Hough transform in visual product quality control

Aleksandra Marjanović, Sanja Vujnović and Željko Đurović

***Abstract*— Product quality inspection is one of the indispensable steps in the production process, and there are more and more factories that are trying to automate that procedure by using computer vision algorithms. Additional efforts are made to keep these algorithms simple and fast when time is of the essence. This paper relies on Hough transform as a standard tool in image processing and discusses its possibilities in a time-constrained scenario. Being that the considered product is ball-shaped, the extension of Hough transform for circle detection is used to detect product in appropriate cells on the conveyor belt. The problem setup may seem easy, but unpredictable parameters of the industrial surroundings make it challenging. The detection algorithm is tested on a real-life image database collected at one chemical factory in Serbia.**

***Index Terms*—Visual product quality control, Defect detection, Hough transform, Circle detection.**

I. Introduction

With the development of modern technology, the efficiency and reliability of industrial plants is increasing, whether it is in terms of improving the hardware of existing systems or in terms of applying intelligent control laws that can monitor and regulate a large number of signals simultaneously. The automation of the production process is especially important in places that do not represent an ideal working environment for humans, such as plants in the electric power and chemical industries.

In the last decades advanced algorithms have found their place not only for increasing the quality of the production process, but also because of high expectations from customers, fierce competition, and stricter requirements of regulatory bodies and in quality control of the final product [1]. One of the basic forms of quality control is visual inspection of products and in many factories it is carried out in an old-fashioned way, by a human inspector. This, however, can be a very demanding job that requires a person to be in constant focus during a shift of about 8 hours, looking at the same product thousands of times. Research shows that in this process the error rate is high and goes over 25%. It is only natural that automated solutions for visual inspection of product quality, which rely on the methods of computer vision and artificial intelligence, are becoming more and more common [2], [3]. Apart from lowering the errors in the quality control process, there is another great advantage of implementing these kinds of solutions by the manufacturer. Mainly, the redirection of people from a repetitive non-creative job, which in some industries can be unpleasant for people's physical health, to jobs that are of greater importance, and which could not be done without people [4]. According to Markets Insider estimates, the machine vision sector will have earnings of about $ 12.29 billion from the start of their use until 2023, with an annual growth rate of about 7.61%.

The requirements placed on such a quality control system are very often contradictory. On the one hand, they must be fast enough for the production system to run smoothly, and on the other hand, more advanced algorithms that would increase the accuracy of such systems are also numerically more complex and require more time to execute. This paper discusses a segment of the visual inspection system in a modern chemical production plant that operates with a large capacity of several hundred products per minute. This leaves room for about a hundred of milliseconds for product processing, which should include image recording, image processing and decision making, as well as taking appropriate action. The job of engineers, therefore, is to design the simplest possible decision system with the highest possible success rate. Of course, it should be emphasized that the mechanical part of the system should be fast and reliable, but at the same time simple and cheap enough to be cost-effective for serial production.

The problem tackled in this paper refers to quality control in the production process of scented sanitary balls. Prior to the automation of this process, the inspection was performed by a person by monitoring for several hours the batches of balls that are at the output of the shaping subsystem. Apart from the fact that this kind of work is tiring for the sense of sight, it is also tiring for the sense of smell due to strong vapors in the plant. Due to all these facts, the company's management came up with the idea of automating this segment of production. This paper describes the first step in the product quality assessment procedure, which refers to the detection of products within the intended slot. In real industrial conditions this can be quite challenging, as will be explained later. The algorithm must be simple and fast enough at the same time, so that in combination with the algorithm for checking the regularity of the ball and communication between individual components it is suitable for real time application.

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Following Introduction, Section II provides a review of Hough transform and its application in line and circle detection. Section III describes in detail the setup of product visual inspection process, focusing on the challenges during product detection phase and the possibilities of overcoming them using Hough transform. Finally, Section IV shows main results concerning the influence of image down sampling on detection accuracy, as a tool for reduction of computational efforts.

II. HOUGH TRANSFORM

Hough transform in its original form is a tool that enables fast and efficient detection of straight lines in digital images [5]. Namely, if we want to find among the n points in the plane those that belong to one line, the number of operations that should be done by the brute-force method is proportional to n^3, which is unusable in the context of real time execution. On the other hand, Hough transform starts from the idea that one point (x_i, y_i) located on the line

$$y = ax + b \tag{1}$$

maps to the line in (a, b) space

$$b = -x_i a + y_i. \tag{2}$$

Similarly, any other point on the line (1) will map into the line in (a, b) space, which intersects the line (2) in the point determined by parameters a and b in Eq. (1). In other words, the problem of searching for line parameters is reduced to searching the space (a, b) with the aim of finding the point where the largest number of lines intersect [6]. A limiting circumstance in this consideration is the fact that the vertical line has an infinite slope. This problem is overcome starting from the idea that every point on the line in (x, y) space can be represented by a sinusoid in the parametric space (ρ, θ)

$$x \cos\theta + y \sin\theta = \rho, \tag{3}$$

which is shown in Fig. 1.

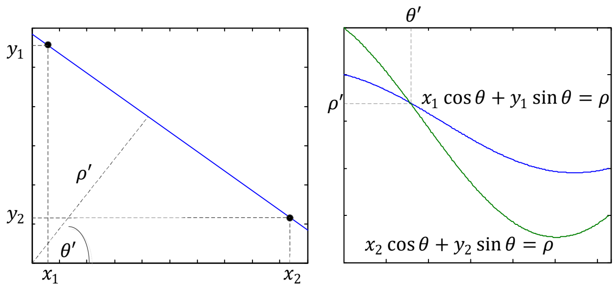

Fig. 1. The concept of Hough transform.

Similarly, the cross section of these sinusoids contains the correct parameters ρ and θ. In this way, the previous search is reduced to a search by angle $\theta \in [-\pi/2, \pi/2]$ and $\rho \in (-\infty, \infty)$. The implementation of this algorithm first involves the quantization of space (ρ, θ) into so-called accumulator cells. Then, each point (x_k, y_k) is observed and the corresponding quantized value ρ is calculated for each quantized value of the parameter θ and the final search for the cell in which the most sinusoids were found. Over time, the extensions of this procedure to the problem of finding second-order curves and arbitrary shapes have been considered [7], [8]. Thus, for the detection of a circular contour, three parameters should be determined, the coordinates of the center of the circle and the radius:

$$(x - x_0)^2 + (y - y_0)^2 = R^2. \tag{4}$$

Similarly as before, a different representation of the circle over the radius and polar angle can be considered:

$$\begin{aligned} x &= x_0 + R\cos\theta \\ y &= y_0 + R\sin\theta, \end{aligned} \tag{5}$$

where $\theta \in [0, 2\pi)$. In this case, the accumulator is three-dimensional, and the procedure for incrementing the cell values is based on the previously described procedure. Namely, each pair of points is a potential center (x_0, y_0), and the radius range is the potential radius. Bearing in mind that the search is now done in three-dimensional space, computational time of single curve detection is high. Over time, improvements to this algorithm have been proposed, such as the use of genetic algorithms [9] and harmony search [10], which shorten computational time and allow sufficiently precise circuit parameters to be found. Also, there are extensions of this algorithm to the detection of arbitrary curved lines.

III. PRODUCT DETECTION ALGORITHM

To better understand the idea of applying Hough transform in the process of visual quality inspection, let us describe the setting of the problem in a little more detail. The balls arrive one by one for individual inspection, sorted on the appropriate conveyor belt, separated by barriers (Fig. 2). The part of the system related to the visualization of the product consists of three cameras separated in space, two on the side and one from above, which have the task to look from different angles at the cell in which the product should be located. After that, in case there is a product in the cell, a quality control algorithm is applied, which should assess whether the ball is defective or not. If there is no defect, the ball should be passed to the next step of the production process. If, however, the ball is defected the pneumatic blower should be signaled to throw the ball off the production line, after which it is sent for recycling, i.e., the beginning of the mixture making step. Processing images from two side cameras can be done in the same way, because the image obtained from them is similar. Namely, it shows a ball leaning on the barrier that is immediately behind the ball when the direction of movement of the conveyor belt is observed, and in one case the ball is leaning on the left and in the other on the right barrier.

Additionally, behind the ball (as seen from the camera), there is a partition that provides an appropriate, contrasting background color depending on the color of the ball. On the other hand, the third camera is placed above the ball, and the picture from it shows the ball leaning on the barrier, but also a part of the base, that is. the conveyor belt on which the ball lies. Precisely because of this difference, processing images from the third camera is somewhat more complicated than the first two. Namely, after a few minutes, and then a few hours of using the system, the belt becomes dirty, sometimes with the color of the balls that previously passed over it, which is shown in Fig. 3 (one and the same belt is often used to process different colors of balls, depending on the requirements). In order for the belt to be cleaned, the machine must be stopped for a few minutes. However, if the cleaning is not carried out in a timely and adequate manner, this can complicate the algorithm for processing images from the third camera.

The step of checking whether there is a ball between the two barriers is the first step in the algorithm, and it should be the fastest one, so that there is enough time to perform a more time-consuming step, which refers to checking the quality of the ball. By analyzing the image from the first two cameras, this is very easy to check, because the background behind the ball is not dirty. However, if the same algorithm is applied to images from the third camera, many false alarms appear, which further leads to a misconception about the number of defective balls, because empty slots are classified as irregular balls in the next step. An additional problem in the analysis of the image from the third camera is the fact that during operation the voltage on the light is variable, so the brightness of the ball changes with it, and it is difficult to automatically adjust the camera exposure, because it is almost impossible to find a reference point that will not be influenced by the color of the ball. These and similar problems are precisely the consequence of working in industrial conditions, which can be very unpredictable.

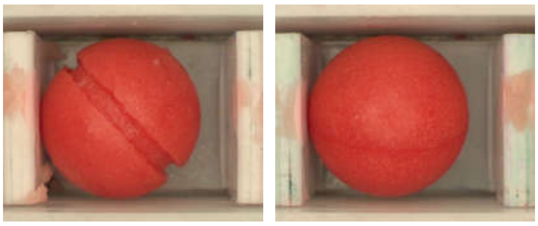

Fig. 2. Examples of full cells.

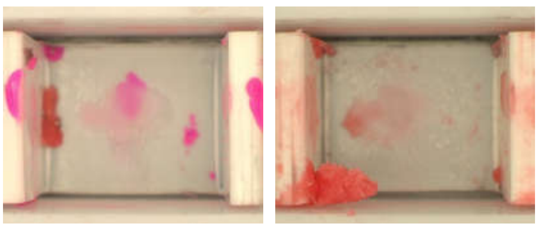

Fig. 3. Examples of empty cells.

This is exactly the problem we will try to solve by applying Hough transform. Because the picture of an empty cell often consists of stains at the bottom of conveyor belt, as well as smaller masses which should not be counted as the ball and will certainly be eliminated from further production process due to smaller dimensions, Hough transform is proposed to find circular contours in an image whose radius is in a predefined range, and in accordance with what the expected radius of the ball is. The algorithm consists of several steps:

- In the first step, depending on the color, it is necessary to find the appropriate color space, i.e. the appropriate representation, in which it will be easier to notice the difference between the ball and the background. In some cases, it will be some of the RGB components, other times HSV space will be more useful, etc.
- In the next step, using the Canny edge detector, the previously selected gray image is translated into a black and white image, by carefully selecting the thresholds of the said detector. The thresholds are chosen so that the edges of the ball are detected as clearly as possible, although in real conditions this implies the detection of background noise.
- Finally, the Hough transformation is applied to check whether among the detected points in the black and white image there are those that belong to the same circular contour of the appropriate size, which indicate the presence of a ball in the image. Due to the nature of the algorithm, it will certainly find a circle, and based on the parameters of the circle and the number of detected points, a decision is made whether the ball exists in the image or not.

Additionally, as mentioned earlier, this procedure involves searching in 3D space, which requires computing resources. Bearing in mind that the ball has some expected size, i.e. the radius, as well as the limited space in which the center of the sphere can appear, the first step in enhancing the speed of the algorithm refers to the appropriate narrowing of the search space for all three parameters. The second step refers to the examination of the extent to which it is possible to work with a resampled image of lower resolution, i.e. the extent to which the decimation procedure affects the finding of the circular contour and its parameters. The results of this consideration are presented in the next chapter.

IV. RESULTS

Testing of the proposed algorithm was done on a database consisting of 3000 images with empty cells and 3000 images with the product (2800 regular products and 200 defects). All images have the same 600x500 resolution. Let us first observe the performance of circular contour detection in different images. Fig. 4 and Fig. 5 clearly show that the extended detection algorithm gives a good result, in terms of successful contour detection. The images on the left show the original images of the balls, and on the right is the result of the application of Canny edge detector, together with a drawn contour whose parameters correspond to a circle that fits the largest number of points. Fig. 6 shows the results in the case of images without products. What can be noticed at first glance is that the algorithm again managed to find a circular contour, although it is not obvious in the original image. But that is still the expected result, because the algorithm finds the circle on which the largest number of points from the BW image is located. The essential difference between these two cases is in the number of points which the detected circle fits.

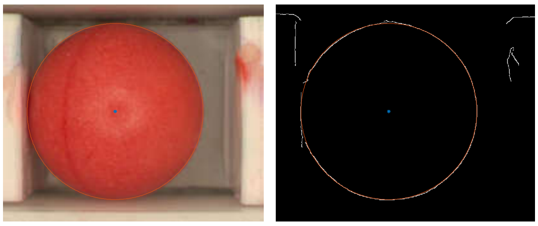

Fig. 4. Examples of circle detection on a regular product.

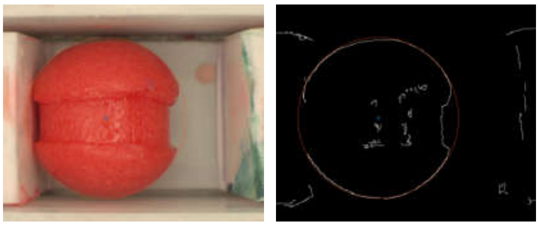

Fig. 5. Examples of circle detection on a defect.

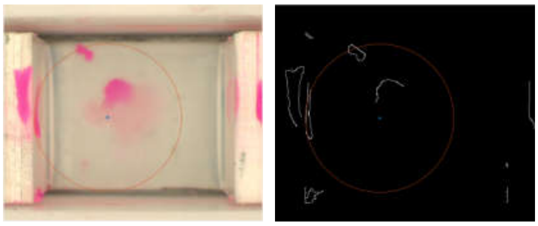

Fig. 6. Examples of circle detection on an empty cell.

Table 1 shows first- and second-order statistics for the number of detected points per circle N, as well as the execution time of the algorithm T on the Intel(R) Core(TM) i7-9700KF CPU at 3.60 GHz configuration It can be observed that the number of detected points is significantly higher in the case when the ball exists than when the cell is empty. A more detailed analysis showed that there is a clear gap between these two cases, which means that the detection problem can be successfully solved by setting an appropriate threshold. In addition, another interesting fact is that in the case off a defect, the number of detected points is slightly smaller than in the case of regular products. This result is justified bearing in mind that the defect of the product is often reflected in its irregular contour, which deviates from the circular contour in a few segments. However, for most products, this deviation is not significantly pronounced, which is why these two cases are not linearly separable considering this parameter space. Execution time analysis in different cases also gives the expected results. Namely, in the case of a defective ball, the output from the Canny edge detector is slightly higher than in the case of a regular one. Therefore, the number of points that need to be processed during the formation of the accumulator matrix is higher. On the other hand, one could expect that in the case of empty cells, the number of points returned by the Canny edge detector is not large. However, depending on the lighting and the degree of conveyor belt contamination, the number of points may be approximately the same as in the case of regular balls. Therefore, the execution time of the algorithm in that case is somewhat less, but not significant. Even though 30ms does not sound like a long time, it is not affordable when there is around 150ms available for the overall product inspection process.

TABLE I
AVERAGE DETECTION PARAMETERS PER DIFFERENT TYPES OF IMAGES

	N_{mean}	N_{std}	T_{mean}	T_{std}
Regular product	312.6	76.3	29.5ms	2.1ms
Defect	265.9	65.9	32.1ms	3.3ms
Empty cell	41.5	13.17	26.8ms	4.2ms

The last result led us to the idea of decimation, i.e. downsampling. Several cases depending on the degree of decimation were considered. Table 2 presents the results that show the degradation of detection parameters depending on the degree of decimation. In addition to the two parameters discussed earlier, this analysis also observed the extent to which the position of the center and the radius of the detected circle change with decimation in comparison to the case of no decimation. What can be noticed from the last two columns is that the relative changes in the position of the center and the radius are very small. What is perhaps a slightly more indicative information is that the maximum absolute deviation in the center position in the case of an empty cell is between 80 and 90 pixels, and in the case of a full cell between 18 and 22 pixels depending on the parameter k. Similarly, during decimation, there is a maximum absolute change in the radius of 12-18 pixels for full cells, and 26-28 pixels for empty cells. In other words, the difference obviously exists, but it is negligible when compared to the radius. Another important parameter is the mean execution time of the algorithm. The results show that this parameter is smaller for higher k, and that it decreases by about 30% for higher decimation.

TABLE II
AVERAGE DETECTION PARAMETERS FOR DIFFERENT DEGREE OF DECIMATION

		N_{mean}	T_{mean}	$\Delta x/R$	$\Delta R/R$
$k=2$	Full	156.9	24.1ms	4.4e-3	0.7e-3
	Empty	22.9	21.8ms	25.3e-3	9.0e-3
$k=3$	Full	103.9	21.4ms	3.3e-3	1.5e-3
	Empty	14.6	20.2ms	26.4e-4	11.5e-3
$k=4$	Full	79.7	20.2ms	6.5e-3	2.2e-3
	Empty	11.9	19.3ms	36.4e-3	16.3e-3
$k=5$	Full	62.9	19.7ms	5.1e-3	4.6e-3
	Empty	9.3	18.9ms	35.9e-3	19.3e-3

Based on previous considerations, the introduction of decimation is justified. Let us analyze how this procedure affects the number of points N as a crucial parameter for decision making. The mean value of the number of points on the detected circle decreases with a higher degree of decimation, which is expected. Again, when looking at the mean value in these two cases, it would seem that there is a large enough gap between the classes, however it turns out that they are closer to each other with higher decimation, primarily due to irregular products. Therefore, although the previous arguments are in favor of a higher degree of decimation, one must still be cautious and a compromise must be made. In this sense, it is shown that for $k = 4$ it is still possible to set a threshold on the number of detected points for classification purposes, and yet significantly speed up the execution of the algorithm.

V. Conclusion

The paper discusses the possibilities of applying Hough transform in detection of a ball-shaped product in the appropriate cell on the conveyor belt during the product quality control, based on the digital image. Firstly, it was shown that images without a product can be classified quite easily from the case when the cell is full by setting a decision threshold. The possibilities of the BW image decimation procedure for the purpose of accelerating the detection algorithm, are further discussed. This step was evaluated by the execution time and individual parameters of object detection in relation to the case when no decimation exists. It has been shown that the execution time is significantly reduced to about 20 ms, which is about 30% shorter than in the original case. In terms of the parameters of the detected circle, the algorithm is not too sensitive, while the unfavorable influence of the degree of decimation is reflected in the reduction of the gap between the two classes in terms of the number of detected points on the circle. As a compromise solution, the decimation parameter $k = 4$ is proposed, for which the proposed algorithm does not make any mistakes during the decision-making process on the available database.

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