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Research on Bottom Detection in Intelligent Empty Bottle Inspection System

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Abstract

Intelligent empty bottle inspection system is an important inspection equipment of empty bottle before filling beer, and it is a blend of machine vision, precision machine and real-time control. They need to cooperate perfectly to achieve the desired effect. In the design of the empty bottle inspection system, one of the key technologies is the bottle bottom detection which affects the speed and accuracy of the system. It includes positioning and defect recognition of bottle bottom. For the problems such as the slow detection speed and low detection precision of bottle bottom detection, some new methods are proposed in this paper. The positioning algorithm of the bottle bottom in images is studied after preprocessing the obtained images, and the accurate positioning is achieved by improving the Randomized Hough transform. In the defect recognition of bottle bottom, a method of calculating optimum radius in Fourier spectrum is used to solve the problem of the detection accuracy being influenced by the antiskid veins of bottle bottom. It can improve the recognition accuracy effectively. Experiments show the methods proposed in this paper can effectively improve the precision and speed of the bottle bottom detection.

Keywords: *intelligent empty bottle inspection system, machine vision, positioning of bottle bottom, defect recognition*

1. Introduction

Empty bottle inspection before filling beer is one of the important processes of the beer production project. It is difficult to guarantee the reliability and adapt to the requirements of modern high-speed production line using the traditional way of manual detection. Therefore, it results in some substandard beer influx into the market and brings damage to the corporate image [1]. Intelligent empty bottle inspection system based on machine vision technology can not only overcome the defects of the traditional manual inspection, but also can achieve the automatic control of a production line through computer processing, which can greatly improve the degree of automation of the beer production lines [2-4].

Intelligent empty bottle inspection system is a high-speed online testing equipment, which gather machine vision, precision machinery and real-time control in one system. It mainly consist of pre-inspection unit, residue inspection unit, bottle mouth inspection unit, bottom inspection unit, bottle walls inspection unit, control unit and man-machine interface unit, as is shown in Figure 1. The main functions include bottle mouth breakage inspection, the dirt and foreign body inspection of the bottle mouth, bottom and the wall, inspecting residue liquid in a bottle and rejecting the bottles unqualified in time. Bottom detection is important in the whole detection system, and the detection speed and accuracy still can't meet the demand of high-speed production line [5]. It includes positioning and defect recognition of bottle bottom. With the improvement of production line automation, it puts forward more needs on speed and precision of bottle inspection. Bottom image positioning is one of the important factors affect detection speed and is the basis of precise detection of bottom defect. Moreover, in the bottle bottom defect detection, the accuracy of the defect detection is influenced greatly because of the existence of the bottom antiskid veins.

In order to improve the detection speed and accuracy, some methods are proposed in this paper. A bottom positioning algorithm is proposed after reprocessing the image obtained. Because the bottom image does not have a clear edge and there are many interferences coming from antiskid veins, we process the image with edge detection and chain-code tracing to

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calculate the chain-code's circumference. Then we filter off some small clutter edge by setting thresholds. Finally we can locate the center of the bottom by using an improved randomized Hough transform. There are many surface defect detection algorithms [6]-[9], and the algorithm generally used is Blob analysis [8,9]. However, these algorithms can't be used directly because of the antiskid veins on bottle bottom. Therefore, in the defect recognition of bottle bottom, because the antiskid veins of bottle bottom influence the detection accuracy, we solved this problem using a method of calculating optimum radius in Fourier spectrum. It can improve the recognition accuracy effectively. Experimental results show that this method can not only improve the inspection speed, but can also improve the inspection accuracy.

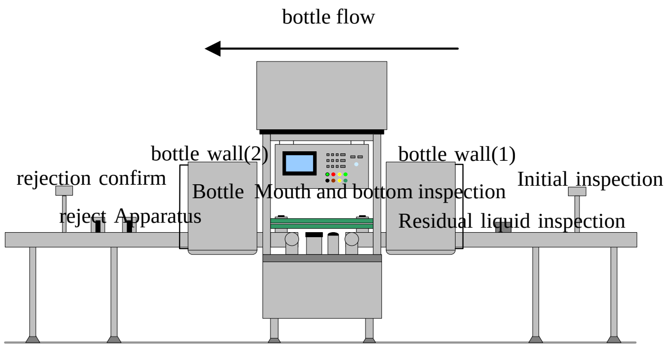


Figure 1. Structure diagram of the empty bottle inspection system

2. Image Preprocessing

In the intelligent empty bottles inspection system, the original images obtained by CCD camera have a certain degree of noise because of being subjected to various noise sources during their generation and transmission. At the same time, the slight sloshing of bottles in transmission and the non-uniform illumination will lead to the gray of the obtained image increase or decrease suddenly. This will give birth to the edge formed by false objects, which causes image blurring, and then bring difficulties to the image analysis. So it is necessary to take measures of image pre-processing methods. For example, using morphology methods to remove the noise and correct the uneven illumination to highlight the interesting characteristics of the images.

First a median filter shown in Equ.1 is used to remove the noise of the image obtained, and then image contrast enhancement is achieved by a gray transformation function shown in Figure 2.

$$g(i, j) = median\{ f(m-k, n-l)(k,l) \in w\} \tag{1}$$

Where (m, n) is the coordinate of central pixel, and (i, j) is the coordinate of processing pixel. $K, l = -1,0,1$.

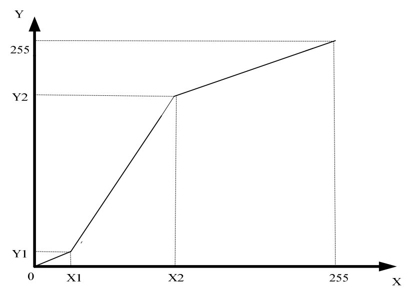


Figure 2. Gray transform function

According to experiments, when the value of (x_1, y_1) is (*30, 15*) and the value of (x_2, y_2) is (*120, 200*), the results of images gray stretching are much better. We use Canny operator [10] to detect the edge of the bottle bottom. It not only effectively detects edges of objects but also filters out partial edge points that are not important, which is helpful to the follow-up chain code tracing and image localization.

3. Location of Bottle Bottom

In the course of inspecting empty bottles, shake or tilt of bottles will cause the difference of the image acquired each time. So it is necessary to locate the empty bottles precisely to make sure the images within the regions of interest every time. In real application, the speed of the empty bottle inspection can be up to a maximum of 20 bottles per second. However, the location processing algorithm occupies most time of the whole image processing. So a rapid and efficient location algorithm is essential for improving the overall performance of the intelligent empty bottle inspection system.

The principle of image positioning takes the best feature points of the empty bottles as the locating points first. Then search for the locating points and get their coordinates in each image. The offset of the image can be obtained by calculating the different value of the locating points of two continuous images. At last, the same offset can be made to make sure that the regions of interest move precisely to the detecting areas.

Because the image of bottle bottom is a circle, bottle bottom locating is same as inspecting for circle and finds the center and radius precisely according to the geometric feature of circle. At present, the main methods of circle detecting include detecting circles with Hough transformation, fitting circles with edge detecting and least square method [11], template matching for active circles [12, 13] and so on. Because there is interference of antiskid veins in the bottom image, it is difficult to find the edge points accurately. We adopt chain-code tracking combined with the improved Randomized Hough transform to detect the circle in this paper. This method not only resolves the shortcoming of the slow transformation speed of traditional Hough transform, but also can obtain the circle center accurately.

3.1. Chain Code Tracing

After the edge detection, the bottom image contains rich edge information, which has some unimportant points or points not related to the location. These unnecessary edges will affect the location accuracy of the bottle bottom. Therefore, after detecting the edge, we must use Chain code tracing to filter out that clutter edge according to the calculation of the perimeter of chain code. The perimeter can be given as,

$$perimeter = n_e + \sqrt{2}n_0 \qquad (2)$$

Where n_e is the number of even numbers in the chain code, n_o is the number of odd numbers in the chain code. The even numbers in the chain code represent horizontal direction and vertical direction, and the odd numbers represent the other directions.

After each edge perimeter is calculated by means of chain-code tracing, we can remove the unnecessary edges according to set perimeter threshold. After Canny detection, the location edge of bottle bottom is discontinuous sometimes. In this paper, the threshold of perimeter is set to 100 by repeated tests.

3.2. Improved Randomized Hough Transform Algorithm for Circle Inspection

Hough transform has high precision and strong anti-interference characteristics, which can be applied to detect arbitrary curve with analytic form. However, its obvious disadvantage is the computational complexity and the slow speed. Therefore, the Randomized Hough Transform algorithm is usually used in the requiring rapid inspection situation.

Randomized Hough Transform algorithm is to select the smallest point set randomly in image space, and then map it into a point in the parameter space. Because this algorithm belongs to many-to-one mapping, it avoids the large computational complexity of traditional Hough transform. However, because the smallest point set of circle is composed of three non-collinear points of the edge, the smallest point set may be not on the same real circle when there are more than one circle characteristics in the images. This not only introduces invalid units, but also becomes interfering factors if the parameter list contains the circle parameters calculated by this kind of smallest point set. We can solve it by testing the smallest point set. For the same batch of empty bottles, the values of bottom radius will change in a certain range. Therefore, we add a constraint condition of the radius value range for the smallest point set. When select three points non-collinear randomly, calculate the radius of the circle determined by these three points, and compare it with the value range. If it is within the scope, then continue the following steps. If not, then re-select another three points, and calculate the radius value.The steps of the improved algorithm are as follows,

(1) Set the range of radius value, and structure an edge point set D. Initialize the parameter unit set $P=NULL$, the loop number $K=0$, and the number of circles inspected $n=0$;

(2) Select a smallest point set from D randomly, and calculate the radius of a circle determined by these three points;

(3) Judge whether the radius obtained in the range. If it is, then solve circle parameter, otherwise go to (2);

(4) Search a circle parameter p_c meeting the condition of $\|p_c-p\|<\delta$ at P, if find then go to (6), otherwise go to (5);

(5) Insert p into the parameter unit set P, and set its corresponding accumulator value as1, then go to (7);

(6) Let t, the value of the accumulator corresponding p_c, add one. If t less than the threshold T, then go to (7), otherwise go to (8);

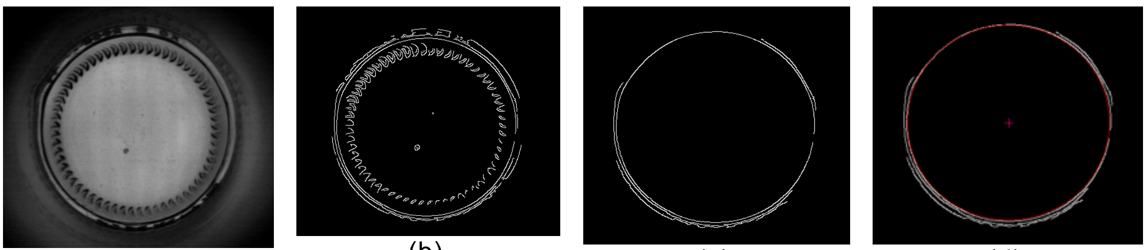
(7) $K=K+1$. If $K>K_{max}$, then the algorithm end, otherwise go to (2);

(8) p_c is the candidate circle parameter. Calculate the number Mp_c of the pixels on the circle corresponding to the parameter. If $Mp_c>M_{min}$, then go to (9), otherwise p_c is a false circle parameter. Remove this parameter from P and go to (2);

(9) Structure an edge point set with the edge points on the corresponding circle of p_c , and make least squares fitting to get the precise parameters of a circle, then remove the point set from D, $n=n+1$. Set $P=NULL$, $K=0$, and continue to inspect the rest circles to determine whether the number of the circles has been inspected reach the prescribed number. If it is, then end, otherwise, go to (2).

The improved algorithm can reduce a lot of invalid operation and increase the computation speed, and it can detect the circle more accurately with less computation.

The positioning results are shown in Figure 3. (a) is original image, (b) is the result of Image edge detection, (c) is the image filtered by chain code tracking, (d) is the detected result by improved random Hough transform, and the red cross is the located center of the circle.



(a) (b) (c) (d)

Figure 3. The results of the bottom positioning

4. Defect Detection of Bottle Bottom

In defects detecting process, the image of bottle bottom is divided into two regions, shown as Figure 4, according to its characteristics. ‘A’ is the region containing antiskid veins, which have great influence on detection results. Therefore, special algorithm must be used to filter out the veins and then the Blob algorithm based on connected domain is used to detect defects. ‘B’ is the surface region which can be detected by Blob algorithm directly.

In this paper, Fourier transforms is used to remove the regular texturing of a bottle bottom image. There is a certain relationship between regularity texture and Fourier spectrum

[14]. Therefore, according to the characteristics of antiskid veins, we filtered out the regular texture in the image by selecting an optimum radius in Fourier spectrum.

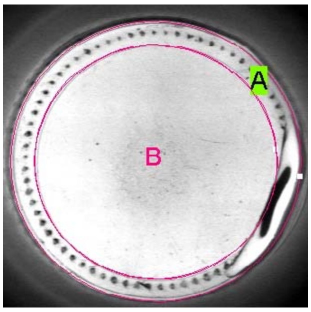


Figure 4. The partition of a bottle bottom detection region

4.1. Two Dimensional Discrete Fourier Transform

Suppose the size of a two-dimensional image is $N \times N$, and the gray value of pixel (x, y) in the image is $f(x, y)$. $x=-N/2,\dots,N/2$, $y=-N/2,\dots,N/2$. The two dimensional discrete Fourier transform is,

$$F(u,v)=\frac{1}{N}\sum_{x=-\frac{N}{2}}^{\frac{N}{2}}\sum_{y=-\frac{N}{2}}^{\frac{N}{2}} f(x,y)\cdot \exp\left[-j\cdot 2\pi(ux+vy)/N\right] \tag{3}$$

Where u and v are frequency variables, and $u,v=-N/2,\dots,N/2$. The two-dimensional Fourier transform can be expressed using complex number,

$$F(u,v)=R(u,v)+jI(u,v) \tag{4}$$

Where

$$R(u,v)=\sum_{x=-\frac{N}{2}}^{\frac{N}{2}}\sum_{y=-\frac{N}{2}}^{\frac{N}{2}} f(x,y)\cos\left[2\pi(ux+vy)/N\right]$$

$$I(u,v)=\sum_{x=-\frac{N}{2}}^{\frac{N}{2}}\sum_{y=-\frac{N}{2}}^{\frac{N}{2}} f(x,y)\sin\left[2\pi(ux+vy)/N\right]$$

Therefore, image power spectrum can be defined as,

$$P(u,v)=\left|F(u,v)\right|^2=R^2(u,v)+I^2(u,v) \tag{5}$$

Where the amplitude function, $|F(u, v)|$, is image spectrum.

If there are defects in an image, the frequency of gray change will be low, and $P(u,v)$ will concentrate in low frequency area. Otherwise, If there is period texture in the image, the frequency of gray change will be high, and $P(u,v)$ will concentrate in high frequency areas. Therefore, we can filter out periodic texture according to the distribution of spectrum energy. First, we get an optimum radius, r_{opt}, in Fourier power spectrum, and then remove the frequency elements of the center and outside of optimum radius from Fourier spectrum. Last, the image without regular texture can be obtained by inverse Fourier transform.

4.2. Selecting the Optimum Radius

Suppose the size of an image is $N \times N$, and define energy mean $E(r)$,

$$E(r) = \frac{1}{N_r} \sum_{u^2+v^2=r^2} P(u,v) \tag{6}$$

Where N_r is the number of the frequency elements inside the circle with radius r, and $P(u,v)$ is the power spectrum.

$E(r)$ denotes the average value of the energy intensity of all frequency elements inside the circle with radius r, and $r=0,1,2,3,\ldots,N/2$. Defining $E(r)$ as vertical axis and r as horizontal axis, we can obtain average energy curve. Calculate the slope angle of the curve,

$$\psi(r) = \tan^{-1}\left(\frac{E(r) - E(r-s)}{s}\right) \tag{7}$$

Where s is spacing, and $\psi(r)$ is the slope angle of the curve $E(r)$ when the radius is r.

The curvature of curve $E(r)$ can be obtained using the equation as follow,

$$k(r) = \frac{\Delta \psi(r)}{\Delta s} = \tan^{-1}\left(\frac{\psi(r) - \psi(r-s)}{s}\right) \tag{8}$$

Where $k(r)$ is the curvature of the curve $E(r)$ when the radius is r. Then the optimum radius r_{opt} can be obtained,

$$r_{opt} = \arg\left\{\max_{r} k(r)\right\}$$

After obtaining the optimum radius, Fourier transform can be expressed as,

$$\hat{F}(u,v) = \begin{cases} 0, & if\ u^2 + v^2 > r_{\max}^2\ or\ (u,v) = 0 \\ F(u,v), & otherwise \end{cases} \tag{9}$$

4.3. Images Restore using Inverse Fourier Transform

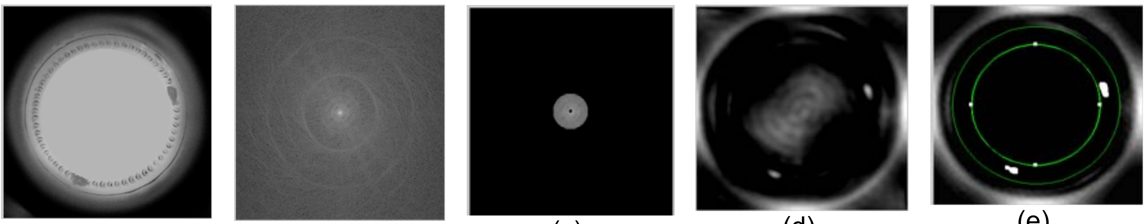
In the Fourier spectrum, set the frequency elements at the center and outside of the optimum radius as zero. The remaining frequency elements within the optimum radius are defect information. Using inverse Fourier transform, we can obtain the original image which has been filtered interference information such as regularity texture on the premise of retaining useful information. The equation of inverse Fourier transform is,

$$f(x,y) = \frac{1}{N} \sum_{u=-\frac{N}{2}}^{\frac{N}{2}} \sum_{v=-\frac{N}{2}}^{\frac{N}{2}} F(u,v) \cdot \exp\left[j \cdot 2\pi (ux + vy) / N \right] \tag{10}$$

After obtaining the image without regularity texture, we can get the binary image by binarization processing, and then obtain the characteristic data of defect correctly using Blob analysis.

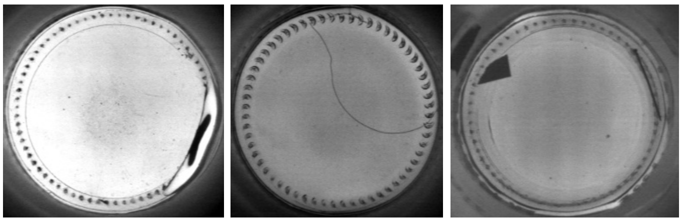
Using the methods proposed above, we can detect defects correctly even if they exist in and their gray value close to the antiskid veins area. The experimental results are shown in Figure 5. Figure 5 (a) is the original image. (b) is the Fourier spectrum of image (a). (c) is the image of filtering regular texture using optimum radius. (d) is the image of Inverse Fourier transform and (e) is the image after Binarization processing.

The results of bottle bottom defects recognition based on the above algorithm are shown in Figure 6.

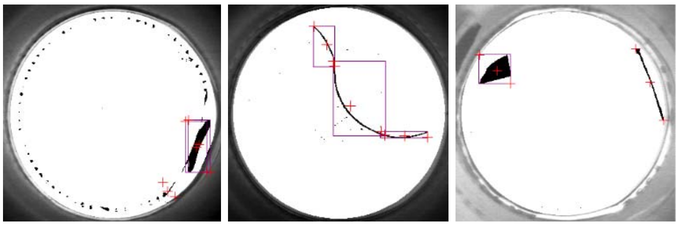


(a) (b) (c) (d) (e)

Figure 5. The partition of a bottle bottom detection region



(a) Original images



(b) Detection results

Figure 6. The defect detection of bottle bottom

5. Conclusion

The detection of bottle bottom is one of the key technologies in the intelligent bottle inspection system based on the machine vision, and it has a direct effect on inspection speed and accuracy of the system. In this paper, we studied the bottle bottom location and defect detection methods on the basis of pre-processing and edge inspection of the bottom image. In the location of bottom, we use the chain code tracing method to filter out the unwanted edge, and adopt the improved Random Hough Transform to inspect circle. The improved Random Hough Transform can reduce a lot of invalid operation by increasing the constraint conditions of radius, which can significantly improve the speed and precision of location. In the detection of bottom defects, we mainly discussed how to eliminate the effect of antiskid veins on detection results. Fourier transform technique is used in this paper to remove the regular texture by calculating optimum radius and the defect detection is achieved by Blob analysis at last. Experiment results show that the algorithm used in this paper can improve the efficiency and accuracy of defect detection and has high practical value.

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