Image Acquisition and Automated Inspection of Wine Bottlenecks by Tracking in Multiple Views

Miguel Carrasco[1,3]
[1]Université Pierre et Marie Curie-Paris 6
Institut Systèmes Intelligents et Robotique FRE 2507
3 rue Galilée, 94200 Ivry-sur-Seine
FRANCE
miguel.carrasco@robot.jussieu.fr

Luis Pizarro[2]
[2]Saarland University
Mathematical Image Analysis Group
Building E1.1, 66041 Saarbrücken
GERMANY
pizarro@mia.uni-saarland.de

Domingo Mery[3]
[3]Pontificia Universidad Católica de Chile
Departamento de Ciencia de la Computación
Av. Vicuña Mackenna 4860 (143), Santiago
CHILE
dmery@ing.puc.cl

Abstract: In this paper we propose a prototype for image sequence acquisition of glass wine bottlenecks, whose main novelty is the use of an inner lighting source for better capturing of potential defects. A novel approach for automatic inspection of the bottlenecks based on tracking potential flaws along the acquired sequence is also presented. Our inspection system achieves performance rates of 87% true positives and 0% false positives.

Key–Words: Image acquisition; Automated inspection; Tracking; Multiple views; Wine bottle inspection; Defect detection; Control quality.

1 Introduction

The bottle inspection systems appeared in the literature can be classified in two categories: Approaches that make use of a single view/camera for detecting flaws, e.g. [1, 2, 3, 4, 5, 6]; and frameworks that exploit the utilisation of multiple views/cameras to reinforce the detection process, e.g. [7, 8, 9, 10, 11]. Our proposed inspection device employs a single camera for image acquisition. However, we emulate the use of multiple cameras by recording an image sequence of a wine glass bottle in successive rotations along its principal axis.

In every image acquisition device the lighting conditions play a major role in the quality of the acquired images and therefore in the inspection task. Since natural lighting conditions are dynamic and change all the time it is not feasible to implement algorithms that are robust to illumination changes without burning important computational time [12]. Therefore, the use of artificial lighting is a requisite for reaching good and uniform illumination for real-time inspection systems. There exist several studies, e.g. [13], concerning the placement of external light sources around the object under examination. However, we do not know any work reporting on light sources placed inside a glass bottle. We proposed the design of an electro-mechanical device for image acquisition and inspection of glass wine bottles using an internal illuminating system. This allows us to obtain high-quality images for capturing very small defects, and to avoid the intrinsic reflections produced by external light sources.

Numerous methods for automated glass bottle inspection attempt to identify defects in the lips, body and bottom of the bottles [1, 7, 8, 9, 10, 3, 4, 5, 6, 11]. However, there are only few works that deal with the problem of detecting flaws in the bottleneck [9, 2]. The neck is the bottle's part where most of the defects appear during fabrication, due to its narrow and hence difficult to manipulate structure. In this paper we focus our research on the inspection of necks in empty wine glass bottles.

For the inspection of the bottlenecks we propose a novel methodology that performs tracking of potential flaws along the acquired image sequence. The key observation is that only real flaws can be successfully traced, since they do induce spatio-temporal relations between the views where they appear. Conversely, potential defects that cannot be tracked correspond to false alarms. We effectively track and thus identify real flaws by means of geometry of multiple views [14]. In particular, we employ bifocal and trifocal analysis. Although several published methods work with multiple views, this is, to the best of our knowledge, the first work on multiple view tracking for inspection of wine glass bottles.

Our paper is organised as follows: In Section 2 we present our prototype for image acquisition and inspection of wine bottlenecks. Section 3 describes our proposed algorithm for tracking real flaws along multiple views. Section 4 shows the performance achieved by our inspection system in comparison with other methods proposed in the literature. Finally, we summarise our contributions and succinctly describe some ongoing and future work in Section 5.

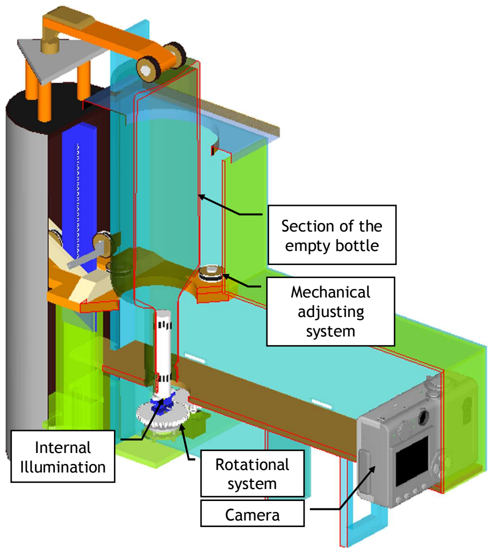

Figure 1: Proposed electro-mechanical prototype for image acquisition.

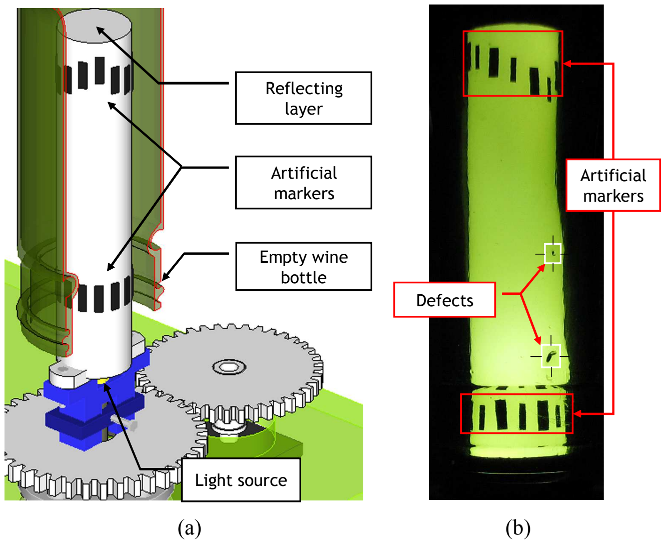

Figure 2: (a) Details of the illuminating tube; (b) Example image captured by the CCD camera.

2 Electro-Mechanical System for Image Sequence Acquisition

In this section we describe an electro-mechanical device we have designed for the automatic acquisition of an image sequence of the bottleneck of an empty glass bottle under inspection. Two are the main components of our mechanism: An internal illumination system and a rotor that rotates the bottle during acquisition. The image sequence is recorded by a standard CCD camera. The device we have built is schematically shown in the Fig. 1.

As observed in the Fig. 1, an illuminating tube has been placed inside the bottle. Four LEDs (T1 3.5v-20mA) emitting white light uniformly are located at the bottom of the tube. To improve light uniformity a reflecting layer has been fixed at the other extreme of the tube. To the best of our knowledge, there is no inspection system for glass bottles proposed in the literature that places the illumination system inside the bottle. This greatly improves the definition of the acquired images, increasing therefore the probability of capturing the smallest defects around the bottleneck. Another important characteristic of the illuminating tube is the set of artificial markers situated on both extremes, as displayed in the Fig. 2. They will later allow us to know the relative position of a defect along the image sequence.

The rotational system shown in the Fig. 1 permits rotating the bottle and the light source at the same time. An image sequence of the bottleneck is thus composed by views taken at successive rotations by a configurable spin angle α, controlled by a step motor. The images are captured by a CCD sensor with high resolution. In our experimental prototype we use a CANON S3 IS camera with a resolution size of 2592 $\times$ 1944 pixels and a dynamic range of 24 bits. The camera is placed around 20 cm from the bottleneck. No additional light sources are utilised. The device also includes a mechanical adjusting system to adapt the inspection to different bottleneck lengths. An adjustable arm holds the bottle from its body, and a press mechanism pushes the bottle against the rotor to keep its vertical position.

The electro-mechanical system is commanded by a Basic Stamp micro-controller PIC16C57 connected to a standard personal computer via a RS232 communication port. The micro-controller is programmed in Pbasic. For a specified spin angle α (degrees) the micro-controller synchronises the step motor with the illumination system. The camera's acquisition method is triggered by a camera control system via Matlab. The image sequence consists thus of $\lfloor 360/\alpha \rfloor$ different views, where $\lfloor \cdot \rfloor$ is the floor function.

For the sake of simplicity, we have built our prototype considering an upside down bottle[1]. However, it is also possible to assemble the system with a right side up bottle. Our bottle inspection apparatus employs a single camera only. However, by recording an image sequence of the bottle under examination we are able to emulate a system using multiple cameras [7, 8, 9, 10, 11]. It is important to mention that no camera calibration procedure is considered at all.

[1]Similar to the inspection of wineglass in [15].

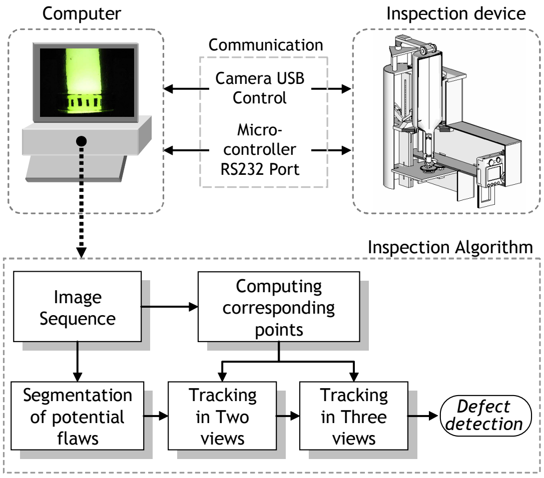

Figure 3: Proposed bottle inspection system.

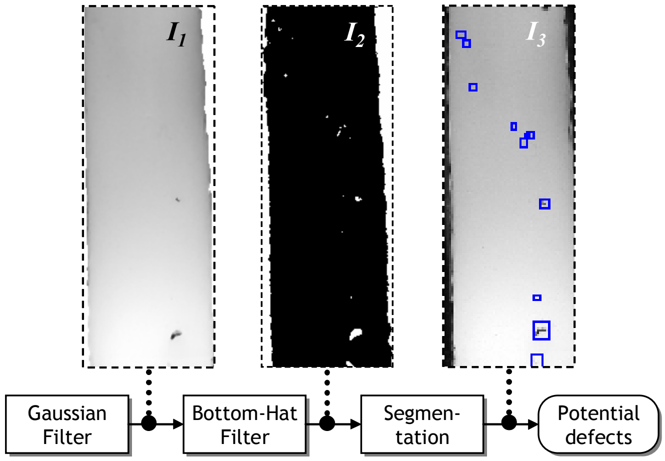

Figure 4: Segmentation of potential defects.

Therefore, we actually obtain *uncalibrated* image sequences, which we will utilise in the next section for tracking and detecting real defects in bottlenecks using geometry of multiple views [14].

3 Detection of Real Flaws by Tracking in Multiple Views

In the previous section we described an electromechanical device specially designed for capturing image sequences of bottlenecks using a single camera. In some applications, a unique image might be enough for inspecting certain objects or materials. However, the use of multiple views can reinforce the diagnosis made with a single image. That is the case for example for low signal-to-noise ratio imaging systems, where the identification of real defects with poor contrast entails the appearance of numerous false alarms as well. Here, we aim at exploiting the redundant information present in the multiples views of the bottle under inspection in order to discriminate real defects from false alarms. In fact, only real flaws can successfully be tracked along an image sequence. This is the main idea that will allow us to distinguish real flaws from other artifacts. Based on such observation, we propose a three-steps methodology for detecting real flaws in the bottleneck of a glass bottle: segmentation of potential flaws, computation of corresponding points, and tracking potential flaws. Similar ideas has been treated in [16, 2, 17, 18]. Apart from dealing with another application and proposing a system for image acquisition, the main differences between this contribution and these works lie in our clever choice of corresponding points and in the utilisation of several filters for defect segmentation. The Fig. 3 shows a general overview of our proposed methodology for image acquisition and defect detection.

3.1 Segmentation of potential flaws

The segmentation of potential defects in every image of the sequence is outlined in the Fig. 4. First, the original image is filtered with a Gaussian filter in order to reduce the amount of noise intrinsic to any CCD image acquisition process (I_1). Second, a bottom-hat filter is applied to isolate potential defects from the background (I_2). Third, potential defects are segmented in every image using the Valley Emphasis method [19]. For each potential defect, the mass centre is taken and stored in homogeneous coordinate. As a result, numerous potential defects appear as observed in the segmented image (I_3). Nevertheless, only few of them correspond to real flaws.

3.2 Computation of corresponding points

As stated before, our final goal is tracking real defects in an image sequence. For this purpose, accurate corresponding points between every pair of views are required. We solve this problem by placing equidistant artificial markers on both extremes of the illuminating source, as shown in the Fig. 2. The lower markers are positioned at the same vertical level, while the upper ones follow a sinusoidal wave. Using these markers we can compute a set of corresponding points between each pair of consecutive or non-consecutive views. This is schematically outlined in the Fig. 5. The upper and lower markers of each view are connected through vertical lines between their mass centres, which were also extracted in the segmentation step. Since the length of a vertical line connecting

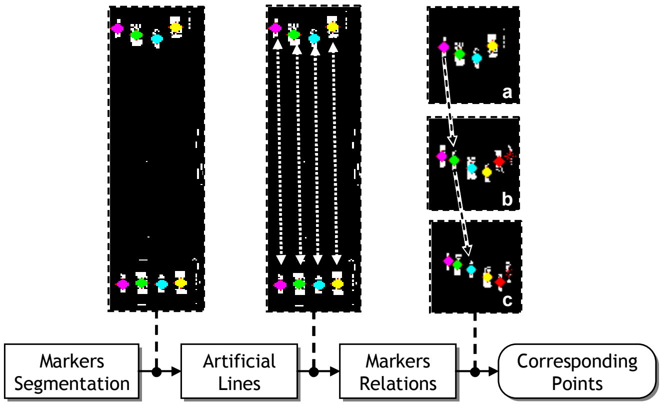

Figure 5: Computation of corresponding points.

two particular markers remains constant along the image sequence, we know the relative position of these markers in different views. Therefore, the set of corresponding points between two views a and b is conformed by the relative positions of their markers. Such correspondences are later used to estimate the *fundamental matrix* $\mathbf{F}_{a,b}$ that relates any pair of points in the views a and b.[2]

3.3 Tracking of potential flaws

In the previous step we have segmented all potential defects along the image sequence. We now turn to the problem of separating real flaws from false alarms. The key observation is the fact that only real flaws could be tracked along the image sequence. A real flaw entails a spacio-temporal relation in the different views where it appears, while a false alarm corresponds to a random event.

In the previous segmentation step each identified potential defect is represented by its mass centre. For instance, the mass centre of the j-th potential defect in the a-th view is stored in homogenous coordinates as $\mathbf{m}_a^i = [x_a^i, y_a^i, 1]^\top$. If this potential defect is actually a real flaw it must have a corresponding point $\mathbf{m}_b^j$ in another consecutive or non-consecutive view b where a potential defect j was also segmented. According to the *principle of multiple view geometry* [14], the points $\mathbf{m}_a^i$ and $\mathbf{m}_b^j$ are in correspondence if they are related by the fundamental matrix $\mathbf{F}_{a,b}$ such that

$$\mathbf{m}_b^{j\top}\,\mathbf{F}_{a,b}\,\mathbf{m}_a^i = 0\,.$$

This relation is known as *epipolar constrained.* It indicates that the point $\mathbf{m}_b^j$ can only lie on the epipolar line of the point $\mathbf{m}_a^i$ defined as $\mathbf{l}_a^i = \mathbf{F}_{i,j}\,\mathbf{m}_a^i = [l_{a,x}^i, l_{a,y}^i, l_{a,z}^i]$. Then, knowing $\mathbf{l}_a^i$ we identify the correspondence associated with the potential defect i as the potential defect j in the view b that satisfies the constraint

$$\frac{|\mathbf{m}_b^{j\top}\,\mathbf{F}_{a,b}\,\mathbf{m}_a^i|}{\sqrt{(l_{a,x}^i)^2 + (l_{a,y}^i)^2}} < \varepsilon_1\,,$$

for small ε_1. If this constraint is fulfilled a potential defect is thus found in the two views. In this case it could be considered as a real flaw with a bifocal correspondence. Otherwise, it is regarded as a false alarm. An example is shown in the Fig. 6a. The same procedure is applied to every potential defect in the view a that is to be found in the view b.

To confirm that a bifocal correspondence represents indeed a real flaw, we try to discover a new correspondence in a third view with the help of trifocal tensors. Let $\mathbf{T} = (T_t^{rs})$ be a $3 \times 3 \times 3$ matrix representing the trifocal tensor that encodes the relative motion among the views a, b, c.[3] Then, we can estimate the hypothetical position of a defect k in a third view c using the correspondences $\mathbf{m}_a^i$, $\mathbf{m}_b^j$ and the ten-

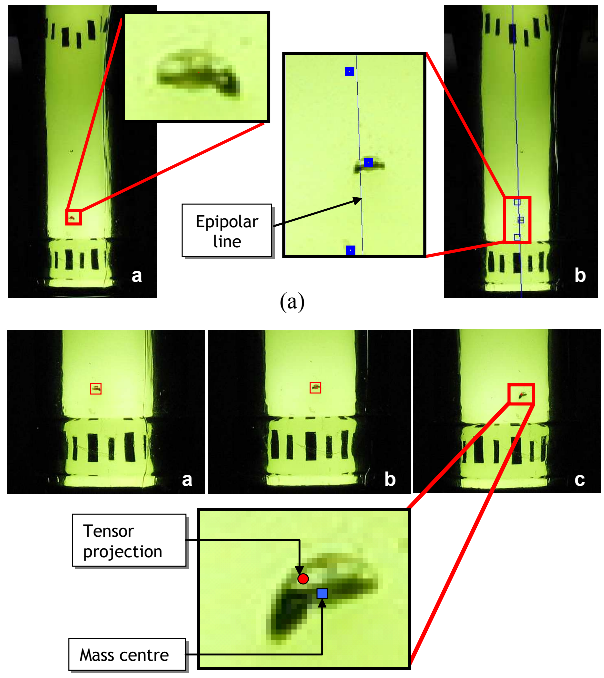

Figure 6: (a) Example of bifocal correspondences; (b) Example of trifocal correspondences.

[2] In estimating $\mathbf{F}_{a,b}$ we combine the algorithm of Hartley [14] with the biepipolar restriction presented in [20].

[3] See [14] for details on the computation of the trifocal tensors.

sor $\mathbf{T}$ as[4]

$$\widehat{\mathbf{m}}_c^k = \frac{1}{\mathbf{m}_a^{i\top}(T_{\cdot}^{13} - x_b^j T_{\cdot}^{33})} \begin{bmatrix} \mathbf{m}_a^{i\top}(T_{\cdot}^{11} - x_b^j T_{\cdot}^{31}) \\ \mathbf{m}_a^{i\top}(T_{\cdot}^{12} - x_b^j T_{\cdot}^{32}) \\ \mathbf{m}_a^{i\top}(T_{\cdot}^{13} - x_b^j T_{\cdot}^{33}) \end{bmatrix}.$$

We compare the estimated position with all potential flaws of the view c, regarding the potential defect k as a real flaw if the constraint

$$\|\widehat{\mathbf{m}}_c^k - \mathbf{m}_c^k\| < \varepsilon_1$$

is fulfilled. In this case a potential defect is thus found in the three views, i.e., a real flaw with a trifocal correspondence has been detected. Potential defects that do not find correspondence in three views are finally discarded and considered false alarms. An example is shown in the Fig. 6b.

4 Comparative Results

We now evaluate the performance of our proposed methodology for inspecting bottlenecks of empty glass wine bottles. In our experiments we used 13 color image sequences of a dozen bottles with real flaws. The area of the smallest defect was around 15 pixels. Each sequence consists of 24 images ($\alpha = 15$ degrees). From the recorded images we extract subimages of the bottlenecks of 1000×250 pixels. The inspection was performed considering trifocal correspondences in consecutive images, where the number of real flaws fluctuates between 0 and 8, with an average of 3.3 flaws/image. We therefore expect our method to identify $13 \times \binom{24}{3} \times 3.3$ flaws approximately. The performance is assessed considering two indicators: the true positive rate (TPR) and false positive rate (FPR), defined respectively as:

$$\mathrm{TPR} = \frac{\mathrm{TP}}{\mathrm{RD}}, \qquad \mathrm{FPR} = \frac{\mathrm{FP}}{\mathrm{RD}},$$

where TP is the number of true positives (defects correctly classified), FP is the number of false positives (regular structures classified as defects, i.e., false alarms), and RD is the number of existing real defects. Ideally, TPR $= 100\%$ and FPR $= 0\%$, i.e., all defects are detected without flagging false alarms.

Our tests showed good performance with TPR $=$ 87% and FPR $= 0\%$. In Table 1 we juxtapose our results with other inspection systems proposed in the literature, indicating the use of single or multiple images. It is important to mention that this is just a quantitative comparison, since the listed methods were tested on different images (or image sequences) and type of bottles, and they inspect one or several bottle parts (lips, mouth, bottleneck, body, bottom). Nevertheless, to the best of our knowledge, our methodology for glass bottle inspection is the first one that performs tracking of potential flaws in multiple views.

Table 1: Comparison with other inspection systems

Inspected parts	Views	Tracking	TPR	FPR
neck [2]	Single	No	85%	4%
lips, body, bottom [5]	Single	No	97%	>1%
lips [3]	Single	No	98%	0%
body [7, 8]	Multiple	No	80%-85%	2%
body, bottom [10]	Multiple	No	100%	>1%
lips, neck [9]	Multiple	No	98%	2%
neck (our method)	**Multiple**	**Yes**	**87%**	**0%**

Concerning the real-time capabilities of our methodology, the computational time required to process trifocal correspondences was 2.8 sec in average, using a Matlab 7.0's implementation running on a Pentium Centrino 2.0 GHz under Windows XP SP2. 34% of computational time is spent reading the images, 35% in the segmentation, 11% in the trifocal analysis, and 20% in other Matlab's internal operations.

5 Conclusions

Our principal contribution was twofold: First, we present a prototyping design of an electro-mechanical device for acquiring image sequences of wine bottlenecks using a single camera. Its main novelty is the placement of the illuminating source inside the bottle, which greatly improves the definition of the inspected images. Second, we introduce a new methodology for detecting flaws in the bottleneck based on tracking potential defects along an image sequence. Our inspection system achieves performance rates of 87% true positives and 0% false positives. Although these good results, our implementation is not yet competitive in terms of computational time. In this sense, several improvements are matter of ongoing work. For instance: the use of a fast industrial camera instead of a slow commercial camera together with a faster bottle rotating mechanism; the transfer of our Matlab implementations to a highly efficient low-level programming language; and the exploitation of multigrid implementation strategies. Additional future work includes the adaptation of our electro-mechanical device for inspecting not only bottlenecks, but other bottle parts as well.

[4]The estimated projection in the third view can be improved applying the point-line-point method proposed in [14, pp.373].

Acknowledgements: We gratefully acknowledge partial funding by CONICYT – Colegio Doctoral Franco–Chilena, grant no. 21050185.

References:

[1] M. Canivet, R. D. Zhang, and M. Jourlin, "Finish inspection by vision for glass production," vol. 2183, pp. 164–169, SPIE, 1994.

[2] D. Mery and O. Medina, "Automated visual inspection of glass bottles using adapted median filtering," *LNCS*, vol. 3212, pp. 818–825, 2004.

[3] Y.-N. Wang, L. H.-J., and F. Duan, "A bottle finish inspect method based on fuzzy support vector machines and wavelet transform," in *International Conference on Machine Learning and Cybernetics*, vol. 8, pp. 4588–4592, 2005.

[4] T.-S. Yan and D.-W. Cui, "The method of intelligent inspection of product quality based on computer vision," in *7th Int. Conf. on Computer-Aided Industrial Design and Conceptual Design (CAIDCD '06)*, (Hangzhou), pp. 1–6, 2006.

[5] F. Duan, Y.-N. Wanga, H.-J. Liua, and Y.-G. Li, "A machine vision inspector for beer bottle," *Eng Appl Artif Intell*, vol. 20, no. 7, pp. 1013–1021, 2007.

[6] Z. Yepeng, T. Yuezhen, and F. Zhiyong, "Application of digital image process technology to the mouth of beer bottle defect inspection," in *8th Int. Conf. on Electronic Measurement and Instruments*, vol. 2, pp. 905–908, 2007.

[7] C. Firmin, D. Hamad, J. Postaire, and R. Zhang, "Gaussian neural networks for bottles inspection: a learning procedure," *Int J Neural Syst*, vol. 8, no. 1, pp. 41–46, 1997.

[8] D. Hamad, M. Betrouni, P. Biela, and J. Postaire, "Neural networks inspection system for glass bottles production: A comparative study," *Int J Pattern Recogn Artif Intell*, vol. 12, no. 4, pp. 505–516, 1998.

[9] H.-M. Ma, G.-D. Su, and J.-Y. W. Z. Ni, "A glass bottle defect detection system without touching," in *Int. Conf. on Machine Learning and Cybernetics*, vol. 2, pp. 628–632, 2002.

[10] F. Shafait, S. Imran, and S. Klette-Matzat, "Fault detection and localization in empty water bottles through machine vision," in *Emerging Technology Conference*, pp. 30–34, 2004.

[11] K. Katayama, T. Ishikura, Y. Kodoma, H. Fukuchi, and A. Fujiwara, "Optical inspection of glass bottles using multiples cameras." US. Patent. 7.329.855 B2, 2008.

[12] S. K. Kopparapu, "Lighting design for machine vision application," *Image Vis Comput*, vol. 24, no. 7, pp. 720–726, 2006.

[13] S. Yi, R. Haralick, and L. Shapiro, "Optimal sensor and light source positioning for machine vision," *Comput. Vis. Image Underst.*, vol. 61, no. 1, pp. 122–137, 1995.

[14] R. Hartley and A. Zisserman, *Multiple View Geometry in Computer Vision*. Cambridge, UK: Cambridge University Press, 2000.

[15] J. Wang and A. Asundi, "A computer vision system for wineglass defect inspection via gabor-filter-based texture features," *Inform Sci*, vol. 127, pp. 157–171, 2000.

[16] D. Mery and D. Filbert, "Automated flaw detection in aluminum castings based on the tracking of potential defects in a radioscopic image sequence," *IEEE Trans Robot Autom*, vol. 18, no. 6, pp. 890–901, 2002.

[17] M. Carrasco and D. Mery, "Automated visual inspection using trifocal analysis in an uncalibrated sequence of images," *Mater Eval*, vol. 64, pp. 900–906, 2006.

[18] L. Pizarro, D. Mery, R. Delpiano, and M. Carrasco, "Robust automated multiple view inspection," *Pattern Anal Appl*, vol. 11, no. 1, pp. 21–32, 2008.

[19] N. Hui-Fuang, "Automatic thresholding for defect detection," *Pattern Recogn Lett*, vol. 27, no. 14, pp. 1644–1649, 2006.

[20] Z. Chen, C. Wu, P. Shen, Y. Liu, and L. Quan, "A robust algorithhm to estimate the fundamental matrix," *Pattern Recogn Lett*, vol. 21, pp. 851–861, 2000.