Liquid Container Inlet Detection Algorithm Utilizing Iot Sensor

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Abstract

Liquid filling machines are being used in various industrial fields. However, the existing liquid filling machine is optimized for a specific environment, so it is difficult to reuse it when the injection container is changed. In addition, when an operator directly injects the liquid, there may be a problem that the liquid is exposed to the external environment. In this study, we propose a position tracking algorithm that can automatically inject liquids in various environments. The proposed algorithm automatically detects the entrance of the container after taking a picture of the filling container using a vision sensor. The proposed algorithm detects the entrance to the container and automatically moves the liquid nozzle to automatically inject the liquid. In this study, an actual model was produced to verify the proposed algorithm, and it was confirmed through experiments that the inlet of the container was accurately identified.

Keywords: Hough transform, Liquid filling, IoT sensor, Object detection, Smart Factory

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1. Introduction

A smart factory refers to a factory in which sensors are installed in the facilities and machines in the factory, and factory data is collected and analyzed in real time to monitor and control all conditions of the factory by itself. Recently, as the product lifecycle is shortened and the customized mass production system is changing, a new production system is required. In this situation, a smart factory is needed for new innovation in the manufacturing field.

As the smart factory develops, the automatic production system is also developed, which has resulted in increased productivity and stability. In the product packaging business, there have been many studies on automation research and liquid filling machines (Baoyun & Daniel, 2016; Solanki et al., 2015). In Lee et. al. research, a smart liquid filling machine that can inject an exact amount of liquid

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was proposed to reduce foaming when injecting liquid into a drum (Lee et al., 2020). As such, the field of liquid filling machines is used to inject various liquids into various containers. In particular, it is widely used when injecting chemical products into drums in factories that handle hazardous chemical products that cannot be directly accessed by humans.

In this study, we propose an algorithm that can automatically find the container inlet in order to solve the problem that the liquid filling machine, which is manufactured once, cannot be used for various liquid containers. The proposed algorithm can be applied if there is a circular injection hole in a circular or other type of container other than the 200L drum widely used in the market. In the algorithm, it is possible to search the injection port even if the injection container is placed in various shapes. In order to extract various shapes of injection holes, the function was implemented using a vision sensor. Vision sensor takes a picture of the container, performs image analysis, and finds the inlet through the analysis. By locating the exact position of the inlet in the container, it is possible to move the dispensing equipment to the inlet and automatically fill the liquid. This algorithm reduces manual liquid filling times and also prevents toxic liquid leaks from chemical plants.

In the previous study, to estimate the position of an object, two or more cameras were used to acquire images, and then the images were combined and analyzed. If more than one image is used when estimating the position in an image, the data will grow proportionally to the image and the calculation time according to the image combination takes a lot of time (Christoph et al., 2018; Hongda et al., 2020). We propose an algorithm using a single camera sensor to reduce the amount of data and reduce the computation time (Luis et al., 2017). Using the proposed algorithm, it is possible to estimate the location of the injection hole faster than the existing method (Yang et al., 2020). In addition, it is possible to operate with a small amount of memory so that it can be operated even in low-spec computers and embedded systems.

2. Related Works

Various methods can be used to find a straight line in an image or video. There are roughly three methods, 1) curve fitting, 2) RANSAC, and 3) Hough transform. Curve fitting is a concept of finding a straight line with many points to find the optimal line with many points. RANSAC is an abbreviation of (Random Sample Consensus) and is an algorithm that obtains an optimal straight line or removes outliers or singularities after randomly extracting two points. Hough transform is a simple algorithm with fast linear processing that can be used in real time. Generalized Hough Transform(GHT) has been published as a paper and is currently being used in many fields. A simple explanation of the Hough transform is that it can detect any figure that can be expressed by an equation (straight line, circle, ellipse, hyperbola, etc.) (Colin et al., 2014).

In order to recognize the position, rotation angle, and size change of an object with the existing GHT algorithm, a four-dimensional parameter data area is required (Daming et al., 2020). A two-dimensional array corresponding to the position of an object and each array corresponding to a change in rotation angle and size are required. First, find the pi value at each point on the boundary of the object in the input image, and then calculate the values of all vectors $\gamma(r,\alpha)$ in the same pi group in the R-table as ratios and rotation angles of all possible sizes. is accumulated at a point on the four-dimensional cumulative array $Acc(X_c, Y_c, S, \theta)$ while changing (Hua et al., 2016).

2.1. Hough Transform

Basic idea of the Hough transform can be explained as follows. A straight line containing a point *(x1,* *y1) is* $y_1 = sx_1 + t$. If this point is expressed as an expression for s and t, it can be expressed as a straight line like $b = -sx_1 + y_1$. That is, all straight lines that a point can have can be expressed as a single straight line in the plane about t and s. When the two points are converted into an equation for s and t, two straight lines appear in the *s* and *t* planes. The intersection of two straight lines means a straight line passing through the two points. This is because a straight line in the *s* and *t* planes means all straight lines that a point can have, and a point that meets at s_1 and t_1 means a straight line that both points can have. The more straight lines overlapping the intersections *(s1, t1)* of the straight lines, the more likely it is that a straight line *is* $y = s_1x + y_1$ exists in the image. So, the intersections of the *s* and *y* spaces are checked, and if the value is higher than the threshold, the straight line is detected.

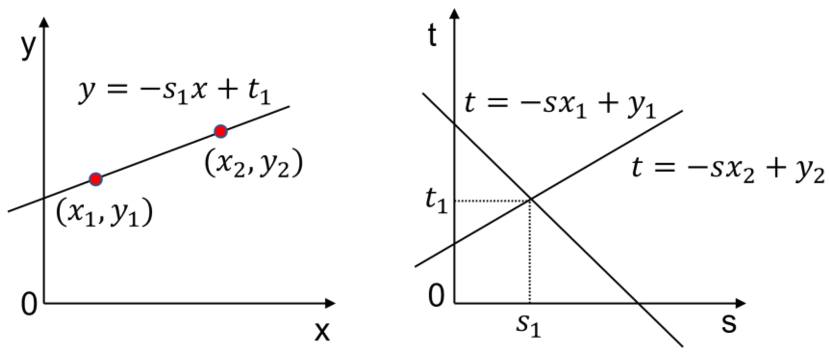


Fig. 1. Hough transform

In actual implementation, the *s*, *t* plane is expressed as an array, and *s* and *t* corresponding to the straight line are accumulated and used. If the array is finite, but the straight line is parallel to the y-axis, we can see that there is a problem because the slope, i.e., *s*, is a range of infinity. For example, if there is a straight-line y = x in the *s* and *t* planes, it becomes the concept of adding 1 only to the elements of the diagonal of the array. Then, if we have a straight-line $y = 2x$, we will add 1 to the element with a slope of about 75 degrees, and the intersection of $y = x$. (0,0) has an element of 2. Therefore, if the number is higher than the threshold while comparing arrays of finite size, it can be confirmed that the $y=sx + t$ line corresponding to the *s* and *t* values are detected.

2.2. Hough Circle Detection

To detect linear shapes in an image, the Hough Transform algorithm is used (Hao et al., 2019; Hong et al., 2020; Weichen et al., 2021). The features of Hough Circle Detection are as follows. If there are shapes in the image that can be mathematically modeled, the algorithm can discover them. After that, the Hough Transform can be applied to equation model of the circle. However the problem is that the formula for the circle consists of three parameters, the center point (x, y) and the radius (r), It is asking for storage. Since a three-dimensional array is used, a problem arises that requires a lot of computation time. As an improvement on this, Hough Transform can be applied using Gradient (the gradient value at the edge), and OpenCV provides the *cv2.HoughCircles* function as an implementation for this.

The cv2.HoughCircles function uses many arguments. The first argument is an image, which is an 8-bit single-channel grayscale image. The second analysis method currently supports only *cv2.HOUGH_GRADIENT*. The third is usually set to 1, in which case the same resolution as the input image is used. The fourth is the minimum distance value from the center of the detected circle. If it is less than this minimum value, it is not identified as a circle. And param1 is the factor value transmitted to Canny Edge, and *param2* is a value that needs to be adjusted appropriately while watching the detection result. If it is small, the error is high, and if it is large, the detection rate is low. *minRadius* and *masRadius* are the minimum and maximum radii of the circle, respectively. If set to 0, they are not used. Figure 2 shows the detection of circles in the image using the Hough Circle Method.

Fig. 2. Circle Detection using Hough Circle Method

2.3. Object Detection

When a person sees an image, the details of the objects inside the image can be grasped at a glance. (What objects are, where they are located, what kind of relationship they have, etc.) This is the reason why complex actions such as driving can be performed with little conscious intervention. However, recent detection systems such as R-CNN show insufficient parts to imitate the human visual system due to complex processing.

YOLO (You Only Look Once) considers the bounding box and class probability within an image as a single regression problem, and guesses the type and location of an object by looking at the image once. This is a method to calculate class probability for multiple bounding boxes through a single convolutional network as shown below.

Compared with the existing object detection method, the relative advantages of YOLO are as follows. It is a simple process, and the speed is very fast. In addition, compared to other existing real-time detection systems, the mAP is twice as high. By looking at the entire image at once, the contextual understanding of the class is high. This results in a low backgound error (False-Positive). Learn more general characteristics of objects. For example, when learning a natural image and testing it on artwork, it shows much higher performance than other detection systems.

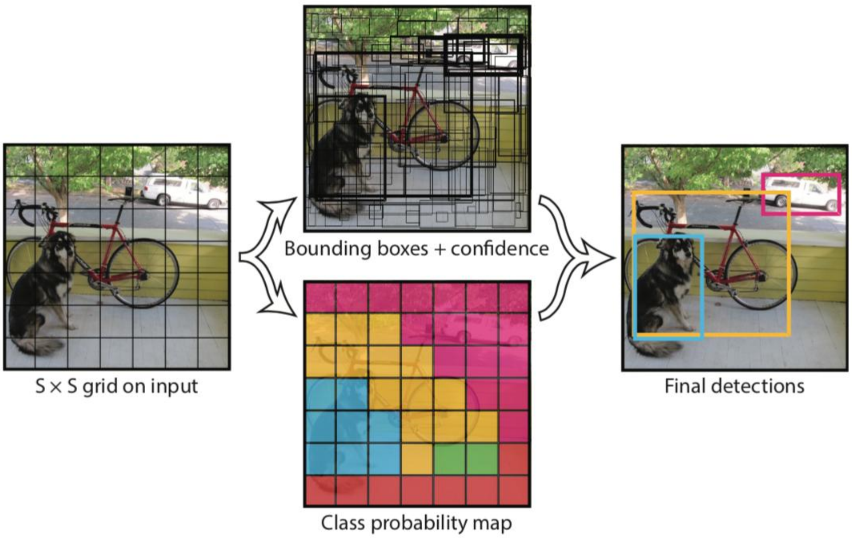


Fig. 3. Object detection using Yolo

3. Proposed Method

Figure 4 shows the environment in which the automatic inlet recognition algorithm proposed in this paper operates. The proposed algorithm is assumed to operate in a factory with conveyors. Various containers can be delivered to the conveyor system, and in the case of small containers, several containers are placed on a pallet and moved at once. A traverse system is installed next to the conveyor system, and the proposed automatic inlet recognition algorithm is performed through a camera mounted on this system. Various cameras were considered in this study, and the FZ-SZ of Omron was selected among them. Although this vision sensor is equipped with a 300,000-pixel sensor, it has characteristics that allow it to work in dusty places such as factories. An image of the inlet of the vessel is acquired through a vision sensor and an algorithm is used to analyze the inlet. When the inlet is identified, the liquid injection nozzle mounted on the traverse system is automatically moved to the inlet. After the transfer, the correct amount of liquid can be injected.

The algorithm proposed in this paper can operate even when several containers are placed on the pallet of the conveyor system at the same time. For example, even if six 60L drums are loaded on one pallet, the injection hole can be analyzed at once. In addition, not only 200L drums, but also IBC tanks, etc. can be analyzed in the inlet. It is possible to inject liquid by grasping the inlet of various containers used in the factory at once and automatically moving the liquid injection nozzle. Using this algorithm, liquid filling plants can ensure operational efficiency and safety.

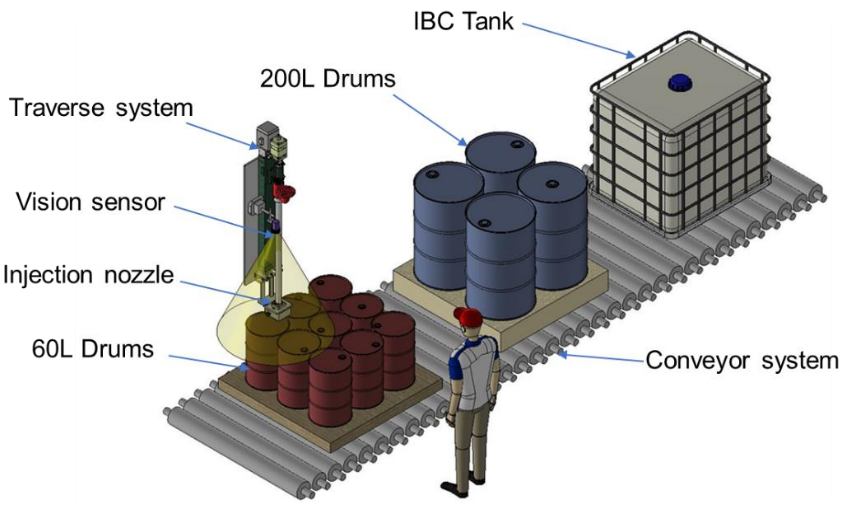


Fig. 3. Operating environment of automatic inlet recognition algorithm

4. Implementation Results

Hough Transform algorithm is widely used in the field of computer vision and is mainly used to detect lines in digital images (Hua et al., 2016). In this study, the Hough Circle Detection algorithm is used. Hough Circle Detection detects circles by applying Hough Transform (Colin et al., 2014; Daming et al., 2020). While developing the algorithm, before applying it to the factory, a prototype was made using a popular Raspberry Pi and camera. The manufactured prototype operates in an indoor environment and enables finding the inlet of a virtual drum container. Figure 4 shows the manufactured prototype. It was checked whether the inlet of various containers could be found even in the prototype.

Figure 4 shows the manufactured prototype. In the prototype, it was tested whether the inlet of various containers could be found. During the experiment in an indoor environment, it was confirmed that the inlet detection algorithm according to the lighting was malfunctioning. It was found that when the lighting is dark, the border of the container and the border of the floor cannot be clearly distinguished. For this reason, it showed a problem of analyzing one inlet into several. In order to solve the error of the inlet identification, two methods were found. The first is to brighten the lighting of the operating environment. Lighting issues can be a temporary workaround as they can vary depending on the environment of the plant. The second is to clarify the boundary between the container and the floor by preprocessing the image acquired using the vision sensor. Both methods were performed in the study. The second image preprocessing will be further strengthened by the assumption that the lighting may not be as desired when testing in the factory.

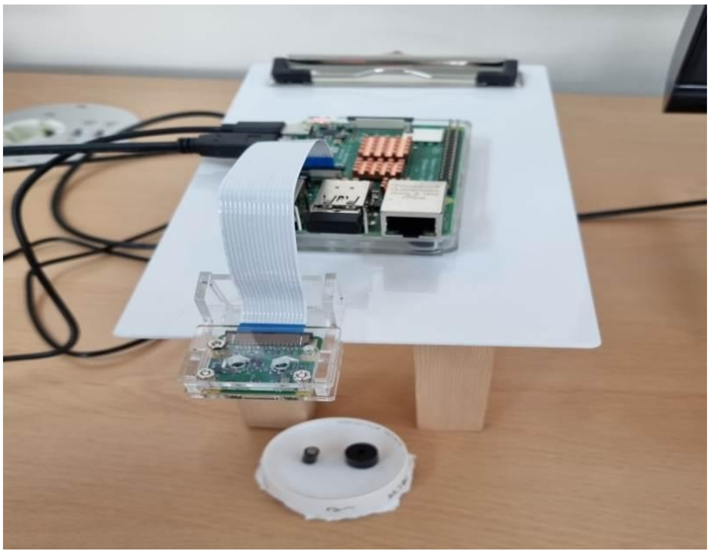


Fig. 4. Prototype of circle detection system

Figure 5 shows how to identify the inlet of a container using the proposed inlet detection algorithm. Figure 5(a) shows the original image using the vision sensor, and Figure 5(b) shows the image where the inlet was found in the pre-processed image.

a) Original image from vision sensor **b) Result of circle detection**

Fig. 5. Circle detection using pre-processed image

Figure 6 shows the algorithm for finding the inlet in the liquid container. In this paper, the algorithm is divided into four steps and briefly explained. The first step is to acquire an image of the liquid container on the factory conveyor system using a vision sensor. At this time, images are acquired in units of pallets, and the inlet of the container in the pallet is identified at once. Several sensors were tested for image acquisition. In the case of a general web camera, it was confirmed that it operates normally in a laboratory environment, but it is difficult to use in a factory where dust and lighting are not constant. For this reason, Omron's FZ-SZ vision sensor was selected because it has a low pixel count but can be used in an extreme environment in a factory.

In the second step, the image acquired on the palette is converted to gray scale. This is to clearly distinguish the floor from the container. In particular, when extracting a circle from an image, the Hough Transform is used, because a problem occurs in that the center point of the circle cannot be found in the case of a color image. Before solving this problem, the color image is converted to grayscale as a preprocessing operation before the actual circle search. In the third step, a Gaussian blur algorithm is used and applied to the image processed in the second step. The reason is that the accuracy of the result of the original detection algorithm decreases according to the degree of inclusion in the noise included in the image. Therefore, Gaussian blur is used to remove noise from the image. In the final step, Hough Circle Detection is used to extract the container inlet from the image acquired on the pallet. In this study, the parameter values of the *HoughCircles* function were set appropriately through many experiments in a factory environment. It was confirmed that there may be differences even when the same parameter values are used while conducting experiments in various environments.

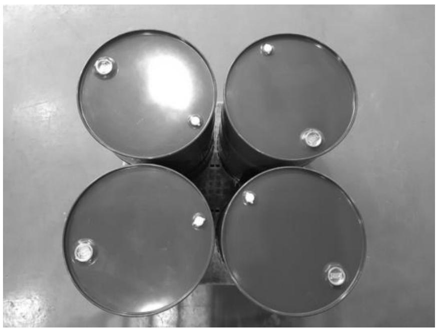
```
src : read original image
if src then
    gray : convert src to gray image
    blur : add Gaussian Blur to gray image
    while finding circles do
        setting some variable values for the algorithm
        circles : finding circles in an blur image using Hough
          Transformation
    end
    if circles then
        draw a circles on the original src image
        save the src image
    end
end
```

Fig. 6. Algorithm for finding an inlet in a liquid container

To verify the proposed algorithm, an experiment was conducted in an actual factory, and the results are shown in Figure 6. The performance results are explained using pictures. Figure 6(a) shows the image of the drum taken on the pallet. When shooting an image, set the entire palette as a range and put all the drums into one image. In Figure 6(b), the previously acquired image is converted to gray scale in order to distinguish the drum container from the external area. In figure 6(c), the grayscale-converted image is blurred using Gaussian blur algorithm. This is to increase the original detection probability by removing noise in the image. In the last step of the algorithm, all inlets within the image are found. If the inlet is found, the original image is copied and the inlet is marked on the copied image. Mark the inlet on the copied image to avoid damaging the original image. In figure 6(d) shows that the inlet was correctly found in the drum container. In the lower left of the figure, it shows an incorrectly searched circle. This circle can be easily removed compared to the size of the drum inlet or compared to the area in the image where the inlet can be located.

(a) Image of drums on the pallet

(b) Gray scale converting



(c) Gaussian blur image

(d) Result of inlet detection

Figure 6. Result of performing the algorithm in the factory

5. Conclusion

In this study, we proposed an algorithm that can automatically detect the inlet of a liquid container on a pallet in a factory. The proposed algorithm can quickly search the inlets of multiple liquid containers at once using a vision sensor. Through experiments, it was confirmed that the proposed algorithm works normally. It was confirmed that an error occurred in a specific environment, but the accuracy could be improved through repeated experiments. Algorithms developed in research can increase the efficiency of plants that manually inject liquids, and plants that handle chemical liquids can ensure worker safety and protect the environment. In future research, it will be possible to search for inlets of various types of liquid containers as well as drum containers. Lastly, we plan to use deep learning to learn various liquid containers and to further improve the accuracy of inlet judgment.

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