Method for Parameter Adjustment for Automated Visual Inspection of Botteled Liquids

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***Abstract* — A method for parameter adjustment for automated visual control of bottled liquids is presented, aiming at reducing the execution time of bottling when liquid colors are similar and not easily visible. Edge profile detection is applied to find the transition points where a line fitting algorithm connects them in a line. The obtained short execution time and very good accuracy enable inspection of bottles in a moving condition. The proposed algorithm is tested with blurred images of beer and mineral water bottles, according to real production conditions. The represented method could be applied in any related cases in which the liquid level is not easily visible and the execution time is a crucial component.**

Keywords - visual inspection; image processing; line fitting; execution time.

I. Introduction

There are many automated systems for automated visual inspection of the liquid level in the bottling industry [1][2][3][4][5]. The specifics of this production demand liquid level control in the moving condition of the conveyer belt. In the case of sparkle liquids and beer bottled production, one problem is fixing the fill level of foamed surfaces in moving condition, all within a short execution time, even when the bottle and liquid colors are very similar. Thus, the optimization of the decisive algorithm parameters in terms of quick-operation and high accuracy is imperative. In addition, the problem has to be solved with a simple and inexpensive technology equipment, aiming at reducing the production costs.

In this research, a method is proposed for liquid level inspection in moving condition, when the bottle and liquid colors are very similar and the transition between them is not easily visible. Edge profile detection is applied to find the transition points where a line fitting algorithm connects them in a line. The algorithm's parameters are adjusted to minimize execution time, based on the analysis of the influence of the significant image parameters over the execution time. The benefits of the obtained short execution time and very good accuracy enable inspection of bottles in moving condition, thus, eliminating the need of additional technological appliances applying a single smart camera.

The experiments are implemented using a Smart Camera NI 1742. Triggered infrared lighting is used to eliminate the variations in environmental lighting. To simulate the blur noise added to the images because of the conveyer belt movement, the calculated blur for typical conveyer belt velocities in number of pixels is added to each image. Further tests with cameras having different image resolution, by different light intensities, are foreseen.

Section I-A describes the state-of-the-art. In Section II, the overall proposed method for liquid level detection is defined. Section III-A describes the image parameters that influence the execution time/accuracy. Line fitting algorithm is represented in Section III-B. In Section IV, the developed algorithm for parameter adjustment is explained, after the analysis of the execution time. The experiments and the obtained results for images, resembling the moving conveyer belt conditions for many examples are represented and discussed in Section V.

A. State-of-the-Art

Machine vision is implemented nowadays in the modern automated production systems for real-time control of different product parameters [1][3][6]. In automated bottle filling production, most of the checks are concentrated on the presence/absence, position or quality of different bottle parts, such as cap, label or defects. Liquid fill level control is relatively rarely accomplished, especially when the bottle and liquid colors are very similar. For example, the *Q Check* verification system [4] inspects flat and sipper caps on beverage bottles for cap presence and height, dust cap presence and fill level. Because the check is in moving condition, the liquid surface is often falsly recognized and the bottle is incorrectly automatically rejected. *Mettler Toledo system* [5] demonstrates a Full Bottle Inspection system (FBI) with simple part setup, very intuitive train tools with training in less than one minute, rejection off the line of all defective bottles. It checks the liquid level in movement, but without discussion and recommendations about achieved accuracy when fixing the fill level of foamed surfaces. *DATALOGIC* [6] is a system using a complex multiple cameras/mirrors structure for cap and label detection and defective rejection. It represents no fill level control, thereby the rest of the bottle components are checked with fixed parameter values with no discussion about the execution time. In some systems [2], this control is completed in a stop conveyor belt condition, adding to the production line a technological appliance. In this case, the technological cycle time increases together with raising the cost of the system.

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In conclusion, we did not succeed to find in the existing similar systems any analysis of the influence of the significant image parameters over the execution time for foamed liquid level determination, while maintaining accuracy. As result of the implemented time analysis, a method for parameter adjustment is proposed. The proposed method is verified with many blurred images, aiming to simulate the real production conditions. The experiments are implemented using only simple machine vision components with no need of adding to the production line some special technological appliances. The main advantage of the presented approach is the non-intuitive, but based on the image parameter analysis method for training the vision system for fast real-time execution. It could be applied in any related case where the liquid level is not easily visible and the execution time is a crucial component.

II. METHOD FOR LIQUID LEVEL LINE DETECTION

The proposed method is based on analyzing the edge strength profiles along different parallel, preliminary fixed lines in a search direction. The algorithm finds the first pixel along each edge strength profile having more than a minimum chosen difference between the intensity values of the edge and the surrounding pixels. The method of least squares is used to determine the best fit line to the data set, formed by detected pixels along all lines. The influence of four parameters – *edge strength, kernel size, projection width* and *interline gap* over the execution time and level line accuracy are analyzed and a method for their adjustment is proposed. The method and its algorithm are tested on 30 samples of brown bottles of beer and 30 samples of white bottles of mineral water. Infrared triggered lighting is used for image acquisition of moving bottles.

III. DEFINITION OF PARAMETERS AND LINE FITTING ALGORITHM

Four parameters – *edge strength, kernel size, projection width* and *interline gap* have the strongest influence over the execution time and accuracy when determining the liquid level line. They are used to detect the liquid level edge points.

A. Definition of Used Parameters

Edge strength – This is the edge contrast. It determines the variation in the grayscale values between the background and the edge. Figure 1 shows the Grayscale profile in a search direction. The edge strength can vary for the changes in lighting conditions. That is reason to use infrared triggered lighting on the acquisition moment to eliminate these changes. The edge length characterizes the slope of the edge. Edges with gradual transitions between the background and the edge have a longer edge length.

Kernel size - A kernel is usually a 3x3, 5x5, 7x7, etc. structure that represents a pixel and its relationship to the pixel neighbors [7]. The chosen size of the kernel should be based on the expected sharpness, or slope of the searched edge.

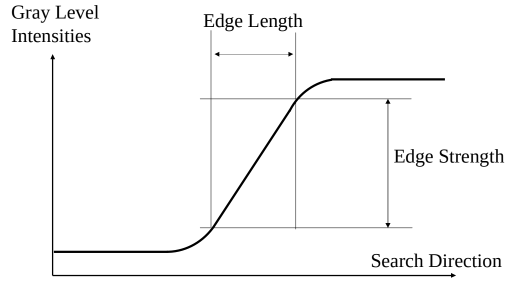


Figure 1. Greyscale profile

Projection width – Determines the amount of pixels perpendicular to the search direction [7], that are averaged at each pixel along the search line to calculate the edge profile strength. The projection width has to be increased when the image is noisy or blured because of the movements of the aquisiting object.

Interline gap – Defines the distance between two neighboring search lines in pixels.

B. Line Fitting

The algorithm finds the first pixel along each edge strength profile having less than a minimum chosen difference/threshold between the intensity values of the edge and the surrounding pixels. All such pixels are considered to be Liquid Level Pixels (LLP) or border pixels. The method of least squares is used to determine the best fit line to the LLPs data set, formed by the detected pixels along all lines. When n LLPs with coordinates $[x_i, y_i]$ are found, the approximating straight line will have the equation

$$Y = f(x) = \alpha_0 + \alpha_1 X \,. \tag{1}$$

Then, α_0 and α_1 values are searched, so that a minimum Mean Square Distance (MSD), according to Figure 2, will be obtained.

$$MSD = \min_{\alpha_0,\alpha_1} \sum_{i=1}^{n} d_i^2 \tag{2}$$

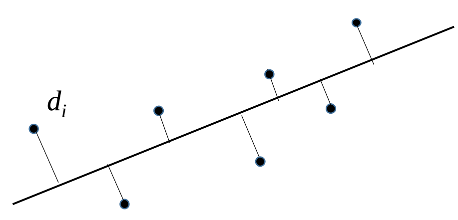


Figure 2. Line fitting

Foreseeing the expressions $\overline{x} = \frac{1}{n}\sum_{i=1}^{n} x_i$; $\overline{y} = \frac{1}{n}\sum_{i=1}^{n} y_i$ and

$$\sum_{i=1}^{n}(x_i-\overline{x})^2 = \left(\sum_{i=1}^{n} x_i^2\right) - n.\overline{x}^2 = \left(\sum_{i=1}^{n} x_i^2\right) - \frac{1}{n}\left(\sum_{i=1}^{n} x_i\right)^2 \quad (3)$$

the coefficients α_1 and α_0 get the values of

$$\alpha_1 = \frac{\left(\sum_{i=1}^{n} x_i y_i\right) - n.\overline{x}.\overline{y}}{\left(\sum_{i=1}^{n} x_i^2\right) - n.\left(\overline{x}^2\right)} \quad (4)$$

$$\alpha_0 = \overline{y} - \alpha_1.\overline{x} \quad (5)$$

The line with the best quality is the line that shows the lowest MSD [8]. The quality of the line is further improved by successively removing the furthest pixels from the current line until a preliminary minimum score is obtained.

The result of the line fitting algorithm is a line that is fit to the best set of the LLPs after ignoring the outlying pixels.

IV. PARAMETER ADJUSTMENT

The inspection of the liquid level in motion condition sets requirements of short execution times. The phase of detection of the liquid level, together with the phase of image acquisition, are the most time consuming steps in the algorithm.

A. *Execution Time Analysis*

As the parameter values are decisive for accuracy of liquid line determination, it is important to analyze the influence of the four above mentioned parameters over the execution time. On the base of analyses, optimum proportion parameter values and execution time have to be found. The two graphics in Figures 3 and 4 show that the execution time needed for liquid level detection, including edge detection and line fitting, increases linear with increasing the kernel size and the projection width values. However, the increase in the projection width essentially influences the execution time.

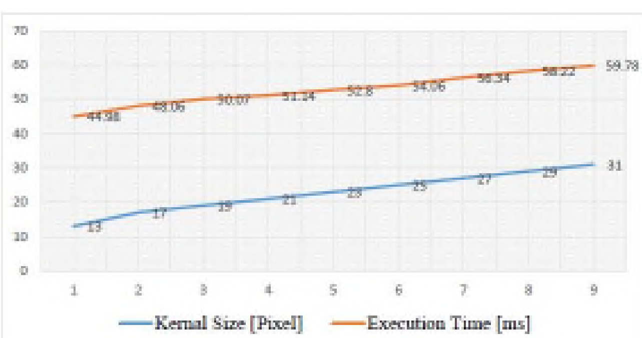


Figure 3. Influence of the Kernel size variations over the Execution time

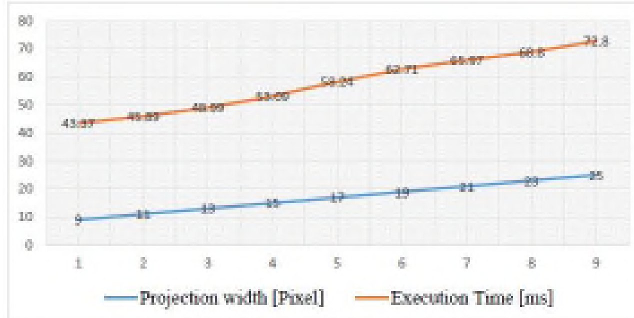


Figure 4. Influence of the Projection width variations over the Execution time

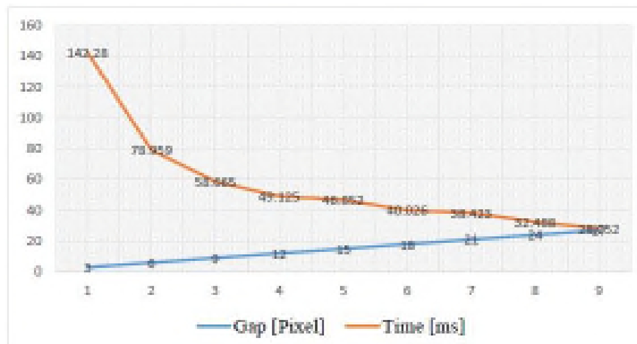


Figure 5. Influence of the Interline gap variations over the Execution time

Figure 5 shows that the increase in the interline gap reduces more rapidly the execution time.

B. *Proposed Method for Parameter Adjustment*

Taking into account that the bottles are inspected in moving condition, obviously some froth is generated, especially in the case of beer production. That means that the intensity along the edge line changes gradually and finding the liquid level edge points requires an increase in the kernel size. Also, it is well known [8] that if the image is noisy, an increase in the projection width is necessary. So, considering these circumstances and aiming at high accuracy, it is reasonable to begin searching the edge profiles with high values of kernel size and projection width and low interline gap value. To reduce the execution time, the following parameter adjustment method is proposed:

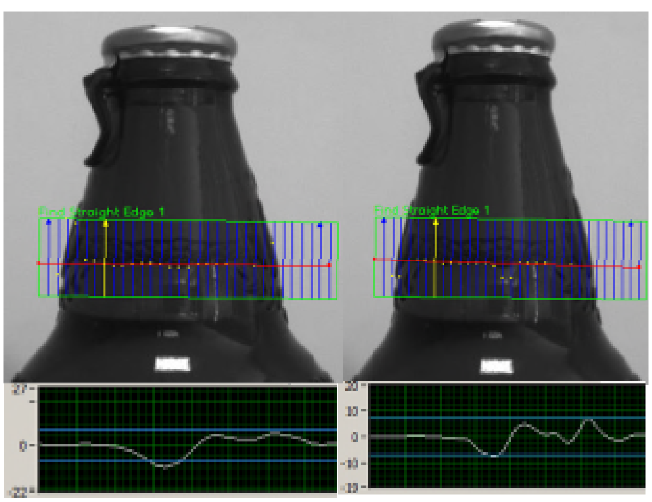
1. Choose high values of kernel size and projection width, choose low values of interline gap to obtain right edge points and right line fitting.
   Straight edge minimum threshold is chosen based on empirical approach.
2. Reduce the kernel size till line fitting is still correct.
3. Reduce the projection width till line fitting is still correct. Stop reducing when line fitting errors appear.
4. Increase interline gap till line fitting is still straight.
5. If no straight edges are found, reduce the straight edge minimum threshold until the step finds a straight edge again.

V. EXPERIMENTS AND RESULTS

The experiments are implemented using a Smart Camera NI 1742 with triggered infrared lighting and software Vision Builder AI 2011. To simulate the blur noise [9] added to the images because of the conveyer belt moving, the calculated blur in number of pixels is added to each image. For a typical conveyer belt velocity of 25m/min ≈ 417 mm/sec and image resolution of 300 dpi ≈ 118,11 dp(cm) ≈ 11,81 dp(mm), the calculated conveyer belt velocity measured in Pixel per second is V_p = 417x11,8 = 4920 Pix/sec. Then, the resulting Motion Blur = V_p * Exposure time = 4920 x 1/125 ≈ 40 Pix Motion Blur. In our case, a short value of Exposure time = 1/500 is chosen which corresponds to 9 Pix Motion Blur. This value is added to the test images to simulate the motion of the bottles [10][11]. Figures 6, 7 and 8 represent the subsequent steps for parameter adjustment and show the change in Edge Strength Profile moving through the steps of the proposed algorithm for parameter adjustment. Finally, the obtained parameter values with line fitting still correct for all of the 60 exemplars are found as: edge strenght 5, kernel size 5, projection width 5 and interline gap 21 pixels. Execution time for 60 exemplars is 60.424 msec.

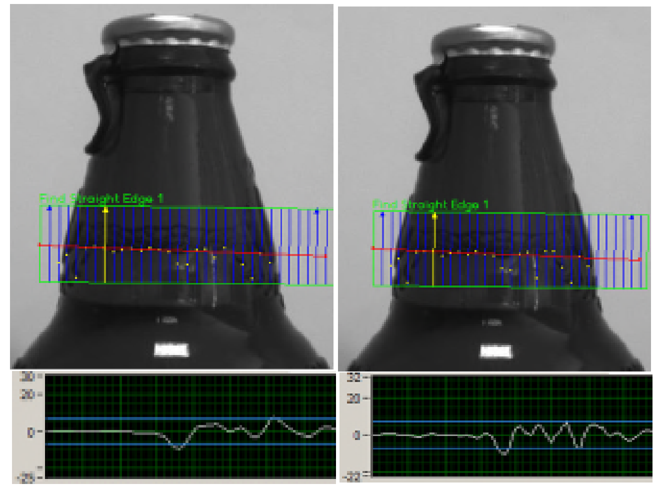
Figure 8 shows the final line fitting with a distinct Edge Strength Profile and an appropriate Minimum Edge Strength/threshold (MES). Figure 10 represents the finally obtained line fitting for some of the tested bottled mineral water samples. Table I. represents the execution time and accuracy for 20, 40 and 60 bottles when moving through the steps of the proposed algorithm.

The accuracy is calculated as [(number of all exemplars - number of exemplars with bad line fitting)/ number of all exemplars].100 [%]. Figure 9 shows the influence of the parameter value reduction over the execution time and over the accuracy according to the data in Table I. The first rising line in the graphic represents cases 1, 2, 3, the second rising line represents cases 4, 5, 6, etc. It is visible that the reduction of parameter *projection width* influences stronger the reduction of execution time (rising lines 3,4, cases 7 to 12) then reduction of kernel size (cases 4, 5, 6). The strongest is the influence of inceasing the interline gap (cases 16, 17, 18).



(a) (b)

Figure 6. Edge Strength Profile for search line 8: (a) edge strenght 7, kernel size 23, projection width 23 and interline gap 9 pixels; (b) edge strenght 7, kernel size 9, projection width 23 and interline gap 9 pixels



(a) (b)

Figure 7. Edge Strength Profile for search line 8: (a) edge strenght 7, kernel size 9, projection width 9 and interline gap 9 pixels; (b) edge strenght 7, kernel size 5, projection width 5 and interline gap 9 pixels

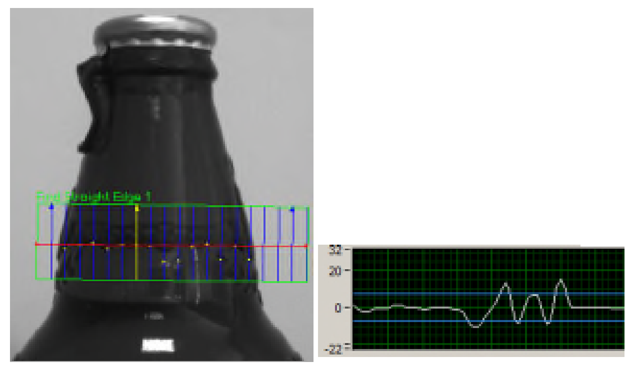


Figure 8. Edge Strength Profile for search line 8: edge strenght 5, kernel size 5, projection width 5 and interline gap 21 pixel

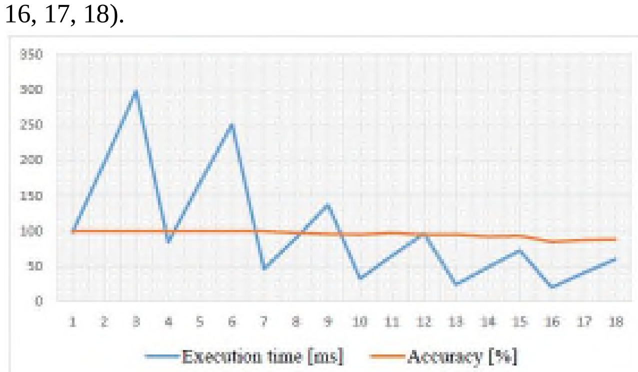


Figure 9. Execution time and accuracy for 20, 40 and 60 tested exemplars according to the cases 1 to 18 in Table I.

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Figure 10. Line fitting for bottled mineral water - edge strenght 32, kernel size 9, projection width 9 and interline gap 77 pixels

TABLE I. EXECUTION TIME AND ACCURACY

Line fitting parameters	*Case*	*Test Samples*	*Time[ms]*	*Accuracy[%]*
MES=7; Gap = 9 Kernel Size = 23; Projection Width = 23	1	20 bottles	97.642	100.00
	2	40 bottles	196.462	100.00
	3	60 bottles	297.709	100.00
MES=7; Gap = 9 Kernel Size = 9; Projection Width = 23	4	20 bottles	84.176	100.00
	5	40 bottles	168.692	100.00
	6	60 bottles	250.847	100.00
MES=7; Gap = 9 Kernel Size = 9; Projection Width = 9	7	20 bottles	46.216	100.00
	8	40 bottles	90.418	97.50
	9	60 bottles	137.102	96.00
MES=7; Gap = 9 Kernel Size = 5; Projection Width = 5	10	20 bottles	32.941	95.00
	11	40 bottles	64.988	97.50
	12	60 bottles	96.494	95.00
MES=7; Gap = 15 Kernel Size = 5; Projection Width = 5	13	20 bottles	24.434	95.00
	14	40 bottles	48.811	92.50
	15	60 bottles	72.461	93.30
MES=5; Gap = 21 Kernel Size = 5; Projection Width = 5	16	20 bottles	20.431	85.00
	17	40 bottles	41.047	87.50
	18	60 bottles	60.424	88.30

The optimum execution time reduction is obtained and the parameter value adjustment stops when accuracy falls between 88.5% and 88.3%, because further parameter adjustments will reduce the obtained accuracy.

VI. CONCLUSION

The obtained results show that the proposed method for liquid level inspection with parameter adjustment is suitable even when the bottle and liquid colors are very similar and the transition between them is not properly visible. It was tested with blurred images to simulate the conveyer belt movement in real production. The experiments are implemented using only simple machine vision components with no need of adding to the production line some special technological appliances. The main advantage of the represented approach is non-intuitive, but based on the image parameter analysis method for training the vision system for fast real-time execution. The represented method could be applied in any related task where the execution time is a crucial component. In order to generalize this method, further tests with cameras having different image resolution, by different light intensities, are possible. Although having in mind that the most up-to-date automated visual systems use triggered infrared lighting, we expect these variations will not impact significantly the proposed methodology.

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