

Development of an Automatic Measurement and Classification System for a Robotic Arm Using Machine Vision

Ngoc Vu Ngo^{1,*} and Van Cuong Duong²

¹ Faculty of Mechanical Engineering, Thai Nguyen University of Technology (TNUT), Thai Nguyen, Vietnam

² Faculty of Mechanical Engineering, Technical and Technological Vocational College (TTVC), Hanoi, Vietnam
Email: ngocvu@tnut.edu.vn (N.V.N.); duongcuong1981@gmail.com (V.C.D.)

*Corresponding author

Abstract² The purpose of this study is to present an automatic measurement and classification system using a back-lighting source for a robotic arm with four Degrees of Freedom (DOF), employing machine vision technology. The objects utilized in this study are bolts and nuts, placed randomly within the workspace of the robotic arm. During operation, image data from a Metal-Oxide-Semiconductor (CMOS) camera is transmitted to a personal computer to calculate the geometric parameters of the objects, including shape, angle, and position, which are then sent to the controller of the robotic arm. The robotic arm subsequently picks up the objects from the workspace and places them into target zones. With the proposed system, the world coordinates of components are accurately determined and utilized for the manipulation of the robotic arm. The research results demonstrate that the automatic classification system can detect and identify the shape and orientation of objects correctly. This system proves to be effective and easy to use

Keywords² robotic arm, automatic optical inspection, image measurement, classification

I. INTRODUCTION

The use of advanced machine vision systems is increasingly prevalent across various manufacturing and quality control processes. Machine vision facilitates the acquisition of quicker, more accurate, and repeatable results in both mass-produced and custom product manufacturing. Basic machine vision systems typically consist of one or more cameras directed at the area of interest, a frame grabber for capturing and transmitting images, a computer and display for running the machine vision software application and manipulating captured images, and appropriate illumination focused on the area of interest.

Many applications of machine vision involve inspecting components [1, 2] and surfaces for defects that affect quality [3]. Additionally, machine vision has been employed to varying degrees to assist in manipulating manufacturing equipment for specific tasks. For example,

a workpiece held in a robot manipulator can be guided to a target using a machine vision feedback procedure. The robot is programmed with a general set of movement instructions.

As machine vision is considered an essential sensing function for robots, a range of special purpose and general purpose image processing hardware has been developed to enhance visual sensing performance. Typical image processing systems are designed to deliver high-resolution and high-speed homogeneous processing across the entire screen.

There is a wealth of research applying machine vision to robotic arms. For instance, Inoue et al. [4] introduced a high-performance robot vision system capable of real-time tracking of moving objects. In the study by Blasco et al. [5], two vision systems mounted on the machine were utilized. One system detected weeds and transmitted their coordinates to the robot arm control, while the other corrected inertial perturbations affecting the position of the end effector. The primary vision system successfully located 84% of weeds and 99% of lettuces. Shafik et al. [6] proposed an innovative 3D piezoelectric ultrasonic actuator using a flexural vibration ring transducer for machine vision and robot guidance applications. Hozayounzadeh and Keshmiri [7] developed an observer-based impedance controller for a robot arm during constrained motion. This controller required measurements of link position and interaction force. In the research by Ngo et al. [8], a machine vision system was constructed to measure three-dimensional objects. Image data from a double Complementary Metal-Oxide-Semiconductor (CMOS) was transmitted to a computer for parameter calculation. With the proposed system, the size of parts is determined quickly and accurately. Moreover, the system is simple, inexpensive, and easy to use. Narakae et al. [9] proposed a flexible automatic assembly system for a SCARA robot arm. This research developed the primary prototype of a flexible automatic pick-and-place assembly system integrating machine vision with the robot arm. Currently, Hsueh et al. [10] developed a vision-based

measurement and classification system for a robotic arm in another study, Yang et al. [18] proposed a method for detecting missing bolts using machine vision and deep learning. Three deep learning network models, namely YOLOv4, YOLOv5s, and YOLOx, were employed for comparison with YOLOv5s selected as the bolt target detection model. The study also introduced a missing bolt detection method based on perspective transformation and Intersection Over Union (IOU). Results showed that the proposed method accurately identified bolt targets with a confidence level exceeding 80% and detected missing bolts under various conditions such as different image distances, perspective angles, light intensities, and image resolutions. In a separate research effort, Mushtaq, Faisal et al. [19] presented a deep learning and image processing based approach for identifying mechanical fastening elements in an aerospace assembly line. The study utilized the YOLO-V5 two-vanishing point calibration method for a roadside algorithm to classify components based on their head and camera, which proved to be accurate and practical. To enhance the accuracy of the calibration results, they also incorporated multiple observations of vanishing points and components, including thread pitch. Building upon previous research, this study primarily focuses on applying image processing and machine vision techniques under a backlighting source. The goal is to achieve automatic measurement and classification of bolts and nuts for a robotic arm equipped with four degrees of freedom.

Within a machine vision system, calibration work is crucial as its performance relies on the accuracy of the calibration process. Let et al. [11] investigated a relationship between various conditions such as different image distances, parameters and lens distortion effects of the camera. The study results demonstrated that the proposed algorithm could effectively avoid local optima and accurately presented a complete visual identification tasks.

In another research, You and Zheng [12] introduced a two-vanishing point calibration method for a roadside camera, which proved to be accurate and practical. To enhance the accuracy of the calibration results, they also incorporated multiple observations of vanishing points and components, including thread pitch.

Another dynamic calibration method suitable for outdoor environments. Ivet et al. [13] introduced a novel structured light pattern for a structured light scanner, aimed at obtaining accurate anthropometric body segment parameters rapidly and reliably. This technique enabled the acquisition of volumetric parameters for both artificial objects and human body segments through scanning.

In the study conducted by Pachón-Suescún et al. [14], they presented a machine vision algorithm designed to identify objects within a workspace and determine their polar coordinates relative to the observer. This algorithm can be applied with either a fixed camera or a mobile agent. The proposed algorithm underwent evaluation in two scenarios, involving the determination of the positions of six objects. Experimental results were compared with the actual positions of each object.

To date, there has been considerable research focused on calibration work for machine vision systems. Their study, Shin and Mur [15] proposed a new calibration method for a multi-camera setup using a wand dance procedure. With this method, calibration for the 3D frame parameters was first estimated using the Direct Linear Transformation (DLT) method. Subsequently, the parameters estimated in the initial step were iteratively improved through nonlinear optimization using the wand dance procedure. The proposed method was validated by comparing the Root Mean Square (RMS) error and the mean difference between the proposed method, the DLT method, and the wand method.

In the research by Tapas [16], a machine vision system was utilized to recognize and sort objects, specifically bolts and nuts. Images of the objects were acquired using a web camera and processed through MATLAB for sorting. The study demonstrated that the system accurately detected moving objects on the belt conveyor and sorted them as required. Similarly, in the research by Murali et al. [17], a machine vision system was developed for the identification and counting of mechanical components, particularly nuts and bolts using Matlab. The study reported a success rate of over 90%, which could be further improved to 95% by employing an additional spotlight on the object and camera.

II. EXPERIMENTAL SYSTEM

A. Architecture of the Proposed System

The architecture of the system is divided into two parts. The first part is the image measurement system and hardware equipment. This includes a CMOS camera with a resolution of 640x450 pixels, which is connected to a computer via a USB port. This computer is set up with image processing and machine vision software. The specifications of the camera are shown in Table I. The backlighting source is mounted under the workspace zone of the system. A four-axis robotic arm with an electric gripper is used for the classification process.

TABLE I. SPECIFICATION OF CAMERA

Name	Specification
Image resolution	640 x 450 Pixel
Video resolution	720 Pixel
Connection COM	USB
Type of product	Webcam
Manufacturer	OEM
Sound	Yes
Model	High Resolution
	- Autofocus with 720p recording mode 30 fps.
Other description	- 2.0 Megapixel image capture Right light technology.
	The rotation angle is 360°

In addition, the experimental system includes a workspace zone and five target zones for the classification process. The objects used for testing include bolts with a size of 10 mm in diameter and 60 mm in length (D10 x L60 mm), bolts with a size of D8 x L60 mm, bolts

with a size of D8xL40 mm, and nuts, respectively, as shown in Fig.1. All objects are randomly placed in the workspace.

The system operates in the following steps: First, the camera image captures images of the objects in the working area. Next, the system finds and identifies the objects in the image and proceeds to classify them while determining the image coordinates. If no objects are detected, the system continues to wait for image frames from the camera. In the next subsequent step, the system calculates and determines the world coordinate coordinates of the object objects from the image coordinates and sends this information to the robot arm for the classification process. This working process is performed continuously until there are no objects in the system's workspace. Throughout the operation, the camera must remain fixed in place. The camera is repositioned, the system will need to be recalibrated. The block diagram of the system is shown in Fig. 2.



Fig. 1. Experiment diagram

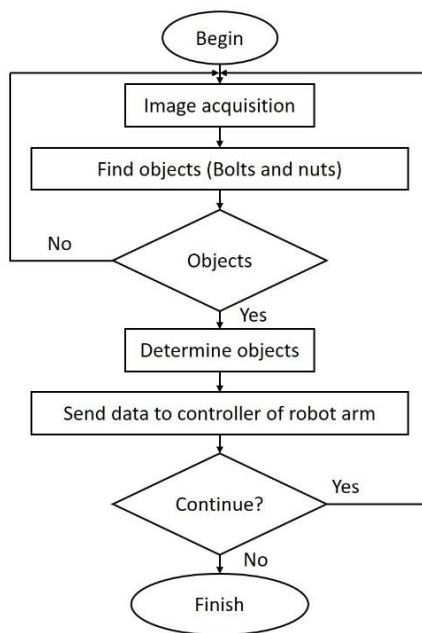


Fig. 2. The block diagram of the proposed system

B. Measurement and Classification Process

In this study, a backlighting source is utilized. The controlled light source facilitates the adjustment of the

binarization threshold for the object images, making it easier to account for variations in ambient light conditions during the measurement process. This method enhances the clarity of the object boundaries.

To classify all objects, parameters such as area, perimeter and compactness are calculated. Based on the value of compactness, the bolt with dimensions D10x60 mm has the largest compactness, followed by the bolt with dimensions D8x60 mm and then D8x40 mm. The nut with dimensions D8 mm has the smallest compactness.

All nuts are non-directional, so it's not necessary to identify their angle. However, for bolts, it's important to determine their angle and head. To identify the angle of bolts, the boundary rectangular method is used. With this method, first, the four vertices of the rectangle surrounding the bolt are determined, named ABCD. Next, the coordinates of these vertices are used to define the sides of the rectangle. For bolts, the edge passing through the top of the bolt head is smaller than the longitudinal edge of the bolt body; let this edge be named AB. Let point E be the midpoint of edge AB, and G be the centroid of the bolt.

Next, the system determines the head of the bolt by comparing the Y direction coordinates of points E and G. If $Y_E > Y_G$, the bolt head will be in the second quadrant of the circle, as illustrated in Fig. 3. If $Y_E < Y_G$, then the bolt head will be in the third quadrant of the circle, as shown in Fig. 4. If $Y_E = Y_G$, the bolt will be horizontal, and the bolt head will depend on the coordinates of point E compared to point G, as depicted in Fig. 5. The angle of the bolt is also determined by the angle between the line passing through point E and point G with the horizontal axis. The positive direction of the angle is clockwise.

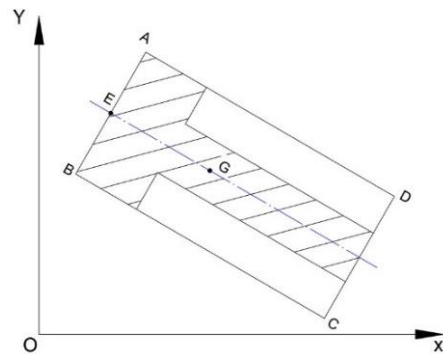


Fig. 3. The Y coordinate of point E is higher than point G

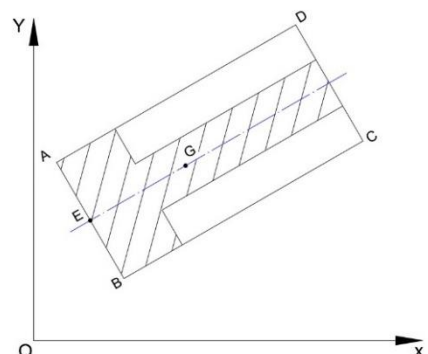


Fig. 4. The Y coordinate of point E is lower than point G

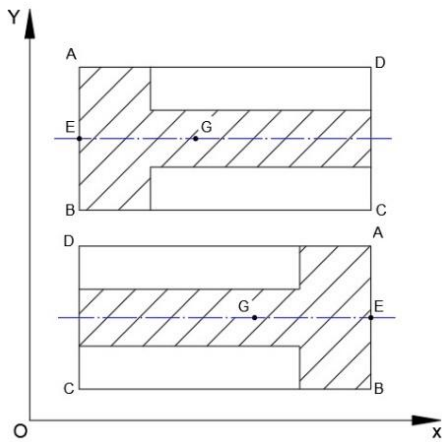


Fig. 5. The Y coordinate of the point E is equal to the point G

III. ROBOTIC ARM DESIGN

The robotic arm used in this study is ~~solid~~. The kinematic diagram of the robotic arm is presented in Fig. 6, and the relationship between each joint can be analyzed using Denavit-Hartenberg (D-H) parameters, as shown in Table II.

The operating system of the robotic arm uses a Cartesian coordinate system, where the coordinate values {X, Y, Z, C} are input respectively. Point-to-point movement is employed for manipulation, with the ~~X~~ axis representing the electric gripper.

The robot operates based on the inverse kinematics problem and is integrated with a vision system. It consists of a robotic arm with four degrees of freedom. Each degree of freedom is controlled by a stepper motor and tooth belt transmission. The gripper operation is controlled by a servo motor.

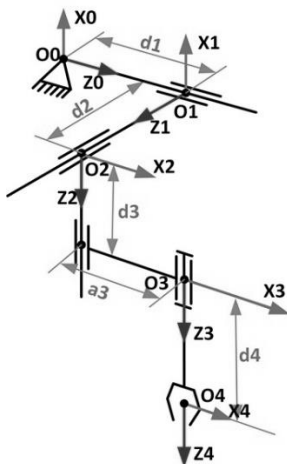


Fig. 6. Kinematic diagram of the robotic arm

TABLE II. D-H PARAMETERS TABLE

\$ [L V	D	G	D	T
01	0	(d ₁)	90°	0
12	0	(d ₂)	90°	90°
23	a ₃	(d ₃)	0	0
34	0	d ₄	0	(T)

where

- x d_i represents the distance between O_{i-1} and O_i along the Z_{i-1} axis.
- x a_i represents the distance between two adjacent joints along the X-axis
- x T represents the angle around Z_{i-1} to move X_{i-1} to X_i based on the right-hand rule along the Z-axis.
- x D represents the angle around X_i to move Z_{i-1} to Z_i based on the right-hand rule.
- x q_i is the joint variable of the robot

where i = 1 to n (where n represents the number of joints).

The transformation matrix Aⁱ⁻¹ can be defined as Eqs.(1) (2):

$$A_i^{i-1}(q_i) = R_{z, T} \bar{U}_{z, d_i} \bar{U}_{x, a_i} U_{x, D} \quad (1)$$

where R represents the rotation matrix and \bar{U} represents the translation matrix

$$A_i^{i-1} = \begin{bmatrix} C_D & -S_{\alpha_i} C_{\theta_i} & S_{\alpha_i} S_{\theta_i} & a_i C_D \\ S_D & C_{\alpha_i} C_{\theta_i} & -C_{\alpha_i} S_{\theta_i} & a_i S_D \\ 0 & S_{\theta_i} & C_{\theta_i} & d_i \\ 0 & 0 & 0 & 1 \end{bmatrix} \quad (2)$$

$$C_D = \cos D, C_{\theta_i} = \cos \theta_i, S_{\alpha_i} = \sin \alpha_i, S_{\theta_i} = \sin \theta_i$$

By substituting the values from Table II into the elements of matrix Aⁱ⁻¹, we will determine the corresponding transformation matrices A⁰, A¹, A², and A³. Then:

$$A_4^0 = A_1^0 U_3^2 U_4^3 = \begin{bmatrix} n_x & S_x & a_x & P_x \\ n_y & S_y & a_y & P_y \\ n_z & S_z & a_z & P_z \\ 0 & 0 & 0 & 1 \end{bmatrix} \quad (3)$$

A₄⁰ matrix describes the direction and position of the final coordinate system compared to the original fixed coordinate system

The inverse kinematics of the robotic arm involves determining the joint variables based on the desired end effector's world coordinates obtained from the vision system, namely, its position and orientation in the operational space.

IV. RELATIONSHIP BETWEEN IMAGE COORDINATE AND THE WORLD COORDINATE

The robotic arm operates based on the world coordinates in space. Therefore, it is necessary to accurately determine the actual coordinates from the image coordinates. In this study, the world coordinates of objects will be determined using Eq(4) and(5), as follows:

$$X = \frac{Pixel(X) \cdot 50}{100} \quad (4)$$

$$Y = \frac{Pixel(Y) \cdot 50}{100} \quad (5)$$

where X and Y represent the world coordinate system along the X and Y axes, respectively. Pixel(X) and Pixel(Y)

denote the coordinates of an image point in the xdirection and ydirection, respectively.

V. RESULTS AND DISCUSSION

The implementation of the proposed system proceeds as follows: Initially, all bolts and nuts are randomly placed in the workspace zone while the robot is in the home position. Subsequently, the backlighting source is activated, and the CMOS camera captures images of all objects, which are then sent to the computer, as shown in Fig. 7. Image processing is carried out using the Python programming language and the OpenCV image processing library. The system then proceeds to classify and determine the parameters of all objects, including shape, angle, and position, as shown in Fig. 8. Finally, the measurement data is transmitted to the controller of the robotic arm for the manipulation process.

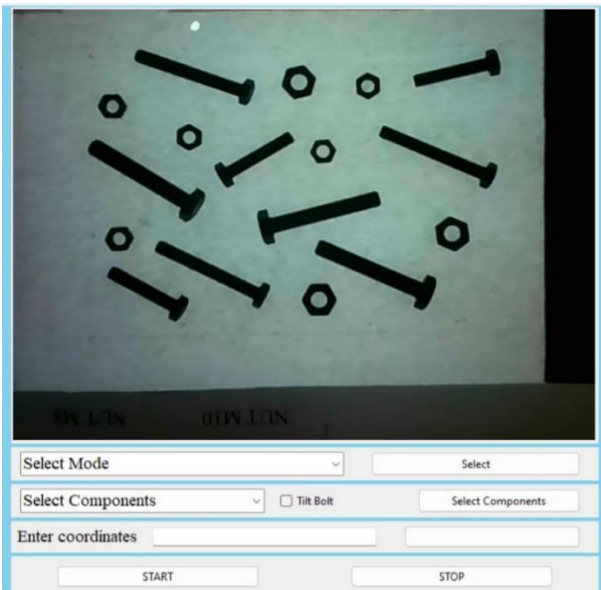


Fig. 7. Picture of researched objects



Fig. 8. Results of recognition and classification

Tables III and IV display the image coordinates of bolts and nuts, respectively. These coordinates are then transformed into world coordinates for manipulation by the robotic arm, as illustrated in Table V.

TABLE III. IMAGE COORDINATE OF BOLTS

% R O'	[\	& f	2 U L H Q W D \
Bolt 2	71	316	16	Counter-clockwise
Bolt 3	404	295	13	Counter-clockwise
Bolt 4	222	294	13	Counter-clockwise
Blot 7	331	229	91	Counter-clockwise
Bolt 9	150	190	17	Counter-clockwise
Bolt 10	263	160	63	Counter-clockwise
Bolt 11	472	165	12	Counter-clockwise
Blot 16	202	75	9	Counter-clockwise
Bolt 17	492	69	6	Clockwise

TABLE IV. IMAGE COORDINATE OF NUTS

1 X W	[\	& f	2 U L H Q W D \
Nut 1	337	324	0	Non
Nut 5	117	256	0	Non
Nut 6	483	130	0	Non
Nut 8	340	159	0	Non
Nut 12	194	143	0	Non
Nut 13	110	109	0	Non
Nut 14	390	86	0	Non
Nut 15	314	82	0	Non

TABLE V. THE WORLD COORDINATE OF ALL OBJECTS

2 E M H	; P P	< P P	& R	2 U L H Q W D \
Bolt 2	34.5	158	16	Counter-clockwise
Bolt 3	202	147.4	13	Counter-clockwise
Bolt 4	111	147	13	Counter-clockwise
Bolt 7	165.4	114.4	91	Counter-clockwise
Bolt 9	75	95	17	Counter-clockwise
Bolt 10	131.4	80	63	Counter-clockwise
Bolt 11	236	82.4	12	Counter-clockwise
Blot 16	101	37.4	9	Counter-clockwise
Bolt 17	246	34.4	6	Clockwise
Nut 1	168.4	162	0	Non
Nut 5	58.4	128	0	Non
Nut 6	241.4	65	0	Non
Nut 8	170	79.4	0	Non
Nut 12	97	71.4	0	Non
Nut 13	55	54.4	0	Non
Nut 14	195	43	0	Non
Nut 15	157	41	0	Non

The automatic operation of the robotic arm is divided into two phases. In the first phase, the robotic arm picks up three types of bolts and places them in three designated zones. In the second phase, it picks up two types of nuts and places them in two designated zones. The proposed system is depicted in Fig. 9.



Fig. 9. The proposed system

VI. CONCLUSIONS

This study has successfully developed an automatic measurement and classification system for a robot arm using machine vision technology under backlighting. The conclusions drawn from this work are as follows:

- x Under backlighting conditions, the automatic measurement and classification system has successfully performed and achieved accurate positioning of objects. The system is capable of recognizing and classifying all objects, as well as determining the angle and head of bolts.
- x A robotic arm with four degrees of freedom was also successfully developed and integrated with a vision system, including components such as a CMOS camera, lighting source, and computer system.
- x Based on the data from the system, the robotic arm is controlled to pick up and place all objects into their designated zones accurately during the classification process.
- x Improving the resolution of the camera is necessary to enhance object location and classification accuracy. Additionally, the system should be tested in various lighting environments to ensure adaptability to real industrial conditions.
- x The proposed system is simple, effective, and easy to implement for automation processing in industrial manufacturing lines.

CONFLICT OF INTEREST

The authors declare no conflict of interest

AUTHOR CONTRIBUTIONS

Ngo Ngoc Vu is the first and corresponding author, responsible for writing, reviewing, editing, and methodology. Duong Van Cuong is the second author and co-author, responsible for writing the original draft, visualization, validation, and configuration. All authors had approved the final version.

ACKNOWLEDGMENT

The work described in this paper was supported by Thai Nguyen University of Technology (TNUT), Thai Nguyen, Vietnam

REFERENCES

[1] R. Xiang, W. He, X. Zhang, D. Wang, and Y. Shan, Y, "Size measurement based on a camera machine vision system for the bayonets of automobile brake pads," *Measurement* vol. 122, pp. 106-116, 2018.

[2] A. D. Thomas, M. G. Rodd, J. D. Holt, and C. J. Neill, "Real-time industrial visual inspection: A review," *RealTime Imaging* vol. 1, pp. 139-158, 1995.

[3] V. Chauhan and B. Surgenor, "Fault detection and classification in automated assembly machines using machine vision," *The International Journal of Advanced Manufacturing Technology* vol. 90, pp. 2491-2512, 2017.

[4] H. Inoue, T. Tachikawa, and M. Inaba, "Robot vision system with a correlation chip for real-time tracking" in *Proc. International Conference on Robotics and Automation, Optical Flow and Depth Map Generation*, 1992, vol. 2.

[5] J. Blasco, N. Aleixos, J. M. Roger, G. Rabatel, and E. Molto, "Robotic weed control using machine vision," *Biosystems Engineering* vol. 83, no. 2, pp. 149-157, 2002.

[6] M. Shafiq, B. Nyathi, and S. Fekkai, "An innovative 3D ultrasonic actuator with a multi-degree of freedom for machine vision and robot guidance industrial applications using a single vibration ring transducer," *International Journal of Engineering and Technology Innovation* vol. 3, no. 3, pp. 168-179, 2013.

[7] M. Homayounzadeh and M. Keshmiri, "Observer-based impedance control of robot manipulators," in *Proc. International Conference on Robotics and Mechatronics*, 2013, pp. 230-235.

[8] N. V. Ngo et al, "Development of a simple three-dimensional machine vision measurement system for process mechanical parts," *Advances in Mechanical Engineering* vol. 9, no. 10, 2017.

[9] P. Nerakae, P. Uangpaioj, and K. Chamniprasart, "Using machine vision for flexible automatic assembly system," in *Proc. 20th International Conference on Knowledge-Based and Intelligent Information and Engineering Systems*, 2016, pp. 5-7.

[10] Q. C. Hsu et al, "A vision-based measurement and classification system for robot arm under controlled lighting condition," in *Proc. International Conference on Engineering Research and Applications*, 2020, vol. 2.

[11] L. Deng et al, "A novel camera calibration technique based on differential evolution particle swarm optimization algorithm," *Neurocomputing* vol. 174, pp. 456-465, 2016.

[12] X. You and Y. Zheng, "An accurate and practical calibration method for a roadside camera using two vanishing points," *Neurocomputing* vol. 204, pp. 222-230, 2016.

[13] S. Ivo, J. Musić, and V. Zanchi, "Improved structured light 3D scanner with application to anthropometric parameter estimation," *Measurement* vol. 46, no. 1, pp. 716-726, 2013.

[14] G. P. Suesan et al, "Robotic navigation algorithm with machine vision," *International Journal of Electrical and Computer Engineering* vol. 10, 2020.

[15] K. Y. Shin and J. H. Mun, "A multi-camera calibration method using a 3-axis frame and wand," *International Journal of Precision Engineering and Manufacturing* vol. 13, no. 2, pp. 283-289, 2012.

[16] T. Pramanik, "Computer vision-based recognition of nut and bolt system," *Int. J. Sci. Prog. Res.* vol. 4, 2014.

[17] G. B. Murali et al, "Detection and counting of nuts and bolts with image processing using MATLAB," *Applications of Computational Methods in Manufacturing and Product Design* pp. 13-20, 2022.

[18] Z. L. Yang et al, "Detection of missing bolts for engineering structures in the natural environment using machine vision and deep learning," *Sensors* vol. 23, no. 12, 2023.

[19] F. Mushtaq et al, "Nuts & bolts: YOLOv5 and image processing based component identification system," *Engineering Applications of Artificial Intelligence* vol. 118, 2023.

Copyright © 2024 by the authors. This is an open access article distributed under the Creative Commons Attribution License BY-NC-ND 4.0, which permits use, distribution and reproduction in any medium, provided that the article is properly cited, the use is non-commercial and no modifications or adaptations are made.