Aluminum CT Image Defect Detection Based on Segmentation and Feature Extraction

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Abstract. Industrial computed tomography (CT) scanning has been used in many areas of industry for internal inspection of components. Some of the key uses for CT scanning have been flaw detection, failure analysis, metrology, assembly analysis and reverse engineering applications. In this paper we present the approach to detecting defects follows a general image processing scheme based on three steps: segmentation, feature extractions, and classification. In the first step (segmentation), potential defects are segmented using the region method. In the step of feature extraction, two main features of the potential defects are considered: geometric and intensity features. The third step, design a proper classifier. The classifier assigns a feature vector z to one of the two classes: regular structure or defects, that are assigned "0" and "1", respectively. A good metric defining the similarity must be established. Experiments demonstrate that proposed method is fast and accurate to defects detection in CT image, and the method has high robustness for illumination.

Keywords: CT image, Defect detection, Feature extraction, Histograms of gradients.

1 Introduction

The purpose of industrial non-destructive testing (NDT) method is to identify defects or flaws in industrial parts, which are difficult to detect for the human eye. X-ray testing is a traditional method for the evaluation and detection of defects in castings and welds, therefore digital image processing and computational intelligence and be used to automate this process. The use of visual inspection systems are used in many industrial and commercial applications. There are various visual inspection systems such as defect detection of tiles, metal, fabric inspection and etc. The base knowledge for research work has been collected from various resource materials. M.Ghazvini, A.Monadjemi, K.Jamshidi [1] said defects can be identified using detail matrices which consist of median, max and min points. J.L.Sobral [2] emphasized wavelet sub

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A. Marcus (Ed.): DUXU 2014, Part II, LNCS 8518, pp. 446–454, 2014.

band and optimized gabor filters can be used for texture defect detection. Hamid Alimohamadi [3] highlighted the use of filter banks and optimized filter for defect detection and extraction of feature image. Ajay Kumar and Grantham Pang [4] revealed Gabor filters can be deployed for fabric defect detection using bernoulli's rule of combination. Kaicheng Yin and Weidong Yu [5] used segmentation for defect detection in garments production system. Henry Y.T.Ngan, Grantham K.H.Pang, S.P.Yung, Michael K.Ng [6] highlighted the use of golden image subtraction method in the area of patterned fabric defect detection. Jun Xie,Yifeng Jiang,Hung-tat Tsui [7] highlighted the use segmentation technique in medical imaging. Yi-leng chen,Tse-Wei Chen,Shao-Yi Chien [8] revealed how wavelet transform can be used for fast texture feature extraction. A. Serdaroglu, A.Ertuzun, A.Ercil [9] revealed the use the wavelet transforms for identifying defects in texture fabric images. In this research work the minimum, maximum and median values are calculated for each row of the image to frame the feature vector. The high frequency components are eliminated using the median value of each row and at last the low frequency compo-nent image along with the median value of each row is used to detect the defected points with sudden intensity variation from the former picture element or sudden variation from the median value. In summary, it is found out the difficulties of current ray inspection of welding in which image is expected to improve, which is small brightness, gray-focus and low contrast, big image noise and blur edge of photoreceptor ray film. Clustering is a process of organizing the objects into groups based on its attributes in [10]. Bardera et al. pay more attention on the use of excess entropy to locate the optimal thresholds in image segmentation. The most important problem is to choose optimal thresholds. Sathya and Manavalan[11] make the great efforts in clustering methods research in image segmentation. They do the main work in FCM, which the short name for fuzzy C-means clustering, and K-means clustering algorithms as well as improved algorithms of these two kind of clustering methods. Usamentiaga et al. [12] presented a simple and maintainable method to investigate steel manufactures. By using a laser ranging technique, based on shape-line meter approaches, a configurable method was proposed. Chen et al. [13] presented the automated defect detection system applied to bearing cylindrical surfaces, in which the performance of the system was related to predefined functions.

Typically, the automatic process used in fault detection in industrial parts, as shown in Figure 1, can be summarized in two general steps [14]:

a) Identification of the potential defects:

- Image pre-processing: The quality of the X-ray image is improved in order to enhance the detail of the X-ray image.
- Image segmentation: Each potential flaw of the X-ray image is found and isolated from the rest of the scene.

In step a), the identification of real defects must be ensured. Nevertheless, using this strategy an enormous number of regular structures (false alarms) is identified with. For this reason, a detection step is required. The detection attempts to separate the existing defects from the regular structures.

b) Detection:

- Feature extraction: the potential flaws are measured and some significant characteristics are quantified.
- Classification: The extracted features of each potential flaw are analyzed and assigned to one of the following classes: 'defect' or 'regular structure'.

In step b), since several features can be extracted from the potential defects, a feature selection must be performed.

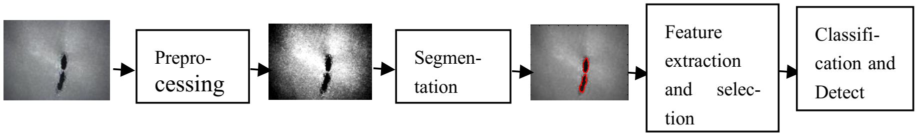


Fig. 1. Phases of pattern recognition in automated flaw detection

In this paper, a defect detection algorithm for ICT images was proposed based on segmentation and feature extraction.

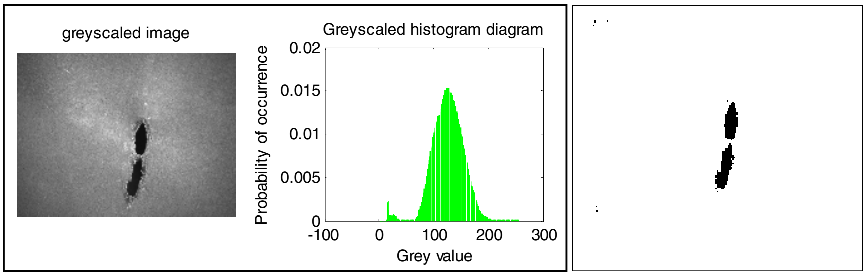
2 Defect Detection Method

2.1 Segmentation

Image segmentation is defined as the process of subdividing an image into disjointed regions. In image processing for detection faults in castings, such regions correspond to potential defects and the background. While there are many methods for segmenting images, two approaches for segmenting potential defects in x-ray image are used within the nondestructive testing community. We take K-means clustering method.

In K-means algorithm data vectors are grouped into predefined number of clusters. At the beginning the centroids of the predefined clusters are initialized randomly. The dimensions of the centroids are same as the dimension of the data vectors. Each pixel is assigned to the cluster based on the closeness, which is determined by the Euclidian distance measure. After all the pixels are clustered, the mean of each cluster is recalculated. This process is repeated until no significant changes result for each cluster mean or for some fixed number of iterations. The algorithm is composed of the following steps [11].

- Place K points into the space represented by the objects that are being clustered. These points represent initial group centroids.
- Assign each object to the group that has the closest centroid.
- When all objects have been assigned, recalculate the positions of the K centroids. Repeat steps 2 and 3 until the centroids no longer move. This produces a separation of the objects into groups from which the metric to be minimized can be calculated. Figure 2 shows the result using k-means clustering method segmentation.



(a) Original image and histogram (b) segmentation result

Fig. 2. K-means clustering segmentation

2.2 Feature Extraction

After initial pre-processing and segmentation, the given image is subjected to feature extraction strategy. Given an input image, our method first extracts dense HOG (histogram of oriented gradients [14]). This feature has been proven successful in various vision tasks such as object classification, texture analysis and face recognition, etc. HOG is complementary in the sense that HOG mainly focuses on shape information. Figure 3 shows a flow diagram of object detection using the original HOG algorithm. Scanning on the input image is based on detection window. The window is divided into cells, for each cell accumulating a histogram of gradient orientations over the pixels of the cell. For better invariance to illumination, histogram normalization can be done by accumulating a measure of the local histogram energy over blocks and using the results to normalize all cells in the block. The normalized histograms (HOG features) are collected over the detection window.

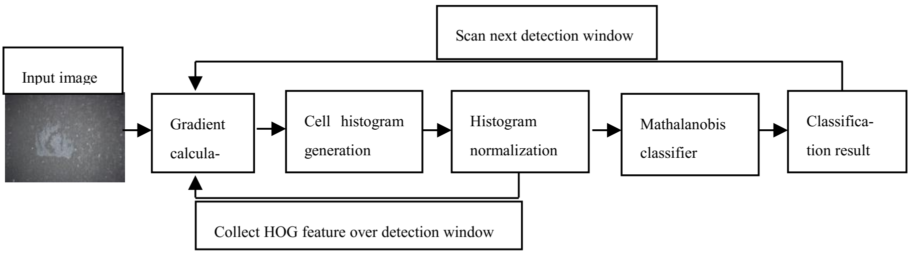


Fig. 3. HOG algorithm flow

In this paper HOG algorithm for defect detection using the following techniques. The first step of calculation is the computation of the gradient values. The most common method is to simply apply the 1-D centered, point discrete derivative mask in one or both of the horizontal and vertical direction. Specifically, this method requires filtering the color or intensity data of the image with following kernels: $[-1,0,1]$ and $[-1,0,1]^{\mathrm{T}}$. The second step of calculation involves creating the cell histograms. Each pixel within the cell casts a weighted vote for an orientation-based histogram channel based on the values found in the gradient computation. The cells themselves can either be rectangular or radial in shape, and the histogram channels are evenly spread over 0 to 180 degrees or 0 to 360 degrees, depending on whether the gradient is "unsigned" or "signed". In order to account for changes in illumination and contrast, the gradient strengths must be locally normalized, which requires grouping the cells together into larger, spatially connected blocks. The HOG descriptor is then the vector of the components of the normalized cell histograms from all of the block regions. These blocks are generally square grids, represented by three parameters: the number of cells per block, the number of pixels per cell, and the number of channels per cell histogram. In our experiments, the optimal parameters were set to be 3×3 cell blocks of 6×6 pixel cells with 9 histogram channels. The last step is for block normalization. Let v be the non-normalized vector containing all histograms in a given block, $\|v\|_k$ be its k-norm for $k=1,2$ and e be some small constant. Then the normalization factor can be the following L2-norm equation:

$$f=\frac{v}{\sqrt{\|v\|_2^2+e^2}} \tag{1}$$

2.3 Feature Selection

In feature selection we have to decide just which features of the regions are relevant to the classification. The n extracted features are arranged in n-vector : $w=[w_1\cdots w_n]$ that can be viewed as a point in a n-dimensional space. The features are normalized as:

$$\tilde{w}_{ij}=\frac{w_{ij}-\overline{w}_j}{\sigma_j} \quad \text{for } i=1,\ldots,N_0 \text{ and } j=1,\ldots,n \tag{2}$$

w_{ij} denotes the jth feature of the ith feature vector, N_0 is the number of the sample, and $\overline{w}_j$ and σ_j are the mean and standard deviation of the jth feature. The normalized features have zero mean and a standard deviation equal to one.

The key idea of the feature selection is to select a subset of m features ($m<n$) that leads to the smallest classification error. The selected m features are arranged in a new m-vector $z=[z_1\cdots z_m]^{\mathrm{T}}$. The selection of the features can be done using sequential forward selection. This method selects the best single feature and then adds one feature at a time that, in combination with the selected features, maximizes classification performance. The iteration is stopped once no considerable improvement in the performance is achieved on adding a new feature. By evaluating selection performance we ensure: (a) a small intra-class variation, and (b)a large interclass variation in the space of the selected features. For the first condition the intra-class covariance is used:

$$C_b=\sum_{k=1}^{N}p_k[\overline{z}_k-\overline{z}][\overline{z}_k-\overline{z}]^{\mathrm{T}} \tag{3}$$

where N means the number of classes, p_k denotes the priori probability of the kth class, $\overline{z}_k$ and $\overline{z}$ are the mean value of the kth class and the mean value of the selected features. For the second condition the inter-class covariance is used:

$$C_w = \sum_{k=1}^{N} p_k C_k \tag{4}$$

where the covariance matrix of the kth class is given by:

$$C_k = \frac{1}{L_k - 1} \sum_{j=1}^{L_k} [z_{kj} - \overline{z}_k][z_{kj} - \overline{z}]^{\mathrm{T}} \tag{5}$$

where z_{kj} is the jth selected feature vector of the kth class.

2.4 Classification

Once the proper features are selected, a classifier can be designed. Typically, the classifier assigns a feature vector z to one of the two classes: regular structure or flaw, that are assigned "0" and "1", respectively. Using a representative sample we can make a supervised classification finding a discriminant function $d(z)$ that provides us with information on how similar a feature vector z is to the feature vector of a class. We use the Mathalanobis classifier. The Mahalanobis classifier employs the same concept as the nearest neighbor classifier. It uses a new distance metric called the "Mahalanobis distance." The Mahalanobis distance between z and $\overline{z}_k$ is defined as:

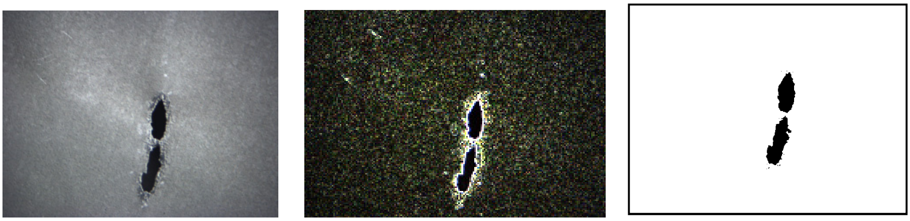
$$d_k[z, \overline{z}_k]^{\mathrm{T}} C_k^{-1} [z - \overline{z}_k] \tag{6}$$

The Mahalanobis classifier takes into account errors associated with prediction measurements, such as noise, by using feature covariance matrix to scale features according to their variances.

3 Experiments and Analysis

In order to access the effectiveness of the proposed method, several real ICT images are used in the experiments. The results processed by the proposed method are compared with those yielded by three threshold techniques widely used in the literature, such as Principal Component Analysis (PCA) method and Gabor Filter method. Around 100 samples of image have been tested with the help of the proposed algorithm. We have given three samples hereby.

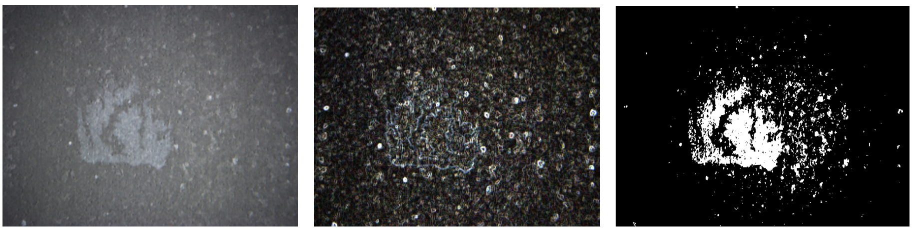
The sample 1 image which of size 1024×768 consists of defect in an aluminum CT image. Figure 4(a) shows the original image, Figure 4(b) shows the HOG of image including defect which defects have been identified and Figure 4(c) shows the segmented image.



(a) (b) (c)

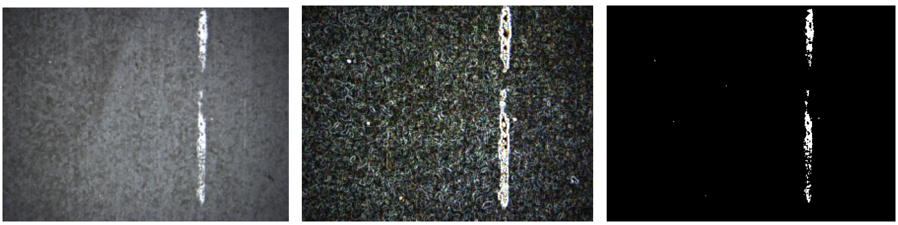
Fig. 4. (a) Original image (b) HOG result of image (c) Segmented image

The second sample is a Bitmap image which shows a material speckle flaws on an aluminum CT image. The Figure 5(a) shows the original image. Figure 5(b) shows the image of the HOG and Figure (c) shows the defects in the original image with the defect areas the size of sample 2 is 1024×768.



(a) (b) (c)

Fig. 5. (a) Original image (b) HOG of image (c) Segmented image



(a) (b) (c)

Fig. 6. (a) Original image (b) HOG of image (c) Segmented image

Sample 3 is image with bright chain crack in an aluminum CT image. Figure 6(a) shows the original image Figure 6(b) consists of HOG result including the defected area and Figure 6(c) shows the defected area in sample 3 images.

We used around 100 samples for testing the efficiency of algorithm. We have obtained around 88% to 92% of accuracy in all the samples.

Table 1. Comparative result analysis

No.	Name	Proposed Algorithm		PCA Method		Gabor Filter Method	
		Defect detection Accuracy %	Elapsed Time (seconds)	Defect detection Accuracy %	Elapsed Time (seconds)	Defect detection Accuracy %	Elapsed Time (seconds)
1	Sample 1	88.38	0.1598	82.07	0.1611	79.84	0.5843
2	Sample 2	91.84	0.1458	78.19	0.1604	84.43	0.5722
3	Sample 3	91.19	0.1574	69.12	0.2004	85.55	0.5014

The above statistics show the proposed algorithm is better than other algorithms used above. Apart from the accuracy there is no Error rate detected in the algorithm. The PCA method uses defect free samples for more accuracy which is not the case for proposed algorithm.

4 Conclusion

In this paper, a new approach for detect detection in aluminum CT images based on segmentation and feature extraction is presented. The best performance was achieved using the simplified model in the case of the aluminum castings and the complete model in the case of defect detection in welds. This algorithm can be deployed in Automated Visual inspection Systems. However to increase the efficiency of the algorithm to be suited for all forms of defects some future work has to be done.

Acknowledgments. This work was supported by the national natural science foundation of China (Grant nos. 61103130,61271435,61202245,61370138,U1301251); National Program on Key Basic Research Projects (973 programs) (Grantnos. 2010CB731804-1, 2011CB706901-4); The Importation and Development of High-Caliber Talents Project of Beijing Municipal Institutions (No. IDHT20130225). The Project of Construction of Innovative Teams and Teacher Career Development for Universities and Colleges Under Beijing Municipality (no. CIT&TCD20130513).

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