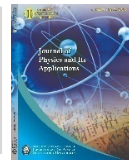
Journal of Physics and Its Applications

Journal homepage : https://ejournal2.undip.ac.id/index.php/jpa/index



Characteristics of Blue, Red, and Green Lasers for an Object Recognition System as Unique Markers

Iyon Titok Sugiarto[1]*, Jasmine Aulia[3], Zahrah Radila[3], Zaenal Afif Azhary[3] and Wildan Panji Tresna[1,2]*

[1]Research Center for Photonics, National Research and Innovation Agency, KST BJ Habibie 442 Building, South Tangerang, Banten, 15314, Indonesia
[2]School of Electrical Engineering, Telkom University, Bandung, 40257, Indonesia
[3]Department of Physics Engineering, Sepuluh Nopember Institute of Technology, Gedung C dan E, Sukolilo, Surabaya, 60111, Indonesia

**Corresponding author:*
iyon.titok.sugiarto@brin.go.id
wildanpanji@telkomuniversity.ac.id

ARTICLE INFO

Article history:
Received: 31 May 2025
Accepted: 20 November 2025
Available online: 27 November 2025

Keywords:
Computer Vision
Image Processing
Object Recognition System
Unique Marker
Laser Blinking

ABSTRACT

Computer Vision (CV) is an automation technology with applications in national defense, particularly for enabling automated object targeting systems. This study focuses on developing a unique marker detection system to support such targeting capabilities. The markers consist of laser beams characterized by distinct colors, shapes, sizes, and blinking patterns, designed to be identifiable only by a programmed computer system. Incorporating these laser properties as input parameters is essential for effective object recognition. Experimental results indicate that the detection threshold was calibrated to identify red, green, and blue colored objects under indoor lighting conditions of 71.3 Lux. The CV system successfully identified a circular marker positioned 680 cm away from triangular and square markers. In distance estimation tests using a Logitech C615 HD camera, the system achieved average error rates of 4% for circles, 5% for rectangles, and 6% for triangles. Overall, the system demonstrated a tracking accuracy of 95.24% for unique markers placed at distances ranging from 50 to 300 cm.

1. Introduction

Computer Vision (CV) exemplifies the rapid progress of automation technology [1,2], driven by efforts to replicate human sensory capabilities, particularly vision. In this context, a camera functions as a surrogate eye, capturing visual details such as geometry, color, size, and shape [3,4]. Computers and software then process these inputs to enable object detection and identification. As a result, CV has been widely adopted across various domains for object tracking and recognition tasks [4,5].

Alongside automation, military technology has also seen significant advancements. Consequently, there is a growing need for systems capable of tracking, detecting, marking, locking onto, and engaging targets using image processing, specifically through an automated unique marker system [6,7]. Markers are generally artificial indicators designed for easy recognition and identification [8].

Despite the proliferation of marker-based tracking systems, most existing approaches rely on static or continuous laser beams, which are susceptible to evasion, obstruction, or environmental interference. Moreover, conventional systems often lack dynamic encoding mechanisms that could enhance marker distinctiveness and resistance to distraction. This presents a critical gap in the development of robust, interference-resistant marker recognition systems, particularly in real-time, multi-object environments.

To address this gap, this study introduces a specialized form of marker. These unique markers are derived from conventional designs but are enhanced through light intensity modulation using Pulse Width Modulation (PWM). This technique creates a blinking laser effect, which not only improves visibility but also encodes temporal information that the system can uniquely interpret. PWM is also employed to control the system's servo motor [9,10]. The experimental setup utilizes commercially available red, green, and blue lasers as unique markers.

In this system, the camera serves as the input device, capturing object-related data such as color, pattern, and size through CV techniques [4,11,12]. One application of CV explored here is Vision Marker Recognition, which is advanced into a Recognizing Unique Marker system [13]. The detection process uses the HSV (Hue, Saturation, Value) color space for segmentation and contour analysis [14,15]. The marker itself is a laser beam characterized by a distinct color, shape, size, and blinking pattern, making it recognizable only by a computer programmed for this purpose. Once an object is marked, the camera tracks it and coordinates with a servo motor to follow its movement. Each identified object is assigned a unique marker [16,17], designed to resist interference or distraction [4].

The cameras used in this study are equipped with image processing capabilities, enabling them to identify and locate objects accurately. They typically feature a 78° field of view, a resolution of 640 × 480 pixels, and a frame rate of 30 frames per second (fps). Image processing and analysis are conducted using the OpenCV library, which supports integration with programming languages such as Android, .NET, Java, and iOS, and is compatible with platforms like Eclipse and Visual Studio across Windows, macOS, and Linux [4,10,11]. The Unique Marker Recognizing System, developed within OpenCV, is employed for target identification in this setup [4,13,18].

The novelty of this research lies in the integration of PWM-based blinking laser markers with CV-based recognition and servo-controlled tracking, forming a distraction-resistant and dynamically encoded marker system. Unlike prior works that rely on static visual cues, this approach leverages temporal modulation to enhance marker uniqueness and robustness.

Mono cameras can detect multiple objects with predefined shapes and colors, contributing to the refinement of marker recognition. This study investigates the properties of blue, red, and green lasers in an object recognition system that utilizes blinking lasers as unique markers. This feature, originating from a specific blinking frequency and forming a complex code sequence, provides crucial feedback for decision-making and represents a significant step toward achieving precise and reliable object labeling.

The structure of this paper is as follows: Section 1 provides an introduction, Section 2 outlines the proposed method for generating unique object recognition markers, Section 3 presents the experimental results, and Section 4 offers a summary and conclusion.

2. Methods

The computer vision (CV) system was implemented using Python within the Visual Studio Code (VSC) environment, leveraging the OpenCV library for image processing tasks. This integration allows OpenCV to process images and extract key features such as color, pattern, and size. These parameters enable the CV system to identify, track, and lock onto objects using designated markers. Furthermore, image processing techniques are employed to derive distance and positional data, which are transmitted serially to serve as input for the microcontroller.

The experimental framework designed to evaluate the object identification system using unique markers consists of two main components: object recognition via distinctive markers and a blinking laser mechanism. The following subsections provide a detailed explanation of these two system configurations.

2.1. Object Recognition by Unique Marker

As illustrated in Fig. 1, a PWM-based encoding laser is utilized to build the unique marker and drive system [8,9].

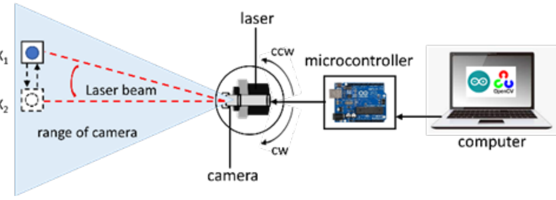


Fig. 1: The experimental setup analyzes the object recognition system using unique markers.

An encoding laser refers to a laser modulated using Pulse Width Modulation (PWM) to produce a blinking pattern that serves as a temporal identifier. Specifically, the system assigns a distinct frequency to each marker, allowing the camera to differentiate objects based on their blinking rate. This frequency is extracted through frame-based intensity sampling and matched against predefined values for marker identification. The target marker is generated using an Arduino Uno to drive the PWM method [8,9,19], a technique applied in previous studies to regulate laser illumination intensity via a dimmer circuit.

The dimmer circuit operates on the principle of voltage regulation through PWM. This PWM signal is a time-controlled pulse pattern directed at a target, and the system measures the time taken for the pulses to be reflected to a receiver, such as a camera.

Object detection based on color involves several stages, beginning with connecting the camera to a computer and configuring it for real-time image capture. The captured images are stored in memory as a 640 × 480-pixel matrix in the RGB (Red, Green, Blue) color space. These images are then converted to HSV (Hue, Saturation, Value) format for color segmentation. Segmentation is performed by setting lower and upper thresholds for hue, saturation, and value, which are adjustable via a trackbar ranging from 0 to 255. HSV thresholding is preferred for its robustness against lighting variations. Each pixel is classified: if it falls within the defined HSV range, it is assigned a value of 1 (white); otherwise, it is set to 0 (black).

During segmentation, OpenCV loads the image into an array format and converts it from RGB to HSV. To reduce noise and minimize detection errors, the image is separated from the background using OpenCV's threshold function. The object's position is then identified by detecting contours with the findContours function. The system iterates through all detected contours and selects those with an area greater than 100 pixels. Detection is based on analyzing the number of edges derived from the object's corner points using the approxPolyDP function. Finally, the number of sides for each shape is determined according to the program's logic, allowing the system to label objects as triangles, squares, or circles based on their geometric features.

To estimate object size, OpenCV functions analyze the contours from the thresholded image. The calculated pixel-based width and height are displayed on the frame and are later used for distance calibration.

The camera used in this experiment has a 78° field of view, a resolution of 640 × 480 pixels, an approximate focal length of 3.7 mm, and a frame rate of 30 fps. It identifies objects using OpenCV-based image processing software [4,11,16,20]. The system adheres to the triangle similarity principle, utilizing a biconvex lens that defines the relationship between the object and its image. According to this principle, the ratio of the actual object distance from the camera to the image width is proportional to the focal length divided by the sensor width. As the object moves farther from the camera, its captured size decreases. If the object's actual size and the camera's focal length are known, the real distance can be calculated.

This study employs OpenCV's unique marker detection to identify objects. The markers are defined by several criteria: color, pattern, size, and blinking laser frequency. The system integrates a laser and camera with a servo motor to enable dynamic tracking and alignment with detected objects. Figure 1 illustrates the camera's coverage area, and object recognition is performed on the computer using OpenCV.

2.2. Blinking Laser

Figure 2 illustrates how the PWM method induces a blinking effect in the laser when integrated into the system [8,9,19].

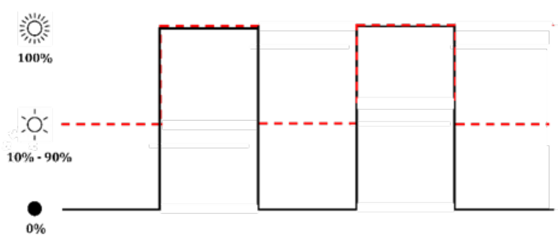


Fig. 2: The schematic of the blinking effect works

The dim-bright modulation mechanism enables the system to perform continuous observation while incorporating meaningful feedback into the blinking pattern. This dynamic light behavior, typically controlled via Pulse Width Modulation (PWM), serves as both a visual cue and a coded signal for the detection system to interpret. By assigning specific blinking frequencies to different markers, the system not only tracks objects in real-time but also conveys distinct identification or status information to the decision-maker. This dual function enhances both monitoring efficiency and decision-making accuracy.

In this setup, the marker serves as a synthetic cue to support object identification. The lasers employed include a red laser (650 nm, 5 mW), a blue laser (405 nm, 5 mW), and a green CNC laser module (532 nm, 2500 mW). The blinking behavior, generated by the system's operation, is integrated into the laser encoding mechanism to produce a distinctive marker.

The encoding laser is driven by a PWM signal, which consists of a time-regulated pulse pattern used to determine the duration for the reflected signal to travel from the target back to the camera. The laser beam itself serves as the marker, while the PWM-based control system, implemented via an Arduino Uno, manages the electrical input through a dimmer circuit. This dimmer generates the PWM signal using a voltage modulation technique.

The marker is designed with distinct attributes in terms of size, color, and pattern to ensure easy recognition. A key innovation of this study is the use of a blinking laser signal as a coded identifier to create a unique marker.

3. Result and discussion

In this experiment, the focus is on analyzing the colors of different laser diodes, specifically blue, red, and green, as distinctive markers within an object recognition system. As illustrated in Fig. 3, the study examines the intensity response of each laser type by applying specific voltage inputs, allowing a comparative evaluation of their performance characteristics.

To the best of our knowledge, this study is the first to utilize a green CNC laser as a unique marker, allowing comparative analysis with standard red and blue lasers. The green CNC laser demonstrated the highest intensity, likely due to its lower threshold voltage and the material properties inherent to CNC laser construction.

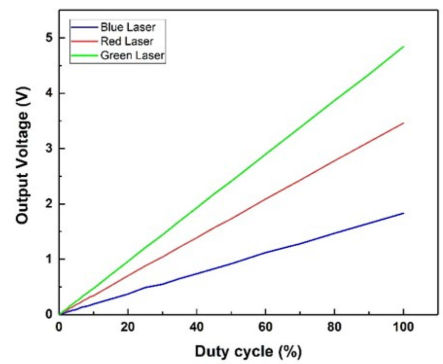


Fig. 3: The voltage input of blue, red, and green lasers toward the intensity.

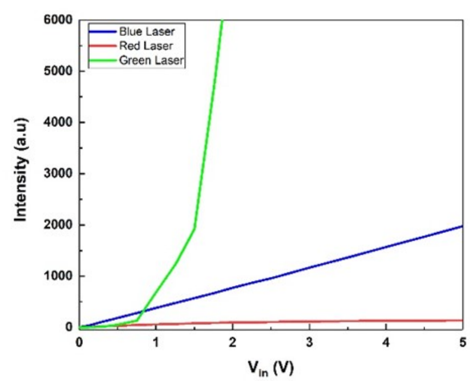
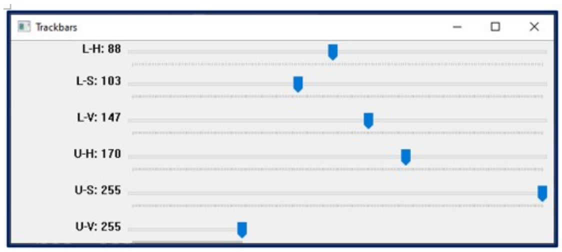


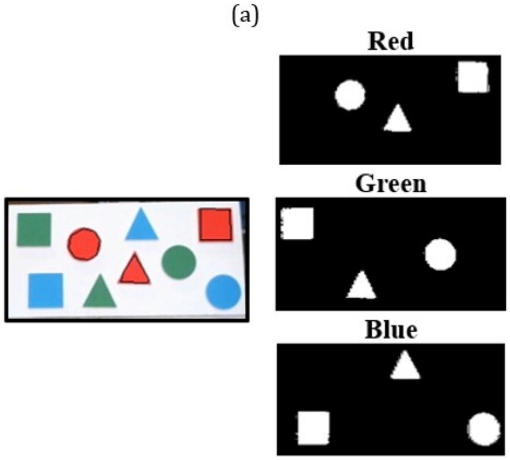
Fig. 4: The duty cycle of blue, red, and green lasers toward the output voltage.

Additionally, Fig. 4 illustrates the relationship between duty cycle variation and the output voltage of the encoding lasers. Tests were conducted using blue, red, and green lasers, revealing that the green laser consistently produced the highest output voltage across all duty cycle settings.

PWM signal control is utilized to generate the blinking effect of the lasers. As shown in Fig. 4, duty cycle variations were applied to blue, red, and green lasers to observe their output behavior. The duty cycle, defined by the ratio of the on-time (t_{on}) to the total cycle time, represented in Fig. 2 as 100% t_{on} and 0% t_{off}, directly influences the laser's output voltage. Figure 4 demonstrates that as the duty cycle percentage increases, the corresponding output voltage also rises, highlighting the system's responsiveness to PWM modulation.



(a)



(b)

Fig. 5: (a) Display trackbars to set the threshold (b) Color detection results of indoor objects.

The selection of the green CNC laser module over the red and blue lasers was based on several practical and performance-driven considerations. First, the green CNC laser offers significantly higher brightness and visibility, which is crucial for reliable detection in both indoor and outdoor environments. Its beam is more easily recognized by standard camera sensors, especially under varying lighting conditions. Second, the CNC laser module provides stable output and precise beam control, making it suitable for consistent marker tracking. In contrast, red and blue lasers, while useful for basic detection, have lower power and visibility, which can limit their effectiveness in long-range or high-interference scenarios. Although the green CNC laser operates at a higher power level, its use was intended to ensure robust performance during early-stage testing. Future experiments will consider power normalization across laser types to enable fairer comparisons and address safety concerns.

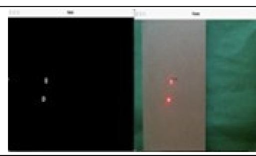
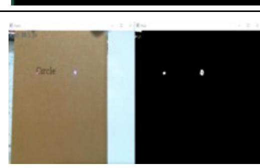
Furthermore, laser detection based on variations in color, pattern, size, and blinking behavior is performed using CV techniques, specifically through two core processes: color segmentation and contour detection. For color analysis, laser data in RGB format is converted to HSV using the OpenCV library, enabling more effective segmentation. HSV-based processing allows the system to identify target objects with distinct colors, shapes, and dimensions.

Pattern detection through threshold adjustment for specific colors is illustrated in Fig. 5. To identify blue-colored objects, the HSV lower threshold is set to L-H: 88, L-S: 102, L-V: 211, and the upper threshold to U-H: 135, U-S: 255, U-V: 255. For red object patterns, detection is achieved by configuring the lower threshold to L-H: 0, L-S: 102, L-V: 211, and the upper threshold to U-H: 90, U-S: 255, U-V: 211. Similarly, green-colored patterns are recognized by setting the lower HSV values to L-H: 34, L-S: 86, L-V: 125, and the upper values to U-H: 84, U-S: 255, U-V: 255. These threshold configurations enable the system to segment and identify objects based on their color profiles accurately.

As illustrated in Fig. 5(a), the HSV parameters are adjusted via a trackbar to establish threshold values for detecting blue-colored markers. The thresholding process involves filtering each pixel's HSV value to isolate relevant features. As shown in Fig. 5(b), this segmentation technique separates the target object from its background, producing a camera-captured image where the background has been removed or darkened, following the approach described in [14] and [15].

In parallel, segmentation data is used to identify and highlight objects by enclosing them within bounding boxes, while object detection relies on a trackbar interface to filter colors. The system processes images captured by the camera using the ReadImage function, converting them from RGB to HSV format. This conversion enables the program to determine the minimum and maximum HSV values for each color, with the upper bounds set at L-H: 180,

Table 1: Laser detection testing with different blinking.

Laser	Data retrieval	Duty Cycle	HSV Value
Red		Blinking 1: 50% and 5% Delay 1: 7s Blinking 2: 50% and 5% Delay 2: 1s	L-H: 155 L-S: 0 L-V: 209 U-H: 180 U-S: 255 U-V: 255
Green		Blinking 1: 50% and 5% Delay 1: 7s Blinking 2: 50% and 5% Delay 2: 1s	L-H: 155 L-S: 0 L-V: 209 U-H: 180 U-S: 255 U-V: 255
Blue		Blinking 1: 50% and 5% Delay 1: 7s Blinking 2: 50% and 5% Delay 2: 1s	L-H: 114 L-S: 0 L-V: 0 U-H: 180 U-S: 255 U-V: 255

L-S: 255, L-V: 255, and U-H: 180, U-S: 255, U-V: 255. As depicted in Fig. 5(b), the test objects, which are styrofoam shapes wrapped in red, green, and blue cardboard, include triangles, squares, and circles. These color variations are used to evaluate the system's ability to detect objects under indoor lighting conditions. The results confirm that the HSV-based color detection method effectively distinguishes object colors across diverse scenarios.

Table 1 presents the outcomes of laser beam detection tests, which demonstrate the effectiveness of using Computer Vision (CV) to identify lasers based on their color, shape, size, and blinking behavior. The system successfully detects blinking lasers, also referred to as dimmers, by leveraging CV techniques such as color segmentation and contour-based shape recognition. These results confirm that the camera can consistently recognize lasers with identical visual attributes when blinking is introduced. Furthermore, the data in Table 1 highlights the reliability of the unique marker system, particularly when combined with the optimized duty cycle settings used in this experiment.

In this experiment, both laser sources were configured to have identical visual attributes. Specifically, the same color, size, and beam pattern, under blinking conditions. The only distinguishing factor was the duration of their blinking cycles: Laser 1 (duty cycle 50% and 5%) emitted a signal lasting 7 seconds, while Laser 2 (duty cycle 50% and 5%) blinked for only 1 second. Despite their identical appearance, the camera system successfully detected and differentiated the two lasers based solely on their temporal blinking behavior. This result confirms the system's ability to recognize and interpret time-based encoding, demonstrating a key feature: the capacity to detect user-defined unique markers. The successful identification of these markers validates the implementation of a programmable recognition framework, in which blinking duration serves as a dynamic identifier beyond static visual characteristics.

The accuracy of pattern detection in this system is highly dependent on the threshold parameter settings; incorrect values can introduce noise during color segmentation, leading to suboptimal recognition. The process begins with color detection to isolate the object based on its hue, followed by contour analysis to determine its shape. Color segmentation enables the system to identify and separate patterns, using the object's color as the basis for region extraction.

Table 2: Evaluation of object detection range in indoor environments.

Indoor Condition Testing									
No	Distance of objects to system (cm)	Experiment to- (1=correct, 0=failed)							Accuracy of the system (%)
		1	2	3	4	5	6	7	
1	50	1	0	1	1	1	1	1	85.71
2	100	1	1	1	1	1	1	1	100
3	150	1	1	1	1	1	1	1	100
4	200	1	1	1	1	0	1	1	85.71
5	250	1	1	1	1	1	1	1	100
6	300	1	1	1	1	1	1	1	100
Average accuracy testing									95.24

The system has been configured to perform real-time monitoring by identifying objects based on their color and geometric shape, consistent with methodologies described in [13] and [18]. Utilizing a commercial camera, the system effectively detects laser-encoded markers within a range of 50 to 300 cm. After synchronization, the tracking response time is recorded at 1.11 seconds. As evidenced in Tables 2 and 3, the system demonstrates robust performance, achieving an average detection accuracy of 95.24% in indoor conditions and 85.74% outdoors.

Table 3: Evaluation of object detection range in outdoor environments.

Indoor Condition Testing									
No	Distance of objects to system (cm)	Experiment to- (1=correct, 0=failed)							Accuracy of the system (%)
		1	2	3	4	5	6	7	
1	50	1	1	1	1	1	1	1	100
2	100	1	1	1	1	1	1	1	100
3	150	1	1	1	1	0	1	1	85.71
4	200	1	1	1	1	0	1	1	85.71
5	250	1	1	1	1	0	0	1	71.42
6	300	1	1	1	0	1	0	1	71.42
Average accuracy testing									85.71

The experimental results reveal notable performance differences between indoor and outdoor environments, primarily due to variations in ambient light intensity, which significantly influence the system's detection accuracy. For effective detection, the laser's emitted intensity must exceed the surrounding ambient brightness. Using a Logitech C615 HD camera as a distance sensor, the system demonstrated average measurement errors of 4%, 5%, and 6% for circular, square, and triangular objects, respectively, as illustrated in Fig. 5(b). These findings underscore the critical role of environmental lighting conditions in maintaining consistent object recognition performance.

Among the three shape-based tests, the circular object yielded the lowest measurement error at 4%. The object size estimation results demonstrate that the computer vision system can accurately calculate pixel dimensions, enabling reliable recognition based on color attributes. These findings provide a solid basis for employing various laser types as unique markers within this experimental framework.

Experimental results confirm that the green CNC laser exhibits a significantly higher power density compared to other laser colors. To quantify this, calculations were performed using a color spectrum calculator, which evaluates intensity based on wavelength and input power. Under identical power conditions, the green CNC laser was found to be 16,405 times brighter than the red laser, highlighting its superior visibility. This enhanced brightness, combined with low power consumption, makes the green CNC laser highly suitable as a unique marker for object recognition systems. Its strong detectability by camera sensors reinforces its practical advantage. These insights underscore the need for future development of detection algorithms that can accommodate diverse object sizes and patterns to achieve greater precision in recognition tasks.

4. Conclusion

This research demonstrates the effectiveness of using laser-based unique markers for object recognition systems, particularly through the integration of computer vision techniques such as color segmentation and contour detection. Among the tested laser types, the green CNC laser stands out due to its superior intensity, lower threshold voltage, and higher output voltage, making it highly suitable as a distinctive marker. The system successfully identified and tracked objects based on color, shape, size, and blinking behavior, achieving high accuracy rates of 95.24% indoors and 85.71% outdoors across distances ranging from 50 cm to 300 cm.

For future development, the implementation of invisible laser markers could enhance security and reduce visual distraction. Furthermore, refining detection algorithms to better accommodate variations in object size, shape, and environmental lighting will be essential for improving robustness and expanding the system's applicability in dynamic or outdoor settings.

Acknowledgment

This project was partially funded by a research grant from the Research Center for Photonics, National Research and Innovation Agency (BRIN). The first and last authors served as the principal contributors to this work, overseeing its conceptual development, experimental design, and manuscript preparation.

References

[1] J. Chai, H. Zeng, A. Li, and E. W. T. Ngai, "Deep learning in computer vision: A critical review of emerging techniques and application scenarios" Mach. Learn. with Appl., 6, 100134, (2021).

[2] F. Rubio, F. Valero, and C. Llopis-albert, "A review of mobile robots: Concepts, methods, theoretical framework, and applications" Int. J. Adv. Robot. Syst., 16(2), (2019).

[3] T. Kurita, N. Kasashima, and M. Matsumoto, "Development of a vision-based high precision position and orientation measurement system to facilitate automation of workpiece installation in machine tools" CIRP J. Manuf. Sci. Technol., 38, 509–517, (2022).

[4] A. Al-Noman, A. N. Eva, T. B. Yeahyea, and R. Khan, "Computer Vision-based Robotic Arm for Object Color, Shape, and Size Detection" J. Robot. Control, 3(2), 180–186, (2022).

[5] A. Ali, A. Ghosh, and S. S. Chauduri, "Real-time tracking of moving objects through efficient scale space adaptation and normalized correlation filtering" Signal Image Video Process., 18(1), 679–689, (2024).

[6] S. Paneru and I. Jeelani, "Computer vision applications in construction: Current state, opportunities & challenges" Autom. Constr., 132, 103940, (2021).

[7] A. I. Khan and S. Al-habsi, "Machine Learning in Computer Vision" Procedia Comput. Sci., 167, 1444–1451, (2020).

[8] W. P. Tresna, U. A. Ahmad, R. R. Septiawan, I. T. Sugiarto, and A. Lukmanto, "Encoding LED for Unique Markers on Object Recognition System" Int. J. Adv. Comput. Sci. Appl., 12(12), 678–683, (2021).

[9] D. Setiawan, Ishak, and M. S. Ardiansyah, "Control System for Adjusting the Brightness Level with PWM Technique Using Visual Net Microcontroller-Based" J. Robot. Control, 1(4), 102–108, (2020).

[10] R. Wahrini, "Development of Color-Based Object Follower Robot Using Pixy 2 Camera and Arduino to Support Robotics Practice Learning" J. Edukasi Elektro, 7(2), 161–168, (2023).

[11] A. Sharma, J. Pathak, M. Prakash, and J. Singh, "Object Detection using OpenCV and Python" in 2021 3rd Int. Conf. Adv. Comput. Commun. Control Netw., 501–505, (2021).

[12] N. Dardagan, B. Adnan, D. Dzigal, and A. Akagic, "Multiple Object Trackers in OpenCV: A Benchmark" in 2021 IEEE 30th Int. Symp. Ind. Electron., 1–6, (2021).

[13] A. Sarsenov, A. Yessenbayeva, A. Shintemirov, and A. Yazici, "Detection of Objects and Trajectories in Real-time using Deep Learning by a Controlled Robot" in Proc. Int. Conf. Robot. Comput. Vis. Intell. Syst. (ROBOVIS 2020), 131–140, (2020).

[14] B. Garcia-garcia, T. Bouwmans, and A. J. R. Silva, "Background subtraction in real applications: Challenges, current models and future directions" Comput. Sci. Rev., 35, 100204, (2020).

[15] H. Hamadi, Supriyono, and D. Riansah, "Detection and measurement of obstacles on a track using color segmentation with background subtraction and morphological operation" in IOP Conf. Ser. J. Phys. Conf. Ser., 1436, (2020).

[16] H. M. Zangana, "A New Algorithm for Shape Detection" IOSR J. Comput. Eng., 19(3), 71–76, (2017).

[17] Y. Jusman, L. Hinggis, R. O. Wiyagi, N. A. M. Isa, and F. Mujaahid, "Comparison of Background Subtraction and Frame Differencing Methods for Indoor Moving Object Detection" in 1st Int. Conf. Inf. Technol. Adv. Mech. Electr. Eng., 214–219, (2020).

[18] N. H. Abdulghafoor and H. N. Abdullah, "A novel real-time multiple objects detection and tracking framework for different challenges" Alexandria Eng. J., 61(12), 9637–9647, (2022).

[19] Z. Abidin, A. G. R. Mahendra, D. F. Mahendra, M. R. N. Imami, and W. M. H. Mehanny, "Performance Analysis of LED Driver for Transmitter of Visible Light Communication Using Pulse Width Modulation" in 2020 10th Electr. Power, Electron. Commun. Control. Informatics Semin., 178–182, (2020).

[20] J. Liu and R. Zhang, "Vehicle Detection and Ranging Using Two Different Focal Length Cameras" J. Sensors, 2020, 4372847, (2020).