METAL SURFACE CONTROL SYSTEM BASED ON SUCCESSIVE CONTOUR ESTIMATION

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ABSTRACT

A nondestructive control system is proposed. We consider an application of defect detection in metal workpieces. To solve this defect detection problem, we propose an image processing system including denoising, segmentation, and mapping. A contour preserving denoising method based on wavelet decomposition is adapted; various tools of contour based image segmentation are combined adequately, to segment successively high contrast and low contrast contours; generalized Hough transform is adapted to map processed and reference workpieces without defects. Comparative results are proposed which involve the proposed image processing system, and two region based segmentation methods.

Index Terms— Nondestructive testing, Metals industry, Image segmentation, Morphological operations

1. INTRODUCTION

Various control system applications, in particular nondestructive surface inspection, can be handled by contour detection methods. Nondestructive surface inspection is a largely encountered problem in several contexts such as woven inspection, defect detection on wafers, metallic surface inspection [1]. A widely employed method for nondestructive surface inspection is feature selection in the Fourier domain. Fourier transform permits to decouple the information about defects on the one hand and material on the other hand [1], but assumes regular texture of the background. Several methods retrieve object frontiers, assuming these are straight lines or circles, such as the Hough transform [2, 3]. Multiple freeform contour detection is considered by several algorithms such as levelset [4] active contours, such as active contours without edges [5].

We consider an application to non-destructive testing of metal surfaces, which requires the successive segmentation of high contrast, and low contrast free-form contours. To solve the problem raised by this application, we propose an adequate image processing system, which includes a denoising step, performed by an edge-preserving denoising "ForWaRD" method [6]; a two-step contour detection method, and an image mapping method which aligns the processed image which possibly contains defects with a reference image. Section 2 presents the considered industrial issue. Section 3 presents the proposed method. Section 4 presents the results obtained for contour and defect detection. Comparative results show that the proposed method provides better results on this complex industrial problem than sophisticated algorithms. mds January 20, 2010

2. PROBLEM STATEMENT

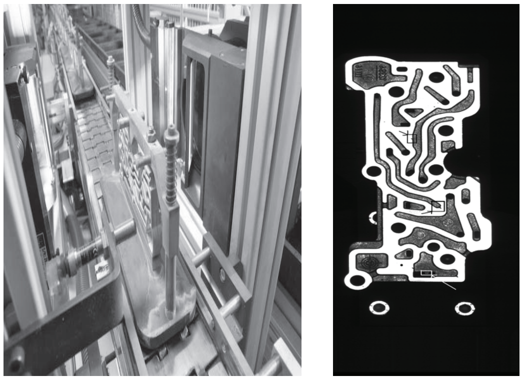
The issue presented in this paper is the development of a robust algorithm to segment several dark regions in photographs of manufactured metal workpieces. An adequate image processing system aims at detecting possibly present defects in these metal workpieces. The expected defects are structural ones, so we choose direct illumination [1], which enhances the contrast between defects and material. The acquisition system is presented on Fig. 1(a). A workpiece with defects is presented in Fig. 1(b). The final goal is to detect the most significant defects, including the low contrasted ones, such as the defects pointed out in Fig. 1(b). The image acquisition system is such that the resolution is 1 pixel for 0.1 mm. The minimum size of the defects is 0.3 mm. The aim of the proposed method is to detect both low contrast fuzzy and high contrast contours with at least a 1.5 pixel precision.

3. PROPOSED ALGORITHM

In order to retrieve efficiently all contours and to avoid parasite contours despite noise, texture and illumination variations, we associate "ForWaRD", an edge-preserving denoising method [6] with the proposed contour detection method.

3.1. Successive estimation of low contrast and high contrast contours

The principles of the proposed algorithm results from the two following remarks:



(a) (b)

Fig. 1. (a) Industrial image acquisition system; (b) Industrial metal workpiece with defects

- Canny edge enhancement can be applied to retrieve the high contrast contours. However the presence of noisy regions prevents the user from choosing the parameter setup that yields the segmentation of the small defects;

- the low contrast contours delimitate highly noisy regions. We seek for a contour detection method which is robust to noise, segments simultaneously several regions, and provides continuous contours. Therefore we focus on a levelset method [4]. However, the convergence of levelset active contour should not be influenced by the presence of the high contrast contours.

An appropriate solution to the problems raised above is to estimate successively and independently the high contrast and the low contrast contours. For this, the undesired parts of the image must be each time either smoothed or canceled to avoid parasite contours. Let J be the input image. We assume that it is a noisy image modeled by: $J = I + N$, where N represents the noise image. ForWaRD algorithm yields a denoised version $\hat{I}$ of the image where contours are preserved. Fig. 2 summarizes the proposed contour detection method. As presented in Fig. 2, a mask is created by mathematical morphology operators out of the image denoised by ForWaRD. This mask is used prior to:

- Canny edge enhancement, to select and strongly denoise the inner noisy regions;

- levelset algorithm, to select and suppress the high contrast contours and enable the convergence of levelset active contours towards the low contrast contours.

At this point the contour map $\hat{I}_{HC}$ containing only high contrast contours is available. In next subsection, we detail the way to obtain $\hat{I}_{LC}$, the contour map containing only the low contrast contours.

3.2. Low contrast contour detection

We consider a digital image $I(x, y)$, $x = 1 : X$, $y = 1 : Y$, having X lines indexed by x, Y columns indexed by y. In the formalism proposed in [4], a temporally changing auxiliary function Φ is introduced. The contour $\vec{v}(t) = (x(t), y(t))$ is represented as the set of points for which the Φ function exhibits a zero value. The contour $\vec{v}(t)$ is given by:

$$\vec{v}(t) = \{(x(t), y(t)) | \Phi(x(t), y(t), t) = 0\} \qquad (1)$$

The evolution of the contour can be described by the temporal change of the function $\Phi(\vec{v}(t), t)$. Let $\vec{v}(t)$ be the contour at time t. The evolution of the contour is regarded exclusively toward the normal direction to this contour. It is described by a speed function F. A typical speed function for the segmentation is:

$$F(x, y) = G(x, y)(1 + \alpha(\kappa)) \qquad (2)$$

The inputs to levelset method are then normal speed field image $G(x, y)$, the initial auxiliary function $\Phi_{t=0} = \Phi_0$ and $\alpha(\kappa)$.
$G(x, y)$ can be for instance the image gradient:

$$G(x, y) = 1/(1 + \|\nabla(\gamma * I(x, y))\|)^2 \qquad (3)$$

γ is a Gaussian filter, symbol $*$ denotes convolution. ∇ denotes gradient. $\kappa = div(\frac{\nabla\Phi}{|\nabla\Phi|})$ is the curvature of Φ. $\alpha(\kappa)$ is a function of the curvature, $\alpha(\kappa) = div(\frac{\nabla\Phi}{|\nabla\Phi|}) + \nu$, where ν is a correction term chosen so that the quantity $\alpha(\kappa)$ remains always positive [4]. The output of levelset is the final auxiliary function Φ computed at the last iteration t_f, $\Phi_{t=t_f}$. The segmented contour coordinates $\vec{v}(t_f)$ are:

$$\vec{v}(t_f) = \{(x(t_f), y(t_f)) | \Phi(x(t_f), y(t_f), t_f) = 0\}. \qquad (4)$$

The initial auxiliary function is obtained as follows. Firstly, we apply entropic threshold to the denoised image $\hat{I}$, where high contrast contours were suppressed. We get image $\hat{I}_{TH}$ which contains a connexe background region with 0 value, and several disconnected regions with 1 value. A closing operation removes the isolated pixels, an erosion operation reduces the size of the 1-valued regions. Let $\mathcal{V}_0^-$ denote the 0-valued regions of the threshold image. $\mathcal{V}_0^+$ denotes the 1-valued regions of the threshold image. $\mathcal{V}_0$ denotes the limit between $\mathcal{V}_0^-$ and $\mathcal{V}_0^+$. $\mathcal{V}_0^-$ is the "forbidden" region where the active contour cannot evolve [4]. $\mathcal{V}_0^+$ is the "authorized" region where the active contour can evolve. Secondly, we refer to the constraints of the implementation from [4]:

$$\Phi_0(x, y) \begin{cases} < 0 & \text{if}(x, y) \in \mathcal{V}_0^- \\ = 0 & \text{if}(x, y) \in \mathcal{V}_0 \\ > 0 & \text{if}(x, y) \in \mathcal{V}_0^+. \end{cases} \qquad (5)$$

We propose the following implementation: we set $\Phi_0(x, y) = -1$ if $(x, y) \in \mathcal{V}_0^-$. We set $\Phi_0(x, y) = \hat{I}$ if $(x, y) \in \mathcal{V}_0^+$.

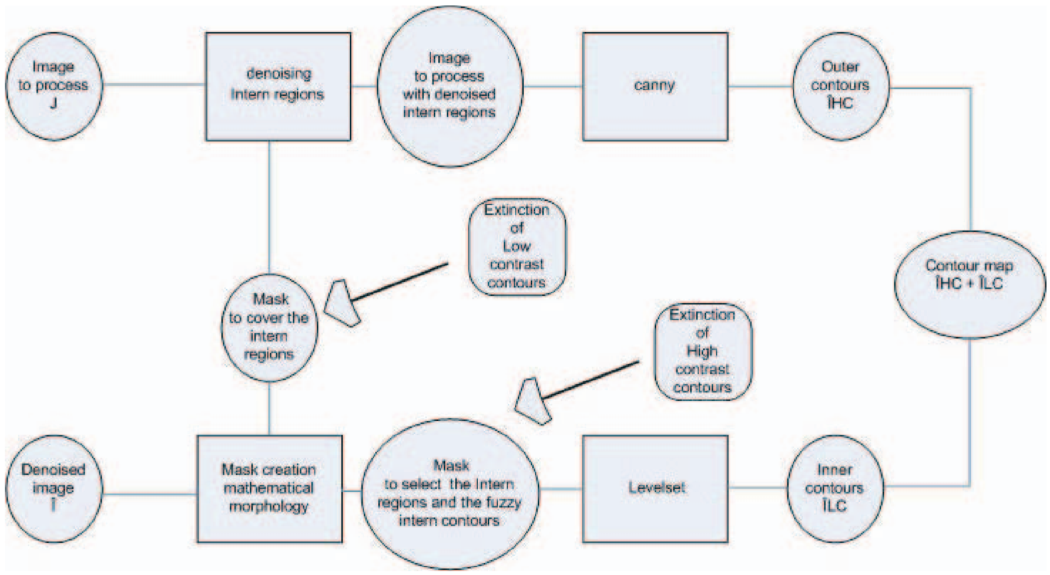
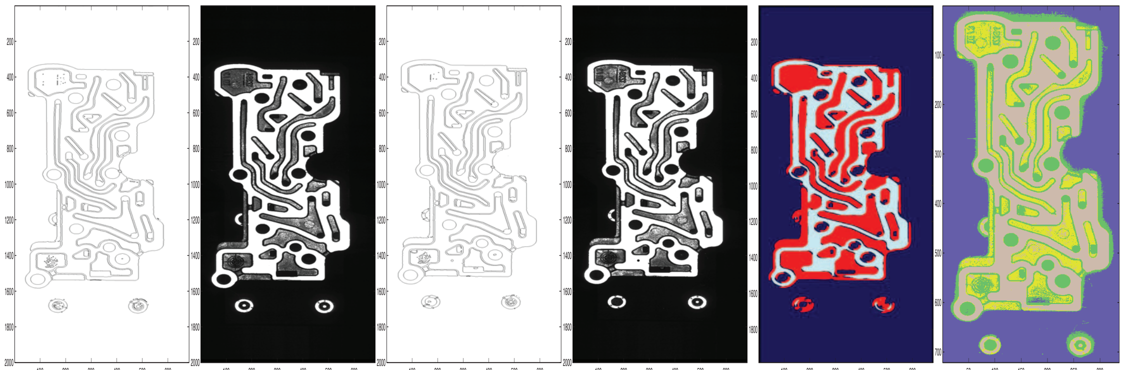


Fig. 2. Adequate combination of mathematical morphology tools and levelset algorithm: successive high and low contrast contour estimation

At this point we know the procedure to obtain all inputs for levelset method, that is, image G and function Φ_0. Therefore we can obtain the expected contour coordinates $\vec{v}(t_f)$ and draw the contour map $\hat{I}_{LC}$. The final output of the proposed method is the summation image $\hat{I}_{HC} + \hat{I}_{LC}$ which contains both high contrast and low contrast segmented contours.

4. SIMULATION RESULTS

The experimental conditions and parameter values hold for all experiments, performed with a PC double core 2.6 GHz running Windows. We process several images, among which a reference image and an image containing defects are considered in detail to emphasize defect detection results. These images are chosen randomly among many photographs, with different texture and illumination properties and noise magnitude [7]. Images have size 2000×682. The parameter values are as follows: in the denoising process the signal to noise ratio [6] is supposed to be 10 dB. This is a rather elevated value which permits to denoise the images while preserving the contours. The number of iterations of levelset can be set to a low value. Indeed, the initialization function Φ_0 and the normal speed field G are finely estimated. In particular the null values in the Φ_0 function are close to the expected low contrast contours. We set $t_f = 3$ iterations. In the following, we present contour detection, and then defect detection results. In these conditions the denoising procedure lasts 18.8 sec. The contour detection method requires 22.0 sec. from which 2.2 sec. are dedicated to the iterations of levelset. Numerous experiments have shown that the ForWaRD denoising method turns the contour detection method robust to the choice of the contour detection parameters. It also reduces the computational load of contour detection by avoiding parasite contours. The proposed method is applied to the workpiece without defect (see Fig. 3(a) and (b)). Fig. 3(b) shows that there is no bias between expected and retrieved contours. Fig. 3(c) and (d) presents the result obtained by the proposed method from an image containing defects. A texture based method [8] and a Markov based method [9] are applied to one reference workpiece without defect (see Figs. 3(e) and (f)). These two comparative methods cannot distinguish clearly between low contrast and high contrast contours and provide too much parasite pixels. As a balance concerning the results of the proposed method, all high and low contrast contours are segmented without bias. In particular, the proposed method segments the inner regions without providing unexpected pixels. Other experiments involving similar workpieces proved the robustness of the proposed method with respect to varying texture characteristics and acquisition conditions. Results are available at [7]. Consequently, the proposed method is appropriate to perform defect detection, and is much preferable to the two comparative segmentation methods. To perform defect detection, the defect map must be mapped to the non-defect map. For this, we adapt generalized Hough transform [2] which finds the position of the center of two reference circles in both images. A shift maps the two top circles and a rotation maps the two bottom circles. Fig. 4 presents detailed defect detection results, obtained from the two images of Fig. 3. Fig. 4 show that all contours (low and high contrasted) and then all defects are retrieved without any pixel bias. No unexpected pixel is present in the defect map.



(a) (b) (c) (d) (e) (f)

Fig. 3. (a) reference workpiece -segmentation result, (b) reference workpiece -superposition; (c) defect workpiece -segmentation result, (d) defect workpiece -superposition, (e) texture method, (f) Markov method

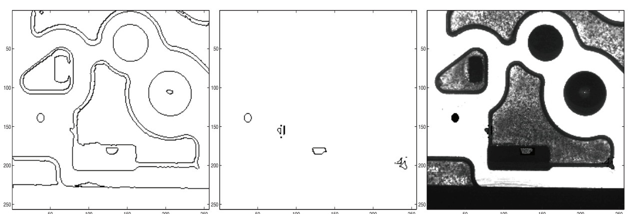


Fig. 4. Contour map of the defect image, detected defects, superposition

5. CONCLUSION

In this paper, we solve a nondestructive testing problem: defect detection in metal workpieces. For this, we propose a self-contained image processing system, which includes denoising, contour detection, and defect detection process. The principles of the proposed image segmentation method are as follows: undesired parts of the image are successively estimated and suppressed from the image to enable a fine estimation of all contours. Mathematical morphology operations are adequately combined to select regions of interest. High contrast contours are segmented by Canny edge enhancement, and a levelset type multicontour segmentation algorithm is adapted to retrieve solely the low contrast contours. The proposed contour detection method is associated with ForWaRD denoising algorithm. This turns the whole image processing system robust to noise impairment, texture and illumination variations. The proposed method is adequate for a nondestructive testing application: segmentation of metal surface photographs involving several types of contours in a highly noisy environment.

6. REFERENCES

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