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A new machine vision real-time detection system for liquid impurities based on dynamic morphological characteristic analysis and machine learning

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ABSTRACT

Impurity in transparent-bottled liquid is a serious production accident in the field of beverage and medicine industry. However, the existing detection systems are difficult to distinguish impurities with dynamic interference (bubbles and stains) and detect impurities located at the edge of the bottle. In order to solve the problems stated above, a new machine vision system for detecting tiny and dynamic impurities is proposed in this paper. In the system, circularity calculation, longitudinal frame-difference method, orthogonal-axis inspection and K-Nearest Neighbor (KNN) machine learning algorithm are combined together to realize the automatic and real-time detection. Experimental results demonstrate that, after completing machine learning, the weighted error of the proposed system for detecting impurities can be effectively controlled at about 0.9% even in dynamic interference environment, which is great significance to safety production in beverage and medicine industry.

1. Introduction

Beverage and medicine industry is an important part of industrial production. Transparent-bottled liquid accounts for a great proportion in the whole products of beverage and medicine industry [1]. In the process of liquid production, inevitably, some transparent-bottled liquid may include impurities, such as floc (indicating that the liquid has gone bad), residue (indicating a filtration system error) and glass fragment (directly damaging the human body). Therefore, detection of impurities is of great significance for production safety in beverage and medicine industry.

However, impurity detection is mainly based on manual-visual inspection traditionally, which is time-consuming and inefficient. Especially in the situation of long working hours (about 2 h), serious discomfort with visual deterioration and impaired concentration may occur to inspectors, which overwhelmingly damages the quality of impurity inspection and the health of workers. With the development of automatic detection technologies, a series of automatic inspection systems have been proposed based on High Performance Liquid Chromatography (HPLC) by researchers [2–4], which have a satisfactory performance. However, the HPLC systems are difficult to realize real-time impurity detection of products on assembly line.

Because of the advantages of stability, accuracy and cheapness [5–9], machine vision has become one of the development tendencies for impurity detection, and a great many of detection systems have been proposed. Huang, Li, Wang, et al., have proposed a least squares filtering detection system [10], which uses least squares filtering algorithm to obtain low noise images, and take the closed pattern in the image as impurity. Huang, Ma, Lv, et al., have proposed a fuzzy least squares support vector machine system [11], which uses fuzzy least squares support vector machine to recognize the impurities which are similar with bubbles. However, the least squares filtering detection system is hard to distinguish impurities and dynamic bubbles, and fuzzy least squares support vector machine system may misjudge the stains on the surface of bottle as impurities. Besides, impurities at the edge of bottles (the impurity images may become deformed) is difficult to be recognized in the existing impurity detection systems.

In this paper, a new real-time detection system for impurities in transparent-bottled liquid is proposed based on machine vision. The system combines technologies such as circularity calculation, longitudinal frame-difference method, orthogonal-axis inspection and K-Nearest Neighbor (KNN) machine learning algorithm to solve the problems in existing detection systems.

1. The orthogonal-axis inspection method uses two CCD cameras, the optical axes of which are configured to be orthogonal so that at least

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one camera captures the undeformed image of impurity at the same time.
2. The circularity calculation calculates the circularity of every closed pattern, which is able to separate tiny impurities from bubbles.
3. The longitudinal frame-difference operation identifies all objects that have longitudinal motion components, which is responsible for distinguishing impurities and stains on the surface of bottles.
4. By contrasting with the database, K-Nearest Neighbor (KNN) machine learning algorithm determines whether there is any impurity in the detected sample, which can improve adaptability of the system in complex detection environment.

On the experimental platform in the laboratory, massive experiments are carried out to test the impurity detection effectiveness of the system. Experimental results demonstrate that, after completing machine learning, the weighted error of the designed system for detecting impurities with dynamic interference is about 0.9%.

In this paper, Section 2 describes the principle of digital image processing method (circularity calculation, longitudinal frame-difference method and orthogonal-axis inspection) used in the system. Section 3 represents the mathematical model of KNN machine learning algorithm and the effect of this algorithm. Section 4 illustrates the structure and detection process. Sections 5 and 6 individually display experimental scheme & results and conclusion.

2. Visual recognition method

In the actual detection environment, the kinestate of detected samples can be divided into two stages–rotation and translation. In the process of rotation, the samples rotate 180 degrees quickly in vertical direction, which stirs the impurities contained in the samples and improves the accuracy of impurities identification. However, a large number of bubbles may appear in the liquid when the impurities are stirred. In the process of translation, samples are measured horizontally in constant speed, yet stains on the surface of samples may be misjudged as impurities. Besides, impurities at the edge of bottles are really difficult to be detected because of the deformation of them. In this paper, the digital image processing method of the designed system can filter out above interference effectively.

2.1. Circularity calculation

Circularity calculation is able to realize separation of impurities and stains from bubbles in the field of morphology [12–15]. Impurities in bottled liquid are mainly composed of flocs, glass ballast and food debris, meanwhile the stains attached to the surface of samples are mainly composed of glue marks, glass cracks and dust. The commonness of above impurities and stains is that they are all irregular shapes in the detection images. By contrast, bubbles in detection images are regular circles because of the minimal volume. The different morphological features of impurities/stains and bubbles are shown in the Fig. 1. In this paper, the calculated circularity is used as a reference standard to distinguish impurities/stains and bubbles in the process of detecting impurity.

The formula of calculating circularity is shown as follows.

$$C = \frac{4\pi A}{P^2} \tag{1}$$

In formula, C is the circularity of geometric figures, A is the area of geometric figures, and P is the perimeter of geometric figures.

The laboratory has received about 50 random impurity samples (the impurity samples and the qualified samples each account for half) provided by the cooperative enterprise and measured the circularity of impurities and bubbles successively. The measuring results show that the circularity of most impurities and stains is within the range of 0.1–0.5, meanwhile the circularity of subtotal bubbles is within the range of 1.0–1.3. The circularity difference of impurities and bubbles is shown in Fig. 2.

Based on the above principle, circularity calculation method can effectively avoid error detection in case of impurities mixing with a large number of bubbles. Circularity and area from circularity calculation are involved in machine learning as important parameters.

2.2. Longitudinal frame-difference algorithm

Longitudinal frame-difference algorithm realizes separation of impurities and stains on the surface of bottles in the field of kinematics. Transparent bottles on assembly lines are occasionally scratched and stained. Most stains attached to the surface of bottles are hardly to be distinguished from impurities only based on their morphological characteristics.

Different from the traditional frame-difference method, this paper merely detects objects with longitudinal motion component by frame-difference operation.

The formula of longitudinal frame-difference method is as follows.

$$T(k) = A(k) - B(k) \tag{2}$$

In this formula, $A(k)$ and $B(k)$ are longitudinal location-component vectors of objects conforming circularity constraints in two consecutive-detected images. $T(k)$ is longitudinal motion-component vectors of objects, which conforming circularity constraints. And $T(k)$ is involved in machine learning as an important parameter.

2.3. Orthogonal vision inspection

After overturning of bottle, impurities may be anywhere in bottles and move irregularly with liquid. Once they are excessively close to the side of glass bottles, they may become deformed or even disappeared in detection images because of the refraction and reflection of light.

Therefore, an orthogonal vision inspection method is proposed. The optical axes of two HR CCD cameras are arranged orthogonally. The main CCD camera is responsible for shooting the side of glass bottles; meanwhile, the auxiliary CCD camera is responsible for shooting the other side of glass bottles. The impurities missed by the main CCD camera can be captured by the auxiliary CCD camera. In Fig. 3, the image of main camera does not contain any impurity, however, there is an obvious impurity in the image of auxiliary camera, which can effectively avoid the vision blind area of the main camera.

Specifically, as shown in Fig. 4, the two HR CCD cameras are immobilized at the side of samples, whose optical axes are orthogonal to each other. The edge positions of samples captured by main camera are at the central positions in camera B. The orthogonal vision inspection guarantees that at least one CCD camera obtains images of the undeformed impurities, thus the problem of deformed impurity recognition can be solved effectively.

3. Machine learning based on K-Nearest Neighbor

Traditionally, the detection systems realize the identification of impurities by artificially determining the threshold of sensitive parameters. However, the threshold segmentation method is too subjective to adapt to complex detection environment (parameters such as illumination, shape of samples, and movement state of samples vary all the time). Subsequently, some dynamic adjustment algorithms were proposed for determining the threshold. Yet a single-deterministic threshold is unable to satisfy the increasing accuracy requirement of detection systems. Therefore, the K-Nearest Neighbor (KNN) machine learning algorithm is adopted to discriminate impurities because of its satisfactory parameter clustering performance [16–19].

Identifying impurities requires three key parameters: circularity, area and longitudinal motion component. Each parameter can form a parameter vector independently. Because the parameters are