

# Contour Estimation in Synthetic and Real Weld Defect Images based on Maximum Likelihood

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**Abstract**—This paper describes a novel method for automatic estimation of the contours of weld defect in radiography images. Generally, the contour detection is the first operation which we apply in the visual recognition system. Our approach can be described as a region based maximum likelihood formulation of parametric deformable contours. This formulation provides robustness against the poor image quality, and allows simultaneous estimation of the contour parameters together with other parameters of the model. Implementation is performed by a deterministic iterative algorithm with minimal user intervention. Results testify for the very good performance of the approach especially in synthetic weld defect images.

**Keywords**—Contour, gaussian, likelihood, rayleigh.

## I. INTRODUCTION

WE intend by Nondestructive Testing (NDT) any examination of industrial materials and assemblies using methods that don't alter their structure, permitting further utilization. Each method is specific and is destined to measure certain properties or to make conspicuous certain types of defects. Then, they have to be chosen in terms of examined material and the property or the imperfection we want detect. One of the most techniques used in NDT is Radiography which is based on the transmission of X-rays or gamma-rays through an object to produce an image on radiographic film. This method is used for inspecting several types of welded assemblies such as pipe-lines, boilers, pressure vessels etc. Inspected zones may present multifarious defects listed under official norms of NDT.

This radiogram is examined by experts in industrial radiography whose task is to detect, recognize and quantify eventual defects, but the radiogram quality, the welding over-thickness, the bad contrast, the noise and the weak sizes of defects make difficult their job. The defect quantification in these conditions is exposed to a certain subjectivity that can compromise testing performances.

One of the essential processes in computer vision consists

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in reduce the huge quantity of information, contained in image of objects which we have to recognize by preserving only the most important points [6]. Therefore, generally, the edge detection is the first stage we apply before the recognition stage.

Generally, the edge detection is the first operation which we apply in the visual recognition system in order to reduce the initial quantity of information, by preserving only the most important points. However, on the one hand, numerous works have been proposed about the pattern recognition of weld defects [5], [6],[7], [8] and so on. In [5], the authors detect the weld defects using texture features. Authors in [6] use the artificial neural networks trained by the back propagation, to the primary classification of the weld defects in radiogram images (planer defect, volumetric defect), through image analysis by geometric invariant moments. In [7], the authors use the adaptive thresholding to extract the weld defect in industrial radiography images. The authors in [8] employ invariant attributes in the feature vector of weld defect images. On the other hand, many works have been proposed about the active contour models in the different fields especially in medical imaging [1],[2],[3],[4] and so on.

In this paper, we describe a new method for automatic estimation of weld defect contours in radiography images. As mentioned above, this is the key step in an automatic measurement system. To deal with the low quality of radiography images, we describe the contour shapes using low order parametric deformable models. This low-order parameterization is sufficient to accommodate the expected shape and size variations, yet provides robustness against noise, image artifacts and regions of missing data. The problem is formulated in a statistical estimation framework, and implementation is carried out by unsupervised deterministic iterative algorithms.

## II. PROBLEM FORMULATION

### A. Probabilistic Image Model

Our approach consists of a maximum likelihood estimation approach to parametric deformable models. The basic building block is a probabilistic observation model  $P(Z/\theta)$  characterizing the observed data  $Z$  given the parameter vector  $\theta$  which describes the contour shape. Under the maximum likelihood (ML) criterion, the best estimate of  $\theta$  denoted by  $\hat{\theta}_{ML}$ , ML is given by

$$\hat{\theta}_{ML} = \arg \max_{\theta} (p(Z/\theta)) \quad (1)$$

To derive the likelihood function  $p(Z/\theta)$ , we adopt a region based approach; this has been shown to provide robustness with respect to local artifacts and poor image quality, [1]. In our region-based model,  $Z$  consists of all the image data, thus being less sensitive to noise and image artifacts than methods that use local derived information (such as gradients or edges). In particular, we consider a simple model in which the image is divided into two regions, *inside* and *outside*, separated by the boundary to be estimated.

The observed image  $Z$  (an array of gray levels), is modelled as a random function of the object's boundary curve  $v(\theta)$ , which is a function of the unknown parameters  $\theta$ . Moreover,  $Z$  may also depend on some additional observation parameters  $\phi$ . Accordingly, our likelihood function can be written as  $p(Z/\theta, \phi)$ .

The simplest possible region-based model is characterized by the two following hypotheses: conditional independence (given the region boundary, all the pixels are independent); and region homogeneity (the probability distribution of each pixel only depends on whether it belongs to the inside or outside region). Thus, the likelihood function can be written as

$$p(Z/\theta, \phi) = \prod_{(i,j) \in I(v(\theta))} p(Z_{(i,j)}/\phi_{in}) \times \prod_{(i,j) \in O(v(\theta))} p(Z_{(i,j)}/\phi_{out}) \quad (2)$$

With  $Z_{(i,j)}$  denoting the value of pixel  $(i, j)$ , while  $I(v(\theta))$  and  $O(v(\theta))$  are, respectively, the inside and outside regions of the contour  $v(\theta)$ . Finally,  $p(Z_{(i,j)}/\phi_{in})$  and  $p(Z_{(i,j)}/\phi_{out})$  are the pixel-wise probability functions of these two regions.

Given that radiography images are well described by Rayleigh or Gaussian distributions, Rayleigh density has the form:

$$p(x/\phi) = \frac{x}{\phi} \exp\left(-\frac{x^2}{2\phi}\right) \quad (3)$$

and thus  $\phi = [\phi_{in}, \phi_{out}]$ , where  $\phi_{in}$  and  $\phi_{out}$  are the variances for the inside and outside regions, respectively.

Gaussian density has the form:

$$p(x/\phi) = \frac{1}{\sigma\sqrt{2\pi}} \exp\left[-\left(\frac{x-\mu}{\sigma\sqrt{2}}\right)^2\right] \quad (4)$$

and thus  $\phi = [\mu, \sigma]$  with  $\mu = [\mu_{in}, \mu_{out}]$ , where  $\mu_{in}$  and  $\mu_{out}$  are the means for the inside and outside regions, respectively.  $\sigma = [\sigma_{in}, \sigma_{out}]$ , where  $\sigma_{in}$  and  $\sigma_{out}$  are the standard deviations for the inside and outside regions, respectively.

### B. Complete Estimation Criterion and Algorithm

To obtain an unsupervised scheme, we must estimate, from an observed image  $Z$ , not only the parameters that define the contour,  $\theta$ , but also the other parameters. Accordingly, we

extend the maximum likelihood criterion to include also these parameters:

$$(\hat{\theta}, \hat{\phi}) = \arg \max_{\theta, \phi} (p(Z/\theta, \phi)) \quad (5)$$

Since solving (4) simultaneously with respect to  $\theta$  and  $\phi$  would be computationally very difficult, we settle for a suboptimal solution given by iterative schemes of the type

$$\hat{\theta}^{(t+1)} = \arg \max_{\theta} (p(Z/\theta, \hat{\phi}^{(t)})) \quad (6)$$

$$\hat{\phi}^{(t+1)} = \arg \max_{\phi} (p(Z/\hat{\theta}^{(t+1)}, \phi)) \quad (7)$$

where  $\hat{\theta}^{(t)}$  and  $\hat{\phi}^{(t)}$  are the estimates of  $\theta$  and  $\phi$  at iteration  $t$ , respectively.

### Algorithm

**Inputs:** initial valid points  $P_{ini}^0 = [P_1^0, P_2^0, \dots, P_N^0]$  (given by the user).  $\varepsilon$  algorithm convergence threshold

**Outputs:** The estimates  $P_{fin}$  and  $\hat{\phi}$ .

#### Step 0

Set  $t = 0$  (iteration counter).

Set  $P_{ini}^t = P_{ini}^0$

#### Step 1

The estimates  $\phi_{in}^t$  and  $\phi_{out}^t$  inside and outside the contours as a closed  $N$ -point interpolating spline.

#### Step 2

Update the contour parameters according to

$$P_1^{(t+1)} = \arg \max_{P_1 \in N(\hat{P}_0^{(t)})} \log P(Z/[P_1, P_2^t, \dots, P_N^t], \hat{\phi})$$

where  $N(P_1)$  is the set of 8 nearest neighbors of  $P_1$ ,

for  $i = 1, 2, \dots, N$ . Similar expressions are used for

$P_2^{(t+1)}, \dots$  and  $P_N^{(t+1)}$ .

if  $|P(Z/P^{(t+1)}, \hat{\phi}^t) - P(Z/P^t, \hat{\phi}^t)| > \varepsilon$

go to step 1

else

end.

## III. RESULTS AND DISCUSSION

We have implemented two contour estimation algorithms: one with Rayleigh distribution, and another with Gaussian distribution. In both cases, the underlying criterion and type of algorithm are those in Equations (4), (5), (6) and (7).

The first two examples simply illustrate the results of the algorithm using synthetic images generated according to the Rayleigh and Gaussian models. In Fig. 1, we simulate a weld defect by Gaussian model, with the inner and outer parameters set to  $(\mu_{in} = 80, \sigma_{in} = 3)$  and  $(\mu_{out} = 150, \sigma_{out} = 4)$  respectively. The final parameter estimates are  $(\hat{\mu}_{in} = 81.55, \hat{\sigma}_{in} = 2.91)$  and  $(\hat{\mu}_{out} = 148.67, \hat{\sigma}_{out} = 4.15)$ . In the example of Fig. 2, we simulate a weld defect by Rayleigh

model, with the inner and outer variances set to 80 and 150, respectively. The image model parameter estimates obtained were  $\hat{\phi}_m = 80.65$  and  $\hat{\phi}_{out} = 151.26$ .

In the final example (Fig. 2), we employ our method to extract the defect contour from radiography image with Rayleigh model. Fig. 2a shows the selected initial contour. We can see the initial contour is far from the reel one. Fig. 2b is obtained after some iterations, we remark that the selected contour come close to the defect one. In Fig. 2c, the rapprochement between the both is more significant than in the last figure. Finally, the deformable contour is closed-fitting to the defect edge.

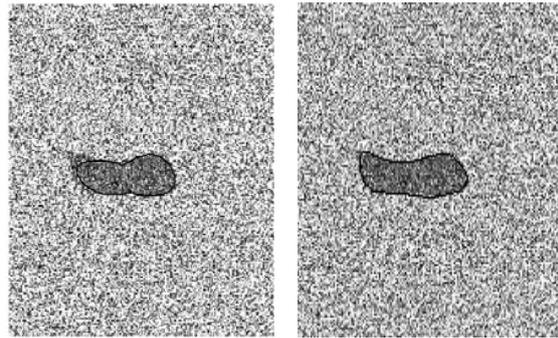


Fig. 2 Synthetic image with Raleigh model, initial contour, intermediate contours and final contour

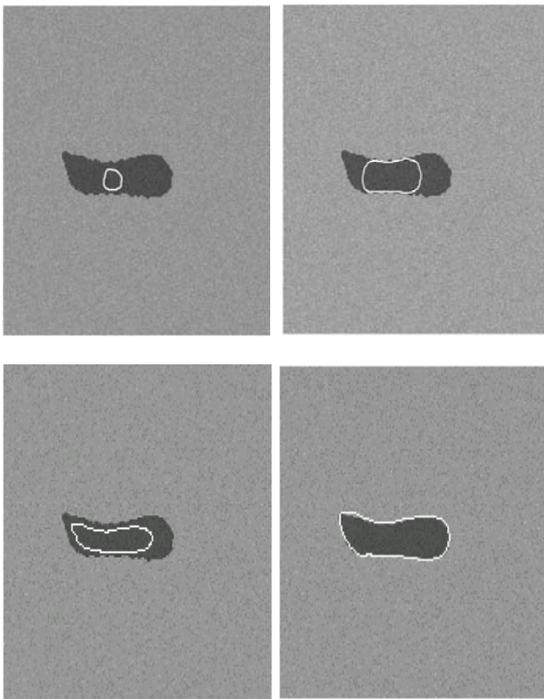


Fig. 1 Synthetic image with Gaussian model, initial contour, intermediate contours and final contour

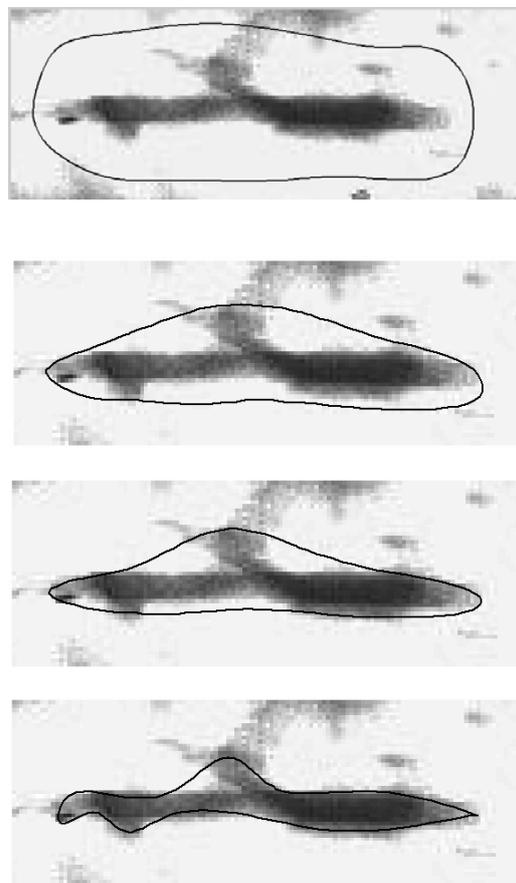
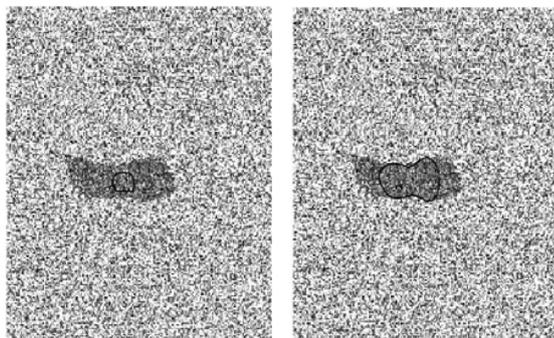


Fig. 3 Real image of weld defect with Raleigh model, initial contour , intermediate contour and final contour

#### IV. CONCLUSION

We have described an approach about contour estimation in radiography images, based on a maximum likelihood formulation of deformable parametric models. Experiments on synthetic images have shown the ability of the proposed



method to estimate contours in an unsupervised manner, *i.e.* adapting to not completely known shapes and completely unknown observation parameters. However, there's still a lot of researches into the problem of weld defect contour extraction in the radiography images in order to improve its quality by using the maximum likelihood.

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