Embedded Sensors, Communication Technologies, Computing Platforms and Machine Learning for UAVs: A Review

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Abstract: **Unmanned aerial vehicles (UAVs) are increasingly becoming popular due to their use in many commercial and military applications, and their affordability. The UAVs are equipped with various sensors, hardware platforms and software technologies which enable them to support the diverse application portfolio. Sensors include vision-based sensors such as RGB-D cameras, thermal cameras, light detection and ranging (LiDAR), mmWave radars, ultrasonic sensors, and an inertial measurement unit (IMU) which enable UAVs for autonomous navigation, obstacle detection, collision avoidance, object tracking and aerial inspection. To enable smooth operation, UAVs utilize a number of communication technologies such as wireless fidelity (Wi-Fi), long range (LoRa), long-term evolution for machine-type communication (LTE-M), etc., along with various machine learning algorithms. However, each of these different technologies come with their own set of advantages and challenges. Hence, it is essential to have an overview of the different type of sensors, computing and communication modules and algorithms used for UAVs. This paper provides a comprehensive review on the state-of-the-art embedded sensors, communication technologies, computing platforms and machine learning techniques used in autonomous UAVs. The key performance metrics along with operating principles and a detailed comparative study of the various technologies are also studied and presented. The information gathered in this paper aims to serve as a practical reference guide for designing smart sensing applications, low-latency and energy efficient communication strategies, power efficient computing modules and machine learning algorithms for autonomous UAVs. Finally, some of the open issues and challenges for future research and development are also discussed.**

A.1 Introduction

Recent advances in sensor miniaturization, ubiquitous wireless connectivity, en-

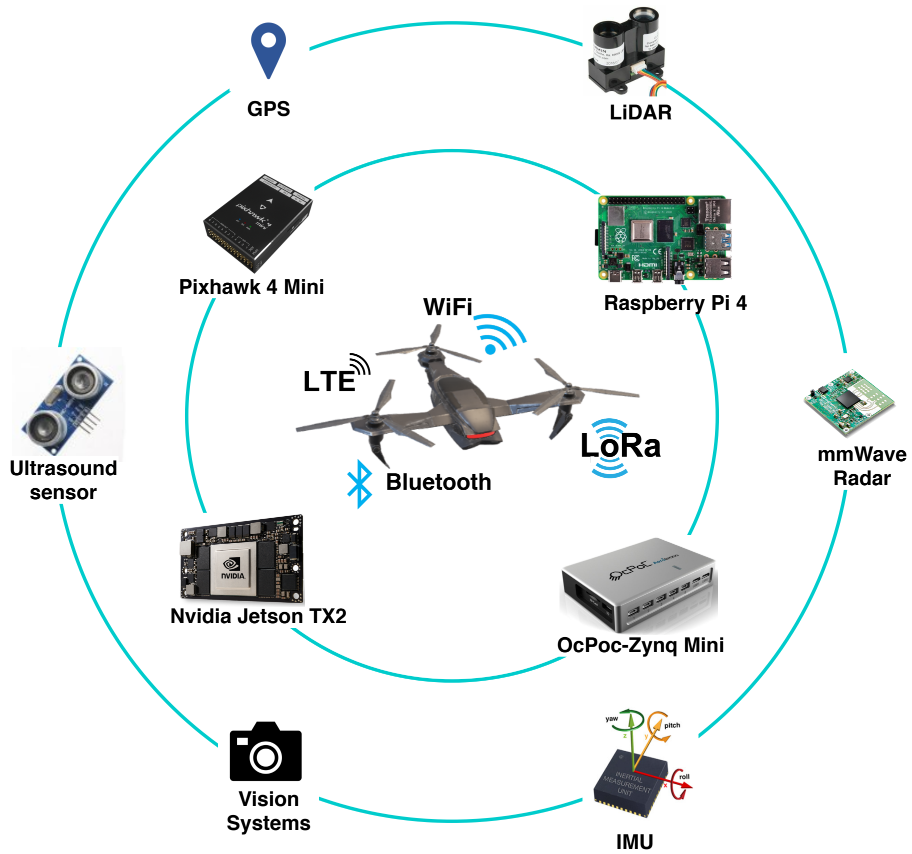

Figure A.1: Diagramatic overview of the survey

hanced processing power and low complexity algorithms have contributed to the growing demand for unmanned aerial vehicle (UAV) or drone-based applications. According to market estimates, the revenue generated from these broad range of UAV applications is expected to exceed 8.5 billion dollars by 2027 [1]. Additionally, UAV-based architectures are explored for the development and implementation of next generation technologies such as 5G, vehicle-to-everything (V2X) communications, etc.

UAVs are originally used in military applications to survey and target enemy territory. However, recent technological advancements have led to the use of UAVs in a wide range of applications spanning multiple industries. Agriculture, disaster management, surveillance, package delivery, and aerial photography are some of the common applications for UAVs. UAVs are used in agriculture to monitor crop health and irrigation. [2]. In defense, they are used for intruder detection and attack [3]. Surveillance applications use UAVs for mapping large areas [4]. UAVs with remote sensing capabilities are useful for scanning large geographical areas for archaeological applications [5]. Recently, UAVs have made their way into the e-commerce industry. Amazon has demonstrated a UAV-based package delivery system called Prime Air [6] that can deliver shipments to customers in remote areas within a specific time.

UAVs provide enhanced aerial inspection, improved line-of-sight (LoS) communication, reliable data acquisition and seamless obstacle free movement which contribute for their wide spread adoption across diverse applications. Furthermore, their ability to access remote locations and capture images makes them far superior and more flexible than ground-based systems. In addition, factors such as cutting-edge computational resources, readily available components, and low cost have made UAVs the obvious choice for a wide range of application requirements.

To accommodate the wide range of supported applications, UAVs are outfitted with highly sophisticated hardware and software modules. Embedded sensors, communication modules, and computing platforms are among the hardware components, while the software stack supports UAV configuration aspects, control and stabilization algorithms, mission planning, and testing. Additionally, machine learning and deep learning approaches are also utilized to support the various collision avoidance and stabilization algorithms. The hardware and software components are tightly coupled and work in tandem to allow UAVs to fly and perform various operations. As a result, comprehending and appreciating UAV operations requires an understanding of the complex interplay of the underlying technologies.

There are some survey papers in the literature that provide information on the various technologies used in UAVs. In [7], the authors have provided a brief description of the different sensors used in autonomous systems. The principle of operation of each sensor along with their key performance metrics are outlined. Whereas, in [8], a comprehensive review of the diverse computing platforms along with on-board flight controller software is discussed. Information about the different communication technologies used in UAVs together with the open research challenges is presented in [9] and [10]. Recently, the use of machine learning algorithms for UAV and ground control station (GCS) applications have gained prominence [11], [12]. In [13], the use of UAVs for smart agriculture is explored. The authors attempted to describe the various agricultural sensors used on board UAVs, as well as potential future research directions and challenges. Table B.2 provides a brief comparison of existing surveys with the current survey.

As can be seen, the preceding studies focus on specific aspects of UAVs such as applications, components, and software and thus fail to provide a high level practical overview of the system in general. There is a need for a coherent and concise review of UAV literature that can serve as a practical guide for the novice learner, given the abundance of literature on the subject. As a result, the primary goal of this paper is to provide a practical perspective of the UAV system and equip the reader with the tools and techniques needed to deploy a UAV system especially focusing on sensors aspects. The following are the main contributions of this survey article:

- Overview of the UAV system describing the various components and their interactions.

- Description of various embedded sensors used in UAVs outlining their operating principle, along with key performance metrics and limitations.

- Communication technologies used in UAVs to transfer information among UAVs and GCS modules.

Table A.1: Comparison between existing surveys and this survey

Year	Reference	Focus areas	ES	CT	CP	ML
2018	[8]	UAV flight controller hardware and software	✗	✗	✓	✗
2019	[10]	UAV wireless communication, cellular-connected UAVs	✗	✓	✗	✗
2019	[11]	Machine learning for cellular-connected UAVs	✗	✓	✗	✓
2020	[9]	UAV communication technologies	✗	✓	✗	✗
2020	[7]	Embedded sensors for autonomous systems	✓	✗	✗	✗
2021	[13]	Communication and sensor technologies for UAVs focussed on agriculture applications	✓	✓	✗	✗
2021	[12]	Deep learning for UAVs	✗	✗	✗	✓
2021	**This work**	Embedded sensors, computing platforms, communication technology, machine learning with focus on sensing and communication for UAVs	✓	✓	✓	✓

ES - Embedded Sensors; **CT** - Communication Technology; **CP** - Computing Platform; **ML** - Machine Learning.

- Computing platforms that can be equipped on UAVs with emphasis on computational resources and easy integration of hardware and software.
- Machine learning algorithms that are primarily focused on sensor fusion and communication for UAVs.
- Finally, potential future research directions are presented.

The remainder of this paper is organized as shown in Fig. A.2. Section II provides an overview of the UAV system. Section III summarizes the various embedded on-board sensors in UAVs. Section IV focuses on the different on-board communication modules. Section V discusses the computing platforms (hardware and software) that are used in tandem with UAVs. Section VI investigates the various machine learning algorithms employed in UAVs. Section VII explores the relevant potential future directions and finally, section VIII concludes the paper.

A.2 UAV System Overview

In order to better understand and appreciate the content of this paper, it is necessary to first learn about the various components/subsystems used in UAVs. A more

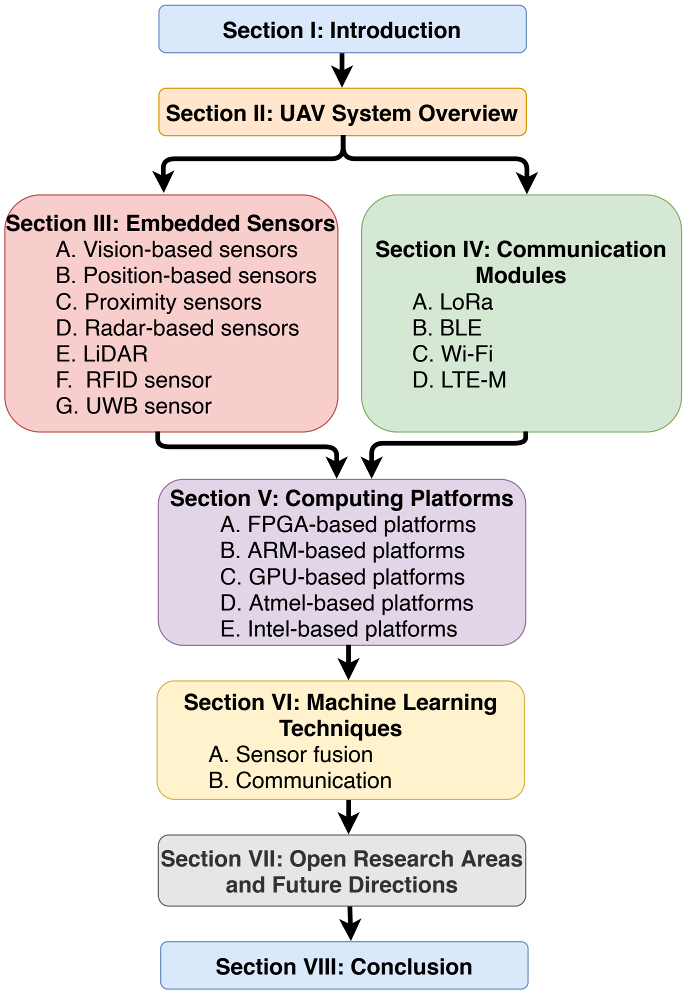

Figure A.2: Structure of the article.

comprehensive approach would be to represent the UAV system abstractly, as shown in Fig. A.3. This view of the UAV system is built by taking into account the flexibility and portability provided by various UAV components in order to cater to a variety of applications.

The ability of UAVs to sense and perceive their surroundings is enabled by various hardware sensor modules. Each sensor is unique in terms of its operation, form factor, cost, performance and output information. Based on application requirements, sensors with varying form factor and performance can be used on UAVs. Agricultural applications rely heavily on temperature and vision-based sensors to monitor crop health, whereas surveillance and remote sensing primarily use camera and light detection and ranging (LiDAR)-based modules.

UAVs are equipped with communication modules that allow data to be transmitted between UAVs and the GCS. Each communication module operates at the specified frequency, bandwidth, power, and coverage. Depending on the application, a suitable communication technology must be chosen, taking into account its capabilities and characteristics. Wireless fidelity (Wi-Fi) modules are used to transfer information among UAVs in applications that require a high data rate, whereas long range (LoRa) modules are used in search and rescue operations that require information transfer over a long distance.

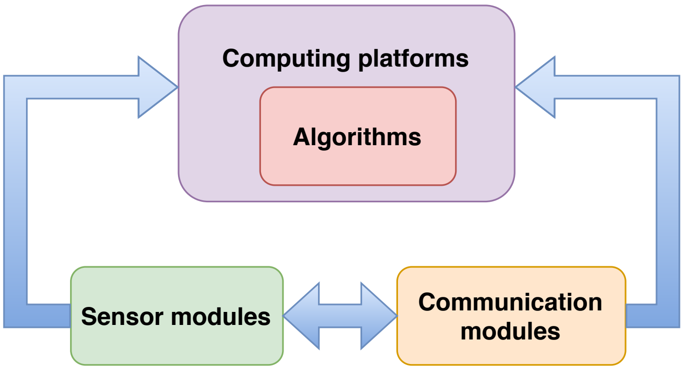

Figure A.3: UAV system overview.

Various sensor and communication modules are integrated on UAVs using computing platforms. Computing platforms are hardware processing units that can connect and act as a medium for processing data from various sensor and communication modules. The type of computing platform to be used on UAVs is determined by the application's requirement specifications. Processing power, interfacing options for connecting with hardware sensor and communication modules, form factor, weight, and other factors are considered when selecting a computing unit for UAVs.

Additionally, the computing platforms host a variety of algorithms that are critical to ensuring the safe and secure operation of UAVs. The algorithms are designed to cater to various application scenarios while also being low in complexity and power consumption. Sensor fusion techniques, interference mitigation schemes, control and stabilization strategies, and so on are examples of these algorithms. Several machine learning and deep learning algorithms have recently been shown to improve performance in various aspects of UAV operations. This review will concentrate on some of the most recently developed machine learning algorithms that can be used in a variety of UAV applications.

Decoupling the UAV system into the building blocks depicted in Fig. A.3 allows for selective analysis and learning of the various aspects of UAVs. This paper's content focuses on each of these blocks separately, providing useful and necessary information from a practical standpoint.

A.3 Embedded Sensors

Embedded sensors are critical in many UAV functions, including autonomous operations, collision avoidance, tracking, communication, and so on as shown in Fig. A.4. These sensors have been classified into vision-based sensors, position-based sensors, proximity sensors, radar, and LiDAR sensors depending upon the type of information they produce. This section provides a high-level overview of these sensors, as well as information on their operating principles and key performance metrics. Other considerations include cost, output format, and power consumption.

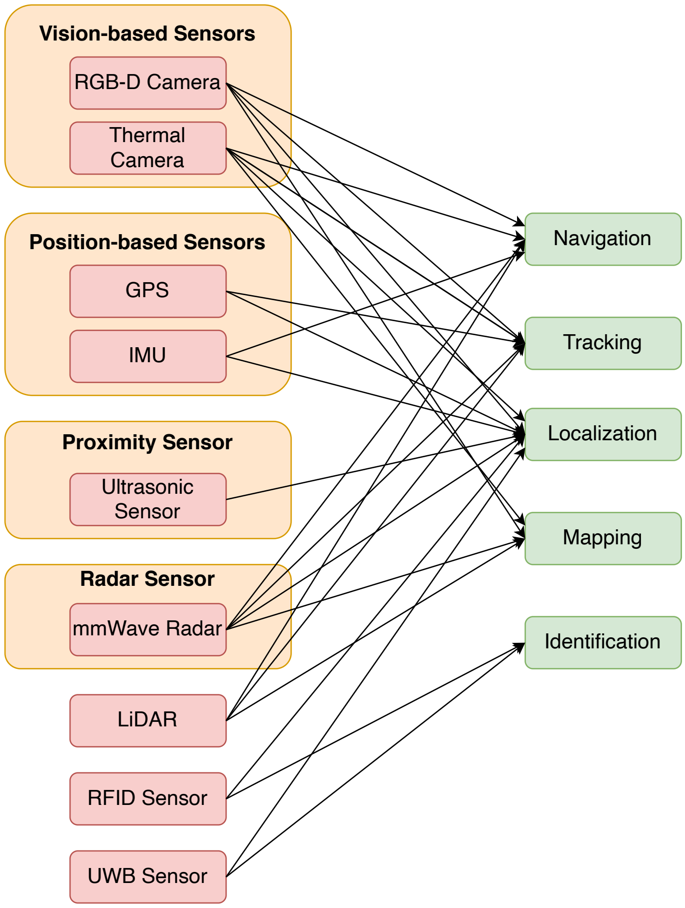

Figure A.4: UAV embedded sensor applications.

A.3.1 Vision-based Sensors

Vision-based sensors generate an image of the captured scene, providing a visual perception of the environment. The generated image is then processed and used with various image processing and computer vision algorithms to ensure and enable a variety of UAV operations and services. The RGB-D cameras and thermal cameras are two popular vision-based technologies, and they are summarized in the following paragraphs.

A.3.1.1 RGB-D Camera

The most common sensors used on UAVs are RGB-D cameras. These sensors provide perception of the surroundings in the form of RGB images. Because RGB images are closely related to human visual perception, it is simple to make sense of the information obtained. Nonetheless, the images can be fed into image processing and computer vision algorithms to perform target detection, localization, and tracking. Furthermore, depth information can be used to calculate the spatial distance of targets from the camera, which is useful for collision avoidance operations. The resolution of RGB cameras and other considerations such as the camera's frame rate, shutter type, and aperture determine their image quality [14], [15].

RGB-D cameras on board UAVs are used for object detection, collision avoidance,

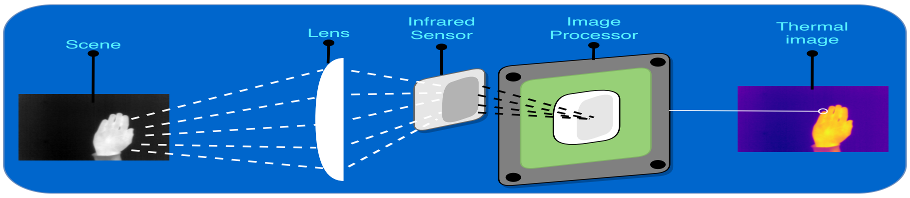

Figure A.5: Working principle of thermal camera.

and tracking. This can in seen in [16] where the authors have used a single RGB-D camera to implement a collision avoidance system which when integrated with a bin-occupancy filter can be used for tracking. Another setup described in [17] uses RGB-D camera along with the inertial measurement unit (IMU) data to provide simultaneous localization and mapping (SLAM).

A.3.1.2 Thermal Camera

Thermal cameras mounted on UAVs can aid in search and rescue operations, disaster management, and surveillance applications. These cameras can work in low-light and robust weather conditions. Thermal cameras use special sensors which can capture the infrared radiations falling on them. The captured radiation information is then processed to generate a temperature profile which is used to improve detection and classification performance. Fig. A.5 depicts the working principle of thermal cameras. When choosing thermal cameras, some of the key parameters to consider are image resolution, range, refresh rate, and lens focal length [18], [19].

When integrated with UAVs, thermal imaging has a wide range of applications. The authors of [20] used UAV equipped with thermal cameras to capture thermal images, which were then processed to detect heat leaks in buildings. In [21], thermal camera mounted UAVs are used to autonomously monitor and detect wildlife. UAVs equipped with thermal cameras are also used to detect, identify, and track objects in the ocean [22].

A.3.2 Position-based Sensors

Position-based sensors detect movement and can also provide relative position information in relation to a known reference point. These sensors are used in UAVs to pinpoint the precise location of UAVs in a given area. Furthermore, these sensors can provide odometric information about UAVs, which helps to determine the orientation of the UAV. Some of the relevant positional sensors used in UAVs are the global positioning system (GPS) and IMUs, which will be discussed in the following subsections.

A.3.2.1 GPS

The GPS is a global radio navigation system that is used in a variety of applications that utilize positional information. GPS works on the trilateration principle [23] using a system of atleast 24 active satellites and GCSs as shown in Fig. A.6.

Figure A.6: Working principle of GPS.

GPS modules provide accurate position and time information for UAV-based applications [24]. Special GPS modules such as the real-time kinematic (RTK) GPS [25] provide high update frequency and are able to withstand the UAVs' high velocity and maneuverability. But despite their benefits, GPS systems consume a significant amount of power due to the constant synchronization and locking of the GPS signal.

UAVs equipped with GPS modules provide precise positional and temporal information that is used for localization, stabilization, tracking, and navigation. GPS-enabled UAVs are used in [26] for accurate landmine detection. The authors of [27] use a high precision RTK GPS to determine the ground control target locations. In [28], the authors use GPS and camera data along with the hierarchical A* algorithms to determine the best flight path for UAVs. Further, GPS enabled UAVs find applications in precision agriculture to monitor crop health, map agricultural areas, and for cropdusting [29].

A.3.2.2 IMU

IMUs are electronic devices that measure inertial quantities such as acceleration, angular motion, and orientation of an object. Accelerometers, gyroscopes, and magnetometers are common components of IMUs for UAVs. IMUs in UAVs work in tandem with GPS modules to form the inertial navigation system (INS), which is responsible for UAV localization, stabilization, and tracking.

Because IMUs are critical components for maintaining stable flight control and guidance for UAVs, understanding some of their key performance metrics is critical. The quality of the IMU is determined by the performance of its internal components, such as accelerometers, gyroscopes, and magnetometers. The range provided by the accelerometer and gyroscope is one of the most important parameters to consider. Another key parameter is the bias instability property which captures the accumulated sensor bias and unknown drift error in the IMUs over time. Aside from the aforementioned factors, bandwidth, output data rate, temperature sensitivity, dimensions, number of axes and weight are other IMU parameters to consider [30],

Table A.2: Key Performance Metrics for Various On-board Sensors

Sensor	Key metrics	Output format	Interfacing options	Power (W)	Vendor	Cost (USD)	Limitations	References
RGB-D camera	RGB resolution: up to 1920 x 1280 Maximum range: 10 m Depth FoV: 87° x 58° RGB FoV: 69° x 42°	RGB and depth image	SPI, USB, MIPI	0.35 – 3.5	Intel RealSense	200 – 600	Rain, fog, mist, ambient lighting, etc.	[14], [15], [16], [17],
Thermal camera	Thermal resolution: 336 x 256 / 640 x 512 Thermal accuracy: ±5° C Spectral range: 7.5˘13.5 μm	Thermal image	UART, USB, I2C, SPI, SDIO	0.5 – 1.55	FLIR	1500−8000	Fails to distinguish objects when they are at the same temperature	[18], [19], [20], [21], [22]
GPS	Velocity accuracy: 0.1 m/s Horizontal position accuracy (RTK): $\approx$ 2.5 m Sensitivity (navigation): −160 dBm Time to first fix: 28 s	NMEA, UBX, RTCM	UART, USB, SPI, DDC	-	u-blox, EMLID	-	Increased power consumption, cannot penetrate through solid walls or structures.	[24], [25], [26], [27], [28], [29]
IMU	Gyro bias instability: $\approx 0.05°/hr$ Accelerometer bias instability: $\approx 15\ \mu g$ Data rate: 1 to 1000 Hz	Digital output for gyroscope, accelerometer and magnetometer	RS-422, I2C	5	KVH, InvenSense	-	Drift in the values over time leading to incorrect measurement values	[30], [31], [32], [33], [34]
Ultrasonic sensor	Range: $\approx$ 10 m Range resolution: $\approx$ 1 mm Measure angle: 15° Frequency: 30 – 80 kHz	Pulse width, real-time analog voltage envelope, analog voltage output, serial digital output	I2C, RS232, TTL, USB, UART	< 1	XL-MaxSonar, Sparkfun, Marvelmind	10˘60	Wind, acoustic disturbances, etc.	[35], [36], [37], [38], [39], [40], [41], [42], [43], [44]
mmWave FMCW radar	Radial range: $\approx$ 200 m Range resolution: $\approx$ 4 cm FoV: 5° – 160°	Raw IF sample (time series data), range profile, velocity profile, angle profile	CAN, CSI-2, I2C, LVDS, QSPI, SPI, UART	1 – 3	Texas Instruments	25˘35	Angle estimation can be error prone	[45], [46], [47], [48], [49], [50], [51], [52], [53], [54], [55]
LiDAR	Range: $\approx$ 100 m Range accuracy: $\approx$ 3 cm FoV (Horizontal): 360° FoV (Vertical): +15° – −15° LiDAR data points: $\approx 600,000$ points/s	3D Point cloud	Ethernet, UDP	8 – 22	Velodyne, Ouster	100˘6000	Rain, fog, mist, etc.	[56], [57], [58], [59], [60]
RFID sensor	Reader antenna ports: 2, 4 Frequency: 860 – 960 MHz Tag memory: 96 bits Tag antenna size: 94 x 24 mm	Digital serial output through USB, Ethernet, etc.	Ethernet, USB	Reader: 0.01 – 1.4	Zebra, Smartrac	-	Affected by metals and liquids, prone to interference and jamming	[61], [62], [63], [64], [65], [66], [67]
UWB sensor	Detection Range: 40 m Frequency: 3.1 – 4.8 GHz Accuracy (LoS): 2.1 cm Max Operating Range (LoS): 300 – 1100 m	Digital serial output through USB, Ethernet, etc.	Ethernet, USB, SPI, CAN, UART, GPIO	2	TDSR, Decawave	-	Co-existence with other technologies, interference issues, etc	[68], [69], [70], [71], [72]

[31], [32].

Attitude determination, localization, and navigation are three of the most important functions of IMUs in UAVs. This is demonstrated in [33], where the authors created a single frequency GPS IMU system to provide real-time information to UAVs to aid in localization, guidance, and navigation. Another application for IMUs is stabilization. In [34], authors developed a method for using IMU data to provide real-time video stabilization of images captured by a fixed camera mounted on a UAV.

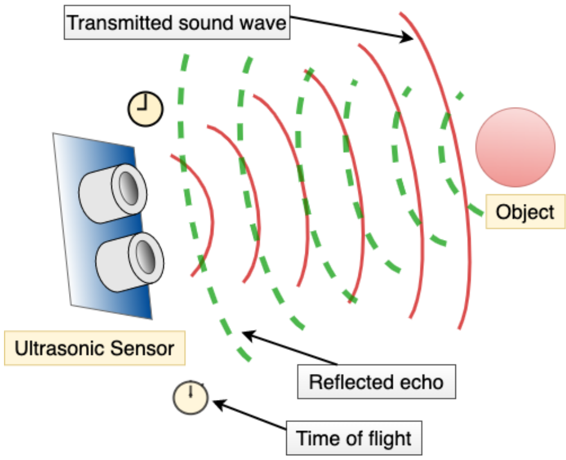

Figure A.7: Operating principle of ultrasonic sensor.

A.3.3 Proximity Sensors

Proximity sensors provide information regarding objects that are placed within a short distance from the sensor. The section that follows discusses ultrasonic sensors, which are one of the most common proximity sensors used in UAVs.

A.3.3.1 Ultrasonic Sensor

Ultrasonic sensors [35], [36] are used in UAVs for target detection, flight navigation, and collision avoidance [37], [38]. They are used in industry for quality control and fault detection [39]. Ultrasonic sensors are widely used in autonomous systems for smart car parking and vehicle detection due to their robust sensing capabilities [40]. Ultrasonic sensors operate by measuring the distance between the sensor and the target object using high-frequency sound waves [41] as shown in Fig. A.7. They are extremely reliable and can detect transparent objects in situations where other vision-based systems may fail. Some of the key performance metrics for ultrasonic sensors can be found in Table A.2.

In addition to providing proper navigation, accurate obstacle detection and timely obstacle avoidance [37], [38], ultrasonic sensors are also used for ensuring safe landing for UAVs. In [42], a sonar-based model is developed which measures the reflected sound waves to determine the suitability of the landing field. If there are obstacles in the landing field that are higher than the UAV legs, the landing is considered unsafe. Precise indoor localization and navigation of UAVs is also achieved by using the ultrasonic system developed by Marvelmind [43]. A network of stationary ultrasonic nodes are placed in an area and connected wirelessly through the license free band. The mobile object carrying another ultrasonic node frequently sends beacons which is captured by these stationary nodes. The propagation delay between the beacons is measured and using trilateration, precise localization is achieved in order of around ± 2 cm. Ivan *et al.* in [44] has demonstrated the use of Marvelmind technology by developing a precise localization system that would enable accurate position estimation for vertical takeoff and landing (VTOL) of UAVs.

Table A.3: Key Performance Metrics for mmWave FMCW Radar

Parameter	Expression
Radial range (d)	$d = f_i c/2S$
Radial velocity (v)	$v = \lambda\Delta\Phi/4\pi T_c$
AoA (θ)	$\theta = \sin^{-1}(\lambda\Delta\Phi/2\pi h)$
Range resolution (d_{res})	$d_{res} = C/2B$
Velocity resolution (v_{res})	$v_{res} = \lambda/2T_f$
AoA resolution (θ_{res})	$\theta_{res} = \lambda/Mh.\cos(\theta)$

f_i - Intermediate frequency; c - Velocity of light; S - Chirp slope; $\Delta\Phi$ - Phase difference between the consecutive chirps; λ - Chirp wavelength; T_c - Time interval between consecutive chirps; h - Spacing between two adjacent receiver antennas; B - RF bandwidth; T_f - Chirp frame time; M - Number of receivers.

In [39], the authors create a prototype ultrasonic inspection system using UAVs that provides information about the structural integrity of an industrial unit.

A.3.4 Radar-based Sensor

Another type of sensor that is proving to be extremely useful for UAVs is radar sensors. Radars have traditionally been used to detect targets by measuring how long it takes an emitted electromagnetic wave to reflect back after striking the target object. Radars were originally used to detect and identify approaching enemy targets in military and defense applications. Their use in self-driving cars has recently demonstrated that they can be used effectively outside of their intended application fields. Radars have since been installed on UAVs to improve their perception and detection capabilities. Due to size and power constraints, the mmWave frequency modulated continuous wave (FMCW) class of radars has shown promise for UAV-based applications. The section that follows provides an overview of these radar sensors, including their advantages, disadvantages, and potential applications.

A.3.4.1 mmWave FMCW Radar

The mmWave FMCW radars [45], [46] are well-known for providing accurate target range and velocity information [47]. Due to their resistance to extreme weather and lighting conditions, mmWave FMCW radars are the obvious choice for UAV-related applications. Furthermore, the combination of their high bandwidth and accurate range and velocity resolution makes them appealing for use in detection and collision avoidance scenarios [48]. mmWave FMCW radars work in the same way that traditional radars do. A frequency modulated continuous chirp waveform is transmitted by the radar and reflected by nearby objects. The reflected chirp is received at the receiver and processed to determine the radial range, velocity, and angle of arrival (AoA) of the target.

As shown in Fig. A.8, A.9 and A.10, the raw IF samples from the mmWave FMCW radar are processed to obtain the range-plot, range-doppler and range-azimuth heatmaps respectively. The plots are directly obtained from the TI mmWave demo visualizer which was used along with the TI AWR1843 mmWave FMCW radar to detect the objects. The range-plot shows that the radar has detected four objects at a radial distance that is less than 3 meters. They are stationary as observed from the range-doppler heatmap, as the higher intensity red colour is situated close to 0 m/s. From the range-azimuth plot, it is inferred that the objects are placed at an angle of 10° from the radar. Some of the key mmWave radar parameters along with their expressions is summarized in Table A.3.

mmWave FMCW radars are used in UAVs for object detection, identification, and tracking due to their excellent sensing capabilities. Detecting and identifying UAVs and birds using the micro-Doppler spectrum obtained from mmWave FMCW radars has been proposed in [49]. Similarly, the work in [50] contributes to the identification of micro-UAVs in low grazing angle scenarios using the mmWave FMCW radar micro-Doppler spectrum. This has broad applications in electronic warfare, where terrain clutter can make detecting micro-UAVs difficult. Additionally, the authors in [51] have used mmWave FMCW radars for localization and activity classification of objects using convolutional neural network (CNN). Similarly, Siddharth *et al.* in [52] has used the range-angle images obtained from mmWave radars along with YOLO and Faster RCNN models to achieve accurate target classification in the range of $87.68\% - 99.7\%$. One of the limitations of mmWave radars is their poor AoA estimation. As seen in [53] and [54], novel machine learning techniques and mechanical rotation of radar in the horizontal direction improves the AoA estimation and field of view (FoV) in both azimuth and vertical directions. This method has the advantage of providing accurate angle estimation while only requiring one transmitter and receiver. In addition, the authors of [54] introduced techniques for estimating the height and angle of UAVs from the GCS using mmWave FMCW radars.

A.3.5 LiDAR

LiDAR is a sophisticated remote sensing technology used to generate 3D maps of the environment. The LiDAR system works by beaming a large number of lasers onto a surface. The beam's wavelength is typically in the optical, infrared, or ultraviolet range. The reflected beam from the object in focus is captured by a laser scanner, and the time of flight between the transmitted and reflected beams is measured and used to calculate the source's distance from the LiDAR. This distance calculation process is repeated several times to produce a complex image map (3D point cloud) of the scanned surface, as shown in Fig. A.11.

One of the most important characteristics of LiDARs is the range over which the laser beam can be focused. The power of the laser beam is restricted to conform to eye safety regulations, which in turn, limits the maximum detectable range of LiDARs. Other factors such as laser type and focal length of lens also impact on

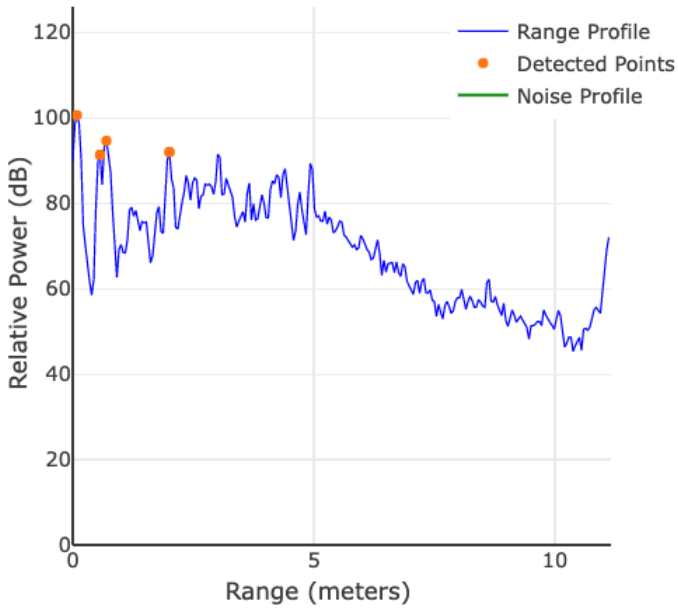

Figure A.8: Range plot.

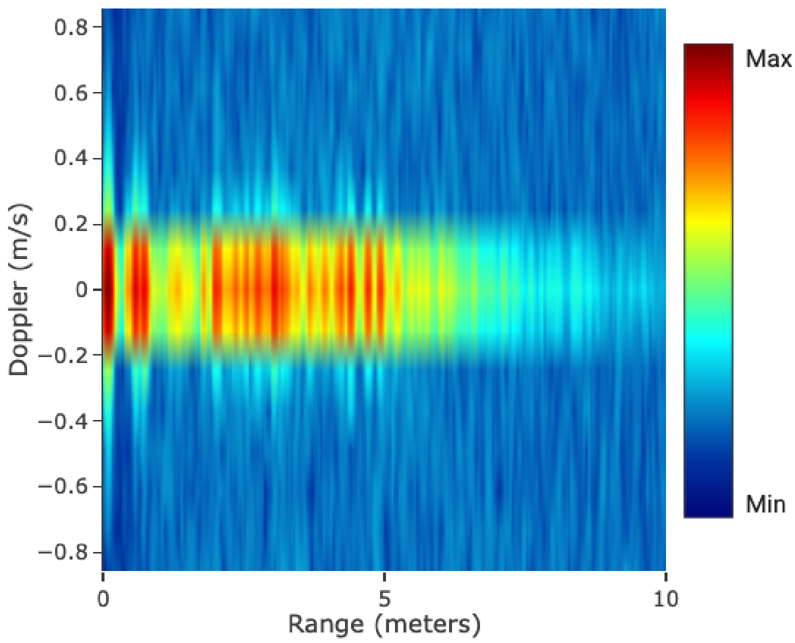

Figure A.9: Range-doppler heatmap.

LiDAR range. Another critical parameter for LiDARs is the density of the LiDAR point cloud which determines the resolution of the images obtained after LiDAR scanning. Other parameters such as range resolution, scan rate, dimension, FoV, and weight are also considered based on application requirements [56], [57].

UAVs equipped with LiDAR modules are used in agriculture, mining, forestry and civil engineering to name a few. A LiDAR-based UAV system is used in [58] for classification of forest vegetation and structure measurements. The authors represent the area's vegetation and topography gradient using a LiDAR-hyperspectral image fusion method. LiDARs are also used to map coastal areas as seen in [59].

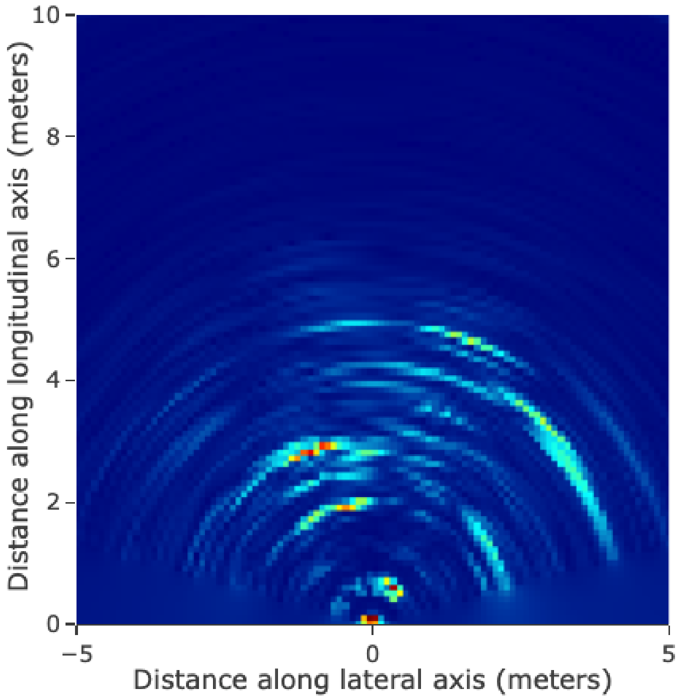

Figure A.10: Range-azimuth heatmap.

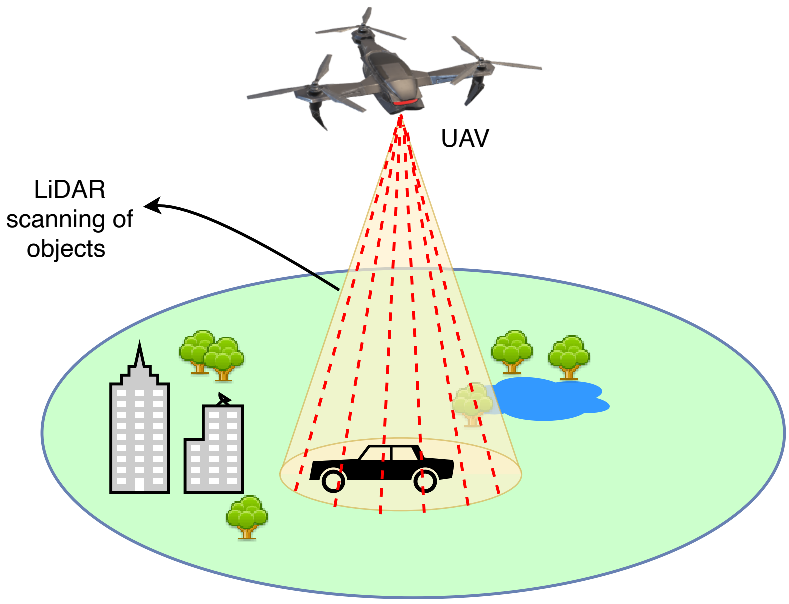

Figure A.11: LiDAR scanning.

LiDAR images provide more information for monitoring shoreline changes. LiDARs are also used to provide navigation capabilities for UAVs in GPS-denied environments for localization and collision avoidance [60].

A.3.6 Radio-Frequency Identification (RFID) Sensor

The RFID is a contactless wireless system that uses radio frequency waves to track and identify objects. The RFID system primarily consists of a RFID reader and RFID tags. RFID tags are placed on objects that require tracking or identification.

The RFID reader transmit radio frequency waves which interact with these attached RFID tags to obtain useful information about the respective object. RFID technology finds applications in a number of diverse areas such as inventory management, supply chain, security, pharmaceutical, transport and airline industry. RFIDs are equipped in UAVs for identifying and tracking objects. Additionally, they are also used for UAV localization [61].

The criteria to determine the best RFID system for a particular UAV application requires the knowledge of key parameters such as operating frequency, power requirements and environmental conditions. RFID systems can operate in low frequency (LF), high frequency (HF), and ultra-high frequency (UHF) ranges. RFID for UAVs primarily uses the UHF (865˘960 MHz) that provides read range of around $4-6$ meters or more depending upon the type of tags used [62]. Depending upon the application use case, the RFID tags employed can be passive or active. The passive tags does not require any external power source to operate whereas the active tags are equipped with a limited battery source to ensure its operation. Environmental factors include the location of the tag, the material on which the tag is attached, temperature, pressure, vibration sensitivity, etc. Other important include communication interface for RFID readers, antennae ports, read accuracy, data rate, cost, etc., [63], [64], [65].

Traditional applications of RFID systems are enhanced using UAV systems. This is evident in RFly [61], where the authors have developed a UAV-based RFID relay for improving the read range of an RFID system. Additionally, they have also developed an RF based localization algorithm for localizing non-line-of-sight (NLoS) objects. Another system in [66], uses passive RFID tags to estimate the 6 degrees-of-freedom (DoF) pose of a controller. The pose is estimated by utilizing a singular value decomposition (SVD)-based approach that uses the position of the tags with respect to the controller. This method provides seamless UAV navigation in indoor environments. In [67], Zhang *et al.* developed a RFID enhanced UAV system that estimates the precise pose of the UAV. The system works by utilizing the phase measurements from the different RFID tags attached to the UAV to determine the 6-DoF pose of the UAV system.

A.3.7 Ultra-Wideband (UWB) Sensor

UWB sensors uses short-range radio frequency pulses to determine location of nearby objects. The operating principle is more or less similar to the RFID technology, where the UWB transmitter sends billions of pulses over a wide frequency spectrum which is captured by the UWB receiver to determine the location of the target. UWB primarily uses two techniques for positioning, the time difference of arival (TDoA) approach and the two way ranging (TWR) method. In TDoA, UWB sensors are placed at multiple locations in an indoor space. The moving UWB tag continuously sends signals which is captured by these different UWB tags. Subsequently, by using multilateration, the location of the moving tag is accurately determined. In TWR, when two devices using UWB come close to each other, they start ranging to determine their distance. The time taken to transmit and receive the signal is used to calculate the distance between the two objects [68].

UWB sensors provide highly accurate distance measurements (in order of 2 cm) [69], [70]. As the time duration of the pulses gets narrower the accuracy of the measurement is improved. Moreover, UWB is less affected by multipath interference and hence it is preferred in highly crowded environments to achieve reliable positioning. However, as UWB uses a wide range of frequencies, co-existence of UWB with other technologies is a challenge. Additionally, since UWB requires an always ON sensing strategy to capture the transmitted signal, power consumption is more as compared to the RFID sensors.

In UAVs, UWB sensors are primarily used for localization purposes in GPS-denied environments. In [71], the authors propose a target-relative tracking and positioning method using UWB sensors. To estimate the speed of the target, initially the UWB range measurements are fused with other on-board sensor data using an extended kalman filter (EKF). Next, the target orientation is transferred to the quadcopter by using UWB-based communication. The experiment results demonstrate the autonomous capability of the proposed approach to relatively position the quadcopter with respect to the target. Additionally, UWB sensors in UAV can also help in autonomous docking. In [72], the authors have developed UWB-vision approach to facilitate the autonomous landing of quadcopters in GPS-denied environments. The system initially uses a combination of distance and relative displacement measurements to approach the landing zone. Once the landing pad is detected, the measurements from UWB and vision-based systems are fused to provide an accurate landing position.

A.4 Communication Modules

UAVs must constantly update the GCS about their position, battery health, on-board sensor data and other critical information in order to enable and maintain seamless autonomous operations. The requirement for telemetry or sensed data transfer necessitates the use of efficient and reliable communication technology for UAVs. The following section provides insight into some of the characteristics associated with each communication protocol so that the user can make an informed decision about the choice of communication module to equip on board UAVs. Furthermore, Table A.4, highlights the key attributes of various communication protocols used in UAVs.

A.4.1 LoRa

LoRa is a low-power, long-range communication technology that is primarily used in the internet-of-things (IoT) applications [73]. The technology is developed by Semtech corporation. The protocol is designed and implemented in such a way the LoRa physical layer employs a proprietary chirp spread spectrum (CSS) modulation [74], while its MAC layer known as LoRaWAN is open source and maintained by the LoRa Alliance [75]. LoRa transmits over unlicensed bands at frequencies of 433 MHz, 868 MHz, 915 MHz, and 923 MHz with an approximate maximum range of about 10 to 15 km. One of the main limitations of using LoRa in UAVs is its data rate, which can reach only upto a maximum of 50 kbps [76].

A.4.2 Bluetooth Low Energy (BLE)

BLE or Bluetooth Smart is an enhanced version of the classic Bluetooth technology that is designed for low-power, short-range application demands [77]. The Bluetooth Special Interest Group (SIG) designed and developed the protocol in order to provide low-power solutions for applications such as health care, beacons, and fitness. Furthermore, BLE has a data rate of 1 Mbps and range of about 50 meters, similar to traditional Bluetooth. The protocol supports a variety of topologies such as star, mesh, p2p, and broadcast. BLE is not backward compatible with its predecessor, however it uses the same frequency as traditional Bluetooth, 2.4 GHz to 2.48 GHz. Because of its low power consumption and high data rate, BLE is a promising technology for use in UAVs [13], [78].

A.4.3 Wi-Fi

Wi-Fi is a widely used short-range communication protocol found in laptops, tablets, smartphones, digital televisions, and other devices. Wi-Fi is based on the IEEE 802.11 protocol stack and comes in a variety of versions with varying levels of power consumption, data rate, and bandwidth. Wi-Fi operates in the unlicensed spectrum band of frequencies, specifically 2.4 GHz and 5 GHz [79]. Wi-Fi employs the orthogonal frequency division multiplexing (OFDM) modulation, which is responsible for its high data rate and resistance to interference issues. These properties make Wi-Fi an ideal choice for use in UAVs. Furthermore, because of its modular design, it can be deployed in both infrastructure and ad-hoc modes. In [80], Wi-Fi is set up in an ad-hoc manner to be used with UAV relay networks.

A.4.4 Long-Term Evolution for Machine-Type Communication (LTE-M)

LTE-M is a low-power wide-area communication standard developed by the 3GPP to support machine-to-machine communications and IoT applications. [81]. The protocol provides a high data rate as well as increased bandwidth. It operates within 3GPP specified licensed spectrum band. The increased adoption of LTE-M protocol in UAV applications can be attributed to its design architecture which allow seamless integration with existing cellular infrastructure. Furthermore, its long range, low latency, resistance to interference, and weather conditions have all contributed to its growing popularity

Table A.4: Key Performance Metrics for Communication Technologies

Protocol	Range (km)	Throughput (Mbps)	Power (W)	Frequency (GHz)	Topology
BLE	≈ 0.1	0.125 - 1.36	0.01 - 0.5	2.4	Star, Mesh, Broadcast, P2P
LTE-M	≈ 10	≈ 1	0.1 - 0.2	LTE bands	Star
Wi-Fi	≈ 0.1	$\approx 10^4$	≈ 2	2.4, 5	Star, Mesh
LoRa	≈ 10	0.01 - 0.05	≈ 0.025	0.433, 0.868, 0.915, 0.923	Star

A.5 Computing Platforms

Computing platforms are on-board hardware and software modules that facilitate the integration of various sensor and communication technologies to ensure safe and secure operation of UAVs. The most important component of a UAV computing platform is the flight controller. The flight controller is in charge of interpreting data from on-board sensors in order to facilitate real-time decision making. Flight controllers are also in charge of telemetry, communication with the GCS, power management, and other duties. In addition to flight controllers, the computing platforms also responsible for executing object detection tasks, collision avoidance algorithms, UAV stabilization schemes, and control algorithms. The sections that follow describe the available hardware and software platforms for implementing flight controller systems and other necessary algorithms on UAVs.

A.5.1 Hardware Platforms

UAV hardware platforms are embedded processing units that implement flight controller capabilities. The hardware flight controller systems are in charge of controlling the UAV's altitude and mobility, avoiding collisions, interacting with other sensing and communication modules, controlling and stabilizing the UAV, navigation, and so on. Because of the numerous tasks that these units must perform, the performance of these platforms is primarily determined by the type of processor, speed, and computational memory. When selecting a flight controller module for UAV applications, other factors such as form factor and power consumption are taken into account. Furthermore, these hardware components aid in the execution of sophisticated algorithms required to meet the demands of the UAV applications. The most recent widely used UAV hardware platforms are presented in this section, along with some key metrics such as processor specifications, available memory, form factor, supported operating system, and power consumption.

A.5.1.1 FPGA-based Platforms

***a) OcPoC-Zynq Mini*:** The OcPoC-Zynq Mini [82] is a fully programmable

FPGA+ARM-based system-on-chip (SoC) that is developed by the Aerotenna company. The on-board Artix-7 FPGA enables the seamless integration and interfacing of various sensor and hardware modules. Additionally, the coupled dual-core ARM A9 processor increases the computational capability and input/output (I/O) flexibility. The module comes with on-board IMU with 9-DoF and a high-resolution barometer that is used to measure the atmospheric pressure. The hardware board is also capable of interfacing devices using the following protocols: SPI, CAN, I2C, USB-OTG, and USB-UART. The OcPoC-Zynq Mini is lightweight and has a small form factor, making it an appealing option for use with UAVs [83].

A.5.1.2 ARM-based Platforms

a) Pixhawk 4: Pixhawk 4 [84] is the latest flight controller board designed and developed by Holybro and Auterion [85]. The board is optimized to run the latest PX4 autopilot software stack and comes with advanced features which makes it flexible and reliable for autonomous operations. The board is equipped with a STM32F765 processor which consists of a powerful 32-bit ARM Corex M7 chip. It additionally houses a STM32F100 32-bit ARM Cortex M3 processor dedicated to handle the I/O operations between the board and the various on-board peripherals. The various on-board sensors equipped on the board include gyroscope, accelerometer, magnetometer and barometer. Other peripherals include an on-board u-blox Neo-M8N GPS/GLONASS receiver that aids in the acquisition of better positional information [86]. In order to support real-time operations, the Pixhawk 4 uses the NuttX operating system. Furthermore, the multi-threaded capabilities of NuttX allow for Linux/Unix programming of the flight controller [87].

b) Pixhawk 4 Mini: The Pixhawk 4 Mini [88] flight controller board is intended for use with smaller UAVs commonly used by hobbyists and researchers. With the exception of a dedicated I/O processor unit, the hardware configuration of the Pixhawk 4 Mini is similar to that of the Pixhawk 4 [89]. The Pixhawk 4 Mini also includes the STM32F765 processor, as well as an accelerometer, gyroscope, magnetometer, and barometer. It has a smaller dimensional form factor than the Pixhawk 4, which is detailed in Table A.5. Pixhawk 4 Mini also uses the NuttX operating system for real-time operations.

c) BeagleBone Blue: The BeagleBone Blue [90], [91] is a miniaturized Linux-based system that can be used as a flight controller in UAVs and autonomous vehicles. The Octavo OSD3358 board features an ARM Cortex-A8 processor and 512 MB DDR3 RAM. It is equipped with a NEON floating-point accelerator for performing complex digital signal processing computations. The board can be programmed in Linux using a variety of supported softwares such as MATLAB, Python, ROS and ArduPilot, making it ideal for developers and hobbyists looking to quickly prototype their applications. Bluetooth 4.1, BLE, and Wi-Fi are among the integrated communication modules used to ensure the reliable transmission of sensor and telemetry data. In addition, the board includes built-in sensors such as an IMU, a barometer,

Table A.5: Commonly Used UAV Flight Controller Boards

Platform	Processor	On-board sensors	Available memory	Power (W)	Supported interfaces	Form factor (cm)	Weight (g)	References
OcPoC-Zynq Mini	CPU: ARM-A9 dual-core FPGA: Artix-7	IMU, Barometer	512 MB DDR3	≈ 3	I2C, USB-OTG, USB-UART, SPI, CSI, GSI, CAN	9.2×6.3	25˜35	[82], [83]
Pixhawk 4	CPU: ARM Cortex-M7 IO Processor: ARM Cortex-M3	Accelerometer, Magnetometer, Barometer, GPS	512 KB	-	UART, I2C, SPI, CAN, PWM, R/C	4.4×8.4	≈ 33	[84], [85], [86], [87]
Pixhawk 4 Mini	CPU: ARM Cortex-M7	Accelerometer, Magnetometer, Barometer, GPS	512 KB	-	UART, I2C, SPI, CAN, PWM, R/C	3.8×5.5	≈ 37	[88], [89]
BeagleBone Blue	CPU: ARM Cortex-A8	IMU, Barometer, Thermometer	512 MB DDR3	-	USB 2.0, UART, SPI, I2C, GPIO	17.5×11.2	≈ 36	[90], [91], [92]
Raspberry Pi 4 Model B	CPU: ARM Cortex-A72	-	1/2/4/8 GB DDR4	-	USB 2.0, USB 3.0, UART, CSI, DSI, GPIO	8.5×5.6	≈ 66	[93]
Nvidia Jetson Nano	CPU: ARM Cortex-A57 quad-core GPU: Maxwell 128-core	-	4 GB DDR4	$5 - 10$	USB 2.0, UART, SPI, I2C, I2S, GPIO	6.96×4.5	≈ 17	[94], [95]
Nvidia Jetson TX2	CPU: Nvidia Denver 2 64-bit dual-core and ARM Cortex-A57 quad-core GPU: Pascal 256-core with 256 CUDA cores	-	8 GB DDR4	$7.5 - 15$	USB 3.0, USB 2.0, UART, SPI, I2C, I2S, GPIO, CAN	5.0×8.7	≈ 88	[95], [96], [97], [98]
Nvidia Jetson AGX Xavier	CPU: ARM v8.2 Carmel 64-bit 8-core GPU: Volta 512-core with 64 Tensor cores	-	32 GB DDR4	$10 - 30$	USB 3.0, UART, SPI, CAN, I2C, I2S, DMIC, DSPK, GPIO	10.0×8.7	≈ 280	[95], [99], [100]
Arduino Mega 2560	CPU: ATmega2560	-	256 KB flash	-	USB 2.0, UART, SPI, I2C, GPIO	10.15×5.33	≈ 37	[101], [102], [103]
Intel UP boards	CPU: Intel Atom x5-z8350 quad-core FPGA: Intel FPGA Altera Max V	-	1/2/4 GB DDR3L	≈ 13	USB 2.0, USB 3.0, UART, GPIO, CSI, I2C, I2S	8.56×5.65	≈ 98	[104], [105], [106]

and a thermometer [92].

e) Raspberry Pi 4 Model B: The Raspberry Pi 4 Model B is the latest version in the Raspberry Pi series with a quad-core ARM Cortex-A72 processor and 2, 4 or 8 GB of RAM depending upon the requirements. The board comes with Bluetooth 5.0, BLE, Gigabit Ethernet and 2.4/5.0 GHz wireless LAN support for connectivity. The Pi 4 board has a 40 pin GPIO header with support for USB 2.0, USB 3.0, CSI, and DSI ports. As the wireless LAN and Bluetooth are compliance certified, the Raspberry Pi 4 can easily be used in UAVs and autonomous applications [93].

A.5.1.3 GPU-based Platforms

Hardware boards which are integrated with GPUs have recently become popular due to the deployment of deep learning algorithms on embedded platforms. This section lists some of the popular GPU-based platforms which can be used on UAVs for enabling machine learning based operations.

a) Nvidia Jetson Nano: The Nvidia Jetson Nano is a low form factor board intended to be used with small-sized autonomous vehicles. The board consists of a 128-core Maxwell architecture GPU and quad-core ARM Cortex A5 CPU [94]. The Nano comes with 4 GB RAM and supports Gigabit Ethernet, USB 3.0, USB 2.0 Micro-B, GPIO, I2C, I2S, SPI, UART interfaces for connecting with various peripherals. Jetson Nano is reported to provide an AI performance of approximately 472 GFLOPS to accelerate deep learning frameworks [95].

b) Nvidia Jetson TX2: A slightly higher end version of the Jetson Nano, the Nvidia Jetson TX2 gives more performance for computer vision and deep learning applications. The Jetson TX2 board comes with a dual-core 64-bit Nvidia Denver 2 CPU [96]. The GPU features a 256-core Pascal architecture with 256 CUDA cores. The board has 8 GB RAM and supports USB 3.0, USB 2.0, UART, SPI, I2C, I2S, GPIO and CAN interfaces for peripheral connections [97]. The TX2 is reported to provide 1.33 TFLOPs of AI performance as compared to the Jetson Nano [95] and hence the TX2 can be used for slightly higher end and demanding applications. In [98], the authors demonstrate a prototype system that uses the computing capabilities of the Jetson TX2 to run the YOLOv3 algorithm for UAV surveillance in airports.

c) Nvidia Jetson AGX Xavier: The Jetson AGX Xavier board is primarily developed to integrate machine learning and deep learning algorithms for various autonomous applications. The board is based on a 512-core Volta architecture GPU with 64 tensor cores and a 64-bit 8-core Carmel ARM architecture CPU [99]. It has 32 GB RAM memory and is integrated with a dedicated deep learning accelerator, vision accelerator and encoder/decoder units for various computer vision tasks. For interfacing with peripherals, the Jetson AGX Xavier supports RJ45, USB-C, USB 2.0, UART, etc. In terms of performance, the Jetson AGX Xavier is capable of accelerating deep learning algorithms in the order of 32 TFLOPS [100], [95].

A.5.1.4 Atmel-based Platforms

a) Arduino Mega 2560 R3: The Arduino Mega 2560 board [101] is based on the ATmega2560 microcontroller. It has digital I/O and analog input pins for interfacing with peripherals. Out of the 54 digital I/O pins, 15 can be used for PWM output. Additionally, the board also supports UART, I2C and USB connections [102]. As seen in [103], the Arduino Mega 2560 is used to study adaptive control of a quadcopter by using a serial-stage proportional-integral-derivative (PID) controller. The design utilizes the Arduino board to act as the core control board. The board in turn is interfaced with various sensors such as infrared sensor, bluetooth module, gyroscope and laser ranging sensor.

A.5.1.5 Intel-based Platforms

a) Intel UP board series: The Intel UP boards are Raspberry Pi 2 sized boards that are primarily developed for robotics, UAV, smart home, IoT and digital signage applications [104]. The board is powered by an Intel Atom x5-z8350 quad-core processor along with the Intel FPGA Altera Max V. It can have 1/2/4 GB DDR3L RAM of memory and supports interfacing options such as USB 2.0, USB 3.0, UART, CSI, DSI, and GPIO [105]. Although the board doesn't have dedicated on-board sensors, it is powerful to run Linux, Android and even Windows 10 operating system. The powerful CPU performance can be seen in [106], where the Intel UP boards are used as companion computers to power the TF Mini LiDAR for height estimation.

A.5.2 Software Platforms

In order to interact and maintain proper functionality of the various hardware modules, flight controller software modules are deployed on to UAV computing platforms. The flight controller software stack consists of control and localization algorithms, stabilization techniques, navigation strategies, and other services that enable UAV operations to run smoothly. There are numerous flight controller software packages on the market today. To name a few, selecting the right flight controller software for UAVs would entail taking into account several factors such as UAV application requirements, communication constraints, power consumption, and ease of interacting with other hardware components. The section that follows provides a brief overview of some of the most popular open source flight controller software that is used for commercial and research purposes

A.5.2.1 ArduPilot

ArduPilot is a trustworthy open source flight controller software that can control UAVs like gliders, conventional and VTOL planes, multirotors, and helicopters [107]. ArduPilot which was started by hobbyists in 2009, is now used for commercial and research purposes. It supports a wide range of hardware platforms, including Maverick, Raspberry Pi and Odroid to name a few [108]. The ArduPilot software stack includes control algorithms for UAV localization and navigation. GCS software is also included with ArduPilot, which can help with vehicle configuration, mission planning, and testing. Additionally, the software supports RTK GPS, magnetometers, barometers, airspeed sensors, brushless motors, actuators, and gimbals. ArduPilot is licensed under GPL Version 3. It is free to download and use. Further, it has a rich documentation and source code which can be found in [107] and [109] respectively.

A.5.2.2 PX4

PX4 provides adaptable tools and algorithms to assist UAVs in autonomous navigation. The Dronecode foundation hosts the software, which is distributed under the BSD license [110]. Its modular architecture, configurability, and license permissions make it a viable commercial option. The documentation and source code can be found on GitHub [111].

A.6 Machine Learning Techniques

Unlike static terrestrial systems, UAVs are dynamic and move in three dimensions which makes UAV detection, localization, control, and communication operations challenging. Furthermore, to ensure efficient and reliable UAV operations, a large number of variables such as altitude, speed, and power needs to be optimized. This has put a limit on how far traditional techniques can progress. Recently, machine learning algorithms have shown promise in resolving some of these complex issues. These algorithms are highly scalable and adaptable to a wide range of variables, making them an appealing option for UAV networks. Machine learning algorithms can also retain relevant previous information, which can help with successful UAV operations decision making. Furthermore, because of their inherent data analysis and prediction capabilities, these algorithms are capable of changing the real-time dynamics of UAV networks with ease, which has contributed to their popularity. Control, navigation, detection, collision avoidance, interference management, sensor fusion, computer vision, and communication are just a few of the fields in which the algorithms can be used in UAVs. There is a large body of literature on the use of machine learning in a subset of these fields. A comprehensive analysis and review of the use of machine learning for sensing and communication, on the other hand, is limited. As a result, in this section, the major contributions of machine learning are summarized from a sensing and communication application standpoint, as we discovered that this approach is most beneficial for a novice reader to quickly ramp up on UAV-based machine learning algorithms.

A.6.1 Sensor Fusion

Because a single sensor cannot provide perfect sensing capability, the fusion of sensors with different modalities has demonstrated superior performance. Traditional sensor fusion techniques extract features from each sensor modality separately and then combine them to produce meaningful information. The evolution of deep learning algorithms has added a new dimension to this space by automating feature extraction from input data-sets. This automatic feature extraction in deep learning algorithms has accelerated the rate of sensor fusion to unprecedented levels, allowing us to envision full-scale autonomous operations [112], [113].

Sensor fusion techniques can be divided into three categories. Depending on the stage at which the feature processing and fusion is performed, there are three types: (1) early fusion, (2) deep fusion, and (3) late fusion. [114]. Early fusion is accomplished by fusing the various sensor modalities directly at the input. This enables greater cross-modal interaction but necessitates extreme caution in terms of data alignment, synchronization, and input data format compatibility. Deep fusion, as opposed to early fusion, operates at an intermediate level, where the features of the various sensor modalities are combined at a halfway point after necessary processing and feature extraction. However, deep fusion is difficult to design and implement. Finally, late fusion employs separate networks to independently process and extract features from each modality. The extracted features are combined towards the end of the processing chain to produce a fused output. Late fusion is simpler to design and can easily handle alignment, synchronization, and data redundancy.

The vast majority of sensor fusion literature is focused on object detection applications. In [115], the RetinaNet architecture is used to fuse 2D camera images and sparse radar data using a novel deep learning framework called CameraRadarFusionNet. The model is intended to intelligently determine the level at which sensor fusion occurs so as to obtain improved 2D object detection performance. The proposed approach shows better performance as compared to the baseline image network by approximately 10%. This can be further improved by feeding the raw radar detections through a noise filter in order to reduce unwanted detections and improve performance. Further, with this approach the improved performance comes with additional latency due to data processing of the radar projections. The authors in [116], use a different approach to improve 3D object detection, a middle fusion center point method. A center point detection network is used to detect the center point of the objects in the RGB images. Based on these center points, a 3D frustum is created to include the radar detections in the image plane. The associated radar detections are then used to generate radar feature maps which can complement the image-based features. The fused feature map can then be used to accurately determine additional object properties such as depth, rotation, and velocity. However, it should be noted that in this approach the frustum is created based on the depth estimated from images. This can lead to include the nearby objects in the generated frustum and hence should be carefully considered.

The combination of LiDAR point clouds and camera images is also used for sensor fusion. On this front, the work by Danfei *et al.* [117], has gained popularity due to its application agnostic nature. The raw point cloud obtained from LiDAR modules is fed into a PointNet architecture, which produces multiple 3D box hypotheses with the input 3D points acting as spatial anchors. The network learns to predict the best hypothesis, which is then combined with CNN-processed image features to detect objects. The approach offers a simple design with no environment and sensor specific assumptions while guaranteeing state-of-the-art performance. However, the algorithm can fail if the number of points are below the recommended threshold. Additionally, issues can also result due to partially visible objects. Another work by Pang *et al.*, [114], uses a low complexity object detection framework to fuse output from camera and LiDAR data using a 2D CNN. The approach used is a late fusion technique that operates on the fused output candidates prior to nonmaximum suppression (NMS). Thus, the semantic and geometric properties of the output can be used to produce more meaningful and accurate results. According to the authors, the results obtained demonstrated high performance in the KITTI benchmark as well as the best performance for long distance object detection. Zhao *et al.* have used the fusion of 3D LiDAR and camera data to perform object detection [118]. The authors employ 3D LiDAR to generate object-region proposals, which are then mapped on to the camera image. The new superimposed image is then used to generate regions-of-interest (ROI) proposals, which are then fed into CNNs to detect objects. The proposed approach has an average processing time of about 66.79 ms making it ideal for real-time operations. However, the proposed approach under performs while trying to detect tiny objects that is beyond 60 m of the LiDAR scanning range. Hence, the future work can employ mmWave radars to improve the detection capability by generating more accurate object-region proposals. LiDAR and camera fusion is also utilized for tracking purposes. In [119], full surround online multi-object tracking (MOT) framework is implemented using a LiDAR and calibrated camera array fusion technique. The tracking problem is formulated using markov decision processes (MDPs) which treats the target appearance/disappearance as state transitions within the MDP. The framework is modular and can support various sensor modalities to improve localization and tracking of objects in 3D. In [120], the authors utilize PointFusion [117] and VoxelFusion for camera and LiDAR fusion by leveraging the VoxelNet architecture. This research focuses on resolving the interfacing problem that exists between highly sparse LiDAR point clouds and region proposal networks (RPN). PointFusion involves mapping of 3D points on to the image plane. VoxelFusion divides the point cloud into equally spaced 3D voxels and then encodes groups of points to each of these voxels based on where they reside. The concatenated output from PointFusion or encoded points from VoxelFusion is then fed into a novel voxel feature encoding layer (VFE) and then used for detection. As a result, this method greatly simplifies feature extraction and bounding box prediction and provides an end-to-end trainable deep network in a single stage. Other LiDAR-based sensor fusion techniques include the TransFuser [121], which investigates the limitations of geometric sensor fusion in dealing with complex scenarios and uncontrolled traffic situations. In this work, the authors create a multimodal transformer to combine the LiDAR birds eye representation with image data. The fusion is based on an attention-based approach that captures the entire global 3D scene with a focus on dynamic objects, greatly improving detection performance. However, this approach under performs in red light conditions and hence requires further improvement. The attention-based approach is also used in [122], where the authors perform 3D object detection of LiDAR bird's eye view (BEV) representations with camera images using a gated feature fusion. Using an auto-calibrated projection mechanism, the 2D camera features are used in the first stage to create a smooth spatial feature map with high correlation with the corresponding LiDAR points. In the second stage, a gated feature fusion network is used to combine these spatial attention maps for camera and LiDAR data fusion based on region. Following this, the camera-LiDAR fusion is achieved using a subsequent proposal refinement stage. The proposed method shows significant gain when used with the KITTI and nuScenes datasets. It should be noted that this approach uses a two-stage training method which increases training time. Moreover the data augmentation has to be performed carefully without adding distortion. In [123], a LiDAR and vision-based sensor fusion technique is discussed to achieve reliable object classification with minimal loss. The authors employ an innovative method of upsampling LiDAR point clouds to produce pixel-level depth information, which is then associated with the corresponding RGB data points. For object classification, the fused image is now fed into a CNN. However, it should be noted that the mapping of the upsampled LiDAR feature maps to each of the pixels in the RGB leads to increased processing time and hence can be reduced.

Sensor fusion algorithms help to ensure reliable pose estimation in addition to object detection, tracking, and classification. This is especially beneficial for UAV-based systems, as accurate pose estimation allows for better tracking and collision avoidance operations. One such notable work includes the DenseFusion [124], where the authors fuse the RGB images along with the depth images to implement a reliable 6-DoF pose estimation system. The model employs a heterogeneous architecture in which two input data sources are fused using a novel dense fusion method, after which the pixel-wise embedded features are extracted and used for accurate pose estimation. In addition, an iterative pose refinement algorithm is used to improve the system so that it can handle real-time inference. The proposed approach outperforms the state-of-the-art in terms of better pose estimation, robustness towards occlusions and reduced runtime. In [125], RGB image is combined with depth information in an early fusion to output low-dimensional latent features. This is fed into a deep neural network to perform pixel-wise semantic segmentation for scene understanding. The proposed approach is able to demonstrate increased success rate in both static navigation tasks and dynamic traffic. One of the limitation of the proposed approach is its inability to utilize ego-speed as an input modality. Adding ego-speed can cause the inertia problem which can render the agent unable to restart after it stops for obstacle avoidance. Table A.6 summarizes the above mentioned sensor fusion algorithms which can be tailored to be used with UAV-based applications.

A.6.2 Communication

UAV-based communication systems faces a number of challenges due to the three-dimensional motion, constantly changing channel model, frequently varying orientation and limited energy source associated with UAVs. Moreover, interference issues, cyber-physical attacks, coexistence with existing cellular infrastructure, spectrum sharing, reliable message routing and inclement weather are other challenges for UAV-based communication. As UAV-based communication systems are inherently complex, machine learning algorithms have been found to provide the necessary boost to enable and ensure the various communication requirements for UAVs. These algorithms can accommodate a large number of variables and outperform

Table A.6: Sensor Fusion Techniques

Year	Method	Sensors modalities	Architecture	Fusion level	Application	References
2021	TransFuser	Camera image, LiDAR BEV representation	Transformer with gated recurrent units	Late	3D object detection, Motion forecasting	[121]
2021	Fusion of RGB and depth images	RGB image, Depth image	ResNet architecture	Early	Scene understanding	[125]
2020	CenterFusion	Camera image, Radar point cloud	CNN, Frustum association	Middle	3D object detection	[116]
2020	3D-CVF	Camera image, LiDAR BEV representation	Adaptive gated feature fusion network	-	3D object detection	[122]
2020	CLOC fusion network	Camera image, LiDAR point cloud	2D CNN	Late	3D object detection	[114]
2020	CameraRadar-FusionNet	Camera image, Radar point cloud	RetinaNet, VGG architecture	Early, Late, Halfway	2D object detection	[115]
2020	Fusion of 3D LiDAR and camera data	Camera image, 3D LiDAR data	Region proposal generation, VGG architecture	-	3D object detection	[118]
2019	VoxelFusion	RGB image, LiDAR point cloud	Faster RCNN, VoxelNet	Late	3D object detection	[120]
2019	DenseFusion	RGB image, Depth image	CNN, PointNet architecture	-	6D pose estimation	[124]
2019	Online MOT	Full-surround camera images, LiDAR point clouds	MDP with support vector machines	Early	Multi-object tracking and detection	[119]
2018	PointFusion	Camera image, LiDAR point cloud	CNN, PointNet architecture	Early	3D object detection	[117]
2018	CNN-based fusion of vision and LiDAR	Camera image, LiDAR data	AlexNet	-	Object classification	[123]

traditional algorithms in terms of performance. Furthermore, the algorithms are easily scalable, can be tuned for low complexity, and can predict future states, allowing the UAV system to adapt to changing conditions. Some recent contributions to machine learning algorithms used for UAV-based communication are discussed in the following paragraphs.

In order to ensure reliable communication, it is critical to obtain an accurate channel model estimation. Wang *et al.* in [126] has described an approach where the channel parameters for the air-to-ground (A2G) links between UAV and GCS is predicted using an unsupervised learning algorithm. Received signal strength (RSS) data from mobile users is collected and used to forecast a temporary 3D channel model for the UAV-GCS link. The channel features are then classified using the k-means clustering technique based on LoS/NLoS parameters. The LoS/NLoS parameters are then classified and used to calculate the path loss between the UAV and the GCS. The proposed model is evaluated by comparing simulation results to a conventional statistical channel model and is found to achieve approximately 91.8% accuracy. However, the proposed approach suffers from shadowing effects which can lead to decrease in system performance and hence should be resolved. Another channel modelling approach by William *et al.* in [127] uses generative neural networks to model the channel at millimeter wave frequencies. Firstly, the proposed model predicts whether each link is LoS or NLoS or in outage. This state information is then fed into a variational autoencoder, which generates the delays, AoAs, and so on for each propagation path. The methodology is tested for UAVs with 28 GHz A2G channels in an urban environment where the training data sets are produced using Wireless Insite [128] ray tracing software. The proposed model is found to effectively capture the scattering effect from nearby buildings. However, in order to completely validate the accuracy of the model, comparison with real-world channel measurements also needs to be studied and verified for different scenarios. In [129], the authors have used an alternate two-stage method to model the millimeter wave channel model for UAVs. The first stage involves developing an effective channel estimation technique to collect millimeter wave channel information so that each UAV can train a local channel model using generative adversarial networks (GAN). In the second stage, a novel distributed GAN framework is developed, allowing each UAV in the UAV network to share channel information with each other while maintaining privacy. According to simulation results, the proposed approach improves average UAV downlink rate by more than 10% when compared to baseline real-time channel estimation schemes. The results also show that sharing more generated channel samples increases the learning rate, but decreases as the total number of UAVs in the network increases. Additionally, in comparison with a perfect CSI scheme, the proposed method yields lower data rate due to the inevitable training error.

Improved interference mitigation schemes are also required for reliable and low-latency communication between multiple UAVs. In [130], the authors used a deep reinforcement learning (DRL)-based echo state network (ESN) to address interference issues in cellular-connected UAVs. Each UAV is designed to reduce its interference from the ground network as well as its energy consumption and wireless latency. The proposed approach models the problem as a dynamic game in which each UAV uses the ESN architecture to determine the best path, transmission power, and cell associations. Furthermore, the computational complexity of the proposed algorithm is reduced by determining an upper and lower bound for each UAV's altitude. The simulation results show that the proposed scheme reduces interference for ground users while also improving wireless latency per UAV. One of the limitations of the proposed approach is the increase in runtime complexity of the algorithm when the performance of the ground UEs is improved. In addition to interference mitigation, UAVs are prone to eavesdropping attacks. The work by [131] provides a method for detecting eavesdropping attacks in a UAV assisted wireless network using unsupervised learning methods. The eavesdropping attack is assumed to occur during the authentication process in this case. In order to detect eavesdropping, the authors build predictive models that use one-class support vector machines (OC-SVM) and the k-means clustering algorithm. To train and test the above algorithms, the authors have also developed novel approaches for generating the data sets under varying channel conditions. The results show that k-means clustering performs better when the eavesdropper has a high SNR, however, in terms of stability, the OC-SVM outperforms the k-means.

There is growing interest in integrating UAVs to provide assistance to the existing cellular infrastructure. On this front, the work done by Lins *et al.* in [132], demonstrates the use of UAVs in search and rescue missions by utilizing the existing

5G infrastructure. The authors show that for search and rescue missions, the system intelligence (SI) unit should handle and optimize decision making, communication-computation tradeoffs, and connection establishment while the edge intelligence (EI) unit should take care of optimization of artificial intelligence based end-user applications. The authors further presents a virtualized testbed to demonstrate the above concepts. The demonstration utilizes various DNN partitioning strategies to evaluate the effects of CPU and memory usage, transmission bit rate, and object detection accuracy. Future research can change the transport infrastructure from fixed to dynamic and provide dynamic system adaptation to the propagation channels for search and rescue operations. Another work by Galkin *et al.* in [133], focuses on establishing reliable 5G cellular connectivity in a UAV-based communication system in presence of interferers. A supervised approach is proposed, followed by neural network training, in which the UAV selects the GCS based on distances to the GCS, channel conditions, received signal power, and interferer location. The authors consider a UAV that is equipped with two sets of antennas: an RF omni-directional antenna and a directional antenna. Based on the received signal power from omni-directional antenna and other information, the neural network is trained to establish the connection with the GCS from the directional antenna while achieving best channel quality. The proposed scheme outperforms other schemes, such as the strongest-signal and closest-neighbor association techniques. The proposed method can be further extended by introducing UAV mobility which can lead to handovers complexities to the UAV association problem.

In [134], the three-dimensional spectrum sharing between UAVs and device-to-device (D2D) communication is studied. It is assumed that UAVs share spatial spectrum in the same licensed bands as D2D networks. A machine learning-based stochastic geometry approach is proposed to optimize the area spectral efficiency (ASE) of UAVs while maintaining the required ASE for D2D networks. For training, a gaussian kernel non-linear regression is used with various input parameters such as D2D density, UAV flight height, UAV spectrum sensing radius, fading factor, and so on. The resulting output provides statistics for an approximated log-normal distribution, which can then be used to derive various insights such as false alarm probability, spatial missed detection probability, and so on. The reported simulation results show that as the spatial spectrum sensing radius decreases, so does the coverage probability of UAVs, but there is an improvement in the ASE of UAVs. The proposed method also aids in determining the best spatial spectrum sensing radius given certain network parameters.

In [135], the power allocation issue of a UAV-assisted visible light communication system using non-orthogonal multiple access (NOMA) is considered. The problem is formulated such that the sum-rate of all users is maximized subject to the constraints on power allocation, quality of service of users and UAV position. The proposed method employs the harris-hawkins optimization (HHO) algorithm in conjunction with a fully connected artificial neural network. The optimization algorithm aids the artificial neural network to avoid the "local minima" trap and hence makes it suitable for real-time applications. According to the numerical simulation results, the proposed algorithm outperforms conventional optimization schemes and algorithms. One of the future extensions for this work is to extend the approach to fixed-wing UAVs to achieve joint 3D trajectory optimization and power allocation. Currently, the algorithm suffers from a performance loss of about 10%, which should be investigated and improved. To meet the power requirements of UAV swarms, the authors of [136] proposed a distributed federated learning (FL) approach. According to this approach, the UAV swarm is made up of a leader UAV and its follower UAVs. Each follower UAV runs a local FL model based on the data it collects and sends the trained data to the leader UAV. The leader UAV gathers these trained models and combines them into a global FL model. The trained global FL model is now being used to create a UAV swarm power allocation and scheduling algorithm. The proposed algorithm outperforms traditional algorithms in terms of energy consumption and delay for the UAV swarm, according to simulation results. It is to be noted that the convergence of the FL model largely depends upon the UAV antenna angle deviations, where a larger angle deviation variance requires additional communication round for convergence. Beamforming is another area of UAV-based communication where machine learning is used. The authors of [137] propose a machine learning-based beamforming technique to enable low-latency communication in a multi-UAV network. If the channel or signal-to-interference noise ratio (SINR) information is provided, the proposed method employs Q-learning to predict the beamforming coupling coefficients. According to simulation results, the proposed method outperforms conventional rapid beam tracking methods. Furthermore, the new method computes the best digital weights for SINR maximization and thus achieves better performance compared to traditional gradient based schemes for large angle deviation scenarios. A brief summary of the discussed machine learning algorithms for UAV communication can be found in Table B.6.

A.7 Open Research Areas and Future Directions

As seen in the preceding sections, the wide range of sensors, hardware and software solutions for UAVs raises a number of issues and potential future research directions. To enable a complete visual perception of the environment, we need to use sensor fusion algorithms backed by machine learning. Even though the sensor fusion algorithms listed above have excellent accuracy for object detection and classification, their performance and reliability in extreme weather conditions and lighting needs to be evaluated further. There is also a scarcity of data sets which can aid in analyzing and evaluating the sensing performance of UAVs in such harsh weather conditions. Moreover, the algorithms listed in [120] and [121] perform 3D object detection which can significantly increase the computational overhead and hence have to optimized to port to UAV systems. Further research into dynamic sensor fusion techniques, depending on the requirements of the imaging scene, is required. Due to the strict requirements for inference time for autonomous systems, low-complexity sensor fusion algorithms are also essential. Another potential future extension work, as seen

Table A.7: Machine Learning Techniques for UAV-based Communication

Year	Method	Application	Merits	Demerits	References
2021	Distributed GAN	Channel modelling	10% improved average UAV downlink rate compared to baseline	Lower data rate with respect to perfect CSI	[129]
2021	Deep neural networks (SSD-VGG16)	Cellular assistance	Virtualized testbed to demonstrate DNN partitioning for 5G infrastructure	Dynamic system adaptation for propagation channels is not present	[132]
2020	Variational autoencoder	Channel modelling	Accurate channel parameter estimation and scattering effect	Validation with real-world channel measurements is not provided	[127]
2020	Artificial neural networks	Cellular assistance, Interference management	Improved directional beamforming	UAV mobility can introduce handover issues	[133]
2020	Gaussian kernel non-linear regression	Spectrum sharing	Optimal spatial spectrum radius with maximum ASE for UAV networks	Decreased spatial spectrum radius can lead to increased inter-UAV interference	[134]
2020	Artificial neural networks	Power allocation	Real-time applications	10% performance loss	[135]
2020	Distributed federated learning	Scheduling, Power allocation	Better energy consumption and lower delay for UAV swarms	Large angle deviation requires additional computation time	[136]
2020	OC-SVM, K-means	Physical layer security	OC-SVM is less sensitive to change in signal power whereas k-means is more resistant towards high SNR attacks	Verification with real-time experiments is not provided	[131]
2020	Q-learning	Beamforming, Interference mitigation	Enhanced beamforming due to improved coupling coefficient estimation	Noise and interference can distort the received coupling coefficient power leading to performance loss	[137]
2019	DRL ESN	Interference management	Reduces interference to ground users and improves wireless latency	Increased runtime complexity	[130]
2019	K-means	Channel modelling	91.8% accuracy with respect to statistical channel model	Shadowing effects	[126]

in [121], is to improve red light detection performance in the transformer model under various conditions. In [116], the authors provide a novel method of fixed pillar expansion to reduce the height inaccuracies from radar detections. This can help in reducing computational complexity but it can lead to inaccurate estimate of the center point of the object. Employing adaptive pillar size can be one possible future extension. Performing joint detection and tracking using videos and point cloud streams is also an interesting research direction. As some fusion algorithms rely on active sensors such as radars and LiDARs, the interference effects of these sensors must be investigated. A possible research direction in this regard is to develop novel interference mitigation techniques for mmWave FMCW radars [138]. Even though work has been done to improve the AoA and AoA resolution [54], [53], there is still room for advancement in this area for mmWave FMCW radars such as accurate estimation using low-complexity algorithms with reduced inference time.

In terms of communication, when UAVs are outfitted with various communication modules for different applications, obtaining an optimized communication scheme that takes into account various constraints such as energy, latency, and spectrum availability is a potential research direction. Moreover, devising algorithms which perform equally well during UAV motion also requires further investigation. One of the future extensions for [129] can be to improve the distributed GAN model to incorporate UAV mobility and NLoS aspects to ensure robust and reliable communication. For [132], the optimal utilization of available UAV resources to accomodate the various machine learning enhanced communication algorithms is a possible future extension. Furthermore, there is growing interest in the research community in integrating existing cellular networks with UAV networks in order to enable future wireless technologies. Efficient handovers and association in cellular-connected UAVs where the UAVs are in motion provides interesting directions for further research. Apart from the above, an important area of future research is joint sensing and communication for mmWave and UWB sensors. The authors of [139] has provided proof of concept simulations for joint sensing and communication in mmWave radars, yet this area is still nascent and shows huge potential. Expanding joint sensing and communication with enhanced machine learning models can also be explored provided the UAV resource constraints are adequately met. Other potential research directions include efficient and power-optimized routing protocols for UAV wireless networks to cater to different channel conditions and applications.

A.8 Conclusion

We provided a brief overview of the various hardware and software technologies used for UAVs in this survey article. Various on-board sensors, communication components, and computing platforms were discussed, as well as some practical information about the technologies' key metrics. Among on-board sensors, RGB-D cameras provide better visual information related to the static environment whereas radars and LiDARs provide better dynamics of the different objects present. From the perspective of UAV-based communication, LoRa provides long distance coverage, whereas better reliability can be achieved using Wi-Fi for short distances. Pixhawk 4 provides dedicated computational resources and flexibility to operate UAVs. To cater to deep learning applications, the Nvidia boards offer an excellent choice in terms of performance and form factor. There is also discussion of software solutions that aid in various UAV applications. A brief description of the current state-of-the-art machine learning and deep learning algorithms used in UAVs for sensing and communication is also provided. CNNs offer reliable object detection and flexibility to be used with other sensor modalities. For UAV communication, based on the application, a number of machine learning algorithms ranging from deep neural networks to deep reinforcement learning are in use. The information in this article is intended to provide the reader with the most recent sensor, communication and computing technologies for UAVs, as well as research directions for emerging UAV-based applications.

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