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EMPTY BOTTLE INSPECTOR BASED ON MACHINE VISION

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Abstract:

A machine-vision-based empty bottle inspector is presented in this paper. The mechanical structure and electric control system are illustrated in detail. A method based on the histogram of edge points is applied for real-time determination of inspection area. For defect detection of bottle wall and bottle bottom, a derivative algorithm from Canny edge detector is proposed. In bottle finish inspection, two artificial neural networks are used for low-level inspection and high-level judgment respectively. A prototype is developed and experimental results demonstrate the feasibility of the inspector. Inspections performed by the prototype have proved the effectiveness and value of the proposed algorithms in automatic real-time inspection.

Keywords:

Machine vision; empty bottle inspector; image processing; edge detection; artificial neural network

1. Introduction

Reusable glass containers, such as beer bottles, are widely adopted in the beverage production. Recycled bottles probably have some defects that may cause negative even dangerous consequences for production. Hence, all recycled bottles must be cleaned and inspected before refilling and any empty bottles with defects (shown in Figure 1) must be ejected from the production line. Inspection of empty bottles by human inspectors results in low speed and efficiency, because the whole inspection process is subjective and very tedious. As a replacement of human inspector, the empty bottle inspector (EBI) equipped with specific high-speed image capture and processing system is able to perform inspection automatically with high speed and accuracy[1][2]. This paper presents a novel empty bottle inspector utilizing state-of-art machine vision technologies to implement automatic inspection of bottle wall, bottle bottom and bottle finish. A prototype is developed and inspection algorithms are proved to satisfy the requirements of practical production.

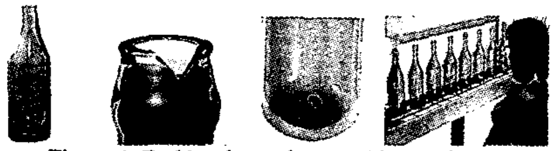

Figure 1. Bad bottles and manual inspection

2. Mechanical structure and system configuration

2.1. Mechanical Structure

The EBI has two popular structures: line and rotary. Being simple in mechanical structure and convenient to maintain, line structure is chosen in our system. Figure 2 indicates its architecture, which includes the following components and modules. A separator at the entrance of EBI is used to separate the bottles from each other in a certain distance. In this way, subsequent inspection can be performed reliably. A special conveyor including two belts that can grip the bottles enables bottles to be conveyed without anything touching the bottom and consequently bottom inspection is available. Under the conveyor, a cleaner is equipped for the purpose of erasing any possible defect or foam clinging under the bottle bottom, which may affect bottom inspection. Due to the excellent consistence of illumination and long life expectancy of LED light, we adopt this efficient light to illuminate the inspection area of empty bottle. Several photoelectric sensors equipped at different place in the EBI are responsible for detection of bottles and providing related information to the center control system. Above each inspection position, an industry CCD Camera is utilized to capture the image of fast moving bottles. At the output of EBI, the bad bottles will be ejected off the production line by an ejector. Several position limit switch are equipped in the EBI. Some dangerous operations can stop the machine. Alarm light and whistle also work in urgent situation.

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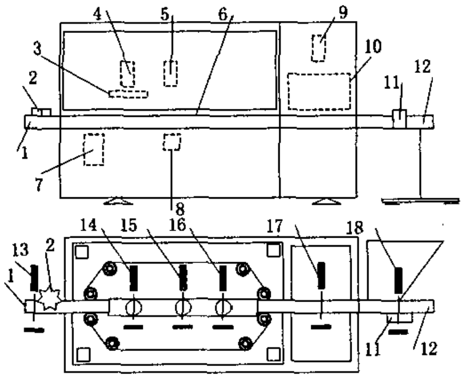


1-Bottle entry 2-Separator 3,8,10-Light 4,5,9-Camera 6-Conveyor 7-Cleaner 11-ejector 12-Bottle output 13,14,15,16,17,18-photoelectric sensor

Figure 2. In-line empty bottle inspector

2.2. Electronic control system

Figure 3 shows the electronic configuration of EBI. Due to processing of large image of bottle at very high speed especially in bottle wall inspection, two high performance industry PCs are needed, of which one is responsible for bottle wall inspection, the other is responsible for bottle finish and bottle bottom inspection. A PLC is used as low level controller, which is responsible for the control of conveyor, ejector, sensors, protection system and so on. Before empty bottles enter into the EBI, the separator will separate the empty bottles at a certain interval firstly. Then the cleaner will clean possible foam under the bottom. The related sensors will be triggered when the empty bottles are conveyed through different inspection position. At the same time, the two industry PCs will start the image capture and complete the real-time inspection. The inspection results will be transferred to PLC, which will control the ejector to reject the bad bottles at last.

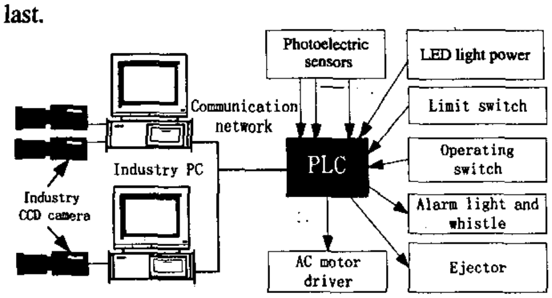


Figure 3. Electric configuration of EBI

2.3. Light, illumination system and optical structure

Dedicated illumination and optical system are very crucial in machine vision applications. Stable and reliable light is an important factor for obtaining excellent image. The direction of light must be carefully controlled and some special filters are used to produce polarized light for the detection of transparent scraps. In empty bottle inspection, LED light is the first choice due to its high efficiency, excellent performance and easiness in control. Figure 4 shows the optical structure for different inspection of bottle. In order to capture the image of bottle shoulder in a high resolution, there need two cameras, which are responsible for inspection of wall and bottle shoulder respectively. 360-degree inspection of bottle wall is realized by a special optical system, which can combine image of bottle wall from different degree in one image. It is also possible to use dedicated mechanical instrument to rotate the bottle in 180 degree during the conveying process and perform two bottle-wall inspections to realize 360-degree inspection.

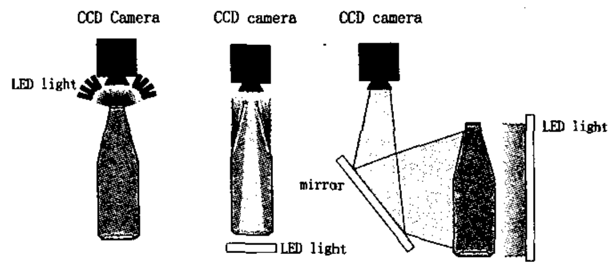


Figure 4. Optical and illumination structure

3. Inspection algorithms

The EBI is one of the typical applications of machine vision and digital image processing technology in industry production. The most important module of the software is the inspection algorithms, which must be capable for high-speed and accurate application. In the empty bottle inspection, the spoiled part or polluted part of bottle varies in size and position. And there are many factors will cause disturbance, such as the bulb and texture of the bottle itself, surroundings light and so on. More than this, the fast moving bottle causes a blurred image, which is more difficult to deal with. Hence, a very ideal and stable image is often unavailable even utilizing a dedicated light and image capture system. The EBI used in high-speed beer production line must inspect about ten bottles per second. Such speed requirement causes many conventional image processing algorithms incapable.

For bottle wall and bottle bottom inspection, a specific algorithm is presented to search the cracks and tears in the half transparent background (glass). But for bottle finish inspection, we need to detect an annular shape and evaluate its quality. Therefore, a different algorithm is required.

3.1. Mark and location of inspection area

It is necessary to mark the inspection area manually in previous to decrease the time cost by image processing. Further more, previous determination of the inspection area manually is more accurate than completing the same thing by computer. This increases the reliability of the whole system. In Figure 5, the inspection area is marked in dot line. The computer only deal with the image data in the inspection area. Due to much useless image data being omitted, high efficiency is available.

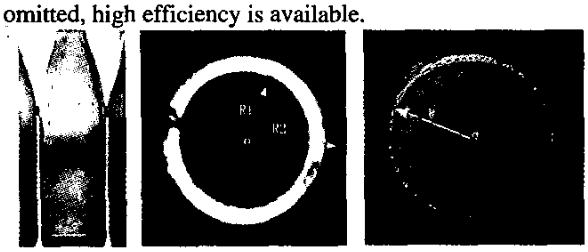


Figure 5. Mark of inspection area

Several photoelectric sensors will trigger the image capture when the bottles come to the inspection positions. But this trigger system cause observable difference between captured images. Further more, bottles may sway a little in the fast running conveyor. Consequently, the position of target varies in captured images as shown in Figure 6. So it is necessary to use a certain algorithm to locate the inspection area in the captured image. In other words, this means to locate the center of bottle bottom and finish and the vertical axis of bottle wall.

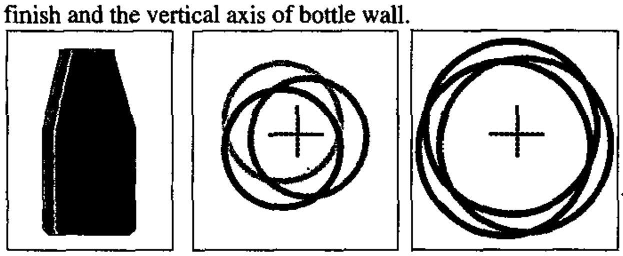
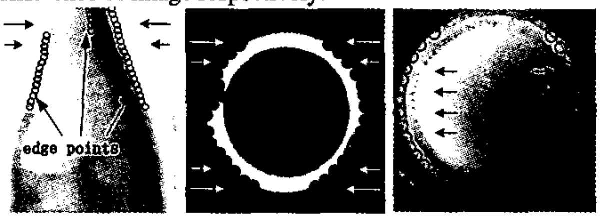


Figure 6. Position of target varies in captured images

The algorithm must be accurate, fast and capable to against large disturbance because in real-time application the bottle image contain many uncertain factors and sometime is disturbed in great extend. The conventional Hough transform algorithm is very slow and not useful in such high-speed application. Another algorithm using center of gravity of image may produce large error when the image is disturbed greatly. This paper presents a brief and very efficiency algorithm, which uses the histogram of edge points to locate the inspection area. For example, in bottle wall inspection, the bottle wall image will firstly be divided into two parts (right and left part), in which formula (1) and formula (2) are used to calculate the difference of image respectively.



a b c

Figure 7. Edge points in bottle images

$$\nabla f(i,j) = 2f(i,j) - f(i+1,j) - f(i,j+1) \quad (1)$$

$$\nabla f(i,j) = 2f(i,j) - f(i-1,j) - f(i,j+1) \quad (2)$$

$$Xr_i = \frac{L_i + R_i}{2} \quad (i=1,2,3.....n) \quad (3)$$

In the second step, the edge points from bottle shoulder to bottle finish (shown in Figure 7a) can be found according to a carefully selected threshold. In each line of a image, only two edge points (L_i, R_i) are needed, of which one is in the left part, the other is in the right part. A reference coordinate of vertical axis of bottle wall is calculated by formula (3). The histogram of X_r (shown in Figure 8) is obtained through the statistic of X_r. Supposing a window which width is T slides from C_1 to C_m in the histogram, we can get the sum of histogram in the sliding window by formula (4). According formula (5), the coordinate of axis of bottle wall can be calculated when the maximum of S(x) is found. For the location of center in the image of bottle bottom and bottle finish, the same algorithm is also available. This algorithm utilizes the statistic to delete distribute disturbance with large value. The final result is accurate due to aids of weight addition in the sliding window. Experiments have proved this algorithm is robust. Even if there is great error in the detection of edge points, this algorithm still output a very accurate value. This character is crucial in real application.

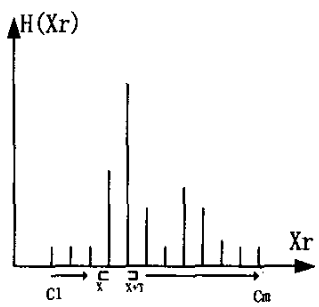


Figure 8. Histogram of Xr

$$S(X)=\sum_{Xr=X}^{X+T} H(Xr) \quad (4)$$

$$Xd=\frac{\sum_{Xr=X}^{X+T}[Xr\cdot H(Xr)]}{\sum_{Xr=X}^{X+T} H(Xr)} \quad (5)$$

Where X meets $S(X)=\max_{X\in[C_1,C_m]} S(X)$

3.2. Inspection of bottle wall and bottle bottom

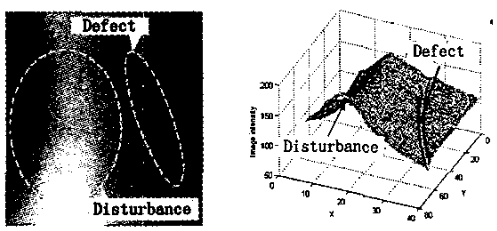


Figure.9 Disturbance and defect in the image

As shown in Figure 9, on the boundary of the defects there are larger changes of image intensity. In other words, edges occur around the defects. Therefore, it seems that edge detector may be used to search the defect. However, due to the unevenness of bottle glass, there are notable number of disturbances that have even clearer edges than the defect. Under these conditions, conventional edge detection algorithms are not suitable. As shown in Figure 10g, the Canny edge detector, which is good at edge detection, cause many errors. In fact, another important characteristic of defect is its darker image intensity than neighbor pixels. Hence, if we scan the image from left to right and top to bottom, for defects, we firstly meet falling edge and then rising edge, while for disturbance, rising edge first and then falling edge. So we can obtain correct results using following algorithm:

Step1: Scan each line of the image, from left to right, to find the falling edge using formula(6) and threshold T_H. When the gradient G_H calculated by formula (6) satisfy T_H, (i.e. $G_H>T_H$), a candidate point for falling edge is found and G_H is saved in G_{HS}.

$$G_H(i,j)=2f(i,j)-f(i+1,j)-f(i+1,j+1) \quad (6)$$

$$G_V(i,j)=2f(i,j)-f(i,j+1)-f(i-1,j+1) \quad (7)$$

Where $f[i,j]$ is the image intensity of pixel [i, j]

Step2: Continue scanning and calculating G_H. If $G_H>G_{HS}$, using the new point to replace the previously found point as the candidate point for falling edge. If $G_H<-T_H$, the previously found point will be confirmed as a point of falling edge and the new point will be regarded as a candidate point of rising edge. The G_H of the new point is also saved in G_{HS}.

Step3: Continue Scan and calculate G_H. If $G_H<G_{HS}$, using the new point to replace the previously found point as the candidate point of rising edge and current G_H is saved in G_{HS}. If $G_H>=0$ or the scan of the line is completed, then previously found point is confirmed as a rising point.

Step4: If the distance between the falling edge and the rising edge is smaller than threshold T_w, all points between the two edge points are marked as defective points.

Step5: Scan each row of the inspection area, from top to bottom in the same way as above, but using formula(7) to calculate the gradient

Step6: using formula (8) and threshold T_a to find all very dark point. If $f(i,j)<(I_a-T_a)$, the point [i,j] is regarded as a defective point.

$$I_a(i,j)=\{f(i+4,j)+f(i-4,j)+f(i,j+4)+f(i,j-4)+f(i,j+8)+f(i,j-8)\}/6 \quad (8)$$

Step7: Using recursive algorithm[7] to calculate the number of defective points N_c connected together in each connected region. If the $N_c>T_{size}$, then those connected points are confirmed as the defect region in the image.

Using above algorithm, besides the position of defect we also obtain the size of defect, which is very useful to evaluate the final quality of the bottle wall or bottle bottom. Figure 10 shows a test sample, in which T_H=4, T_w =7, T_a=10. Table 1 shows the execution time comparison between the proposed algorithm and other edge detector. It is obvious that the proposed algorithm can distinguish the defect and the disturbance correctly and efficiently.

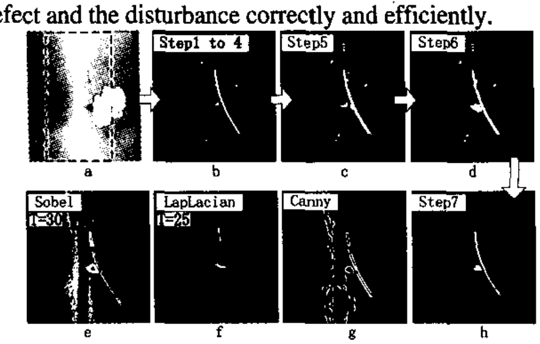


Figure.10 Detection results

Table.1 Execution time comparison

Algorithm	Sobel	Laplacian	Canny	Proposed
Execution time for a image of 60000 pixels (milliseconds)	30	20	76	51

3.3. Inspection of bottle finish

The method used in the inspection of bottle wall and bottle bottom is unable to search defect in the image of bottle finish, because the image of finish has clear edges that can not be distinguished from defects. A different algorithm based on neural network is adopted in finish inspection. As shown in Figure 11, two neural networks are used for low-level inspection and high-level judgment respectively.

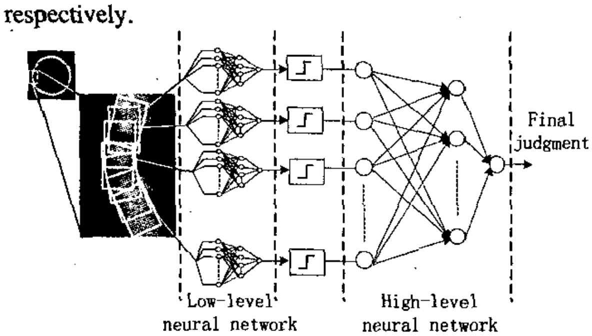


Figure 11. Inspection using neural networks

Firstly, the low-level neural network inspects serial parts of the finish that overlay with each other in some extent. Consequently it is possible for the low-level neural network to inspect the same point of the finish with several different input patterns. Before input into the high-level neural network, the output of the low-level neural network will be transformed to binary value by a threshold to greatly decrease the number of all possible input patterns to high-level neural network. As a result, even the low-level neural network is sensitive to the input patterns and occasionally causes wrong output, the final judgment is supposed to be reliable and robust enough due to the high-level neural network eliminates the errors caused by low-level neural network. The low-level neural network is a feed-forward neural network with 10 input nodes, 8 hidden nodes and 1 output node. The high-level neural network has 10 input nodes, 6 hidden nodes and 1 output node. And BP learning strategy is adopted.

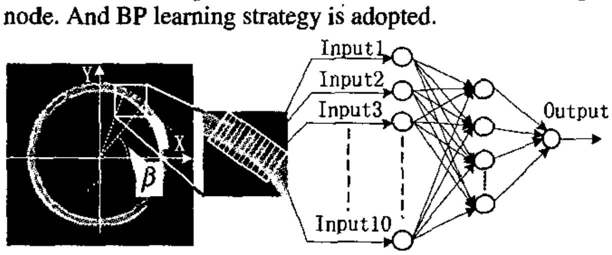


Figure 12. Low-level inspection

As for the low-level neural network(shown in Figure 8), the input of No.1 to No.9 node, representing the difference of the image, is calculated by formula(9) and the input of No.10 node, charactering the brightness of the inspection region is calculated by formula(10).

$$Input_i = \sum_{r=R1}^{R2} G(X(i+1,r),Y(i+1,r)) - \sum_{r=R1}^{R2} G(X(i,r),Y(i,r)) \quad (i=1 \ to \ 9) \tag{9}$$

$$Input_{10} = \sum_{i=1}^{9}\sum_{r=R1}^{R2} G(X(i,r),Y(i,r)) \tag{10}$$

Where

$$X(i,r) = X_{center} + r \cdot \cos(\beta + i \cdot STEP) \tag{11}$$

$$Y(i,r) = Y_{center} + r \cdot \sin(\beta + i \cdot STEP) \tag{12}$$

$G(X,Y)$ is the pixel value of the image; R_1 and R_2 are the inner radius and the outer radius of the region of interest; X_{center} and Y_{center} are the center coordinates of the finish obtained previously. $STEP$ is the sampling step. Sampling starts from β, ranges from R_1 to R_2 and continues for 9 steps. The output of neural networks is defined as "1" for good part of the finish and "0" for defective part. The input of high-level neural network is defined by formula (13)

$$I_{HNN} = \begin{cases} 0.8 & if \ Output_{LNN} > T_1 \\ 0.2 & otherwise \end{cases} \tag{13}$$

Where $Output_{LNN}$ is the actual output of the lower-level neural network, T_1 is a threshold previously decided. If the output of high-level neural network $>T_2$, a defect is confirmed and the bottle should be rejected. In our application, T_1=0.3, T_2=0.5. The whole inspection process is very simple due to the neural networks complete all complex analysis. All that inspection workers need to do is training the neural network in a proper way. The training processes for two neural networks are separately. The low-level neural network is firstly trained. When the low-level neural network works well enough, we begin the training of the high-level neural network, which is quite easy due to the small number of possible input patterns.

4. Experimental Results

We developed a prototype equipped with an annular conveyor that enables us to realize the production line for continual inspection as practical production.

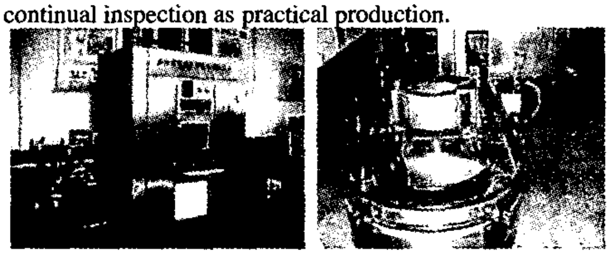


Figure 13. The prototype with an annular conveyor

In the prototype, bottle samples are inspected for 50 times at a speed about 30000 bottles per hour. Figure 14, 15 show the image of some typical bottles used in our inspection. After completed enough experiments to adjust some thresholds and train the neural network-based finish inspection system, we finally achieve quite satisfied results as shown in Table.2, Table3 and Table 4. All defects larger than about 50 pixels in the bottle wall or bottle bottom can be correctly detected. And all defective finishes with cracks larger than 1mm can be inspected correctly. Other very small clinks are also detected with a high correct rate. In addition, the misdetection rate of good bottles is very low.

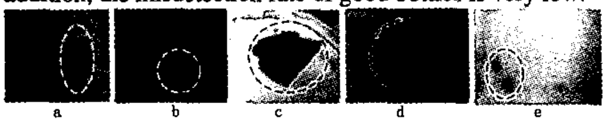


Figure 14. Some defects in bottle wall and bottom

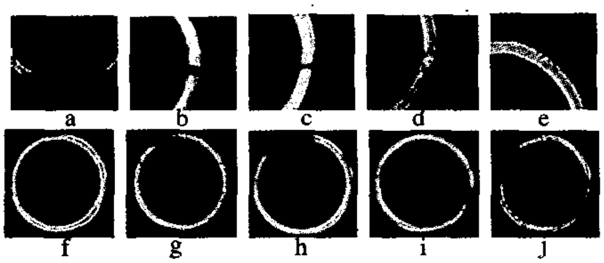


Figure 15. Some typical finish image

Table 2: Inspection results of defective bottle walls and bottoms

Defect Samples	Fig.14a	Fig.14b	Fig.14c	Fig.14d	Fig.14e
Inspection Times	50	50	50	50	50
Correct Inspection Rate	100%	100%	100%	92%	82%

Table 3: Inspection results of defective finish

Defect Samples	Fig.15a	Fig.15b	Fig.15c	Fig.15d	Fig.15e
Inspection Times	50	50	50	50	50
Correct Inspection Rate	100%	100%	100%	94%	90%

Table 4: Inspection results of good finish

Defect Samples	Fig.15f	Fig.15g	Fig.15h	Fig.15i	Fig.15j
Inspection Times	50	50	50	50	50
Correct Inspection Rate	100%	100%	96%	94%	92%

5. Conclusions

We have developed a successful prototype, which proves the feasibility of the system architecture. Enough online inspection on dozens of carefully selected bottle samples have proved that the inspection algorithm presented in this paper are able to achieve high correct inspection rate both to defective bottles and good ones. In addition, we use artificial neural network in bottle finish inspection, which is proved to be very convenient for users to adjust the system for their specific applications.

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References

[1] Canivet, Michel; Zhang, Ruo Dan; Jourlin, Michel. Finish inspection by vision for glass production. SPIE Proceedings Vol. 2183, pp.164-169,1994

[2] Huimin Ma, Guangda Su, Junyan Wang, Zheng Ni. A Glass Bottle Defect detection System Without Touching. Proceedings of the First International Conference on Machine Learning and Cybernetics, Vol2: pp.628-632, Beijing, 4-5 November, 2002

[3] LINATRONIC 713 M1 In-line Empty Bottle Inspector. http://www.krones.de/pdf/713m1_e.pdf

[4] Firmin, C.; Hamad, D.; Postaire, J. G.; Zhang, Ruo Dan. Fault detection by a Gaussian neural network with reject options in glass bottle. SPIE Proceedings Vol.2785,pp.152-162,1996

[5] Sieczka, Eric J.; Harding, Kevin G. Light source design for machine vision. SPIE Proceedings Vol.1614, pp.2-10, 1992

[6] The Benefits of LED Light Sources. http://www.machinevisiononline.org/public/articles/NER_TheBenefitsofLEDLightSources.pdf

[7] Ramesh Jain, Rangachar Kasturi, Brian G. Schunck. Machine Vision, McGraw-Hill Companies,1995

[8] Easton, Richard A.; Hamilton, Ronald J. Machine vision: recent advances in CCD video camera technology. SPIE Proceedings Vol.3205, pp.198-201,1997

[9] Bartleet, Trevor C.; de Jager, Gerhard. Real-time machine vision inspection of plastic bottle closures SPIE Proceedings Vol.2598,pp.362-370,1995

[10] Schubert, Erhard; Klicker, Juergen; Schroeder, Axel. A Vision system for empty PET-bottle classification inside the box. SPIE Proceedings Vol.2350, pp.148-156, 1994