Contour Detection for Industrial Image Processing by Means of Level Set Methods

J. Marot[1], Y. Caulier[1], A. Kuleschov[1], K. Spinnler[1], and S. Bourennane[2]

[1] Fraunhofer Institut IIS
Am Wolfsmantel, 33, 91058 Erlangen, Germany
[2] Univ. Paul Cézanne, Ecole Centrale Marseille, Institut Fresnel (CNRS UMR 6133),
Dom. Univ. de Saint Jérôme, F-13013 Marseille cedex 20, France
julien.marot@fresnel.fr

Abstract. We consider the problem of the automatic inspection of industrial metal pieces. The purpose of the work presented in this paper is to derive a method for defect detection. For the first time in this context we adapt level set method to distinguish hollow regions in the metal pieces from the grinded surface. We compare this method with Canny edge enhancement and with a thresholding method based on histogram computation. The experiments performed on two industrial images show that the proposed method retrieves correctly fuzzy contours and is robust against noise.

1 Introduction

In the modern industry it is of the highest importance to turn the production process as efficient as possible. To improve the quality of such a process is required not only the automatization of manufacturing, but also the quality control of the products. This work concerns defect detection in industrial images, by image segmentation methods. Image segmentation and contour detection was the purpose of several studies [1,2,3,4,5,6].

For edge detection, the most common method is still the derivative approach with linear filtering. Many derivative filters have been studied and used to compute the intensity gradient of gray-level images: Roberts, Sobel, Prewitt or Canny operators [7]. Other approaches have been followed, such as mathematical morphology, Markov random fields, surface models, histogram automatic threshold [8,9].

In [10], defect detection is performed by selection of specific features in the Fourier domain. This method is applied to industrial tissues. However such a Fourier-based algorithm assumes a periodic structure in the processed images. The method we propose is competitive with this approach as it does not assume any specific periodic structure for the image features.

Some edge detection methods assume *a priori* knowledge of the object shape. Among these are least-squares methods [2], which seek to minimize the squares sum of error-of-fit with respect to measures; Hough transform [4] and array processing methods [5], which retrieve straight lines, or circles [6]. Some other

J. Blanc-Talon et al. (Eds.): ACIVS 2008, LNCS 5259, pp. 655–663, 2008.

edge detection methods are meant for free-form object segmentation. Among those are parametric [11,12,13], and geometric [14,15] snakes methods.

The remainder of the paper is organized as follows: section 2 states the problem, section 3 presents the proposed method, section 4 presents the results obtained by the proposed method and two comparative methods. Section 5 concludes the paper.

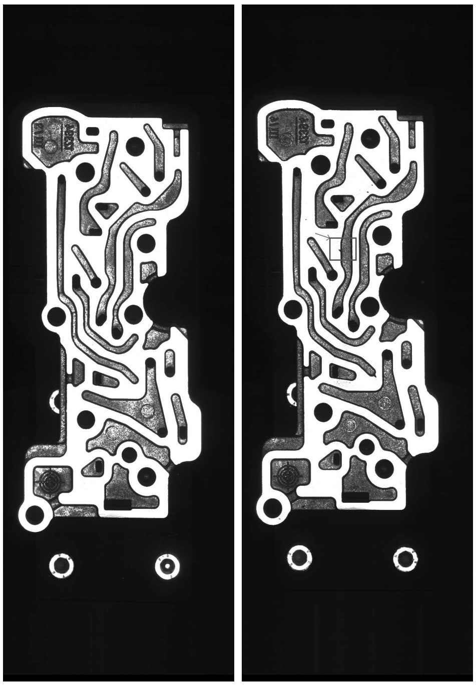
2 Problem Statement

Our purpose is to develop a robust algorithm to segment several dark regions in photographies of manufactured metal pieces acquired in an industrial context. These dark regions are hollow parts of the manufactured piece.

The considered images may exhibit some defects, such as in Fig. 1(b), compared to a reference image without defect, such as Fig. 1(a). Both images have size 2000 $\times$ 682 pixels.

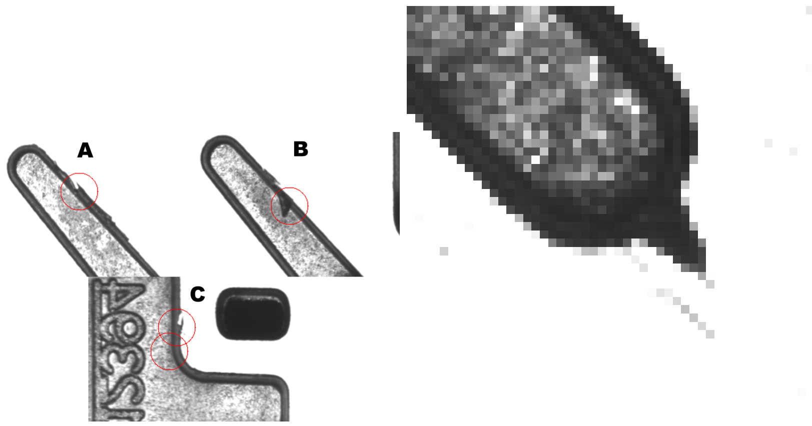
The final goal is to detect the most significant defects, such as the defect pointed out in Fig. 1(b) and the defects referenced in Fig. 2.

In order to detect correctly the defects, the segmentation method should provide both inner and outer parts of the contours of the hollow regions, as shown in Fig. 3. Moreover the contours should be continuous.



(a) (b)

Fig. 1. Detail of image "Adapterplatte": (a) no defect (b) one defect



(a) (b)

Fig. 2. (a) A, B, C: Marked failures (b) Zoom on one defect

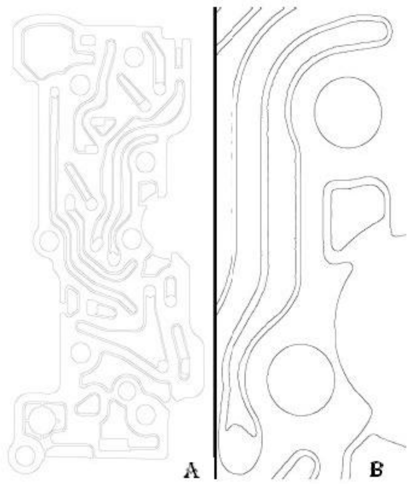


Fig. 3. Expected contours: A) Inner and outer contours; B) zoom

Contour detection is a mostly preprocessing step whose purpose is to retrieve the region of interest in the image. In the case of the type of images of Fig. 1, a specific classification method shall be applied to the white grinded surfaces, whereas the inner part corresponding to the rough surface of the metal workpiece has to be processed with an appropriate denoising method.

In the next section we justify the choice of level set methods and describe a comparative method.

3 Proposed Method

We aim at correctly detecting all contours in the considered industrial images. To cope with the considered application we seek for free-form object segmentation methods. In this frame, pixel-based and region-based techniques can be seen as the two major categories of approaches [3,14]. The considered industrial images exhibit several regions with different texture properties, so region-based techniques appear more adapted, since the texture characteristics are defined at the region level. Indeed, pixel-based texture segmentation generally relies on the use of local texture features computed within a predefined window around each pixel. Hence, texture features extracted for pixels close to region boundaries involve a mixture of texture characteristics, which may lead to a lack of accuracy in localizing the boundaries of the texture region. Region-based snakes techniques can be classified into two categories: parametric snakes and geometric snakes. Parametric snakes are maintained by a spline, explicitly represented as parametrized curves, while geometric snakes are represented implicitly. Parametric snakes methods [11], such as Gradient Vector Flow (GVF), were largely used [12], to retrieve concavities. A generalized version of GVF was proposed to retrieve edges with blurred boundaries [13]. The main limitation of GVF is its high computational load. Geometric snakes [14] are based on the theory of curve evolution implemented via level set algorithms and do not need to reparameterize the curve or to explicitly handle topological changes. Level set algorithms automatically handle changes in topology when numerically implemented using level sets. Hence, unknown numbers of multiple objects can be detected simultaneously. The provided contours are always closed and continuous.

We seek for an efficient contour detection method, which is as fast as possible, segments simultaneously several regions, and provides continuous contours. Therefore we focus on a level set method [15], as it fulfills all these requirements. In the formalism proposed in [15] is introduced a temporally changing auxiliary function Φ. The contour $\mathbf{v}(t) = (x(t), y(t))$ is represented as the set of points for which the Φ function exhibits a zero value. The contour $\mathbf{v}(t)$ is given through $\mathbf{v}(t) = \{(x(t), y(t))|\Phi(x(t), y(t), t) = 0\}$. The movement of the contour can be described by the temporal change of the function $\Phi(\mathbf{v}(t), t)$. From an implicit differentiation arises:

$$0 = \frac{\partial \Phi}{\partial t} = \frac{\partial \Phi}{\partial \mathbf{v}}\frac{\partial \mathbf{v}}{\partial t} + \frac{\partial \Phi}{\partial t}\frac{\partial t}{\partial t} = \frac{\partial \Phi}{\partial \mathbf{v}}\mathbf{v}' + \Phi_t \tag{1}$$

Generalizing this method, we do not only consider the value 0 for function Φ but a set of values which are called "levels". For this application one level only is enough to retrieve the expected contours, and it is the only required parameter.

We compare the results obtained by level set with the results obtained by two comparative methods which are on the one hand a canny edge enhancement, on the other hand an adaptive thresholding method [9]. This thresholding method is based on histogram computation, inspired by the well-known Otsu method [8]. The main characteristic of adaptive thresholding method is to respect human perception features, in order of relevance boundary, texture, background. It consists in the following steps:

1. Calculation of the average image brightness in a small neighbourhood;
2. Comparison of a current image brightness with averaged value; marking the pixels, where the normalized difference exceeds the selected threshold;
3. Collection of all marked pixels into blobs;
4. Execution of the adaptive boundary searching procedure for every blob;
5. Recognizing and removing the duplicates.

The adaptive thresholding method requires few parameters which are the averaging filter size, the contrast threshold level and the watching window size. Threshold value is computed automatically from the histogram of the window. The basic advantage of this adaptive thresholding method is the high speed of calculations due to local application of stages 4 and 5 of the algorithm. In the next section we exemplify the proposed and comparative methods on two industrial images, one with a defect and another without defect.

4 Results

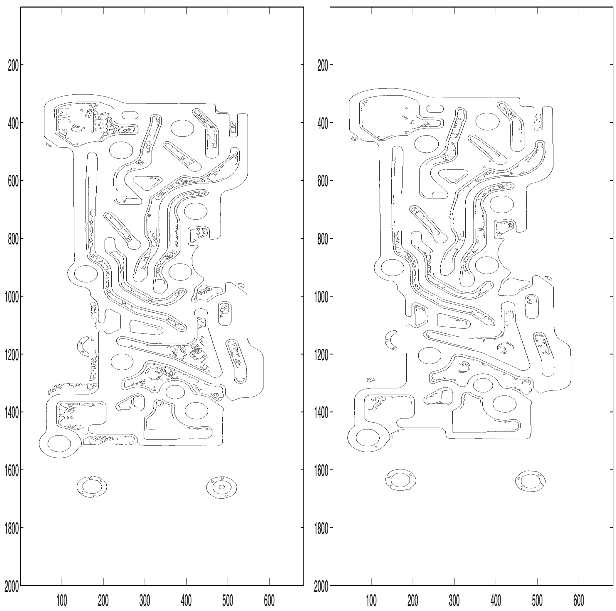
The proposed method and the two comparative methods are applied to the two "Adapterplatte" industrial images presented in Fig. 1. Their size is 2000 $\times$ 682 pixels. In the following we provide the parameter values which are employed and the required computational times. Experiments are performed on a 3.0 GHz PC running Windows.

4.1 Inner and Outer Contour Segmentation

The Canny edge enhancement method is followed by a threshold at level 0.2. Required computational time is 3.9 sec. Fig. 4 shows that some of the inner contours are skipped, and that some noise is remaining. Figs. 5(a) and (c) show that a grey level value variation inside the hollow region can be considered as a defect in the final segmentation result.

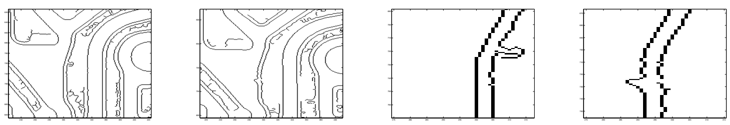
The adaptive thresholding method is run with a window of size 10 $\times$ 10 pixels [9]. Required computational time is 0.4 sec. for this method. The threshold method does not retrieve the inner contour. This is due to several difficulties: several contours are present within the window, and the inner contour is low-contrasted. So the histogram exhibits several modes which are difficult to distinguish automatically, and the pixels of both sides of the contour do not belong to two clearly distinguishable modes of the histogram. An additional drawback for this application is that the provided contours are not closed.

The level set method is run with a level parameter of 0.26, which is fixed empirically. Required computational time is 1.17 sec. for this method. The level set method provides continuous contours, and distinguishes the inner and outer contours.



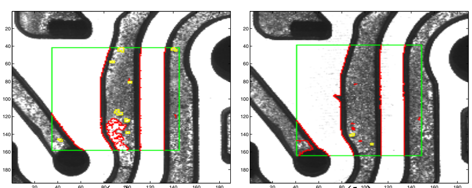
(a) (b)

Fig. 4. Image Adapterplatte, result obtained with Canny edge enhancement applied on the two images of Fig. 1



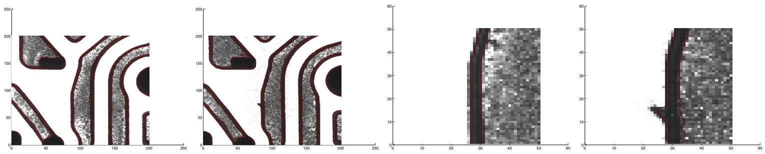
(a) (b) (c) (d)

Fig. 5. Details of image Adapterplatte, result obtained with Canny edge enhancement: (a) and (c) Image of Fig. 1(a) without defect (b) and (d) Image of Fig. 1(b) with defect



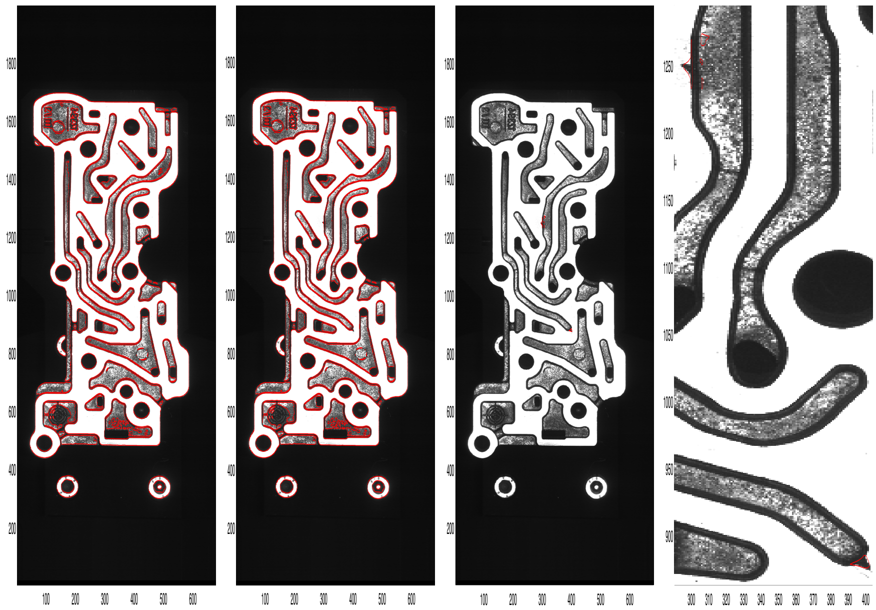
(a) (b)

Fig. 6. Detail of image Adapterplatte, result obtained with adaptive threshold : (a) Image of Fig. 1(a) (b) Image of Fig. 1(b)



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

Fig. 7. Detail of image "Adapterplatte", result obtained with level set : (a) and (c): Image of Fig. 1(a); (b) and (d): Image of Fig. 1(b)



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

Fig. 8. Detail of image Adapterplatte, result obtained with the proposed method : (a) Image of Fig. 1(a) (b) Image of Fig. 1(b) (c) Defect detection (d) Zoom on the defect

The main outcomes of the results obtained are the following:

Canny edge enhancement is not reliable when fuzzy contours are considered. As a consequence, for this application, it enhances unexpected contours in noisy regions, and fails in retrieving some inner fuzzy contours. The adaptive thresholding method fails in retrieving the inner contours. Level set method provides both inner fuzzy and outer contours, and only few noisy pixels remain in the result image.

4.2 Defect Detection by Means of the Proposed Method

As the proposed method provides the most valuable results in terms of contour segmentation, it will be used to detect defects in the considered images. Fig. 8

presents the segmentation results obtained with two similar images. Fig. 8(b) only exhibits two defects. Fig. 8(c) is the difference between the two segmentation image results and Fig. 8(d) is a zoom on the detected defects. Figs. 8(c) and (d) show that the two defects are correctly detected.

5 Conclusion

In this paper, we considered an industrial application of contour detection in images. We justify the use of level set method to retrieve inner and outer contours of hollow portions of a manufactured surface. By retrieving correctly both contours we distinguish clearly the outer white grinded surface and the inner rough surface. This permits to apply further a characterization method, and a denoising method for both surface types.

Contour detection also permits to enhance the defects in the faulty metal pieces. We exemplified the proposed method on two images, one containing two defects, and correctly isolated the defects. The main advantage of the proposed method is that it permits a direct retrieval of closed contours, and only one level parameter is necessary to retrieve all the relevant contours. As further works, we could set a classification method to distinguish several types of defects, and study the robustness of the proposed method to variations in illumination. The proposed method could be applied to other types of images, such as medical ones.

Acknowledgements

We gratefully acknowledge the french "délégation générale de l'armement" (DGA) and "centre national de la recherche scientifique" (CNRS) for their support.

References

1. Pal, N., Pal, S.: A review on image segmentation techniques. Pattern Recognition 26(9), 1277–1294 (1993)
2. Ayache, N., Faugeras, O.D.: HYPER: a new approach for the recognition and positionning of two-dimensionnal objects. IEEE-PAMI 8(1), 44–54 (1986)
3. Karoui, I., Fablet, R., Boucher, J.-M., Augustin, J.-M.: Region-based segmentation using texture statistics and level-set methods. IEEE ICASSP 2(12), 693–696 (2006)
4. Kiryati, N., Bruckstein, A.M.: What's in a set of points? [straight line fitting]. IEEE Trans. on Pattern Analysis and Machine Intelligence 14(4), 496–500 (1992)
5. Aghajan, H.K., Kailath, T.: Sensor array processing techniques for super resolution multi-line-fitting and straight edge detection. IEEE IP 2(4), 454–465 (1993)
6. Marot, J., Bourennane, S.: Subspace-Based and DIRECT Algorithms for Distorted Circular Contour Estimation. IEEE-IP 16(9), 2369–2378 (2007)
7. Canny, J.: A computational approch to edge detection. IEEE Trans. Pattern Anal. Machine Intell. 8, 679–714 (1986)

8. Otsu, N.: A threshold selection method from gray level histogram. IEEE Trans. Syst. Man Cybern. 9, 62–66 (1979)
9. Kuleschow, A., Spinnler, K.: New Methods for Segmentation of Images Considering the Human Vision Principles. In: Computer Vision and Graphics ICCVG, Warsaw Proc, pp. 1037–1042 (2004)
10. Chi-Ho, C., Pang, G.K.H.: Fabric defect detection by Fourier analysis. IEEE Transactions on Industry Applications 36(5), 1267–1276 (2000)
11. Kass, M., Witkin, A., Terzopoulos, D.: Snakes: Active Contour Model. Int. J. Computer Vision, 321–331 (1988)
12. Xu, C., Prince, J.L.: Gradient vector flow: a new external force for snakes. In: IEEE Comp. Soc. Conf. Comp. Vis., Pat. Rec., pp. 66–71 (1997)
13. Xianghua, X., Mirmehdi, M.: RAGS: region-aided geometric snake. IEEE Trans. on IP 13(5), 640–652 (2004)
14. Aujol, J.F., Aubert, G., Blanc-Féraud, L.: Wavelet-based level set evolution for classification of textured images. IEEE Trans. on Image Processing 12(12), 1634–1641 (2003)
15. Mitchell, I.M.: The Flexible, Extensible and Efficient Toolbox of Level Set Methods. Journal of Scientific Computing (December 2007)