Segmentation of the Weld Radiographic Images by the Level Set Method using the Kernel Fuzzy C-Means Clustering

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***Abstract*-- In this paper, we are interested to segment weld radiographic images using the level set method (LSM) based on kernel fuzzy c-means clustering (KFCM) in order to extract the region of interest (weld defects) and to improve the precision of segmentation. The proposed approach contains two successive necessary stages. The first one consists in the application of kernel fuzzy c-means algorithm to get a clustered image. The second stage is based on the using of the appropriate class of the clustered image as an initial contour of the level set method to extract the defects boundaries. The experimental results have shown that the proposed model can extract successfully the interest region from image and confirm its efficiency for welding defects segmentation.**

***Index Terms*--Level set; kernel fuzzy c-means; weld defects; weld radiographic images; image segmentation.**

1. INTRODUCTION

The segmentation of images is the most important operation in the image treatment systems, because it is situated in the hinge between the acquisition of the images and the use of semantics which they contain. The segmentation of images is to search the main constituents of an image (research of objects) in order to extract them. So, it allows to label the dissociated regions with descriptors and it is on this labeling that we are going to apply the algorithms of recognition. The segmentation is a stage required for a large number of high-level tasks necessary for the autonomous systems of vision (for example in robotics), medical [1], Agronomics [2], or relative to the road safety and the surveillance (parkings , airports, etc.) [3]. Of this fact, the number of researchers have been working on the development of methods and dedicated algorithms. Moreover, it constitutes, since a few years, an important axis of research. For proof, the number of published works dealing with this problem is difficult to assess. It is the consequence of several elements: the diversity of the images, the complexity of the problem, the evolution of the calculation machines and an evaluation of the results rather empirical.

In the industrial welding, manufacturing process is widely used in the manufacture of automotive, shipbuilding and aerospace industry [4]. The main defects of welding that occur for the region are the porosity, cracks, the lack of penetration, etc. These defects occur generally due to the lack of penetration, overlap, incomplete fusion, and internal discontinuities in the welded joints. The computer vision plays the most important role in many applications of industry to make effectiveness and precision of automatic detection processes. One of the applications of computer vision is dedicated to the Non-Destructive Testing NDT by radiographic technique. The NDT is a set of techniques used in the industry to estimate the properties of a component, a material, or a system without causing damage. In this paper, The level set method [5-13] and kernel fuzzy c-means (KFCM) Clustering [14-18] are two types of fundamental tools proposed in this work for segmentation of the weld radiographic images.

We use radiographic images which are the outcomes of radiographic operation; because they are widely used for nondestructive method for detection of internal defects in the industrial weld images [19, 20]. The application of kernel fuzzy c-means algorithm is used to get a clustered image. In the second stage level sets are used to extract the defects boundaries. This combined method gives good segmentation quality.

2. THE LEVEL SET METHOD

The Level Set method was developed in the 1980s by the mathematicians Stanley Osher and James Sethian [6], [21]. It has become popular in many disciplines, such as image processing, computer graphics, computational geometry, optimization, and computational fluid dynamics. The level set method tracks the motion of an interface by embedding the interface as the zero level set of the signed distance function. The advantage of the level set method is that it makes it very easy to follow shapes that change topology, for example when a shape splits in two, develops holes, or the reverse of these operations [6].

A. Front propagating with curvature-dependent speed

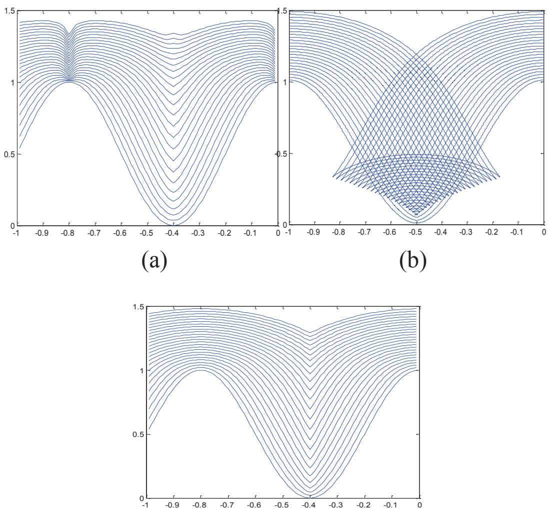
The fundamental aspects of front propagation in our context can be illustrated as follows. Let $\gamma(0)$ be a smooth, closed initial curve in R^2 , and let $\gamma(t)$ be the one–parameter family of curves generated by moving $\gamma(0)$ along its normal vector field with speed $F(K)$. Here, $F(K)$ is a given scalar function of the curvature K. Thus, $n.x_t = F(k)$, where x is the position vector of the curve, t is the time and n is the unit normal to the curve. Consider a speed function of the form $1 - \epsilon K$, where ϵ is a constant. An evolution equation for the curvature K, see [22], is given by

$$K_t = \epsilon K_{\alpha\alpha} + \epsilon K^3 - K^2 \quad (1)$$

where we have taken the second derivative of the curvature K with respect to arclength α . This is a reaction-diffusion equation; the drive toward singularities due to the reaction term ($\epsilon K^3 - K^2$) is balanced by the smoothing effect of the diffusion term ($\epsilon K_{\alpha\alpha}$). Indeed, with $\epsilon = 0$, we have a pure reaction equation $K_t = -K^2$. In this case, the solution is $K(s,t) = K(s,0)/(1 + tK(s,0))$,which is singular in finite t if the initial curvature is anywhere negative. Thus, corners can form in the moving curve when $\epsilon = 0$. As an example, consider the periodic initial cosine curve propagating with speed $F(K) = 1 - \epsilon K, \epsilon > 0$.

$$\gamma(0) = (-s, [1 + \cos 2\pi s]/2) \quad (2)$$

As the front moves, the troughs at s = n + 1/2, n = 0,±1,±2, ...are sharpened by the negative reaction term (because K < 0 at such points) and smoothed by the positive diffusion term (see Figure 1a).



(a) (b)

(c)

Fig.1. Propagating Cosine Curve.

The figure.1b and figure.1c shows two possibilities of weak solution for this problem, one is called "swallowtail", which is generated by letting the front pass through itself, the other is called "entropy solution", which can be viewed as simply remove the " tail" from "swallowtail". The entropy solution is constructed through Huygen's principle. Another way to obtain the entropy solution is through the notion of an entropy condition posed by Sethian in [23], [22]. The weak solution figure. 1c given by the entropy condition is the weak solution we want, it satisfies most physical phenomena.

B. Surface moving

Given a moving closed hypersurface $\Gamma(t)$, that is, $\Gamma(t = 0) : [0,\infty) \to R^N$ we wish to produce an Eulerian formulation for the motion of the hypersurface propagating along its normal direction with speed F, where F can be a function of various arguments, including the curvature, normal direction, etc. The main idea is to embed this propagating interface as the zero level set of a higher dimensional function φ. Let $\varphi(x, t = 0)$ where $x \in R^N$ be defined by

$$\varphi(x, t = 0) = \pm d \quad (3)$$

And where d is the distance from x to $\Gamma(t = 0)$ and the plus (minus) sign is chosen if the point x is outside (inside) the initial hypersurface, $\Gamma(t = 0)$. Thus, we have an initial function $\varphi(x, t = 0)$: $R^N \to R$ with the property that

$$\Gamma(t = 0) = (x/\varphi(x, t = 0) = 0) \quad (4)$$

Now, our goal is to produce an equation for the evolving function $\varphi(x, t)$: which contains the embedded motion of, $\Gamma(t)$ as the level set $\varphi = 0$: Let $x(t)$, $t \in [0, \infty)$ be the path of a point on the propagating front. That is, $x(t = 0)$ is a point on the initial front $\Gamma(t = 0)$, and $x(t) = F(x(t))$ with the vector x_t normal to the front at $x(t)$. Since the evolving function φ is always zero on the propagating hypersurface, we must have.

$$\varphi(x(t), t) = 0 \quad (5)$$

By the chain rule,

$$\varphi_t + \nabla\varphi(x(t,t)).x'(t) = 0 \quad (6)$$

Since F already gives the speed in the outward normal direction, then $x'(t).n = F$ where $n = \nabla\varphi/|\nabla\varphi|$. Thus, we then have the evolution equation for φ, namely

$$\begin{cases} \varphi_t + F|\nabla\varphi| = 0 \\ \varphi(x, t = 0) \quad \text{was given} \end{cases} \quad (7)$$

We refer to this as a Hamilton-Jacobi "type" equation because, for certain forms of the speed function F, we obtain the standard Hamilton-Jacobi equation. However, the level surface $\varphi = 0$, and hence the propagating hypersurface $\Gamma(t)$, may change topology, break, merge, and form sharp corners as the function φ evolves, see [6].

The major advantage of this Eulerian formulation concerns numerical approximation. Because $\varphi(x, t)$ remains a function as it evolves, we may use a discrete grid in the domain of x and substitute finite difference approximations for the spatial and temporal derivatives. For example, using a uniform mesh of spacing h, with grid nodes (i, j) and employing the standard notation φ_{ij}^n, we might write:

$$\frac{\varphi_{ij}^{n+1} - \varphi_{ij}^n}{\Delta t} + F(\nabla_{ij}\varphi_{ij}^n) = 0 \quad (8)$$

The second major advantage of the above formulation is that intrinsic geometric properties of the front may be easily determined from the level function φ. For example, at any point of the front, the normal vector is given by $n = \frac{\nabla\varphi}{|\nabla\varphi|}$ and the curvature is easily obtained from the divergence of the gradient of the unit normal vector to front, i.e.,

$$K = \nabla.\frac{\nabla\varphi}{|\nabla\varphi|} = \frac{\varphi_{xx}\varphi_y^2 - 2\varphi_x\varphi_y\varphi_{xy} + \varphi_{yy}\varphi_x^2}{(\varphi_x^2 + \varphi_y^2)^{3/2}} \quad (9)$$

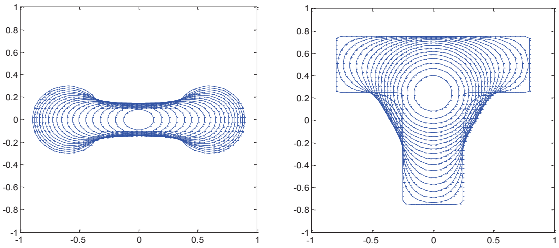


Fig.2. Propagating Surfaces.

3. The Formulation of Level Set

The level set method defined in Eq. (7) can be extended to set up a mathematical model for image segmentation. There are various models based on this idea [24], [25], [26], [7], which are slightly different from each other. One typical model is the following [21-26]:

$$\varphi_t + g_I(1 - \epsilon k)|\nabla\varphi| = 0 \tag{10}$$

Where $F = g_I(1 - \epsilon k)$ is the speed function, $g = e^{-\alpha|\nabla(G * I_0(x))|}, \alpha > 0, G * I_0(x)$ is the convolution of the original image $I_0(x)$ with a Gaussian function G. For the level set equations, a reinitialization phase is necessary. The purpose of reinitialization is to keep the evolving level set function close to a signed distance function during the evolution. It is a numerical remedy for maintaining stable curve evolution. The reinitialization step is to solve the following evolution equation:

$$\varphi_t + sgn(\varphi_0)(|\nabla\varphi| - 1) = 0 \tag{11}$$

Here $\varphi(x, t = 0) = \varphi_0(x)$

A. Numerical Implementation

To solve the Eq. (10), we need to discretize the domain and apply an appropriate finite difference method. Naively applying central difference approximations will cause oscillation, unless the time step is small enough. There is no time step that can produce a scheme which correctly incorporates the entropy condition [21]. Therefore, in practice, there are some numerical schemes solving the Eulerian.

First, we define some notations which will be used in the numerical implementation:

D^{+x} is the forward difference approximation for the spatial derivative. Similarly, D^{-x} is the backward difference approximation and D^{0x} is the central difference approximation, which are defined respectively as follows:

$$D^{+x}u = \frac{u(x+h,t) - u(x,t)}{h}$$

$$D^{-x}u = \frac{u(x,t) - u(x-h,t)}{h}$$

$$D^{0x}u = \frac{u(x+h,t) - u(x-h,t)}{2h} \tag{12}$$

The operators $\nabla^+$and $\nabla^-$are calculated as follows:

$$\nabla^+ = \left[max\left(D_{ij}^{-x}, 0\right)^2 + min\left(D_{ij}^{+x}, 0\right)^2 + max\left(D_{ij}^{-y}, 0\right)^2 + min\left(D_{ij}^{+y}, 0\right)^2\right]^{1/2}$$

$$\nabla^- = \left[max\left(D_{ij}^{+x}, 0\right)^2 + min\left(D_{ij}^{-x}, 0\right)^2 + max\left(D_{ij}^{+y}, 0\right)^2 + min\left(D_{ij}^{-y}, 0\right)^2\right]^{1/2}$$

(13)

In general, the numerical implementation for the level set equations defined above is based on the algorithm introduced in [21-26]. In brief, it can be denoted as the following equation:

$$\varphi_{ij}^{n+1} = \varphi_{ij}^n + \Delta t\Big[v\big(min(g_{ij}, 0)\,\nabla^- + max(g_{ij}, 0)\nabla^+\big) + (g_{ij}k_{ij}((D_{ij}^{0x})^2 + (D_{ij}^{0y})^2)^{1/2})\Big] \tag{14}$$

B. Essentially non-oscillatory schemes

Finite difference and finite volume schemes are based on discrete interpolation data using polynomials or other simple functions. It is known that if more points are used in the stencil then more accuracy is obtained for the drawings. But if the stencil contains a singular point, it produces an oscillation. ENO schemes are introduced by Harten, Engquist, Osher and Chakravarthy [27]. The purpose of these schemes is to choose the stencil without singular point.

$$Q^0(x) = \varphi_{i,j}$$

For $k^1 = \{i - 1, i\}$:

$$Q^1(x) = \frac{\varphi_{k^1+1,j} - \varphi_{k^1,j}}{\Delta x}(x - x_i)$$

$$d_{i,j}^{(1)} = \frac{dQ^1}{dx}(x) = \frac{\varphi_{k^1+1,j} - \varphi_{k^1,j}}{\Delta x}$$

$$a^1 = \frac{\varphi_{k^1+1,j} - 2\varphi_{k^1,j} + \varphi_{k^1-1,j}}{2\Delta x}$$

$$b^1 = \frac{\varphi_{k^1+2,j} - 2\varphi_{k^1+1,j} + \varphi_{k^1,j}}{2\Delta x}$$

$$c^1 = \begin{cases} a^1 & if\ |a^1| \le |b^1| \\ b^1 & elseif \end{cases}$$

$$k_2 = \begin{cases} k^1 - 1 & if\ |a^1| \le |b^1| \\ k^1 & elseif \end{cases}$$

$$\boldsymbol{Q^2(x) = Q^1(x) + c^1(x^2 - (x_{k^1} + x_{k^1+1})x + x_{k^1}x_{k^1+1})}$$

$$\boldsymbol{\frac{dQ^2(x)}{dx}(x_i) = \frac{dQ^1(x)}{dx}(x_i) + c^1(2(i - k^1) - 1)\Delta x = d_{i,j}^{(2)}(k^1)}$$

$$\begin{cases} if\ k^1 = i - 1\ then\ \varphi_x^- = \dfrac{dQ^2(x)}{dx} = d_{i,j}^{(1)} + c^1\Delta x \\ if\ k^1 = i\ \ then\ \varphi_x^+ = \dfrac{dQ^2(x)}{dx} = d_{i,j}^{(1)} - c^1\Delta x \end{cases}$$

4. KERNEL FUZZY C-MEANS ALGORITHM

The kernel fuzzy c-means (KFCM) [28] is an improvement of the FCM method [29-30]. By basing itself on the theoretical development of this algorithm, we modified the objective function of the classical fuzzy c-means algorithm (FCM) [31]. We used a distance "induced kernel" spatial metric and a penalty on the membership functions. First of all, the Euclidean distance original in the FCM is replaced by a distance induced kernel, and therefore the corresponding algorithm called kernel fuzzy c-means (kFCM) is derived. It is shown to be more robust than the FCM. The steps required for the KFCM algorithm are the following:

1- Fix c, t_{max}, $m \geq 2$, and $\varepsilon > 0$ for some positive constants. Where t_{max} is the maximum iterative number.
2- Initialize the memberships matrix u_{ik}^{0}.
3- Select initial class prototypes $\{v_i\}_{i=1}^{c}$.
4- For $t = 1$ to t_{max} do:
  - ✓ Update all prototypes v_i
  - ✓ Update all memberships u_{ik}.
  - ✓ Compute $E^t = \max_{i,k}\left|u_{ik}^{t} - u_{ik}^{t-1}\right|$, if $E^t \leq \varepsilon$, stop;

End

5. PROPOSED APPROACH

In this paper, we have proposed a method which combines between level set method and kernel fuzzy c-means algorithm to extract the defects boundaries. The main steps can be explained as follows:

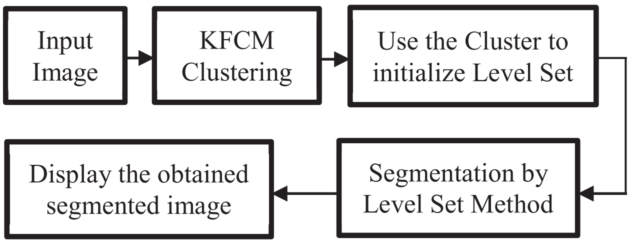
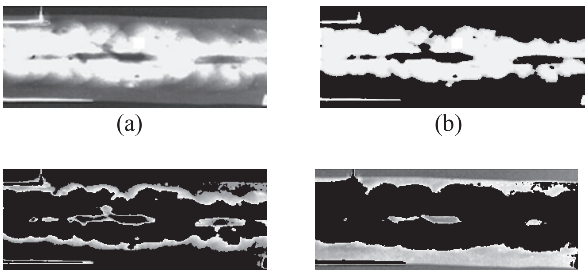


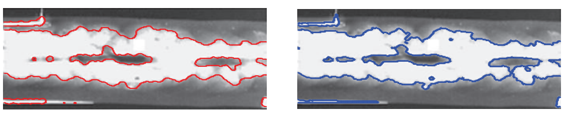
Fig.3. A flowchart of the proposed method.

We applied our solution to some of radiographic images weld that include defaults that could happen during the welding operation. Figures 4, 5, 6 and 7 represent a result the proposed method. The figures 4 and 6 show the results of kernel fuzzy c-means clustering, that is, clusters obtained after applying KFCM. The results of segmentation after taking the cluster N° 1 as initial contour of the level set method to extract the defects boundaries (Figures 5 and 7).



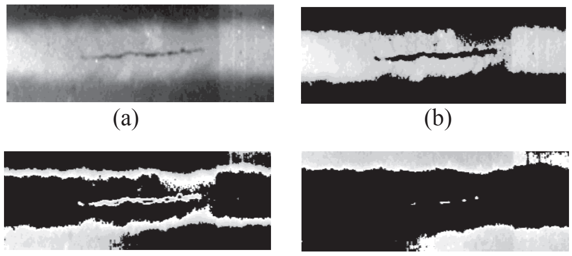
(a) (b) (c) (d)

Fig.4. Clusters obtained after applying KFCM. (a) Original Image; (b) Cluster N° 1 ; (c) Cluster N° 2 ; (d) Cluster N° 3.



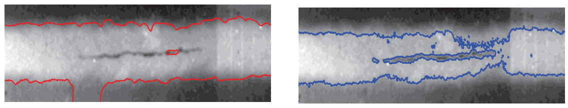
(a) (b)

Fig.5. Detection of defects in weld radiographic image by proposed method. (a) Initial contour; (b) Final segmentation after 150 iterations.



(a) (b) (c) (d)

Fig.6. Clusters obtained after applying KFCM. (a) Original Image; (b) Cluster N° 1 ; (c) Cluster N° 2 ; (d) Cluster N° 3.



(a) (b)

Fig.7. Detection of defects in weld radiographic image by proposed method. (a) Initial contour; (b) Final segmentation after 150 iterations.

The results obtained in this case are very satisfactory and we could surround the area defects.

6. CONCLUSION

In this manuscript, we have presented a model that allows a fast implementation, adaptive and robust methods for weld radiographic images segmentation; we have described the many interesting properties of the methods level set and kernel fuzzy c-means. The results were very satisfactory. All objects were surrounded. The simulation covers weld radiographic images used in Non Destructive Testing (NDT) to delineate the weld defects.

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