Al-Khwarizmi Engineering Journal
ISSN (printed): 1818–1171, ISSN (online): 2312–0789
Vol. 21, No. 2, June (2025), pp. 72–92

Al-Khwarizmi Engineering Journal

Improving Barcode Vision Scanning Process using a Drone-based Tracking PID Controller for Warehouse in Industry 4.0

Samer Al-hamadani[1*], Izzat Al-Darraji[2] and Houssem Jerbi[3]

[1, 2]*Department of Automated Manufacturing ,Al-Khwarizmi College of Engineering, University of Baghdad, Baghdad, Iraq*

[3]*Department of Industrial Engineering, College of Engineering, University of Hail, Saudi Arabia*

Corresponding Author's Email: samer.razaq2204@kecbu.uobaghdad.edu.iq

(Received: 23 May 2024; Revised: April 2024; Accepted: 10 November 2024; Published: 1 June 2025)

https://doi.org/10.22153/kej.2025.11.002

Abstract

Drones play a vital role in the fundamental aspects of Industry 4.0 by converting conventional warehouses into intelligent ones, particularly in the realm of barcode scanning. Various potential issues frequently arise during barcode scanning by drones, specifically when the drone camera has difficulty obtaining distinct images due to certain factors, such as distance, capturing the image whilst flying, noise in the environment and different barcode dimensions. In addressing these challenges, this study proposes an approach that combines a proportional–integral–derivative (PID) controller with image processing techniques. The PID controller is responsible for continuously monitoring the camera's input, detecting the difference between the planned and the real barcode image dimensions, and making immediate changes to the drone position to improve the process of detecting the potential barcode. The aforementioned procedure is implemented on the DJI Tello drone to verify the practical performance of the methodology introduced in this study. Results showed that drones can achieve remarkable barcode scanning performance by incorporating sophisticated computer vision technologies into PID controllers. PID computer vision algorithms are capable of analysing visual data acquired from the drone's cameras and retrieving barcode information under a variety of situations, such as the size of the barcode, location of the barcode and noise of the warehouse environment.

Keywords: *Drone; barcode scanning; vision camera; PID controller; warehouse; industry 4.0*

1. Introduction

Drones, a type of unmanned aerial vehicles (UAVs), are essential in several civil and military uses where they are becoming increasingly popular due to their versatility and ability to explore remote areas [1]-[5]. Moreover, drones are equipped with cameras, sensors and other tools that allow them to autonomously perform various tasks.

Recently, drones have gained significant technological importance and become a crucial element of modern progress, substantially modernising several industries toward Industry 4.0. The incorporation of modern technologies, such as the internet of things (IoT) and artificial intelligence (AI), in Industry 4.0 improved industrial processes by increasing flexibility. Consequently, production increased, and product quality improved [6]-[9]. For instance, the implementation of Industry 4.0 at the Hannover Messe in 2011 resulted in substantial transformations in industrial infrastructure and logistical operations. Industry 4.0 plays a crucial role in supply chain management by transforming it into an intelligent system and enhancing its agility. IoT is a fundamental component of Industry 4.0 where effectively managing warehouse inventory is a crucial aspect of supply chain management [10].

Currently, the field of logistics is experiencing significant application in Russia and across the world. An estimation of the inventory velocity using a quadcopter was conducted, along with an evaluation of the available solutions in the market

[11]-[14]. Drones can automate a variety of warehouse duties, such as the evaluation and inspection of inventory, the execution of orders and surveillance [15]-[17]. Furthermore, drones are excellent candidates for usage in applications, such as inventory checking in huge warehouses. Given that drones are flexible enough to navigate the restricted warehouse corridors, they make it easy to reach the towering racks. Drones can not only carry the sensors needed for warehouse inspection but also maintain flight for extended periods [18].

The DJI Tello drone is extensively utilised as an instructional platform in the domain of control engineering. This device provides an affordable and small-scale option for performing research in laboratory environments where GPS signals are unavailable [19]. The drone's hardware and software design, together with its mathematical model, have been described in academic articles, demonstrating its potential as an experimental platform. Students and young scientists have utilised drones in a range of studies, including trajectory generation and person detection and tracking [20]. The utilisation of drones in control engineering courses has offered important practical experience and enhanced comprehension of fundamental principles [21]. Although drones are inexpensive, they have demonstrated impressive performance and have been effectively utilised in laboratory practice courses and advanced control projects [22].

The term 'drone' has gained significant prominence in the logistics industry in recent years. Drone deliveries offer a dual benefit by potentially reducing delivery time by bypassing road congestion and having an intrinsic design that minimises its carbon footprint compared with conventional transportation methods, subject to certain limitations. Several firms worldwide have designed and evaluated drones for practical use to exploit this potential [23]. An intermediate is required to facilitate data transmission and information retrieval from inventory using a drone. This intermediary should provide product information in a digital format that can be easily accessed by the drone. The barcode system serves as an effective solution for this purpose. The simplicity and effectiveness of the barcode system demonstrate its ability to effectively eliminate data entry errors and enhances data entry efficiency at a low cost [24].

Barcodes efficiently manage storage by creating an inventory of items and recording their locations. Furthermore, barcodes are finite multisets of intervals on the real line that summarise the persistent homology groups of filtrations in topological data analysis [25], [26]. The field of barcode recognition and analysis has attracted significant interest in academic and commercial spheres. Barcodes are widely recognised as the fundamental element of supply chain management due to their notable benefits, such as their strong dependability and low cost [27]. In the last decade, barcodes have been extensively utilised. A key factor in this phenomenon is the utilisation of sophisticated technology, such as radio frequency identification (RFID), which is highly complex and entails substantial initial capital expenditures, including the costs of tags, readers and software systems [28], [29]. Since the introduction of barcodes, they have gained significant attention due to their large storage capacity, enhanced security, durability and various other features. Consequently, barcodes are likely to remain in use in the foreseeable future [30], [31].

Inventory management in large warehouses involves challenges related to precision, time allocation and potential hazards. In the context of large-scale inventory management, the use of traditional portable barcode scanners poses difficulties as every barcode must be manually scanned, requiring significant human labour. The utilisation of computer vision technology for barcode reading enhances productivity in conducting large-scale scanning operations in vast warehouses [32], [33]. The extensive utilisation of drones has made a substantial contribution to several applications, such as natural resource management [34] and warehouse inventory management [31]. In addition, warehouses are progressively utilising drones equipped with cameras for a variety of functions in operational oversight. These applications encompass inventory verification and visual response. Drone cameras are capable of capturing static pictures for further analysis or providing live video feeds for monitoring from a first-person perspective. This approach enables a rapid and effective inventory verification of goods and objects within the warehouse [35], [36].

Warehouse inventory management is optimised through the utilisation of drones equipped with barcode scanners that use advanced camera technology. Consequently, barcode scanning-based drones are crucial in modern logistics and inventory management systems. Nevertheless, obstacles frequently arise during barcode scanning, particularly when the camera struggles to capture distinct pictures due to factors, such as distance, diverse barcode dimensions or when the barcode is positioned at an angle due to the box's movement. When utilised with drones, barcode scanning systems typically face challenges that prevent the consistent collection of data. Significant challenges must be overcome in barcode detection, including drone movement, vibrations and varying light conditions. This study proposes a strategy that leverages the capabilities of a proportional–integral–derivative (PID) controller in conjunction with an image scanning method to address these challenges. The PID controller is responsible for continually monitoring the input from the camera, recognising any variations between the intended and actual barcode picture, and making rapid modifications to optimise the camera's performance. This approach is used to accomplish these tasks.

2. Methodology

In this study, barcode scanning and the PID controller are integrated into a single algorithm to enhance barcode scanning by drone. The versatility of the algorithm makes it a promising solution for improving barcode scanning across various logistics and inventory management settings.

2.1 Barcode Scanning

Computer vision has an extensive and well-established history spanning several decades. This field focuses on altering and examining digital images using different algorithms and methods to extract meaningful information [37], [38]. Image processing almost involves one or more of the following techniques: mathematical operations, filters or modifications on an image to enhance its quality, extract important information or achieve specific goals, such as object detection or recognition [39], [40]. The advancement of methodologies that enable computer systems to interpret and evaluate visual data closely parallels human interaction with their own vision. This development pertains to the progress in comprehending pictures and movies, demonstrating the broad areas of computer vision. Computer vision is an essential and versatile technology in robotics, allowing for tasks, such as measuring and placement [41]. Specifically, computer vision functions as the primary sensory mechanism utilised in drones to collect information on the immediate environments [42]. Meanwhile, barcode advancements, along with advanced computer vision technology, provide several advantages for drone applications. Barcode scanning is essential in areas, such as transportation, inventory management and retail, where precise and rapid data collection is of utmost importance. The need for enhanced efficiency and precision in data collection can be addressed by improving barcode recognition skills in drone applications. However, the purpose of creating barcodes was to make a 1D European Article Number (EAN) barcode.

The EAN barcode is a well-recognised method used for product identification, extensively utilised in Europe and several international markets. The EAN barcode consists of 13 digits and encodes information, such as country, manufacturer and product codes. The structure of the EAN-13 barcodes (Figure 1) consists of the following elements [43]:

- The number system refers to the initial two digits of the EAN number, which are used to identify the numbering authority of a nation or region.
- The manufacturer code is a unique code assigned to each manufacturer by the numbering authority indicated by the number system code. Every product manufactured by a certain business will share a common manufacturer code.
- The manufacturer assigns the product code. The product code directly follows the manufacturer code. The combined length of the manufacturer and product codes must be exactly 10 digits.
- The check digit serves to validate the accuracy of barcode generation or scanning. This digit is derived from the remaining digits of the barcode using a calculation process.

Fig. 1. ENA-13 barcode structure

This method guarantees the creation of EAN barcodes whilst following the defined format and incorporating crucial product details. The aforementioned actions are executed by controlling the drone and managing its functions whilst also generating barcodes using Python. Python has been chosen due to its broad capabilities, libraries, ease of programming and ability to deliver good results. Drone control involves the use of the OpenCV library to perform remarkable image and video processing through the drone's camera. Once a barcode is captured, it is promptly decoded and instantaneously read by using the Pyzbar library. Pyzbar is a Python package developed by L. Hudson [44] that provides an interface for decoding barcodes and extracting information from video files captured by the drone camera via the OVC library. The Pyzbar library works by analysing video frames and identifying areas that may contain a high frequency of barcodes. Thereafter, this library processes these regions to extract barcode data. The library provides functions to easily integrate barcode decoding into Python applications. Pyzbar allows the decoding of various types of barcodes, including QR codes and EAN-13. This library provides correct reading and decoding ratios for barcodes with a detection rate of up to 95% [45].

2.2 PID Controller

The PID controller is typically regarded as the predominant control technology in control applications, providing robust and dependable performance for most systems. This controller is extensively used in various applications is due to its simplicity and resilient framework in different operational environments [46]-[50]. The PID controller comprises three main parameters, namely, proportional (K_P), integral (K_I) and derivative (K_D). Several conventional techniques exist for adjusting PID parameters, including the trial-and-error method and Ziegler–Nichol's method. The commonly used approach is the 'Manual Tuning' method [51]-[53]. In this study, the PID controller is paired with computer vision to improve the accuracy of barcode scanning by drones, as mentioned in Section 3.1. Figure 2 illustrates the block diagram of the PID controller used in this study, where the PID controller enables the DJI Tello drone to stop upon correctly capturing the barcode of the potential product. Hence, this PID controller is designed to regulate the required barcode area in terms of pixels. R_b represents the required value of the barcode area in terms of pixels. Meanwhile, A_b is the actual value of the barcode area, which is obtained from the camera of the DJI Tello drone in the scanning process.

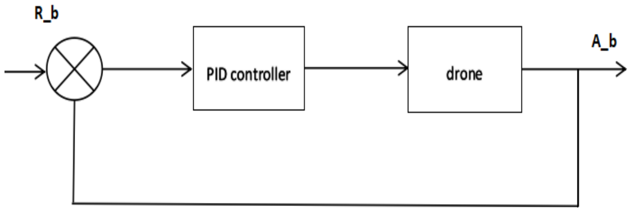


Fig. 2. PID controller block diagram of the DJI Tello drone in the scanning process

For instance, the area pixel of the barcode shown in Figure 3 during the DJI Tello drone scanning process was around 15,000 pixels, allowing the barcode to be read. Consequently, R_b in Figure 3 is equal to 15,000. Meanwhile, A_b represents the current and actual value of the area scanned by a drone camera. When the A_b reaches R_b, the drone will immediately stop, and the barcode will be detected.

Fig. 3. Barcode of the potential product

Integration of the PID controller with computer vision enhances the drone vision system by adjusting the DJI Tello drone position to ensure effective barcode scanning. The PID controller utilises real-time data on the barcode rectangular area, measured in pixel values from the computer vision system, to precisely regulate the drone's distance to the position of the barcode to guarantee precise and efficient barcode scanning. Consequently, the PID controller ensures accurate distance tracking between the DJI Tello drone and the barcode, whilst the computer vision (Section 3.1) utilises a barcode recognition algorithm that instantly identifies and decodes barcodes with improved accuracy. The PID controller-based image processing is expressed in Equation (1) as follows:

$$U_{ba}(t) = K_p err_d(t) + K_i \int_0^t err_d(t)dt + K_d \frac{derr_d(t)}{dt},$$

...(1)

where $U_{ba}(t)$ is the control value at time t, representing the area of the rectangle around the barcode code, measured in pixel values; and $err_d(t)$ is the error in time$t$between the current location of the DJI Tello drone and the barcode codelocation (Figure 5).

The PID controller-based image processing is based on three key components:

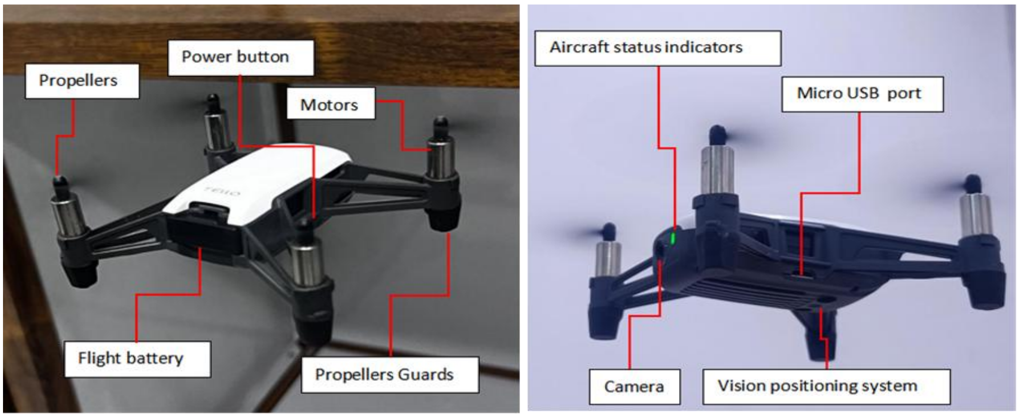
- The proportional gain K_P regulates the drone's reaction in direct proportion to the discrepancy between the intended and the current locations. The K_P term in barcode scanning applications helps the drone in achieving a stable and precise position for accurate scanning.
- The integral term K_I gain considers the cumulative inaccuracy over time and modifies the drone's flight behaviour. This variable allows the drone to compensate for any systemic inaccuracies, such as drift, that may arise over extended flights.
- The derivative gain K_D is responsible for considering the rate of change of error and aids in stabilising the DJI Tello drone's flight by reducing sudden movements or overshooting.

This approach guarantees seamless and regulated motions when scanning barcodes. The incorporation of these three concepts in the PID controller enables the DJI Tello drone to uphold stability, precision, and agility throughout flights, rendering them an effective technique for barcode scanning applications in warehouse 4.0.

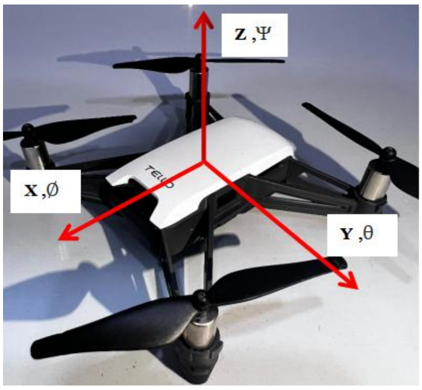
3. Experimental Setup

This study utilised a quadcopter drone, namely, DJI Tello (Figure 4(a)), equipped with a 5 MP camera capable of capturing photographs and 720 p video footage. The drone is equipped with a high-resolution camera, allowing it to capture and produce clear images that are well-suitable for the immediate processing of photographs and videos. Given that this drone has a battery capacity of 1100 mAh, it can travel a distance of 100 m and has a wonderful flying length of 13 min without any interruptions. In addition, this drone is capable of travelling a distance of 100 m. The drone has been programmed and controlled using Python and its various libraries, ensuring a streamlined and efficient programming process. Python is a programming language extensively utilised in scientific and computational domains. This tool has been developed to manage scale sequencing data, simplifying the process of crafting scripts, for data analysis [54]. Pycharm is used to write a code, and it is a popular Python integrated development environment (IDE) that offers various features, such as auto-completion, code analysis, debugging capabilities and interoperability with version control systems [55]. This programming facilitated seamless integration for real-time processing of photos and videos. The versatility, ease of programming and wide range of capabilities of the DJI Tello drone makes it an ideal instrument for acquiring high-quality data in various scenarios.

Figure 4(b) denotes the coordinate axis of the drone in terms of its body, where Roll $\emptyset$, θ Pitch and Yaw Ψ represent the rotation of the drone around the X, Y and Z axes, respectively. Roll is the rotation of the drone around the X-axis, pitch is the rotation of the drone around the Y-axis, and yaw is the rotation of the drone around the Z-axis. Figure 5 shows the main three components that are implemented to verify the methodology of this study, namely: (1) a DJI Tello drone, (2) a potential barcode of the product, and (3) a laptop. Table 1 shows the summary of the dimensions and specifications of these components.



(a)



(b)

Fig. 4. (a) DJI Tello drone components; (b) the roll, pitch and yaw angles of the DJI Tello drone

Table 1,
Dimensions and specifications of the experiment setup components

Component	Parameter	Description
DJI Tello	Weigh	80 g
	Dimension	98×92.5×41 mm
	Flight feature	Maximum flight distance: 100 m Maximum speed: 8 m/s
	Battery	Detachable: 1.1 Ah/3.8 V Life: approximately 13 min
	Camera	Photo: 5 MP Video: 720p FOV: 82.6
	CPU	Intel i7-7200U
	RAM	DDR4 12 GB
	Connectivity	WiFi 2.4 Ghz
	Programming Environment	–Python programming language –Pycharm IDE
Barcode 1	Type	Printed on the carton
	Dimension	14.75 × 2.9 cm
Barcode 2	Type	Labeled on the carton
	Dimension	9.6 × 7.1 cm
Barcode 3	Type	Labeled on the carton
	Dimension	5.3 × 4 cm
Laptop	Device name	MSI
	Processor	Intel(R) Core (TM) i5-10500 H CPU @ 2.50 GHz
	Ram	8 GB
	System	Windows 10

The PID controller and image processing algorithm are written in Python code on the laptop. The written code is uploaded into the quadcopter to control the intended task through WIFI. The quipped camera of the drone captures the scanned barcode information, which is transmitted via WIFI to be processed by the Python code. Figure 6 shows the block diagram of the experimental system.

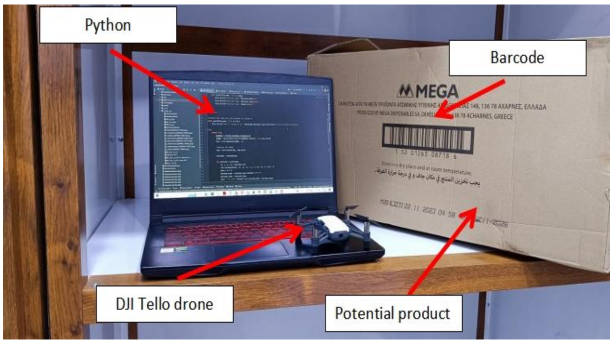


Fig. 5. Main components of the experimental tools

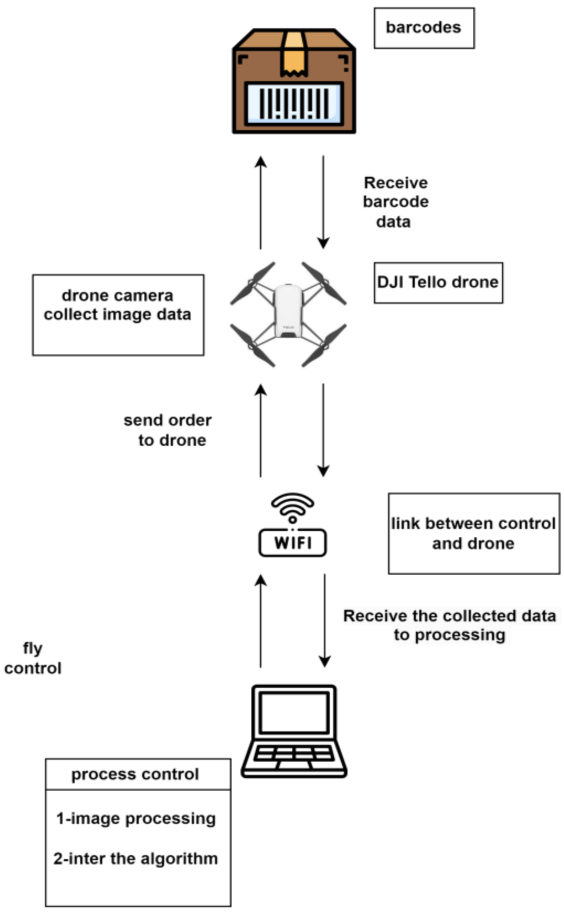


Fig. 6. Block diagram of the experimental system

4. PID Controller Design

In this section, the PID gains are practically set to enable the DJI Tello drone to accurately detect barcodes. The required PID gain values are set to ensure that the DJI Tello drone movements are relatively steady during barcode tracking. Nonetheless, these gains are susceptible to alteration. Alternative values are used to evaluate the effect of PID gains on the drone's motion and reaction during the barcode detection process through trial and error. The objective of the train and error was to minimise the error between the desired and the actual areas of the barcode in terms of pixel values. Table 2 presents the values of the PID gains that are set in a trial-and-error method where the amount of overshoot is noted during the experiment to reach the best result. Test 2 was used as a case study for this value. Some values resulted in a quick response to commands by the drone, causing fast and irregular movements. Moreover, the delay in error processing resulted in a high level of oscillation and instability in the motion. Consequently, the best values of K_P, K_I and K_D are set as 0.5١ ٠.3, and 0.٦4, respectively. Given these gain values, the system will exhibit a quick response to errors, ranging from moderate to fast, whilst also demonstrating effective error management capabilities. A higher K_I value indicates that the system will efficiently minimise accumulated errors and achieve a stable state. In addition, stable control is achieved when the K_D parameter of the system effectively minimises potential oscillations by counteracting the effect of sudden variations in error. The system can detect additional fixed points. However, these points will be of utmost importance in this study.

Table 2,
Overshoot, steady-state error and accuracy value during the trial and error

Test	K_P	K_I	K_D	Overshoot value in pixels	Steady state error in pixels	Accuracy
1	0.53	0.25	0.7	2500	150	0.375%
2	0.56	0.2	0.6	3750	130	0.325%
٣	0.59	0.15	0.7	5150	170	0.425%
4	0.62	0.3	0.75	6250	160	0.4%
5	0.71	0.25	0.8	7400	200	0.5%
6	0.58	0.28	0.58	4325	140	0.35%
7	0.6	0.32	0.78	5240	170	0.425%
8	0.54	0.35	0.85	3150	190	0.475%
9	0.55	0.4	0.9	2100	185	0.4625%
١٠	0.53	0.28	0.74	50٥1	140	0.35%
11	0.55	0.3	0.75	1600	150	0.375%
١٢	0.53	0.3	1.1	3900	210	0.525%
13	1	0	1	7000	230	0.575%
14	0	1	1	5500	210	0.525%
15 Best value	0.51	0.3	0.64	1250	100	0.25%

5. Experimental Tests

The DJI Tello drone camera captures the warehouse environment in a particular situation through video streaming. The presented technique in this study utilises OpenCV and the pyzbar library (Section 3.1) for the recognition and decoding of barcodes. These libraries are utilised in the vision processing, which includes built in AI functions in conjunction with accurate machine learning and neural networks. These libraries offer a system for processing encryption and vision processing in terms of images. However, the OpenCV and the Pyzbar library in Python programming are utilised to facilitate the DJI Tello Drone vision in executing the objective tasks of barcode code detection. The vision data obtained from the DJI Tello Drone camera serves as input, controlling the position of the drone to the potential barcode in the warehouse. The height of the drone flight is set as a variable input rather than a constant in the programming code to account for and adjust various elevations. This mechanism enabled the potential to manipulate various elevations of barcodes. As a starting point, the drone is programmed to be located at the level of the product boxes of the experiment, which is 180 cm (Figure 7).

This notion indicates that the distance between the product on the shelf and the drone before take-off is 180 cm. Upon execution of the algorithm, the drone will automatically take off at a constant speed and proceed to the designated destination at speed (10 cm/s) to bein the process of scanning the product box. At the specified elevation of 180 cm, if the drone fails detect the barcode within 3 s, then it will travel ahead towards the product box at a distance equal to 30 cm. This distance is consistently minimised and computed from the drone’s last capture, guaranteeing continual progress towards the target box. If the drone is unable to scan at this distance, then it will return to the original distance of 30 cm before proceeding to scan another barcode to prevent any possible collisions. This process guarantees precise identification when the potential box of a product has no barcode.

The developed PID controller-based image processing algorithm of this study is shown in Figure 8. The algorithm closely depends on the pixel area of the drawn rectangle around the barcode for accurate navigation and positioning. When the barcode detection process is initiated, the drone scans it and moves onward until the pixel area meets the specific threshold. A tolerance of ±٤000 pixels has been implemented for the specified barcode area to consider drone vibration and camera noise during a flight. This level of tolerance, ±٤000 pixels, is determined through a process of trial and error and is granted or awarded. As the drone flies, it naturally moves, resulting in a constantly changing and non-fixed area. This tolerance is appropriate for any potential circumstance that could occur due to drone vibration and camera noise. When assessing the tolerance and measuring it, the distance between the barcode and the drone has been found to be 2 cm to 4 cm. This distance is considered appropriate because it ensures that the drone does not collide with the object or shelf.

Three tests are implemented for various barcode features to verify the results of the suggested technique of this study. Moreover, three barcodes of different sizes are utilised to measure the pixel area of each barcode. The words large, medium and small are selected to represent the relative size between the three selected barcodes of this study. In terms of the PID controller gains (Table 1), the optimal values of K_P, K_I and K_D have been set to 0.51, 0.3 and 0.64, respectively, across all three tests, effectively minimising the error.

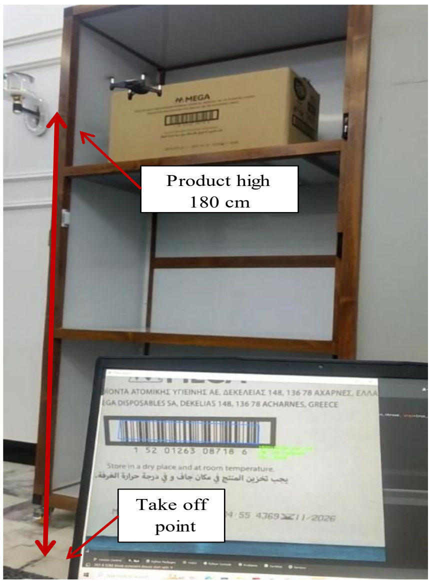


Fig. 7. Practical drone barcode scanning

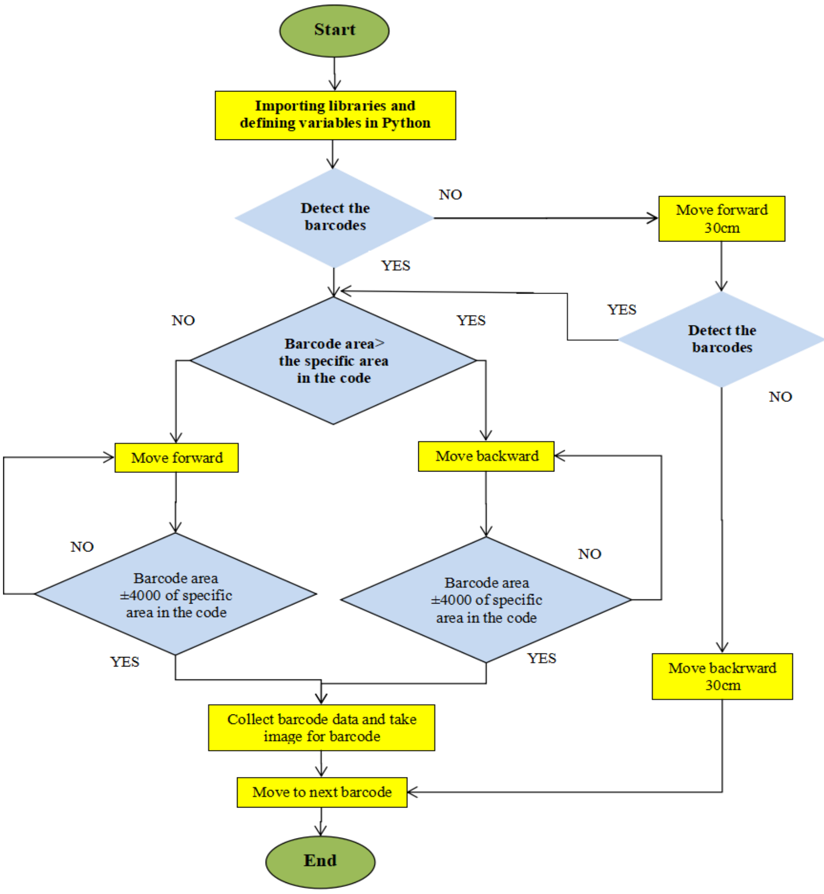


Fig. 8. Flow chart of the implemented algorithm

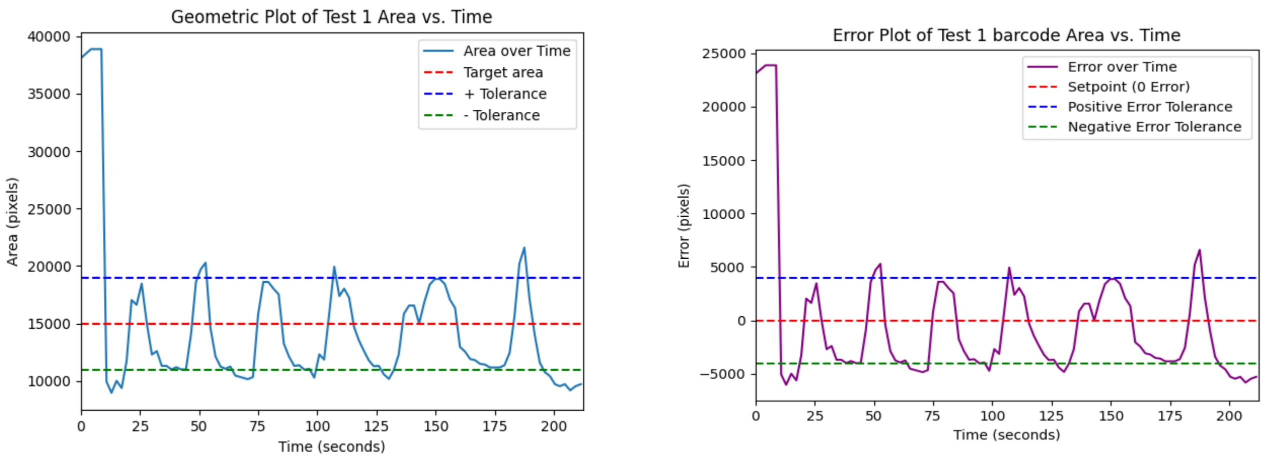
5.1 Test 1

In test 1, the large-size barcode 1 measured 14.75 cm in width and 2.9 cm in length. This barcode type is affixed and printed on the product carton (Figure 9). The pixel area is found to be $R_b = 15{,}000$ pixels for reading and capturing a sharp image of the barcode, providing a suitable corresponding approximate reading distance of 55 cm (Figure 10).

Fig. 9. Barcode data and area of the large-size barcode 1 of test 1

The process of detecting the barcode is implemented without considering the PID controller. In this case, the response of the process of detecting barcode 1 is shown in Figure 11. The steady-state error is large, reaching an average of about 4800 pixels (Figure 11(b)). Accordingly, the detecting rate of the barcode area reached approximately 20,000 pixels (Figure 11(a)), which is not close to the desired value of 15,000 pixels. Thus, the intended barcode 1 could not be detected, even considering tolerance in the range of 4000 pixels.

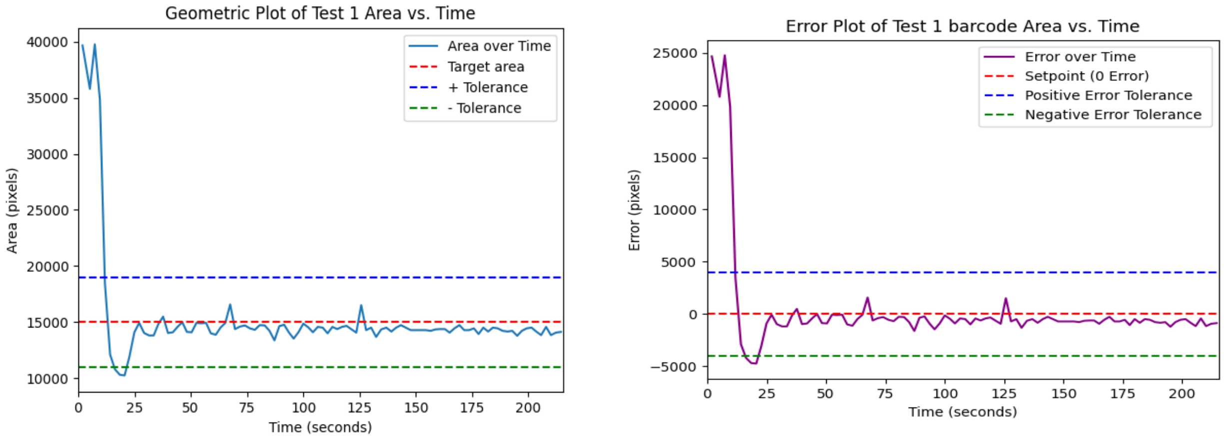
Fig. 10. Distance to barcode 1 detection



(a) **(b)**

Fig. 11. Barcode scanning without a PID controller: (a) barcode 1 image area; (b) barcode 1 image area error

The designed controller of this study is considered in the process of detecting barcode 1. The implementation of the PID controller demonstrates its ability to minimise the image area error to ±200 pixels (Figure 12(b)). This mechanism enhances the process of detecting the barcode, wherein the actual image area ‘ A_b’ reached the desired image area ‘R_b’, which is equal to 15,000 pixels (Figure 12(a)). In this situation, the PID controller showed its ability to detect the barcode whilst maintaining a smooth drone motion.



(a) **(b)**

Fig. 12. Barcode image area versus time with a PID controller: (a) barcode image area; (b) barcode image area error

5.2 Test 2

In test 2, the medium barcode 2 dimension is set to 9.6 cm in width and 7.1 cm in length. Unlike in test 1, this label is drawn by us. This label barcode is utilised on product packaging solely as a label (Figure 13). The barcode area is 40,000 pixels, whilst the distance between the DJI Tello drone and the barcode label is 40 cm (Figure 14).

Fig. 13. Barcode data and area of the medium-size barcode 2 of test 2

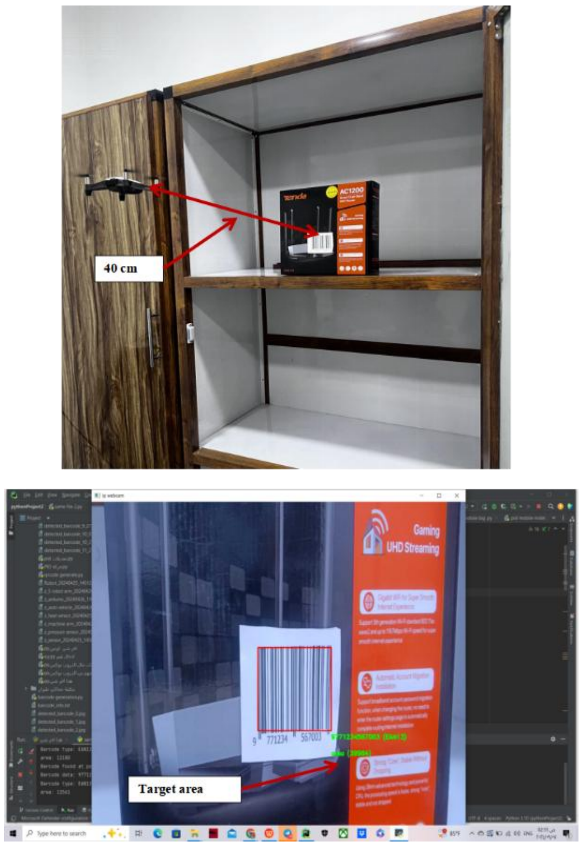
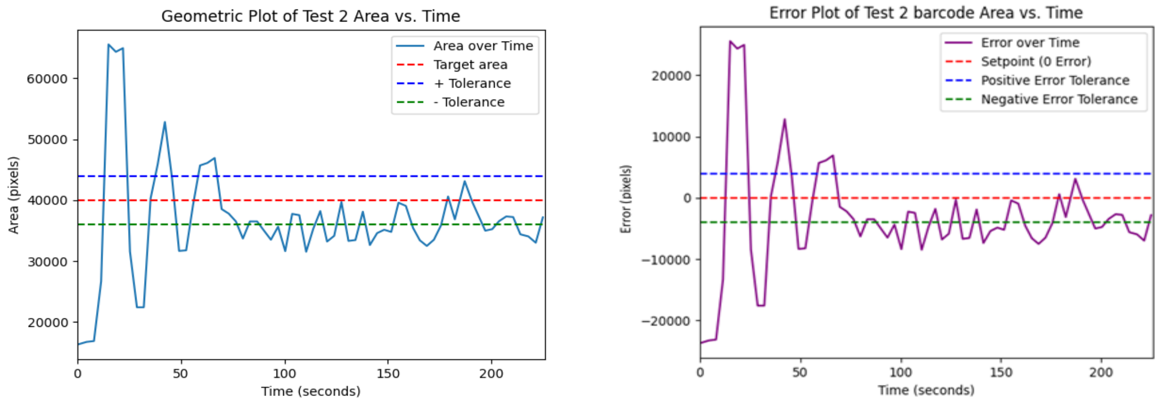


Fig. 14. Distance to barcode 2 detection

The task of detecting the barcode is performed without the implementation of the PID controller. In this situation, the response of the process of detecting barcode 2 is presented in Figure 15. The steady state error was large, reaching an average of about 7000 pixels, due to the exclusion the PID controller in the barcode detection process (Figure 15(b)). Consequently, the detection rate of the barcode area reached approximately 47,000 pixels

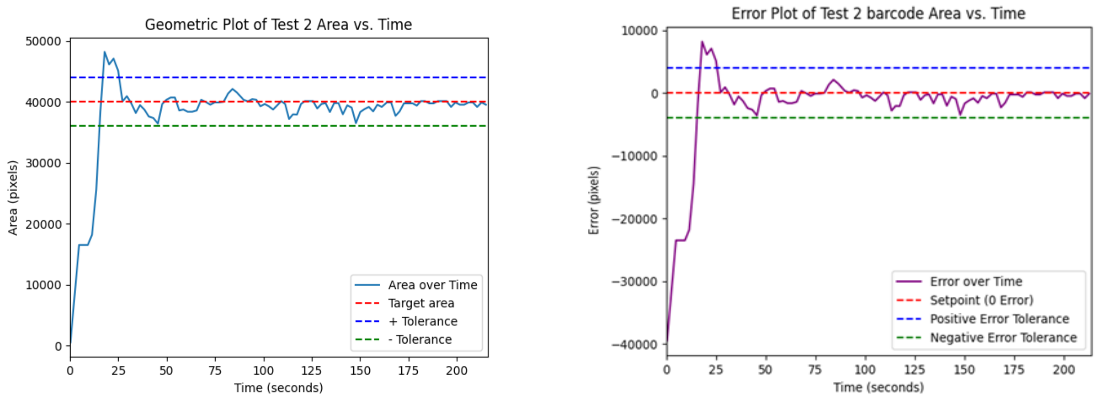
(Figure 15(a)), which is not close to the desired value of 40,000 pixels. This sitation resulted in the inability to detect the intended barcode 2, even when considering tolerance in the range of 4000 pixels.



(a) **(b)**

Fig. 15. Barcode 2 scanning without a PID controller: (a) barcode 2 image area; (b) barcode 2 image area error

The developed controller of this study is considered in the task of detecting barcode 2. The implementation of the PID controller showed its ability to minimise the image area error to ±100 pixels (Figure 16(b)). This mechanisn enhances the process of detecting the barcode, wherein the actual image area 'A_b' reached the desired image area 'R_b', which is equal to 40,000 pixels (Figure 16(a)). In this situation, the PID controller showed its ability to detect the barcode whilst maintaining a smooth drone motion.



(a) **(b)**

Fig. 16. Barcode 2 image area versus time with a PID controller: (a) barcode 2 image area; (b) barcode 2 image area error

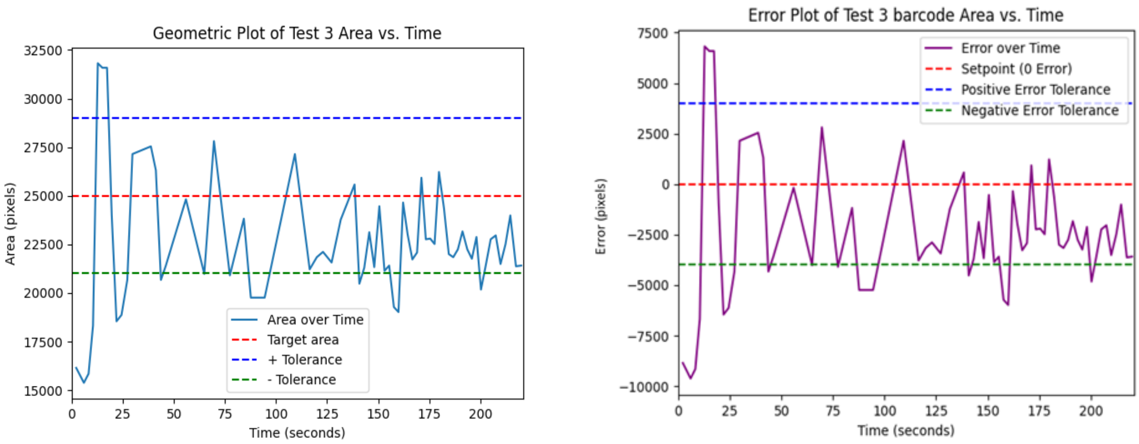
5.3 Test 3

In test 3, the small barcode 3 is selected as the smallest amongst the three tests. This barcode is measured to be 5.3 cm in width and 4 cm in length. The barcode 3 label is also affixed to the product packaging (Figure 1٧). The barcode area is 25,000 pixels, corresponding to a distance of 25 cm between the DJI Tello drone and the barcode label (Figure 18).

Fig. 17. Barcode data and area of the small-size barcode 3 of test 3

Fig. 18. Distance to barcode 2 detection

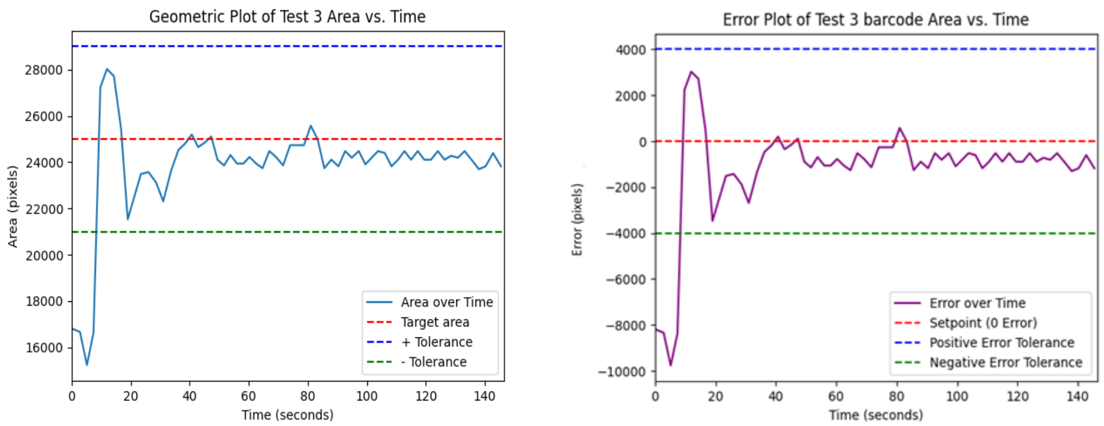
The task of detecting the barcode is applied without considering a PID controller. In this situation, the response of the process of detecting barcode 3 is presented in Figure 19. The steady state error was large, reaching an average of more than 4250 pixels, due to the exclusion of the PID controller in the barcode detecting process (Figure 19(b)). Consequently, the detection rate of the barcode area reached approximately 29,250 pixels (Figure 19(a)), which is not close to the desired value of 25,000 pixels. This situation resulted in the inability to detect the intended barcode 2 even considering tolerance in the range of 4000 pixels due to the oscillation in the drone when moved or stopped.



(a) **(b)**

Fig. 19. Barcode 3 scanning without a PID controller: (a) barcode 3 image area; (b) barcode 3 image area error

The developed controller in this study is considered in the task of detecting barcode 3. The implementation of the PID controller showed its ability to minimise the image area error to ±٦٥٠ pixels (Figure 20(b)). This situation caused the enhancement of the process of detecting the barcode, wherein the actual image area ‘A_b’ reached the desired image area ‘R_b’, which is equal to 24,000 pixels (Figure 20(a)). In this situation, the PID controller showed its ability to effectively detect the barcode whilst maintaining a smooth drone motion.

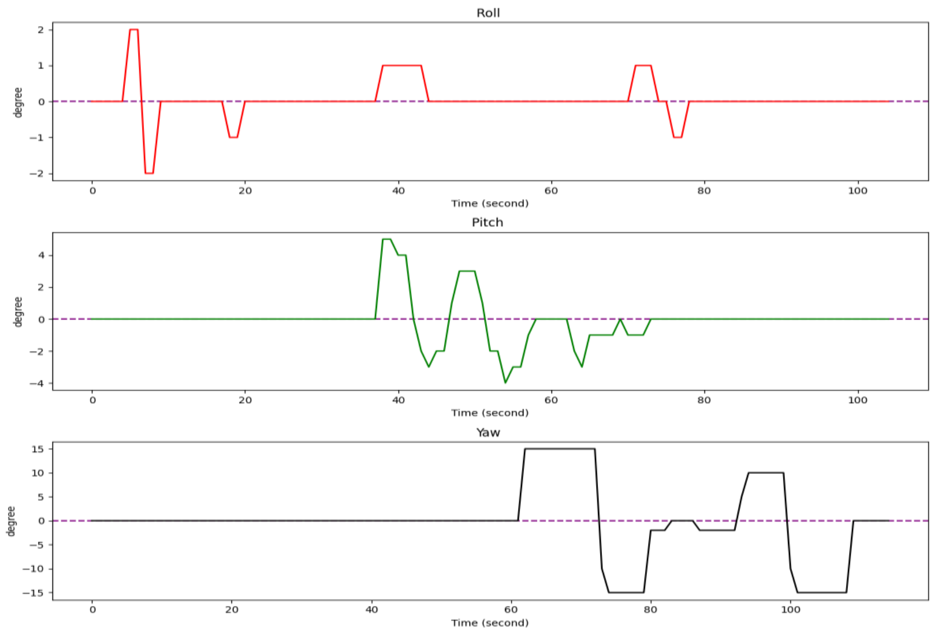


(a) **(b)**

Fig. 20. Barcode 3 image area versus time with PID controller: (a) barcode 3 image area; (b) barcode 3 image area error

5.4 Test 4

In monitoring the flight behaviour of the DJI Tello drone during scanning and detecting a potential barcode, test 4 is implemented to address the roll, pitch and yaw angles of the DJI Tello drone specified in Figure 4 (b) and its altitude over time. The aforementioned drone flight behaviour is monitored using the designed PID controller and the proposed algorithm developed in this study for barcode detection. This test is conducted using the configuration parameters from test 2 as a case study for barcode 2 whilst also considering the influence of noise. However, in this test, the noise is assumed in the form of image data, where an unclear image is obtained due to the presence of dust in the warehouse environment. Dust is considered a potential source of unclear image acquisition data. The roll value exhibits minor fluctuations caused by the lateral motion of the drone during the initial approach to the barcode and thereafter reaches a stable state at 0° (Figure 21). The pitch value initially changes as the drone moves towards barcode 2 whilst reading the barcode area, to attain the intended area. The associated oscillations can be observed throughout this motion. However, the value reaches a stable state at 0° after the barcode 2 area is detected. The noticeable differences in yaw result from the drone veering clockwise and counterclockwise to precisely adjust its angle for an accurate barcode reading.



Figs. 21. Relation between the initial values of roll, pitch and yaw

In terms of drone altitude, the targeted height is equal to 180 cm (Figure 7), which represents the height of barcode 2. When the drone approaches the intended altitude, it initiates a deceleration process at time 13 s to reach the targeted height location at 16 s (Figure 22). Subsequently, the drone ascends again to reach the precise objective, slightly surpassing it before entering the stabilisation phase. Thereafter, the drone exhibits oscillations between 16 s and 25 s around the predetermined altitude due to the minor vibrations of the drone during flight. Nevertheless, this drone exhibits a good stabilising capability, consistently achieving an accuracy of 1–3 cm around the intended altitude. Between 1 s and 10 s, the initial bias of 80 cm results from the drone starting its flight at a predetermined height of 80 cm, as specified in its programming.

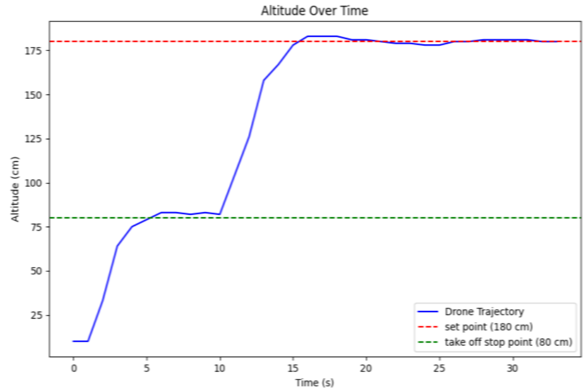


Fig. 22. Altitude over time for the DJI Tello drone

Afterward, the ability of the introduced PID controller and algorithm in this study to overcome noise existing in the image data is tested (Figure 23). The results showed that the introduced technique in this study can effectively mitigate the influence of noise, allowing for accurate reading of barcodes, as the OpenCV and Pyzbar libraries provide processing without affecting the area or barcode data.

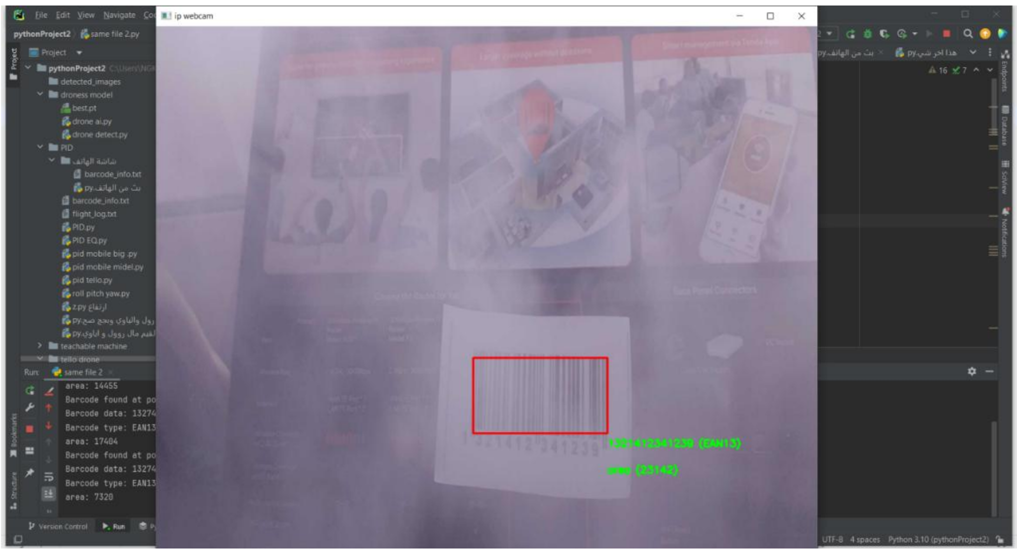


Fig. 23. Barcode data extraction with noise

6. Discussion

The experimental results obtained from tests 1, 2 and 3, as evidenced by the comparisons of Figure 11 with Figure 12, Figure 15 with Figure 16 and Figure 19 with Figure 20, validate the efficacy of the developed PID controller in minimizing errors throughout the barcode scanning process. The oscillation of the drone body caused by the rotation of the propellers made it impossible to minimise the average barcode area tracking error to zero. In addition, even when the propellers are not rotating, the captured images still exhibit variability due to the noise in the drone camera itself. The efficacy of the constructed PID controller, in conjunction with the developed algorithm, to scan various barcode sizes is demonstrated in tests 1, 2 and 3, which detect large, medium and small barcode sizes, respectively. The gathered barcodes encompass large, medium and small sizes frequently utilised in storage warehouses as potential case studies. Consequently, the introduced methodology demonstrated a significant ability to successfully recognise all the specified potential barcodes whilst utilising the PID algorithm, as demonstrated by the data in Table 3.

Table 3,
Comparison between using a PID controller and without a PID controller

Feature	With PID	Without PID
Barcode reading accuracy	High; reads various barcode sizes	Less accurate due to the lack of dynamic correction. Problems with small barcode sizes
Reading response	A little longer; due to time taken to adjust barcode area tracking	Faster response
Read error rate	Low; PID minimises error fluctuation	Higher, performance fluctuation is occurs
Dealing with changing environmental conditions	Better; as PID helps in adapting to changes	Significantly affected by changes
Performance stability	More stable; due to dynamic control.	Unstable in some conditions
Ease of implementation	More complex and requires precise settings.	Easier to implement but less efficient

Test 4 evaluates the DJI Tello drone's performance, demonstrating the efficacy of the proposed PID controller in tracking the barcode region, resulting in a relatively smooth flight behaviour. Figure 21 illustrates the roll, pitch and yaw angles of flying behaviour, whereas Figure 22 represents the altitude. Table 4 presents the effect of integrating integrated PID controller with image processing in our study.

Table 4,
Comparison of the average error without a PID controller and error with a PID controller

Tests	Average error without a PID	Average error with a PID
Test 1	5000 pixels	200 pixels
Test 2	4000 pixels	100 pixels
Test 3	3800 pixels	600 pixels

According to Table 4, the PID value for the second test exhibited greater stability than that of the first test, despite being smaller, due to the enhanced clarity of the second barcode, which featured more distinctly defined edges for the drone camera's reading. By contrast, the first test presented a diminished length-to-width ratio due to its relatively small length compared with its width. The second barcode is comparatively large, facilitating clearer readability by the drone camera. In test 3, the area was challenging to be detected because to the barcode's small size. The minimal distance between the drone and the barcode (Figure 18) results in an adequate reading of the area. Nonetheless, a discernible variation can be observed from 600 in test 3 to 100 in test 2, resulting in a comparatively low error rate in test 2 relative to test 3. In the first three tests, the larger barcode was detected at a greater distance by the drone (Table 5). This phenomenon is attributed to the cameras that can more clearly see larger objects than smaller ones from a greater distance.

Table 5,
Results of the three barcode areas and distances between the DJI Tello drone and the barcode label

Test	Dimension (cm)	Area (pixel)	Distance (cm)
1	14.75 × 2.9	51,000	55
2	9.6 × 7.1	40,000	40
3	5.3 × 4	25,000	25

The response time of barcode detection is shown in Table 6, based on Figures 11, 12, 15, 16, 19 and 20. The PID controller minimises the time of barcode detection. The response of detecting the barcode reduced with the decrease in the size area of the barcode. This phenomenon is reflected in the results presented in Table 5, which show that the distance for barcode detection decreases with the decrease in the size of the barcode.

Table 6,
Time response for the barcode scanning area.

Tests	Without PID	With PID
Test 1	40 s	26 s
Test 2	38 s	23 s
Test 3	30 s	18 s

Drones can achieve exceptional barcode scanning performance by utilising sophisticated computer vision technology based on a PID controller, which includes image processing and machine learning algorithms embedded in the OpenCV and Pyzbar libraries. An inherent advantage of using PID computer vision for barcode identification is its ability to adapt to changing circumstances, such as noise in the warehouse, which affects the acquired image data (Figure 23 of test 4).

7. Conclusions

The advancements in barcode scanning, combined with the application of the PID computer vision methodology, can offer new opportunities for drones to detect barcodes in a highly precise manner, even in the presence of potential noise in warehouse environments. The methodology introduced in this study demonstrated the drone's ability to avoid collisions with boxes or warehouse infrastructure, even in amidst noise, by ensuring that the drone maintains a consistent distance from the barcode. However, accuracy, response time and challenges are amongst the key points highlighted in this study. The accuracy of the designed integrated computer vision PID controller reached 0.25% through the trial-and-error technique. This result is acceptable and showed its effectiveness in detecting barcodes in various situations and environmental conditions, even in amidst noise and quadcopter vibrations. Furthermore, the response time for barcode detection indicates that the PID controller minimises the detection duration. The efficacy of barcode detection decreases with the decrease in the size of the barcode area. This phenomenon is attributable to the reduction in the distance between the DJI Tello drone and detected barcode with the decrease in the barcode size. One of the challenges is the necessary inclusion of a tolerance of ±٤000 pixels for the barcode area, aimed at accommodating oscillations that are caused by the movement of the drone whilst it is in flight to improve the algorithm's consistency. This adjustment aimed to improve the algorithm's reliability. Another challenge is the use of a suitable barcode threshold area. The drone can maintain a suitable distance from the barcode whilst reducing the likelihood of collisions with nearby objects or warehouse equipment. These pixel areas have been selected as the optimal threshold, which is a significant achievement in terms of guaranteeing precise and efficient barcode tracking in warehouse settings. In future work, optimisation techniques can be applied to determine the optimal values for the PID controller gains.

Reference

[1] Fadhillah, A. H. I., Safrudin, A. T., & Darma, S. (2020, April). Unmanned aerial vehicle object tracking and following. In *Journal of Physics: Conference Series* (Vol. 1528, No. 1, p. 012018). IOP Publishing.

[2] Idrissi, M., Salami, M., & Annaz, F. (2022). A review of quadrotor unmanned aerial vehicles: applications, architectural design and control algorithms. Journal of Intelligent & Robotic Systems, 104(2), 22.

[3] Tamilarasan, V., Stallone, A., Gnanaseka, R., Dhanapa, B.R., Jebastin, J., Kandhampalayam, M.S., & Arthanarisamy, N.H. (2023). Development of Surveillance Quadcopter. NanoWorld Journal.

[4] Mariani, M., & Fiori, S. (2023). Design and Simulation of a Neuroevolutionary Controller for a Quadcopter Drone. Aerospace.

[5] Koulouris, C., Dimitrios, P., Al-Darraji, I., Tsaramirsis, G., & Tamimi, H. (2023, May). A Comparative Study of Unauthorized Drone Detection Techniques. In *2023 9th International Conference on Information Technology Trends (ITT)* (pp. 32-37). IEEE.

[6] Sartori, F. (2024). EFFECTIVE IMPLEMENTATION OF INDUSTRY 4.0 APPROACHES FOR PROCESS MONITORING IN THE BATCH MANUFACTURING OF SPECIALTY CHEMICALS.

[7] Salah, B. (2021, November). Real-time implementation of a fully automated industrial system based on IR 4.0 concept. In *Actuators* (Vol. 10, No. 12, p. 318). MDPI

[8] Tsaramirsis, G., Kantaros, A., Al-Darraji, I., Piromalis, D., Apostolopoulos, C., Pavlopoulou, A., ... & Khan, F. Q. (2022). A modern approach towards an industry 4.0 model: From driving technologies to management. *Journal of Sensors*, *2022*, 1-18.

[9] Mohammed, N. A., Abdulateef, O. F., & Hamad, A. H. (2023). An IoT and machine learning-based predictive maintenance system for electrical motors. *Journal Européen des Systèmes Automatisés*, *56*(4), 651-656.

[10] Warehousing 4.0: A proposed system of using node-red for applying internet of things in warehousing

[11] Tamilarasan, V., Stallone, A., Gnanaseka, R., Dhanapa, B.R., Jebastin, J., Kandhampalayam, M.S., & Arthanarisamy, N.H. (2023). Development of Surveillance Quadcopter. NanoWorld Journal.

[12] Kostin, A.S. (2021). MODERN TRENDS IN THE DEVELOPMENT OF WAREHOUSE LOGISTICS IN ACCOUNTING THE APPLICATION OF DRONES.

[13] Mariani, M., & Fiori, S. (2023). Design and Simulation of a Neuroevolutionary Controller for a Quadcopter Drone. Aerospace.

[14] Roy, A., Rasal, A., Gavhane, V., & Javali, R. (2024). Autonomous Quadcopter for Surveillance. International Journal of Advanced Research in Science, Communication and Technology.

[15] Lichao Xu, Vineet R. Kamat & Carol C. Menassa (2018) Automatic extraction of 1D barcodes from video scans for drone-assisted inventory management in warehousing applications, International Journal of Logistics Research and Applications, 21:3, 243-258, DOI: 10.1080/13675567.2017.1393505.

[16] D. Cristiani, F. Bottonelli, A. Trotta and M. Di Felice, "Inventory Management through Mini-Drones: Architecture and Proof-of-Concept Implementation," *2020 IEEE 21st International Symposium on "A World of Wireless, Mobile and Multimedia Networks" (WoWMoM)*, Cork, Ireland, 2020, pp. 317-322, doi: 10.1109/WoWMoM49955.2020.00060.

[17] Qi, P.; Zhang, L.; Wang, Z.; Han, H.; Müller, J.; Li, T.; Wang, C.; Huang, Z.; He, M.; Liu, Y.; et al. Effect of Operational Parameters of Unmanned Aerial Vehicle (UAV) on Droplet Deposition in Trellised Pear Orchard. *Drones* 2023, *7*, 57. https://doi.org/10.3390/drones7010057.

[18] Stanko, F. Stec, L. Palkovic, J. Rodina and D. Rau, "Towards Automatic Inventory Checking Using an Autonomous Unmanned Aerial Vehicle," *2022 IEEE 27th International Conference on Emerging Technologies and Factory Automation (ETFA)*, Stuttgart, Germany, 2022, pp. 1-8, doi: 10.1109/ETFA52439.2022.9921460.

[19] Boonsongsrikul, A., & Eamsaard, J. (2023). Real-time human motion tracking by tello EDU drone. *Sensors*, *23*(2), 897.

[20] Virbora, N., Sokoeun, U., Saran, M., Channareth, S., & Saravuth, S. (2022, October). Implementation of Matrix Drone Show Using Automatic Path Generator with DJI Tello Drones. In *2022 International Conference on Engineering and Emerging Technologies (ICEET)* (pp. 1-5). IEEE.

[21] Giernacki, W., Rao, J., Sladic, S., Bondyra, A., Retinger, M., & Espinoza-Fraire, T. (2022, June). DJI tello quadrotor as a platform for research and education in mobile robotics and control engineering. In *2022 International Conference on Unmanned Aircraft Systems (ICUAS)* (pp. 735-744). IEEE.

[22] Muñoz, J., Monje, C. A., Mena, L., & Balaguer, C. (2022). Educational low cost platform for control engineering. In *XLIII Jornadas de Automática* (pp. 295-301).

Universidade da Coruña. Servizo de Publicacións.

[23] Alok Raj, Bhawesh Sah, Analyzing critical success factors for implementation of drones in the logistics sector using grey-DEMATEL based approach, Computers & Industrial Engineering, Volume 138, 2019, 106118, ISSN 0360-8352, https://doi.org/10.1016/j.cie.2019.106118.

[24] Elaskari, S., Imran, M., Elaskri, A., & Almasoudi, A. (2021). Using barcode to track student attendance and assets in higher education institutions. *Procedia Computer Science*, *184*, 226-233.

[25] Jaramillo-Rodriguez, E. (2022). Barcode Posets: Combinatorial Properties and Connections. arXiv preprint arXiv:2206.05613.

[26] Burghelea, D. (2023). " Barcodes" for continuous maps and a brief introduction to Alternative Morse Theory. arXiv preprint arXiv:2305.19828.

[27] L. McCathie, "The advantages and disadvantages of barcodes and radio frequency identification in supply chain management", 2004

[28] S. Ajami and M. W. Carter, "The advantages and disadvantages of radio frequency identification (RFID) in health-care centers; Approach in emergency room (ER)", *Pakistan J. Med. Sci.*, vol. 29, no. 1, pp. 443-448, Feb. 2013

[29] Mohammed, S. Q., Abdullah, M. N., & Al-Araji, A. S. (2023). One decade of radio frequency identification (RFID) Network Planning (RFID-NP). *Measurement: Sensors*, *26*, 100696..

[30] Gallo, O., & Manduchi, R. (2011). Reading 1D barcodes with mobile phones using deformable templates. *IEEE transactions on pattern analysis and machine intelligence*, *33*(9), 1834-1843.

[31] Xu, L., Kamat, V. R., & Menassa, C. C. (2017). Automatic Barcode Extraction for Efficient Large-Scale Inventory Management. In Computing in Civil Engineering 2017 (pp. 340-348).

[32] Xu, L., Kamat, V. R., & Menassa, C. C. (2018). Automatic extraction of 1D barcodes from video scans for drone-assisted inventory management in warehousing applications. International Journal of Logistics Research and Applications, 21(3), 243-258.

[33] Horcher, A., & Visser, R. J. (2004). Unmanned aerial vehicles: applications for natural resource management and monitoring. Proceedings of the Council on Forest Engineering Proceedings, 5.

[34] Xu, L., Kamat, V. R., & Menassa, C. C. (2018). Automatic extraction of 1D barcodes from video scans for drone-assisted inventory management in warehousing applications. International Journal of Logistics Research and Applications, 21(3), 243-258.

[35] Bayas, M.O., Modhe, M.K., Kulkarni, M.A., Londhe, M.A., & Chaitanya, D.S. (2023). Smart Surveillance Drone – Warehouse Operations. International Journal of Advanced Research in Science, Communication and Technology.

[36] Yoon, B., Kim, H., Youn, G., & Rhee, J. (2021, October). 3D position estimation of drone and object based on QR code segmentation model for inventory management automation. In 2021 IEEE International Symposium on Safety, Security, and Rescue Robotics (SSRR) (pp. 223-229). IEEE.

[37] Szeliski, R. (2022). Computer vision: algorithms and applications. Springer Nature.

[38] Xu, S., Wang, J., Shou, W., Ngo, T., Sadick, A. M., & Wang, X. (2021). Computer vision techniques in construction: a critical review. Archives of Computational Methods in Engineering, 28, 3383-3397.

[39] Xiao, Y.; Ming, Z. 1D Barcode Detection via Integrated Deep-Learning and Geometric Approach. *Appl. Sci.* 2019, *9*, 3268. https://doi.org/10.3390/app9163268

[40] Oudah, N., Esmaile, M. F. and Abdulredaa, E. (2018) “Optical Character Recognition Using Active Contour Segmentation”, Journal of Engineering, 24(1), pp. 146–158. doi: 10.31026/j.eng.2018.01.10

[41] M. Demirhan and C. Premachandra, "Development of an Automated Camera-Based Drone Landing System," in *IEEE Access*, vol. 8, pp. 202111-202121, 2020, doi: 10.1109/ACCESS.2020.3034948

[42] I. Kalinov *et al*., "WareVision: CNN Barcode Detection-Based UAV Trajectory Optimization for Autonomous Warehouse Stocktaking," in *IEEE Robotics and Automation Letters*, vol. 5, no. 4, pp. 6647-6653, Oct. 2020, doi: 10.1109/LRA.2020.3010733.

[43] https://www.morovia.com/kb/EAN13-Specification-10633.html.

[44] L. Hudson, “Pyzbar: Read one-dimensional barcodes and QR codes from Python 2 and 3” [Internet], PyPI, [cited 2022 Feb 2], Available from: https://pypi.org/project/Pyzbar

[45] FERANO, F. C. A., OLAJUWON, J. K., & PUTRA, G. (2022). QR CODE DETECTION AND RECTIFICATION USING PYZBAR AND PERSPECTIVE TRANSFORMATION. Journal of Theoretical and Applied Information Technology, 100(21).
[46] Wonghong, T., & Engell, S. (2011, September). Real-time PI controller tuning via unfalsified control. In 2011 IEEE International Symposium on Intelligent Control (pp. 1008-1013). IEEE.
[47] Ai, T., Yu, J. Q., Liu, Y. F., & Zhou, J. (2010, May). Study on neural network self-tuning PID control for temperature of active solar house heating system. In 2010 2nd International Workshop on Intelligent Systems and Applications (pp. 1-4). IEEE.
[48] Al-Isawi, M. M., Attiya, A. J., & ADOGHE, J. O. (2020). UAV control based on dual LQR and fuzzy-PID controller. Al-Khwarizmi Engineering Journal, 16(3), 43-53.
[49] Abbas, Y. K. (2012). Genetic Algorithm Based PID Controller Design for a Precise Tracking of Two-Axis Piezoelectric Micropositioning Stage. *Al-Khwarizmi Engineering Journal*, *8*(4), 40-52.
[50] Kara, T., & Mary, A. H. (2018). Robust trajectory tracking control of robotic manipulators based on model-free PID-SMC approach. *Journal of Engineering Research*, *6*(3).
[51] Nassim, M., & Abdelkader, A. (2021). Speed Control of DC Motor Using Fuzzy PID Controller. arXiv preprint arXiv:2108.05450.
[52] Dagher, K. A., & Al-Araji, A. S. (2013). Design of an adaptive PID neural controller for continuous stirred tank reactor based on particle swarm optimization. Al-Khwarizmi Engineering Journal, 9(4), 46-53.
[53] Al-Khayyt, S. Z. S. (2013). Tuning PID controller by neural network for robot manipulator trajectory tracking. *Al-Khwarizmi Engineering Journal*, *9*(1), 19-28.
[54] Anders, S., Pyl, P. T., & Huber, W. (2015). HTSeq—a Python framework to work with high-throughput sequencing data. bioinformatics, 31(2), 166-169.
[55] Peirce, J. W. (2007). PsychoPy—psychophysics software in Python. Journal of neuroscience methods, 162(1-2), 8-13

مسح الباركود باستخدام طائرة كوادكوبتر بدون طيار باستخدام كاميرا الرؤية وتقنيات التحكم PID للمستودع في مصانع الجيل الرابع

سامر رزاق هلال[١*]، عزة عبدالرزاق عبد الكريم[٢]، حسام جربى[٣]
١، ٢ قسم هندسة التصنيع المؤتمت، كلية الهندسة الخوارزمي، جامعة بغداد، بغداد، العراق
٣ قسم الهندسة الصناعية، كلية الهندسة، جامعة الحائل السعودية العربية
*البريد الالكتروني: samer.razaq2204@kecbu.uobaghdad.edu.i

الخلاصة

تلعب الطائرات بدون طيار دورًا حيويًا في الجوانب الأساسية للصناعة ٤,٠ من خلال تحويل المستودعات التقليدية إلى مستودعات ذكية، لا سيما في مجال مسح الباركود. تنشأ العديد من المشكلات المحتملة بشكل متكرر أثناء مسح الباركود بواسطة الطائرات بدون طيار، خاصة عندما تواجه كاميرا الطائرة بدون طيار صعوبة في الحصول على صور مميزة بسبب عوامل مثل المسافة، أو التقاط الصورة أثناء الطيران، أو أبعاد الباركود المختلفة. ولمواجهة هذه التحديات، يقترح هذا العمل نهجًا جديدًا يجمع بين وحدة التحكم المتناسبة والتكاملية والمشتقة (PID) مع تقنيات معالجة الصور. وحدة التحكم PID مسؤولة عن المراقبة المستمرة لمدخلات الكاميرا، واكتشاف الفرق بين صورة الباركود المخططة والحقيقية، وإجراء تغييرات فورية على موضع الطائرة بدون طيار لتحسين أداء الكاميرا. تم تطبيق المنهجية المذكورة على طائرة DJI Tello بدون طيار للتحقق عمليا من أداء المنهجية المقترحة لهذه الدراسة. وكشفت النتائج العملية أن الطائرات بدون طيار يمكنها تحقيق أداء رائع في مسح الباركود من خلال دمج تقنيات رؤية الكمبيوتر المتطورة في وحدات التحكم PID. إن خوارزميات رؤية الكمبيوتر PID قادرة على تحليل البيانات المرئية التي تم الحصول عليها من كاميرات الطائرة بدون طيار واسترجاع معلومات الباركود في ظل مجموعة متنوعة من المواقف.