Robotics and Autonomous Systems 161 (2023) 104342

Contents lists available at ScienceDirect

Robotics and Autonomous Systems

journal homepage: www.elsevier.com/locate/robot

A Review of quadrotor UAV: Control and SLAM methodologies ranging from conventional to innovative approaches

Güray SONUGÜR

Mechatronics Engineering, Faculty of Technology, Afyon Kocatepe University, Afyonkarahisar, Turkey

ARTICLE INFO

Article history:
Received 15 October 2021
Received in revised form 30 November 2022
Accepted 12 December 2022
Available online 20 December 2022

Keywords:
UAV
Quadrotor
Flight control
SLAM

ABSTRACT

There are two indispensable methodologies for autonomous flights performed by unmanned aerial vehicles (UAV). The first is flight control, and the other is simultaneous localization and mapping (SLAM). In the literature, these two issues are generally considered separately. However, they have very close relationships with each other. In this study, both methods were extensively examined in the literature, especially for quadrotors. Quadrotors, also known as quadrotors, are rotary-wing UAVs capable of vertical take-off and landing. As their use becomes widespread worldwide, the number of studies conducted to enable autonomous tasks is growing. The study was prepared under three subtitles. First, a fast and simple introduction of quadrotors was made, and the advances in this area were discussed. In the next section, studies on the position, attitude, and altitude control methods required for the autonomous use of such aircraft are analyzed based on linear, nonlinear, and intelligent methods. As the third subheading, research on SLAM techniques was widely discussed. Frequently used performance metrics, application environments, and results were presented in detailed tables for studies in both areas. Comparative studies were particularly emphasized, and the best results obtained were expressed in tables. The hardware implementations of the mentioned applications were also reviewed. Thus, hardware and method-based quick reference resource were created for researchers. As a consequence, the objective of this research is to provide a comprehensive resource for researchers working on quadrotor navigation systems to effectively select the flight control and SLAM methods they will employ.

1. Introduction

Unmanned aerial vehicles (UAVs) have become the subject of research interest because they can support humans in unsafe and inaccessible conditions and be used effectively in military activities, search and rescue, security, and remote sensing. UAVs can be classified based on management, structural, or weight. In management-based classifications, they can be categorized into remotely operated, semi-autonomous, and fully autonomous. Flight management in remote-controlled UAVs is completely carried out by the pilot through a ground station. Although the vehicle's control system may make certain decisions, a pilot still controls semi-autonomous vehicles, often in emergencies. It can, for example, avoid an obstacle on its path or make an emergency landing decision to avoid falling when the battery runs out. There is no pilot control in any flight phase in fully autonomous UAVs. The vehicle's control system produces all decisions. UAVs weighing less than 150 kg are classified as micro, mini, and small UAVs. UAVs weighing less than 2 kg are classified as micro, those between 2–4 kg as mini, and those between 4–150 kg as small. The structural classification of UAVs is given in two categories: fixed wings and rotating wings. However, there are intermediate classes that have the characteristics of both classes. Fixed-wing UAVs require a runway for landing and take-off, and skill training is essential. They can fly for long periods when fossil-fuel engines are used. Vertical Take-off and Landing (VTOL) features can be added to Fixed Wing Hybrid UAVs. These types of UAVs are currently under development [1]. Rotary wing UAVs are classified into two groups by the number of rotors: single-rotor and multi-rotor. UAV systems have a range of advantages and drawbacks.

- Due to the vibrations caused by the wind at high altitudes, the center of gravity will shift rapidly, and there is a high risk of breaking when control is lost [2].
- Due to limited flight time, limited remote sensing, and limited power consumption, it can not be used in critical missions, particularly for mini UAVs weighing less than 4 kg [3].

E-mail address: gsonugur@aku.edu.tr.

https://doi.org/10.1016/j.robot.2022.104342

However, considering the benefits given below, their importance is increasing today.

- High speed, not being impacted by obstacles on land, being able to have an advantageous view from high altitude, not being detected due to high altitude [4]
- Using high maneuverability to navigate in narrow indoor environments [4]
- Less damage to the ecosystem [5].

Quadrotors, a sub-class of rotary-wing UAVs, are favored because of their agility, vertical landing and take-off, hovering performance, low cost, and production ease [6]. In quadrotors, the rotors are mounted in an upward direction with their propellers parallel to the ground and placed squarely at an equal distance to the center of gravity of the main body (chassis) [7]. Rotors on the same horizontal axis must rotate in opposite directions for the rotors to generate a stable upward thrust. The first UAVs were used by the Austrians in August 1849. During the siege of Venice, the Austrian army sent about 30 balloons filled with bombs toward Venice, and at least one balloon reached the city [8]. The concept of a quadrotor is not new. Its development and testing go back to the early 1900s. In 1907, French brothers Jacques and Louis Breguet constructed and tested the Gyroplane No. 1, a quadrotor, in an attempt to take off with a multi-rotor aircraft. With impractical analysis, they were able to take off despite the aircraft's unstable design. In 1920 prototypes of four-rotors were tested by Oehmichen and Bothezat. During World War I, the first UAVs with a flight control system were built and deployed to attack zeppelins. Radio signals were used to remotely control these UAVs. Since World War I, quadrotor UAVs have been under development; the Curtiss N2C-2 quadrotor was built in 1937 by the United States military as the first radio-controlled aircraft. Reginald Denny created the Radio plane OQ-2 (fixed-wing UAV), which was the first mass-produced drone used for military objectives in 1941 [9]. Due to a lack of sensitive sensors and reliability difficulties, no development on quadrotors has been done since this date. However, developments in technology in the latter part of the 2000s, specifically micro electro-mechanic systems, made it possible to manufacture low-cost and lightweight sensor components such as accelerometers, GPS, barometers, and cameras. These advancements were made possible by the advent of new technologies. Because of its compact size and fairly simple mechanical design, the quadrotor has emerged as a popular choice for use as a research platform for novel concepts in a variety of domains, including flight control theory, navigation, real-time systems, and robotics [10,11]. Today, they have become very popular due to their useful load capacity, remote management, maneuverability, cheap maintenance costs, mechanical simplicity, independent control of rotors, and ease of electronic control. They are also less likely to crash with external objects such as helicopters with huge blades or other aircraft because they can be used with smaller propellers [12]. Quadrotors can perform six degrees of freedom (DoF) movements with yaw, pitch, and roll maneuvers and translational movements in three separate axes (x, y, z). These movements are shown in Fig. 1.

There are various types of quadrotor designs available. When reviewing the literature, it was observed that the researchers generally operate on mini quadrotors, which are less than 4 kg, as in this study. In larger quadrotors, the flight parameters are substantially influenced by weight. The number of studies is, therefore, lower [13]. The design of the quadrotor offers a range of advantages over traditional helicopters and fixed-wing aircraft. For instance, by adjusting the speed of each rotor, the thrust can be changed easily, thereby avoiding complex and variable pitching components. Furthermore, because of the rotation of the rotors in the opposite direction, the overall torque is equalized. Therefore, this design does not need a tail rotor [14].

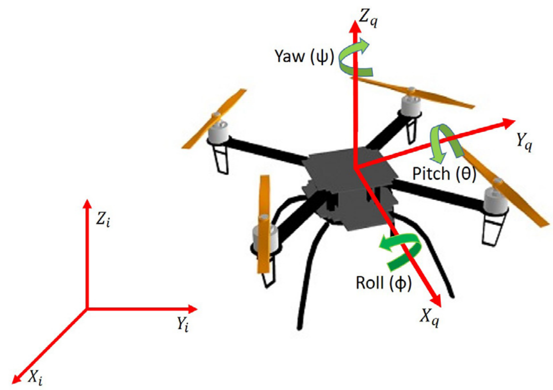

Fig. 1. Quadrotor maneuvers. (X_q, Y_q, Z_q) denotes the quadrotor's coordinate axes, and (X_i, Y_i, Z_i) denotes the reference coordinate axes, $(\varnothing, \theta, \Psi)$ denotes the roll, pitch, and yaw angles.

In order to fly a quadrotor autonomously, the data obtained from the sensors is of great importance. There are size and weight limitations for the sensors to be used in quadrotors. As UAVs become popular, smaller sensors are produced with higher sensitivity and accuracy. One of the most important sensors is the Inertial Measurement Unit (IMU). IMUs are integrated sensors consisting of an accelerometer and a gyroscope. Accelerometers measure the orientation of the quadrotors, while gyro sensors measure axial angles. Depending on the type of sensors, they calculate axial angles of rotation in two or three axes. While the vehicle is hovering or flying straight, the IMUs detect any imbalance in the vehicle and send feedback to the control system to correct the balance [15–17]. IMUs can also be used to estimate the speed of quadrotors using a fine-tuned sensor fusion filter [18]. LIDAR (Laser Imaging Detection and Ranging) sensors, which measure laser beam-based distance, are mostly used for obstacle avoidance, altitude measurement, and navigation [19,20]. Some LIDAR models can make exact measurements, but it should be taken into account that as the precision increases, the size and weight of LIDAR will also increase. Global Positioning System (GPS) sensors, which are used to determine the current position and route of the quadrotors, are also critical sensors [21–24]. The sensitivity of GPS devices that can be used in quadrotors generally varies between one and five meters. Global Navigation Satellite System (GNSS) devices, which are more sensitive than GPS sensors, cannot be used in quadrotors smaller than 4 kg due to their size and weight. Besides, GPS alternative mechanisms should be considered in GPS-denied environments and military operations where signals may be disturbed. Cameras are among the most widely used sensors in quadrotors [22,25,26]. They are used to perform many important tasks such as capturing video from the air and transmitting it to the ground station instantly, object detection and recognition operations, obstacle avoidance, and providing feedback for control systems. In more advanced applications, velocity measurements are also made using the optical flow method [27]. When the literature is examined, it is discovered that the quadrotor modeling is performed with Newton-Euler-based [14,23,28–31] or Euler–Lagrange-based [32,33], with generally similar results. Therefore, modeling is not covered in this paper.

Navigation, obstacle avoidance, and target tracking are as important as stability control during flight for an autonomous quadrotor or any UAV. Therefore, we tried to evaluate control and SLAM applications together in this study. Furthermore, because

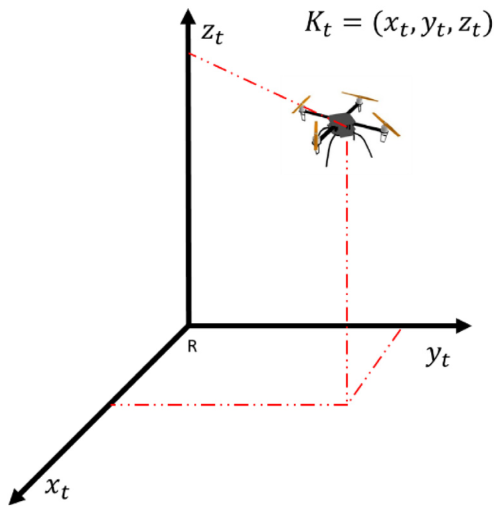

Fig. 2. Quadrotor position with respect to the reference point R.

quadrotors have a relatively small structure, these applications' hardware is essential. As a result, evaluations based on hardware types are also included in our research. In other survey studies in the literature, two subjects, control [34,35] or SLAM [36,37], were handled individually, and the hardware part was not evaluated in general. In this study, it was attempted to decide whether conventional or innovative methods, such as intelligent and hybrid approaches, should be used to develop a robust control and navigation system for quadrotors. The following sections of this paper are as follows. Flight control methods of quadrotors are discussed in Section 2. SLAM methods required for autonomous flight are presented in Section 3. Finally, in Section 4, the concluding points are evaluated.

2. Flight control in quadrotors

Quadrotors are becoming more popular due to their agility, vertical take-off and landing, hovering performance, low cost, ease of manufacture, navigation in narrow indoor environments, aerial observation capabilities [6], etc. Because of these benefits, it has become a major topic in autopilot and low-level controlled UAV research [14]. The most important requirements for the autonomous flight of a quadrotor are effective position control, altitude control, and attitude control (stabilization) [23]. However, quadrotors are highly complex and difficult-to-control vehicles due to their non-linear, underactuated, multivariable and unstable nature [38]. UAVs have size, weight, and power constraints that other systems do not. Because they operate in situations where humans may be present, they are also safety-critical systems [39–41]. Position control is the control of the displacement of the UAVs according to a certain reference point. Extracting the position information of a quadrotor is shown in Fig. 2.

Here, K_t is the location vector of the quadrotor containing the x (longitudinal), y (lateral), and z (altitude) coordinates. The displacement of an autonomously operated quadrotor takes place in accordance with a trajectory tracking procedure. Therefore, such control procedures are also called trajectory tracking control. There are fewer target tracking and altitude tracking studies in the literature than trajectory tracking studies. In Altitude tracking, only the z-axis is controlled and is a sub-topic of trajectory tracking. On the other hand, Target tracking is an open subject and is mostly studied under the heading of vision-based control [27]. For effective control, the stabilization parameters $(\theta_t, \phi_t, \psi_t)$ which

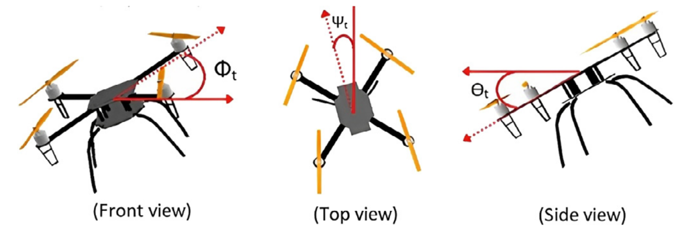

Fig. 3. Stabilization parameters of a quadrotor.

expresses the Euler angles of the UAVs should be controlled together with the position vector. These parameters are shown in Fig. 3.

In the Fig. 3, θ_t represents the pitch angle, ϕ_t represents the roll angle and ψ_t represents the yaw angle. In the literature, in many flight control research, the mathematical model was derived from quadrotors. We did not thus include in our study the mathematical model. Quadrotors are controlled by setting the angular speeds of four brushless motors in specific combinations. Each rotor combination produces thrust, yaw torque, pitching torque, and rolling torque. As a result, the rotor revolutions determine the vehicle's thrust, torque, and speeds on the x, y, and z axes [42]. Creating a difference in the speeds of the right and left propellers for the rolling motion of an X-type quadrotor is an example of rotor combinations. Similarly, the relative speeds of the front and rear rotors for the pitching motion are changed [43]. A simple control loop of a quadrotor is shown in Fig. 4.

A quadrotor control loop consists of two nested loops. The outer loop performs position control. The inner loop performs attitude control. Here, x, y, and z are the desired positions, and φ, θ, and φ are the desired attitude angles. Consequently, the state vector is $X = [x_t, y_t, z_t, \theta_t, \varnothing_t, \varphi_t]$ and the input vector is $U = [U_1, U_2, U_3, U_4]$. If m_1, m_2, m_3 and m_4 are considered as quadrotor motor speeds;

$$U_1 = k_f(m_1^2 + m_2^2 + m_3^2 + m_4^2) \tag{1}$$

$$U_2 = k_f(-m_2^2 + m_4^2) \tag{2}$$

$$U_3 = k_f(m_1^2 - m_3^2) \tag{3}$$

$$U_4 = k_m(m_1^2 - m_2^2 + m_3^2 - m_4^2) \tag{4}$$

where k_f is aerodynamic force, k_m is moment constant, U_1 is total thrust, U_2, U_3 and U_4 are the roll, pitch, and yaw torques, respectively. In quadrotor control, position control is slower than attitude control. Also, since the roll, pitch, and yaw angles produced at the output are generally low, position control can be regarded as an approximately linear system around the equilibrium points [46].

Powerful control algorithms are required for successful autonomous flights with quadrotors. As a consequence of an effective control method, efficient navigation, obstacle avoidance, and stabilization should be accomplished. As interest in UAVs grows, control algorithms are also growing and getting more complex. A quadrotor is a system with four inputs and six output parameters [28]. Therefore, their control is a complex and difficult process. The control of six degrees of freedom, three rotation axes, and three translation axes must be carried out with only four inputs (angular speed of brushless motors). Quadrotor dynamics have different features for different flight missions such as take-off-landing, horizontal flight, aggressive maneuvers, and navigation [47]. To perform such movements, it is necessary to make precise altitude and location controls. However, for the

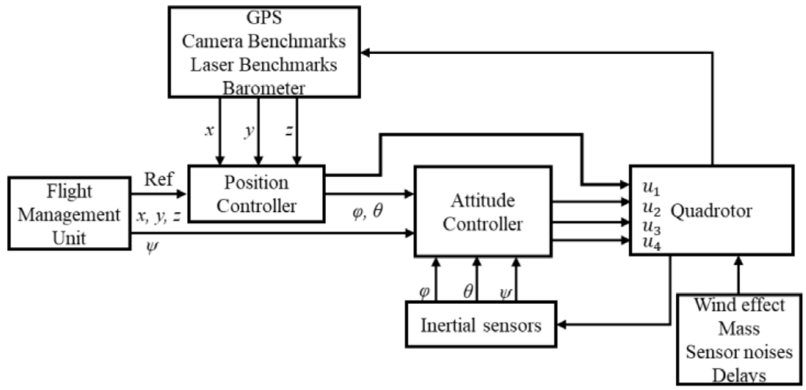

Fig. 4. The simple control loop of a quadrotor [44,45].

accurate control of quadrotors, there are challenges such as dynamic non-linearity, parametric uncertainty, disturbance effects, delays in communication, vehicle weight, wind effect, noise in sensor measurements, and activator efficiency [14,28,48]. It is important to build an efficient mathematical model considering the abovementioned factors to overcome these challenges [16]. The literature indicates that quadrotor control approaches are usually classified into three as linear, nonlinear, and artificial intelligence assisted.

2.1. Linear control methods

Linear control strategies are based on linear models of system dynamics around the desired operating point. In particular, linear control is favored in autopilot applications where maneuvering angles are limited [49]. Linear control methods include Proportional–Integral–Derivative (PID) [50–55], Linear Quadratic Regulator (LQR) [31,56,57] and Proportional-Derivative (PD) [30,58,59]. LQR is an optimal control method using state feedback. This method calculates state feedback coefficients that will provide the predetermined output parameters [60]. This method can be used in position control by using a unit quaternion approach [57]. The Linear Quadratic Gaussian (LQG) controller is created by integrating a Kalman filter into the LQR controller. In LQG controllers, system dynamics are assumed to be linear, and measurement and process noises are assumed to be stochastic [61]. In the study by Varghese and Srekala [62], the performances of LQG and H-infinity controllers are compared. Model-based predictive control (MPC) [63] refers to a class of sophisticated control approaches that use a process model to predict the future behavior of the controlled system. Dynamic Matrix Control (DMC) [64] and Generalized Predictive Control (GPC) [65] are control algorithms in this class. Model-based predictive control can even control systems that conventional feedback controllers are unable to control. This method can be applied to both linear and nonlinear systems. MPCs designed for linear systems will be examined in this section. The functions that make up the system parameters are linearized in linear MPCs. For linear MPCs, there is a comprehensive stability theory. Non-linear optimization problems with hard input constraints, on the other hand, are common. For non-linear situations, establishing robust stability is extremely challenging. This is owing to the lack of an explicit functional description of the control method, which is necessary for the majority of stability analyses [66]. MPCs are designed based on dynamic models of the process. It iteratively optimizes the current timeframe, taking into account future timeframes. MPC can predict future processes and reorganize control processes accordingly. However, the computational cost of the control loop rises as a result of this [67]. Eskandarpur and Sharf [32] proposed a linear constrained MPC to solve the path-following problem for autonomous quadrotors. Jaffery et al. [68] developed and tested a new linear MPC-based model using an indoor motion-captured testbed in their study. They compared results with PID and LQR methods and observed that PID had a smaller tracking error.

One of the most common linear methods is PID. The PID method calculates the error between the controlled signal and the desired reference value, then applies a correction based on the error's P, I, and D components. Many commercial and open-source quadrotors available on the market are PID controller-based and available in wide varieties [34]. However, there are opinions that the PID method, which is a linear method, cannot be applied efficiently in quadrotors, which is a nonlinear system [69]. Accordingly, the PID method cannot adapt to highly nonlinear systems with strong and high-frequency distortion effects and does not take into account the dynamics of the sensor and actuators that cause problems in real-time applications [70]. However, the PID approach has certain advantages that cannot be overlooked. Easy implementation, flexible parameter adjustment, easy design, and satisfactory performance [58,69]. Simulation environments are frequently used as an application area because their settings can be easily tuned [71–73]. Though less than PID, PD studies are also available in the literature [74,75]. While the PD approach produces very similar results to the PID, it is more sensitive to offset and steady-state errors [76]. In order to increase the reliability of PID and PD methods in quadrotor systems containing highly nonlinear components, the outputs are generally optimized with different methods.

2.2. Non-linear control methods

Mathematical models are completely or partially linearized to control systems having nonlinear dynamics, such as quadrotors. An example of this is the Feedback Linearization (FBL) approach [14,31,77,78], which is one of the feedback control methods. In this method, feedback control techniques are applied after linearization. Other nonlinear methods include Backstepping (BS) [79–81], Sliding Mode Control (SMC) [82–84], nonlinear H - infinity ($H\infty$) [85], and inverse dynamic control [28,86–89]. The H∞ method is one of the control methods based on the linearization principle of nonlinear systems at certain operating points, called gain scheduling [90]. H∞ is a method for controlling nonlinear systems [34], but it can also be used with linearized models [91]. In this method, firstly, the mathematical model of the system must be derived. Especially for quadrotors, a linearization process is required when creating the model. Generally, this model is optimization-based, and the controller tries to solve this optimization. The mathematical model plays the most significant role in this technique. The better the model is created, the better the controller will perform. A successful performance was obtained by using the H∞ method for trajectory tracking control in the study by Raffo et al. [85]. In the BS method, a state-space model in a chain structure is used between inputs and outputs. In this model, each state variable is used to stabilize the others. As a result, the stabilization of each state variable is calculated independently. In this method, the distinctive features and essential differences of the system controlled should be well defined [14]. Madani and Benallegue [92] have proposed a different variant of this method, the adaptive BS controller, to control a quadrotor mini-helicopter. In the study carried out by Choi and Ahn [23], the entire control system was divided into three subsystems: altitude, angular, and position. All subsystems were inspected by the BS-like feedback control method. The purpose of SMC is to push and hold the error signal against the sliding surface, also known as the switching surface. Since the sliding surface is linearly dependent on state variables, the degree of the system can be reduced to the number of independent input variables. After this stage, the system can be controlled with lower-degree control rules [93]. There are four types of SMC. These are conventional sliding mode, terminal sliding mode, fast terminal sliding mode, and nonsingular terminal sliding mode [38]. Xu and Özgüner [82] suggested a new SMC-based quadrotor control approach and succeeded in stabilizing the quadrotor. Another example is the fuzzy logic-based SMC method [29,83,84]. In this process, a knowledge base composed of linguistic expressions prepared by experts is used to ensure that the signals to be controlled do not deviate from the reference signals. Inverse dynamic control is a powerful nonlinear controller commonly used in robotic vehicles. It is based on the FBL method. This controller works correctly if both dynamic and physical parameters are defined but fails when dynamic parameters are changed [87].

2.3. Hybrid flight control methods

In hybrid methods, there are two types of integration. The first is the use of different methods to control various subsystems in a quadrotor [94], and the second is the use of multiple methods (e.g., Fuzzy-PID) when controlling a system or subsystem [55,95]. This research defines hybrid techniques as classical approaches without a learning component and learning-based intelligent approaches.

2.3.1. Classical approaches

In these control strategies, the control of different subsystems has generally been carried out with different methods. In the study conducted by Mian and Daobo [94], the thrust control of the quadrotor was performed by the BS method, and the angular position control was performed by the FBL method. In the study by Wu et al. [88], the UAV flight control system was divided into angular velocity loop, angle loop, flight path loop, and position loop. While the first two loops were controlled by a BS-based control method, the last two loops were controlled by the inverse dynamic control method. The control mechanism of the H-type quadrotor was divided into four subsystems in the study by Costa et al. [89] as location, orientation, an inclination of the rotor, and direction of the camera. The inverse dynamic control method was used for the positioning subsystem and the SMC for the others. Gao et al. [95] developed a system focused on selecting BS or adaptive fuzzy PID methods under different conditions. Either of the two methods is triggered automatically when its set criteria are reached. In the study by Orsag et al. [93], quadrotor control is divided into three subsystems: position control layer, height control layer, and angle control layer. Then PID and LQR methods were used in each layer. In the study conducted by Mercado et al. [96], A quadrotor, which can operate as both an air and a submarine vehicle, was used. PID is used for attitude control, and FBL is used for position control. In [46], two control methods were applied in two different subsystems. While applying extreme learning machine (ELM), a learning-based method, the SMC method was used to reduce external disturbances in attitude control. It has been reported that this method produces better results than applications using only SMC or PD due to its ability to converge fast and resolve unmodeled uncertainties. In another study [90], where visual feedback was used, ID-type (Integral-Derivative) controller was used for altitude control and a PD controller for horizontal motion control.

Active disturbance rejection control (ADRC) was proposed by Han [97]. ADRC is a relatively new control method that was created in recent years with the goal of closing the gap between control theory and control practice. According to Han [97], the ADRC has three main components: State Error Feedback (SEF) controller, Tracking Differentiator (TD), and Extended State Observer (ESO). It is as simple as the commonly used PID control but has more complex capabilities [98]. The standard PID controller does not perform well in heavily coupled systems while sliding mode control provides excellent dynamic control performance but needs an accurate system model. The ADRC, on the other hand, is a model-independent control approach that just requires knowledge of a system's output [99]. In [100], a new approach was developed by using a nonlinear PID instead of State Error Feedback (SEF) controller, which is an important subcomponent of ADRC, and the results were compared with PID. The developed approach was called IADRC by the authors. In [101], a new approach was proposed for the high steady-state error in the ESO component of the ADRC, and the control performances of the developed method and the conventional ADRC were compared.

Disturbance observer (DOB) can actually be considered as a sub-component of control methodologies to reduce plant uncertainties and external disturbances. Internal and external disturbances are estimated using the recognized dynamics and measurable states of plants in DOb-based robust control, and the robustness of systems is accomplished by simply feeding back the disturbance estimates [102]. Ohnishi [103] presented the first DOb-based robust motion control system in 1985. Using classical control methods, this study developed the 2-DoF control structure of a DOb-based robust control system. It was shown both theoretically and experimentally that the robustness and performance of a control system could be separately modified using a DOb and a performance controller (e.g., a PID controller) [102]. Technically, a disturbance observer is a kind of inner loop output-feedback controller that rejects external disturbances and makes the outer loop baseline controller more resistant to plant uncertainties [104]. The DOB-assisted PID approach was utilized in [105] to reduce disturbances in quadrotor position control and to obtain the required position with precision, and the results were tuned using a Q-filter. In [106], a DOB-assisted H-∞ controller was developed to stabilize a VTOL quadrotor in hover position in crosswind disturbance. During the tests, the mean errors were measured with and without DOB enabled, and it was determined that the system generated fewer errors when DOB was enabled.

Recently, UDE-based methods have received a lot of attention and have been widely used by researchers. It was proposed first by Zhong and Rees [107]. The fundamental advantage of UDE-based robust control is that it turns a robust control problem into a filter design problem in a frequency domain. It merely needs the disturbance's spectrum information. As a result, the control design becomes more straightforward to tune. This technique has been used for various linear and nonlinear systems due to its simple structure and outstanding robust performance [108]. As a result, in UDE-based robust control, a continuous disturbance signal is attempted to be matched with suitable frequency domain filters [109]. It is not necessary to have an exact model of the system in order to use UDE-based control, which can be used to control power converters, motor drives, piezoelectric stages, and wind turbines [110]. For example, in trajectory tracking research for quadrotors [111], MPC was employed for route creation and UDE for nonlinear errors in the model or external disturbances. Another research for quadrotor position and attitude control [112] employed nonlinear dynamic inversion (NDI) combined with UDE and compared NDI and NDI+UDE testing.

2.3.2. Intelligent-based hybrid approaches

These control strategies include learning-based components. Some traditional nonlinear control approaches have been integrated with adaptive rules to make them more robust against some of the uncertainties described above [34]. Effective results are obtained by integrating conventional control methods with adaptive-based intelligent methods to build efficient control systems in real-time applications with serious non-linear dynamics such as quadrotors. Controllers optimized using artificial neural networks, fuzzy logic, genetic algorithms, and reinforcement learning (learning-based controllers) receive significant attention in vehicles with high degrees of uncertainty, such as quadrotors. NN-based controllers are used as compensators to amplify the control signal, compensate for uncertainties or eliminate disturbances [38]. For example, in a study by Jiang et al. [28], parameters are corrected with a neural network (NN) to increase the system's sensitivity to high-frequency variations in a quadrotor controlled by the inverse dynamic control method. A NN is an adaptable system that learns by connecting nodes or neurons in a layered structure that resembles the human brain. A NN can be trained to recognize patterns, classify data, and predict future events by learning from data [113]. However, in systems such as quadrotors, where high-frequency changes can occur in their locations and positions, the problem of noise arises due to the inadequate selection of the switching gain. Methods based on gain estimation, such as fuzzy logic, chaotic systems, and extended Kalman filtering (EKF), are used to solve this problem [114–116]. PID is frequently used in such hybrid applications. Learning, prediction, and optimization-based methods are used to correct some of PID deficiencies mentioned in the previous sections. Some of the most used methods to adjust PID parameters are NN [117], fuzzy logic [118], genetic algorithms [55], and Particle Swarm Optimization (PSO) [21,119]. The PSO method [120] is a population-based optimization algorithm developed by analyzing the behavior of various animal swarms in nature. In PSO, each swarm member (particle) represents a candidate solution to the optimization problem. The position of any particle is influenced by the best solution (its own experience) it visited before, and the best location visited in the whole swarm [121]. It is used to optimize control parameters calculated using conventional methods in many UAV subsystems. For example, in the study conducted by Wai and Prasetia [122], PSO was used to optimize energy consumption estimates in the optimal route planning of a quadrotor controlled by ANN. Fessi and Bouallegue [123] used PSO to stabilize the position and direction of a quadrotor controlled by the LQR method. In the study by Yunping et al. [124], the PSO method was used to optimize the parameters of the sliding mode PID controller. In the approach developed by El-Hamidi et al. [118], PSO was used to optimize scaling factors in NN and Fuzzy Logic based PID controller.

2.4. Visual feedback control strategies

This control method uses features extracted from the videos taken from the primary and secondary cameras as feedback in position control and attitude control. In the feedback control loop of autonomous vehicles, vision systems have been a standard option for obtaining information that can be used. Visual landmarks are also used to estimate the position of quadrotors. If the quadrotor knows its location, the required control processes could be used to achieve the next position [125]. A visual feedback control study that estimates 3-D poses using a stereo camera is presented in [59]. Visual data are generally used not standalone but combined with inertial sensors or LIDARs. A motion control application using a fusion of visual data and inertial sensors is presented in [126]. In [72], artificial visual landmarks placed in the ground were used to find the best attitude and position control method. The most efficient method was chosen by performing tests with Nested saturations, BS, and SMC methods. In the study by Urbanski [127], Viola–Jones features [128] extracted from visual sources were used for position control. This feature was designed using a learning process before working in real-time. It was used as the source of position information in the control loop. One of the frequently used visual feedback-assisted position control methods is to use an external camera located on the ground and an onboard camera. The task of the external camera is to provide the visual data required for the quadrotor's pose (position and orientation) estimation. In [129], where no GPS or accelerometer was used, a quadrotor's pose estimation was performed using only internal and external cameras. Then FBL and BS-like control methods were applied using the visual feedback obtained. The ground camera was also mobile in the study conducted by Wzorek et al. [98]. One of the main disadvantages of pose prediction methods using dual cameras is their limited flight volume. Two studies on this subject are presented in [130,131]. The use of visual feedback to control the position of the quadrotor cable-suspended payload in [132] demonstrates the necessity of visual feedback for aircraft, while not being a comprehensive study of quadrotor flight control.

2.5. Comparative analysis of flight control studies

In quadrotor controls, comparative analyses were also carried out. For example, Belkheiri et al. [133] compared a control model decentralized LQR and FBL Erginer and Altuğ [30] performed a comparison of classical PD and Fuzzy PD methods in a VTOL quadrotor control. Bouabdallah et al. [134] compared the test results of a quadrotor controlled by PID and LQR methods. Hybrid studies are often performed, using different approaches to control different subsystems. In the study by Bouabdallah and Siegwart [135], BS and SMC methods were tested for an indoor quadrotor's position and rotation control. It was reported that the BS method produced better results in controlling orientation angles. FBL and BS methods were tested in a visual feedback quadrotor control by Altuğ et al. [129]. It was reported that the BS method gave better results according to the results obtained. In [136], PD and BS methods were tested in Matlab/ Simulink, and it was stated that the BS method gave better results in efficiency and performance. In a study conducted in [137], the performances of four different SMC-based controllers (Super-Twisting algorithm (STA), Continuous Twisting Controller (TC), Continuous Singular Terminal Sliding-Mode Control (STSMC), Continuous Nonsingular Terminal Sliding-Mode Control (NTSMC)) and robustified PID controller were tested on the "QBall2 platform by Quanser ©". As a result of the test studies, it was stated that the most successful performance was obtained in the TC method, and the worst results were obtained in the robustified PID. In a study tested in STARMAC [138] (The Stanford Testbed of Autonomous Rotorcraft for Multi-Agent Control), a nonlinear method and an intelligent method were compared. SMC is used as a nonlinear method, and the Reinforcement Learning (RL) method is used as

Table 1
Analysis of some comparative flight control studies.

Authors	Methods compared	Testing area	Successful method
Khatoon et al. [140]	PID vs. LQR	No information	PID
Bensalah et al. [141]	PID, SMC, BS, FBL	Simulink	PID
Belkheiri et al. [133]	LQR vs. FBL	Simulink	Both of them
Erginer and Altuğ [30]	PD vs. Fuzzy PD	Simulink	Fuzzy PD
Bouabdallah et al. [134]	PID vs. LQR	Real-time	Both of them with average results
Bouabdallah and Siegwart [135]	BS vs. SMC	Indoor test platform (test-bench)	BS
Altuğ et al. [129]	FBL vs. BS	Simulink	BS
Labbadi et al. [136]	PD vs. BS	Simulink	BS
Falcon et al. [137]	STA, TC, STSMC, NTSMC	QBall2 platform by Quanser©	TC
Waslander et al. [138]	SMC vs. RL	STARMAC	Both of them
Shehzad et al. [139]	Intelligent PID vs. LQR	Labview	LQR except “z” position
Varghese and Srekala [62]	LQG vs. $H\infty$	No information	$H\infty$ is better than LQG
Meera et al. [61]	PID, LQR, LQG, SMC	Simulink	SMC is the best, PID is better than LQG
Yu et al. [142]	MPC vs. LQR	Qball-X4	Both of Them
Mohammed [143]	Fuzzy-PID, GA-PID, NN, and ANFIS	Simulink	Fuzzy-PID (with disturbance)
Jaffery [68]	MPC vs. PID, LQR	Indoor motion-capture testbed	PID and LQR had lower tracking errors
Suhail et al. [99]	PID vs. ADRC	Matlab simulation	ADRC is better than PID
Mishra and Zhang [105]	DOB-aided PID vs. PID	Simulink and External flight test	DOB aided PID with Q-filter has lower position error
Dhadekar et al. [112]	UDE-aided NDI vs. NDI	Monte–Carlo simulation	UDE-aided NDI has lower error for attitude (Φ, θ, ψ) and x, y and z axis

an intelligent method. In order to determine the optimal control policy in the RL, a model-based iterative approach was used. As a result, successful results were obtained from both methods. In [139], the intelligent PID and state feedback LQR methods were tested in real-time on a commercial X3D quadrotor. In addition, the experimental studies were simulated in NI Labview. As a result, the LQR method gave better results in all step responses except the “z” axes. More successful results were obtained with PID in the “z” position. In [99], ADRC and PID methods for altitude and attitude control of a quadrotor were tested using Matlab simulations and it was reported that the ADRC method produced more accurate results. In order to better explain the comparative studies, Table 1 was prepared.

2.6. Performance analysis of studies using major methods

In Table 2, some quadrotor control studies were evaluated in terms of method, metrics used, and results obtained. In most studies, results were given on graphics instead of numerical results. Therefore, some of the analyzed results are taken as approximate values. When methodologically analyzed, it was observed that methods such as PID and PD were commonly used. However, control parameters in these methods were optimized by using NN, fuzzy logic, ANFIS, etc., or revised with deep learning techniques. When the comparative studies were analyzed, it was observed that the methods whose parameters were modified using smart methods yielded better results. It was commonly observed that settling time and deviation errors were used as metrics to control x, y, z, Φ, θ, and ψ in the studies analyzed. However, in some studies, it was observed that only certain subsystems such as yaw angle, altitude, or safe landing were controlled. In several studies, visual feedback was also observed for quadrotor location and position controls

2.7. Flight controller platforms

When the literature is examined, it is observed that the developed control algorithms are mostly tested in simulation environments. However, in some studies, control algorithms have been run and tested on embedded electronic systems [148]. These systems are often called flight controllers. Along with attitude, position, and altitude control, they also perform tasks such as reading sensor values and communicating with the ground station. Embedded systems used in such applications can be classified as FPGA-based, arm-based, Atmel-based, and raspberry pi-based [149].

Phenix Pro and OcPoc are examples of FPGA-based systems. Linux-based Robot Operating System (ROS) is used as the operating system. Pixhawk PX4 and Pixhawk 2 are ARM-based. ArduPilot Mega (APM), one of the most widely used flight controllers, is an Arduino Mega-based platform with an Atmel processor. Erle-Brain 3 is a raspberry pi based system. It includes a raspberry pi board and an auxiliary board. Commonly used flight controller platforms, their features, and the studies using these platforms are given in Table 3.

3. Simultaneous Localization and Mapping (SLAM)

There is another challenge to overcome after achieving attitude stabilization in autonomous quadrotor flights. This challenge is to plan successful navigation between the starting and target positions. The environment should be modeled for efficient navigation, and the most appropriate directions to the target should be determined. It is called Simultaneous Localization and Mapping (SLAM) in the literature. SLAM issue was first introduced to the literature by Smith and Cheesman [160] and developed by Dissanayake, Durrant-Whyte, and Bailey [161]. The approach was complemented by Bailey and Whyte [162,163] by making various additions [164].

The SLAM approach includes the autonomous discovery and mapping of an unknown environment without previous information. According to this method, autonomous vehicles would map the environment and, at the same time, predict their positions simultaneously based on this map [165]. In the SLAM algorithms, vehicle trajectories are predicted in real-time without previous information of the obstacle coordinates [166]. For UAV applications, SLAM is a challenging issue to address. The interdependence of localization and mapping raises the difficulty of the issue and demands that these two issues be overcome at the same time [167]. Mobile vehicles' navigation challenge in outdoor conditions is generally solved with GPS signals. However, the GPS receivers have to be very sensitive in this case. These GPS receivers are available but are not appropriate for quadrotors in terms of size and weight. In most SLAM applications where GPS is used, the map and flight route are preloaded on avionic systems. However, the map loses its validity if the obstacles marked on the map change in flight conditions where extremely instantaneous changes occur. In such cases, adaptive systems that can adapt to instant changes are needed. Furthermore, in several cases, GPS signals cannot be used in real-time experiments. Some of those:

Table 2
Analysis of some quadrotor flight control studies.

Authors	Method	Disturbance	Simulation	Metrics	Results
Setyavan et al. [56]	LQR control is used for the safe landing of an X-type quadrotor. Attitude stabilization and altitude were controlled during the landing.	Ignored	Gazebo	**Time spent** on 1 m landing (s)	When the LQR is not applied, 0.175 sn When the LQR is applied 1.74 sn
Koch et al. [117]	The flight parameters of an X-type quadrotor were trained with reinforcement learning and used in attitude stabilization control. Results were compared to PID.	No Information	Gazebo	**Success**: The number of experiments remaining within ±10% of the reference value (%) **Error:** Number of experiments remaining within ±10% error band of reference value 500 ms after start	When using Proximal Policy Optimization (PPO) trained technique $Success: \Phi = 99.8\%$, $\theta = 100\%$, $\psi = 100\%$
Thanh et al. [144]	Anti-collision control has been carried out on a quadrotor. PID was used for speed and rotation angles.	Ignored	Available	**Tracking error**: (degree) **Obstacle distance** (m)	Single obstacle T(11,23): $Tracking\ error \approx 15°$, $Obs.Dist. = 2,5$ m Multi obstacle T(18,24): $Tracking\ error \approx 30°$, $Obs.Dist. \approx 2.5$ m
Lee and Juang [22]	Image processing supported flight control is performed on an X-type quadrotor. PD and Fuzzy PD methods were used.	Ignored	Simulink	**Error in** x, y, and z axes (m)	Better results were obtained from the Fuzzy PD method. $Error_{x,y,z} < 1$ m
Achtelik et al. [126]	The attitude of an X-type quadrotor was controlled with PID and yaw angle (ψ) control with PI. The x and yaw angle values were obtained from the images.	Considered	Simulink	**Error in** x, y, and z axes (cm) **Settling time- ST** for yaw angle (s)	$Error_{x,y,z} < 15$ cm $ST \approx 6.5$ s
Mercado Ravell et al. [96]	Trajectory tracking and attitude stabilization control were made for a quadrotor operating both as air and submarine. PID control is used for attitude stabilization, and the FBL method is used for trajectory tracking.	Considered	Simulink	**Altitude (m)** relationship with **Settling time (s)**	Air: 2, 5 m $height\ ST = 15$ s Underwater: -0.5 m $height\ ST = 15$ sn
El-Hamidi et al. [118]	PID/ PD was used for attitude stabilization and location control, but the parameters were adjusted with NN and fuzzy logic. PSO was used to increase the efficiency of the fuzzy logic method.	Considered	Simulink	**Settling time** (s), **Overshot (OS)** (%) and **MSE** for yaw angle (ψ)	For yaw angle (ψ): GS-NNPD: $ST = 0.153$ s, $OS = \%0$, 0, 0028 MSE FPID-PSO: $ST = 0.225$ s, $OS = \%0$, 0.0046 MSE
Kutay [145]	PID, BS, inverse dynamic control, and SMC methods were tested to control the attitude stabilization.	Considered	Simulink	**Settling time (s)** for Φ, θ, ψ	The best method is SMC, $\pi/3$ starting point: $ST_{\Phi,\theta,\psi} \approx 0.28$ s $\pi/10$ starting point $ST_{\Phi,\theta,\psi} \approx 0.36$ s
Gomez-Avila et al. [146]	PD controller optimized with EKF assisted NN.	No information	Gazebo, Real-time	**Root Mean Square Error (RMSE)** of x, y and z axis	
Mekky and Alberts [147]	ANN was used for learning unknown aerodynamics of SMC controller	Considered	Numerical simulation	**Position errors and angular position errors**	Position errors $< \left\|5 \times 10^{-6}\right\|$ m Angular position errors $< \left\|2 \times 10^{-4}\right\|$ rad considering State-Dependent Uncertainties

(*continued on next page*)

- Military applications using GPS signal blockers
- Applications carried out underwater or in mines
- Indoor environments such as caves, museums, and large buildings
- Applications where GPS devices cannot be used due to size and weight

In the conditions above, quadrotors must determine their direction by avoiding obstacles according to the data they collect from their environment through their sensors. Effective autonomous navigation depends on the SLAM algorithm developed and on the precision and accuracy of the obtained environmental data.

Table 2 (*continued*).

Authors	Method	Disturbance	Simulation	Metrics	Results
Eskandarpour and Sharf [32]	Error-based MPC was used in translational and rotational subsystems. Advanced error, standard error, linear error, and nonlinear error-based MPC performances were compared.	Considered	Numerical simulation	**The integral of the absolute value of error (IAE)**	For scenario 1: $x = 46.04$ m, $y = 30.94$ m, $z = 17.60$ m $\varnothing = 4.25$ rad, $\theta = 2.81$ rad, $\varphi = 0.11$ rad
Najm and Ibraheem [100]	ADRC for altitude and attitude control	Considered	Simulink	**Integrated time absolute Error (ITAE)**	$z = 0.001054$, $\Phi = 0.000077$, $\theta = 0.001105$, $\psi = 0.000672$
Lyu et al. [106]	DOB-aided H-∞ control for hover stabilization of a VTOL quadrotor	Considered	No information	**Mean Error (me)**	Me = 0.193 (Constant Wind-DOB off) Me = 0.028 (Constant Wind-DOB on)
Dhadekar et al. [112]	UDE-aided NDI for attitude and position tracking control of a quadrotor	Considered	Monte Carlo simulation	**RMSE**	Longitudinal position:0.21 Lateral position:0.093 Altitude:0.68 Yaw angle:0.0802

Table 3
Microprocessor-based flight controllers.

Class	Platform	Works
FPGA-based	Phenix OcPoc	Klenke [150] Grillmayer et al. [151] Christophersen et al. [152] Schmid et al. [153]
ARM-based	Pixhawk PX4 Pixhawk 2	Oettershagen et al. [154] Priandana et al. [155] Yamunathangam et al. [156]
Atmel-based	APM	Venkatesh et al. [157] Zelenka et al. [158] Er et al. [159]
Raspberry pi-based	Erle-Brain	Ebeid et al. [41] (Review)

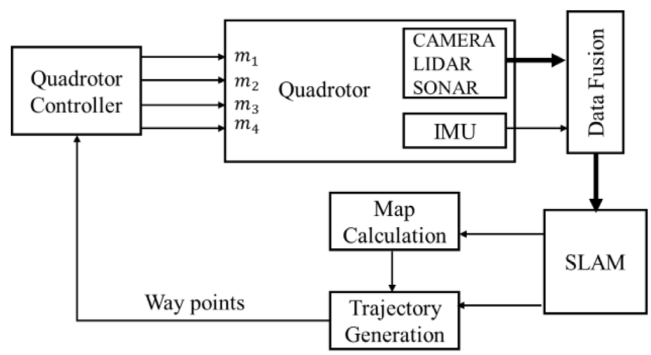

Fig. 5. Simple SLAM mechanism.

Three key components of SLAM applications are observation, pose, and odometer. It will be beneficial to describe these components to fully comprehend the SLAM approaches.

Observation: It is the data gathered by UAVs from their surroundings via sensors. These sensors are often camera or Lidar-like in nature. Depending on the type of sensor and methods utilized, the data format may differ. The observation is the extraction of the features of the determined landmarks using the sensors mentioned above. These features can sometimes be edge and corner descriptors or sometimes special features (Surf, Orb, etc.). Assuming that data is received from the sensor at time t; An observation data can be expressed as in Eq. (5), where n is the landmark index and N is the total number of landmarks.

$$Z_t^n = \left\{Z_t^1, Z_t^2, \ldots, Z_t^N\right\} \tag{5}$$

Pose: It expresses the position and orientation of a UAV at any time t. The pose vector can be expressed as in Eq. (6) as x, y, z are 3-D coordinate information, $\varnothing$, θ, φ are roll, pitch, and yaw angles, respectively.

$$P_t = \left\{P_x^t, P_y^t, P_z^t, P_\varnothing^t, P_\theta^t, P_\varphi^t\right\} \tag{6}$$

Odometry: It estimates the poses of mobile robots at time t relative to their poses at time $t-1$. It can be expressed as in Eq. (7) specifically for aircraft.

$$U_t = \left\{\Delta P_x^t, \Delta P_y^t, \Delta P_z^t, \Delta P_\varnothing^t, \Delta P_\theta^t, \Delta P_\varphi^t\right\} \tag{7}$$

SLAM is an iterative process. Therefore, if a quadrotor cannot precisely determine the map and position of its environment, the orientation error will grow incrementally in each iteration, and the vehicle will be lost as a result [168]. Fig. 5 illustrates a specific SLAM mechanism that can be used in quadrotors.

In the figure, m_1, m_2, m_3 and m_4 are quadrotor motor speeds. SLAM algorithms can be applied in quadrotors as well as in unmanned ground vehicles (UGV) [169–174] and unmanned underwater vehicles (UUV) [175,176]. When we consider UAVs specifically for quadrotors, it is understood that SLAM algorithms are complex and challenging. Because the vertical axis (z-axis) and pitch and roll movements are not considered in UGVs. SLAM algorithms used in UGVs are easier than UAVs. Because in these vehicles, the movement takes place in two dimensions and is relatively slow. Thus, the mathematical model used in the algorithm would be less complex [168]. Quadrotor SLAM applications can be broadly classified into indoor-outdoor, view-based, visual-based, and single - multiple.

3.1. Indoor SLAM

Since GPS signals cannot be used in indoor quadrotors, SLAM must be used for autonomous navigation. They are primarily used for exploration purposes. Mines are one of the major fields of use [177]. Also; They are used to collect visual data for inspection in industrial elements such as heat boilers, pressure boilers, pipes, or chimneys, to collect data from areas that may be dangerous for people to enter, such as nuclear power plants, and to enter areas that are difficult for people to access such as sewers, mines and even amusement parks [178].

Because indoor quadrotors [177,179–186] are typically run in areas where people are present, they may harm people through impact. This is why they are often produced with a cage around them. This type of vehicle has some disadvantages in SLAM applications, and these are [187]:

- Owing to the office placement, they encounter quite a lot of obstacles,
- Difficulty in extracting features due to walls painted in uniform colors.
- Due to mirror and glass objects, they have vision and signal perception difficulties.

Most of the SLAM implementations are developed for external applications. Increased capabilities in computer equipment and tools have enabled SLAM implementations, and, as a result, the interest in researchers in this topic has increased. It is known that all activities of the US Air Force, except logistics, cargo activities, and casualty evacuation, are planned to be carried out by UAVs until 2035 [188]. Thus, there are further studies in the literature about outdoor quadrotors [189–202].

3.2. View-based SLAM approaches

SLAM applications can be divided into two classes based on sensors: View-based and Visual-based. Lidars are widely used in view-based SLAM applications [179,180,203–206]. Lidars emit laser pulses from their sources. These pulses return after hitting the objects around them. Lidars can also detect the returning pulses and calculate the distance to the object using the total flight time of the signals. In SLAM applications, it is used for mapping by detecting the distances of obstacles around quadrotors. They are mounted on the front of vehicles and scan their surroundings with a certain horizontal and vertical scanning angle. Both localization and mapping are performed by calculating the relative motion of the vehicle from sequential laser scanning data. This process is called scan matching or laser odometry. In order to generate a map from the scanning data, the coordinate system of the lidar must be converted into the coordinate system of the space where the motion takes place [187]. This conversion requires intensive mathematical modeling. As laser scan devices can work with very high frequencies, they can easily map the environment. However, it should be taken into account that high-frequency lidar devices will be a disadvantage in terms of weight, power consumption, and cost, especially for quadrotors in the mini class [207]. For this reason, fewer study has been performed than visually based SLAM.

3.3. Visual-based SLAM approaches

Visual SLAM (vSLAM) applications are alternatives to Lidar-based SLAM applications. vSLAM systems are used more to solve the problem of localization and mapping because they can take precise measurements of their environment. It is performed using visual sensors such as single cameras, RGB-D cameras, or stereo cameras. In visual techniques, the features of sequential image frames from cameras are extracted and matched using various methods. The obtained features are generally called landmarks. The change between matching features is then analyzed. The transition between two frames is analyzed as 2-D for single cameras [185,186,192,193,208–213] and 3-D for stereo cameras [172,199,214–216] and RGB-D cameras [174,217–221]. As a result of the analysis, the quadrotor's displacement in real space is calculated using the difference between the frames. SLAM methods based on extracting features from camera images are generally called feature-based methods [167]. Fig. 6 shows the landmarks determined by the quadrotor in the field of view. Each star in the figure corresponds to a landmark. These landmarks can be the corner of a building, the center of a pool, or a tree in the image captured by the camera. The important thing is that these markers can be extracted in many consecutive frames and matched between two frames. Therefore, it is essential to select algorithms to extract features from images. Extracting so many landmarks and little matches in image frames implies a lack of knowledge and a waste of computing energy.

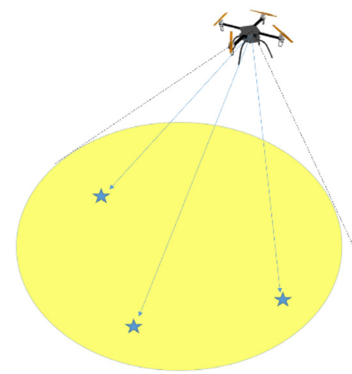

Fig. 6. A quadrotor's determination of landmarks in the field of view.

In feature-based methods, the scan data are mostly camera images, but rarely lidar-sonar scan data can also be used. SLAM implementations are complicated and challenging systems, as there are no ideal conditions for real-time operations. Sensors also produce noise and have limited ability. In addition, activators can produce unexpected results. These uncertain circumstances forced researchers to produce probabilistic solutions [222]. Most probabilistic solutions are subsets of state estimation techniques. If the position and orientation (pose) is not given, the vehicle must estimate its pose using landmarks [165].

3.4. SLAM methods

Some of the main SLAM methods are;

EKF SLAM, EKF is an optimal iterative estimator that can be used to estimate the state of nonlinear systems. It is a recursive algorithm renowned for its high convergence rate, which greatly improves efficiency. Compared to other nonlinear approaches, its algorithm has a better dynamic response and resistance to uncertainty and noise [223]. In order to make predictions in an uncertain environment, it is necessary to reduce errors arising from both measurement (observation) and activator uncertainties. In this context, filter-based pose estimating methods are often used for SLAM applications [224,225].

ORB SLAM [195] is a method that can be applied to both single and stereo and RGB-D cameras. It is feature-based and can be used in real-time applications. In the ORB-SLAM method, the features of the images are extracted by the ORB method, and a 3-D point cloud is obtained using these features. It creates a sparse map by selecting its landmarks from this point cloud and determines the location. ORB-SLAM2 [226] and CORB-SLAM [227] methods derived from ORB-SLAM.

LSD-SLAM [195,228] performs image-to-image alignment with simultaneous tracking, depth map estimation, and optimization. This method, however, has a high computational cost and needs a lot of computing resources. It is sensitive to camera calibration. Despite map optimization involving loop closure detection, the resulting trajectory has a lower sensitivity than ORB-SLAM [195].

Visual Odometry (VO) [229,230] is one of the fundamental methods many vSLAM methods are focused on. It is divided

Table 4
Analysis of some comparative SLAM studies.

Authors	Methods compared	Testing area	Superior method
Gabdulin et al. [195]	ORB-SLAM vs. LSD-SLAM	Real-time and ROS	ORB-SLAM
Meyer et al. [238]	Lidar-based SLAM vs. Visual-based SLAM	ROS and Gazebo	Both of them
Tsai et al. [226]	Collaborative SLAM vs. ORB-SLAM2	Real-time	Collaborative SLAM
Alborzi et al. [232]	Gmapping vs. Adaptive Monte Carlo Localizing (AMCL)	ROS and Gazebo	Both of them
Lemaire et al. [215]	Stereo vision-based SLAM vs. Monocular vision-based SLAM	Real-time	Monocular vision-based SLAM
Santos et al. [231]	EKF-SLAM vs. SM-SLAM	No information	SM-SLAM for reducing estimation errors.
Abbyasov et al. [227]	CORB SLAM vs. CCM SLAM	ROS and Gazebo	CORB SLAM in F-shaped trajectories
Jung et al. [235]	Graph SLAM vs. Lidar-based SLAM	Real-time	Proposed Graph SLAM

into two classes as mono VO and stereo VO. Using visual information, the position and direction of the vehicle, i.e., 6-DoF movement, are estimated. However, certain inconsistencies in scale may trigger problems with the mono VO method.

Hector-SLAM [203] is based on 2-D laser scanning data. The algorithm can be used to construct 2-D maps and location information. For accurate mapping, the coordinate system of laser scanning data must be converted to the environment's coordinate system.

Sliding Mode SLAM (SM SLAM) [231] is a method resistant to limited amounts of disturbance. Suitable for nonlinear systems. This approach performs locating and mapping more simpler. It consists of three sub-phases as estimation, observation, and updating.

Gmapping [232,233] is a Lidar-based SLAM method using a kind of particle filter. This method uses an adaptive re-sampling strategy and solves the existing serious difficulties with the standard particle filter methods, which have a high computational cost and a problem with depletion.

Pose Graph SLAM: It is a probabilistic method based on pose estimation using data obtained from sensors. LIDAR, camera, or both are used as sensors. In this method, some nodes and edges connect the nodes. Nodes contain the pose information of the vehicle. Edges are called constraints and represent odometry information. The formulation used was first proposed by Liu and Milios [234]. It is more popular with UGVs as fewer parameters represent pose and odometry information. However, its use in UAVs is also becoming widespread. Bridge inspection was performed with a quadrotor using the pose-graph SLAM technique in the study conducted by Jung et al. [235]. Chen et al. [236] used it in online 3D SLAM research, and Moura et al. [237] used it in indoor warehouse logistics.

3.5. Comparative analysis of SLAM studies

In the quadrotor SLAM studies reviewed in the literature, the number of studies comparing various approaches is fewer than the number of flight control studies. The authors generally compared their methodology with other methods. Table 4 includes some of the comparative research.

A methodical analysis of some SLAM studies was made in Table 5. In these studies, it was observed that stereo and RGB-D cameras are frequently used in quadrotors due to their direct depth calculation, lightness, and low cost. In studies using mono cameras, auxiliary hardware and algorithms were used for calculating 2-D image depth. In SLAM studies, since the 3-D map of the surrounding environment is produced with sensors such as camera, LIDAR, and Kinect sensor, great importance is given to depth measurement or estimation.

It was observed in the studies that depth was frequently used as the measurement metric. In addition, mean square errors of metrics such as angular and spatial trajectory deviation and estimation error were mostly used. It was observed that various datasets were used as well as real-time experiments. One of the reasons why datasets are frequently used is that some of the datasets have ground-truth values. In this way, researchers can compare their results with correct outputs. In some studies, Lidar-based SLAM applications and visual-based SLAM applications were used to verify each other [187]. There are also studies on sensor fusion. An example of this is the study of combining inertial sensor data with camera images made by Heng et al. [200]. The ORB-SLAM method stands out in the studies in the literature. This method is used as the main method of studies or as an auxiliary method for comparison [229].

Stereo cameras are frequently used in SLAM applications. However, since stereo cameras consist of two cameras as left and right cameras and depth information can be extracted using these image pairs, some changes in the algorithms are required. For example, one of the methods used for mono cameras is ORB-SLAM. However, the ORB-SLAM2 [214] method has been developed for stereo cameras. Stereo cameras are lightweight, energy-efficient, and customizable devices that can deliver data at high speeds. Intensive stereo matching is required in the CPU to estimate the depth map. This means an increase in the processing time [199]. The features extracted from camera images should be increased to improve the performance rate in practice. This necessitates the use of high-resolution stereo cameras. In this case, the quadrotor loses the advantage of lightness and high processing speed. Therefore, less studied than single cameras in the literature [199,200,215,216,221,245]. In addition to these, there are also SLAM applications performed with RGB-D cameras integrated with the Kinect depth sensor [228,239,240,245].

3.6. FPGA usage in SLAM applications

The use of Field Programmable Gate Arrays (FPGAs) in UAVs has recently become widespread. It is made up of a number of customizable logic blocks that may be programmed to execute the functions that the designer needs. The FPGA also has a programmable connection matrix, which allows the designer to customize the internal wiring of the FPGA.

They are highly suitable for real-time applications due to their hardware flexibility, processing speed, low power consumption, and parallel processing capabilities. For this reason, they have been widely used in various subsystems of UAVs. These subsystems are; stability control, autonomous navigation, visual operations, sensor interfaces, motor control, SLAM, object recognition and tracking, obstacle avoidance, ego-motion estimation, and communication systems [246]. In this study, we examined FPGA use, especially in SLAM subcomponents. In a study by Rachid and Saddik [247], an FPGA was used in a visual-based SLAM application of a UAV, but the details of the UAV were not given. In the study conducted by Boikos and Bouganis [248], an LSD-SLAM application was carried out, which was stated to be applicable to UAVs as well. As a result of this application, it is stated that 2x gain in acceleration and 4.3x gain in energy efficiency. In the deforestation detection study by Torres et al. [249], FPGA was implemented in two subsystems. The first is the decision-making subsystem, and the second is the visual detection and odometry system. In a SAR application by Schmid et al. [153], flight control, autonomous navigation, and obstacle avoidance were implemented using an FPGA board and a stereo camera.

Table 5
Analysis of some SLAM studies.

Authors	Methods	RT/ D	Sensors	Environment	Metrics	Results
Esrafilian and Taghirad [239]	In this study, a 3D map was created with monocular orb slam, and then a road map that was free of obstacles was created with the Rapidly exploring Random Trees algorithm. Comparative analysis of the trajectory produced with EKF and the trajectory produced without EKF was done.	RT	Camera	Outdoor	Trajectory deviation for altitude, Trajectory deviation for yaw angle (ψ)	Altitude: $TD_{with\ EKF} = 30$ cm; $TD_{without\ EKF} = 10$ cm Yaw angle: $TD_{with\ EKF} < 10°$; $TD_{without\ EKF} = 50°$
Santos et al. [231]	SM-SLAM was applied and compared to EKF-SLAM for a quadrotor navigation	D	Camera	–	RMSE for rotating angle RMSE for spatial displacement	Max values for rotational angles: $RMSE_{GKF-Slam} \approx 1.6$; $RMSE_{SM-Slam} \approx 1$ Max values for spatial displacement: $RMSE_{GKF-Slam} \approx 0.75$; $RMSE_{SM-Slam} \approx 0.2$
Munguia and Martinez [240]	A slam study based on depth map estimation was conducted in this study. The orb-slam2 method designed for RGB-D cameras was adapted to monocular cameras. Results were compared with RGB-D cameras.	D	Camera	Outdoor	Errors for depth estimation (m)	$Average\ error = 0.12\,\text{m}$
Lopez et al. [229]	This study proposed an integrated SLAM method based on image, laser, and inertial measurements using EKF. In this context, LSD slam and orb slam approaches were tested.	RT+D	Camera, LIDAR	Indoor	RMSE for trajectory deviation	Orb slam was more accurate than LSD slam. $RMSE_{Lidar} \approx 73.7$ cm, $RMSE_{Orb-slm} \approx 179.4$ cm
Gee et al. [204]	This study proposes a method to obtain a more intense 3d map by matching laser scanning data with stereo camera images.	RT	Camera, LIDAR	Outdoor	RMSE for depth estimation	$RMSE_{proposed\ method} = 42.8$ $RMSE_{Lidar} = 41$, $RMSE_{V-Slam} = 88.4$
Yang et al. [241]	Depth was estimated using unsupervised CNN-based methods for 3d mapping with a monocular camera. In the study, the method used was compared with other studies that worked on the same dataset.	D	Camera	Outdoor	Accuracy (%) and Error RMSE value for depth estimation	$RMSE_{accuracy} = 23.1\%$ $RMSE_{error} = 0.787$
Haddadi and Castellan [242]	Images taken using a monocular camera were primarily obtained using ORB-SLAM for pose predictions. EKF was used to integrate inertial sensor data with these poses. Scaling factor estimates were created to calculate the map's scale with the integrated data obtained.	RT	Monocular Camera	Outdoor	Trajectory Deviations in x, y, and z positions Position holding (PD) Deviations in x, y, and z positions	$TD_x < 1.5$ m $TD_y < 0.9$ m $TD_z < 0.3$ m $PD_x < 0, 2$ m $PD_y < 0, 3$ m $PD_z < 0, 1$ m
Jung et al. [235]	Bridge inspection was performed using a variant of Graph-based SLAM.	RT	Monucular Camera, LIDAR	Outdoor	Estimation error of the measurements of some areas on the bridge (d1, d2, h1, h2, w1, w2)	All errors < 1.6 m
Araujo et al. [243]	Visual Slam was performed with a stereo camera. Keypoint attributes were extracted using the rBRIEF method.	RT	Stereo camera	Outdoor	Average translational error on a trajectory.	-4 m $< error_x < 3$ m; $0 < error_y < 2$ m; $0 < error_x < 1$ m;
Titas et al. [244]	Window detection was made in the indoor environment, and a Quadrotor's navigation through this window was ensured. ORBSLAM was used as the SLAM method.	RT	Monocular Camera	Indoor	Accuracy	%100 success rate

4. Conclusion

Today, the needs of humanity are evolving from the human-controlled driving of UAVs to unmanned driving. As a result of these requirements, the interest of researchers is increasing, and hundreds of studies have been published. Quadrotors are one of the most appropriate UAV classes for autonomous use. In this study, 249 publications were reviewed in the context of flight control and SLAM applications of quadrotors. Flight control and SLAM issues were discussed only for quadrotors. Reviewed studies have been classified under the topics mentioned above and presented to assist researchers. Apart from the software and algorithms, the hardware on which the applications are installed was also discussed, and the analysis results were given in the form of summary tables. Comparative research was carefully examined, and the study's findings were summarized in tables with better outcomes. Additionally, commonly used performance metrics, application environments, and results from the research reviewed were summarized and provided in tables. With this study, the studies in this area were evaluated and classified methodologically and hardware. Thus, hardware and method-based quick reference resource were created for researchers. Finally, the conclusions drawn from the reviewed studies are given below:

- For controlling aircraft with powerful nonlinear dynamics, such as quadrotors, linear or nonlinear conventional methods alone are not sufficient. Therefore, more robust hybrid approaches should be developed by combining conventional methods with intelligent algorithms. The application of hybrid methods has been performed in two ways. First, different methods were used for different subsystems. For example, PID for altitude control and SMC for attitude control. Second, multiple methods were run collaboratively to manage any subsystem. For example, tuning the PID coefficients using the NN method in trajectory tracking.

- The importance of deep neural network-based intelligent methods has lately increased in developing flight control and SLAM algorithms.

- MPC and RNN-based methods have become widespread, especially in learning-based algorithms, where future values of quadrotor dynamics are used as well as instant and past values.

- Because of the rapid increase in swarm UAV work, control algorithms should be developed in accordance with the swarm UAV structure and be scalable.

- Integrated LIDAR and camera studies are more effective in SLAM research than studies employing either LIDAR or camera alone. Due to the size and weight of LIDAR, however, it is required to increase the thrust of quadrotors.

- Since stable flight alone is not enough for a quadrotor or any aircraft, it is necessary to develop hybrid control algorithms that can manage SLAM applications such as navigation and obstacle avoidance.

- It has been observed that MPC-based methods, which use future value estimations as well as instant and previous values of quadrotor dynamics, are becoming more popular. In this context, it is expected that Recurrent Neural Network (RNN)-based methods using similar methodology will become more common in control applications.

Declaration of competing interest

The author has no competing interests to declare that are relevant to the content of this article.

Data availability

No data was used for the research described in the article.

References

[1] A. Tahir, J. Böling, M.H. Haghbayan, H.T. Toivonen, J. Plosila, Swarms of unmanned aerial vehicles — A survey, J. Ind. Inf. Integr. 16 (1) (2019) 100106.
[2] J.M.G. Ramos, R. de, Slam for drones, 2012, pp. 1–185.
[3] M. Coppola, K.N. McGuire, C. De Wagter, G.C.H.E. de Croon, A Survey on Swarming with Micro Air Vehicles: Fundamental Challenges and Constraints, Vol. 7, Frontiers Media S.A., 2020, p. 18.
[4] B. Mohr, D. Fitzpatrick, Micro air vehicle navigation system, IEEE Aerosp. Electr. Syst. Mag. 23 (4) (2008) 19–24.
[5] A. Kushleyev, D. Mellinger, C. Powers, V. Kumar, Towards a swarm of agile micro quadrotors, in: Autonomous Robots, Springer, 2013, pp. 287–300.
[6] J. Brossard, D. Bensoussan, R. Landry, M. Hammami, Robustness studies on quadrotor control, in: 2019 International Conference on Unmanned Aircraft Systems, ICUAS 2019, 2019, pp. 344–352, (1).
[7] T. Luukkonen, Modelling and Control of Quadcopter, Espoo, 2011.
[8] F. Haydon, Military Ballooning During the Early Civil War, John Hopkins University Press, 2000.
[9] A.V. Narule, R. Denny, FEA : CFD Analysis of Quad Copter Drone 5 (5) (2021) 105–111.
[10] G. Hoffmann, D.G. Rajnarayan, S.L. Waslander, D. Dostal, J.S. Jang, C.J. Tomlin, The stanford testbed of autonomous rotorcraft for multi agent control (STARMAC), in: AIAA/IEEE Digital Avionics Systems Conference - Proceedings, Vol. 2, 2004.
[11] S. Espen, K. Sho, Quadrotor Modeling and Control, University of Tromsoe, 2016.
[12] A. Nemati, M. Kumar, Modeling and control of a single axis tilting quadcopter, in: Proceedings of the American Control Conference, 2014, pp. 3077–3082.
[13] P. Pounds, R. Mahony, Design principles of large quadrotors for practical applications, in: Proceedings - IEEE International Conference on Robotics and Automation, 2009, pp. 3265–3270.
[14] N.S. Özbek, M. Önkol, M.Ö. Efe, Feedback control strategies for quadrotor-type aerial robots: A survey, Trans. Inst. Meas. Control 38 (5) (2015) 529–554.
[15] S. Gupte, P.I.T. Mohandas, J.M. Conrad, A survey of quadrotor unmanned aerial vehicles, in: Conference Proceedings - IEEE SOUTHEASTCON, 2012.
[16] R. Baranek, F. Solc, Model-based attitude estimation for multicopters, Adv. Electr. Electr. Eng. 12 (5) (2014) 501–510.
[17] J. Dunfied, M. Tarbouchi, G. Labonte, Neural network based control of a four rotor helicopter, in: Proceedings of the IEEE International Conference on Industrial Technology, Vol. 3, 2004, pp. 1543–1548.
[18] R.C. Leishman, J.C. MacDonald, R.W. Beard, T.W. McLain, Quadrotors and accelerometers: State estimation with an improved dynamic model, IEEE Control Syst. 34 (1) (2014) 28–41.
[19] N. Xuan-Mung, S.K. Hong, Improved altitude control algorithm for quadcopter unmanned aerial vehicles, Appl. Sci. (Switzerland) 9 (10) (2019).
[20] M. Rabah, A. Rohan, M. Talha, K. Nam, S.H. Kim, Autonomous Vision-based Target Detection and Safe Landing for UAV 16 (6) (2018) 3013–3025.
[21] M.S. Sumardi, M.A. Riyadi, Particle swarm optimization (PSO)-based self tuning proportional, integral, derivative (PID) for bearing navigation control system on quadcopter, in: Proceedings - 2017 4th International Conference on Information Technology, Computer, and Electrical Engineering, ICITACEE 2017, Vol. 2018-Janua, 2017, pp. 181–186, (1).
[22] Y.S. Lee, J.G. Juang, Color identification for quadcopter flight control and object inspection, Adv. Mech. Eng. 11 (2) (2019) 1–16.
[23] Y.C. Choi, H.S. Ahn, Nonlinear control of quadrotor for point tracking: Actual implementation and experimental tests, IEEE/ASME Trans. Mechatronics 20 (3) (2015) 1179–1192.
[24] J.S. Cervantes-Rojas, F. Muñoz, I. Chairez, I. González-Hernández, S. Salazar, Adaptive tracking control of an unmanned aerial system based on a dynamic neural-fuzzy disturbance estimator, ISA Trans. 101 (2020) 309–326.
[25] H. Li, A.V. Savkin, B. Vucetic, Autonomous area exploration and mapping in underground mine environments by unmanned aerial vehicles, Robotica 38 (3) (2020) 442–456.
[26] C. Gheorghe, N. Filip, Image processing applied in road traffic using a quadcopter, in: The 30th SIAR International Congress of Automotive and Transport Engineering, Springer International Publishing, 2020, pp. 297–303.
[27] A. Santamaria-Navarro, J. Solà, J. Andrade-Cetto, High-frequency MAV state estimation using low-cost inertial and optical flow measurement units, in: IEEE International Conference on Intelligent Robots and Systems, Institute of Electrical and Electronics Engineers Inc., 2015, pp. 1864–1871.
[28] F. Jiang, F. Pourpanah, Q. Hao, Design, implementation, and evaluation of a neural-network-based quadcopter UAV system, IEEE Trans. Ind. Electron. 67 (3) (2020) 2076–2085.
[29] Q. Jing, Z. Chang, H. Chu, Y. Shao, X. Zhang, Quadrotor attitude control based on fuzzy sliding mode control theory, in: Chinese Control Conference, CCC, Vol. 2019- July, 2019, pp. 8360–8364.
[30] B. Erginer, E. Altuğ, Design and implementation of a hybrid fuzzy logic controller for a quadrotor VTOL vehicle, Int. J. Control Autom. Syst. 10 (1) (2012) 61–70.
[31] E. Kuantama, I. Tarca, R. Tarca, Feedback linearization LQR control for quadcopter position tracking, in: 2018 5th International Conference on Control, Decision and Information Technologies, CoDIT 2018, Institute of Electrical and Electronics Engineers Inc., 2018, pp. 204–209.
[32] A. Eskandarpour, I. Sharf, A constrained error-based MPC for path following of quadrotor with stability analysis, Nonlinear Dynam. 99 (2) (2019) 899–918, 2019 99:2.
[33] Y.C. Choi, H.S. Ahn, Nonlinear control of quadrotor for point tracking: Actual implementation and experimental tests, IEEE/ASME Trans. Mechatronics 20 (3) (2015) 1179–1192.
[34] H. Mo, G. Farid, Nonlinear and adaptive intelligent control techniques for quadrotor UAV – A survey, Asian J. Control 21 (2) (2019) 989–1008.
[35] A. Zulu, S. John, A review of control algorithms for autonomous quadrotors, Open J. Appl. Sci. 04 (14) (2016) 547–556.

[36] S. Yuan, H. Wang, L. Xie, Survey on localization systems and algorithms for unmanned systems, Unmanned Syst. 9 (2) (2021) 129–163.
[37] Y. Lu, Z. Xue, G.S. Xia, L. Zhang, A survey on vision-based UAV navigation, Geo-Spatial Inf. Sci. 21 (1) (2018) 21–32.
[38] S. Raiesdana, Control of quadrotor trajectory tracking with sliding mode control optimized by neural networks, Proc. Inst. Mech. Eng. I 234 (10) (2020) 1101–1119.
[39] C. Howard, UAV command, control & communications, Mil. Aerosp. Electr. (7) (2013) 62–75.
[40] I. Sadeghzadeh, Y. Zhang, A review on fault-tolerant control for unmanned aerial vehicles (UAVs), in: AIAA Infotech At Aerospace Conference and Exhibit 2011, 2011.
[41] E. Ebeid, M. Skriver, K.H. Terkildsen, K. Jensen, U.P. Schultz, A survey of Open-Source UAV flight controllers and flight simulators, Microprocess. Microsyst. 61 (2018) 11–20.
[42] W. Kuntjoro, A.H.M. Saleh, R.E.M. Nasir, M.R. Abdullah, M.G. Suada, Flight thrust performance of quadcopter, J. Mech. Eng. 5 (Specialissue1) (2018) 210–221.
[43] A. Alkamachi, E. Ercelebi, Modelling and control of H-shaped racing quadcopter with tilting propellers, Facta Univ., Ser.: Mech. Eng. 15 (2) (2017) 201–215.
[44] F. Santoso, M.A. Garratt, S.G. Anavatti, I. Petersen, Robust hybrid nonlinear control systems for the dynamics of a quadcopter drone, IEEE Trans. Syst., Man, Cybern.: Syst. 50 (8) (2020) 3059–3071.
[45] R.I. Pérez, G.R. Galvan, A.J.M. Vázquez, S.F. Melo, D.L. Alabazares, Attitude control of a quadcopter using adaptive control technique, Adapt. Robust Control Syst. (2017).
[46] Y. Zhang, Z. Fang, H. Li, Extreme learning machine assisted adaptive control of a quadrotor helicopter, Math. Probl. Eng. 2015 (2015).
[47] X. Zhang, X. Li, K. Wang, Y. Lu, A survey of modelling and identification of quadrotor robot, Abstr. Appl. Anal. 2014 (2014).
[48] F. Santoso, M.A. Garratt, S.G. Anavatti, Adaptive neuro-fuzzy inference system identification for the dynamics of the AR. Drone quadcopter, in: Proceeding - 2016 International Conference on Sustainable Energy Engineering and Application: Sustainable Energy for a Better Life, ICSEEA 2016, 2017, pp. 55–60.
[49] M.D. Hua, T. Hamel, P. Morin, C. Samson, Introduction to feedback control of underactuated VTOL vehicles, IEEE Control Syst. 33 (1) (2013) 61–75.
[50] E. Kuantama, T. Vesselenyi, S. Dzitac, R. Tarca, PID and Fuzzy-PID control model for quadcopter attitude with disturbance parameter, Int. J. Comput. Commun. Control 12 (4) (2017) 519–532.
[51] M. Liu, G.K. Egan, F. Santoso, Modeling, autopilot design and field tuning of a UAV with minimum control surfaces, IEEE Trans. Control Syst. Technol. 23 (6) (2015) 2353–2360.
[52] P. Burggräf, A.R. Pérez Martínez, H. Roth, J. Wagner, Quadrotors in factory applications: design and implementation of the quadrotor's P-PID cascade control system, sN Appl. Sci. 1 (7) (2019).
[53] R. Miranda-Colorado, L.T. Aguilar, Robust PID control of quadrotors with power reduction analysis, ISA Trans. 98 (2020) 47–62.
[54] A.L. Salih, M. Moghavvemi, H.A.F. Mohamed, K.S. Gaeid, Flight PID controller design for a UAV quadrotor, Sci. Res. Essays 5 (23) (2010) 3660–3667.
[55] J. Yoon, J. Lee, Approximate multi-objective optimization of a quadcopter through proportional–integral–derivative control, Trans. Korean Soc. Mech. Eng., A 39 (7) (2015) 673–679.
[56] G.E. Setyawan, W. Kurniawan, A.C.L. Gaol, Linear quadratic regulator controller (LQR) for AR. Drone's safe landing, in: Proceedings of 2019 4th International Conference on Sustainable Information Engineering and Technology, SIET 2019, Institute of Electrical and Electronics Engineers Inc., 2019, pp. 228–233.
[57] E. Reyes-Valeria, R. Enriquez-Caldera, S. Camacho-Lara, J. Guichard, LQR control for a quadrotor using unit quaternions: Modeling and simulation, in: 23rd International Conference on Electronics, Communications and Computing, CONIELECOMP 2013, 2013, pp. 172–178.
[58] J.J. Castillo-Zamora, K.A. Camarillo-Gomez, G.I. Perez-Soto, J. Rodriguez-Resendiz, Comparison of PD, PID and sliding-mode position controllers for v-tail quadcopter stability, IEEE Access 6 (2018) 38086–38096.
[59] E. Altuğ, J.P. Ostrowski, C.J. Taylor, Quadrotor control using dual camera visual feedback, in: Proceedings - IEEE International Conference on Robotics and Automation, 2003, pp. 4294–4299.
[60] Ö Özdemir, İ Yazici, 'Ayrik-zaman kkk, lqr ve pid kontrolör performanslarinin alçaltici tip da-da dönüştürücü üzerinde kiyaslanmasi'. saü, Fen Bilimleri EnstitüsÜ Dergisi 22 (1) (2018) 1.
[61] M.P. Nair, R. Harikumar, Longitudinal dynamics control of UAV, in: 2015 International Conference on Control, Communication and Computing India, ICCC 2015, 2016, pp. 30–35.
[62] A. Varghese, D.S.-I.J. Engineering, undefined: 'Modeling and design of UAV with LQG and H∞ controllers, 2019, academia.edu, no date.
[63] J. Richalet, A. Rault, J.L. Testud, J. Papon, Model predictive heuristic control: Applications to industrial processes, Automatica 14 (5) (1978) 413–428.
[64] C.R. Cutler, B.L. Ramaker, Dynamic matrix control? A computer control algorithm, in: Joint Automatic Control, 1980, p. 72.
[65] D.W. Clarke, C. Mohtadi, P.S. Tuffs, Generalized predictive control—Part I. The basic algorithm, Automatica 23 (2) (1987) 137–148.
[66] M. Schwenzer, M. Ay, T. Bergs, D. Abel, Review on model predictive control: an engineering perspective, in: The International Journal of Advanced Manufacturing Technology 2021, 2021, pp. 1–23.
[67] T.P. Nascimento, M. Saska, Position and attitude control of multi-rotor aerial vehicles: A survey, Annu. Rev. Control 48 (2019) 129–146.
[68] M.H. Jaffery, L. Shead, J.L. Forshaw, V.J. Lappas, Experimental quadrotor flight performance using computationally efficient and recursively feasible linear model predictive control. 86 (12) (2013) 2189–2202. http://dx.doi.org/10.1080/00207179.2013.804256.
[69] R.P. George, V. Prakash, Real-Time Human Detection and Tracking Using Quadcopter, in: Lecture Notes in Electrical Engineering, Springer Verlag, 2018, pp. 301–312.
[70] A. Junaid A. Bin, Y. Zweiri, M.N. Sahinkaya, L. Seneviratne, Autonomous wireless self-charging for multi-rotor unmanned aerial vehicles, Energies 10 (6) (2017) 1–14.
[71] S. Khatoon, M. Shahid, H. Ibraheem Chaudhary, Dynamic modeling and stabilization of quadrotor using PID controller, in: Proceedings of the 2014 International Conference on Advances in Computing, Communications and Informatics, ICACCI 2014, Institute of Electrical and Electronics Engineers Inc., 2014, pp. 746–750.
[72] K.U. Lee, H.S. Kim, J.B. Park, Y.H. Choi, Hovering control of a quadrotor, in: International Conference on Control, Automation and Systems, 2012, pp. 162–167.
[73] J. Li, Y. Li, Dynamic analysis and PID control for a quadrotor, in: 2011 IEEE International Conference on Mechatronics and Automation, ICMA 2011, 2011, pp. 573–578.
[74] Z. He, L. Zhao, A simple attitude control of quadrotor helicopter based on Ziegler–Nichols rules for tuning pd parameters, Sci. World J. 2014 (2014).
[75] B. Erginer, E. Altuğ, Modeling and PD control of a quadrotor VTOL vehicle, in: IEEE Intelligent Vehicles Symposium, Proceedings, Institute of Electrical and Electronics Engineers Inc., 2007, pp. 894–899.
[76] Comparison between P, PI, PD and PID controllers - Industrial Automation - Industrial Automation, PLC Programming, scada & Pid Control System.
[77] M. Belkheiri, A. Rabhi, A. El Hajjaji, C. Pegard, Different linearization control techniques for a quadrotor system, in: 2nd International Conference on Communications Computing and Control Applications, CCCA 2012, 2012, pp. 0–5.
[78] I. Tanyer, E. Tatlicioglu, E. Zergeroglu, Output tracking control of an aircraft subject to additive state dependent disturbance: An optimal control approach, Arch. Control Sci. 31 (2) (2021) 267–286.
[79] F. Chen, R. Jiang, K. Zhang, B. Jiang, G. Tao, Robust backstepping sliding-mode control and observer-based fault estimation for a quadrotor UAV, IEEE Trans. Ind. Electron. 63 (8) (2016) 5044–5056.
[80] T. Madani, A. Benallegue, Backstepping control for a quadrotor helicopter, in: IEEE International Conference on Intelligent Robots and Systems, Institute of Electrical and Electronics Engineers Inc., 2006, pp. 3255–3260.
[81] K.M. Zemalache, L. Beji, H. Marref, Control of an under-actuated system: Application to a four rotors rotorcraft, in: 2005 IEEE International Conference on Robotics and Biomimetics, ROBIO, 2005, pp. 404–409.
[82] R. Xu, Özgüner. Ü, Sliding mode control of a quadrotor helicopter, in: Proceedings of the IEEE Conference on Decision and Control, Institute of Electrical and Electronics Engineers Inc., 2006, pp. 4957–4962.
[83] A. Medjghou, N. Slimane, K. Chafaa, Fuzzy sliding mode control based on backstepping synthesis for unmanned quadrotors, Adv. Electr. Electr. Eng. 16 (2) (2018) 135–146.
[84] W. Jie, W. Xiaozhou, W. Jinhuan, Trajectory tracking controller design for a quadrotor aircraft based on fuzzy sliding-mode control, in: Chinese Control Conference, CCC, IEEE Computer Society, 2017, pp. 1354–1358.
[85] G.V. Raffo, M.G. Ortega, F.R. Rubio, An integral predictive/nonlinear H∞ control structure for a quadrotor helicopter, Automatica 46 (1) (2010) 29–39.
[86] İ.C. Dikmen, A. Arısoy, H. Temeltaş, Dikey iniş-kalkış yapabilen dört rotorlu hava aracının(quadrotor) uçuş kontrolü, Havacılık Ve Uzay Tek. Dergisi 3 (2010) 33–40.
[87] F. Piltan, Design adaptive artificial inverse dynamic controller : Design sliding mode fuzzy adaptive new inverse dynamic fuzzy controller, Int. J. Robot. Autom. (IJRA) (3) (2011) 13–26.
[88] J. Wu, H. Wang, N. Li, Z. Su, UAV path following based on BLADRC and inverse dynamic guidance approach, in: 2017 Asian Control Conference, ASCC 2017, Institute of Electrical and Electronics Engineers Inc., 2018, pp. 400–405.
[89] T.L. Costa, J.C. Vendrichoski, E.S. El'Youssef, E.R. De Pieri, Modeling and control of an unmanned aerial vehicle with tilt rotors equipped with a camera, in: 2019 19th International Conference on Advanced Robotics, ICAR 2019, Institute of Electrical and Electronics Engineers Inc., 2019, pp. 167–172.

[90] D.J. Leith, W.E. Leithead, Survey of gain-scheduling analysis and design, Internat. J. Control 73 (11) (2000) 1001–1025.
[91] O. Falkenberg, J. Witt, U. Pilz, U. Weltin, H. Werner, Model Identification and H∞ Attitude Control for Quadrotor MAV' s', Vol. 7507 LNAI, in: Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics), 2012, pp. 460–471, (PART 2).
[92] T. Madani, A. Benallegue, Control of a quadrotor mini-helicopter via full state backstepping technique, in: Proceedings of the IEEE Conference on Decision and Control, Institute of Electrical and Electronics Engineers Inc., 2006, pp. 1515–1520.
[93] K. Kayişli, S. Tuncer, M. Poyraz, Kayma mod denetleyc kullanilarak aktf güç faktörü düzeltm (no date).
[94] A.A. Mian, W. Daobo, Nonlinear flight control strategy for an underactuated quadrotor aerial robot, in: Proceedings of 2008 IEEE International Conference on Networking, Sensing and Control, ICNSC, 2008, pp. 938–942.
[95] Q. Gao, F. Yue, D. Hu, Research of stability augmentation hybrid controller for quadrotor UAV, in: 26th Chinese Control and Decision Conference, CCDC 2014, IEEE Computer Society, 2014, pp. 5224–5229.
[96] D.A. Mercado Ravell, M.M. Maia, F.J. Diez, Modeling and control of unmanned aerial/underwater vehicles using hybrid control, Control Eng. Pract. 76 (2016) (2018) 112–122.
[97] J. Han, From PID to active disturbance rejection control, IEEE Trans. Ind. Electron. 56 (3) (2009) 900–906.
[98] A. Brown, J. Zhang, Active disturbance rejection control of a neutralisation process, Comput. Aided Chem. Eng. 33 (2014) 739–744.
[99] S.A. Suhail, M.A. Bazaz, S. Hussain, Altitude and attitude control of a quadcopter using linear active disturbance rejection control, in: 2019 International Conference on Computing, Power and Communication Technologies (GUCON), 2019, pp. 281–286.
[100] A.A. Najm, I.K. Ibraheem, Altitude and attitude stabilization of UAV quadrotor system using improved active disturbance rejection control, Arab. J. Sci. Eng. 45 (3) (2020) 1985–1999.
[101] W. Xiyang, L. Mingqiu, Y. Yang, D. Hongtao, Quadrotor flight control based on improved active disturbance rejection control technology, J. Phys. Conf. Ser. 1948 (1) (2021).
[102] E. Sariyildiz, R. Oboe, S. Member, K. Ohnishi, Disturbance observer-based robust control and its applications, 2018, pp. 611–612.
[103] K. Ohishi, K. Miyachi, Torque – speed regulation of DC motor based on load torque estimation method, in: International Power Electronics Conference, 1983.
[104] H. Shim, Disturbance observers, in: Encyclopedia of Systems and Control, 2020, pp. 1–8.
[105] S. Mishra, W. Zhang, A disturbance observer approach with online Q-filter tuning for position control of quadcopters, in: Proceedings of the American Control Conference, 2017, pp. 3593–3598.
[106] X. Lyu, J. Zhou, H. Gu, Z. Li, S. Shen, F. Zhang, Disturbance observer based hovering control of quadrotor tail-sitter VTOL UAVs using H ∞ synthesis, IEEE Robot. Autom. Lett. 3 (4) (2018) 2910–2917.
[107] Q.C. Zhong, D. Rees, Control of uncertain LTI systems based on an uncertainty and disturbance estimator, J. Dyn. Syst. Meas. Control 126 (4) (2004) 905–910.
[108] J. Dai, B. Ren, UDE-based robust boundary control for an unstable parabolic PDE with unknown input disturbance, Automatica 93 (2018) 363–368.
[109] Z. Tian, Q.C. Zhong, B. Ren, J. Yuan, UDE-based robust control for systems with mismatched uncertainties via feedback compensation, 94 (7) (2019) 1723–1733. http://dx.doi.org/10.1080/00207179.2019.1669826.
[110] A. Uslu, UDE based robust control of grid tied inverters, Int. J. Appl. Math. Electron. Comput. 8 (4) (2020) 209–213.
[111] J. Betancourt-Vera, P. Castillo, R. Lozano, B. Vidolov, Robust control scheme for trajectory generation and tracking for quadcopters vehicles: Experimental results, in: 2018 International Conference on Unmanned Aircraft Systems, ICUAS 2018, 2018, pp. 1118–1124.
[112] D.D. Dhadekar, P.D. Sanghani, K.K. Mangrulkar, S.E. Talole, Robust control of quadrotor using uncertainty and disturbance estimation, J. Intell. Robot. Syst. 101 (3) (2021) 1–21, 2021 101:3.
[113] What is a neural network? - MATLAB & Simulink, 2022, https://www.mathworks.com/discovery/neural-network.html, accessed March 2022.
[114] D. Gautam, C. Ha, Control of a quadrotor using a smart self-tuning fuzzy PID controller, Int. J. Adv. Robot. Syst. 10 (2013) 1–9.
[115] S. Lin, W. Zhang, Chattering reduced sliding mode control for a class of chaotic systems, Nonlinear Dynam. 93 (4) (2018) 2273–2282.
[116] M. Ghanai, A. Medjghou, K. Chafaa, Extended kalman filter based states estimation of unmanned quadrotors for altitude-attitude tracking control, Adv. Electr. Electron. Eng. 16 (4) (2018) 446–458.
[117] W. Koch, R. Mancuso, R. West, A. Bestavros, Reinforcement learning for UAV attitude control, ACM Trans. Cybern.-Phys. Syst. 3 (2) (2019) 1–21.
[118] K. El Hamidi, M. Mjahed, A.E. El Kari, H. Ayad, Neural network and fuzzy-logic-based self-tuning PID control for quadcopter path tracking, Stud. Inform. Control 28 (4) (2019) 401–412.
[119] G. Sonugür, C.O. Gökçe, Y.B. Koca, Ş.S. Inci, Z. Keleş, Particle swarm optimization based optimal pid controller for quadcopters, C. R. Acad. Bulg. Sci. 74 (12) (2021) 1806–1814.
[120] J. Kennedy, R. Eberhart, Particle swarm optimization, in: Proceedings of the IEEE International Joint Conference on Neural Networks, 1995, pp. 1942–1948.
[121] İ Kocaarslan, E. Bal, K.K. Gümüş, H. Tiryaki, Parçacık sürüsü optimizasyonu (PSO) yönteminin güç sistemi kararlı kılıcısında (PSS) uygulanması application of particle swarm optimization (PSO) method on power system stabilizer (PSS) elektrik- elektronik mühendisliği bölümü, in: ELECO '2012 Elektrik - Elektronik Ve Bilgisayar Mühendisliği Sempozyumu, 2012, pp. 99–103.
[122] R.J. Wai, A.S. Prasetia, Adaptive neural network control and optimal path planning of UAV surveillance system with energy consumption prediction, IEEE Access 7 (2019) 126137–126153.
[123] R. Fessi, S. Bouallègue, LQG controller design for a quadrotor UAV based on particle swarm optimisation, Int. J. Autom. Control 13 (5) (2019) 569–594.
[124] Y. Liu, X. Yan, F. Yan, Z. Xu, W. Shang, Sliding-mode PID control of UAV based on particle swarm parameter tuning, Comput. Mater. Contin. 63 (1) (2020) 469–487.
[125] L.R.G. Carrillo, A. Dzul, R. Lozano, Hovering quad-rotor control: A comparison of nonlinear controllers using visual feedback, IEEE Trans. Aerosp. Electron. Syst. 48 (4) (2012) 3159–3170.
[126] M. Achtelik, T. Zhang, K. Kühnlenz, M. Buss, Visual tracking and control of a quadcopter using a stereo camera system and inertial sensors, in: 2009 IEEE International Conference on Mechatronics and Automation, ICMA 2009, 2009, pp. 2863–2869.
[127] K. Urbanski, IN:2018 18th international conference on mechatronics - Mechatronika (ME), in: Control of the Quadcopter Position using Visual Feedback, 2018.
[128] P. Viola, M. Jones, Rapid object detection using a boosted cascade of simple features, in: Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition, 2001.
[129] E. Altuğ, J.P. Ostrowski, R. Mahony, Control of a quadrotor helicopter using visual feedback, in: Proceedings - IEEE International Conference on Robotics and Automation, Vol. 1, 2002, pp. 72–77.
[130] L.D. Minh, C. Ha, Modeling and control of quadrotor MAV using vision-based measurement, in: 2010 International Forum on Strategic Technology, IFOST 2010, 2010, pp. 70–75.
[131] H. Oh, D.Y. Won, S.S. Huh, D.H. Shim, M.J. Tahk, A. Tsourdos, A indoor UAV control using multi-camera visual feedback, in: Journal of Intelligent and Robotic Systems: Theory and Applications, Springer, 2011, pp. 57–84.
[132] S. Li, K. Huang, L. Feng, Z. Lv, Y. Wu, ADRC-based position control of QCSP with vision feedback, in: Proceeding - 2021 China Automation Congress, CAC 2021, 2021, pp. 5062–5068.
[133] M. Belkheiri, A. Rabhi, A. El Hajjaji, C. Pegard, Different linearization control techniques for a quadrotor system, in: 2nd International Conference on Communications Computing and Control Applications, CCCA 2012, 2012.
[134] S. Bouabdallah, A. Noth, R. Siegwart, PID vs LQ control techniques applied to an indoor micro Quadrotor, in: 2004 IEEE/RSJ International Conference on Intelligent Robots and Systems, IROS, 2004, pp. 2451–2456.
[135] S. Bouabdallah, R. Siegwart, Backstepping and sliding-mode techniques applied to an indoor micro Quadrotor, in: Proceedings - IEEE International Conference on Robotics and Automation, 2005, pp. 2247–2252.
[136] M. Labbadi, M. Cherkaoui, Y. El Houm, M. Guisser, A comparative analysis of control strategies for stabilizing a quadrotor, in: Smart Innovation, Systems and Technologies, Springer Science and Business Media Deutschland GmbH, 2019, pp. 625–630.
[137] R. Falcón, H. Ríos, A. Dzul, Comparative analysis of continuous sliding-modes control strategies for quad-rotor robust tracking, Control Eng. Pract. 90 (2019) 241–256.
[138] S.L. Waslander, G.M. Hoffmann, J.S. Jang, C.J. Tomlin, Multi-agent quadrotor testbed control design: Integral sliding mode vs. Reinforcement learning, in: 2005 IEEE/RSJ International Conference on Intelligent Robots and Systems, IROS, IEEE Computer Society, 2005, pp. 3712–3717.
[139] M.F. Shehzad, A. Bilal, H. Ahmad, Position attitude control of an aerial robot (quadrotor) with intelligent PID and state feedback LQR controller: A comparative approach, in: Proceedings of 2019 16th International Bhurban Conference on Applied Sciences and Technology, IBCAST 2019, Institute of Electrical and Electronics Engineers Inc., 2019, pp. 340–346.
[140] S. Khatoon, D. Gupta, L.K. Das, PID & LQR control for a quadrotor: Modeling and simulation, in: Proceedings of the 2014 International Conference on Advances in Computing, Communications and Informatics, ICACCI 2014, Institute of Electrical and Electronics Engineers Inc., 2014, pp. 796–802.

[141] C. Bensalah, N.K. M'Sirdi, A. Naamane, Comparative study of control approaches designed for a quadrotor in a visual servoing task without observers, in: 2019 8th International Conference on Systems and Control, ICSC 2019, Institute of Electrical and Electronics Engineers Inc., 2019, pp. 13–20.
[142] B. Yu, Y. Zhang, I. Minchala, Y. Qu, Fault-tolerant control with linear quadratic and model predictive control techniques against actuator faults in a quadrotor UAV, in: Conference on Control and Fault-Tolerant Systems, SysTol, 2013, pp. 661–666.
[143] R. Mohammed, Comparative study and robustness analysis of quadrotor control in presence of wind disturbances, ADMT J. 12 (2) (2019) 27–37.
[144] H.L.N.N. Thanh, N.N. Phi, S.K. Hong, Simple nonlinear control of quadcopter for collision avoidance based on geometric approach in static environment, Int. J. Adv. Robot. Syst. 15 (2) (2018) 1–17.
[145] A.T. Kutay, Dört rotorlu bİ rİ nsansiz hava aracinin gerİ - Adimlama yöntemİİ le yol takİ bİ kontrolü, Havacılık Uzay Teknol. Dergisi 7 (2) (2014) 1–13.
[146] J. Gomez-Avila, C. Villaseñor, J. Hernandez-Barragan, N. Arana-Daniel, A.Y. Alanis, C. Lopez-Franco, Neural PD controller for an unmanned aerial vehicle trained with extended Kalman filter, Algorithms 13 (2) (2020) 40.
[147] A. Mekky, T.E. Alberts, Design of a stochastic basis function artificial neural network controller for quadrotors flight in the presence of model and aerodynamic uncertainties, in: Proceedings of the IEEE National Aerospace Electronics Conference, NAECON, Institute of Electrical and Electronics Engineers Inc., 2018, pp. 395–402.
[148] R. Czyba, L. Stajer, Dynamic contraction method approach to digital longitudinal aircraft flight controller design, Arch. Control Sci. 29 (1) (2019) 97–109.
[149] E. Ebeid, M. Skriver, J. Jin, A survey on open-source flight control platforms of unmanned aerial vehicle, in: Proceedings - 20th Euromicro Conference on Digital System Design, DSD 2017, 2017, pp. 396–402.
[150] R.H. Klenke, A UAV-based computer engineering capstone senior design project, in: Proceedings - 2005 IEEE International Conference on Microelectronic Systems Education, MSE '05 - Promoting Excellence and Innovation in Microelectronic Systems Education, 2005, 2005, pp. 111–112.
[151] G. Grillmayer, M. Hirth, F. Huber, V. Wolter, Development of an FPGA based attitude control system for a micro-satellite, in: Collection of Technical Papers - AIAA/AAS Astrodynamics Specialist Conference, 2006, Vol. 2, 2006, pp. 1238–1251.
[152] H.B. Christophersen, W.J. Pickell, A.A. Koller, S.K. Kannan, E.N. Johnson, Small adaptive flight control systems for UAVs using FPGA/DSP technology, in: Collection of Technical Papers - AIAA 3rd 'Unmanned-Unlimited' Technical Conference, Workshop, and Exhibit, Vol. 2, 2004, pp. 780–787.
[153] K. Schmid, T. Tomic, F. Ruess, H. Hirschmuller, M. Suppa, Stereo vision based indoor/outdoor navigation for flying robots, in: IEEE International Conference on Intelligent Robots and Systems, 2013, pp. 3955–3962.
[154] P. Oettershagen, A. Melzer, T. Mantel, et al., A solar-powered hand-launchable UAV for low-altitude multi-day continuous flight, in: Proceedings - IEEE International Conference on Robotics and Automation, 2015-June, 2015, pp. 3986–3993, (June).
[155] K. Priandana, M. Hazim, Wulandari, B. Kusumoputro, Development of autonomous UAV quadcopters using pixhawk controller and its flight data acquisition, in: 2020 International Conference on Computer Science and Its Application in Agriculture, ICOSICA 2020, 2020.
[156] D. Yamunathangam, J. Shanmathi, R. Caviya, G. Saranya, Payload manipulation for seed sowing unmanned aerial vehicle through interface with pixhawk flight controller, in: Proceedings of the 4th International Conference on Inventive Systems and Control, ICISC 2020, 2020, pp. 931–934.
[157] G.A. Venkatesh, P. Sumanth, K.R. Jansi, Fully autonomous UAV, in: Proceedings - 2017 International Conference on Technical Advancements in Computers and Communication, ICTACC 2017, Vol. 2017- October, 2017, pp. 41–44.
[158] J. Zelenka, T. Kasanicky, Outdoor UAV control and coordination system supported by biological inspired method, in: 23rd International Conference on Robotics in Alpe-Adria-Danube Region, IEEE RAAD 2014 - Conference Proceedings, 2015.
[159] M.J. Er, S. Yuan, N. Wang, Development control and navigation of octocopter, in: IEEE International Conference on Control and Automation, ICCA, 2013, pp. 1639–1643.
[160] R. Smith, P. Cheesman, On the representation of spatial uncertainty, Int. J. Robot. Res. 5 (4) (1987) 56–68.
[161] G. Dissanayake, H. Durrant-Whyte, T. Bailey, Computationally efficient solution to the simultaneous localisation and map building (SLAM) problem, in: Proceedings - IEEE International Conference on Robotics and Automation, 2000, pp. 1009–1014.
[162] H. Durrant-Whyte, T. Bailey, Simultaneous localization and mapping: Part I, IEEE Robot. Autom. Mag. 13 (2) (2006) 99–108.
[163] T. Bailey, H. Durrant-Whyte, Simultaneous localization and mapping (SLAM): Part II, IEEE Robot. Autom. Mag. 13 (3) (2006) 108–117.
[164] E. Duymaz, Otonom Araçların Yöngüdümünde Paf Tabanlı Ezkh Yönteminin Geliştirilmesi, İstanbul Teknik Üniversitesi, 2018.
[165] N.E. Özkucur, Design and Implementatıon of Multi-Agent Visual-Slam Algorıthms on Autonomous Robots, BOĞAZİÇİ ÜNİVERSİTESİ, 2006.
[166] M. Bakır, Yörüngeye Dayalı Slam Probleminde Topolojik Haritalama Yöntemi, İstanbul Teknik Üniversitesi, 2008.
[167] S. Saeedi, M. Trentini, M. Seto, H. Li, Multiple-robot simultaneous localization and mapping: A review, J. Field Robotics 33 (1) (2016) 3–46.
[168] A.E. Oğuz, Uçak üzeri eş zamanlı konumlama ve haritalama (ezkh)'da artırılmış tutarlılık İçin gözlenebilirlik kısıtlı Kalman filtreleri, Hava Harp Okulu Havacilik Uzay Teknol Enstitüsü (2012).
[169] S.B. Williams, G. Dissanayake, H. Durrant-Whyte, An efficient approach to the simultaneous localisation and mapping problem, in: Proceedings - IEEE International Conference on Robotics and Automation, 2002, pp. 406–411.
[170] S. Yavuz, Z. Kurt, M.S. Bi??er, Genişletilmiş Kalman filtresi yöntemine dayali eş zamanli konum belirleme ve haritalama algoritmasi, in: 2009 IEEE 17th Signal Processing and Communications Applications Conference, SIU 2009, 2009, pp. 700–703.
[171] F. Demim, A. Nemra, K. Louadj, et al., Visual SVSF-SLAM Algorithm Based on Adaptive Boundary Layer Width, in: Lecture Notes in Electrical Engineering, Springer Verlag, 2019, pp. 97–112.
[172] F. Demim, A. Nemra, A. Boucheloukh, K. Louadj, M. Hamerlain, A. Bazoula, Robust SVSF-SLAM algorithm for unmanned vehicle in dynamic environment, in: 2018 International Conference on Signal, Image, Vision and their Applications, SIVA 2018, 2019.
[173] L. Xu, C. Feng, V.R. Kamat, C.C. Menassa, A scene-adaptive descriptor for visual SLAM-based locating applications in built environments, Autom. Constr. 112 (2019) (2020) 103067.
[174] B. Fang, Z. Zhan, A visual SLAM method based on point-line fusion in weak-matching scene, Int. J. Adv. Robot. Syst. 17 (2) (2020) 1–11.
[175] C. Bibby, I. Reid, A hybrid SLAM representation for dynamic marine environments, in: Proceedings - IEEE International Conference on Robotics and Automation, 2010, pp. 257–264.
[176] J. Choi, J. Park, J. Jung, Y. Lee, H.T. Choi, Development of an autonomous surface vehicle and performance evaluation of autonomous navigation technologies, Int. J. Control Autom. Syst. 18 (3) (2020) 535–545.
[177] S. Thrun, S. Thayer, W. Whittaker, et al., Autonomous exploration and mapping of abandoned mines: Software architecture of an autonomous robotic system, IEEE Robot. Autom. Mag. 11 (4) (2004) 79–91.
[178] Flyability.
[179] S. Grzonka, G. Grisetti, W. Burgard, Towards a navigation system for autonomous indoor flying Slawomir Grzonka Giorgio Grisetti Wolfram Burgard, in: Proceedings - IEEE International Conference on Robotics and Automation, 2009, pp. 2878–2883.
[180] A.G. Bachrach, Autonomous Flight in Unstructured and Unknown Indoor Environments, Massachusetts Institute of Technology, 2009.
[181] A. Buyval, M. Gavrilenkov, Vision-based pose estimation for indoor navigation of unmanned micro aerial vehicle based on the 3D model of environment, in: Proceedings of 2015 International Conference on Mechanical Engineering, Automation and Control Systems, MEACS 2015, Institute of Electrical and Electronics Engineers Inc., 2016.
[182] K. Yakovlev, V. Khithov, M. Loginov, A. Petrov, Distributed control and navigation system for quadrotor UAVs in GPS-denied environments, Adv. Int. Syst. Comput. 323 (2015) 49–56.
[183] A. Buyval, M. Gavrilenkov, E. Magid, A multithreaded algorithm of UAV visual localization based on a 3D model of environment: implementation with CUDA technology and CNN filtering of minor importance objects, Proc. Int. Conf. Artif. Life Robot. 22 (Icarob) (2017) 356–359.
[184] A. Buyval, I. Afanasyev, E. Magid, Comparative analysis of ROS-based monocular SLAM methods for indoor navigation, in: Ninth International Conference on Machine Vision (ICMV 2016), Vol. 10341, 2017, 103411K.
[185] K. Çelik, S.J. Chung, M. Clausman, A.K. Somani, Monocular vision SLAM for indoor aerial vehicles, in: 2009 IEEE/RSJ International Conference on Intelligent Robots and Systems, IROS 2009, 2009, pp. 1566–1573.
[186] S.P. Soundararaj, A.K. Sujeeth, A. Saxena, Autonomous indoor helicopter flight using a single onboard camera, in: 2009 IEEE/RSJ International Conference on Intelligent Robots and Systems, IROS 2009, 2009, pp. 5307–5314.
[187] I.Z. Ibragimov, I.M. Afanasyev, Comparison of ROS-based visual SLAM methods in homogeneous indoor environment, in: 2017 14th Workshop on Positioning, Navigation and Communications, WPNC 2017, Institute of Electrical and Electronics Engineers Inc., 2018, pp. 1–6.
[188] U.S. army road map for UAS, 2010.
[189] A. Aditya, Implementation of a 4D fast SLAM including volumetric sum of the UAV, in: Proceedings of the International Conference on Sensing Technology, ICST, 2012, pp. 78–83.

[190] Wang, X. Bin, G.R. Zhao, S. Pan, Overview on simultaneous localization and mapping for uninhabited aerial vehicle vision, in: Proceedings of the 30th Chinese Control Conference, CCC 2011, 2011, pp. 3913–3918.
[191] J. Kim, S. Sukkarieh, Autonomous airborne navigation in unknown terrain environments, IEEE Trans. Aerosp. Electron. Syst. 40 (3) (2004) 1031–1045.
[192] J.A. Hesch, D.G. Kottas, S.L. Bowman, S.I. Roumeliotis, Observability-Constrained Vision-Aided Inertial Navigation, Tech. Rep 1, University of Minnesota, Dept. of Comp. Sci. & Eng. MARS Lab., 2012, (612).
[193] M. Wzorek, J. Kvarnström, P. Doherty, Choosing path replanning strategies for unmanned aircraft systems, in: ICAPS 2010 - Proceedings of the 20th International Conference on Automated Planning and Scheduling, Icaps, 2010, pp. 193–200.
[194] C. Wang, T. Wang, J. Liang, Y. Chen, Y. Zhang, C. Wang, Monocular visual SLAM for small UAVs in GPS-denied environments, in: 2012 IEEE International Conference on Robotics and Biomimetics, ROBIO 2012 - Conference Digest, 2012, pp. 896–901.
[195] A. Gabdullin, G. Shvedov, M. Ivanou, I. Afanasyev, Analysis of onboard sensor-based odometry for a quadrotor UAV in outdoor environment, in: Proceedings of International Conference on Artificial Life and Robotics, Vol. 23, 2018, pp. 196–199.
[196] M.J. Milford, F. Schill, P. Corke, R. Mahony, G. Wyeth, Aerial SLAM with a single camera using visual expectation, in: Proceedings - IEEE International Conference on Robotics and Automation, 2011, pp. 2506–2512.
[197] J. Courbon, Y. Mezouar, N. Guenard, P. Martinet, Visual navigation of a quadrotor aerial vehicle, in: 2009 IEEE/RSJ International Conference on Intelligent Robots and Systems, IROS 2009, 2009, pp. 5315–5320.
[198] R. Munguia, S. Urzua, A. Grau, Delayed monocular SLAM approach applied to unmanned aerial vehicles, PLoS One 11 (12) (2016) 1–24.
[199] R. Ait-Jellal, A. Zell, Outdoor obstacle avoidance based on hybrid visual stereo SLAM for an autonomous quadrotor MAV, in: 2017 European Conference on Mobile Robots, ECMR 2017, 2017.
[200] L. Heng, L. Meier, P. Tanskanen, F. Fraundorfer, M. Pollefeys, Autonomous obstacle avoidance and maneuvering on a vision-guided MAV using on-board processing, in: Proceedings - IEEE International Conference on Robotics and Automation, 2011, pp. 2472–2477.
[201] H. Yu, R.W. Beard, J. Byrne, Vision-based local multi-resolution mapping and path planning for miniature air vehicles, in: Proceedings of the American Control Conference, 2009, pp. 5247–5252.
[202] J.H. Kim, S. Sukkarieh, S. Wishart, Real-time navigation, guidance, and control of a UAV using low-cost sensors, Springer Tracts Adv. Robot. 24 (2006) 299–309.
[203] S. Zahran, A. Moussa, A. Sesay, N. El-Sheimy, Enhancement of real-time scan matching for uav indoor navigation using vehicle model, ISPRS Ann. Photogramm. Remote Sens. Spat. Inf. Sci. 4 (1) (2018) 171–178.
[204] T. Gee, J. James, W. Van Der Mark, P. Delmas, G. Gimel'Farb, Lidar guided stereo simultaneous localization and mapping (SLAM) for UAV outdoor 3-D scene reconstruction, in: International Conference Image and Vision Computing New Zealand, 2016.
[205] L. Kaul, R. Zlot, M. Bosse, Continuous-time three-dimensional mapping for micro aerial vehicles with a passively actuated rotating laser scanner, J. Field Robotics 33 (1) (2016) 103–132.
[206] G. Grisetti, C. Stachniss, W. Burgard, Improved techniques for grid mapping with Rao-Blackwellized particle filters, IEEE Trans. Robot. 23 (1) (2007) 34–46.
[207] R. Ait-Jellal, A. Zell, Outdoor obstacle avoidance based on hybrid visual stereo SLAM for an autonomous quadrotor MAV, in: 2017 European Conference on Mobile Robots, ECMR 2017, Institute of Electrical and Electronics Engineers Inc., 2017.
[208] S. Ahrens, D. Levine, G. Andrews, J.P. How, Vision-based guidance and control of a hovering vehicle in unknown, gps-denied environments, in: Proceedings - IEEE International Conference on Robotics and Automation, 2009, pp. 2643–2648.
[209] A. Angeli, D. Filliat, S. Doncieux, J.-A. Meyer, 2D simultaneous localization and mapping for micro air vehicles, 2006.
[210] M. Blösch, S. Weiss, D. Scaramuzza, R. Siegwart, Vision based MAV navigation in unknown and unstructured environments, in: Proceedings - IEEE International Conference on Robotics and Automation, 2010, pp. 21–28.
[211] M.J. Milford, G.F. Wyeth, Mapping a suburb with a single camera using a biologically inspired SLAM system, IEEE Trans. Robot. 24 (5) (2008) 1038–1053.
[212] D. Prasser, M. Milford, G. Wyeth, Outdoor simultaneous localisation and mapping using RatSLAM, in: Springer Tracts in Advanced Robotics, Springer Verlag, 2006, pp. 143–154.
[213] M. Milford, G. Wyeth, Persistent navigation and mapping using a biologically inspired SLAM system, Int. J. Robot. Res. 29 (9) (2010) 1131–1153.
[214] R. Mur-Artal, J.D. Tardos, ORB-SLAM2: An open-source SLAM system for monocular, stereo, and RGB-D cameras, IEEE Trans. Robot. 33 (5) (2017) 1255–1262.
[215] T. Lemaire, C. Berger, I.K. Jung, S. Lacroix, Vision-based SLAM: Stereo and monocular approaches, Int. J. Comput. Vis. 74 (3) (2007) 343–364.
[216] J. Engel, J. Stückler, D. Cremers, Large-scale direct SLAM with stereo cameras, in: IEEE International Conference on Intelligent Robots and Systems, Institute of Electrical and Electronics Engineers Inc., 2015, pp. 1935–1942.
[217] J.Y. Baek, S.H. Park, B.S. Cho, M.C. Lee, Position tracking system using single RGB-D camera for evaluation of multi-rotor UAV control and self-localization, in: IEEE/ASME International Conference on Advanced Intelligent Mechatronics, AIM, Institute of Electrical and Electronics Engineers Inc., 2015, pp. 1283–1288.
[218] F. Endres, J. Hess, J. Sturm, D. Cremers, W. Burgard, 3-D mapping with an RGB-D camera, IEEE Trans. Robot. 30 (1) (2014) 177–187.
[219] H. Zhang, Y. Liu, J. Tan, N. Xiong, RGB-D SLAM combining visual odometry and extended information filter, Sensors 15 (8) (2015) 18742–18766.
[220] B. Fang, Z. Zhan, A visual SLAM method based on point-line fusion in weak-matching scene, Int. J. Adv. Robot. Syst. 17 (2) (2020) 172988142090419.
[221] R. Mur-Artal, J.D. Tardos, ORB-SLAM2: An open-source SLAM system for monocular, stereo, and RGB-D cameras, IEEE Trans. Robot. 33 (5) (2017) 1255–1262.
[222] S. Thrun, W. Burgard, Probabilistic Robotics, MIT Press, Cambridge, MA, 2012.
[223] M. Ghanai, A. Medjghou, K. Chafaa, Extended Kalman filter based states estimation of unmanned quadrotors for altitude-attitude tracking control, 2018.
[224] A.E. Oguz, H. Temeltas, On the consistency analyzing of A-SLAM for UAV navigating in GNSS denied environment, Acta Polytech. Hungarica 10 (4) (2013) 119–132.
[225] T. Suzuki, Y. Amano, T. Hashizume, Development of a SIFT based monocular EKF-SLAM algorithm for a small unmanned aerial vehicle, in: Proceedings of the SICE Annual Conference, 2011, pp. 1656–1659, (D).
[226] C.-C. Tsai, C.-F. Hsu, X.-C. Lin, F.-C. Tai, Cooperative SLAM using fuzzy Kalman filtering for a collaborative air-ground robotic system, J. Chin. Inst. Eng. 43 (1) (2020) 67–79.
[227] B. Abbyasov, R. Lavrenov, A. Zakiev, et al., Comparative analysis of ros-based centralized methods for conducting collaborative monocular visual slam using a pair of uavs, in: Robots in Human Life- Proceedings of the 23rd International Conference on Climbing and Walking Robots and the Support Technologies for Mobile Machines, CLAWAR 2020, CLAWAR Association Ltd, 2020, pp. 113–120.
[228] J. Engel, T. Schöps, D. Cremers, LSD-SLAM: Large-scale direct monocular SLAM, in: Lecture Notes in Computer Science (Including Subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics), Springer Verlag, 2014, pp. 834–849.
[229] E. López, S. García, R. Barea, et al., A multi-sensorial simultaneous localization and mapping (SLAM) system for low-cost micro aerial vehicles in GPS-denied environments, Sensors 17 (4) (2017) 802.
[230] S. Weiss, M.W. Achtelik, S. Lynen, et al., Monocular vision for long-term micro aerial vehicle state estimation: A compendium, J. Field Robotics 30 (5) (2013) 803–831.
[231] S.O. Santos, W. Yu, E. Zamora, Sliding mode three-dimension SLAM with application to quadrotor helicopter, in: 2018 15th International Conference on Electrical Engineering, Computing Science and Automatic Control, CCE 2018, 2018, pp. 1–6.
[232] Y. Alborzi, B.S. Jalal, E. Najafi, ROS-based SLAM and navigation for a Gazebo-simulated autonomous quadrotor, in: 2020 21st International Conference on Research and Education in Mechatronics, REM, IEEE, 2020, pp. 1–5.
[233] R. Yagfarov, M. Ivanou, I. Afanasyev, Map comparison of lidar-based 2D SLAM algorithms using precise ground truth, in: 2018 15th International Conference on Control, Automation, Robotics and Vision, ICARCV 2018, 2018, pp. 1979–1983.
[234] F. Lu, E. Milios, Globally consistent range scan alignment for environment mapping, Auton. Robots 4 (4) (1997) 333–349.
[235] S. Jung, D. Choi, S. Song, H. Myung, Bridge inspection using unmanned aerial vehicle based on HG-SLAM: Hierarchical graph-based SLAM, Remote Sens. 12 (18) (2020) 3022, 2020, Vol. 12, Page 3022.
[236] Y. Chen, S. Huang, R. Fitch, L. Zhao, H. Yu, D. Yang, On-line 3D active pose-graph SLAM based on key poses using graph topology and sub-maps, in: Proceedings - IEEE International Conference on Robotics and Automation, Vol. 2019- May, 2019, pp. 169–175.
[237] A. Moura, J. Antunes, A. Dias, A. Martins, J. Almeida, Graph-SLAM approach for indoor UAV localization in warehouse logistics applications, in: 2021 IEEE International Conference on Autonomous Robot Systems and Competitions, ICARSC 2021, 2021, pp. 4–11.

[238] J. Meyer, A. Sendobry, S. Kohlbrecher, U. Klingauf, O. Von Stryk, Comprehensive simulation of quadrotor UAVs using ROS and Gazebo, in: Lecture Notes in Computer Science (Including Subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics), Springer, Berlin, Heidelberg, 2012, pp. 400–411.

[239] O. Esrafilian, H.D. Taghirad, Autonomous flight and obstacle avoidance of a quadrotor by monocular SLAM, in: 4th RSI International Conference on Robotics and Mechatronics, ICRoM 2016, 2017, pp. 240–245.

[240] R. Munguia-Silva, J. Martinez-Carranza, Autonomous flight using RGB-D SLAM with a monocular onboard camera only, in: 2018 28th International Conference on Electronics, Communications and Computers, CONIELECOMP 2018, Institute of Electrical and Electronics Engineers Inc., 2018, pp. 200–206.

[241] X. Yang, H. Luo, Y. Wu, Y. Gao, C. Liao, K.T. Cheng, Reactive obstacle avoidance of monocular quadrotors with online adapted depth prediction network, Neurocomputing 325 (2019) 142–158.

[242] S.J. Haddadi, E.B. Castelan, Visual-inertial fusion for indoor autonomous navigation of a quadrotor using ORB-SLAM, in: Proceedings - 15th Latin American Robotics Symposium, 6th Brazilian Robotics Symposium and 9th Workshop on Robotics in Education, LARS/SBR/WRE 2018, 2018, pp. 112–117.

[243] P. Araujo, R. Miranda, D. Carmo, R. Alves, L. Oliveira, Air-SSLAM: A visual stereo indoor SLAM for aerial quadrotors, IEEE Geosci. Remote Sens. Lett. 14 (9) (2017) 1643–1647.

[244] T. Bera, A. Sinha, A.K. Sadhu, R. Dasgupta, Vision based autonomous QuadCopter navigation through narrow gaps using visual servoing and monocular SLAM, in: 2019 6th Indian Control Conference, ICC 2019 - Proceedings, 2019, pp. 25–30.

[245] M. Labbé, F. Michaud, Online global loop closure detection for large-scale multi-session graph-based SLAM, in: IEEE International Conference on Intelligent Robots and Systems, Institute of Electrical and Electronics Engineers Inc., 2014, pp. 2661–2666.

[246] M. Bouhali, F. Shamani, Z.E. Dahmane, A. Belaidi, J. Nurmi, FPGA applications in unmanned aerial vehicles - A review, in: Lecture Notes in Computer Science (Including Subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics), in: LNCS, vol. 10216, 2017, pp. 217–228.

[247] R. Latif, A. Saddik, SLAM algorithms implementation in a UAV, based on a heterogeneous system: A survey, in: Proceedings of 2019 IEEE World Conference on Complex Systems, WCCS 2019, 2019.

[248] K. Boikos, C.S. Bouganis, Semi-dense SLAM on an FPGA SoC, in: FPL 2016-26th International Conference on Field-Programmable Logic and Applications, 2016.

[249] V.A.M.F. Torres, B.R.A. Jaimes, E.S. Ribeiro, et al., Combined weightless neural network FPGA architecture for deforestation surveillance and visual navigation of UAVs, Eng. Appl. Artif. Intell. 87 (2020) 103227.

Guray SONUGUR was born in Balıkesir, Turkey, in 1973. He received his B.S. degrees from Anadolu University, Eskisehir, Turkey in 1994. He received his M.S. and Ph.D. degrees from Afyon Kocatepe University, Afyonkarahisar , Turkey in 2014 and 2016 respectively. He is currently a Assistant Professor in the Department of Mechatronics Engineering, Afyon Kocatepe University. His research interests focus on image processing, pattern recognition, autonomous vehicles and machine learning in mechatronic systems.