BLOW-MOLDED PLASTIC TUBE DEFECT DETECTION USING A SINGLE UNCALIBRATED CAMERA

Luis Unzueta, Javier Barandiaran, Álvaro Segura
{lunzueta, jbarandiaran, asegura}@vicomtech.org

VICOMTech
Mikeletegi Pasealekua, 57
Parque Tecnológico 20009
Donostia / San Sebastián (Spain)

Abstract. In this paper we present computer vision strategies to detect automatically defects on blow-molded plastic tubes used as outer covers of car dampers. A correct quality checking of these tubes is very important as the customers of these pieces are becoming more exigent and, in certain occasions, they reject full sets of thousands of pieces because of some non-valid samples (e.g., a limit of 6 defective tubes per million). The automation of this process is challenging due to the small size of the expected typical defects, the dark color of the molded material and the specular reflection they have. Current standard industrial solutions for this kind of process are not capable of fulfilling the objective. The proposed system uses a laser beam and a single uncalibrated standard camera to scan the tube surface even without the need of any ambient illumination at all. The presented computer vision algorithms reconstruct the tube surface from the observed laser beam deformations and identify the defects by comparing the shape respect to the one expected. Experimental results show the suitability of the proposed methods to detect holes, burrs and deformations on this type of tubes in real time, improving the productivity of the tube quality checking process.

1 INTRODUCTION

The automatic inspection of blow-molded plastic tubes is of key interest for the research community as current existing industrial solutions [1-14] are not usable due to their shape, color and the specularity of their surface. The way these pieces are built is the following: firstly, the casted polymer emerges from a pipe and falls forming an extruded hollow profile called *parison* (left image of Figure 1). Once this has an adequate length, the two part mold covers it and compressed air is injected inside. Consequently, the parison expands to occupy the interior of the mold and then it cools down to get its form. Finally, a set of rotating blades cut the piece with the desired length and the mold opens up to let the tube fall down with its definitive shape (right image of Figure 1).

Therefore, the inspection of this kind of pieces is usually done by operators that practically cannot do anything else. They have to take the tubes just released from the blowing machine, verify their quality visually and reject those with non-admissible failures. As it can be seen in Figure 2, these can be small and difficult to be quickly detected. Apart from being a cumbersome task for humans, it is prone to errors: the operator may not do the work paying the same attention for hours and it is usual to pass some with failures. The problem is that clients are becoming more exigent and, in occasions, they reject full sets of thousands of tubes due to a reduced amount of non-valid pieces (e.g., a limit of 6 defective per million), which can lead to economic and logistic breakthroughs to manufacturing companies.

The typical approach to determine automatically if a piece is correct or not, in Industry, is to obtain its 3D reconstruction and then compare it with respect to a canonical shape, which usually corresponds to the CAD model of its design. There are diverse techniques to reconstruct the real 3D shape of objects for further quality inspection: e.g., stereo vision [1-3], Time-of-Flight (ToF) [4], digital fringe projection [5], space-time stereo [6] or structured light approaches ([7] for a review), which include, laser based solutions [8], binary encoding [9-11], encoding by means of multiple grey-level values [12,13] and De Bruijn sequences based methods [14]. However, these techniques are not the most suitable to reconstruct these tubes, fast enough to increase the productivity of the quality checking process. The dark color of the material and specular reflection of their surface prevent to visualize clearly their projections in 2D images and therefore invalidate the techniques based on directional illumination or light patterns. On the other hand, their tubular shape makes it difficult to obtain the 3D reconstruction quickly as many high resolution calibrated views are needed to obtain a good enough quality to detect the small failures, which is a computationally expensive process.

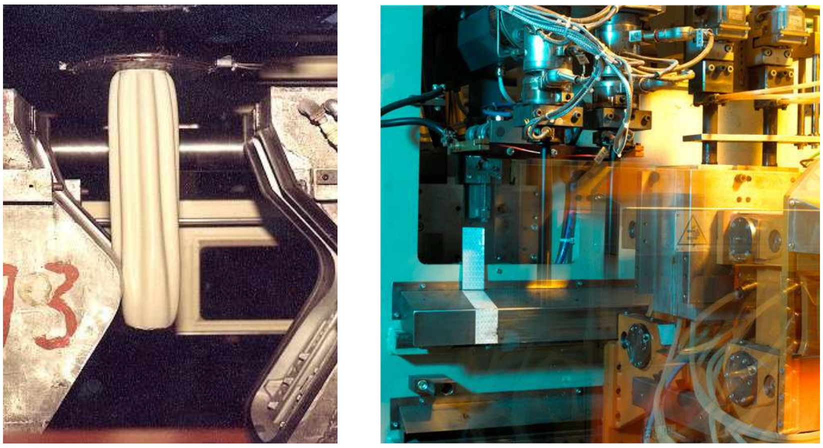


Figure 1: On the left, a plastic parison falling between the mold's two parts, and on the right, the REINER blowing machine for tubes used as outer covers of car dampers [15].

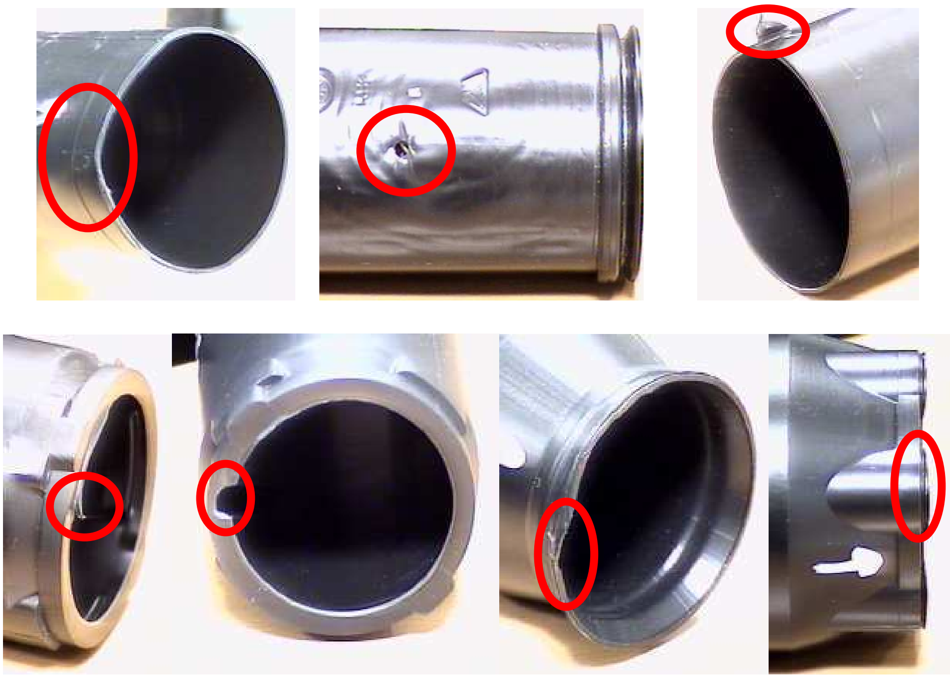


Figure 2: From left to right and top to bottom: a deformed tube, a hole, a burr and diverse defective cuts.

In this work we present computer vision algorithms to reconstruct the shape of the surface of this kind of tubes, concretely those of REINER [15], with precision using a single uncalibrated camera and a laser beam, and also to detect deformations, holes and burrs on them, in real time. Experimental results show the suitability of the proposed methods to detect holes, burrs and deformations on this type of tubes in real time, improving the productivity of the tube quality checking process.

2 TUBE SHAPE RECONSTRUCTION

Two system layouts are proposed to reconstruct the tube shapes. Both are composed of a laser beam perpendicular to the piece and a camera that observes the resulting laser from another point of view but in the same plane (Figure 3). The differences are the relative distances of the components and that in one of them the tube rotates around its axis while in the other the tube moves along it.

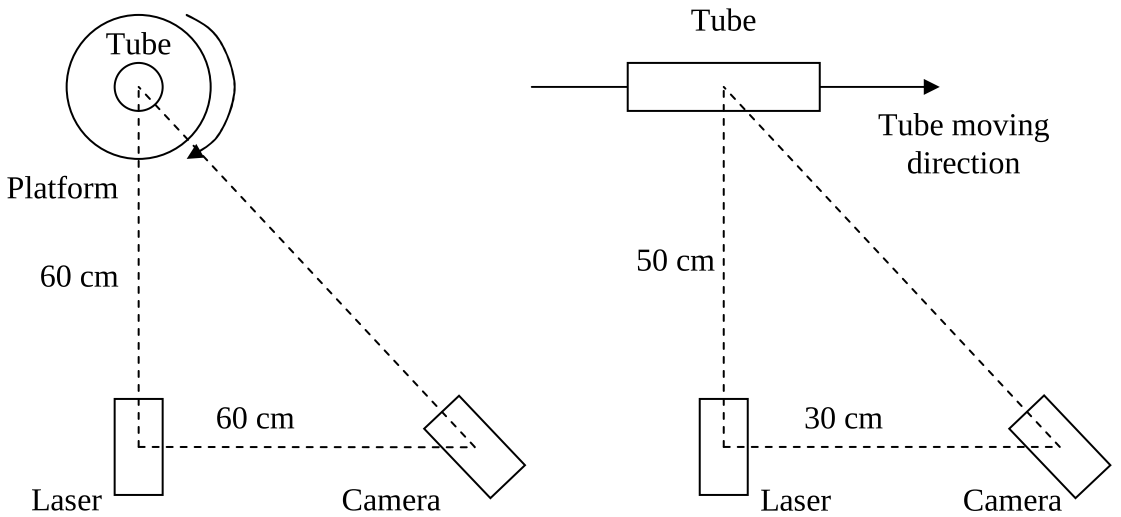


Figure 3: On the left, the rotating tube system outline, and on the right, the translating tube system outline.

The procedure to reconstruct tube surface shapes is the following:

1. Segment the laser beam from the images. This can easily be done if no ambient light is used at all as high grey-level values directly correspond to those of the laser beam. On the contrary, the red color channel would be used from RGB images in the same way.
2. Estimate the first derivative of the laser profile and store it in a grey-level values slice. In order to obtain a smooth profile this is done as follows:
    a. Refer the XY coordinates of the laser pixels with respect to that of its extreme left one.
    b. For each pixel, obtain the mean Y value of the N previous ($meanY_{prev}$) and also the mean Y value of the next N neighboring pixels ($meanY_{next}$) to the current one. In our tests we have set N = 5, but in the extremes, only those available are used.
    c. Subtract $meanY_{next}$ with $meanY_{prev}$ and divide the result by the difference between the previous and the next pixel X positions, i.e., by 2.
3. Normalize the grey-level values of the resulting slice to improve the visualization quality. This is done by rescaling the grey-level values always with the same scaling factor for all slices obtained through time. This value is determined experimentally by the user. This must be done because there can be negative derivatives, while the final grey-level values must always be positive or zero. Therefore, negative derivatives will correspond to lower grey-level values.
4. Add the slice to the image that will conform through time the tube profile.

The final reconstruction speed of the whole system depends on several factors, such as the camera's framerate, resolution, field of view, the tube's motion relative to the view, the tube's size, the laser beam characteristics, the CPU speed, the RAM memory, the programming language, etc., whose relations are not studied in this work, but it can be stated that the proposed algorithm is not computationally expensive for off-the-shelf equipment and that it leads to real-time framerates.

Table 1 shows samples of observed laser profiles and resulting reconstructions for both rotating and translating tube systems. Darker grey-level values correspond to those in which the derivative have lower values, while brighter to higher values, and therefore the reliefs of the tube surface can be appreciated. Moreover, it can be seen that the reconstructions have good enough quality even to allow reading the numbers engraved by the mold on the tube.

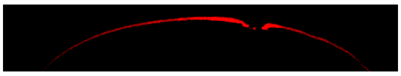
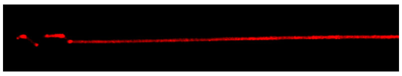
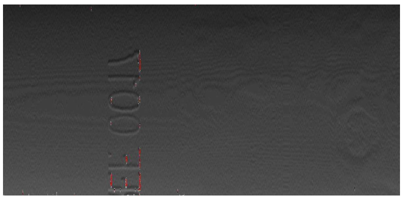
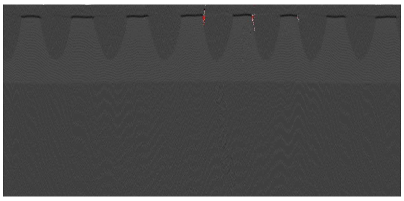
	Translating Tube System	**Rotating Tube System**
Captured Image Sample		
Tube Profile Reconstruction Sample		

Table 1: Captured images samples and resulting tube profile reconstructions in the translating and rotating tube systems.

3 TUBE DEFECT DETECTION

The detection of holes is straightforward because the laser beam in their position is not reflected in the camera. The pixels of the slice where the laser is not detected are marked in the reconstruction image as red pixels. Hence, consecutive slices presenting a hole form a red blob or connected component in the reconstruction image. Thus, these blobs are detected looking for contours in the red channel of the image, and their area is used in order to reject small red regions, which are not real holes, as those produced by the laser being occluded by the embossed letters or symbols (bottom-left image of Table 1). Once a red cluster with a considerable area is localized in the reconstructed image, it is labelled with a message alerting its presence. This algorithm works in the same way in the translating and rotating systems, but in the former the resolution of the camera may be concentrated in a smaller area of the tube, so even the smallest holes can be detected.

The burr automatic detection algorithm is very similar to that of the holes. In the rotating system the burrs produce an occlusion of the laser big enough to be detected as holes. The difference respect to these comes from their shape and position, as burrs usually appear as elongated holes in the tube extremes. In principle, both burrs and holes could be simply labelled as “defects”, but distinguishing explicitly between holes and burrs is interesting for statistics analyses and system parameters adjustment.

The deformations or bulges are detected with the rotating system analyzing the curvature of the laser profile over the straight parts of the tube. The profile of a correct tube is presented as a straight line. On the contrary, when a deformation appears, the profile forms a curve. This way the profile pixels located out of the straight line are marked as blue pixels in the reconstruction image. Therefore, consecutive slices presenting a deformation form a blue blob or connected component in the reconstruction image.

4 EXPERIMENTAL RESULTS

In Figures 4-6 three samples containing holes, a burr and deformations on reconstructed tube shapes are shown. It can be observed how the holes and the burr are correctly labelled, and the deformed regions are highlighted by the system. The shape of the shadow projected by the burr during the reconstruction is marked in red (Figure 5), the same as the shapes of the holes (Figure 4), which correspond to those instants in which the laser beam profile is “cut” while the tubes are being moved. On the other hand, it can be observed that the deformed areas in Figure 6 are big enough to consider the piece as defective and consequently reject it from the production line.

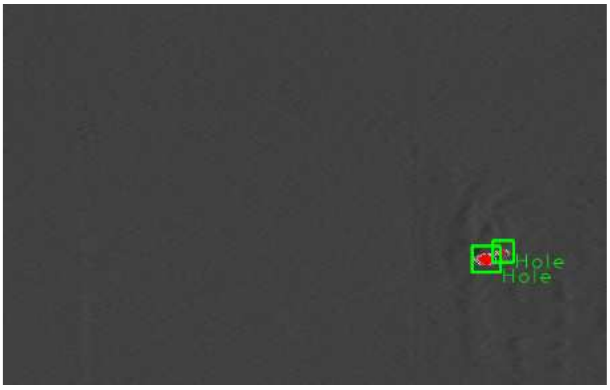


Figure 4: Hole automatic detection.

Figure 5: Burr automatic detection.

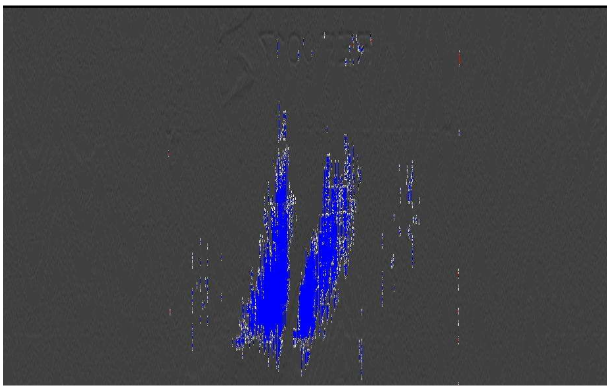


Figure 6: Deformation automatic detection (marked in blue).

5 CONCLUSIONS AND FUTURE WORK

In this work we have presented strategies based on computer vision to reconstruct the shape of the surface of blow-molded tubes used as outer covers of car dampers (REINER tubes [15]) with precision using a single uncalibrated camera and a laser beam, and also to detect deformations, holes and burrs on them, in real time. No ambient illumination is needed at all.

The proposed two systems are composed of a laser beam perpendicular to the piece and a camera that observes the resulting laser from another point of view but in the same plane. In one of them the tube rotates around its axis while in the other the tube moves along it. The tube surface is reconstructed by capturing the laser beam profile and estimating its shape's smooth derivative and rescaling it to show the results as grey-level images. During the reconstruction process, those regions where the laser beam is not reflected are marked in red and consequently the connected red components are located through a contour detection algorithm. Depending on their position and shape, they are labelled as holes or burrs. Finally, the deformations or bulges are detected with the rotating system comparing the curvature of the laser profile over the straight parts of the tube respect to straight lines.

Experimental results show the suitability of the proposed methods to detect the mentioned failures on this type of tubes in real time, improving the productivity of the tube quality checking process. Future work will focus on the detection of more failures in these tubes such as defective cuts (bottom row of Figure 2).

6 ACKNOWLEDGEMENTS

This research is part of ARTIPLAS project in collaboration with REINER E HIJOS S.A. The project is funded by the Basque INTEK programme.

7 REFERENCES

1. Dhond, U., Aggarwal, J., Structure from Stereo-A Review, IEEE Transactions on Systems, Man, and Cybernetics, vol. 19, 6, 1489-1510, 1989.
2. Scharstein, D., Szeliski, R., A Taxonomy and Evaluation of Dense Two-Frame Stereo Correspondence Algorithms, International Journal of Computer Vision, vol. 47, 1-3, 7-42, 2002.
3. Yang, R., Welch, G., Bisop, G., Real-Time Consensus-Based Scene Reconstruction Using Commodity Graphics Hardware, Proceedings of Pacific Graphics, 225-234, Beijing, China, 2002.
4. Massa, J. S., Buller, G. S., Walker, A.C., Cova, S., Umasuthan, M., Wallace, A. M., Time of Flight Optical Ranging System Based on Time-Correlated Single-Photo Counting, Applied Optics Vol. 37, 31, 7298-7304, 1998.
5. Zhang, S., Huang, P. S., High-resolution, Real-time Three-Dimensional Shape Measurement, Optical Engineering, vol. 45, 12, 2006.
6. Davis, J., Ramamoorthi, R., Rusinkiewicz, S., Spacetime Stereo: A Unifying Framework for Depth from Triangulation, Proceedings of the Conference on Computer Vision and Pattern Recognition, 359, 2003.
7. Salvi, J., Pagès, J., Batlle, J., Pattern Codification Strategies in Structured Light Systems, Pattern Recognition, vol. 37, 4, 827-849, 2004.
8. SICK Sensor Intelligence - http://sick.com/
9. Posdamer, J. L., Altschuler, M. D., Surface Measurement by Space-Encoded Projected Beam Systems, Computer Graphics and Image Processing, vol. 18, 1,117, 1982.
10. Inokuchi, S., Sato, K., Matsuda, F., Range Imaging System for 3-D Object Recognition, Proceedings of the International Conference on Pattern Recognition, 806-808, 1984.

11. Gühring, J., Dense 3-D Surface Acquisition by Structured Light Using Off-the-Shelf Components, Video Metrics and Optical Methods for 3D Shape Measurement, vol. 4309, 220-231, 2001.
12. Pan, J., Huang, P., Zhang, S. Chiang, F.-P., Color N-ary Gray Code For 3-D Shape Measurement, Proceedings of the Int. Conference on Experimental Mechanics, 2004.
13. Carrihill, B., Hummel, R., Experiments with the Intensity Ratio Depth Sensor, Computer Vision, Graphics and Image Processing, vol. 32, 337-358, 1985.
14. Zhang, L., Curless, B., Seitz, S. M., Rapid Shape Acquisition Using Color Structured Light and Multi-Pass Dynamic Programming, Proceedings of the International Symposium on 3D Data Processing, Visualization, and Transmission, 24-36, Padova, Italy, 2002.
15. Reiner Rohre International - http://www.reiner-tubos.com/