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Sensor-integrated Machine Vision System for Enhanced Defect Detection in Industrial Applications

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With rapid advancements in high-tech industries, the demand for precision and efficiency in manufacturing has increased significantly. Automated optical inspection (AOI) systems have become essential across various sectors, expanding from electronics to food and pharmaceuticals, as quality control standards and consumer expectations rise. We present a machine vision approach for defect detection in paper cups, specifically targeting quality issues caused by stains or blemishes. Traditional binary detection methods, such as blob analysis, often struggle with light stain detection. Here, we implement an optical inspection method using blemish edge detection, which more accurately identifies subtle defects along the inner edges of paper cups. By enhancing defect detection accuracy, this method is aimed at improving product quality and optimizing production yield, making it a practical solution for large-scale, high-speed inspection requirements in modern manufacturing.

1. Introduction

1.1 Research motivation

Visual inspection (VI) systems have become essential in industries for examining a wide range of products and materials. Initially applied in high-tech fields, their use is now expanding to traditional sectors such as paper, metals, wood, and textiles. VI systems use a variety of software detection techniques, such as texture filtering, which enable detailed analysis for differentiating materials on the basis of surface characteristics. Defect detection has seen substantial growth, particularly in applications such as flat-panel displays(1) and semiconductor chip manufacturing.

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This study is focused on defect detection in food-grade paper containers, specifically targeting foreign particles and black spots inside cups. For large-scale food manufacturers, high standards of quality are critical, as defective products reaching consumers could lead to disputes. Traditionally, operators visually inspect paper containers for contaminants or black spots before packaging. However, owing to high production volumes, a faster, more accurate VI system is necessary to maintain efficient production.

Paper containers are manufactured using food-safe paper with layers of polyethylene (PE) composites. These undergo processes such as printing, cutting, and molding, which can introduce two common defects, namely, black spots (from dust or heat-treatment particles) and blemishes (from colored liquid exposure or other contaminants). Black spots are visually distinct but subtle in color contrast, while blemishes are difficult for machine vision to detect owing to their low-contrast clusters against white backgrounds.

Our method is an innovative approach combining edge detection with grayscale and binary processing to more precisely identify and remove these defects. This method ensures that subtle defects, often missed by traditional binary inspection, are rapidly detected, enhancing product quality and production yield in high-speed manufacturing environments.

1.2 Research purpose

The objective of this study is to understand the core framework and methodologies of automated optical inspection (AOI) systems[2–4] through practical implementation and project-based analysis.[5] By evaluating the strengths and limitations of current AOI techniques, in this research, we seek to determine optimal detection methods. As AOI systems are predominantly applied in manufacturing environments, we employed Banner Engineering's Banner Vision Manager software and hardware systems[6] to address deficiencies in traditional inspection methods. This approach combines advanced edge detection and binary processing techniques, improving upon conventional CCD-based detection for more stable and rapid quality control.

The system also allows for the storage of product images and inspection data, facilitating thorough defect analysis and enabling manufacturers to identify areas for process improvement. With a user-friendly interface supporting multiple languages, the software simplifies training and operation, ultimately enhancing production efficiency and reducing operational costs for manufacturers.

AOI has become one of the most effective methods in industrial automation, where machine vision technology is utilized for quality control. The core concept of a machine vision system is to replicate human visual recognition using mechanical and electronic components. In essence, a machine vision system captures images through an imaging device,[7] which then transmits the data to a processing unit. Here, digital software processes and analyzes the images by evaluating pixel distribution, grayscale intensity, and color information to identify features such as size, shape, and color. Through this analysis, the system controls the equipment actions on-site, essentially replacing human eyes and brain functions with image capture mechanisms and logical processing.[8]

Machine vision systems are widely used to detect product defects, identify object positions, and measure dimensions, making them indispensable in modern factory automation for real-time inspection on production lines. Since AOI offers noncontact inspection, it allows for the examination of semifinished and finished products during manufacturing processes, improving inspection speed and safety. A complete machine vision inspection system typically comprises the following components: the object under test, illumination source, lens and CCD image capture device, image processor, control peripherals, and output units. Figure 1 shows a schematic of the VI system's configuration.(9)

2. Experiments

Disposable paper containers, such as cups and boxes, are essential for delivering fast food quickly, cleanly, and conveniently to consumers. However, the production process and quality requirements for these containers often go unnoticed. Paper containers are primarily made from food-grade paper, which is printed, cut, and shaped into the desired form. For paper cups, an additional coating process is typically required to achieve water- and oil-resistant properties. Understanding the manufacturing process of paper cups not only sheds light on their safety standards but also highlights environmentally responsible usage practices.

The food-grade paper used in paper containers is generally imported from Europe or North America and meets the highest standards in terms of safety and quality. The process begins with a coating application, which involves covering the paper surface with a waterproof and oil-resistant layer, often polyethylene (PE). This coated paper is then shaped by die-cutting into fan-shaped segments, which are the flattened structure of the paper cup wall. These segments are fed into a forming machine, where they are rolled around a cup mold to form the cylindrical cup shape. During this stage, the mold heats the paper along the seam, melting the PE coating to bond the edges, and then attaches the cup's base. The rim of the cup is curled and thermally set to finalize its shape. This forming process is completed in under one second per cup.

The finished cups are then transferred to a machine vision inspection station equipped with CCD technology, with a typical inspection rate of 120 cups per minute. This system ensures that each cup has a flawless shape, with no cracks or structural defects, and a clean inner surface free of contamination. Cups passing the inspection process are then packaged and prepared for

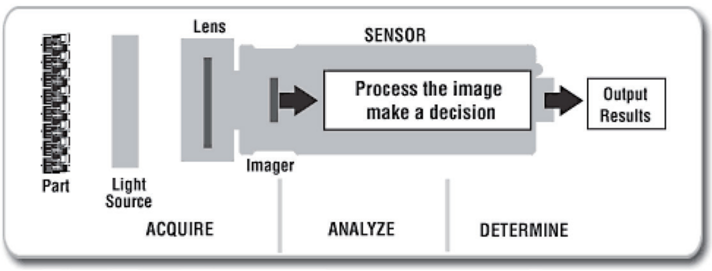


Fig. 1. Schematic of the visual system's configuration. (Source: https://azcomvn.com/news/nguyen-ly-hoat-dong-va-dung-dung-cam-bien-hinh-anh/)(9)

distribution to downstream food production facilities. Figure 2 illustrates the machine vision solution for an automation factory.(9,10)

Lighting is a critical component in any machine vision system as it serves to highlight the features and contours of objects for CCD image capture (Figs. 3 and 4). Successful visual inspection relies on achieving a strong optical contrast between the object's characteristics and its background, measured through grayscale values in the machine vision system. However, achieving optimal contrast depends on selecting and configuring the appropriate lighting source.

A well-designed lighting system can significantly reduce image noise, enhance contrast between the object and its background, and simplify the complexity of subsequent software detection algorithms. The common lighting configurations used in machine vision systems include the following:

(1) backlighting – provides sharp silhouettes for detecting edges or contours;
(2) directional lighting –used to reveal surface textures or detect minor defects;
(3) diffuse lighting – minimizes shadows and provides uniform illumination for consistent image quality.

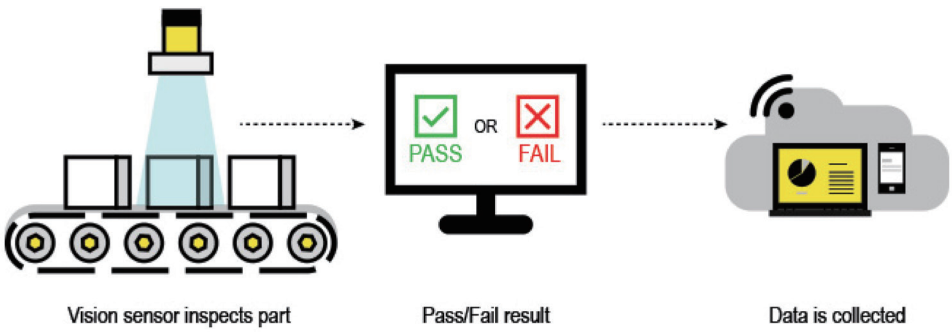


Fig. 2. (Color online) Machine vision: solution for automation factory. (Source: https://azcomvn.com/news/nguyen-ly-hoat-dong-va-dung-dung-cam-bien-hinh-anh/)[9]

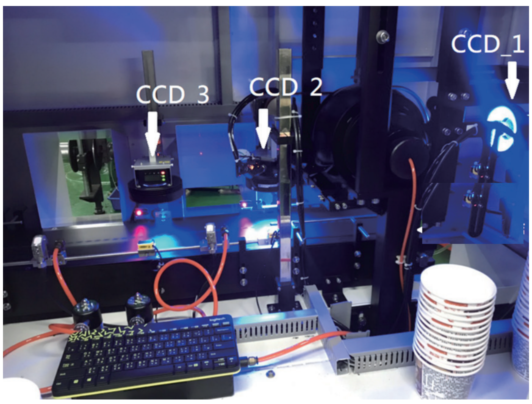


Fig. 3. (Color online) Critical components of any machine vision system to highlight the features and contours of objects for CCD image capture.

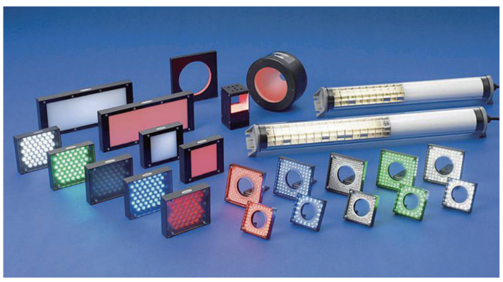


Fig. 4. (Color online) Selecting and configuring the appropriate lighting source.

Each lighting type is selected in accordance with the specific inspection needs, ensuring reliable feature extraction and efficient image processing for the visual inspection tasks.

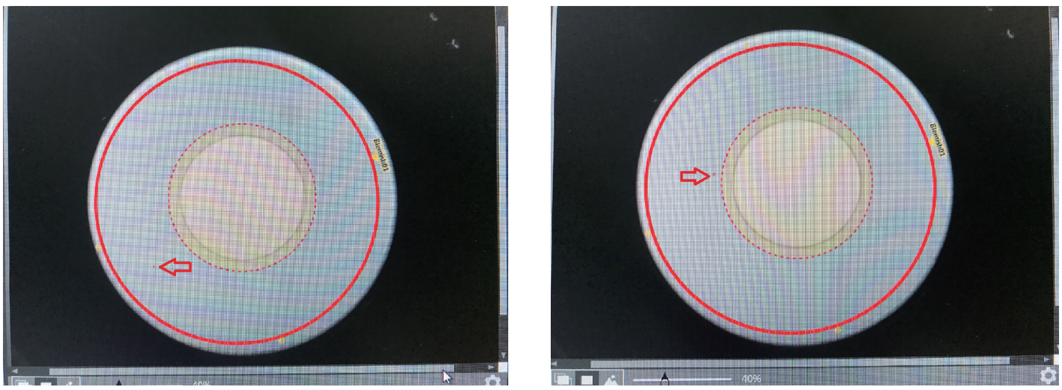
3. Results and Discussion

After inputting the reference images of standard components into the Banner Vision Manager system and configuring the required parameters, the automated inspection process can initiate continuous batch testing. The system records defect results and saves the images of identified flaws in a designated directory on the PC. When performing online inspection, operators load the inspection file for the specific product type. If a preexisting inspection file for the standard component is available, operators assess the current environmental conditions to determine if any stored settings or parameters require adjustment; otherwise, the inspection proceeds without changes.

For components with detected defects, the system triggers a rejection mechanism controlled by a PLC, where defective items are discarded while storing defect image data. If no defects are found, image storage is unnecessary. The CCD inspection system continuously performs the inspection process until all items are fully tested.

This CCD system inspects each item within a field of view (FOV) of 16×15 cm^2. With an inspection time of approximately 280 ms per item, the system achieves an average rate of three products per second, delivering high-speed, accurate inspection suitable for large-scale production environments.

In the experiment, a series of test images were captured (Figs. 5 and 6) from specific regions of the product, with particular attention given to three critical areas: the outer cup bottom, the inner cup bottom, and the inner cup wall. These regions were selected because of their importance in assessing product integrity and the likelihood of defect occurrence. All images were acquired using the same model of machine vision sensors and identical exposure settings were maintained throughout the experiment to ensure image consistency and comparability across the different test areas. This uniform setup allowed for a controlled evaluation of the system's detection capabilities under standardized conditions.



(a) (b)

Fig. 5. (Color online) Using inner cup wall spots as inspection objects. (a) Detection of spot on inner cup wall_#1. (b) Detection of spot on inner cup wall_#2.

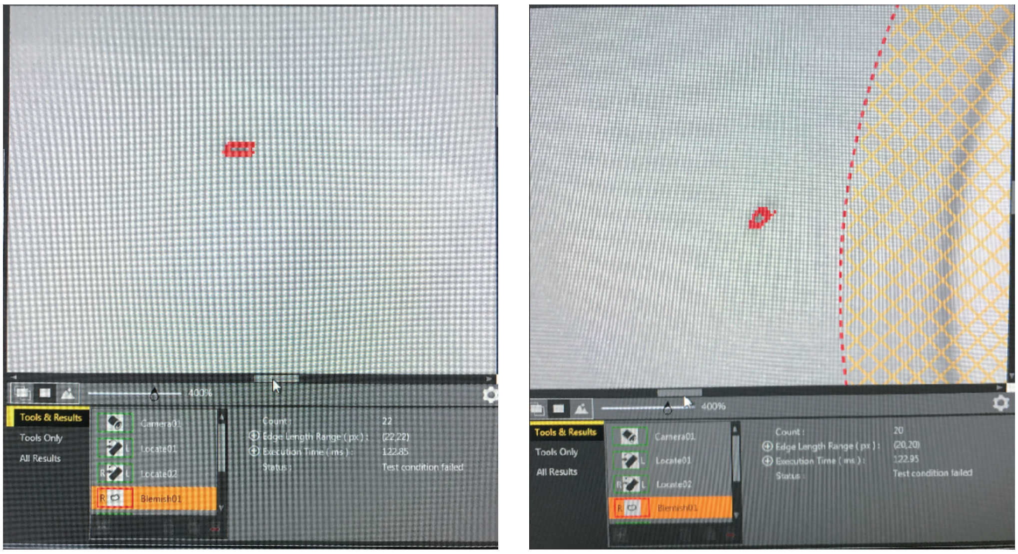


Fig. 6. (Color online) Pixel values of inner cup wall spot_#2. The total pixel count of spots on the inner cup wall was obtained by the edge detection method. The detection results of the total pixel counts of the detected spots are 20 and 22, respectively, obtained from the enlarged images.

Table 1
Performance characteristics of detection methods.

Detection method	Binary detection	Edge detection	Binary + edge detection
Detection Area: Black Spot Defects (Grayscale value below 100)	Effective even with very small pixel counts (under 10 pixels).	Ineffective with very small pixel counts (under 10 pixels).	Both tools combined; blob detection tool identifies defects in this condition.
Advantages	Suitable for dark grayscale images with high-contrast edge pixels.	None	Suitable for dark grayscale images with high-contrast edge pixels.
Disadvantages	Poor performance when background grayscale values are uneven.	Not suitable for dark grayscale images; misinterprets white pixels.	None
Detection Area: Spot Defects (Grayscale value below 150)	Ineffective when the grayscale value of the region of interest (ROI) is uneven.	Effective even when the grayscale value of the ROI is uneven.	Both tools combined; blemish detection tool identifies defects in this condition.
Advantages	None	Suitable for light grayscale images; detects low-contrast edge pixels.	Suitable for light grayscale images; detects low-contrast edge pixels.
Disadvantages	Not suitable for light grayscale images; cannot detect low-contrast spot pixels.	None	None

For the defective (NG) products, flaws were frequently and reliably identified in the inner cup bottom and inner cup wall areas. These areas exhibited small, subtle imperfections, such as black spots or blemishes, which could potentially compromise product quality. Following precise adjustments to the CCD software parameters, including threshold and sensitivity levels, the system successfully detected all defects within the tested products, demonstrating the effectiveness of these optimizations.

The experimental results underscore that the correct parameterization of the CCD inspection software, particularly regarding threshold and sensitivity, is crucial for reliable defect detection. Properly set, these parameters enable the system to consistently identify black spots and other blemishes, enhancing the overall accuracy of the inspection process. Furthermore, training skilled engineers through targeted educational programs in CCD inspection tool adjustments can further optimize system performance. Such training not only ensures that operators are proficient in configuring inspection parameters but also promotes consistency in quality control across production batches, thereby maintaining high standards in defect detection and overall product quality.

Table 1 shows the performance characteristics of our hybrid method and traditional binary detection methods. The table now includes a key performance metric. We believe that these additions provide the rigorous data needed to substantiate our claims.

4. Conclusions

Through testing, several areas for improvement have been identified in our CCD-based vision inspection system. In terms of hardware enhancements, the following modifications are recommended: (1) integrating a laser optical sensor for object positioning to improve accuracy, (2) developing an adaptive lighting module that automatically adjusts exposure in accordance with the object background color to optimize grayscale levels, (3) addressing lighting inconsistencies caused by differences in flatness between the cup base and sides, and (4) using higher-resolution CCD sensors (e.g., 5 megapixels) to achieve superior image quality. Regarding the testing environment, as the inspections were conducted under standard factory conditions, humidity and temperature fluctuations may impact imaging accuracy. Testing in a cleaner environment would help minimize misinterpretations caused by minor dust or particles affecting the image sensor.

Because of the increased demand for disposable food containers following COVID-19 restrictions, there has been a surge in the market need for single-use food packaging. This trend has highlighted the importance of advanced optical inspection solutions. Many manufacturers are now focused on developing intelligent sensor components that respond to environmental factors, such as ambient lighting, LED color, UV detection, and more. These innovations drive applications in smartphones, tablets, smart TVs, and displays, enabling more intuitive interactions. As nanotechnology advances, sensors are becoming more precise, with capabilities extending from motion detection to blood flow and even brainwave analysis. Just as seen in sci-fi movies, future sensors will not only surpass human sensory limitations but will also provide real-time analysis and decision-making, integrating seamlessly with daily life and presenting significant growth potential in various applications.

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