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A machine vision inspector for beer bottle

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Abstract

A machine-vision-based beer bottle inspector is presented. 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, an algorithm based on local statistical characteristics is proposed. In bottle finish inspection, two artificial neural networks are used for low-level inspection and high-level judgment, respectively. A prototype was developed and experimental results demonstrate the feasibility of the inspector. Inspections performed by the prototype have proved the effectiveness and value of proposed algorithms in automatic real-time inspection.

Keywords: Machine vision; Beer bottle inspector; Image processing; Local statistical characteristics; Artificial neural network

1. Introduction

Reusable beer bottles are widely adopted in 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 beer bottles with defect must be ejected from production line. Inspection of beer bottle 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, beer bottle inspector equipped with specific high-speed image capture and processing system is able to perform inspection automatically with high speed and accuracy. Some useful solutions for finish inspection was developed (Huimin et al., 2002; Canivet et al., 1994). This paper presents a novel beer 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.

2. Mechanical structure and system configuration

2.1. Mechanical structure

As shown in Fig. 1, the beer bottle inspector includes the following components and modules. A separator at the entrance of inspector 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, this efficient light is adopted to illuminate the inspection area of beer bottle. Several photoelectric sensors equipped at different place of the inspector are responsible for detection of bottles and providing related information to the central control system. Above each inspection position, an industry CCD camera is utilized to capture the image of fast moving bottles. At the output of the inspector, the bad bottles will be ejected off the production line by an ejector. Several position limit switch are equipped in the inspector. Some dangerous

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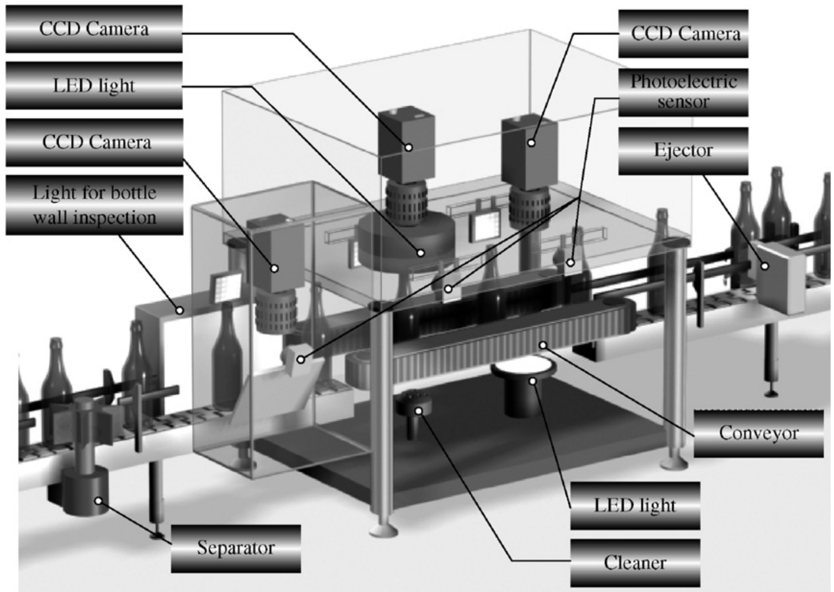

Fig. 1. Beer bottle inspector.

operations can stop the machine. Alarm light and whistle also work in urgent situation.

2.2. Electric control system

Fig. 2 shows the electric configuration of the beer bottle inspector. 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 beer bottles enter into the inspector, the separator will separate the beer bottles at a certain interval firstly. Then the cleaner will clean possible foam under the bottom. The related sensors will be triggered when the beer 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.

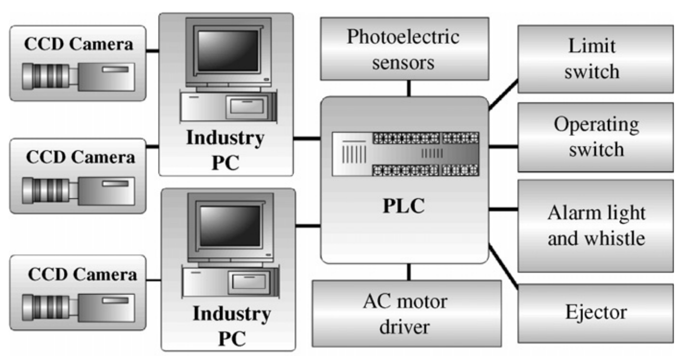

Fig. 2. Electric configuration of beer bottle inspector.

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 beer bottle inspection, LED light is the first choice due to its high efficiency, excellent performance and easiness in control. Fig. 3 shows the optical structure for different inspection of bottle. In

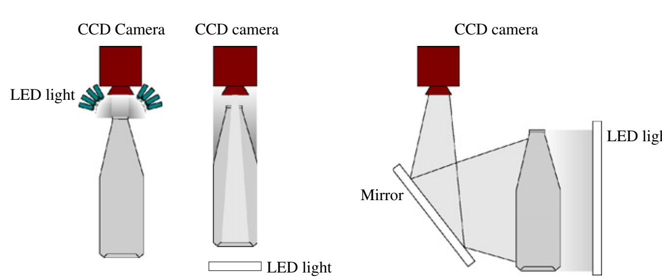

Fig. 3. Optical and illumination structure.

order to capture the image of bottle shoulder in a high resolution, two cameras are needed, which are responsible for inspection of wall and bottle shoulder, respectively. 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 90°

during the conveying process and perform bottle-wall inspection twice to realize 360° inspection.

3. Inspection algorithms

The beer bottle inspector 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 of high-speed and accurate application. In the beer bottle inspection, the spoiled part or polluted part of bottle varies in size and position. And there are many factors that 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 inspector 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). While for bottle finish inspection, the problem is to detect an annular shape and evaluate its quality. Therefore, a different algorithm is required.

3.1. Mark and determination of inspection area

It is necessary to mark the inspection area manually first 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 Fig. 4, the inspection area is marked with dot line. The computer only deals with the image data in the inspection area. Due to much useless image data being omitted, high efficiency is available.

Several photoelectric sensors will trigger the image capture when the bottles come to the inspection positions. But this trigger system causes observable difference between captured images. Furthermore, bottles may sway a little in the fast running conveyor. Consequently, the position of target varies in captured images as shown in Fig. 5. So it is necessary to use a certain algorithm to locate the inspection area in the captured image. In other words, this means to determine the center of bottle bottom and finish and the vertical axis of bottle wall.

The algorithm must be accurate, fast and capable against large disturbance because in real-time application the bottle image contains many uncertain factors and sometime is disturbed to a great extent. 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

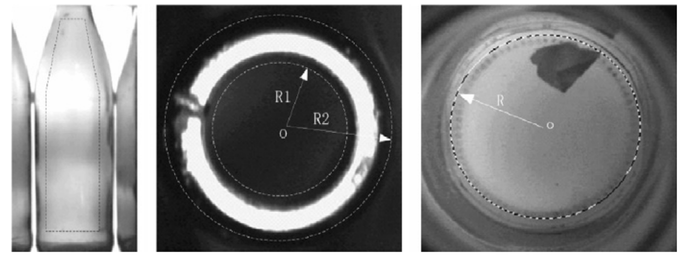

Fig. 4. Mark of inspection area.

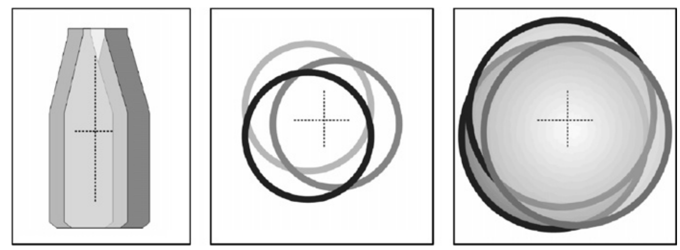

Fig. 5. Position of target varies in captured images.

and very efficient 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 formulas (1) and (2) are used to calculate the difference of image, respectively,

$$\nabla f_1(i,j) = 2f(i,j) - f(i+1,j) - f(i,j+1), \tag{1}$$

$$\nabla f_2(i,j) = 2f(i,j) - f(i-1,j) - f(i,j+1), \tag{2}$$

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

In the second step, the edge points from bottle shoulder to bottle finish (shown in Fig. 6a) can be found according to a carefully selected threshold T_E (In our application, $T_E = 8$). If $\nabla f_i(i,j) > T_E (i = 1,2)$, then points (i,j) is considered as an edge point. 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 Xr (shown in Fig. 7) is obtained through the statistic of Xr. Supposing a window whose width is T (in our application, $T = 6$) slides from C_1 to C_m in the histogram, the sum of histogram in the sliding window is got by formula (4). According to 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 also, the same algorithm is 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 outputs a very accurate value.

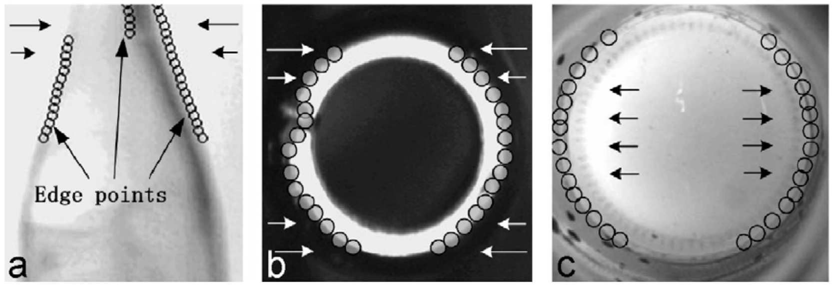

Fig. 6. Edge points in bottle images.

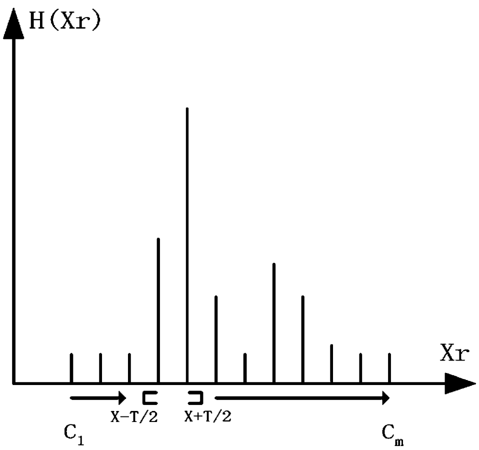

Fig. 7. Histogram of *Xr*.

This character is crucial in real application

$$S(X)=\sum_{Xr=X-T/2}^{X+T/2} H(Xr), \tag{4}$$

$$Xd=\frac{\sum_{Xr=X-T/2}^{X+T/2}[XrH(Xr)]}{\sum_{Xr=X-T/2}^{X+T/2} H(Xr)}, \tag{5}$$

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

3.2. Inspection of bottle wall and bottle bottom

In the inspected image, the cracks and tears are darker than the neighboring parts and usually have clear edges. Based on this fact, the mask (shown in Fig. 8) whose size and structure are optimized by experiments is chosen for pre-processing to obtain information about edge points and difference between points in the inspected image. After pre-processing, the whole inspection area is divided into many small regions, in which some statistical characteristics are obtained for the final evaluation that is based on some special rules.

Step 1: As shown in Fig. 9, pre-processing is performed in the whole inspection area using formulas (6)–(8). $G(x,y)$ is the result of the convolution of inspected image and the mask shown in Fig. 8. $G(x,y)$ is transferred to binary image $B(x,y)$ by threshold $T1$, which has a small value to enable $B(x,y)$ to include more defects. The falling and rising edge points of horizontal and vertical direction are obtained by formula (8). The results are saved in $E_i(x,y)$ $(i=1,2,3,4)$

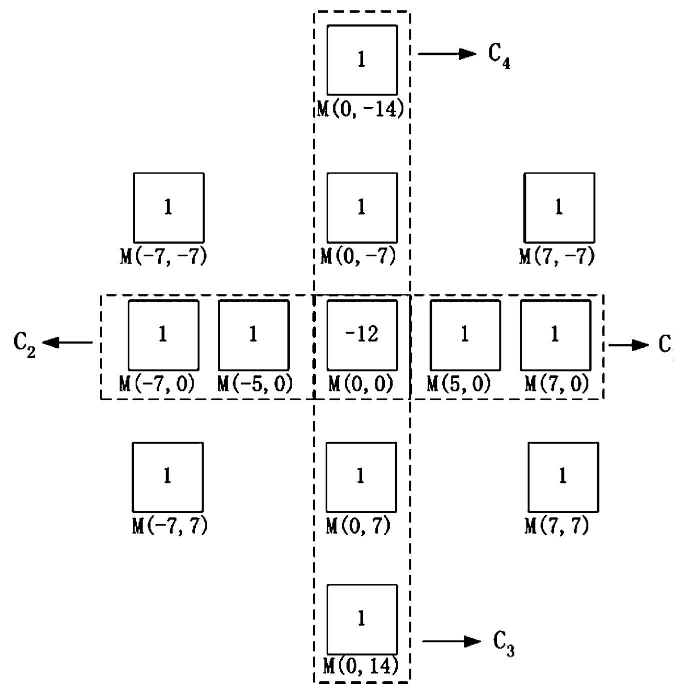

Fig. 8. Mask used in pre-processing.

$$\begin{aligned}G(x,y)=\ &C_1+C_2+C_3+C_4+f(x-7,y-7)\\&+f(x+7,y-7)+f(x-7,y+7)\\&+f(x+7,y+7)-4f(x,y),\end{aligned} \tag{6}$$

$$B(x,y)=\begin{cases}1 & (G(x,y))>T_1),\\ 0 & (G(x,y))\leqslant T_1),\end{cases} \tag{7}$$

$$E_i(x,y)=\begin{cases}1 & (C_i(x,y)>T_2)\\ 0 & (C_i(x,y)\leqslant T_2)\end{cases}\quad (i=1,2,3,4), \tag{8}$$

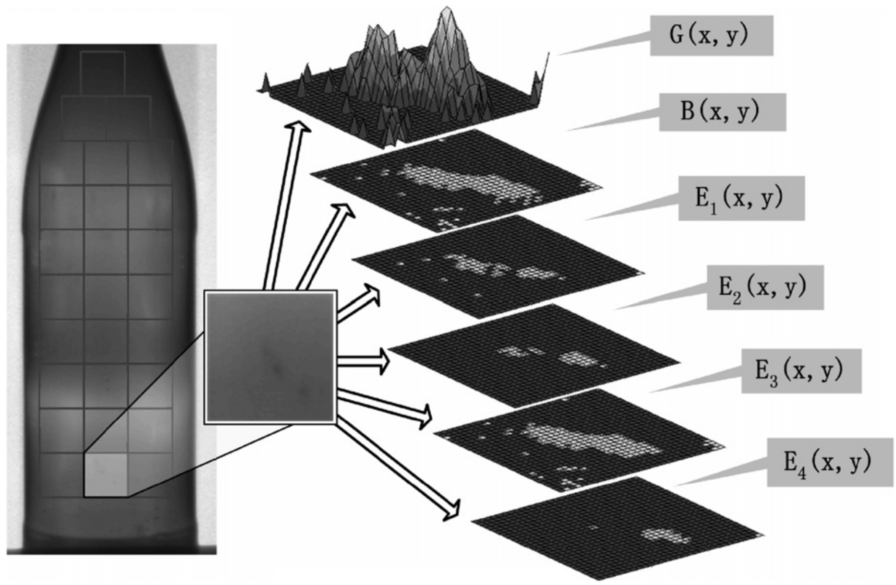

Fig. 9. Pre-processing.

where $f(x,y)$ is the gray value of the inspected image, $C_1 = f(x+7,y)+f(x+5,y)-2f(x,y)$, $C_2 = f(x-7,y)+f(x-5,y)-2f(x,y)$, $C_3 = f(x,y+7)+f(x,y+14)-2f(x,y)$, $C_4 = f(x,y-7)+f(x,y-14)-2f(x,y)$.

Step 2: In each small region, by searching in $B(x,y)$, the connected component can be found, where the following statistical information can be obtained. Fig. 10 shows some samples.

(1) the size of the connected component S,
(2) the number of the falling and rising edge points of horizontal and vertical direction according to the $E_i(x,y)$ ($i = 1,2,3,4$), and then calculate the ratio of the falling and rising edge points of horizontal and vertical direction(Rx,Ry),
(3) histogram of $G(x,y)$Hg. Hg has 60 levels. If $G(x,y) > 60$ then the points is added up to Hg(60).

Step 3: If $S > T3$ then perform the following process and judgment. After calculating Sum and Av according to formulas (9) and (10), if one of the following conditions is satisfied then the defect can be confirmed:

(1) $\mathrm{Av} > T5$,
(2) $T6 < \mathrm{Av} \leqslant T5$ and $\mathrm{Sum} > T7$,
(3) $T10 < \mathrm{Av} \leqslant T6$ and $\mathrm{Sum} > T7$ and ($T8 < Rx < T9$ or $T8 < Ry < T9$)

$$\mathrm{Sum} = \sum_{k=1}^{60} M_k k, \tag{9}$$

$$\mathrm{Av} = \frac{\mathrm{Sum}}{\sum_{k=1}^{60} M_k}, \tag{10}$$

where

$$M_k = \begin{cases} \mathrm{Hg}(k) & \mathrm{Hg}(k) > T4, \\ 0 & \mathrm{Hg}(k) \leqslant T4, \end{cases}$$

In our application, $T1 = 24$, $T2 = 8$, $T3 = 20$, $T4 = 2$, $T5 = 33$, $T6 = 25$, $T7 = 660$, $T8 = 0.49$, $T9 = 2$, $T10 = 20$.

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 cannot be distinguished from defects. A different algorithm based on neural networks is adopted in finish inspection.

It is difficult for a single neural network to achieve perfect result. In order to obtain a satisfied result in single neural network application, huge number of samples must be offered to train the network and the neural network itself may be very complex. Hence, the training process may be very difficult. But multiple neural networks can offer a better solution. In our application, two neural networks are used for low-level inspection and high-level judgment, respectively, as shown in Fig. 11.

Firstly, the low-level neural network inspects serial parts of the finish that overlay with each other to 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, which is therefore very reliable. As a result, even the low-level

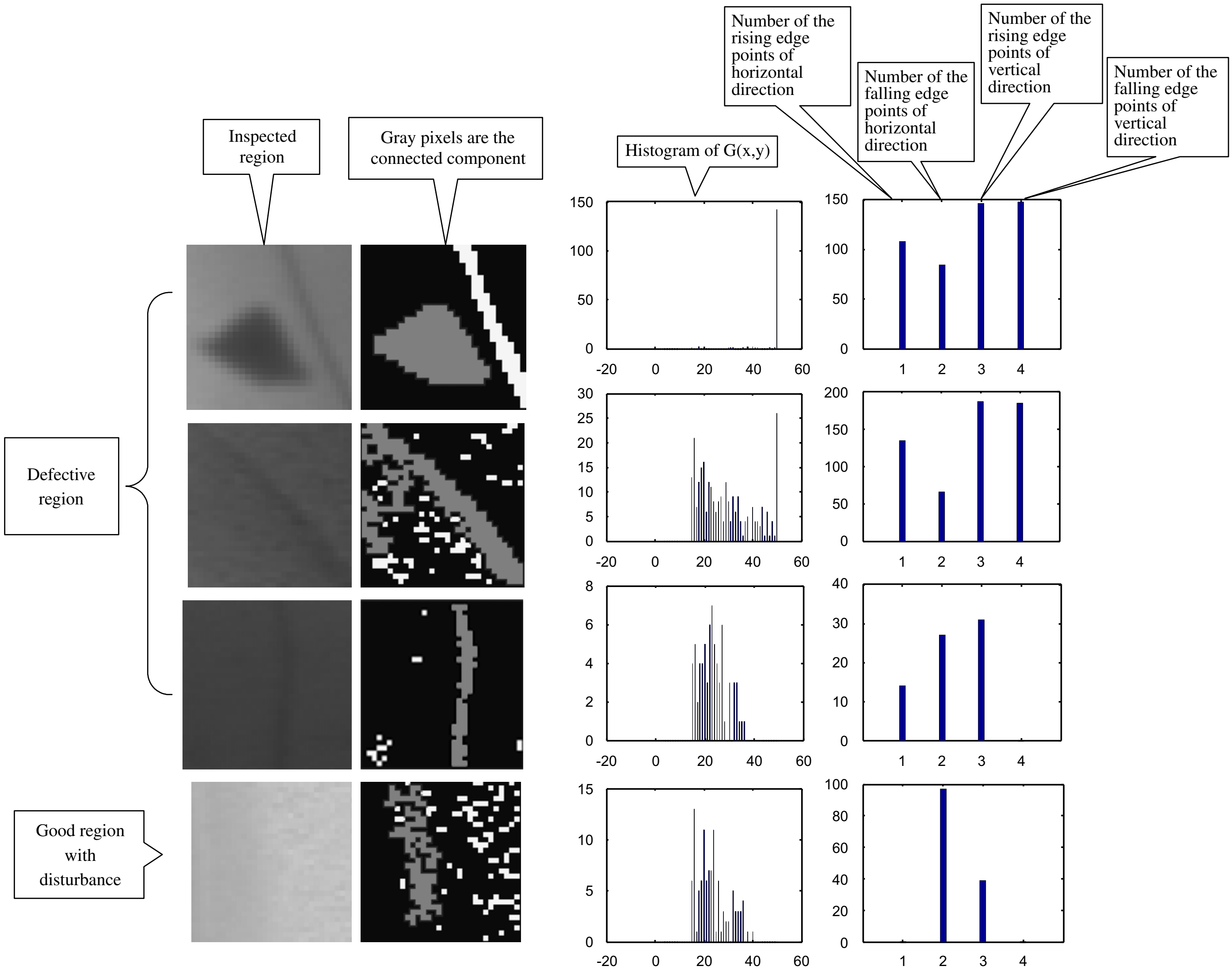

Fig. 10. Local characteristics of some samples.

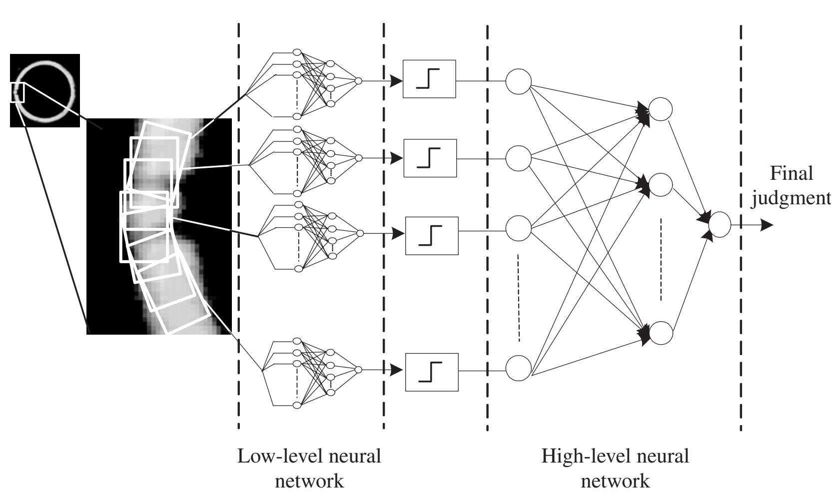

Fig. 11. Inspection using neural networks.

neural network is sensitive to the input patterns and occasionally causes wrong output, the final judgment 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. Levenberg–Marquardt learning strategy is adopted.

As for the low-level neural network (shown in Fig. 12), the input of nos. 1–9 node, representing the difference of the image, is calculated by formula (11) and the input of no. 10 node, characterizing the brightness of the inspection region is calculated by formula (12)

$$\mathrm{Input}_i = \sum_{r=R1}^{R2} G(X(i+1,r), Y(i+1,r)) - \sum_{r=R1}^{R2} G(X(i,r), Y(i,r)) \quad (i = 1 \text{ to } 9), \tag{11}$$

$$\mathrm{Input}_{10} = \sum_{i=1}^{9} \sum_{r=R1}^{R2} G(X(i,r), Y(i,r)), \tag{12}$$

where

$$X(i,r) = X_{\mathrm{center}} + r\cos(\beta + i\mathrm{STEP})$$
$$Y(i,r) = Y_{\mathrm{center}} + r\sin(\beta + i\mathrm{STEP}).$$

$G(X, Y)$ 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

$$I_{\mathrm{HNN}} = \begin{cases} 0.8 & \text{if } \mathrm{Output}_{\mathrm{LNN}} > \mathrm{Th}_1, \\ 0.2 & \text{otherwise,} \end{cases} \tag{13}$$

where $\mathrm{Output}_{\mathrm{LNN}}$ is the actual output of the lower-level neural network, Th_1 is a threshold previously decided. If the output of high-level neural network $> \mathrm{Th}_2$ a defect is confirmed and the bottle should be rejected. In our application, $\mathrm{STEP} = 0.018$, $\mathrm{Th}_1 = 0.3$, $\mathrm{Th}_2 = 0.5$. The whole inspection process is very simple due to the neural networks complete all complex analysis. All that inspection workers need to do is train the neural network in a proper way.

The training processes for two neural networks are separate. The low-level neural network is firstly trained in the way introduced as follows. An image database is used to store all sample images. If huge number of samples is used to train the neural network at one time, it contributes nothing for the convergence of the neural network. Hence, during the training process, we firstly choose 40 samples to train the neural network. Those images (shown in Fig. 13)

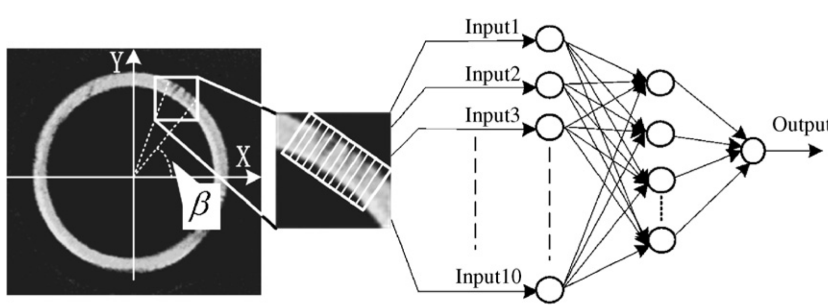

Fig. 12. Low-level inspection.

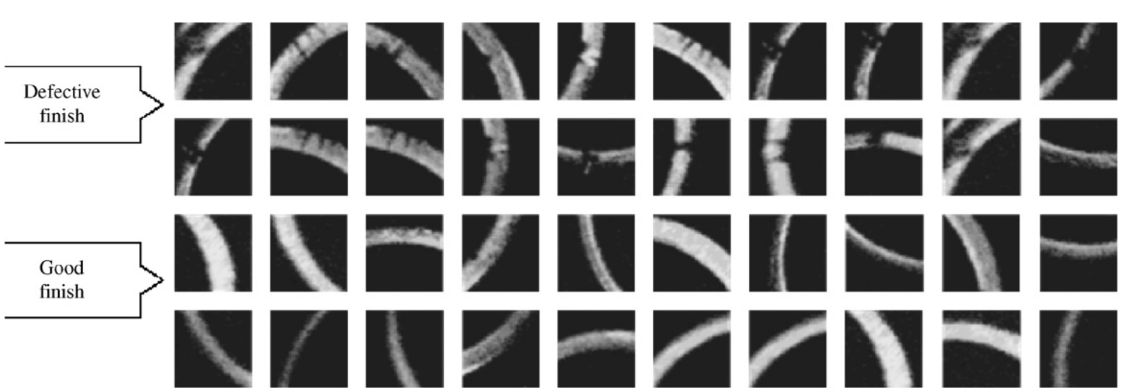

Fig. 13. Samples firstly used to train the neural network.

are very typical and small in number (only 40). Thus, the neural network is quite easy to converge.

In the next step, the neural network is used in practical application. As shown in Fig. 14, when error occurs, inspection workers can decide whether it is necessary to input the wrong inspection case to the sample image database. If the number of new samples input into the database reaches 5, we continue using all the samples in the database to train the neural network. And then the neural network is used in practical application again. In this way, the wrong inspection case gradually appears less frequently and finally satisfies our requirement. In our application, when the neural network achieves satisfied inspection result, we used 185 samples. When the low-level neural network works well, we begin the training of the high-level neural network, which is quite easy due to the small number of possible input patterns.

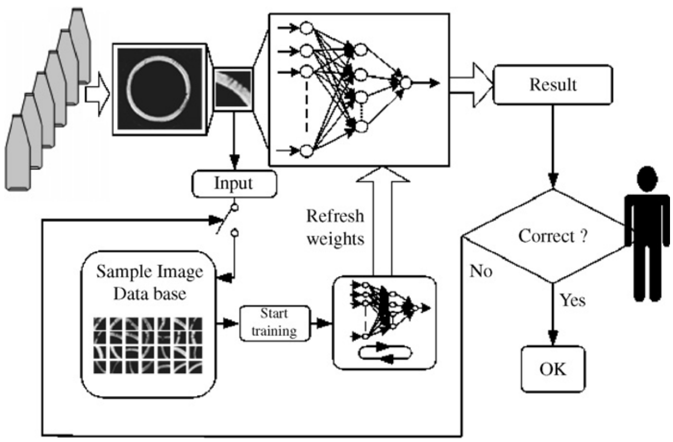

Fig. 14. Training neural network during online inspection.

4. Experimental results

Fig. 15 shows our prototype equipped with an annular conveyor that enables us to realize the production line for continual inspection as practical production.

In the prototype, bottle samples are inspected 50 times at a speed about 30 000 bottles per hour. The industry PC has a P42.4G CPU. The execution time of the inspection of bottle wall and bottle bottom is less than 150 ms and the inspection of bottle finish costs only 56 ms. Figs. 16 and 17 show the image of some typical bottles used in our inspection. After completing enough experiments to adjust some thresholds and train the neural network-based finish inspection system, we finally achieve quite satisfying results as shown in Tables 1–4. All defects larger than about 36

Fig. 15. The prototype with an annular conveyor.

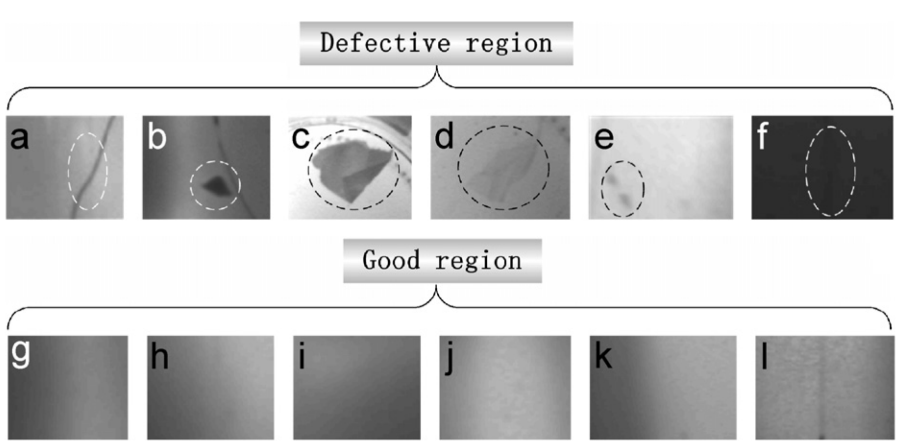

Fig. 16. Some defects in bottle wall and bottom.

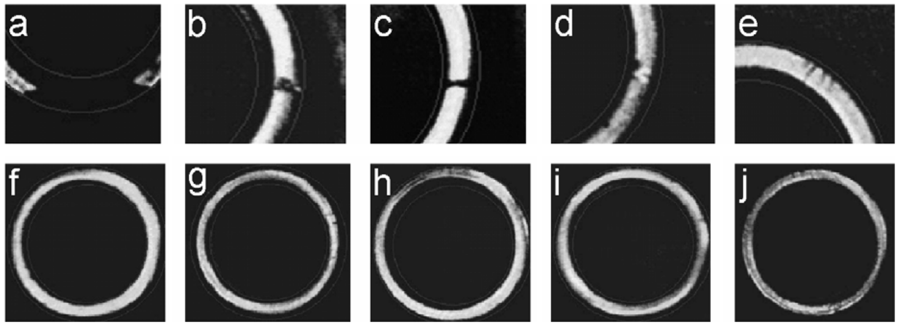

Fig. 17. Some typical finish images.

Table 1
Inspection results of defective bottle walls and bottoms

Samples	Fig. 16a	Fig. 16b	Fig. 16c	Fig. 16d	Fig. 16e	Fig. 16f
Correct inspection rate (%)	100	100	100	98	96	90

Table 2
Inspection results of good bottle walls and bottoms

Samples	Fig. 16g	Fig. 16h	Fig. 16i	Fig. 16j	Fig. 16k	Fig. 16l
Correct inspection rate (%)	100	100	100	100	100	88

Table 3
Inspection results of defective finish

Defect samples	Fig. 17a	Fig. 17b	Fig. 17c	Fig. 17d	Fig. 17e
Correct inspection rate (%)	100	100	100	94	90

Table 4
Inspection results of good finish

Defect samples	Fig. 17f	Fig. 17g	Fig. 17h	Fig. 17i	Fig. 17j
Correct inspection rate (%)	100	100	96	94	92

pixels in the bottle wall or bottle bottom can be correctly detected. And all defective finishes with cracks that may cause leakage (Figs. 17a–c) can be inspected correctly. Other very small chinks (Fig. 17d,e,i,j) are also detected with a high correct rate. In addition, the misdetection rate of good bottles is low. However, it is still not very satisfying in distinguishing between the defect and the texture of the bottle (Fig. 16l). This problem can be partly solved by using a special machine to smooth the outside of the bottle wall before inspection.

5. Conclusions

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

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