International Journal of Advanced Smart Convergence Vol.12 No.3 32-39 (2023)
http://dx.doi.org/10.7236/IJASC.2023.12.3.32

IJASC 23-9-5

Advancements in Unmanned Aerial Vehicle Classification, Tracking, and Detection Algorithms

Ahmed Abdulhakim Al-Absi*

Associate Professor, Department of Smart Computing, Kyungdong University, Korea
absiahmed@kduniv.ac.kr

Abstract

This paper provides a comprehensive overview of UAV classification, tracking, and detection, offering researchers a clear understanding of these fundamental concepts. It elucidates how classification categorizes UAVs based on attributes, how tracking monitors real-time positions, and how detection identifies UAV presence. The interconnectedness of these aspects is highlighted, with detection enhancing tracking and classification aiding in anomaly identification. Moreover, the paper emphasizes the relevance of simulations in the context of drones and UAVs, underscoring their pivotal role in training, testing, and research. By succinctly presenting these core concepts and their practical implications, the paper equips researchers with a solid foundation to comprehend and explore the complexities of UAV operations and the role of simulations in advancing this dynamic field.

Keywords: *UAV, Classification, Tracking, Detection, Simulations, Unmanned aerial vehicles, Drones.*

1. Introduction

Drones or unmanned aerial vehicles (UAVs) are becoming increasingly popular due to their advanced technology, easy deployment, cost-effectiveness, small size, flexibility, and wide range of uses. They are being adopted for various purposes, including military, space, and civilian applications [1]. The drone industry has experienced a remarkable surge, having already reached a substantial value of $100 billion by the end of 2020 [2], [3]. An astounding 7 million drones are anticipated to be operational in the United States alone by 2023. Drones play a pivotal role in acquiring real-time information, encompassing videos, images [4], and environmental data. Such data is indispensable for applications such as search and rescue missions, surveillance, border security, and military reconnaissance, as depicted in Figure 1. In this representation, we envision deploying detectors for small UAVs around areas of interest, which can include both ground-based units and monitoring UAVs. If a small UAV remains within uncontrolled airspace, it's considered safe. However, if it crosses into controlled airspace, it must be detected and managed outside the region. These small UAVs are progressively emerging as pivotal assets in the realm of warfare. Beyond military contexts, drones are being adopted in civilian domains, encompassing tasks such as traffic monitoring, surveillance, disaster management, construction, communications, agriculture, livestock supervision, forest fire control,

Manuscript Received: June. 19, 2023 / Revised: June. 26, 2023 / Accepted: June. 29, 2023
Corresponding Author: absiahmed@kduniv.ac.kr
Tel: +82 336390108, Fax: +82 1021785226
Associate Professor, Department of Smart Computing, Kyungdong University, Korea

and product delivery [5]. The varied landscape of drone applications introduces multiple challenges [6], [7], [8]. Additionally, concerns are mounting about the potential misapplication and accidents involving drones. These devices are sometimes exploited by criminals and terrorists to perpetrate attacks or engage in illicit material smuggling [9], [10], and [11]. Hence, developing counter mechanisms, including small drone interceptors, localization systems, and detection networks, is becoming increasingly critical. As emphasized in [12], detecting small UAVs poses unique difficulties compared to manned aircraft, prompting governmental bodies and law enforcement agencies to formulate new detection and monitoring strategies. Various techniques such as remote control seizure [13], computer vision [14], and radar-based identification [15] are commonly utilized to spot drones.

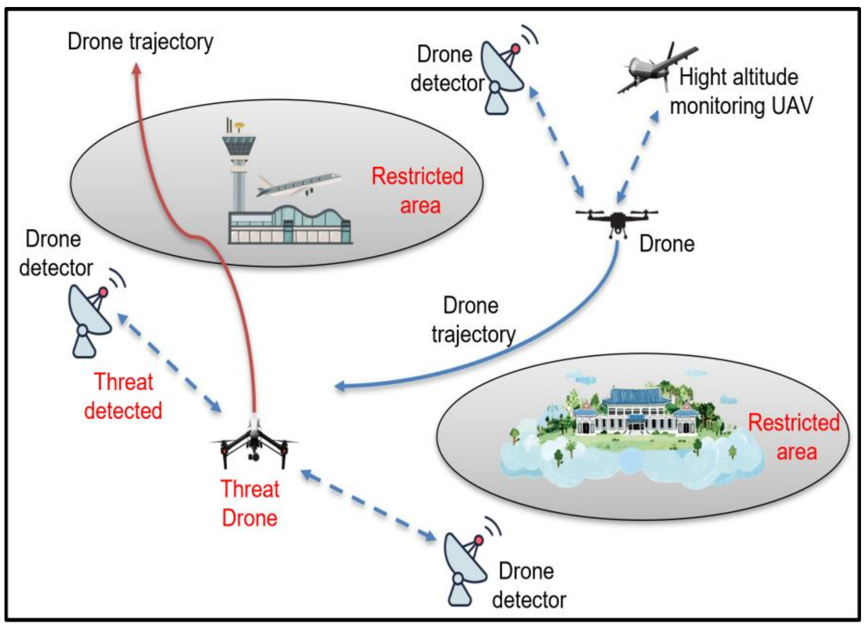

Figure1. Detecting Unauthorized Small UAVs in Restricted Zones

This paper provides a comprehensive overview of UAVs, focusing on their classification, tracking, and detection algorithms. It begins by acknowledging the remarkable growth of the drone industry and the extensive utility of UAVs across military, civilian, and space applications. The paper dissects the intricate world of UAVs by exploring the algorithms and techniques employed for classification, tracking, and detection. The author highlights the significance of these interconnected aspects, where detection enhances tracking, and classification aids in anomaly identification, forming a holistic understanding of UAV operations. Furthermore, the paper underscores the vital role of UAV simulators as versatile tools that bridge theory and practice, enabling safer operations and fostering innovation. This paper equips researchers and practitioners with a profound grasp of UAV fundamentals and their practical implications, positioning them to advance algorithms and technologies with far-reaching implications for various fields. Ultimately, it serves as an invaluable resource in the realm of Unmanned Aerial Vehicles, paving the way for future developments in this dynamic domain.

Table 1.Comparison of UAV *Classification* Algorithms

Classification Method	Description	Pros	Cons	Data Sources	Learning Approach
Electromagnetic Signal Analysis	Identifies drones based on their unique electromagnetic signals using radar and radio signals. Each drone type emits a distinct signal for categorization.	- Effective in identifying specific drone types. - Works well in various weather conditions.	- Limited to detecting drones with active electromagnetic emissions. - May not provide detailed information about drone characteristics or intentions.	Electromagnetic Signals	N/A
Flight Behavior Analysis	Observes drone behavior during flight, including hovering, rapid movement, or specific flight paths, to provide insights into the drone's type and potential use.	- Offers behavioral insights, aiding in threat assessment. - Can work with passive monitoring.	- May require visual observation, which can be limited by environmental conditions. - Limited to behavioral information; may not identify drone types explicitly.	Flight Behavior Data	N/A
Sensor Fusion Algorithms	Combines data from various sources such as cameras, radar, and radio sensors to ensure accurate drone classification. Integrating information from multiple sensors.	- Increased accuracy and reliability through data fusion. - Provides more comprehensive drone profiles.	- Complex integration and calibration of multiple sensors may be required. - Costlier due to the need for multiple sensor types.	Cameras, Radar, Radio Sensors	N/A
Machine Learning Tools	Analyzes data using machine learning techniques (e.g., SVMs, random forests, k-NN) to classify drones based on their traits and features. Learns from labeled data.	- Can adapt to evolving drone characteristics. - Potential for high accuracy with extensive training data.	- Requires substantial labeled data for effective training. - May struggle with previously unseen drone types.	Various Sensors	Supervised Machine Learning
Image-Based Classification	Identifies drones by analyzing images or videos, considering factors like appearance, shape, size, and color. Often uses advanced machine learning (e.g., CNNs).	- Visual identification provides detailed information. - Potential for real-time detection with camera-equipped systems.	- Susceptible to environmental factors like lighting and visibility. - Computational intensity can be high.	Images, Videos	Supervised Machine Learning

2. UAV Classification Algorithms

UAV classification algorithms are like special tools that look at different things about the drones to figure out what kind they are and if they could be a problem. A radar and Radio signal, this method uses to figure out drones by checking their special electromagnetic signals. Each kind of drone has its own unique signal that can be noticed and sorted into groups. Flight Behavior, this technique watches how drones fly and what they do, like staying still, moving fast, or following certain paths. These actions can tell us what kind of drone it is and what it might be used for. Sensor fusion algorithms mix information from different places, like cameras, radar, and radio sensors. They do this to make sure they're right about what kind of drone it is. By using data from all these different sensors, they get a better and fuller understanding of the drone. Machine learning tools, such as support vector machines (SVMs), random forests, and k-nearest neighbors (k-NN), are used to learn from marked data and sort drones according to their traits and features. Image-Based Classification, by looking at pictures or videos, this technique spots drones by how they look, their shape, size, and color. Often, it uses smart computer learning, like convolutional neural networks (CNNs), to learn what drones look like and group them into different types [16]. The advantages and limitations of each method of drone classification are highlighted in Table 1.

3. UAV Tracking Algorithms

UAV tracking algorithms are like GPS for drones to follow moving things. The Kalman Filter is a popular method to track things that are moving. It takes info from sensors and guesses from a model to figure out where the moving thing is. It's good for fast situations where we need answers right away. Extended Kalman Filter (EKF) and Unscented Kalman Filter (UKF) are like upgrades to the Kalman Filter that work better with systems that don't follow straight lines. EKF makes a not-so-straight system look more like a straight one, while UKF uses special points to handle the curvy parts. Particle Filters are helpful when things move in tricky and not-so-normal ways [17]. They work for situations that aren't easy to predict.

Table 2. Comprehensive comparison of UAV Tracking Algorithms

Tracking Method	Description	Pros	Cons	Applicability
Kalman Filter	A widely used method that estimates the position of moving objects by combining sensor data with model predictions. Effective for real-time tracking in fast-paced situations.	- Real-time tracking - Well-suited for fast-moving objects	- Limited performance in complex, non-linear scenarios	Fast-moving objects
Extended Kalman Filter (EKF)	An advanced version of the Kalman Filter, designed for non-linear systems. Helps linearize complex trajectories for improved tracking.	- Handles non-linear object paths - Enhanced accuracy compared to Kalman Filter	- Still limited in scenarios with highly non-linear movements	Objects with curving paths
Unscented Kalman Filter (UKF)	Another variant of the Kalman Filter, better suited for non-linear systems. Utilizes special points to manage complex object trajectories.	- Effective for non-linear trajectories - Enhanced accuracy and robustness	- Higher computational cost compared to Kalman Filter	Objects with curving paths
Particle Filters	Utilizes multiple "particles" or guesses to track objects, with each particle becoming heavier or lighter based on sensor data. Adapts well to unpredictable movements.	- Adaptable to unpredictable object motion - Robust in uncertain environments	- Computationally intensive - Requires a large number of particles for accurate tracking - Can struggle in situations with numerous potential tracks	Objects with unpredictable motion
Multiple Hypothesis Tracking (MHT)	Effective when there is uncertainty in observations and measurements. It handles ambiguous scenarios and multiple potential object tracks.	- Handles situations with unclear observations and measurements - Can track multiple potential objects simultaneously	- Increased computational complexity - Requires managing multiple hypotheses and associations	Unclear or ambiguous scenarios
Convolutional Neural Networks (CNNs)	Machine learning models trained to track objects by analyzing examples. Adaptable to various tracking scenarios and complex environments.	- Can adapt to different object types and tracking scenarios - Effective in complex, diverse environments	- Requires substantial training data - May be limited by the quality of training data and environmental conditions - Computational overhead	Objects with diverse behaviors
Recurrent Neural Networks (RNNs)	Neural network models designed for tracking objects over time. Effective for complex tracking scenarios and situations requiring memory of past movements.	- Can handle complex tracking scenarios - Effective in tracking objects with long-term behaviors	- Requires substantial training data - Computational overhead	Objects with complex trajectories
Long Short-Term Memory (LSTM)	Specialized neural networks for understanding object movements over time. Particularly useful for objects with intricate and prolonged trajectories.	- Effective in tracking objects with complex and long-lasting movements - Can capture temporal dependencies in object behavior	- Requires significant computational resources - Needs substantial training data	Objects with complex trajectories

Instead of using just one guess, they use a bunch of guesses called particles. These particles get heavier or lighter based on how well they match what sensors say. It's like picking the best guesses to figure out where the thing is. Multiple hypothesis tracking (MHT), this works well when we're not sure about what we see and measure, especially in situations where things are unclear. Convolutional neural networks (CNNs) and recurrent neural networks (RNNs) have been used for keeping an eye on objects. These models can learn how to follow things by looking at lots of examples and can manage tricky situations. Long short-term memory (LSTM) is good at understanding how things move over time [18]. They're handy for following objects that move in complicated and long-lasting ways. Table 2 provides a comprehensive comparison of UAV Tracking Algorithms, highlighting their descriptions, advantages, limitations, and the scenarios in which they are most applicable.

4. UAV Detection Algorithms

Detecting UAVs, also known as drones, has become increasingly important due to their widespread use in various applications, both beneficial and potentially harmful. There are several algorithms and techniques that can be employed to detect UAVs [19], [20]: Sound Listeners: Imagine having special ears that can hear the unique sounds drones make. These ears are like acoustic sensors. Smart computer programs (machine learning algorithms) can then learn to tell if the sounds they hear are from a drone or not. Radar Systems: Radar technology can be effective in detecting UAVs due to their ability to detect objects in the air based on radio frequency reflections. Doppler radar can determine the speed and direction of UAVs, aiding in tracking.

Table 3. Comprehensive comparison of UAV Detection Algorithms

Detection Method	Description	Pros	Cons	Applicability
Sound Listeners	Detects drones by listening to unique sounds they emit. Utilizes acoustic sensors and machine learning algorithms.	- Effective for audio-based drone detection - Can be used in various environmental conditions	- Limited to detecting drones with audible sound emissions - May not provide precise location information	Audio-based detection
Radar Systems	Utilizes radar technology to detect UAVs by capturing radio frequency reflections. Doppler radar can determine speed and direction.	- Effective for long-range detection - Works well in various weather conditions	- May not provide detailed drone identification - Requires specialized radar equipment - Can be susceptible to radar jamming	Long-range detection
Video and Image Analysis	Detects drones in videos and images using computer vision techniques. Includes methods like background subtraction, motion detection, and deep learning with CNNs.	- Visual detection provides detailed information - Can adapt to various drone types and environments	- Susceptible to environmental factors like lighting and visibility - Requires substantial computational resources - May struggle with low-quality or obstructed visuals	Visual detection
Radio Frequency (RF) Analysis	Identifies drones based on their unique radio signals. Analyzing these signals helps distinguish drones and track their movements.	- Effective in distinguishing individual drones - Can track drones based on their RF emissions	- Limited to detecting drones with active RF emissions - May not provide precise location information - Susceptible to interference from other RF devices	RF-based detection
Spectrum Analysis	Detects unusual frequency patterns in radio signals emitted by drones. Can identify drones by recognizing irregular signal patterns.	- Effective for identifying drones with distinct RF signal patterns - Can work in diverse RF environments	- Limited to detecting drones with unique RF signal patterns - May require advanced signal processing techniques - Susceptible to interference from other RF devices	RF-based detection
Behavior Analysis	Observes how drones fly, their altitude, and other behaviors to differentiate legitimate drones from potential threats.	- Behavioral analysis provides insights into drone intentions - Can be used in conjunction with other detection methods	- Limited to assessing behaviors, may not identify drone types - May require additional sensors for comprehensive analysis	Behavioral analysis
Infrared Vision and Thermal	Detects drones by capturing their distinct thermal signatures due to heat emissions. Effective in low-light conditions.	- Works well in low-light environments - Effective in identifying drones with heat emissions	- Limited to detecting drones with active heat emissions - May not provide precise location information - May be affected by environmental conditions like fog or rain	Thermal-based detection
LiDAR (Light Detection and Ranging)	Creates a 3D map of the environment by sending out laser beams. Detects drones as moving objects on the map.	- Provides a 3D representation of the environment - Effective for mapping and tracking drones in complex landscapes	- Requires specialized LiDAR equipment - Limited to detecting drones within the LiDAR's field of view - May be affected by obstructions and interference	3D mapping and tracking
Geofencing and Signal Jamming	Geofencing restricts drones from entering specific areas, while signal jamming disrupts drone communication, forcing them to land.	- Effective for securing restricted areas - Immediate response to unauthorized drone presence	- Does not provide detailed information about detected drones - Signal jamming may require regulatory approval and coordination - Limited to designated areas or perimeters	Restricted area protection
Multi-Sensor Systems	Combines multiple sensors, such as radar, optical cameras, and RF sensors, for enhanced detection accuracy. Machine learning improves detection by learning drone patterns.	- Improved detection accuracy through sensor fusion - Adaptable to various detection scenarios - Can handle complex environments	- Requires integration and calibration of multiple sensors - Higher cost due to multiple sensor types - May require substantial computational resources for machine learning	Enhanced detection accuracy

Using special cameras and smart computer tricks, we can spot drones in videos and pictures. One way is "Background Subtraction," where we remove the normal background to see moving things like drones. "Motion Detection" helps a computer notice changes between pictures to find moving objects. Techniques like YOLO and Faster R-CNN act like super detectives, quickly finding drones in videos. "Optical Flow" looks at how things move between pictures to catch drones. Deep learning, which is like a super-smart brain for computers, can teach them to recognize drones using CNNs, training them to know what drones look like in images or videos. Radio Frequency (RF) Analysis: For instance, every drone sends out its own special radio signal. When we study these signals, we can tell which drone is which and follow them around. Spectrum: Detecting unusual frequency patterns. For example, if the song is playing smoothly and all the instruments sound right together, it's normal. But if you suddenly hear a weird sound that doesn't match the song, you notice it. Spectrum analysis does something similar with radio signals. If there's an odd signal that doesn't belong, it might mean there's a drone nearby. Behavior Analysis: By watching how drones fly, how high they go, and other things they do, we can tell the good ones from the ones that shouldn't be there. Infrared Vision and Thermal: UAVs often have distinct thermal signatures due to their heat emissions. Thermal cameras can detect these signatures, especially in low-light conditions. Light detection and ranging (Lidar), is like sending out laser beams and seeing how long they take to bounce back. This makes a 3D map of the place. Drones show up as moving dots on this map. Geofencing and Signal Jamming: Even though they're not exactly ways to find drones, Geofencing keeps drones away from certain places, and signal jamming messes up drone communication, making them land or go back to their controller. Drone detection systems combining multiple sensors, such as radar, optical cameras, and RF sensors, can improve the accuracy of UAV detection. However, when we use machine learning with sensor information, it gets better at finding drones by learning their patterns and actions from the data.

Table 3 compares UAV Tracking Algorithms, summarizing their strengths, weaknesses, and best-use scenarios for detecting and tracking UAVs.

Table 4. UAV-Simulators and their corresponding applications

Reference	Year	Simulator	Open Source	Creators	UAVNet Simulation Support	Purpose	UAV types included	Applications	Example Application Domains/Organizations
[21]	2009	HEXAGON	No	No	No	Development & Research	MicroHawk MH-600/2000	Educational/training	Film-making, Fire department, Sunflower Labs
[22] [23]	2012	Simbeeotic	No	Harvard University	Yes	Development & Research	No	Swarms of micro-aerial vehicles (MAVs)	Swarm for Agriculture, Military
[24]	2001-2004	JSBSim	Yes	JSBSim build team	No	Development & Research	No	Flight Dynamic Model (FDM)	Future Drone traffic control Study, Gaming
[25], 26]	2006	MS Flight Simulator X	No	Microsoft Studios	No	Entertainment	MQ-1 UAV Predator	MS Flights, Gaming	MS Flight Simulator X [25.26]
[27], [28]	2020	FlightGear	Yes	International group volunteers	No	Academic, Research, Entertainment	No	Gaming	Filmmaking, Fire departments, Security
[29]	2017	AVENS	Yes	Marconato	Yes	Development & Research	No	Flying ad hoc Network Development	UAVNet Security, Academic Curriculum
[30], [31]	2013	UAVSim	Yes	Electrical Engineering and Computer Sciences, University of Toledo	Yes	Development & Research	No	Training and Research.	UAVNet Security, Academic Curriculum
[32]	2016	Computational Multicopter Design	Yes	Computer Science and Artificial Intelligence Laboratory; Massachusetts Institute of Technology	No	Design, optimize and fabricate multicopters	No	Academic and Research	DJI, AeroVironment, Parrot
[33]	2017	AirSim	Yes	Microsoft Corporation	No	Development & Research	No	----	Kaggle Datasets, EliteDataScience
[34]	2016	RotorS	Yes	Autonomous Systems Lab at ETH Zurich	No	Development & Research	AscTec: Hummingbird,	micro-aerial vehicles (MAVs)	Military, Humanitarian UAVNet, Drone Farming
[35	2017	D-MUNS	No	Korea University Seoul, Republic Korea	Yes	Development & Research	Pelican, Firefly	----	UAVNet security, Academic Curriculum
[36]	2015	DIMAV	Yes	Kok JM and Chahl JS, niv of South Australia	No	Development & Research	No	----	DIMAV
[37]	2022	VAMPIRE Suite	Yes	AEgis	No	Training and Entertainment	Raven, Wasp, and Puma	Academic and Research	Humanitarian UAVNet, Drone Farming, Film
[38]	2022	Real Drone Simulator	Yes	—	No	Entertainment	No	Learning to fly different drones without breaking your own aircraft	Real Drone Simulator
[39], [40]	2022	Zephyr Sim	No	Little Arms Studios	No	Training	DJI Phantom, Inspire & Mavic Pro, 3DR Solo, Syma X5C5, Autel X-Star, Parrot Bebop 2	Gaming	Humanitarian UAVNet, Drone Farming, Film

5. UAV-Simulators and their Applications

UAV simulators serve as dynamic training grounds for drone operators, offering a virtual platform to hone piloting skills and simulate real-world missions without the risk of physical crashes. Beyond training, these simulators play a pivotal role in testing new drone technologies, facilitating mission planning and rehearsal, preparing emergency responders for various scenarios, educating users about airspace regulations, and advancing research in drone algorithms and systems. In essence, UAV simulators are versatile tools that bridge the gap between theory and practice, enabling safer, more efficient, and innovative drone operations across a spectrum of applications. In Table 4, the UAV-Simulators and their corresponding applications are presented.

Conclusion

This paper provides a valuable contribution to the field of UAVs by offering a comprehensive overview of advancements in UAV classification, tracking, and detection algorithms. The paper highlights the interconnectedness of these concepts and the relevance of simulations in the context of drones and UAVs. By providing a clear understanding of these fundamental concepts and their practical implications, the paper equips researchers with a solid foundation to comprehend and explore the complexities of UAV operations. This understanding can help researchers to develop more effective algorithms and technologies for UAV operations, which can have significant implications for various applications, including military, space, and civilian applications. Overall, this paper provides a valuable resource for researchers and practitioners in the field of UAVs.

Acknowledgement

This work was supported by the 2023 research fund of Kyungdong University.

References

[1] M. Hassanalian, D. Rice and A. Abdelkefi, "Evolution of space drones for planetary exploration: A review", Prog. Aerosp. Sci., vol. 97, no. January, pp. 3560, 2018.
[2] Goldman Sachs Research,"Drones reporting for work",2017, [online] Available: http://www.goldmansachs.com/our-thinking/technology-driving-innovation/drones/.Accessed on Sept 1, 2020
[3] Federal Aviation Administration,"FAA Aerospace Forecast, FY 2016-2036",2016, [online] Available: https://www.faa.gov/data_research/aviation/aerospace_forecasts/media/FY2016-36_FAA_Aerospace_Forecast.pdf
[4] X. Wang, A. Chowdhery and M. Chiang, "Skyeyes: Adaptive video streaming from UAVs", Proc. ACM HotWireless Workshop, pp. 2-6.
[5] H. Wang, H. Zhao, J. Zhang, D. Ma, J. Li and J. Wei, "Survey on Unmanned Aerial Vehicle Networks: A Cyber Physical System Perspective," in IEEE Communications Surveys & Tutorials, vol. 22, no. 2, pp. 1027-1070, Secondquarter 2020, doi: 10.1109/COMST.2019.2962207.
[6] J-P. Yaacoub, H. Noura, O. Salman and A. Chehab,"Security analysis of drones systems: Attacks, limitations, and recommendations," in Internet of Things, vol. 11, no. 100218, pp. 1-39, 2020
[7] P. Boccadoro, D. Striccoli and L. A. Grieco,"Internet of Drones: a Survey on Communications, Technologies, Protocols, Architectures and Services,"2020. [Online]. Available: arXiv:2007.12611
[8] N. Hossein Motlagh, T. Taleb and O. Arouk, "Low-Altitude Unmanned Aerial Vehicles-Based Internet of Things Services: Comprehensive Survey and Future Perspectives," in IEEE Internet of Things Journal, vol. 3, no. 6, pp. 899-922, Dec. 2016, doi: 10.1109/JIOT.2016.2612119.
[9] R. Altawy and A. M. Youssef, "Security privacy and safety aspects of civilian drones: A survey", ACM Trans. Cyber-Physical Systems, vol. 1, no. 2, pp. 7, 2016.
[10] B. Nassi, A. Shabtai, R. Masuoka and Y. Elovici, "SoK—Security and privacy in the age of drones: Threats challenges solution mechanisms and scientific gaps", arXiv:1903.05155, 2019, [online] Available: https://arxiv.org/abs/1903.05155.
[11] M. Ritchie, F. Fioranelli, and H. Borrion, “Micro UAV crime prevention: can we help Princess Leia in Preventing Crime Problems around the Globe through Research Innovations in the 21st Century.” B. L. Savona and E., Eds., TBA.
[12] T. Eshel, “Mobile radar optimized to detect uavs, precision guided weapons,” Defense Update, 2013.
[13] Zhang, D.X. Research on electromagnetic interference mechanism of main remote control data link of UAV. J. Microwave 2016, 32, 90–96.
[14] Jiang, Z.J.; Cheng, X.G.; Peng, Y.Q. Research on UAV identification algorithm based on deeplearning. App. Elec. Tech. 2017, 43, 84–87.
[15] Zhao, J.C.; Fu, X.R.; Yang, Z.K.; Xu, F.T. Radar-Assisted UAV Detection and Identification Based on 5G in the Internet of Things. Wirel. Commun. Mob. Comput. 1–12, 2019.
[16] Mohsan, S.A.H.; Khan, M.A.; Noor, F.; Ullah, I.; Alsharif, M.H. Towards the Unmanned Aerial Vehicles (UAVs): A Comprehensive Review. *Drones* 2022, *6*, 147. https://doi.org/10.3390/drones6060147
[17] R. Fu, X. Ren, Y. Li, Y. Wu, H. Sun and M. A. Al-Absi, "Machine Learning-Based UAV Assisted Agricultural Information Security Architecture and Intrusion Detection," in IEEE Internet of Things Journal, doi: 10.1109/JIOT.2023.3236322.

[18] Fu, R.; Al-Absi, M.A.; Lee, Y.-S.; Al-Absi, A.A.; Lee, H.J. Modified Uncertainty Error Aware Estimation Model for Tracking the Path of Unmanned Aerial Vehicles. Appl. Sci. 2022, 12, 11313. https://doi.org/10.3390/app122211313

[19] Al-Absi, M.A.; Fu, R.; Kim, K.-H.; Lee, Y.-S.; Al-Absi, A.A.; Lee, H.-J. Tracking Unmanned Aerial Vehicles Based on the Kalman Filter Considering Uncertainty and Error Aware. Electronics 2021, 10, 3067. https://doi.org/10.3390/electronics10243067

[20] R. Fu, M. A. Al-Absi, K. -H. Kim, Y. -S. Lee, A. A. Al-Absi and H. -J. Lee, "Deep Learning-Based Drone Classification Using Radar Cross Section Signatures at mmWave Frequencies," in IEEE Access, vol. 9, pp. 161431-161444, 2021, doi: 10.1109/ACCESS.2021.3115805.

[21] E. Capello, G. Guglieri, F. B. Quagliotti, Uavs and simulation: an experience on mavs 81 (2009) 38-50.

[22] I. Bekmezci, O. K. Sahingoz, S_. Temel, Flying ad-hoc networks (fanets): A survey, Ad Hoc Networks 11 (3) (2013)

[23] B. Kate, J. Waterman, K. Dantu, M. Welsh, Simbeeotic: A simulator and testbed for micro-aerial vehicle swarm experiments. (2012) 49{60doi:10.1109/IPSN.2012.6920950.

[24] J. Berndt, Jsbsim: An open source ight dynamics model in c++, in: AIAA Modeling and Simulation Technologies Conference and Exhibit, 2004, p. 4923.

[25] J. Van West, K. Lane-Cummings, Microsoft Flight Simulator X for Pilots: Real World Training, John Wiley & Sons, 2007.

[26] B. Stack, FlightSim.Com - Review: MQ-1 UAV Predator by Abacus, https://tinyurl.com/ybytg3bq, (Accessed: August 16, 2018) (April 2012).

[27] Introduction FlightGear Flight Simulator, http://home.flightgear.org/about/, (Accessed: June 25, 2022).

[28] A. R. Perry, The ightgear ight simulator, in: Proceedings of the USENIX Annual Technical Conference, 2004.

[29] E. A. Marconato, M. Rodrigues, R. d. M. Pires, D. F. Pigatto, C. Q. Luiz Filho, A. R. Pinto, K. R. Branco, AVENS-a novel ying ad hoc network simulator with automatic code generation for unmanned aircraft system, in: Proceedings of the 50th Hawaii International Conference on System Sciences, 2017.

[30] A. Y. Javaid, W. Sun, M. Alam, UAVSim: A simulation testbed for unmanned aerial vehicle network cyber security analysis, in: Globecom Workshops (GC Wkshps), 2013 IEEE, IEEE, 2013, pp. 1432-1436.

[31] A. Y. Javaid, Cyber security threat analysis and attack simulation for unmanned aerial vehicle network.

[32] T. Du, A. Schulz, B. Zhu, B. Bickel, W. Matusik, Computational multicopter design, ACM Transactions on Graphics. (TOG) 35 (6) (2016) 227.

[33] S. Shah, D. Dey, C. Lovett, A. Kapoor, Airsim: High-_delity visual and physical simulation for autonomous vehicles, in: Field and Service Robotics, 2017. arXiv:1705.05065.

[34] F. Furrer, M. Burri, M. Achtelik, R. Siegwart, Robot operating system (ros), Studies Comp.Intelligence Volume Number: 625 The Complete Reference (Volume 1) (978-3-319-26052-5) (2016) Chapter 23, iSBN:978-3-319-26052-5.

[35] W. G. La, S. Park, H. Kim, D-muns: Distributed multiple uavs network simulator (2017) 15{17doi:10.1109/ICUFN. 2017.7993738.

[36] J. M. Kok, J. S. Chahl, A low-cost simulation platform for apping wing mavs, Proc.SPIE 9429 (2015) 9429-9429-7. doi:10.1117/12.2084142.

[37] Unmanned Aircraft Systems - Vampire, https://aegistg.com/unmanned-aircraft-systems-vampire/, (Accessed: June 28, 2022).

[38] Real Drone Simulator, http://www.realdronesimulator.com/, (Accessed: June 28, 2022).

[39] Zephyr-Sim, https://zephyr-sim.com/, (Accessed: June 28, 2022).

[40] A. Pruitt, Hone your drone piloting skills with the Zephyr simulator - TechRepublic, https://tinyurl.com/y8g4byaf, (Accessed: June 28, 2022).