the size criterion is only used to discard parasits, and the detection threshold to select locations inside clouds. Since clouds are the areas with highest gray levels, it is rather easy to choose an appropriate threshold. Once a part of a cloud points has been selected, a standard region growing algorithm is performed to finally obtain the clouds' contours. The images displayed in the following sections use the contour extraction described herein.

6. Initialization

The initialization process is a key component in the overall implicit particle system approximation, because a proper initialization of the 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 the extrema of the distance map. The implementation of the distance map skeleton is the one described in [8]). This choice is dictated by the fact that the distance map plays an important role in the external force field, and because 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 branches' extremities, with a radius equal to the distance from the contour. It should be noted that the external skeleton of a closed shape gives precious information about the concave parts of an object. By external skeleton we mean those portions of the skeleton located outside the interior of the cloud. It can be used at the initialization step for negative control points. This simple initialization process is illustrated in figure 4. Experimentation shows that this kind of initialization accelerates the convergence towards the extracted contour.

7. Results

The model-based image segmentation procedure is applied on real image sequences, both provided by the Laboratoire de Meteorologie Dynamique of the Ecole Polytechnique. Given an image sequence of a spatio-temporal shape, one can apply the previous methods to track and analyze motion in the following way. On the first image, particles are initialized on the skeleton and the energy minimization process is performed using the techniques described in the previous sections. On the next image, one takes as an initialization the results produced by the minimization process on the previous image, and so on iteratively until the end of the sequence.

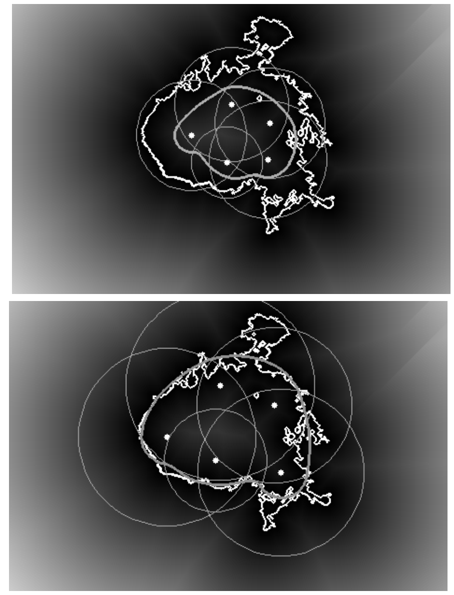

Figure 4. Model initialization on frame 28. Top: particles (in white) are placed on the skeleton endpoints. Bottom: first approximation of the contour (after minimization). The iso-contour is depicted in grey, particles in white, image contours in white, and distance map is in the background. The circles correspond to the radii of the particles.

We illustrate the process on two types of meteorological images in figures 5 and 6. It should be noted from these figures that the result of the segmentation may suffer from local precision. This is quite natural for the cloud shapes coming from the contour extraction process: these shapes are highly irregular, so one needs a high number of particles to precisely represent the shape. In an operational context however, it makes sense to provide the user a less precise, but easily manipulable description of the shape with few control points.

It is important to note that the particle system formulation developped in this study will permit, in a work in progress, a hierarchical representation of the shapes: few control points are used to globally represent a structure, and more particles are added locally to better represent the more complex parts of a structure. Below is a table showing the values of meaningful parameters used in the segmentation process.

Indicative parameters values		
parameter	description	value
α	internal energy weight	10^{-3}
β , γ	external energy weight	1.0
σ	tolerance factor	10^{-2}
ϵ	acceptable approximation threshold	10^{-1}

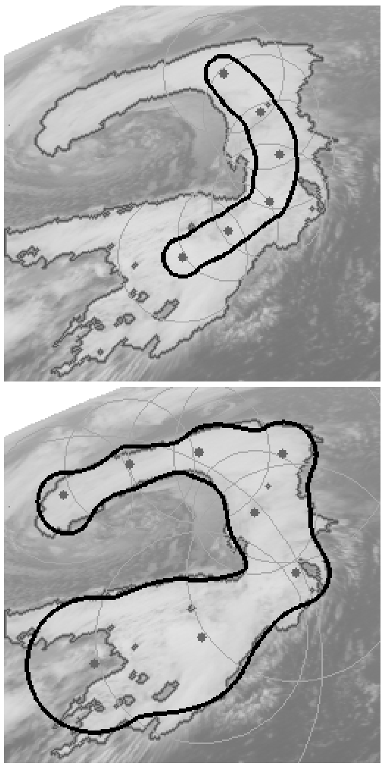

Figure 5. Vortex segmntation. Top: initialization, bottom: result of the segmentation with few control points. Level-sets are in black.

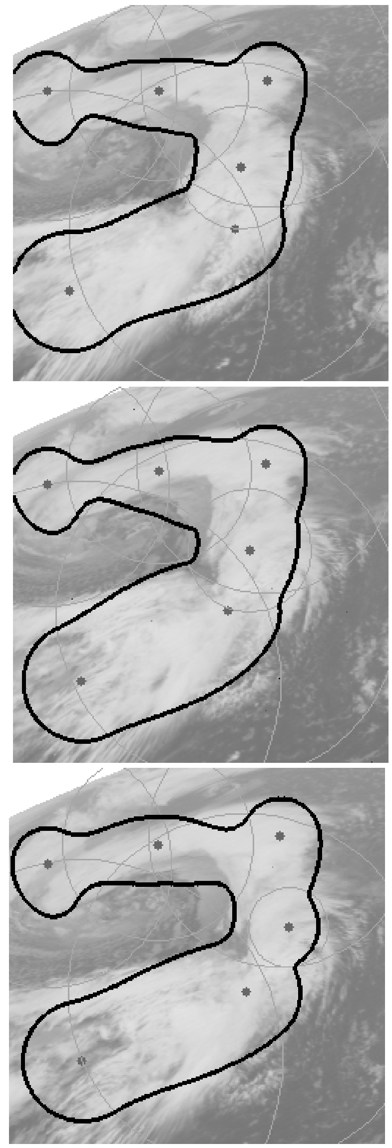

Figure 6. approximation of a vortex' contour on three consecutive images of sequence used in 5. Level-sets are in black.

8. Use of an implicit surface for contour interpolation

In a meteorological application framework, the problem of generating an interpolating surface between two succesive occurences of a template comes from the modeling of motion of time varying deformable structures. The evolution of the structure between succesive temporal occurrences generates a continuous 3D surface, the third dimension being time ([3]). The main objective is to compute the best possible surface. To perform this task, one may require an evolution model, expressed as constraints applied to this surface. The problem is then to find the surface interpolating the two consecutive contours and respecting these constraints. A good interpolating surface should not cross itself, and the surface should not display too much variations in curvature. Here the structures are the clouds approximated by the model presented in the previous sections.

More formally, two 2D contours C_1 and C_2 are placed in two parallel planes $t = 0$ and $t = 1$. In order to focus this study on deformation, one can first apply the rigid motion that performs the best matching between the two contours C_1 and C_2. This enables to manage the global translation motion that is often observed on meteorological image sequences. One then looks for an interpolating surface ϕ, with an elastic behavior, containing C_1 and C_2. At this point, one may put the following observation: implicit interpolating surfaces never self-intersect (indeed, such surfaces always possess tubular neighborhoods [12]). In a work in progress, we want to compute an interpolating implicit surface defined with particle systems. Such an implicit interpolation surface should display nice cross-sections, as there is no self-intersecting problem. The problem is to give a consistent initialization of the particles for the surface. For that matter, we start from the initialization of the templates defined in the previous sections, and we set up a matching between the particles. This matching problem is much more simpler that any contour-matching problem, because it only relates a correrspondance between points. The main idea is to use the particles of the segmentation process performed on two consecutive images to generate an acceptable initialization of the particles for the implicit surface, and then use minimization techniques ([3]) to compute a better implicit surface. The method is only outlined here, we are currently making progress in that direction.

9. Conclusion

A level-set segmentation procedure based on implicit functions defined by particle systems is presented. It has the following advantages:

- interactive control on the shapes,
- the minimization procedure is based on the particles, leading to fast and robust minimization,
- it allows precise initialization of the particles by use of the skeleton,
- it can be generalized to the case of 3D images by using implicit surface interpolation between templates.

Although satellite images provide explicit time cross-sections of deformable structures, we believe that the method outlined here can be of great importance for the case of more general 3D images. We are making some progress in these directions.

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