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A Region-Based Model and Binary Level Set Function Applied to Weld Defects Detection in Radiographic Images

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ABSTRACT

In this paper, we propose a model for active contours to detect boundaries' objects in given image. The curve evolution is based on Chan-Vese model implemented via binary variational level set formulation. The particularity of this model is the capacity to detect boundaries' objects without need to use gradient of the image, this property gives its several advantages: it allows to detect both contours with or without gradient, it has ability to detect automatically interior contours, and it is robust in the presence of noise. For increasing the performance of model, we introduce the level sets function to describe the active contour, the more important advantage to use level set is the ability to change topology. Experiments on synthetic and real (weld radiographic) images show both efficiency and accuracy of implemented model.

KEYWORDS

Image segmentation, Curve evolution, Chan-Vese model, EDPs, Level Set, Radiographic images.

1 INTRODUCTION

Due to the huge evolution of computer vision, several tasks in many fields have been automated. The task in which we are interesting in our work is one of some techniques used in Non Destructive Testing *NDT*. The *NDT* is a set of techniques used in science and industry to evaluate the properties of a material, component or system without causing any damage.

In welding the most famous techniques used for testing are by using the ultrasonic (UT) or Radiography (RT). In this present work, we use Radiographic images that are the outcomes of radiographic operation. This one is similar to medical radiographic, it consists to submit a gamma rays or x-rays from its source through the welded joint. The differences of the densities between the material welded, the welded joind and defects are localized on the radiographic films, as the Figure 1 illustrates it. After the digitalization of films, various image processing and computer vision algorithms was applied to detect the welding defects and to calculate necessary information such as length, width, area and perimeter of the defects.

This paper is concerned with image segmentation, which plays a very important role in many applications. It consists of creating a partition of the image u_0 into subsets R_i called *regions*. Where, no region is empty, the intersection between two regions is empty, and the union of all regions cover the whole image. A region is a set of connected pixels having common properties that distinguish them from the pixels of neighboring regions.

Nowadays, and given the importance of segmentation, multiple studies and a wide range of applications and mathematical approaches are developed to reach good quality of segmentation. The techniques based on variational formulations and called *deformable models* are used to detect objects in a given image u_0 using theories of curves evolution [1]. The basic idea is: from an initial curve *C* which is given; to deform the curve till surrounded the objects' boundaries, under some constraints from the image. There are two different approaches within variational segmentation: *edge-based models* such as the active contours "snakes" [2], and *region-based methods* such as Chan-Vese model [3].

Almost all edge-based models mentioned above use the gradient of the image u_0 to locate the objects' edges. Therefore, to stop the evolving curve an edge-function is used, which is strictly positive inside homogeneous regions and near zero on the edges, it is formulated as follow:

$$g(|\nabla u_0|) = \frac{1}{1+|\nabla(G_\sigma * u_0)|^2} \quad . \qquad (1)$$

The gradient operator is well adapted to a certain class of problems, but can be put in failure in the presence of strong noise and can become completely ineffective when boundaries' objects are very weak. On the contrary, the biased-region approaches avoid the derivatives of the image intensity. Thus, it is more robust to the noises, it detects objects whose boundaries cannot be defined or are badly defined through the gradient, and it automatically detects interior contours [4][5].

In problems of curve evolution, including snakes, the level set method of Osher and Sethian [6][7] has been used extensively because it allows for automatic topology changes, cusps, and corners. Moreover, the computations are made on a fixed rectangular grid. Using this approach, geometric active contour models, using a stopping edge-function, have been proposed in [8][9][10], and [11].

Region-based segmentation models are often inspired by the classical work of Mumford -Shah [12] where it is argued that segmentation functional should contain a data term, regularization on the model, and regularization on the partitioning. Based on the Mumford - Shah functional, Chan and Vese proposed a new model for active contours to detect objects boundary. The total energy to minimize is described, essentially, by the averages intensities inside and outside the curve [3].

The paper is structured as follows: the next section is devoted to the detailed review of the adopted model (Chan-Vese). In the third section, we formulate the chan-vese model via the level sets function, and the associated Euler-Lagrange equation. In section 4, we present the numerical discretization and algorithm implemented. In section 5, we discuss a various numerical results on synthetic and real weld radiographic images. We conclude this article with a brief conclusion in section 6.

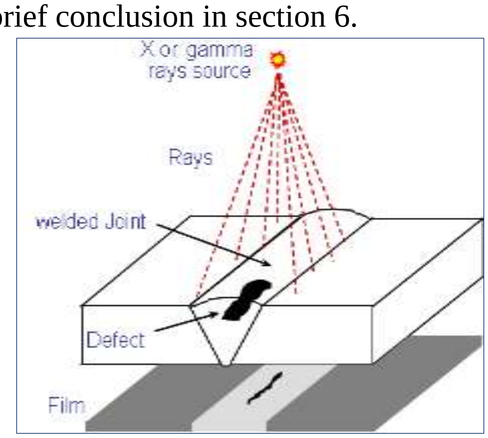


Figure 1. Industry Radiographic technique in welding

2 CHAN-VESE FORMULATION

The more popular, the older, and the core of region-based segmentation is the Mumford-Shah model in 1989 [12]. The model expresses segmentation as combined of image smoothing and boundary detection. It searches a smooth approximation $u: \boldsymbol{x} = (\boldsymbol{x}, \boldsymbol{y}) \in \boldsymbol{\Omega} \subset \mathbb{R}^{\mathbf{2}} \rightarrow u(\boldsymbol{x}) \in \mathbb{R}$ of the original image $u_0: \boldsymbol{\Omega} \subset \mathbb{R}^{\mathbf{2}} \rightarrow \mathbb{R}$ and a set K of discontinuities for representing the image boundaries. To reach that Mumford and Shah had proposed to minimize the functional given by:

$$F(u, K) = \int_{\mathbf{\Omega - K}} (u - u_0)^2 \, d\boldsymbol{x} + \alpha \int_{\mathbf{\Omega - K}} |\nabla u|^2 \, d\boldsymbol{x} + \beta \int_K d\sigma. \qquad (2)$$

Where α and β are nonnegative constants for weighting each integral, and $\int_K d\sigma$ is the length of K. Unfortunately the model as it was proposed has several difficulties to be minimized see [12], [13],[15] for details. Much works have been inspired from the original Mumford-Shah model, for example the model, called "*Without edges*", which was proposed by Chan and Vese in 2001 [3], on what we focus in this paper. The main idea of *without edges model* is to consider the information inside regions, not only at their boundaries. Let us present this model: let u_0 be the original image, c the evolving curve, and c_{in}, c_{out} two unknown constants. Chan and Vese propose the following minimization problem:

$$F_{in}(c) + F_{out}(c) = \int_{inside(c)} |u_0(x, y) - c_{in}|^2 dx\, dy + \int_{outside(c)} |u_0(x, y) - c_{out}|^2 dx\, dy \ . \quad (3)$$

where the constants c_{in}, c_{out} depending on c, they are defined as the averages of u_0 inside and outside c, respectively.
We look for minimizing (3), if we note c_0 the minimum of (3); it is obvious that $c_0$is the boundary of the object, because the fitting term given by (3) is superior or equal zero, always. So its minimum is when $F_{in}(c) \approx 0$ and $F_{out}(c) \approx 0$:

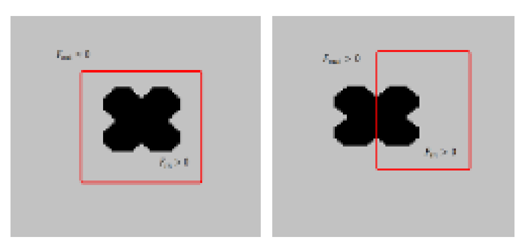
$$inf\{F_{in} + F_{out}\} \approx 0 \approx F_{in}(c_0) + F_{out}(c_0). \text{ so } F_{in}(c_0) \approx 0 \implies u_0(x, y) \approx c_{in}$$

$$F_{out}(c_0) \approx 0 \implies u_0(x, y) \approx c_{out}.$$

Where inf is an abbreviation for infimum.
As formulations show, we obtain a minimum of (3) when we have homogeneity inside and outside a curve, in this case we have $c = c_0$, it is the boundary of object (See fig. 2).
Chan and Vese have added some regularizing terms, like the length of curve c, and the area of the region inside c. Therefore, the functional become:

$$F(c_{in}, c_{out}, c) = \mu . Length(c) + v . Area\big(inside(c)\big) + \lambda_1 \int_{inside(c)} |u_0(x, y) - c_{in}|^2 dx\, dy + \lambda_2 \int_{outside(c)} |u_0(x, y) - c_{out}|^2 dxdy \ . \qquad (4)$$

where $\mu, v \geq 0, \lambda_1, \lambda_2 > 0$ are constant parameters, we note that in almost all practical experiences cases, we set $v = 0, \lambda_1 = \lambda_2 = 1$.



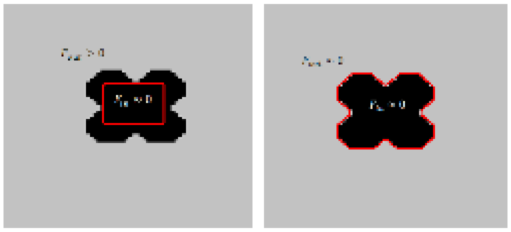


Figure 2. All possible cases in the curve position, and corresponding values of the $F_{in}(c)$ and $F_{out}(c)$.

3 LEVEL SET FORMULATION OF THE CHAIN-VESE MODEL

The level set method evolves a contour (in two dimensions) or a surface (in three dimensions) implicitly by manipulating a higher dimensional function, called level set $\Phi(X,t)$. The evolving contour or surface can be extracted from the zero level set $C(X,t) = \{\Phi(X,t) = 0\}$. The advantages of using this method is the possibility to manage automatically the topology changes of curve in evolution, however, the curve C can be divided into two or three curves, inversely, several curves may merge and become a single curve [15]. By convention we have:

$$\begin{cases} c = \partial w = \{(x,y) \in \Omega : \emptyset(x,y) = 0\}, \\ inside(c) = w = \{(x,y) \in \Omega : \emptyset(x,y) > 0\}, \\ outside(c) = \Omega \backslash \overline{w} = \{(x,y) \in \Omega : \emptyset(x,y) < 0\}. \end{cases}$$

where $w \subset \Omega$ is open, and $c = \partial w$. Fig.3 illustrates the above description of level set function.

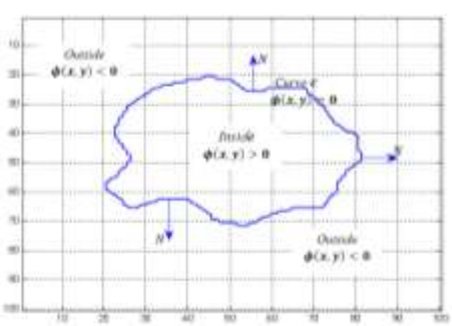


Figure 3. Level sets function, curve $c = \{(x,y): \phi(x,y) = 0\}$

Now we focus on presenting Chan-Vese model via level set function. To express the inside and outside concept, we call Heaviside function H defined as follow:

$$H(z) = \begin{cases} 1, & if\ z \geq 0 \\ 0, & if\ z < 0' \end{cases}$$

$$\delta_0(z) = \frac{d}{dz} H(z), \quad Z \in \mathbb{R} \qquad (5)$$

Using level set $\phi(x,y)$ to describe curve $c(x,y)$ and Heaviside function, the formulation (4) can be written as:

$$F(c_{in}, c_{out}, \phi) = \mu . \int_\Omega \delta(\phi(x,y)) |\nabla \phi(x,y)| dxdy + v \int_\Omega H(\phi(x,y))\, dxdy + \lambda_1 \int_\Omega |u_0(x,y) - c_{in}|^2 H(\phi(x,y)) dx\, dy + \lambda_2 \int_\Omega |u_0(x,y) - c_{out}|^2 \left(1 - H(\phi(x,y))\right) dx\, dy. \qquad (6)$$

Where the first integral express the length curve, that is penalized by μ. The second one presents the area inside the curve, which is penalized by v.

Using level set $\phi(x,y)$ the constants c_{in} and c_{out} can be expressed easily:

$$c_{in} = average(u_0) \quad on\ \phi \geq 0$$
$$= \frac{\int_\Omega u_0(x,y) H(\phi(x,y)) dxdy}{\int_\Omega H(\phi(x,y)) dxdy}. \qquad (7)$$

$$c_{out} = average(u_0) \quad on\ \phi < 0$$
$$= \frac{\int_\Omega u_0(x,y) \left(1 - H(\phi(x,y))\right) dxdy}{\int_\Omega \left(1 - H(\phi(x,y))\right) dxdy}. \qquad (8)$$

If we use the Heaviside function as it has already defined (equation 5), the functional will be no differentiable because H is not differentiable. To overcome this problem, we consider slightly regularized version of H. There are several manners to express this regularization; the one used in [3] is given by:

$$H_\varepsilon(z) = \frac{1}{2}\left(1 + \frac{2}{\pi} \arctan\left(\frac{z}{\varepsilon}\right)\right)$$
$$\delta_\varepsilon(z) = \frac{1}{\pi} . \frac{\varepsilon}{\varepsilon^2 + z^2} . \qquad (9)$$

where ε is a given constant and $z \in \mathbb{R}$.

This formulation is used because it is different of zero everywhere as their graphs show on fig. 4. However, the algorithm tendencies to compute a global minimize, and the Euler-Lagrange equation (10) acts on all level curves, this that allows, in practice, obtaining a global minimizer (object's boundaries) independently of the initial curve position. More detail, comparisons with another formulation of H, and influence of ε value may be find in [3].

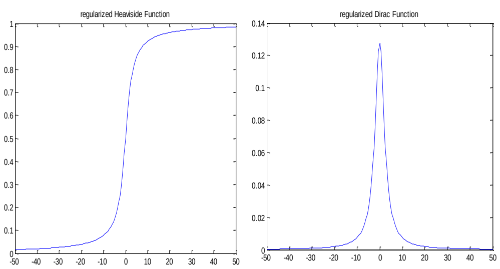


Figure 4. The Heaviside and Dirac function for $\varepsilon = 2.5$.

To minimize the formulation (6) we need their associated Euler-Lagrange equation, which is obtained by calculus of variation principle. This one is given in [3] as follow:

$$\frac{\partial \phi}{\partial t} = \delta_\varepsilon(\phi)\left[\mu \ \mathrm{div}\left(\frac{\nabla\phi}{|\nabla\phi|}\right) - v - \lambda_1(u_0 - c_{in})^2 + \lambda_2(u_0 - c_{out})^2\right] = 0 \ . \quad (10)$$

with $\phi(0,x,y) = \phi_0(x,y)$ is the initial level set function which is given.

4 IMPLEMENTATION

In this section we present the algorithm of the Chan-Vese model formulated via binary level set method implemented during this work.

4.1 Initialization of Level Sets

Traditionally, the level set function is initialized to a signed distance function to its interface. In almost works this one is a circle or a rectangle. This function is used widely thanks to its propriety $|\nabla\boldsymbol{\phi}| = \mathbf{1}$ which simplifies calculations [15]. In traditional level set, re-initialize $\boldsymbol{\phi}$ is used as a numerical remedy for maintaining stable curve evolution [8], [9], [11]. Re-initialize $\boldsymbol{\phi}$ consists to solve the following re-initialization equation [15]:

$$\frac{\partial \phi}{\partial t} = sign(\phi_0)(1 - |\nabla\phi|). \quad (11)$$

Much works, in literature, have been devoted to the re-initialization problem [16], [17]. Unfortunately, in some cases, for example ϕ_0 is not smooth or it is much steeper on one side of the interface than other, the resulting zero level of function ϕ can be moved incorrectly [18]. In addition, and from the practical viewpoints, the re-initialization process is complicated, expensive, and has side effects [17]. For this, there are some recent works avoiding the re-initialization such as the model proposed in [19].

More recently, the level set function is initialized to a binary function, which is more efficient and easier to construct practically, and the initial contour can take any shape. Further, the cost for re-initialization is efficiently reduced [20]. On figure 5 we illustrate an example of binary initialization of level set function which is equal +1 inside the curve and -1 outside.

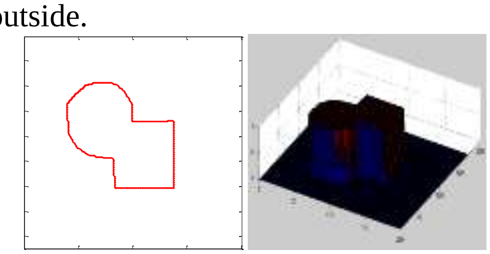


Figure 5. Binary Level Set Function calculate from the curve position

4.2 Descretization

To solve the problem numerically, we have to call the finite differences, often, used for numerical discretization [15].
To implement the proposed model, we have used the simple finite difference schema (forward difference) to compute temporal and spatial derivatives, so we have:

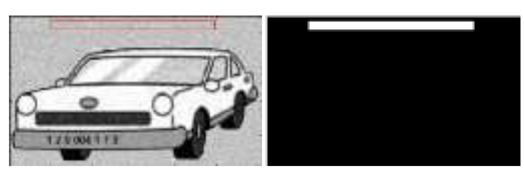
- Temporal discretization:
$$\frac{\partial \phi}{\partial t} = \frac{\phi_{i,j}^{n+1} - \phi_{i,j}^{n}}{\Delta t}$$
- Spatial discretization
$$\nabla^x \phi_{i,j} = \frac{\phi_{i+1,j} - \phi_{i,j}}{\Delta x}$$
$$\nabla^y \phi_{i,j} = \frac{\phi_{i,j+1} - \phi_{i,j}}{\Delta y}$$

4.3 Algorithm

We summarize the main procedures, of the algorithm as follow:
Input: Image u_0, Initial curve position IP, parameters λ_1, λ_2, μ, v, Δt, ε Number of iterations N.
Output: Segmentation Result Initialize Φ_0 to binary function
For all N *Iterations* do
Calculate c_{in} and c_{out} using equations (7,8)
Calculate Curvature Terms K;
Update Level Set Function
$\Phi_{ij}^{n+1} = \Phi_{ij}^{n} + \Delta t . \delta(\phi_{i,j}) . [\mu . K_{i,j} - v - \lambda_1 (u_0(i,j) - c_{in})^2 + \lambda_2 (u_0(i,j) - c_{out})^2]$
Keep ϕ a binary function:
$\phi = 1 \; if \; \phi > 0, otherwise, \phi = -1.$
End

5 EXPERIMENTAL RESULTS

First of all, we note that our algorithm is implemented via Matlab 7.0 on 3.06-GHz and 1Go RAM, intel Pentium IV.
Now, let us present some of our experimental outcomes of the proposed model. The numerical implementation is based on the algorithm for curve evolution via level-sets. Also, as we have already explained, the model utilizes the image statistical information (average intensities inside and outside) to stop the curve evolution on the objects' boundaries, for this it is less sensitive to noise and it has better performance for images with weak edges. Furthermore, the *C-V* model implemented via level set can well segment all objects in a given image. In addition, the model can extract well the exterior and the interior boundaries. Another important advantage of the model is its less sensitive to the initial contour position, so this one can be anywhere on the image domain. For all the following results we have setting $\Delta t = 0.1$, $\varepsilon = 2.5$, and $\lambda_1 = \lambda_2 = 1$.
The result of segmentation on Fig.6 summarizes much of those advantages. From the initial contour, which is on the background of the image, the model detects all the boundaries' objects; even those are inside the objects (interior boundaries) as: Headlights, the windows, and the registration number of the car. Finally, we note also that we have the same outcome for any initial contour position.



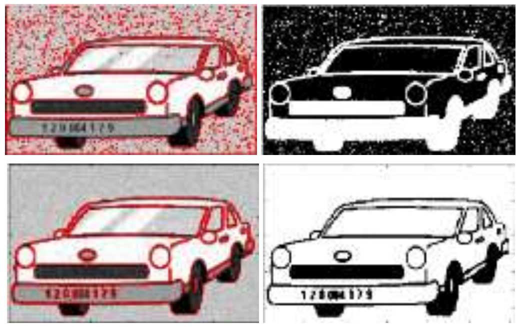
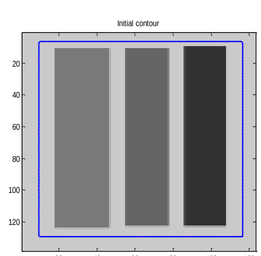
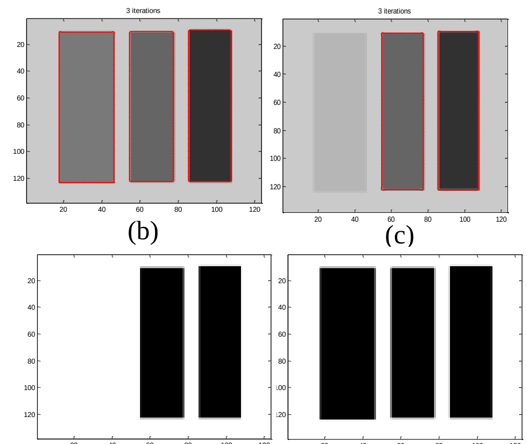


Figure 6. Detection of all boundaries from a noisy image independently of curve initial position, with extraction of the interior boundaries. First row shows the initial curve and its corresponding binary Level set function. Second row intermediate results. Third row final results. We set $\mu = 0.1; \quad v = 30. \; CPU\ time = 14.98s$.

Now, we want to show the model's ability to detect weak boundaries. So we choose a synthetic image which contains three objects with different intensities as follow: Fig. 7 (b): 180, 100, 50, background =200; Fig. 7 (c): 120, 100, 50, background =200. As segmentation results show (Fig. 5) : the model failed to extract boundaries' object which have strong homogeneous intensity (Fig. 7(b)), but when the intensity is slightly different Chan-Vese model can detect this boundaries (Fig.7(c)). Note also, *C-V* model can extract objects' boundaries but it cannot give the corresponding intensity for each region: all objects on the image result are characterized by the same intensity (c_{in}) even though they have different intensities in the original image (Fig.7(d)) and (Fig.7(e)).



(a)

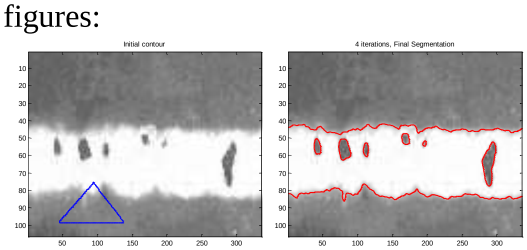


(b) (c)

(d) (e)

Figure 7. Results for segmenting multi-objects with three different intensities (a) Initial contour. Column (b) result segmentation for 180, 100, 50, background =200. Column (c) result segmentation for 120, 100, 50, background =200. For both experiences we set $\mu = 0.1; \quad v = 20.$ $CPU\ time = 38.5s$.

As it has already discussed in the introduction of this paper, our target focuses on the radiographic image segmentation, applied to detect defects that could happen during the welding operation; it's about automatic control operation named *Non Destructive Testing* (*NDT*). The results obtained have been represented in the following figures:



(a) (b)

Figure 8. Detection of all defects in weld defects radiographic image a) curve initialization. b) Curve evolution result. $\mu = 0.2; \; v = 20, CPU\ time = 14.6s$.

Another example of radiographic image on which we have added a Gaussian noise ($\sigma^2 = 0.005$), and without any preprocessing of the noise image (filtering). The model can detect boundaries of defects very well, even though the image is nosy.

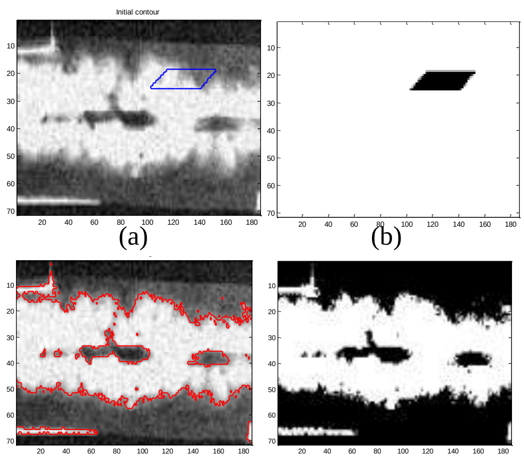


Figure 9. Detection of defects in noisy radiographic image first column (a, c) shows the initial and final contours. Second one (b, d), the corresponding initial and final binary function. $\mu = 0.5;\ \ v = 20, CPU\ time = 13.6s.$

An example of radiographic image that we cannot segmented by Edge-based model because of their very weak boundaries; in this case the Edge-based function (equation 1) is never ever equal or slight equal zero and curve doesn't stop evolution till vanishes. As results show, the *C-V* model can detect very weak boundaries.

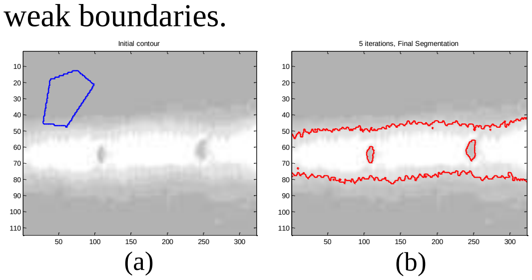


Figure 10. Segmentation of Radiographic Image with very weak boundaries. a) Curve initialization. b) Curve evolution result. $\mu = 0.1;\ \ v = 20.\ CPU\ time = 38.5s.$

Note that the proposed algorithm has less computational complexity and it converge in few iterations, by consequent, CPU time is reduced.

5 CONCLUSION

The algorithm was proposed to detect contours in given images which have gradient edges, weak edges or without edges. By using statistical image information, evolve contour stops in the objects boundaries. From this, The *C-V* model benefits a several advantages including robustness even with noisy data, and automatic detection of interior contours. Also, the initial contour can be anywhere in the image domain.

Before closing this paper, it is important to remember that *Chan-Vese* model separates two regions, so we have as a result the background presented with constant intensity (c_{out}) and all objects presented with (c_{in}). To extract objects with their corresponding intensities; we have to use multiphase or multi-region model. That is our aim for future work.

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