High contrast pixels: a new feature for defect detection in X-ray testing

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Abstract

The detection of defects in X-ray testing follows a pattern recognition scheme where feature extraction plays a very significant role. In this paper we present a new feature based on the number of high contrast pixels located inside a segmented potential defect related to the size of the potential defect. The developed feature can be easily computed and offers a high separability according to the Fischer linear discriminant. The feature depends on only two parameters that can be automatically determined in a training phase. The developed feature and other reported features are tested in 72 radioscopic images of aluminium wheels. The comparison shows that the separability of the developed feature is at least six times higher than the separability achieved by other features.

Key Words: automatic flaw detection, feature extraction, median filter, aluminium castings.

1. Introduction

The automatic detection of flaws in non-destructive testing based on image processing uses a pattern recognition methodology for its implementation. This process has the following stages: image formation, pre-processing, segmentation, feature extraction, and classification (Mery *et al*, 2003). Image formation is obtained by X-ray irradiation of the studied piece creating a digital image of the object on the basis of the original image obtained. The purpose of pre-processing is to improve the quality of the image for better recognition of potential defects, reducing noise, enhancing contrast, and restoring. Segmentation consists of obtaining regions of the images that correspond to potential defects. During feature extraction segmented regions are measured, and finally in classification, in accordance with the extracted features segmented regions are separated into two classes: “defects” (flaws) and “regular structures” (non-flaws).

It is well known that the quality of the extracted features plays an important role in the detection problem. If the extracted features do not offer a high enough separability of the classes, the detection will work erroneously even if sophisticated classifiers are used in this task (Jain et al., 2000).

In this paper we present a new feature based on the number of high contrast pixels located inside a segmented potential defect related to the size of the potential defect. The feature can be computed easily and offers a high separability according to the Fischer linear discriminant. The feature depends on only two parameters that can be automatically determined in a training phase.

The rest of the paper is organized as follows: Section 2 describes the feature and gives a Matlab code used in the implementation. Section 3 compares the performance of the developed feature with other known features. Section 4 gives concluding remarks.

2. Developed feature

As mentioned above, the segmentation process identifies potential defects in X-ray images. Potential defects are those defects that are suspected to be real ones. In order to divide the potential defects into false alarms and real defects, features of the potential defects are extracted. According to the values of the extracted features the classifier determines if the potential defect is a defect or a regular structure (false alarm). Details of a segmentation procedure can be found in Mery (2003), however the feature extraction described in this paper can be used with other segmentation methods. In this section we describe the feature that we developed as follows (see Figure 1).

We define the original X-ray image as the matrix **X**. Now, image **X** is filtered using a median filter with a square mask of $m \times m$ pixels. The filtered image is stored in a new matrix **Y**. It is well known that if the background captured by the median filter is constant, it is possible that structures in the foreground will be suppressed if the number of values belonging to the structure is less than half of the input value to the filter (see for example Castleman 1996, Mery et al , 2002). This means that tuning adequately the size of the mask, certain pixels that belong to the defects can be filtered out. These pixels belonging to the defects are called ‘high contrast pixels’ in this paper. They can be easily detected finding those pixels in $\mathbf{Z} = \mathbf{X}\text{-}\mathbf{Y}$ with a high grey value, i.e., locating $\mathbf{Z} > t$, where t is a threshold. Parameters m and t must be set according to a separability measurement as explained later.

The output of the segmentation process is a binary image **B** with the potential defects. Segmented potential defects define regions in a binary image. A region consists of connected pixels with the value '1'. In our approach we define: i) the area 'a' of the potential defect, i.e., the number of the pixels of the region; and ii) the value 'h' as the number of the high contrast pixels belonging to the region. The new feature is defined as the ratio $r = h/a$. Large values of r should mean real defects. See an example in Figure 1.

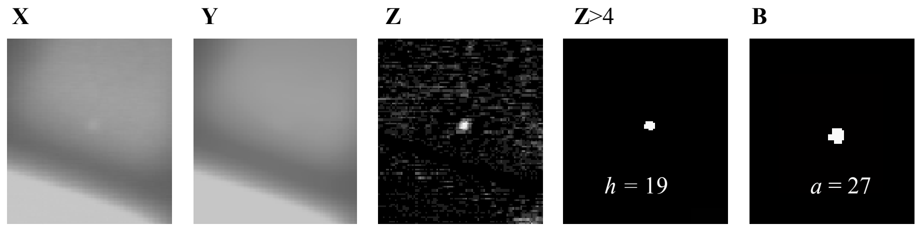

Figure 1: Image **X** shows a small defect in the middle that is filtered out in **Y** with m = 11. The difference image **Z** is thresholded using t=4. The area of the potential defect segmented in **B** is 27 pixels, however only 19 of them are high contrast pixels. The extracted feature r is in this example 19/27 = 0.7037.

The Matlab code of this feature is given in Figure 2. The user must define the input image `X`, the binary image of the segmentation `B` and the parameters of the feature extraction `m` and `t`. Note that in this code there is no problem if image `B` contains only one potential defect or more than one. The extracted features are stored in array `r` with `n` elements, where `n` is the number of potential defects segmented in `B`.

```
% user definitions
X = original X-ray image
B = binary image with segmented regions
m = size of the median mask
t = threshold of the high contrast pixels

Y = medfilt2(X,[m m]);
Z = X-Y;
D = Z>t;
[L,n] = bwlabel(B,4);
stats = regionprops(L,'PixelIdxList','Area');
R = zeros(n,1);
for i = 1:n
   j = stats(i).PixelIdxList;
   a = stats(i).Area;
   h = sum(D(j));
   r(i) = h/A;
end
```

Figure 2: Matlab code of the proposed feature.

The parameters m (size of the median mask) and t (threshold) of the feature can be determined automatically in a training phase. We separate a representative image set with typical defects and perform an exhaustive search for different values of m and t of the filter. For each combination (m,t) we use the Fischer linear discriminant (Duda, et al. 2001) to measure the separability of the classes as follows.

There is one value r for each segmented potential defect. We define vector $\mathbf{r} = [r_1 \quad \cdots \quad r_n]^{\mathrm{T}}$, where n is the number of segmented potential defects in the training data. The features are normalised as

$$\tilde{r}_i = \frac{r_i - \mu}{\sigma} \qquad \text{for} \qquad i = 1,\dots,n \tag{1}$$

where μ and σ are the mean and standard deviation of $\mathbf{r}$. The normalised features have zero mean and standard deviation equal to one. Using a priori information given by an human inspector, we know which segmented potential defects are real defects and which ones are false alarms. We arrange the normalised features of the real defects in vector $\mathbf{r}_1$ with n_1 elements, and the normalised features of the false alarms in vector $\mathbf{r}_2$ with n_2 elements, where $n = n_1 + n_2$. The Fisher linear discriminant is defined by:

$$J = \frac{|\mu_1 - \mu_2|^2}{\sigma_1^2 + \sigma_2^2} \tag{2}$$

where μ_j and σ_j are the mean and standard deviation of $\mathbf{r}_j$ for $j = 1,2$. By maximising J we ensure the best separability because we have a small intraclass variation and a large interclass variation in the space of the features, i.e., the best parameters of the filter should be chosen to optimise:

$$(\hat{m},\hat{t}) = \underset{m,t}{\operatorname{argmax}}(\mathrm{J}) \tag{3}$$

3. Analysis and discussion of results

In this section, we present results obtained in 72 radioscopic images of aluminium die castings using the feature described in previous section. The size of the images is 572 × 768 pixels. The images present 238 real defects. About 25% of these defects were existing blow holes (with ∅ = 2.0 – 7.5 mm). They were initially detected by a visual (human) inspection. The remaining 75% were produced by drilling small holes (with ∅ = 2.0 – 4.0 mm) in positions of the casting which were known to be difficult to detect. Following the segmentation process outlined in Mery, 2003, more than 86,000 regions were segmented as potential defects. Although the number of false alarms in this step is enormous, we have to emphasize that 233 of the 238 existing real defects were successfully segmented, i.e., the detection performance of this step was 97.9%.

Only four images were used to find the best (m,t) combination for the median filter described in previous section. In this step we used for the size of the filter the values m = 3, 5, 7 , … 25, and for the threshold t = 1, 2, 3, … 6. After an exhaustive search we found that the best separability in this training set was given by the combination $\hat{m} = 15$ and $\hat{t} = 4$. A plot of the value J of the Fisher linear discriminant is illustrated in Figure 3.

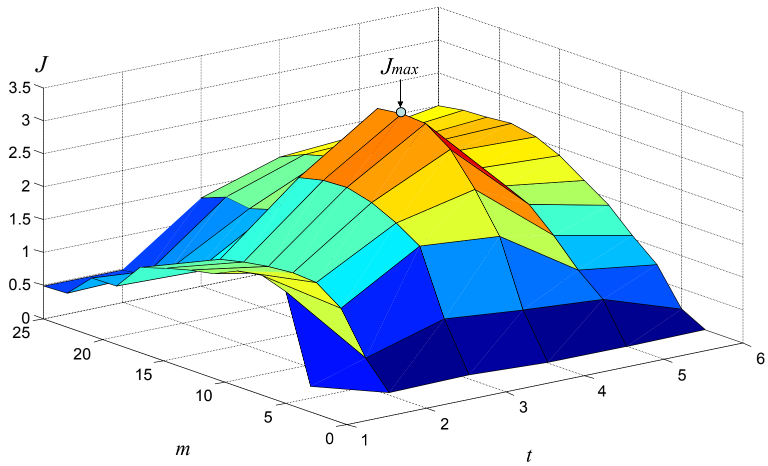

Figure 3: Exhaustive search of the parameters of the median filter. The objective function J is maximised by $\hat{m} = 15$ and $\hat{t} = 4$.

The class distributions in the 72 images is shown in Figure 4a. We see clearly that the false alarms (structures) are distributed at the left, i.e., a small value of r means that the segmented potential defect corresponds to a false alarm. On the other hand, the real defects are located at the right. We observe the high separablity of the classes because the overlapping between the classes is small and the distance between the classes is large.

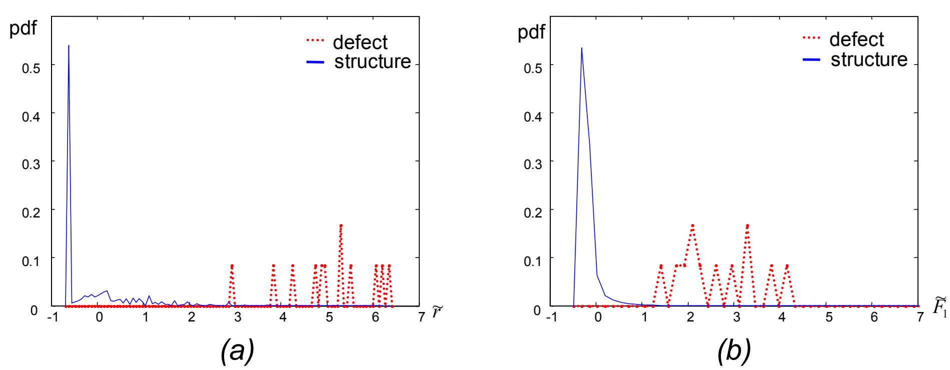

Figure 4: Probability distribution frequency of two features: a) developed feature based on high contrast pixels and b) feature based on crossing line profile (Mery, 2003).

In order to compare the developed feature with other ones reported in the literature, we plot in Figure 4b the class distributions of the normalised feature F_1 of the best crossing line profile (Mery, 2003). Crossing line profiles are 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 defined as the best crossing line profile (BCLP). The feature F_1 corresponds to the first harmonic of the fast Fourier transformation of BCLP. Figure 4b shows evidence that the distance between the classes is smaller than the distance of feature *r*.

Table 1 compares the value of the Fisher linear discriminant *J* of the developed feature *r* based on high contrast pixels with other known features. The comparison shows that the separability of the developed feature is at least six times higher than the separability achieved by other features.

Table 1: Fisher linear discriminant *J* of assessed features.

Feature	*J*	Reference
High contrast pixel ratio *r*	2.9079	Section 2
First harmonic of BCLP	0.4493	Mery, 2003
Standard deviation of BCLP	0.3672	Mery, 2003
Difference between maximum and minimum of BCLP	0.4270	Mery, 2003
Mean grey value	0.2284	Mery & Filbert, 2002
Mean second derivative of grey value	0.5095	Mery & Filbert, 2002
Contrast Ks	0.2018	Mery & Filbert, 2002
Contrast K	0.2312	Mery, 2003
Area	0.00003	Mery & Filbert, 2002
Eccentricity	0.0622	Mathworks, 2005

4. Conclusions

In this paper we presented a new feature based on the number of the high contrast pixels located inside a segmented potential defect related to the size of the potential defect. The high contrast pixels are computed using the median filter. The developed feature can be easily computed and offers a high separability according to the Fischer linear discriminant. After a comparison with other reported features used in the defect detection of aluminium castings, we obtained a separability at least six times higher than the separability achieved by other features. We believe that the performance of the existing classifiers can be increased if they incorporate the developed feature.

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