Automated visual inspection of glass bottles using adapted median filtering

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Abstract. This work presents a digital image processing technique for the automated visual inspection of glass bottles based on a well-known method used for inspecting aluminium die castings. The idea of this method is to generate median filters adapted to the structure of the object under test. Thus, a "defect-free" reference image can be estimated from the original image of the inspection object. The reference image is compared with the original one, and defects are detected when the difference between them is considerable. The configuration of the filters is performed off-line including a priori information about real defect-free images. In the other hand, the filtering self is performed on-line. Thus, a fast on-line inspection is ensured. According to our experiments, the detection performance in glass bottles was 85% and the false alarms rate was 4%. Additionally, the processing time was only 0.3s/image.

Keywords: automated visual inspection, median filter, glass bottles, ROC curves.

1 Introduction

Visual inspection is defined as a quality control task that determines if a product deviates from a given set of specifications using visual data[1]. Inspection usually involves measurement of specific part features such as assembly integrity, surface finish and geometric dimensions. If the measurement lies within a determined tolerance, the inspection process considers the product as accepted for use. In industrial environments, inspection is performed by human inspectors

[1] For a comprehensive overview of automated visual inspection, the reader is referred to an excellent review paper by Newman and Jain [1]. The information given in this paragraph was extracted from this paper.

and/or automated visual inspection (AVI) systems. Human inspectors are not always consistent and effective evaluators of products because inspection tasks are monotonous and exhausting. Typically, there is one rejected in hundreds of accepted products. It has been reported that human visual inspection is at best 80% effective. In addition, achieving human '100%-inspection', where it is necessary to check every product thoroughly, typically requires high level of redundancy, thus increasing the cost and time for inspection. For instance, human visual inspection has been estimated to account for 10% or more of the total labour costs for manufactured products. For these reasons, in many applications a batch inspection is carried out. In this case, a representative set of products is selected in order to perform inferential reasoning about the total. Nevertheless, in certain applications a '100%-inspection' is required. This is the case of glass bottles fabricated for the wine industry, where it is necessary to ensure the safety of consumers. For this reason, it is necessary to check every part thoroughly.

Defects in glassware can arise from an incompletely reacted batch, from batch contaminants which fail to melt completely, from interactions of the melted material with glass-contact refractories and superstructure refractories, and by devitrification. If conditions are abnormal many defects can be produced and even just one defect of only 1-2mg in every 100g article can be enough to give 100% rejection rates. The source identification of these defects can then be a matter of urgency [2].

The inspection of glass bottles is performed by examining each bottle through backlighting. In this case, the bottles are placed between light source and a human or computer aided inspector. This technique makes the defects of the bottle visible. There are two known approaches used in the inspection of glass bottles:

- The automated detection of flaws is performed by a typical pattern recognition schema (segmentation, feature extraction and classification), in which images from at least four view points are taken, potential flaws are segmented and according to the extracted features the defects are detected. Examples with neural networks can be found in [3–5], where a high detection performance was achieved in a laboratory prototype.
- In the second group, the image is taken by a linear scanner that stores the corresponding middle vertical line of the bottle. By rotating the bottle around its vertical axis, an extended image is acquired in which the whole bottle is represented . The flaws are detected by comparing the grey levels of the image with a threshold. Due to the required high-speed inspection (1 bottle/s), this method is employed in the glass industry of wine bottles. However, with this methodology only the body of the bottle can be satisfactorily inspected. Due to the edges of the regular structure of the bottleneck, the inspection requires a human operator for this part of the bottle. No results of this method are reported in the literature.

In this paper, we present the results obtained in the inspection of (empty) wine bottles using a new technique in the inspection of glass. Nevertheless, the presented technique is not new in the automated inspection of aluminium die

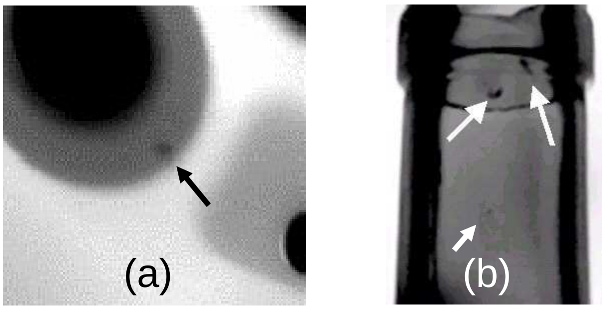

Fig. 1. (a) A flaw in an aluminium wheel. (b) Flaws in a glass bottleneck.

castings [6]. After the observation that the X-ray images acquired in the inspection of aluminium castings are similar to those photographic images obtained in the inspection of glass (see for example Fig. 1), we decided to investigate the inspection of glass bottles using a well known AVI technique for die castings, namely, the MODAN filter [7]. We demonstrate that this approach, based on the adapted median filtering, can be used in the automated quality control of wine bottles successfully.

The rest of the paper is organised as follows: in Section 2 the adapted median filter is outlined; the results obtained using this technique is presented in Section 3; and finally, the concluding remarks are given in Section 4.

2 Adapted median filtering

The adapted median filtering is known as a *reference method* in the automated visual inspection of aluminium die castings [6]. In reference methods it is necessary to take still images at selected programmed inspection positions. The

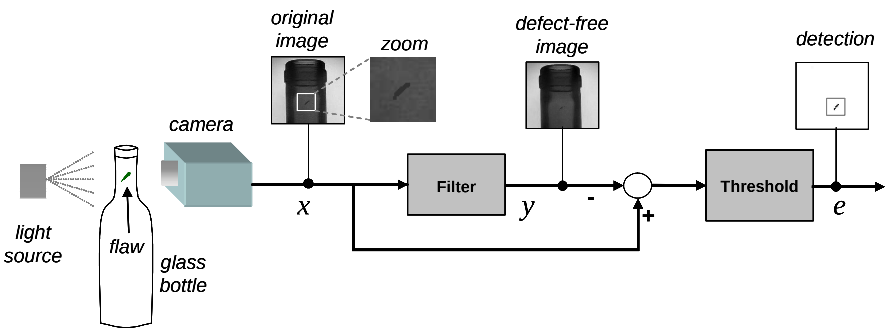

Fig. 2. Flaw detection in a glass bottle using a reference method.

inspection process is illustrated in Fig. 2. The image of the object under test (x) is compared with a defect-free image (y), called the reference image. If a significant difference is identified (e), then the test piece is classified as defective. In these approaches, the reference image is estimated from the test image using a filter consisting of several masks. The key idea of reference methods is that the masks of the filter are configured off-line from a training set of real defect-free images, and the filtering self is performed on-line. Thus, a fast on-line inspection is ensured.

There are several reference methods used in the inspection of aluminium castings, however, as a result of its peak detection performance, the reference methods based on **Mod**ified Medi**an** (MODAN) filter [7] have become most widely established in industrial applications in this field [6]. With the MODAN–Filter it is possible to differentiate regular structures of the piece from defects. The MODAN–Filter is a median filter with adapted filter masks. 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 one half of the input value to the filter. This characteristic is utilised to suppress the defect structures and to preserve the design features of the test piece in the image.

The goal of the adapted median filtering is to create a defect-free image from the test image. Thus, the MODAN–Filter is used in order to suppress only the defect structures in the test image. Locally variable masks are used during MODAN–filtering by adapting the form and size of the median filter masks to the design structure of the test piece. This way, the design structure is maintained in the estimated reference image (and the defects are suppressed). Additionally, the number of elements in the operator are reduced in order to optimise the computing time by not assigning all positions in the mask. This technique is known as a sparsely populated median filter [8]. Typically, only three inputs are used in the MODAN filter. In this case, the reference image is computed as:

$$y[i,j] = \mathrm{median}(x_1, x_2, x_3), \tag{1}$$

with

$$\begin{aligned} x_1 &= x[i,j] \\ x_2 &= x[i+d_{ij}, j+e_{ij}] \\ x_3 &= x[i-d_{ij}, j-e_{ij}], \end{aligned}$$

where $x[i,j]$ and $y[i,j]$ are the grey values at pixel (i,j) in the test and reference images respectively. The filter direction of the masks is determined by the distances d_{ij} and e_{ij}. Defects are detected when

$$|y[i,j] - x[i,j]| > \theta_{ij}. \tag{2}$$

where θ_{ij} is the threshold of pixel (i,j).

The parameters d_{ij}, e_{ij} and θ_{ij} are found in an off-line configuration process. For this task, a bank of 75 different filter masks with three inputs is used [9]. In

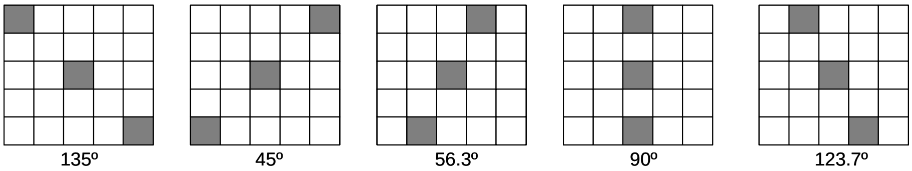

Fig. 3. Some 5×5 masks used in a MODAN filter with 3 inputs.

the bank, there are masks of 3×3, 5×5, ..., 11×11 pixels. Some of them are shown in Fig. 3. Additionally, N training images of different pieces without defects are taken in the same position. A mask is selected for pixel (i, j) when the objective function

$$J_{ij} = \sum_{n=1}^{N} \left[Q_{ij}(d_{ij}, e_{ij}) \right]_n \tag{3}$$

is minimised. In the objective function, $\left[Q_{ij}(d_{ij}, e_{ij})\right]_n$ is computed from the n-th image of the training set for $n = 1, ..., N$ as:

$$\left[Q_{ij}(d_{ij}, e_{ij})\right]_n = \left[Q^1_{ij}(d_{ij}, e_{ij}) + Q^2_{ij}(d_{ij}, e_{ij}) + Q^3_{ij}(d_{ij}, e_{ij})\right]_n , \tag{4}$$

where functions Q^1, Q^2 and Q^3 denote the detection error, flagged false alarms, and the matrix size[2].

Threshold θ_{ij} is computed from the training images as

$$\theta_{ij} = \max(|y_n[i, j] - x_n[i, j]|) + \alpha. \tag{5}$$

With $\alpha = 0$ we ensure that no false alarm is flagged in all training images. However, it is convenient to set $\alpha > 0$ to give a larger confidence region. The selection of this parameter will be studied in next section.

Thus, once the mask is selected, the error-free reference image is estimated on-line using (1) when condition (2) is satisfied.

3 Results

We evaluate the performance of the MODAN filter by inspecting glass bottlenecks, because this part of the bottle is the most difficult to inspect. In our experiments, 56 images (with and without flaws) of 320×200 pixels were taken from 7 (empty) wine bottles at 8 different viewpoints by rotating the bottle around its vertical axis. 20 images without flaws were selected for the training. The other 36 images were used for the inspection.

[2] For three input values (x_1, x_2, x_3) (see equation (1)), the mentioned functions are defined as follows: detection error is $Q^1 = |x_2 - x_1| + |x_2 - x_3|$, flagged false alarms is $Q^2 = x_2 - \text{median}(x_1, x_2, x_3)$, and matrix size is $Q^3 = (d_{\max} - d)^2 + (e_{\max} - e)^2$, where the size of the largest mask in the bank is $d_{\max} \times e_{\max}$ [9].

In order to assess the performance of the inspection, the Receiver Operation Characteristic (ROC) [10] curve is analysed. The ROC curve is defined as a plot of the 'sensitivity' (Sn) against the '1-specificity' ($1 - Sp$):

$$Sn = \frac{TP}{TP + FN}, \qquad 1 - Sp = \frac{FP}{TN + FP}, \tag{6}$$

where

TP is the number of true positives (flaws correctly classified);
TN is the number of true negatives (regular structures correctly classified);
FP is the number of false positives (false alarms, i.e., regular structures classified as defects); and
FN is the number of false negatives (flaws classified as regular structures).

Ideally, $S_n = 1$ and $1 - S_p = 0$, i.e., all flaws are detected without flagging false alarms. The ROC curve permits the assessment of the detection performance at various operating points (e.g., thresholds in the classification). The area under the ROC curve (A_z) is normally used as a measure of performance because it indicates how reliable the detection can be performed. A value of $A_z = 1$ gives a perfect classification, whereas $A_z = 0.5$ corresponds to random guessing.

A ROC curve was computed for the inspection of the 36 test images for $\alpha = 0, 5, 10, 15, 20$. The obtained area was $A_z = 0.8932$ and the best operating point was $S_n = 0.85$ and $1 - S_p = 0.04$, i.e., 85% of the existing flaws were detected with only 4% of false alarms (see ROC curve in Fig. 4). The detection in two of the test images is illustrated in Fig. 5.

In addition, the detection performance was evaluated in real images with simulated flaws. The simulated flaws were obtained using the technique of mask superimposition [11], where certain original grey values of an image without flaws are modified by multiplying the original grey value with a factor p. Fig. 6 shows

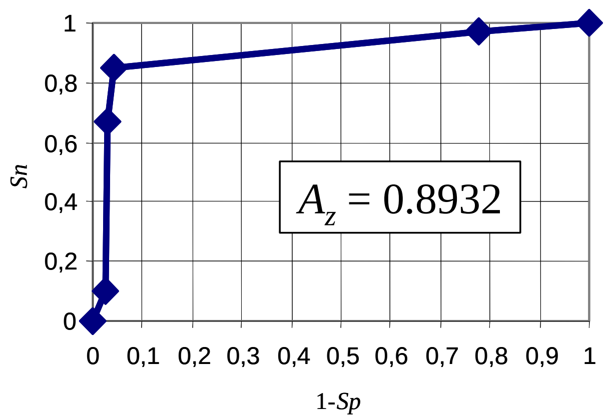

Fig. 4. ROC curve for 36 test images.

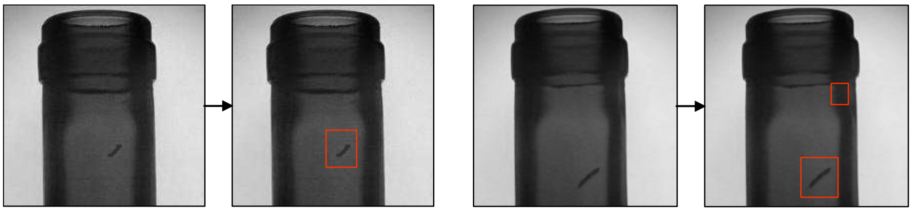

Fig. 5. Test images and their corresponding detections (see false alarm in right detection).

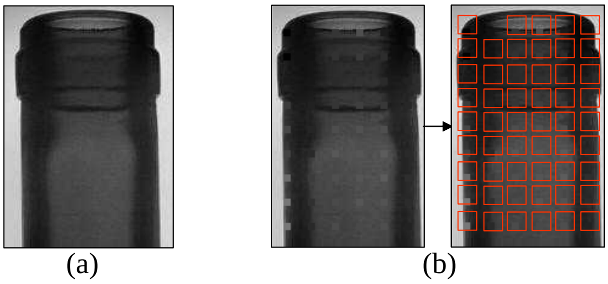

Fig. 6. Detection in images with simulated flaws: a) test image without flaws, b) test image with simulated flaws and its corresponding detection.

the results obtained for $p = 1.10$. In this example, only one simulated flaw was not detected, and there is no false alarm. In the simulation, the obtained area was $A_z = 0.9810$.

Finally, we evaluate the computational time. In our experiments, we used a PC Athlon XP, 1.6 GHz with 128 MB RAM. The selection of the masks was programmed in Matlab. In this case, 7.5 hours were required to find the filters. The detection algorithm, on the other hand, was programmed in C. The median filtering was implemented considering that only three inputs are to be evaluated. The detection was achieved in only 0.3s/image.

4 Conclusions

In this paper, the implementation and evaluation of a well-known technique for inspecting aluminium castings was used for the automated visual inspection of glass bottles. The idea is to generate a defect-free reference image obtained from the original image of the inspection object. The reference image is compared with the original one, and defects are detected when the difference between them is considerable. The filter is configured off-line from a training set of real defect-free images, and the filtering itself is performed on-line. Thus, a fast on-line inspection is ensured.

In our experiments, the detection performance was 85% and the false alarms rate was 4%. Additionally, the detection was achieved in only 0.3s/image. This means that the obtained computational time satisfies industrial requirements.

It is very interesting to demonstrate that a well-known technique used in the automotive industry for inspecting aluminium die castings, can be used in the inspection of glass bottles. In this case, no modification of the original methodology was required.

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References

1. Newman, T., Jain, A.: A survey of automated visual inspection. Computer Vision and Image Understanding **61** (1995) 231–262
2. Parker, J.: Defect in glass and their origin. In: First Balkan Conference on Glass Science & Technology, Vollos, Greace (2000)
3. Firmin, C., Hamad, D., Postaire, J., Zhang, R.: Gaussian neural networks for bottles inspection: a learning procedure. International Journal of Neural System **8** (1997) 41–46
4. Hamad, D., Betrouni, M., Biela, P., Postaire, J.: Neural networks inspection system for glass bottles production: A comparative study. International Journal of Pattern Recognition and Artificial Intelligence **12** (1998) 505–516
5. Riffard, B., David, B., Firmin, C., Orteu, J., Postaire, J.: Computer vision systems for tuning improvement in glass bottle production: on-line gob control and crack detection. In: Proceedings of the 5th International Conference on Quality Control by Artificial Vision (QCAV-2001), Le Creusot, France (2001)
6. Mery, D., Jaeger, T., Filbert, D.: A review of methods for automated recognition of casting defects. Insight **44** (2002) 428–436
7. Filbert, D., Klatte, R., Heinrich, W., Purschke, M.: Computer aided inspection of castings. In: IEEE-IAS Annual Meeting, Atlanta, USA (1987) 1087–1095
8. Castleman, K.: Digital Image Processing. Prentice-Hall, Englewood Cliffs, New Jersey (1996)
9. Heinrich, W.: Automated Inspection of Castings using X-ray Testing. PhD thesis, Institute for Measurement and Automation, Faculty of Electrical Engineering, Technical University of Berlin (1988) (in German).
10. Duda, R., Hart, P., Stork, D.: Pattern Classification. 2 edn. John Wiley & Sons, Inc., New York (2001)
11. Mery, D.: Flaw simulation in castings inspection by radioscopy. Insight **43** (2001) 664–668