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Terminals and Connector Inspection Innovation using Machine Vision

Hendi Herlambang[a*], Humiras Hardi Purba[b], Zulfa Fitri Ikatrinasari[b], Kosasih[c]
[a] Department of Industrial Engineering, Universitas Pelita Bangsa, Bekasi 17530
[b] Departemen of Industrial Engineering, Universitas Mercu Buana, Jakarta 11650
[c] Departemen of Management, Universitas Mercu Buana, Jakarta 11650

* Corresponding author: hendiherlambang@pelitabangsa.ac.id

ABSTRACT

Customer demands for product quality that are increasingly complex and require more accurate inspection are not sufficient if done manually due to high costs and different operator precision. To solve this problem, automatic vision inspection was created to check the product quality of terminal-type electronic components. Machine Vision is robust equipment for examining electrical components, agroindustry, surface mounting technology industry, plastic industry, and glass industry. In this research, the design and application of machine vision are used to inspect terminals and connectors, supporting automotive and electrical equipment components. Machine vision checks three quality functions, namely structural quality, surface quality, and dimensional quality. Optimization of image capture using backlighting and darkfield lighting. Implementing machine vision is carried out by verifying image retrieval's stability using a gage study with the results that there is no measurement bias.

Keywords: Machine Vision, Terminals and Connector, Surface quality, Gage Study, Confusion matrix

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1. Introduction

Inspection by manual with a high-quality level will be costly, complicated, and takes a long time because it involves workers with good abilities [1], [2]. Maintaining product quality levels and identifying types of product defects that require improvement are the objectives of quality control in manufacturing departments. A wide variety of macroscopic, visible, and complex product defects using conventional inspection methods are commonly used, time-consuming, and subjective [3]–[6]. Detecting product defects and classifying product defect types is the goal of automated visual detection. Production departments need a structured and accurate classification of product defects, which serves as a factory database. Frustaci et al. [7] stated inspection of the assembly area is still not done automatically, such as dimensional or geometric measurements. This measurement activity is carried out in direct physical contact with the product, resulting in a long measurement time and the potential for human measurement error. Furthermore, several researchers have documented their research on several industrial processes that use measurement methods without contactless using digital 3D optic techniques [8], [9]. Measurement with the Digital 3D optic technique is not entirely automatic due to the determination of two relative distances still manual, so this technique is less supportive for in-line inspection.

Machine vision is used in the manufacturing industry to perform inspection tasks and machine recognition, influenced by environmental and lighting factors [10]. Machine Vision is widely used to perform contactless geometric inspections [11]. In the beverage bottling industry, color grading and level verification have been successfully detected by automatic visual verification using the Raspberry Pi as the controller [12]. The same was done at a bottling company, performing automated visual inspection for defect detection as well as location detection. The detection includes inspection of the bottle bottom, neck, and wall using the edge point classification method and the least squares adjustment algorithm [13]. In the automotive industry, several researchers have documented their research with gradient detection algorithms cone defects and regional consistency have been successfully detected [14], there is also Optimization of research objects can be achieved using machine learning training methods and vision algorithms [15]. Isolated surface defects on the vehicle body can be well detected by machine vision, with an accuracy of 95.6% for dent defects and 97.1% for scratch defects, the machine speed reaches 1 vehicle every 1 minute and 50 seconds [16]. Similar things have also been done in packaging process research [17]. The novelty of machine vision is that it can detect columnar objects using edge detection, rectangle detection, interception, and feature statistics methods consistently, quickly, and with high accuracy, with 100% accuracy. By combining cable-based parallel robotics and machine vision, it is proposed to detect rusted bolts and leaks at the liner edges during coal bunker maintenance [18]. With low-cost equipment and without human intervention, the detection of color defects and bumps in sandwich panel parts can be easily detected through automatic visual inspection [19]. In electronic companies, machine vision has been developed to improve the degree of automation and accelerate product transformation [20]. In the steel plate industry, machine vision systems are used to detect the quality of cut steel plates by identifying damaged and burned fault zones [21]. The combination of electromechanical systems became the basis for the development of a fully automated non-contact testing method for 608ZZ type bearing testing [22]. When a 3D vision system is applied to inspect parts online, the result can greatly reduce the waste of time and material. Researchers found that the 3D vision system can detect surface heat maps and accurately detect geometric dimensions with an accuracy of less than 0.03 mm [23].

Examining products at high speed and in real-time can not be done by an eye examination method that gives inaccurate results, expensive, and results in fatigue in the eyes [24]. Similarly, Garcia et al. [25] stated that Machine vision could reduce errors during the inspection process carried out in the electronics industry. Thus, Machine vision is very suitable for the electronics industry with a minimal error rate, accuracy, and real-time.

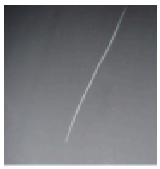
Previous research conducted by Herlambang et al. [19] shows that the application of machine vision can be integrated easily in the production process and can be done in line and in real-time. Therefore, the authors are interested in implementing machine vision in Terminals and Connector companies so that the results of this research can explain the process of machine vision development up to the testing process.

2. Research Method

2.1 The Surface of product quality taxonomy

For an accurate classification process, a well-structured database of types of product defects is required. These products' taxonomy defects are grouped into three primary product defects: dimensional product defects, product surface defects, and product structure defects. As seen in table 1, Grouping is based on the upper and lower thresholds specified from spatial characteristics.

Table 1
Product quality taxonomy

Type		Description	Sample	Dimension (mm)
Dimensions	Deformation	• Change in product dimensions • Large sizes are easy to detect • Small sizes are difficult to detect		± 0.05
Surface	Scratch	• Cuts on the surface • Size varies • Difficult to detect due to light factor		0.1 max
Structure	Crack	• Scratches and structures change • The raw material is visible • Dangerous, resulting in malfuction		No Crack

2.2 Camera selection

From the technical data obtained, the maximum length of the product is 15 mm. Considering the size of the product defect is very small so that the image is visible, it is done setting the number of pixels per product defect with 4 pixels with one axis. To determine the minimum resolution of the camera using the following equation :

$$CR = \frac{FoV\ X\ NoP}{DZ} \quad (1)$$

Where:
CR : Camera resolution
FoV : Field of view
NoP : Number of pixel smallest defect
DZ : Smallest defect size

With the calculation of the camera resolution required for product inspection is, camera resolution = (15 X 4) / 0.05 = 1,200 pixels. The cameras commonly used in the industry are with 2 Mega Pixels with 1,600 X 1,200 pixels on the vertical axis and horizontal axis.

2.3 Lens selection

The camera lens consists of several lens lenses, an iris diffraction ring (brightness), and a focus ring. The iris and focus diaphragm should be adjusted manually by the trial operator to look for image adjustments by looking into the camera monitor screen to ensure that the image is visible and bright, as seen in figure 1.

Figure. 1. Lens structure

In the selection of lenses to fit, two essential points must be taken into account, namely field of view (FoV) and working distance (WD), with the following equation:

$$WD = \frac{FD : CCD\ size}{FoV} \quad (1)$$

Where:
WD : Working distance
FD : Focal distance
FoV : Field of view
CCD : Number of pixel smallest defect

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The illustration of the equation above looks like in figure 2.

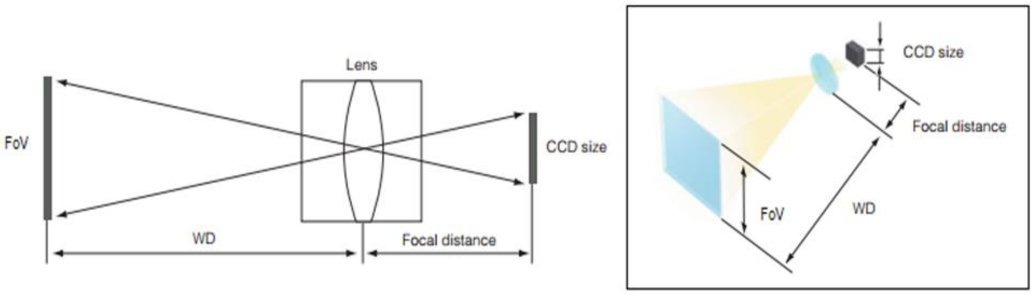


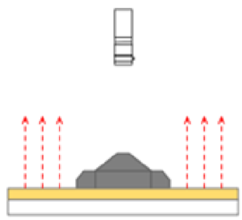
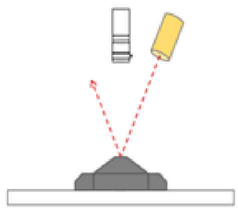
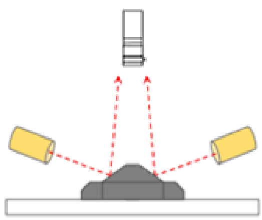
Figure. 2. Illustration of image capture variables

Camera selection variable data has been obtained, namely field of view with a value of 15 mm. The number of pixels needed is 1,600 X 1,200, and the distance of the object or product to the desired lens is 80 mm. Considering that distance will be provided leeway for installing lights with several combinations, and the size of the machine design area later. With this condition, check the availability of lens type and arrangement in the industry using a lens with an additional lens ring with a thickness of 1 mm.

2.4 Lighting selection

The purpose of lighting described in the machine vision reference [26] is to provide a consistent lighting environment that is not interrupted by external and environmental lighting changes, reducing the amount of glare in the image. Most importantly, increase the contrast in the image so that the features being examined are more clearly visible and obscure the target's image. The following four main classifications are:

Tabel 2
Illumination Method

Method	Description	Illustration
Back lighting	Back Lighting type lighting places the light source behind the object being checked towards the camera. This type of exposure is used to check the shape of objects against dimension measurements. The camera captures the object being examined as a dark silhouette against a bright background.	
Bright field lighting	This lighting is commonly referred to as directional lighting, placing the light on the camera axis at an angle of about ±45°, the most commonly used type of exposure, and limited to flat surfaces, as it will produce hotspot reflections on reflective objects.	
Dark field lighting	This exposure is also called directional lighting, but the light source is placed at an angle of ±45° against the horizontal plane; it highlights the edges of the object being examined, while the data surface remains dark, unsuitable for irregular surfaces of objects.	

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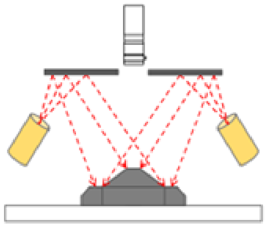
Method	Description	Illustration
Diffuse lighting	This type of lighting is often used on shiny and reflective objects, indicating that the light is evenly distributed and requires many directions. It will result in uniform lighting, with some methods able to create even lighting and eliminate reflections.	

2.5 System configuration

Selection of the type of lamp used and the method used, then it is adjusted to the type of product defect that has been mapped in table 1, followed by experiments to get the most optimal image processing results. As seen in figure 3, machine vision configuration for the data retrieval process.

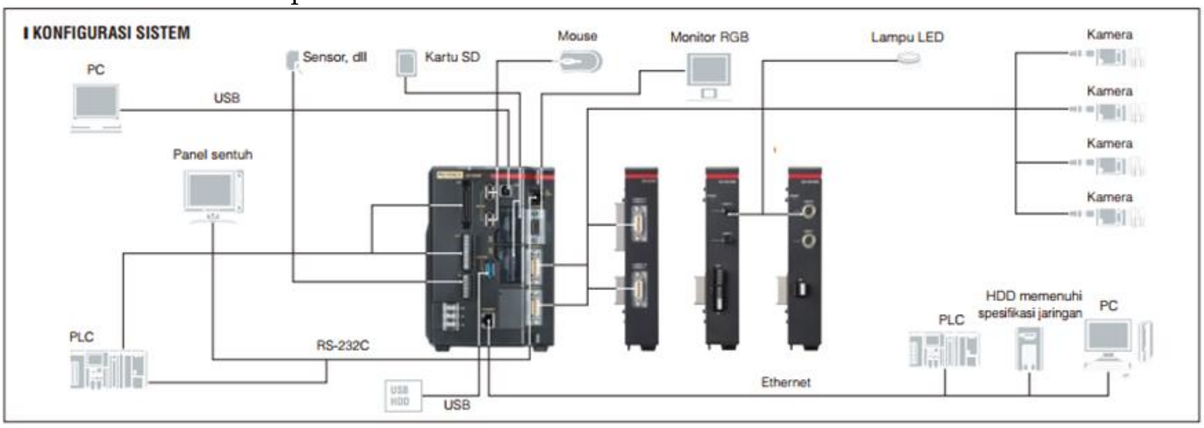


Figure. 3. Configuration of machine vision

Using machine vision can be achieved by conducting experiments using several machine vision equipment choices such as cameras, lenses, and lights with related parties that will later be used as a database. As shown in Table 3, Configure the illumination method to detect product defects that have been tested.

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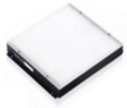
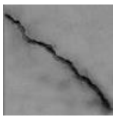
Table 3
Defect taxonomy and illumination method

	Type	Description	Sample	Dimension (mm)	Method (Light type)	Lighting sample
Dimensions	Deformation	• Change in product dimensions • Large sizes are easy to detect • Small sizes are difficult to detect		± 0.05	Back lighting (Back light)	
Surface	Scratch	• Cuts on the surface • Size varies • Difficult to detect due to light factor		0.1 max	Dark field lighting (Ring multi-angle)	
Structure	Crack	• Scratches and structures change • The raw material is visible • Dangerous, resulting in malfuction		No Crack	Dark field lighting (Ring multi-angle)	

3. Result and Discusion

Machine vision application successfully detects product defects that have occurred, both the company's internal findings and customers' findings. Furthermore, this needs to be tested during production. Quality testing on product dimensions has been carried out by taking 50 product data. As seen in Figure 4, experimental data collection and machine vision processing capabilities. Machine vision ability to take measurements obtained Cg values of 2.34 and Cgk 2.26, so it can be said that machine vision process capability is excellent, with no measurement bias.

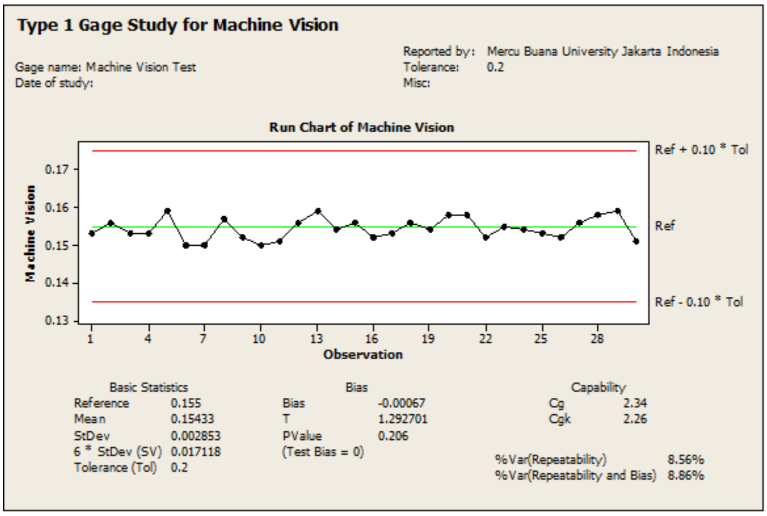


Figure. 4. Gage study machine vision

As explained above, the first thing to do was to collect product data as the initial primary data. Consistent with previous research, achieving optimal image results does not take long (less than one minute), as sensor adjustment is made easy with automatic autofocus and brightness without the need to experiment with distance and exposure settings [1]. Initialization of the product according to specifications is done by observation using a vision camera until an optimal threshold value is obtained. As shown in Figure 5, normal and abnormal product output can be viewed using a 3.5" TFT color screen.

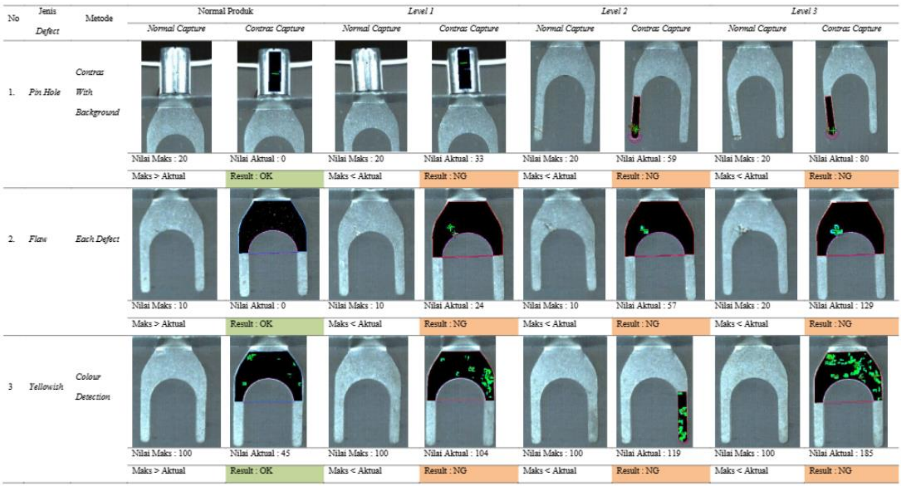


Figure. 5. Result machine vision

As shown in the confusion matrix in Figure 6, there are 80 trials to determine the ability of the machine vision process as a whole. The reliability of the machine vision process is divided into two categories: the ability to check product dimensions and the ability to check product structure. The experiment was conducted in real time with an accuracy of 100% for the product dimension inspection and product structure inspection capabilities.

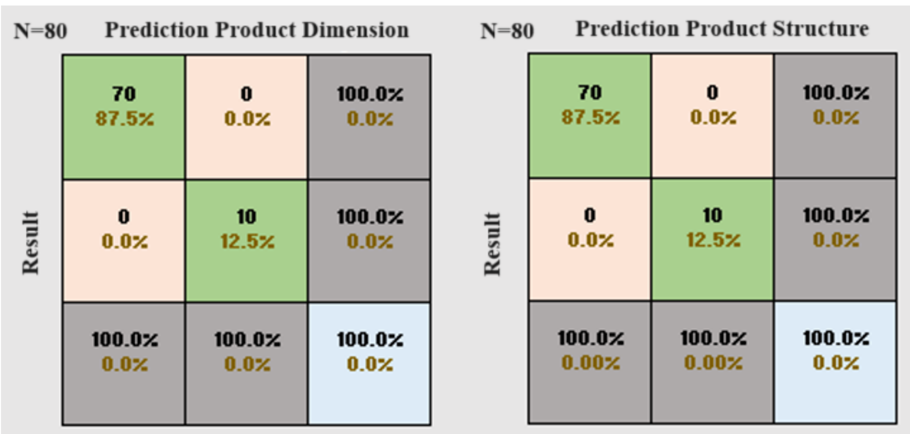


Figure. 6. Machine vision confusion matrix

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4. Conclusions

This research focuses on quality checking in an electronic component company by designing and developing machine vision. From the experimental results, it is found that the success rate of machine vision for checking product dimensions and structure is 100%. Secondly, the manual inspection in the company was changed to automatic by 100%. Future research in this area can focus on defect discovery with more diverse and flexible product variations. The development and design of robotic arms in the production area will increase flexibility in designing machine vision.

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