Diffuse Objects Extraction in Coronal Holes Using Active Contour Means Model

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Abstract

This paper presents the application of active contour models (Snakes) for the segmentation of diffuse objects from coronal holes on the sun imaging telescope by means of active contour. In this paper the partition is less important and the focus is on the extraction of diffuse objects, namely coronal holes in EIT (Extreme Ultraviolet Imaging Telescope) images. Coronal holes are regions of low-density plasma on the sun that have magnetic fields that open freely into interplanetary space. The proposed method is based on level set evolution. Since an active contour is a dynamic spline that can be adjusted to fit onto the boundary of the object based on energy minimization, and this method independent of selective region which we want to extract, hence using this method improved the result of segmentation. In addition to extracting diffuse objects of coronal holes, a new work that has been done to improve results, is that speed algorithm by implementing two methods: Reinitialization and Narrow band which related to the level set method has been used. Received images from satellites have large size so this method is very effective on these images.

Keywords: *Active contour model, Coronal holes, Parametric model, Level set, Reinitialization, Narrow band.*

1. Introduction

In general, the purpose of image segmentation is a partition of the domain of an image into a number of meaningful regions. In this paper the partition is less important and the focus is on the extraction of diffuse objects, namely coronal holes in EIT images [2]. A general description of conditions under which EIT images are acquired can be found in [3]. Extraction coronal holes by means watershed algorithm implemented by Nieniewski in [1].

Image segmentation is a fundamental requirement in image analysis tasks. We aim to develop an effective segmentation technique separating an expected object from background for further processing. An active contour or "snake" [4] is widely used to extract objects of interest. An active contour is a dynamic spline that can be adjusted to fit onto the boundary of the object based on energy minimization. The internal energy maintains continuity and smoothness of the spline while the external energy acquired from a higher level process attracts the spline towards the object. Many efforts have been made to modify the contour model to improve its performance [5].

Existing active contour models can be categorized into two major classes: edge-based models and region-based models. Edge-based models use local edge information to attract the active contour toward the object boundaries. Region-based models aim to identify each region of interest by using a certain region descriptor to guide the motion of the active contour [6].

Some of the practical applications of image segmentation can be found in satellite images such as locating objects (roads, forests, etc.), in face recognition systems, and in Medical Imaging [7].

This paper presents a method for the segmentation of extreme-UV images obtained from EIT experiments of the satellite SOHO mission and for extraction of diffuse objects from such images. The problem of segmentation of solar images has not been the subject of many papers, but one could mention the paper [1], in which solar image segmentation was considered from the point of view of extraction of sunspots in visible light by means of the mean field fast annealing.

Coronal holes are regions of low-density plasma on the Sun that has magnetic fields that open freely into interplanetary space.

During times of low solar activity, coronal holes cover the north and south polar caps of the sun. During more active periods, coronal holes can exist at all solar latitudes, but they may only persist for several solar rotations before evolving into a different magnetic configuration. Ionized atoms and electrons flow along the open magnetic fields in coronal holes to form the high speed component of the SOLARWIND.

One of the reasons that coronal holes are important to study is that they are thought to be the primary sites of acceleration for the high-speed solar wind. Since the supersonic solar wind was first detected by spacecraft plasma instruments in the early 1960s, it has been found to be composed of both high-density, low-speed (300–400 km s− 1) streams and low-density, high-speed (500–800 km s− 1) streams [8].

Extraction of coronal holes is difficult for some reasons:

1. A coronal hole is by no means a solid object, the solar corona consisting of an ionized gas of temperature 1–2 MK
2. Outer layers of the corona are optically thin, and an EIT image depicts a result of integration along a line of sight and not a single shining surface.
3. Coronal holes undergo significant changes during the solar cycle.

The method described is based on the use of a watershed algorithm. The result of the watershed segmentation is a partition of the whole domain of the image into a large number of small regions. These regions are then combined in a region merging process. The proposed region merging algorithm iteratively adds the darkest regions and maximizes the average contrast between a current mask and a set of its neighboring regions [1].

The rest of the paper is organized as follows. In section 2, we give an overview of the active contour model and energy minimization approaches. Some experimental results are presented in Section 3 to show the performance of the proposed modify. Finally, conclusions are given in section 4.

2. Overview of the active contour model

A. Parametric models

The original parametric active contour model was introduced by Kass, Witkin and Terzopoulois [9], and is known as Snakes, due to the way the contour moves to its final position. In this model, the contour has an initial user, specified position and an associated objective function defined as the energy of the snake. The snake may then be defined as a curve $v(s)$ =[$x(s)$, $y(s)$], $s \in [0,1]$ which moves in the image domain to minimize the energy function shown below:

$$\begin{aligned} E^{*}_{snake}(V(s)) &= \int_0^1 E_{snake}(V(s))ds \\ &= \int_0^1 E_{\text{int}}(V(s)) + E_{image}(V(s)))ds \end{aligned} \qquad (1)$$

The first part of the integral is related to the snake's internal energy, and imposes restrictions to its movement by controlling the elasticity and stiffness parameters, which are weighed by α and β , respectively. The second part stands for the external energy, and is responsible for driving the snake towards important features in the image, e.g. edges of specific body structures in a MR image. For a given gray-level image I(x, y), this internal energy E_{int} is identified as:

$$E_{\text{int}} = \frac{\alpha(s)\left|V_s(s)\right|^2 + \beta(s)\left|V_{ss}(s)\right|^2}{2} \qquad (2)$$

and the external energy can be written as:

$$E_{image} = w_{line}E_{line} + w_{edge}E_{edge} + w_{term}E_{term} \qquad (3 - 1)$$

$$E_{line}(x,y) = I(x,y) \qquad (3 - 2)$$

$$E_{edge}(x,y) = -\left|\nabla I(x,y)\right|^2 \qquad (3 - 3)$$

$$E_{term}(x,y) = -\left|\nabla[G_\sigma(x,y) * I(x,y)]\right|^2 \qquad (3 - 4)$$

Where G_σ is a two dimensional Gaussian filter with a standard deviation σ and ∇ is the gradient operator. This filter is applied to the image in order to improve the image's edge map, and also to perform some noise reduction [10].

B. Region Based

An image u can be defined as a bounded real positive function on some (rectangular) domain $\Omega \in R^2$. Let its boundary be denoted $\partial\Omega$ .Typically, in image processing, $u \in \{0,1,...,255\}$, and referred to as a grayscale image. We denote $C:[0,1] \to \Omega$ a curve parameterized by arc length. We assume C is piecewise $C^1([0,1])$. Although the problem of image segmentation has various forms, we will consider the simplest case where we "segment" the image into two region. The definition of the problem is as follows:

Let u_0 be an image in Ω . Suppose can be partitioned into Ω_1 and Ω_2 , where for some image property P, $u_0|\Omega_1$ differ from $u_0|\Omega_2$. Find a curve $C \in \Omega$ such that it partitions $\Omega = \Omega_1 \cup \Omega_2$. Here, P is typically the image intensity (the function value of u_0), but can also be texture, pattern curvatures, etc.

A conventional approach in solving image segmentation is to start with some initial guess $C(0)=C_0$ and evolve C(t) in a time dependent piecewise differential equation (PDE):

$$C_t = F(C(t)) \qquad (4)$$

such that $\overline{C} = \lim_{t \to \infty} C(t)$ solves the problem. In other words, ideally, the model should reach a steady state when C(t) is at the correct solution [11].

C. The Level-Set Method

When evolving a curve C in R^2, the standard approach is to use the *level-set method* (or, level-sets). The idea of level-sets was first discovered by Osher and Sethian in [12]; it exploits the remarkable fact that treating a curve C(s) as a zero level curve of a surface $\phi(x,y)$ simplifies various tasks when evolving C, such as changes in its topological structure. The following is a basic result in level-sets:

Let $C(t_0)$ the zero level curve of $\phi(x,t_0)$ at some time $t=t_0$. If $x_0 \in C(t_0)$ and $v(x_0,t_0)$ denotes the outer normal velocity of $C(t_0)$, then it solves the PDE, $\phi_t = v(x,t)|\nabla\phi|$. The proof of this may be found in, for example, [3].

One widely used type of curve evolution is motion by mean curvature, when $v(x)=k(x)$, the curvature of C at x:

$$\phi_t = \kappa(x)|\nabla\phi| = |\nabla\phi|\nabla.(\frac{\nabla\phi}{|\nabla\phi|}) \quad (5)$$

Prior to the main model described in this report, image segmentation problems were treated in tandem with edge-detecting problems. Denote Ω_b for the correct boundary between Ω_1 and Ω_2 and define an edge function g as , g(0)=1, decreasing and $\lim_{s\to\infty} g(s)=0$. An example of such function is,

$$g(|\nabla u_0|) = \frac{1}{1+\left|\nabla J_p * u_0\right|^2} \quad (6)$$

Where $J_p * u_0{}^2$ is some regularization of image u_0 to a smoother function. See [4] for further examples. One such model is the following geometric active contour PDE:

$$\phi_t = g(|\nabla u_0|)|\nabla\phi|\left(\nabla.\left(\frac{\nabla\phi}{|\nabla\phi|}\right)+\upsilon\right) \quad (7)$$

Where u_0 is the original image, and g is an edge-function.

Note its similarity to the motion by mean curvature equation; the v term, when large enough, enforces C to evolve inwards even when $k=0$. The evolution should stop when $C(t)=\{x : g(|\nabla u_0(x)|)<\varepsilon$ for some ε small. Consider the functional of two functions, u (an image) and C (a curve):

$$F^{MS}[u,C] = \mu.length(C) + \lambda\int_{\Omega}|u_0-u|^2 dx + \int_{\Omega-C}|\nabla u|^2 dx$$

Where u_0 is a (noised) image and μ > 0, λ > 0 parameters FMS is known as the Mumford-Shah functional. The result of the minimization,

$$\inf_{u,c} F^{MS}[u,C] \quad (8)$$

Is an image u smooth in a partition of regions R_i with sharp boundaries C. Hence, it solves the image denoising problem and the segmentation problem simultaneously.

Now, if we consider the same minimization (3) with u restricted to the piecewise constant function space we should obtain an image u with constant values c_i in each R_i; the c_i 's are in fact the averages of u_0 each region R_i. This reduced minimization problem is known as the minimal partition problem.

It will be useful to understand how each term of (2) contributes to the minimization (3).

The first term forces C to be relatively smooth on the boundaries, while the third term forces u to be smooth in areas not on C. The second term, the only term containing the original image u_0, keep the fidelity of u with u_0. In fact, the model introduced in this paper is a particular case of the minimal partition problem, and hence well-related to the Mumford-Shah functional [11].

D. The Active Contour without Edges Model

The active contour without edges model exploits the following simple observation [13]. Given an image u_0 and a closed curve C, let c_1,c_2 be the average value of u_0 in the "inside" of C and "outside" of C, respectively. Define the functional F_i to be,

$$F_1(C) = \int_{insideC}|u_0-c_1|^2 dx\ ,\ F_2(C) = \int_{outsideC}|u_0-c_2|^2 dx \quad (9)$$

With the assumption that u_0 consists of two regions Ω_1 and Ω_2 with boundary $\overline{C}$ each of nearly constant intensities, it is clear that, uniquely,

$$\inf_C \{F_1(C)+F_2(C)\} = F_1(\overline{C})+F_2(\overline{C}) = 0 \quad (10)$$

With additional minimizing terms we have the model:

Definition 2 (Active contour without edges) Let $p \geq 2$, and

$$F(C) = \mu.(length(C))^2 + \upsilon.area(inside(C)) + \lambda_1 F_1(C) + \lambda_2 F_2(C) \quad (11)$$

If $\overline{C}$ solves

$$F(\overline{C}) = \inf_C F(C) \quad (12)$$

Then $\overline{C}$ is a solution to the segmentation problem.

The F in the definition above, the first term accounts for smoothing C and the second term forces C to move inward if ν is large. Note that this model is a particular case of the minimal partition problem where we constrain the minimizing function u to be the piecewise constant function,

$$u = \begin{cases} average(u_0) & inside\ C \\ average(u_0) & outside\ C \end{cases} \quad (13)$$

if $\nu = 0$. The proof of the existence minimizing C is presented in Chan and Vese [1].

$$F(\phi) = (\int_\Omega |\nabla H(\phi)|)^P + \upsilon \int_\Omega H(\phi)\,dx + \lambda_1 \int_\Omega |u_0 - c_1|^2 H(\phi)\,dx + \lambda_2 \int_\Omega |u_0 - c_2|^2 (1 - H(\phi))\,dx \quad (14)$$

Where

$$c_1 = \frac{\int_\Omega u_0 H(\phi)\,dx}{\int_\Omega H(\phi)\,dx} \quad (15 - 1)$$

$$c_2 = \frac{\int_\Omega u_0 (1 - H(\phi))\,dx}{\int_\Omega (1 - H(\phi))\,dx} \quad (15 - 2)$$

$$H(s) = \begin{cases} 1 & if\ s \ge 0 \\ 0 & if\ s < 0 \end{cases} \quad (15 - 3)$$

As stated in the model definition, we seek to minimize (5). From variational calculus, the minimization of a functional asks for the Euler-Lagrange equation to be solved.

$$\begin{cases} \frac{\partial \phi}{\partial t} = \delta_t [\mu\, div\left(\frac{\nabla \phi}{|\nabla \phi|}\right) - \upsilon - \lambda_1 (u_0 - c_1)^2 + \\ \lambda_2 (u_0 - c_2)^2] = 0 \ in\ (0, \infty) \times \Omega \\ \phi(x, y, 0) = \phi_0(x, y) \ \ in \ \ \Omega \\ \frac{\delta_\varepsilon(\phi)}{|\nabla \phi|} \frac{\partial \phi}{\partial \vec{n}} = 0 \ \ on \ \ \Omega \end{cases} \quad (16)$$

3. Improved result

In addition to extracting coronal holes, a new work that has been done to improve results, is that speed algorithm by implementing two methods and reinitialization narrow band related to the level set method has been used. Received images from satellites have large size so this method is very effective on these images.

A. Reinitialization

At each time step, when $\psi_{i,j}^{n+1}$ is computed from $\psi_{i,j}^{n}$, due to the $\delta_h(\phi^n)$ term in the scheme causes sharp gradients in ϕ. The presence of such "shocks" may cause difficulty in the computation as described in [5] (This, in general, happens for the implicit method, while rare for explicit methods). This is resolved by flattening, or reinitializing ϕ into a distance function. A distance function ψ of ϕ can be defined as follows:

1. $\psi(x) = 0 \Leftrightarrow \phi(x) = 0$, i.e. Both zero level-sets are equal
2. $\psi(x) = sign(\phi(x))\, dist(x, c)$

Where $dist(x,c)$ denotes the distance between x and its closest point on the zero level-set of ϕ.

Finding the distance function from ϕ^n can be done by evolving the following time dependent PDE to steady state [5]:

$$\psi_t = sign(\phi^n)\,(1 - |\nabla \psi|)$$
$$\psi(0, x) = \phi^n(x) \quad (17)$$

The numerical scheme in solving this is as follows. Let,

$$\psi_{i,j}^{k+1} = \psi_{i,j}^{k} - \Delta t(sign(\phi^n))\, G(\psi_{i,j}^{k})$$

Where $G(0)$ is defined as,

$$G(\psi_{i,j}) = \begin{cases} \frac{\sqrt{\max((a^+)^2, (b^-)^2) + \max((c^+)^2, (d^-)^2)}}{h} - 1 & if\ \phi^n(X_{i,j}) > 0 \\ \frac{\sqrt{\max((a^-)^2, (b^+)^2) + \max((c^-)^2, (d^+)^2)}}{h} - 1 & if\ \phi^n(X_{i,j}) < 0 \\ 0 & otherwise \end{cases}$$

And

$$a^+ = \max\left(\frac{\Delta^x_{\psi_{i,j}}}{h, 0}\right), b^- = \frac{\max(\Delta^x_+ \psi_{i,j}, 0)}{h, c^+} = \min\left(\frac{\Delta^x_{\psi_{i,j}}}{h, 0}\right)$$

and so on.

B. Narrow Band

The straightforward level set method introduced in [6] is a somewhat time-consuming algorithm. We can make a rough operation count as follows; consider a curve propagating in two-dimensions with speed F=1, and suppose one chooses a time step that exactly matches the CFL condition, so that $\frac{\Delta t}{\Delta x} = 1$.

Then with N points in each space direction, a total of N_2 points are updated every time step, with roughly N time steps required for the interface to propagate its way from the center out to the edge of the computational domain, yielding an $O(N_3)$ algorithm. The narrow band method, introduced in [1], is an adaptive level set method that limits computational labor to a grid points located in a narrow band around the front.

Grid points around the front are kept in a one-dimensional array, and updated using the level set equation until the interface nears the edge of this narrow band, at which point a new narrow band is re-initialized. Figure (1) shows how the narrow band tags a collection of nearby grid points.

By employing this technique, the computational labor for a curve propagating in two dimensions drops to $O(kN_2)$ where k is the width of the narrow band. An extensive discussion about narrow band methods, choice of sizes, accuracy, and other details may be found in [1].

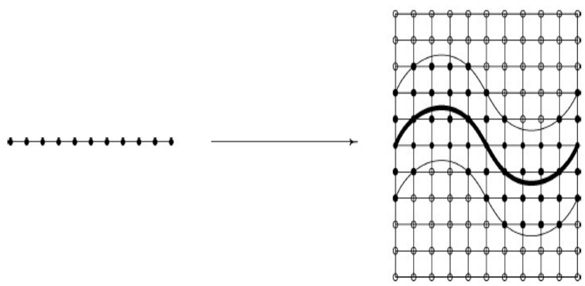

Fig. 1 Shows how the narrow band tags a collection of nearby grid points

C. Algorithm

The main steps of algorithm to detect the coronal holes

1. Initialize $\phi_0, (n = 0)$
2. Compute the speed function (10). (Use (7) where the image gradient is high)
3. Obtain ϕ^{n+1} by solving the PDE in ϕ from (9).
4. Reinitialize ϕ to the signed distant function from (12).
5. Stop when the solution is stationary. If not, n=n+1 and repeat the steps 2-5.
6. Take the result of step (5) as the initial contour. Repeat steps 2-6.
7. Stop when the Contour is stables

4. Conclusions

This paper presents a method for extraction of coronal holes from EIT images. This method uses the Active contour model segmentation with region based model that iteratively adds darkest neighboring regions. A mask of a hole is obtained by maximizing the average contrast between a coronal hole and its surroundings. Using this method we can obtain masks which are in good agreement with intuition. The method does not require any explicit fine-tuning parameters, but the user has to point to an initial seed pixel belonging to the watershed region which should certainly be included in the mask. The algorithmic parameters were obtained experimentally and their main purpose is to restrict the number of iterations. The proposed method could be extended to extraction of other diffuse objects, such as bright active regions in EIT images, or areas with brightness close to some predefined level. Other possible applications might include segmentation of biomedical as well as of industrial-type images, for example for extraction of certain defects.

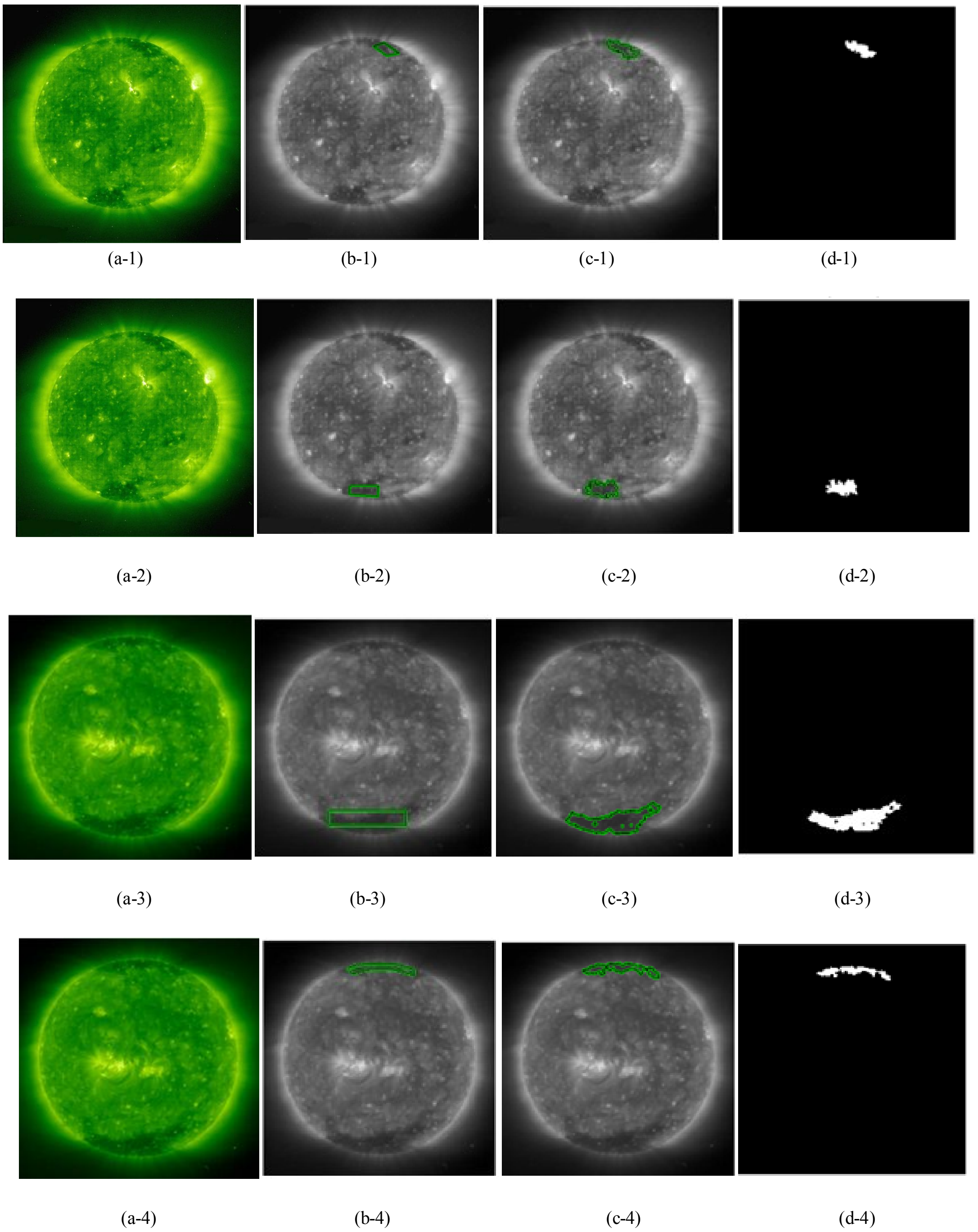

Fig. 2: Solar categories hole for 4 image, first column (a): EIT images of the sun, the second column (b): exposure contour desired Initial position, third column (c): the final contour position, fourth column(d): the final destination categories

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