

# FAULT DETECTION AND LOCALIZATION IN EMPTY WATER BOTTLES THROUGH MACHINE VISION

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## Abstract

*This paper presents a vision-based approach for fault detection for the empty water bottles. The goal of our approach is to find all defects in the empty water bottles. The main constraint is the real time operation as the bottles move continuously on the conveyer belt. Using images obtained from the camera, we first find the position of the bottle in the image by generalized Hough transform. Then we check the bottles for any defects or presence of alien objects using rectangular and circular areas intensity inspection. The bottles with any defects are rejected and so separated from the main stream. In the statistics obtained, our inspection system successfully rejected all the faulty or defected bottles. The good bottle rejection rate was also lower than 1% of the total number of bottles inspected. This system can be used for inspecting any type of empty bottles for defects or presence of alien objects.*

**Keywords:** Bottle Inspection; Surface Inspection; Machine Vision; Quality Control.

## 1. INTRODUCTION

Quality control is an essential part of any bottle production system. When the bottles are produced in a manufacturing plant, they are inspected for manufacturing faults. However when empty bottles returned by the consumers are to be reused, the focus of quality control changes. Reusable bottles are becoming increasingly popular due to their cost effectiveness. Inspection of the returned bottles, for re-using them, is required to ensure quality. The quality control at this stage refers to the detection of any defects (damaged finish, cracks, shape deformation) or the presence of alien objects (dirt particles, sticky objects) in the bottle. There are many potential causes for the presence of such problems including equipment faults, personnel errors, non-standard procedures, or environment [1]. The focus of this paper is to eliminate the personnel errors by replacing manual inspection with vision-based inspection.

Bottle inspection systems can be divided into two categories [2]: *online* inspection systems and *offline* inspection systems. The online inspection systems inspect the bottles while they are moving on the conveyer belt. The offline inspection systems take samples of the bottles, and evaluate them off-line.

Currently, state of the art in bottle inspection includes both vision-based inspection and manual inspection. The ultimate goal of any bottle inspection system is to reject all defected bottles (termed as *true negatives*), while not rejecting any good or perfect bottle (termed as *false negatives*). Manual systems reduce the percentage of false negatives down to 0%, but fail to detect all the defected bottles. A recent study of unsuitable factors for bottle inspection operators [3] shows that continuous stress on bottle inspectors affects their alertness level, resulting in an increase in fault bottles missed rate. Methods based on machine vision, on the other hand, successfully detect all the defected bottles but have a relatively high number of false negatives. The additional advantage of vision-based systems is their on-line operation resulting in more stringent quality control.

The first step required to visually inspect a bottle is to detect the position of the bottle in the camera image. Hough transform [4] based image segmentation is used for this purpose. After obtaining the position of bottle in the camera image, the image area containing the bottle is inspected for the presence of any faults or defects. The inspection is done on the basis of pixel intensity information. We introduce a new approach for fault localization by inspecting small segments similar in shape to that of the area under inspection. This information about fault position is used to investigate the status of the fault under inspection.

Section 2 starts with an overview of camera setup used to inspect the bottles. Then bottle detection using Hough transform is explained. Our approach of fault detection and localization is discussed in the last part of section 2. Section 3 provides some statistical results based on our vision inspection system. Section 4 concludes the

paper by giving a bird's eye view of the techniques used and results achieved.

## 2. METHOD

### 2.1 Camera Setup

We need to have images of a bottle from different positions, to inspect the surfaces of the bottles. To take different views of the bottle under inspection, we have used 3 cameras. The cameras were set into progressive scan mode and their focus was manually adjusted for best picture quality. The exposure time for the cameras was carefully adjusted to eliminate motion blur. This made the presence of external light necessary. Hence two 60 watts flicker-free lamps were used. In order to inspect different surfaces (base, inner sidewall, outer sidewall) of the bottle, the camera positions we have used are as explained below.

**2.1.1 Base View:** We used a high-resolution camera to inspect the bottom of the bottles for the presence of foreign objects, mold and chipped heels. The camera position in Fig. 1a is used for this purpose.

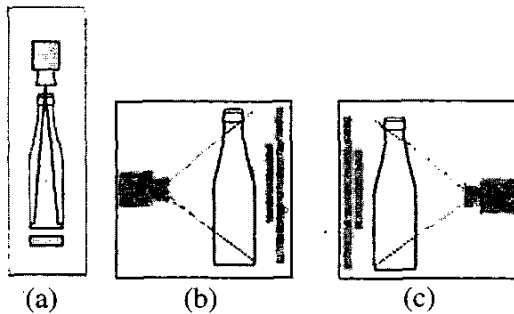


Figure 1: Different camera viewing positions. (a) Top view (b) Outer Sidewall view from left (c) Outer Sidewall view from right.

**2.1.2 Inner Sidewall View:** Image of inner sidewall of the bottle is helpful to find any dirty material inside the bottle. The camera position in Fig. 1a provides this view when the camera is placed close to the bottle's top.

**2.1.3 Outer Sidewall View:** The positions of the camera in Fig. 1b and Fig. 1c are helpful to take outer sidewall images of the bottle. These images are helpful to detect the defected or broken bottles. These images are also helpful in sorting of the bottles with different shapes and sizes.

### 2.2 Bottle Recognition

The first task after obtaining the images from the

cameras is to find the position of the bottle in each image. Real time object recognition using Hough transform is used for this purpose. Fig 2 shows the image of the bottom of the bottle passing through conveyer belt.

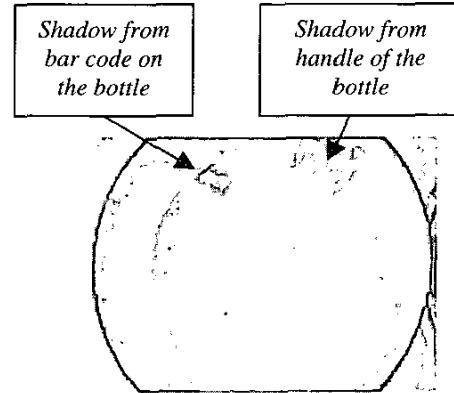


Figure 2: Bottom of the bottle

**2.2.1 Generalized Hough Transform:** A prominent property of the conventional Hough transform is that its applicability is restricted to detect analytic curves. Therefore, Ballard [5] generalized the Hough transform to detect arbitrary shapes. He also took the edge orientation into account, which made the algorithm faster and also greatly improved its accuracy by reducing the number of false positives.

**2.2.2 R-Table Construction:** To perform the offline phase of the GHT, the so-called R-table is constructed using information about the position and orientation of the edges in the reference image. The edges are extracted using Sobel operator [6] as shown in Fig 3. We prefer to use the Sobel filter because it represents a good compromise between computation time and accuracy. Its anisotropic response and its worst accuracy can be balanced by choosing an adequate quantization of the gradient directions.

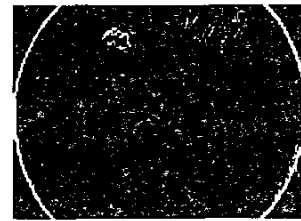


Figure 3: Edge detection of the base of the bottle by Sobel operator.

The first step in generating the R-table is to choose a reference point  $o = (x_o, y_o)$ , e.g., the centroid of all edge points  $p_i^r$  ( $i = 1 \dots N_p^r$ ) in the reference image. Then  $r_i = o - p_i^r$  is calculated for all points and  $r$  is stored as a function

of the corresponding gradient direction  $\phi$ . Assuming the case of rigid motion, in the online phase a three-dimensional accumulator array  $A$  is set up over the domain of parameters, where the parameter space is quantized and range restricted. Each finite cell of that array corresponds to a certain range of positions and orientations of the reference image in the search image, which can be described by the three variables  $x$ ,  $y$ , and  $\theta$ . Here,  $x$  and  $y$  describe the translated position of  $o$  in the search image and  $\theta$  the orientation of the object in the search image relative to the object in the reference image. For each edge pixel  $p_i^s$  in the search image and each R-table corresponding to one orientation  $\theta_k$ , all cells  $r_i + p_i^s$  in  $A$  receive a vote, i.e., they are incremented by 1, within the corresponding two dimensional hyper plane defined by  $\theta = \theta_k$  under the condition that  $\phi_j^s = \phi_i^r$ . Maxima in  $A$  correspond to possible instances of the object in the search image.

As we know the shape of the bottles varies from each other so we used generalized Hough transform to detect different shape of the bottles. In this particular case we have to detect the base of the bottle, and the base of the bottle is in circular shape. So, here we used circular Hough transform, to detect circular area (base) of the bottle as shown in Fig 4.



Figure 4: Bottle detection by Hough Transform

### 2.2.3 Optimizing the Generalized Hough Transform:

The reduction of the high computational complexity of both, the conventional Hough Transform (HT) and the GHT, has been the subject of several publications. Yacoub [7], for example, propose an HT algorithm based on a hierarchical processing for line detection. It performs a classical HT on small sub-images and merges the extracted lines with similar parameters by successively joining four neighboring sub-images until the original image size is reached. In object recognition this approach is not reasonable because the object may be spread over several sub-images, which results in a high sensitivity to clutter and noise. Other approaches reduce the dimension of the parameter space by introducing additional information: SER & SIU [8] use relative gradient angles in the R-table, whereas MA & CHEN [9] consider the slope and the curvature as local properties. These

approaches have a reduced computational complexity in common but on the other hand have serious limitations. The use of relative gradient angles supposes the object not to be occluded, whereas considering the slope and the curvature fails when dealing with shapes that are composed mainly of straight lines.

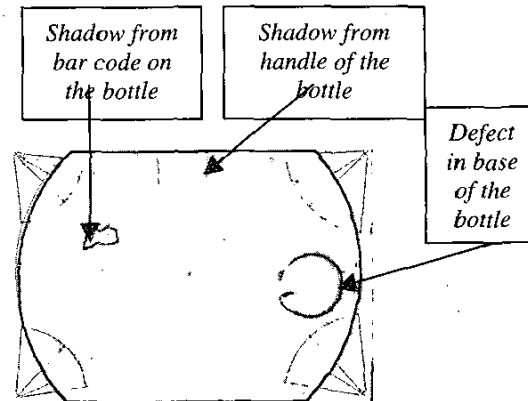


Figure 5: Bottle detection from top view of a typical empty water gallon. The green line represents the detected bottle, while the purple arcs at the four corners represent the points making the best-fit circle.

We use the approach by Ulrich [10] in which the optimization is achieved in four steps. In the first step, a hierarchical strategy is adapted. In this strategy an image pyramid of both images, the reference image and the search image, is generated. This helps in making a rough estimate of object position in the image at a very low computational cost. Then this search is refined in the following steps until the lowest level image in the pyramid is reached. Morphological filtering and tiling is used to reduce the search region while moving from one pyramid level to the other. Using this technique the GHT is calculated in about 15 msec at an Intel<sup>®</sup> Pentium<sup>®</sup> 4, 2.6 GHz workstation.

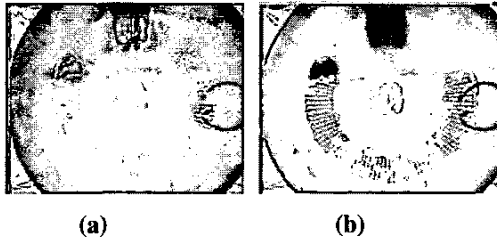
### 2.3 Fault Detection

Once the position of the bottle in the camera images is known, the next step is to inspect the bottle image for any defects. This step requires the examination of each pixel on the bottle. Since we know the pixel intensities of perfect bottles, we inspect individual pixels on that basis. If the intensity of an individual pixel does not lie within the tolerance limit, the pixel is designated as *outlier*. The intensities of an individual pixel, however, may change due to noise, reflection, or change in external lighting condition. Hence if decisions for presence of defects are

made on the basis of individual pixels, these decisions are not very accurate.

Therefore we divide the bottle image into several segments. The exact size of these segments depends on the required accuracy of inspection, since it defines the smallest size of fault that can be detected. All the pixels in a segment are inspected. If the number of outliers in a segment exceeds the pre-defined threshold, the segment is marked as defected.

The shape of the segment is chosen on the basis of shape of the bottle image itself. If the surface under inspection is circular in shape, like the base of water bottles, the image is also segmented into circular regions. These regions are further divided into arcs of equal lengths. Since water bottles usually have circular designs at the base, the segmentation of the base image into circles allows to set different tolerance and threshold values for each segment.



**Figure 6: Fault detection after image segmentation. (a) Handle and bar code shadows are clearly detected. (b) Foreign object inside the bottle is detected.**

Since we know the shape of the bottle under inspection, we can separate the false negatives from true negatives using information about the size and relative position of the detected regions. For example for the bottle in Fig. 2, the bottle handle and the bar code have a fixed size and relative distance, so these can be easily separated from the other negatively detected regions.

### 3. RESULTS AND DISCUSSION

The statistical results obtained using our visual inspection tool are given in Table I. In order to compare the state of the art in the field of bottle inspection with our visual inspection tool, the result obtained from manual inspection are listed in Table II. Since manual inspection was not very precise, only approximate values are used in Table II.

If we compare both of the statistical results in tables II and I, we can see that  $B_{fmr}$  (fault bottle miss rate) is very high in manual inspection of bottles where as  $B_{gr}$  is minimum down to 0%. In our vision based inspection system  $B_{fmr}$  is low down to minimum.

**Table I: Statistics obtained using vision based inspection system.**

No. of Inspected Bottles (B)	Fault Bottle Rejection Rate ( $B_{fr}$ )	Fault Bottle Missed Rate ( $B_{fmr}$ )	Good Bottle Rejection Rate ( $B_{gr}$ )
32261	2.78%	0%	0.52%
35188	2.76%	0%	0.81%
45217	1.72%	0%	0.35%
60496	2.05%	0%	0.47%
58979	2.72%	0%	0.88%

**Table II: Statistics based on manual inspection.**

No. of Inspected Bottles (B)	Fault Bottle Rejection Rate ( $B_{fr}$ )	Fault Bottle Missed Rate ( $B_{fmr}$ )	Good Bottle Rejection Rate ( $B_{gr}$ )
32261	1-2%	1-2%	0%
35188	1-2%	1-2%	0%
45217	1-2%	1-2%	0%
60496	1-2%	1-2%	0%
58979	1-2%	1-2%	0%

It was our main target to minimize  $B_{fmr}$  in our inspection system. If we again observe the tables II & I we can see that  $B_{gr}$  is slightly increased in our inspection system as compared to manual inspection. There are many factors, which are the cause to increase the  $B_{gr}$  (good bottle rejection rate),  $B_{gr}$  mainly depends on environment, proper placement of vision inspection system and minor production faults (e.g. prominent part line) of the bottles. These above mentioned factors are external force to increase the  $B_{gr}$  values independent of the performance of our vision-based inspection system.

### 4. CONCLUSION

In this paper we have presented a vision-based approach for empty water bottle's inspection. State of the art machine vision tools are being used in bottle inspection systems. The main problem in previous manual based inspection system was high missed rate of faulty bottles. Our objective is to minimize fault bottle missed rate.

We have used circular Hough transform for bottle detection, since the bottles under inspection had circular base. Generalized Hough transform can be used to detect

bottles of any shape. After bottle detection, we inspect the bottle for any defects or faults using image segmentation. A special technique of shape dependent segmentation was used to obtain more precise information. The decision for a defect was based on the intensity variations of the image within each segment. This helped to remove the problem of global illumination changes.

Using this vision based approach; we successfully reduced the *fault bottle missed rate* ( $B_{fmr}$ ) down to 0% in real time processing. We got slightly increased *good bottles rejection rate* (lower than 1%), as compared to manual inspection, but the gain in fault bottle rejection rate ensured more stringent quality control as compared to manual inspection. Methods to reduce good bottle rejection rate are open for future investigations.

*Photogrammetrie und Fernerkundung (DGPF)*, pages 571-578, Berlin, 2001

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