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Local Segmentation via an Implicit Region-Based Deformable Model Applied To Weld Defects Extraction

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Abstract—**This paper is devoted to present and discuss a model that allows a local segmentation by using statistical information of a given image. It is based on Chan-Vese model, curve evolution, partial differential equations and binary level sets method. The proposed model uses the piecewise constant approximation of Chan-Vese model to compute Signed Pressure Force (SPF) function, this one attracts the curve to the true object(s)'s boundaries.The implemented model is used to extract weld defects from weld radiographic images in the aim to calculate the perimeter and surfaces of those weld defects. Encouraged resultants are obtained on synthetic and real radiographic images.**

Keywords-Active contour, Chan-Vese Model, binary Level set, local segmentation, weld radiographic images.

I. INTRODUCTION

Nowadays the visual information has being introduced in very large applications, thank to that image processing possess more and more a crucial importance. Many axes had being created to recover all the problems and difficulties related to use images as input for an automatic system. One of those axes is the segmentation with which this present work is concerned. One of the applications of computer vision is devoted to *Non Destructive Testing*NDT by radiographic technique. In welding, industrial radiographic operation is similar to the medical one, it consists to submit a gamma rays or x-rays from its source through the welded joint. The differences of the densities between the based material, the welded joint and defects are reflected on the radiographic films. The objective of our team is to segment those digital images in order to give them the structural forms for ulterior processing, such as computing the surfaces and the perimeters of weld defects with the aim to use them in NDT task.

Segmenting images by deformable models or variationnal methods has known great success and wide using. Many functionals have being proposed. The classification of those models is variable according to on which we are based to do that. Two famous categories are often met in literatures; the first one is based on the terms that link the model to the image: it can be oriented edge or region. The second one is based onthe way to represent the curves: explicit representation or implicit one [1][2].

Almost all edge-based models use the gradient of the image u_0 to locate the objects' edges. Therefore, the curve is locally stopping when it reaches high image gradients [1] [2], [3]. For that an edge-function is often used, which is strictly positive inside homogeneous regions and near zero on the edges, it is formulated as follow:

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

The gradient operator is well adapted to a certain class of problems like robustness to region with inhomogeneous intensity. They have important drawbacks such as:sensitive to noise, they are very sensitive to initial conditions (when the contour initialization is not completely inside or outside the region to segment). Moreover, they are only able to segment regions with sharp edges, so this can result in failure when the region edges are smoother[4]. Many works are focusing in overcoming those problems, for example in [5] the authors managed to improve the sensitivity to initialization, by creating a vector flow driving the active contour to high image gradients, but the sensitivity to noise still remains.

On the contrary, the *region-based*approaches avoid the derivatives of the image intensity and they use statistical information of the image intensity to attract the curve evolution at the objects' boundaries. Often we use the average intensities and standarddeviation. However region-based approaches are more robust to the noises, they detect objects whose boundaries cannot be defined or are badly defined through the gradient, they automatically detect interior contours, and the initialization could be anywhere on the image domain not necessary surrounded the objects.In addition, they have bettertendency to compute a global minimum of the functional [6][7].

In this present work, from a side, we want to benefit from the advantages related region-based Models, and getting local segmentation (extracting desired object) from another side. To achieve that goal, we proposed algorithm based on piecewise Chan-Vese Model and allows a local segmentation.

This paper is organized as follows: section 2 is devoted to a brief background of *contour-based*and *region-based*Models.In section 3 we explain the proposed model called *Local Chan-Vese*, which allows a local segmentation and use statistical image information. The section 4 is dedicated to the implementation in which we introduce the *Binary Level Set*, and the algorithm implemented during this work. The experimental results on synthetic and weld radiographic images are the aim of section5.We enclose the article by conclusion in section 6.

II. IMPLICIT REGION-BASED AND CONTOUR-BASED DEFORMABLE MODELS

A. Implicit Contour-based Models

For image segmentation, the initial contour is moved by image driven forces to the desired objects'boundaries. In such models, two types of forces are considered: the internal forces, defined within the curve, they are designed to keep the curve smooth during the deformation process.While the external forces, which are computed from the underlying image data, are defined to move the model towards an object's boundaries or other desired features within the image.

Several formulations were coupled viscosity term and image data was presented:

- Malladiet al. formulation [8]

$$\frac{\partial \Phi}{\partial t} = g.(K+\propto).\|\nabla\Phi\| \tag{2}$$

Where: g is the edge function given by (1) and $\propto > 0$ constant that shorten the curve, and $\propto < 0$ stretch it.

This scheme works well for objects that have good contrast. When the object boundary is indistinct or has gaps, however, this contour tends to leak through the boundary. To solve this problem, other formulations were proposed.

- Casselleset al. formulation [9]

$$\frac{\partial \Phi}{\partial t} = g.(K+\propto).\|\nabla\Phi\| + \nabla g.\nabla\Phi \tag{3}$$

Where $\nabla g.\nabla\Phi$ is an additional stop term which can pull back the model to the contour if it passes the boundary.

B. Implicit Region-based Models (Chan-Vese)

Inspired from the Mumford-Shah functional [10], Chan and Vese have proposed functional that approximate the M-S Model by set of constants [11][12]. To segment a given image u_0 defined in domain Ω, we have to minimize the functional given by:

$$E^{CV} = F_{in}(c) + F_{out}(c) = \int_{inside(c)} |u_0(x,y) - c_{in}|^2 dx\, dy$$
$$+ \int_{outside(c)} |u_0(x,y) - c_{out}|^2 dx\, dy \tag{4}$$

Where c_{in} and c_{out} are the average intensities inside and outside curve respectively.

Chan and Vese have added some regularizing terms, like the length of curve c, and the area of the region inside curve. Also the functional could be formulated via Level Set function proposed by Osher [13][14] and by introducing Heaviside function to express the inside and outside notions, Chan-Vese model becomes.

$$F(c_{in}, c_{out}, \phi) = \mu.\int_{\Omega} \delta_\varepsilon(\phi(x,y))|\nabla\phi(x,y)|dxdy$$
$$+ v\int_{\Omega} H_\varepsilon(\phi(x,y))\, dxdy$$
$$+ \lambda_1 \int_{\Omega} |u_0(x,y) - c_{in}|^2 H_\varepsilon(\phi(x,y))dx\, dy$$
$$+ \lambda_2 \int_{\Omega} |u_0(x,y) - c_{out}|^2 \left(1 - H_\varepsilon(\phi(x,y))\right) dx\, dy \tag{5}$$

Where $\mu, v \geq 0, \lambda_1, \lambda_2 > 0$ are constant parameters. H_ε is the regularized version of Heaviside function H and δ_ε its derivative. They are formulated by:

$$\begin{cases} H_\varepsilon(z) = \frac{1}{2}\left(1 + \frac{2}{\pi}\arctan\left(\frac{z}{\varepsilon}\right)\right) \\ \delta_\varepsilon(z) = \frac{1}{\pi}.\frac{\varepsilon}{\varepsilon^2 + z^2} \end{cases} \tag{6}$$

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

$$c_{in} = \text{average}(u_0) \quad \text{on } \phi \geq 0$$
$$= \frac{\int_{\Omega} u_0(x,y)H_\varepsilon(\phi(x,y))dxdy}{\int_{\Omega} H_\varepsilon(\phi(x,y))dxdy} \tag{7}$$

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

In almost all cases the equation (5) is transformed to an evolution equation (Euler-Lagrange), and minimized iteratively by using the gradient decent method.

$$\frac{\partial\phi}{\partial t} = \delta_\varepsilon(\phi)\left[\mu \text{div}\left(\frac{\nabla\phi}{|\nabla\phi|}\right) - v - \lambda_1(u_0 - c_{in})^2 + \right.$$
$$\lambda 2u0 - cout2 = 0 \tag{9}$$

As the artificial time $t \to \infty$, $\frac{\partial\phi}{\partial t} \to 0$ which gives the solution to the above equation. Usual choices of $\lambda_1$and λ_2 are 1, v is 0, and the parameter μ controls length curve (size of captured objects). However, with small μ, small objects are captured (fineness segmentation) and with larger μ only larger objects are extracted (coarse segmentation).

III. LOCAL CHAN-VESE MODEL

It is well-known that the region-based models discussed in the above section used global statistical information to drive evolving curve(s) towards the objects' boundaries. However all objects in the given image are extracted, this is called global segmentation. For some specific tasks we are interesting by analyzing only a specific object(s). That is the case for extracting the weld defects in weld radiographic images, more explanation in the experimental section.

To exploit the many advantages of region-based models and getting a local segmentation, we have adopted a model proposed in [15][16]. Authors have inspired from piecewiseconstant Chan-Vese model and they proposed to use a *Signed Pressure Force* (SPF) function. Which is able to control the direction of curve's evolution, it has opposite signs around the object boundary, so the contour can shrink when it is outside the object or expand when it is inside the object. The SPF is formulated as follows:

$$Spf\big(I(x,y)\big) = \frac{I(x,y) - \frac{c_{in} + c_{out}}{2}}{\max\left|I(x,y) - \frac{c_{in} + c_{out}}{2}\right|}, \quad (x,y) \in \Omega$$

Where c_{in} and c_{out} are defined as in Chan-Vese model by the equations (7) and (8).
The evolving equation corresponding to that model is given by equation (10)

$$\frac{\partial\Phi}{\partial t} = spf\big(I(x,y)\big)\left(div\left(\frac{\nabla\Phi}{|\nabla\Phi|}\right) + \alpha\right)|\nabla\Phi| + \nabla spf\big(I(x,y)\big)\nabla\Phi, \quad (10)$$

Where α is a positive constant, its role is increasing the speed up of convergence.

Similarly to the second term in equation (3) the term $\nabla spf\big(I(x,y)\big)\nabla\Phi$ is used to increase the capture of edges. Since the proposed model used statistical information of region this term could be removed because region-based models have a large capture of edges and high capacity of anti-edge leakage. In addition, and as it was pointed out in [17] [18] the curvature-based term ($\mathrm{div}\left(\frac{\nabla\Phi}{|\nabla\Phi|}\right)$), which ensure the smoothness and regularization of the curve during evolution process, could be replaced by a Gaussian kernel filter. The standard deviation of Gaussian filter can control the regularization strength. However the formulation given in (10) might be reduced to the following one:

$$\frac{\partial\Phi}{\partial t} = \alpha.spf\big(I(x,y)\big).\ |\nabla\Phi|,\ (x,y) \in \Omega \qquad (11)$$

IV. IMPLEMENTATION

A. Initialization to Binary Level Set Function

The curve is represented implicitly via function called Binary Level set, which is defined as follows:

$$\Phi(x,y,t=0) = \begin{cases} -\rho(x,y) \in \Omega_0 - \partial\Omega_0, \\ 0 \qquad (x,y) \in \partial\Omega_0, \\ \ \ \rho(x,y) \in \Omega - \Omega_0. \end{cases} \qquad (12)$$

Using such function has many advantages over the classical signed distance function, such as its efficient and easier to construct practically, and the initial contour can take any shape [15].

B. Algorithm

The implemented algorithm needs as enter: the image, the initial curve position from which we compute the binary level set, Δt, ρ, σ, ε and number of iterations N. The outcomes are object's boundaries, and the smooth version of the original image (restored image) with the desired object(s).

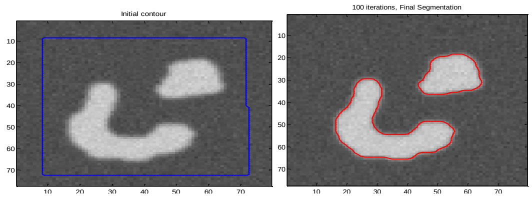
While $n \leq N$
1) Compute the average intensities c_{in} and c_{out}.
2) Compute the SPF value,
3) update the level set :
$$\Phi^{n+1} = \Phi^n + \Delta t.\alpha.spf^n.|\nabla\Phi^n|$$
4) keep the level set as binary function
$\Phi = \rho$ if $\Phi > 0$ otherwise $\Phi = -\rho$
5) Regularize the level set with a Gaussian filter $\Phi = \Phi * G_\sigma$.
6) $n = n + 1$.

End while

V. EXPERIMENTAL RESULTS

In this section, we present and discuss some results of the proposed algorithm. Remember that the algorithm uses statistical image information to stop curve evolution. So it is robust to noise, it can extract interior boundaries, and it handle well image with weak or without edges.

First, let us show the results of segmenting synthetic noisy image for several different initializations.



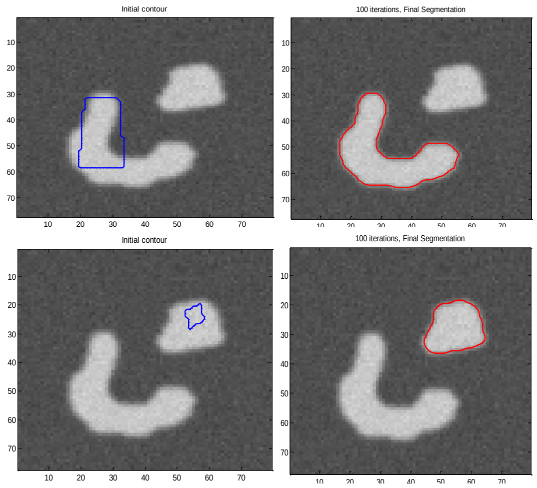


Figure 1. Segmenting a noisy synthetic image. First column: initial curve position (bleu). Second column the final curve position (red) $\propto = 20,\ \Delta t = 1, \varepsilon = 0.1$.

As the results on Fig. 1 show, we get a global segmentation (extract all objects) by surrounding all objects in initialization step, or segmenting desired object by initializing the curve on it. Note that in this example, we have increased the number of iteration (100 iterations) on purpose to show that the algorithm allows a local segmentation when the initialization targets a specific object on the image, otherwise, we can achieving the convergence in less iterations.

The proposed model shares the same drawback as Chan-Vese model in extracting objects that have similar intensities with background. In addition, segmentation could be failure when the image contains some objects with high intensities and others with less intensity than background. The fowling experimental displays that.

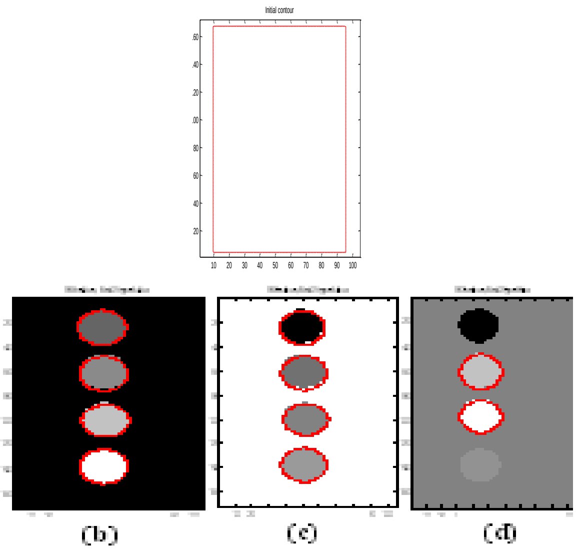


Figure 2. Some special cases (a) Initialization, (b) background has the less intensity (c) background has the highest intensity (d) background has the mean intensity.

Our team deals with industrial radiographic images that are judged very complexes and have mediocre qualities, because of the conditions on which they are taken. Our objective is to segment those digital images in order to give them the structural forms for ulterior processing, such as computing the surfaces and the perimeters of weld defects, such information are very useful in radiographic inspection.

The following experimental reveal the algorithm's outcome for an input thatareweld radiographic imagescharacterized by inhomogeneity intensity, and contains several weld defects.

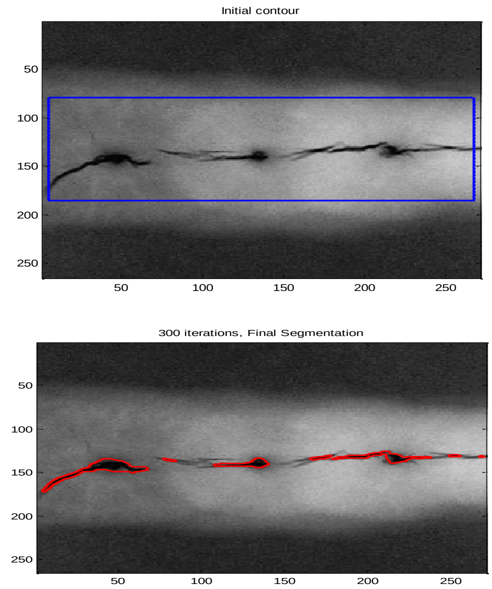
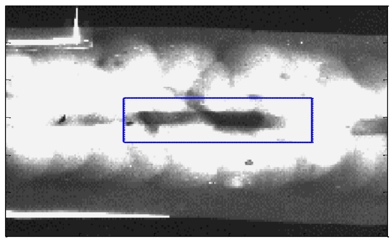
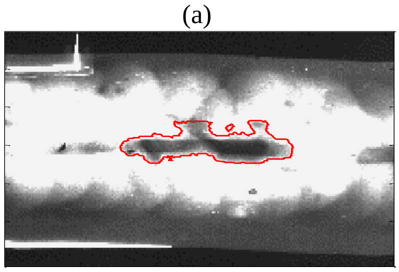


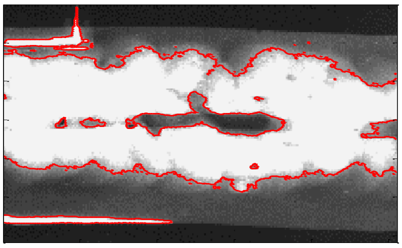
Figure 3. Segmenting a weld radiographic image with inhomogeneity intensity. Top initialization (bleu curve) , low final curve position (red curve), $\propto = 20$

Let us compare the proposed algorithm with some our earlier works summarized in section 2. The Edge-based model presented and developed in [19], and region-based (Chan-Vese) model in [20].

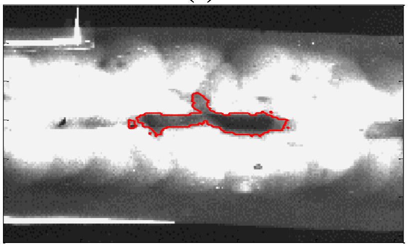


(a)





(c)



(d)

Figure 4. Outcome of three different algorithms, (a) Initialization (b) Segmented via Edge-based, (c) Segmented via region-based (Chan-Vese), (d) Segmented via Local region-based Algorithm $\propto = 5$

To well discuss results, we summarize, in the following table, the iteration number and processing time for the three methods: Edge-based, region-based, and Local region-based model in segmenting the above weld radiographic image of size: 255×123.

TABLE I. ITERATION NUMBER AND PROCESSING TIME FOR THE THREE METHODS

Algorithm	***Iterations***	***CPU time (s)***
Edge-based	690	160.5862
Chan-Vese	100	22.1875
Local Chan-Vese	20	1.28125

According to segmentation results revealed on the figure 4 and what table shows, we can say that successful local segmentation was got (figure 4(d). the defect is extracted from the image and it can be studied. The classical Chan-Vese Model allows also a good segmentation but the defect is incorporated with other regions (figure 4(c)), however a supplementary computation will be necessary to extract just the defect. The Figure 4 (b) displays the segmentation with Edge-based method which gives an extraction of the defect but its contour isn't well pulling out, also, it is very slow compared with the proposed algorithm, furtheredge-based model's outcomes could be worst in the presence of noise.

VI. CONCLUSION

In this paper, we have proposed an algorithm that benefits from the several advantages of region-based models in image segmentation, and allows a global or local segmentation. It is based on the techniques of curve evolution, statistical image information and binary level set. The obtained results are very encouraging. However the proposed model could be improved by introducing multiphase level set to give it the possibility to deal with multi-phase images and can detect multiple objects with different intensities. Other point could be improved which is the sensitive to initial conditions, such point is an open problem in segmenting image by deformable models.

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