Segmentation of circular casting defects using a robust algorithm

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In this paper, we describe three methods for detecting defects in cast aluminium using X-radioscopic images. The first method is based on the assumption that most defects have the shape of a circular high-intensity spot. Therefore, defects are detected using a template matching-like algorithm. This method works well when the defects are far enough from the edges of the major shapes in the image, and when the image gives a closer view of the defect. The second method deals with the defects which are closer to the edges in the image, and therefore are missed by the first method. This method distinguishes between defects and edges by using the following properties of a defect: they are local maxima of the image intensity, and the distribution of the intensity in a patch around the defect should resemble more that of a corner than that of an edge. Both local maxima and corner-like properties are computed using the second order derivatives of the image intensities, and the Harris Corner Detector algorithm. The third algorithm is a simple combination of the aforementioned methods in which a pixel is considered to be a defect if it is detected as a defect by either of the two methods. We present experiments using the third method showing that 94.3% of the defects are correctly detected, with only 1.3 false alarms per image.

1. Introduction

Shrinkage as molten metal cools during the manufacture of die castings, can cause defective regions within the work-piece. These are manifested, for example, by bubble-shaped voids, cracks, slag formations or inclusions. Light-alloy castings produced for the automotive industry, such as wheel rims, steering knuckles and steering gear boxes are considered important components for overall roadworthiness. To ensure the safety of construction, it is necessary to check every part thoroughly. Radioscopy is rapidly becoming a major method for controlling the quality of die-cast pieces through computer-aided analysis of the radioscopic images[1]. The purpose of this non-destructive testing method is to identify internal casting defects, which may be located within the piece and are undetectable to the naked eye. The automated inspection of castings is a quality control task to determine automatically whether a casting complies with a given set of product and product safety specifications.

Two classes of regions are possible in a digital radioscopic image of an aluminium casting: regions belonging to regular structures of the specimen, and those relating to defects. The automatic process used in fault detection in aluminium castings consists of five steps[2]: a) *Image formation*, in which an X-ray image of the casting under test is taken and stored in the computer. b) *Image pre-processing*, where the quality of the X-ray image is improved in order to enhance the details of the X-ray image. c) *Image segmentation*, in which each potential flaw of the X-ray image is found and isolated from the rest of the image. d) *Feature extraction*, where the potential flaws are measured and some significant characteristics are quantified. e) *Classification*, where the extracted features of each potential flaw are analysed and assigned to one of the classes (regular structure or defect).

In an X-ray image, we can see that the defects, such as voids, cracks and bubbles (or inclusions and slags), show up as bright (or dark) features. The reason is that the X-ray attenuation in these areas is shorter (or higher). Since the contrast in the X-ray image between a flaw and a defect-free neighbourhood of the specimen is distinctive, detection is usually performed by analysing this feature. There are several definitions of contrast; they generally give a comparison between the grey level of a region (potential flaw) and the grey level of its corresponding neighbourhood. Nevertheless, the last measurement suffers from accuracy error when the neighbourhood is not homogeneous, for example when the flaw is at an edge of a regular structure of the test object. For this reason, many approaches compute the grey level of the neighbourhood using *a-priori* knowledge of the design structure of the test-piece (see for example [3, 4]). Thus, the defect-free areas are defined in sections where the grey level values have a small variance.

These methods have become the most widely established in industrial applications owing to their high detection performance. However, they require a very precise positioning of the test object and a complicated selection process of the defect-free areas. In order to avoid the mentioned problems, in [5] a new approach to detecting defects without *a-priori* knowledge was proposed. The approach is based on features extracted from *crossing line profiles*, *ie*, the grey level profiles along straight lines crossing each segmented potential flaw in the middle. The profile that contains the most similar grey levels in the extremes is selected. Hence, the homogeneity of the neighbourhood is ensured. Thus, the detection is performed by analysing features from the selected crossing line profile. By combining crossing line profile with other contrast features a small improvement of the performance was obtained[2]. Although the detection rate of these methods is very high (typically 95%), the number of false alarms is not good enough (typically more than four false alarms per image).

In order to reduce the quota of false alarms, this paper proposes three approaches without *a-priori* knowledge of the structure of the test-pieces. The rest of the paper is organised as follows. Section 2 outlines the segmentation approaches. Section 3 shows the experimental results obtained on real data. Finally, Section 4 gives concluding remarks.

2. Segmentation approaches

In this section we describe three methods for detecting flaws in cast aluminium specimens, based on radioscopic imaging.

2.1 Method 1 for segmentation

This method operates based on the assumption that most defects

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have the shape of a circular high intensity spot, and therefore, can be detected using a template matching-like algorithm. The method consists of the following five steps:

- **Pre-processing:** In this application, we cannot perform much pre-processing, since any severe kind of noise removal or smoothing would affect the defects as well. Thus, we use a median filter of size 3 × 3. The result is stored in matrix **I**.
- **Template matching:** We now convolve the image **I** (to get the new image $\mathbf{I}_2$) with a filter $\mathbf{h}_2$:

$$h_2 = \begin{bmatrix} 0 & 0 & -1 & -1 & -1 & -1 & -1 & -1 & 0 & 0 \\ 0 & -1 & -1 & 0 & 0 & 0 & 0 & -1 & -1 & 0 \\ -1 & -1 & 0 & 1 & 1 & 1 & 1 & 0 & -1 & -1 \\ -1 & 0 & 1 & 1 & 1 & 1 & 1 & 1 & 0 & -1 \\ -1 & 0 & 1 & 1 & 2 & 2 & 1 & 1 & 0 & -1 \\ -1 & 0 & 1 & 1 & 2 & 2 & 1 & 1 & 0 & -1 \\ -1 & 0 & 1 & 1 & 1 & 1 & 1 & 1 & 0 & -1 \\ -1 & -1 & 0 & 1 & 1 & 1 & 1 & 0 & -1 & -1 \\ 0 & -1 & -1 & 0 & 0 & 0 & 0 & -1 & -1 & 0 \\ 0 & 0 & -1 & -1 & -1 & -1 & -1 & -1 & 0 & 0 \end{bmatrix}$$

The objective of this filter is to emphasise the parts of the image that have the same pattern as $\mathbf{h}_2$. That is, the maxima that have the shape of a circle with radius about four pixels. This filter is chosen from observations of the pattern that is common among the defects.

- **Thresholding:** We then threshold $\mathbf{I}_2$ to get a binary image $\mathbf{B}_2$, containing candidate failures. A fixed threshold seems to be good enough for this purpose according to the experimental results.
- **Morphological operations and postprocessing:** In this step, we remove images of large structures in $\mathbf{I}_2$ using a morphological operator that determines the structures having a large area in a binary image. After applying the filter $\mathbf{h}_2$, some structures are produced around the edges of the image, which are not of the desired shape, but are caused by the severe changes in intensity around that area. These objects are much larger than the defects; therefore, they can be omitted due to their size. In the end, we threshold $\mathbf{I}_2$ to get the final binary image showing detected defects while masking out the images of large structures as well as the extremely bright and dark areas.

2.2 Method 2 for segmentation

This method deals with the defects around the edges in the image. It distinguishes between defects and edges noticing that the defects are local maxima of the image intensity, and they resemble corners rather than edges. The algorithm consists of the following four steps:

- **Preprocessing, template matching and thresholding:** In this step, we apply the same median and convolution filters as in Method 1. However, for the thresholding, we now want to keep the brightest parts of the image, which are located around the major edges and were neglected by Method 1. Thus, we use an adaptive threshold that keeps the 5% brightest pixels.
- **Harris Corner Detection:** To distinguish the defects from the edges in the image, we use the Harris Corner Detection Algorithm[6]. This algorithm detects points in an image that look like corners, and not like edges. This is a common property of the defects.
- **Computing the Hessian Matrix determinant:** Since another common property of the defects is their local maxima nature, we compute the Hessian Matrix for every pixel in the image, and construct a matrix **H** of the same size as the original image, with entries equal to $\mathbf{I}_{xx}\mathbf{I}_{yy} - \mathbf{I}^2_{xy}$ for every pixel, where $\mathbf{I}_{xx}$, $\mathbf{I}_{yy}$, and $\mathbf{I}_{xy}$ are the second derivatives of the pixel intensities at each point. We then keep the positive entries of **H** at the points where $\mathbf{I}_{xx}$ and $\mathbf{I}_{yy}$ are negative, and mask out others, in order to deal with the local maxima only.
- **Postprocessing:** In the end, we construct an image in which the points having a corner nature and a local maximum nature are emphasised. To get the defects, we use an adaptive threshold keeping 99% of the histogram, and remove the extremely small or large structures.

2.3 Method 3 for segmentation

The defects are detected as the union of the defects detected using Method 1 and Method 2, *ie*, the third algorithm is a simple combination of the aforementioned methods in which a pixel is considered to be a defect if it is detected as a defect by either of the two methods.

3. Experimental results

In our experiments, seven radioscopic image sequences (without frame averaging) of aluminum wheels with twelve known flaws were inspected. Three of these defects were existing blow holes (with ∅ = 2.0 ~ 7.5 mm). They were initially detected by a visual (human) inspection directly on the screen image. The remaining nine flaws were produced by drilling small holes (∅ = 2.0 ~ 4.0 mm) in positions in the casting which were known to have detection difficulties. 60 radioscopic images were extracted from the sequences and the aforementioned methods were tested. One image of each sequence is shown in Figure 1, the squares indicate the twelve existing flaws. The twelve defects are repeated in different images of the sequences, resulting in 88 flaws in the 60 images. The squares in all images of this section were drawn intentionally to show the reader where the defects are located.

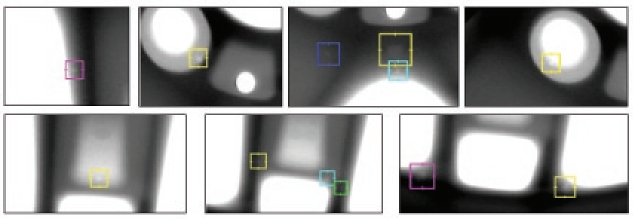

Figure 1. Seven of the 60 X-ray images used in our experiments

As we mentioned before, Method 1 works for the defects which are away from a casting section change or edge. An example is illustrated in Figure 2. Figure 3, however, shows an example of where it does not detect the defect, since it is close to an edge.

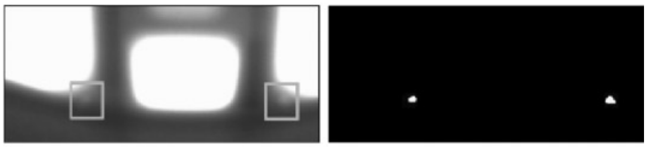

Figure 2. Detection using Method 1: the existing two flaws were detected successfully

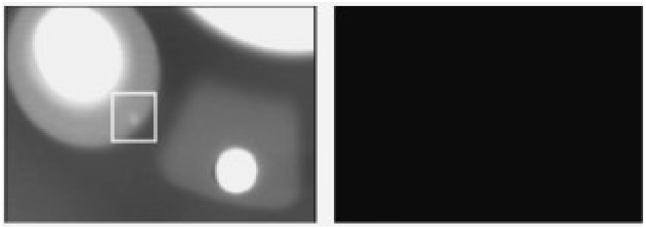

Figure 3. Detection using Method 1: the existing flaw was not detected

Method 2 works well for the defects close to the edges in the image, but not for others. An example of where it works, but Method 1 failed, is shown in Figure 4. However, an example of where it fails where Method 1 works is illustrated in Figure 5.

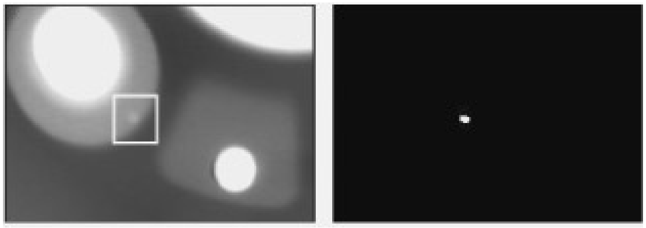

Figure 4. Detection using Method 2: the existing flaw was detected successfully

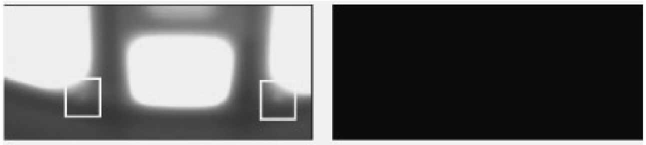

Figure 5. Detection using Method 2: the existing two flaws were not detected

Finally, Method 3 deals with all the defects using both Method 1 and Method 2. It works well where the image has a closer view of the object, or the image is smooth enough around the defect. A result is shown in Figure 6.

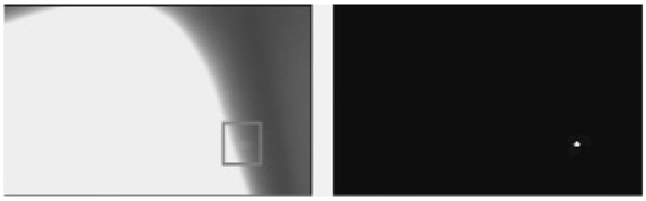

Figure 6. Detection using Method 3: the existing flaw was detected successfully

However, Method 3 does not work ideally where the image does not give a close view of the defect. Figure 7 shows an example where Method 3 misses a defect.

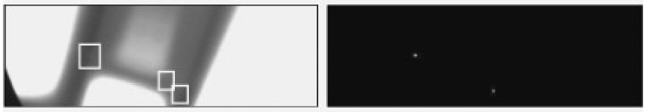

Figure 7. Detection using Method 3: only two of three existing flaws were detected successfully

Additionally, in regions where the image is not smooth enough, Method 3 detects random extra points as defects; however, this problem could be solved by noticing that the images are taken from a sequence, and therefore, points that are detected in one image do not continue to be detected on the frames from the same sequence are not actual defects[7]. Figure 8 shows an example where several extra points (false alarms) are detected as defects.

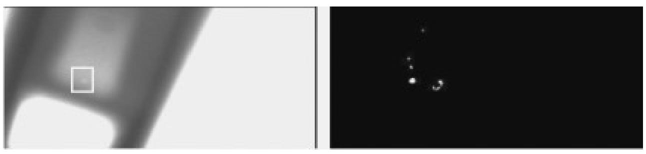

Figure 8. Detection using Method 3: the existing flaw was detected successfully, however, many false alarms were flagged

Table 1. Performance of the detection using Method 3

Method	Ref.	Detected flaws	False alarms/image
Crossing line profile (CLP)	[5]	83/88	6.40
Contrast with CLP	[2]	83/88	4.60
Proposed 'Method 3'	Sec. 2	83/88	1.27

The statistical results of the experiment using Method 3 in comparison with other two reported methods are summarised in Table 1. The experiments were performed on the same data. We observe that in all the cases, 83 of the 88 existing defects were successfully detected, *ie*, the detection rate is 94.3%. The number of false alarms were significantly reduced from 6.40 and 4.60 to 1.27.

4. Concluding remarks

In this paper, a new approach to detecting defects in castings without *a-priori* knowledge of the design structure is proposed. The approach is based on new contrast features. The detection performance was evaluated in 60 radioscopic images with 88 flaws. The best performance was achieved using the suggested third method yielding 94.3% detection rate with only 1.27 false alarms per image. It is known that false alarms flagged in this step can be eliminated using *a-posterior* analysis based on image sequence analysis without eliminating the real flaws[7]. The significance of this result is very important in this automated visual inspection, where it is necessary i) to detect all defects in order to ensure the safety of consumers, and ii) to obtain a low rate of false alarms in order to reduce false rejects.

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