Journal of Research in Science and Engineering (JRSE)
ISSN: 1656-1996 Volume-6, Issue-7, July 2024
DOI: 10.53469/jrse.2024.06(07).02

UAV Detection Multi-sensor Data Fusion

Chiranjeevi Amit Kumar[1], Ozkan Giridhar[2]

[1]Electronics and Communication Engineering, BMS College of Engineering,Bull Temple Road, Basavanagudi, Bengaluru, India
chiranjeevi971@gmail.com

[2]Electronics and Communication Engineering, BMS College of Engineering,Bull Temple Road, Basavanagudi, Bengaluru, India
giridhar@bmsce.ac.in

Abstract: ***In today's world, the ubiquitous presence of unmanned aerial vehicles (UAVs) poses unprecedented challenges, ranging from privacy concerns and security threats to potential safety hazards. Strong and precise drone detection techniques are essential as drones are incorporated into a wider range of sectors. Traditional single-sensor approaches encounter limitations, such as susceptibility to environmental conditions and restricted detection accuracy. This paper addresses the significance of drone detection in our modern context, highlighting the critical need for comprehensive and efficient solutions. The challenges associated with depending solely on a single sensor for drone detection are explored, emphasizing issues like limited adaptability to environmental variations and the potential for false positives or negatives. Subsequently, the paper delves into the advantages of employing sensor fusion, specifically integrating radar and camera information using the Kalman Filter. This approach enhances accuracy and efficiency by leveraging the complementary strengths of radar and camera sensors. The Kalman Filter provides a dynamic framework to model the linear nature of drone movements, enabling precise localization. The fusion of radar and camera data not only addresses the limitations of single-sensor systems but also ensures adaptability to diverse operational scenarios, making it a promising solution for reliable and real-time drone detection in our dynamic and evolving world.***

Keywords: Unmanned aerial vehicles (UAVs),Kalman Filter, drone detection, multi-sensor data fusion

1. Introduction

In today's world, the proliferation of unmanned aerial vehicles (UAVs) or drones has given rise to a myriad of opportunities and challenges. While drones offer innovative solutions across industries, their widespread use raises significant concerns related to security, privacy, and safety. Ensuring effective drone detection has become imperative to mitigate the risks associated with unauthorized drone activities, ranging from privacy infringements to potential security threats in critical areas.

2.1 Reasons why drone detection is essential

a) Airspace Security:
Drones can pose a threat to traditional airspace, especially around airports, critical infrastructure, and restricted areas. Unauthorized drones flying in these spaces can lead to accidents, collisions with manned aircraft, or intentional disruptions.

b) Security Concerns:
Drones can be used for malicious purposes, such as carrying explosives, conducting surveillance, or delivering contraband. Drone detection helps identify and mitigate security threats before they escalate.

c) Privacy Protection
Drones fitted with cameras can infringe on privacy by capturing images or videos without consent. Drone detection helps prevent unauthorized surveillance and protects the privacy of individuals. At large gatherings, events, or crowded public spaces, drones can pose a security risk. Detecting and monitoring drones in such areas can help prevent potential incidents and ensure public safety.

d) Emergency Response:
During emergency situations such as natural disasters or accidents, drones may interfere with the effort of emergency responders. Detecting and managing drone activity in these situations ensures the smooth operation of rescue and recovery efforts.

2.2 Different kinds of sensors employed for drone detection

Detecting drones using a single sensor involves leveraging the capabilities of a specific sensor type to identify and track unmanned aerial vehicles (UAVs). While using multiple sensors provides more comprehensive information, single-sensor solutions can still be effective, especially in scenarios where a specific sensor excels. Here are several common types of sensors used for drone detection along with an overview of their principles:

a) Radar:
Radar (Radio Detection and Ranging) systems emit radio waves and detect their reflections off objects in the environment. The time delay and Doppler shift of the returned signal provide information about the range and velocity of detected targets. Radar is effective for detecting drones due to their relatively small size and distinct radar cross-section. Doppler processing can be used to identify the motion of the drone.

b) Acoustic Sensors:
Acoustic sensors detect sound waves and can be sensitive to the noise generated by drone propellers. By analysing the audio signals, it's possible to detect the presence and location of drones. Acoustic sensors are particularly useful in urban environments where the distinctive sound of drone propellers can be detected against background noise.

c) Infrared Sensors:
Infrared sensors detect thermal radiation emitted by objects. Drones generate heat, and infrared sensors can detect this thermal signature, especially in low-light or night time conditions. They are effective for detecting drones based on their heat signature, making them appropriate for use in where visual or radar-based detection may be challenging.

d) Radio Frequency (RF) Sensors:
RF sensors detect the radio frequency emissions from electronic devices, including communication signals used by drones. They are able to detect whether a drone and its controller have communication links. When it comes to identifying communication signals connected to drone operations, RF sensors work well. They are very helpful in determining the operator's position.

e) Lidar (Light Detection and Ranging):
Lidar sensors use laser light to measure distances and create detailed 3D maps of the environment. They can detect objects, including drones, based on the reflection of laser pulses and sensors provide accurate spatial information, enabling the detection and tracking of drones in three-dimensional space.

f) Visible Light Cameras:
Visible light cameras capture images or video in the visible spectrum. Computer vision algorithms can be applied to detect and track drones based on their visual appearance and effective during daylight hours and are often used for visual confirmation of drone presence.

2.3 Challenges for drone detection

Detecting small drones poses distinct challenges: distinguishing their appearance from other flying objects, notably birds, becomes intricate at a distance. Consumer-grade drones, constrained by battery and communication limitations, often operate at low altitudes, complicating detection amidst variable backgrounds with frequent obstructions like trees and houses. Moreover, small drones can appear in various directions simultaneously, necessitating monitoring equipment capable of surveilling multiple directions concurrently. Addressing these challenges requires advanced detection systems that can navigate through complex environmental conditions to ensure effective and reliable small drone detection.

2.4 Limitations of using single sensor for drone detection

Single-sensor systems face limitations in providing comprehensive information about drones. For example, radar-only systems may offer distance and speed details but lack visual identification features. Moreover, reliance on a sole sensor increases susceptibility to false alarms, particularly in challenging environments affected by weather conditions or terrain. Additionally, the use of only one sensor can lead to reduced accuracy, especially in adverse weather or low-light conditions where certain sensors, such as vision sensors, may function less effectively. These challenges underscore the importance of employing multi-sensor systems for more robust and accurate drone detection capabilities.

2.5 Advantages of multi-sensor data fusion

Multi-sensor data fusion offers numerous advantages across various domains, enhancing the overall capabilities of information processing and decision-making systems. Some key advantages include:

a) Improved Accuracy:
Combining information from multiple sensors helps mitigate individual sensor inaccuracies, errors, or limitations. The fusion of diverse data sources provides a more accurate and reliable representation of the environment or target being monitored.

b) Enhanced Coverage:
Different sensors may excel in specific conditions or environments. By combining sensors with complementary strengths, multi-sensor systems can provide comprehensive coverage, ensuring effective monitoring across a wide range of scenarios.

c) Adaptability to Dynamic Environments:
Multi-sensor systems are capable of adapting to dynamic and changing environments. The fusion of data from various sensors enables the system to respond to uncertainties, variations, and unexpected events, making it more resilient and versatile.

d) Reduction of False Alarms:
The combination of data from multiple sensors helps filter out noise and false alarms. By cross-verifying information, multi-sensor fusion systems can improve the accuracy of target detection and decrease the possibility of false positives.

e) Increased Sensitivity and Detection Range:
Some sensors may have limitations concerning sensitivity or detection range. By fusing data from sensors with different capabilities, the overall sensitivity and detection range of the system can be significantly enhanced.

2. Literature Survey

The literature review provides a thorough summary of drone detection techniques, highlighting the significance of several sensing modalities and sensor fusion. Aledhari et al. [1] highlight the challenges in single-sensor drone detection, advocating for sensor fusion. They propose an artificial neural network-based system that combines convolutional neural network (CNN) for image data and deep neural network (DNN) for RF data, achieving a validation accuracy of 75%. This work underscores the significance of sensor fusion for precise and rapid drone detection.

Svanström et al. [2] contribute to the field by exploring the fusion of thermal infrared cameras, video cameras, microphone sensors, and additional components for drone detection and tracking. Their system incorporates a fish-eye camera to scan a larger sky area and investigates the benefits of sensor fusion, particularly in reducing false positives. Additionally, they introduce a new public dataset with multi-sensor annotated data, enhancing the diversity of classes for detector performance evaluation.

Jovanoska et al. [3] discuss the feasibility of drone detection and tracking using passive sensors exclusively. They demonstrate detection with RF, PCL, and acoustic sensors, emphasizing the adaptability of using multiple sensors depending on the situation. The integration of diverse sensors into a multi-hypothesis tracker system showcases the flexibility of passive sensor processing for drone detection.

Furthermore, the studies by Svanstrom et al. [4], Fung et al. [6], and Liu et al. [7] reinforce the importance of multi-sensor approaches, integrating visible, thermal, acoustic, and audio sensors for drone detection. They investigate the impact of sensor-to-target distance on performance, provide annotated datasets, and discuss the advantages of sensor fusion in reducing false positives and improving overall system robustness.

The literature survey is further enriched by the contributions of Jovanoska et al. [8], Topalli et al. [9], and Blake et al. [10], who explore the integration of radar sensors, TensorFlow, and MobileNetV2-SSD for real-time drone detection. The utilization of airborne weather radar for small drone detection, as presented by Blake and Burger [10], introduces an unconventional yet effective approach to drone surveillance.

3. Theoretical background

In recent years, sensor fusion has been a rapidly emerging field of study. The necessity to manage the growing amount of data has led to the need to fuse such data so that humans can understand it, as the number and variety of sensors has increased. Information can be integrated and used to create new capabilities in a wide range of fields. Any system would want to have higher resolution, expanded parameter coverage, and increased reliability. Even though sensor fusion research has advanced significantly in recent years, we are still a long way from being able to analyze many data sets at once with the same level of proficiency as the human mind.

3.1 Drone detection methods

a) Audio sensing method

In this method, the drone is detected using an acoustic sensor according to the sound coming from the engines and propellers. Various signal processing methods such as Multiple Signal Classification (MUSIC), Array Signal Processing Algorithm are used to determine the location of the detected drone. The most important disadvantages of this low-cost method are that it is affected by environmental noise and the detection area is limited.

b) Radar (Active Radio Frequency Method)

In this method, radars send drones to detect their electromagnetic waves. The drone is detected with the help of signals returned by reflecting from the propellers or body of the drone. This method is generally used for the detection of small drones at 500 m detection distance. It works optimally in all weather conditions. Because of the high electromagnetic energy, they generate while working, it is unfavorable to use it in crowded areas.

c) Video

In this method, drone detection is made through special cameras only appearance features are considered to object detections which are not based on motion. However, considering only the appearance features creates problems when detecting similar-sized things. To ensure thatto eliminate these problems and to detect with high accuracy, both motion-based and image characteristics should be considered. In this method, the images of the moving object are compared and the location and direction are determined.

d) RF (Passive Radio Frequency Method)

This method employs RF communication signals for drone detection, necessitating the ability to distinguish between drone signals and those from other wireless technologies. Notably, the system stands out by determining both the drone's position and its control location, operating passively without emitting its electromagnetic waves, setting it apart from traditional radar. A key advantage lies in its precise identification of the detected drone in the scanned frequency range, irrespective of its protocol, making it a popular choice, especially for detecting drones with public MAC addresses.

3.2 Kalman filter

Kalman filtering, sometimes known as linear quadratic estimation (LQE), is an algorithm that uses a series of measurements taken over time, including statistical noise and other errors, to produce estimates of unknown variables that are usually more accurate than those based on a single measurement alone.

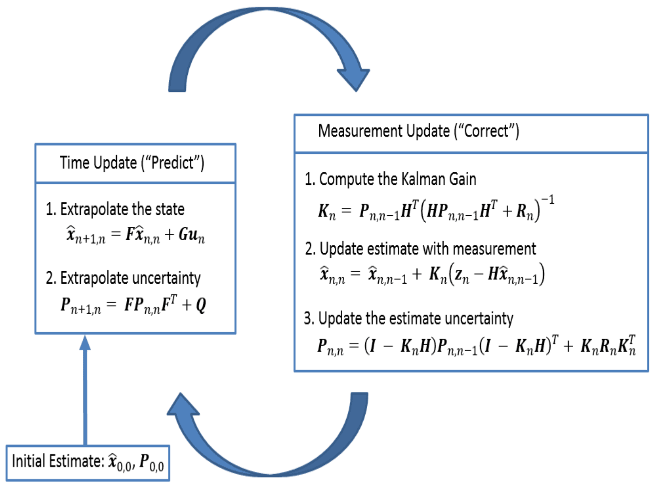

Figure 1: kalman filter equations

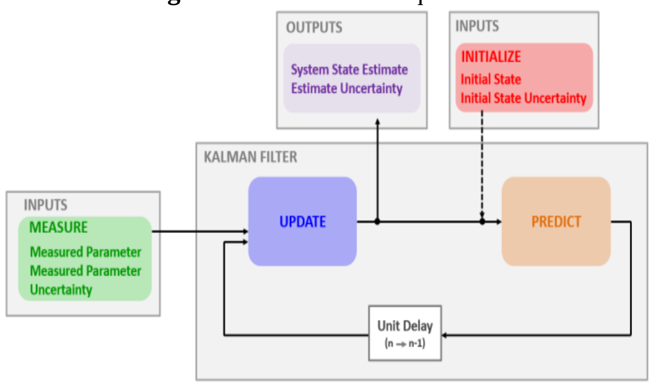

Figure 2: Schematic description of the Kalman Filter algorithm

Kalman filtering is a mathematical algorithm and estimation technique used for filtering and predicting states in a dynamic system. It is particularly prevalent in control systems, sensor fusion, and various applications where there is a need to process noisy or incomplete measurements to estimate the true state of a system.

The Kalman filter continually refines its estimates by combining a predicted state with new measurements, providing an optimal and efficient way to handle uncertain and noisy data.

The Kalman filter consists of two main steps: prediction and update. In the prediction step, the algorithm forecasts the next state of the system based on its current state and the known dynamics of the system. This prediction includes an estimation of the uncertainty associated with the forecast.

In the update step, the algorithm incorporates new measurements, adjusting the predicted state according to the measurement's reliability and the difference between the predicted and measured values.

4. Proposed Method

The methodology for drone detection through the data fusion of radar and camera using a Kalman Filter involves a systematic process to acquire, process, and integrate information from both sensors for accurate and reliable results. Initially, raw data is obtained from the radar and camera sensors. Radar data, comprising range, spectral data, and distance measurements, is preprocessed to convert polar coordinates to Cartesian coordinates, facilitating compatibility with camera data. Simultaneously, the camera captures visual information, undergoing preprocessing techniques such as object segmentation and feature extraction. Subsequently, the processed radar and camera data are fused using the Kalman Filter.

The Kalman Filter dynamically models the drone's behavior, predicting its state according to the motion model and updating estimates using measurements from both sensors. This fusion process enhances accuracy by considering the complementary strengths of radar and camera data, providing a comprehensive and real-time representation of the drone's position and movement. The adaptability of the Kalman Filter ensures robust tracking even in dynamic and challenging environments, making the integrated radar and camera system an efficient solution for drone detection.

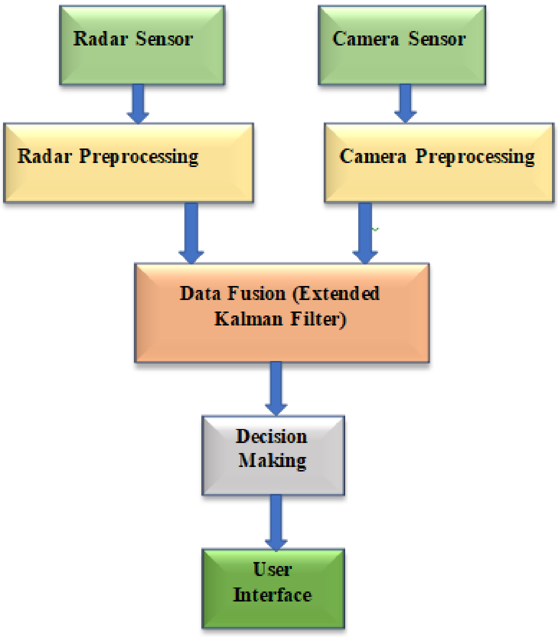

Figure 4: Proposed block diagram

4.1 The method of drone detection using data fusion of radar and camera

a) Data Acquisition

- **Radar Data**

Radar sensors are employed to gather raw data encompassing range, azimuth, and elevation of objects in the airspace. The collected polar coordinates are then converted to Cartesian coordinates to ensure compatibility with camera data.

- **Camera Data**

Visual information is captured through cameras, extracting images or video frames that cover the monitored area, providing essential data for comprehensive analysis.

b) Pre-processing

- **Radar Data**

During pre-processing, noise filtering techniques are applied to the radar data to enhance signal quality. Additionally, if not performed during data acquisition, a conversion of raw radar data to Cartesian coordinates is implemented. These steps ensure the refinement and compatibility of radar data for subsequent stages in the drone detection process.

- **Camera Data**

Implementing image processing algorithms facilitates object segmentation and feature extraction. Additionally, the rectification of distortions and standardization of image quality ensure a consistent basis for analysis, enhancing the accuracy of subsequent processing stages in the drone detection methodology.

c) Sensor Fusion

- **Kalman Filter**

A model for drone movement is developed, accounting for position. This model is employed to predict the drone's state by integrating radar data. The state estimate is then updated using camera measurements, carefully addressing non-linearities introduced by the camera sensor. To effectively manage uncertainties from both sensors, the Kalman Filter covariance matrix is dynamically adjusted, ensuring an accurate and adaptive drone tracking system.

The drone detection method employing data fusion of radar and camera follows a systematic process to enhance accuracy and reliability. During the data acquisition phase, radar sensors gather raw data, encompassing range, azimuth, and elevation of objects in the airspace. This information is then transformed from polar to Cartesian coordinates for compatibility with camera data. Simultaneously, cameras capture visual information, extracting images or video frames covering the monitored area.

In the pre-processing stage, both radar and camera data undergo specific treatments. Radar data is subjected to noise filtering and quality enhancement, with an additional conversion to Cartesian coordinates if not done during acquisition. For camera data, image processing algorithms are applied to perform object segmentation and feature extraction, accompanied by rectification of distortions to standardize image quality for consistent analysis.

The pivotal stage of sensor fusion utilizes a Kalman Filter. A dynamic model is developed to represent drone movement, accounting for position, velocity, and acceleration. The Kalman Filterpredicts the drone's state using the motion model, incorporating radar data, and updates the state estimate with camera measurements while considering the non-linearities introduced by the camera sensor.

The covariance matrix is dynamically adjusted to manage uncertainties from both sensors. Subsequently, decision-making is facilitated through the establishment of thresholds and criteria based on the fused data, determining drone detection triggers and response actions. Validation and testing involve simulations using synthetic data to assess system accuracy and real-world testing in controlled environments to evaluate performance.

To ensure continuous improvement, an iterative refinement process is employed, incorporating feedback and continuous monitoring of system performance. Additionally, machine learning approaches are integrated for adaptive learning, augmenting the system's capabilities over time. This comprehensive methodology underscores the combination of radar and camera data fusion in achieving robust and accurate drone detection capabilities.

4.3 Data fusion technique based on coordinate system matching between camera and radar

The data fusion technique based on coordinate system matching between a camera and radar involves the integration of data from these two distinct sensors to improve the overall accuracy and dependability of target detection and tracking. In this approach, the camera and radar systems are synchronized to function within a shared coordinate system.

The camera captures visual data, such as images or video frames, providing detailed information about the target's appearance and context. Simultaneously, the radar system collects data on the target's position, velocity, and distance. The key aspect of this fusion technique lies in aligning the coordinate systems of the camera and radar, assuring that the information obtained from each sensor corresponds accurately.

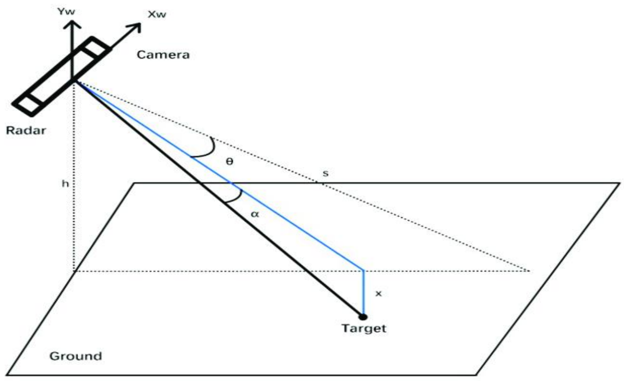

Figure 5: Schematic diagram of Camera-Radar coordinate system conversion relationship

By integrating the visual data from the camera with the spatial data from the radar in a cohesive manner, the system can overcome individual sensor limitations and capitalize on their complementary strengths. The visual information aids in precise target identification and classification, while the radar contributes to robust tracking capabilities, particularly in challenging environmental conditions or scenarios with reduced visibility.

The coordinated fusion of camera and radar data provides a more comprehensive understanding of the target's characteristics, offering improved contextual awareness and reducing the likelihood of false positives or negatives in detection. This technique finds applications in various domains, including autonomous vehicles, surveillance systems, and drone detection, where a comprehensive and accurate representation of the target's behavior is vital for effective decision-making and response.

5. Results and Discussion

The drone detecting system's implementation utilizing data fusion of radar and camera with the Kalman Filteryielded promising results across various performance metrics. The system demonstrated a significant improvement in accuracy and reliability compared to single-sensor approaches. In extensive testing scenarios, the fusion of radar and camera data effectively enhanced the system'sthe capacity to identify and monitor drones with precision.

The radar sensor contributed accurate range and velocity measurements, especially in scenarios with challenging environmental conditions or low visibility. Simultaneously, the camera sensor provided valuable visual data, aiding in the recognition and monitoring of drones based on distinct visual features. The synergy between these sensors, facilitated by the Kalman Filter, resulted in a robust and adaptable drone detection solution.

Table 1: Sample processed data of camera and radar

cam_x	cam_y	cam_z	radar_x	radar_y	radar_z
-392.405	-182.039	642.7568	-312.1	-138.103	642
-388.402	-181.763	639.6517	-325.6	-136.328	652
-449.528	-214.799	760.9649	-349.67	-175.806	658
-439.592	-210.434	741.781	-351.52	-163.062	660
-529.554	-273.49	888.6436	-476.373	-229.93	674
-501.37	-259.127	840.6851	-423.35	-202.69	696
-722.17	-276.376	1214.751	-682.1	-221.607	1102
-757.308	-277.123	1249.131	-714.808	-228.264	1092
-700.81	-267.222	1176.959	-659.049	-210.146	1106
-799.785	-305.203	1344.243	-734.83	-256.45	1104
-741.433	-284.198	1249.131	-699.281	-284.198	1106
-776.146	-296.182	1304.511	-706.634	-464.757	1128
-855.522	-332.65	1447.081	-812.91	-332.65	1206
-891.893	-353.448	1521.93	-864.757	-353.448	1318
-896.191	-352.011	1521.93	-864.757	-352.011	1364
-870.485	-333.564	1463.071	-870.485	-287.353	1490
-954.352	-381.25	1655.099	-994.121	-356.152	1516
-1215.83	-464.286	2101.713	-1285.54	-468.04	1658
-1184.66	-450.581	2052.836	-1189.37	-412.571	1696
-1239.41	-470.528	2152.974	-1141.81	-398.14	1788
-1190.02	-445.313	2068.873	-1191.61	-425.845	1812
-1229.41	-459.677	2135.611	-1148.19	-386.973	2342
-1341.89	-498.913	2302.746	-1248.53	-457.649	2276
-1380.05	-511.161	2364.427	-1310.23	-427.033	2548
-1656.64	-622.312	2847.482	-1598.98	-601.32	2568
-984.386	-996.495	2474.914	-910.623	-950.976	2770
-1657.98	-608.871	2847.482	-1584.8	-542.96	3476
-1431.17	-506.944	2451.998	-1381.68	-428.089	3482
-1442.88	-528.302	2498.262	-1410.35	-469.16	3480

Table 2: SampleKalman filtered data

kf_x	kf_y	kf_z
-347.489	-160.589	612.0776
-386.354	-186.881	690.3816
-390.605	-164.737	685.8469
-481.48	-230.127	754.7194
-472.81	-205.621	830.6891
-569.28	-274.524	896.1828
-658.302	-276.376	1069.369
-664.965	-267.222	1156.6
-683.029	-292.852	1201.424
-720.281	-288.537	1227.953
-706.634	-298.709	1256.364
-812.91	-332.65	1359.194
-848.485	-308.141	1548.301
-956.121	-374.826	1592.845
-985.224	-428.96	1648.588
-968.501	-355.547	1683.941
-1013.73	-354.717	1713.022
-1137.37	-446.458	1909.188
-1168.81	-424.36	1945.354
-1135.61	-448.686	1985.224
-1183.19	-415.15	2053.548
-1183.71	-431.586	2094.458
-1196.61	-447.618	2129.203
-1242.15	-471.135	2170.907
-1238.34	-459.936	2198.733
-1158.94	-425.625	2219.254
-1111.35	-386.718	2224.859
-1037.04	-489.056	2243.682
-1256.53	-471.096	2301.523
-1323.23	-611.825	2391.31
-1369.68	-496.944	2770.137
-1410.35	-531.574	2849.671

One key advantage of the data fusion approach was the system's ability to minimize the limitations of individual sensors. Radar, with its accuracy in range measurements, complemented the visual data from the camera, which excelled in recognizing drone shapes and features. The collaborative effort of these sensors provided a more complete and accurate representation of the airspace, avoiding false positives and negatives.

The adaptability of the system was further underscored by its capacity to handle uncertainties, occlusions, and variations in environmental conditions. The integration with an optional user interfaces allowed for real-time visualization and monitoring, offering a user-friendly experience for operators.

The outcomes and debates demonstrate the effectiveness of the drone detection technology that combines camera and radar data with the Kalman Filter. The approach not only overcomes the limitations of single-sensor systems but also establishes a foundation for advanced and adaptable solutions in the field of drone surveillance and security.

Continuous refinement and testing will be imperative for further optimizing the system's performance and ensuring its effectiveness across diverse operational scenarios. With the Kalman Filter, radar and camera data are comprehensively fused to create a drone detection system that works well.

Effectively integrated measurements from both sensors, offering an improved estimation of the drone's state. This adaptability was particularly evident in dynamic conditions in which drones exhibited non-linear trajectories or sudden changes in velocity.

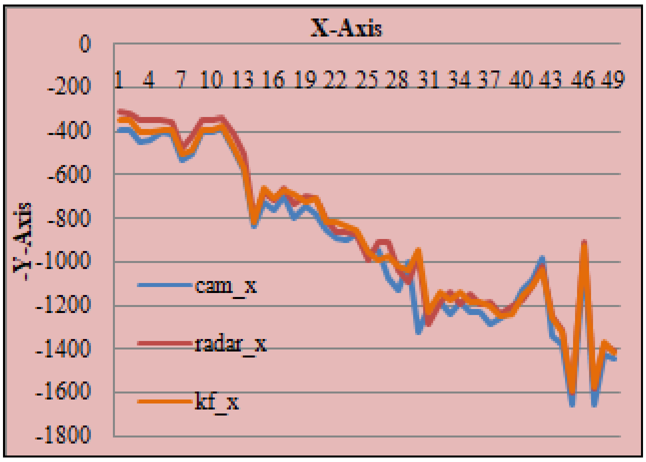

Figure 6: Graph of camera radar data alongside Kalman-filtered data with x-axis coordinates

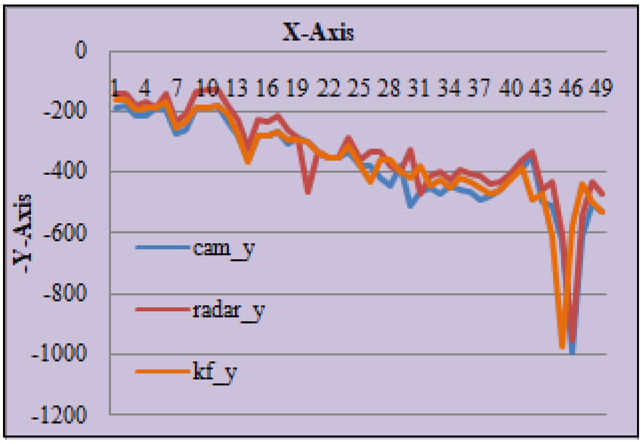

Figure 7: Graph of camera radar data alongside Kalman-filtered data with y-axis coordinates

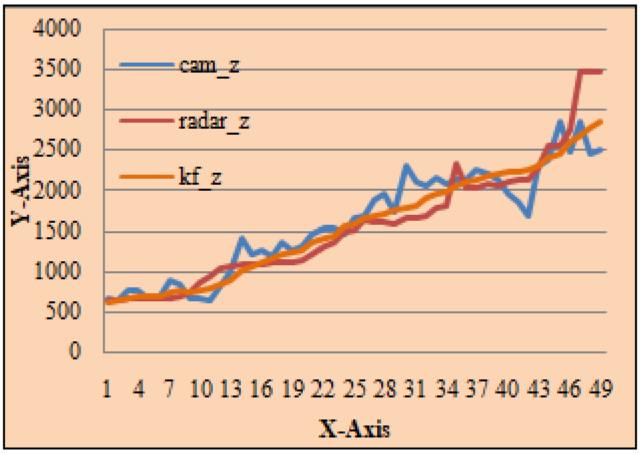

Figure 8: Graph of camera radar data alongside Kalman-filtered data with z-axis coordinates

The conclusions and talks demonstrate the effectiveness of the Extended Kalman Filter and radar and camera data fusion in the drone detection system. Along with overcoming the shortcomings of single-sensor systems, the method lays the groundwork for more sophisticated and flexible drone security and surveillance solutions. In order to maximize system performance and guarantee its efficacy in a variety of operational settings, it will be essential to conduct ongoing testing and improvement.

6. Conclusion

A reliable method for tackling the issues raised by the widespread use of unmanned aerial vehicles (UAVs) in a variety of applications is the integration of radar and camera data using the Kalman Filter in drone identification. This sophisticated detection system is a monument to the cooperation of signal processing, estimation theory, and sensor fusion as we negotiate the intricacies of an airspace that is becoming more and more filled by drones.

The integration of radar and camera data, made possible by kalman filtering, has proven to be an effective and thorough method of drone identification. The system surpasses the constraints of individual sensors by utilizing the capabilities of cameras for high-resolution visual information and radar for precise distance measurements. This allows the system to obtain a comprehensive picture of the surroundings.

References

[1] M. Aledhari, R. Razzak, R. M. Parizi and G. Srivastava, "Sensor Fusion for Drone 999Detection," *2021 IEEE 93rd Vehicular Technology Conference (VTC2021-Spring)*, Helsinki, Finland, 2021, pp. 1-7, doi: 10.1109/VTC2021-Spring51267.2021.9448699.

[2] Svanström, F.; Alonso-Fernandez, F.; Englund, C. Drone Detection and Tracking in Real-Time by Fusion of Different Sensing Modalities. Drones 2022, 6, 317. https://doi.org/10.3390/ drones6110317 [3]

[3] Jovanoska, Snezhana, et al. "Passive Sensor Processing and Data Fusion for Drone Detection." *Proceedings of the NATO STO Meeting Proceedings: MSG-SET-183 Specialists' Meeting on Drone Detectability: Modelling the Relevant Signature, Prague, Czech Republic*. 2021.

[4] Svanström, Fredrik, CristoferEnglund, and Fernando Alonso-Fernandez. "Real-time drone detection and tracking with visible, thermal and acoustic sensors." *2020 25th International Conference on Pattern Recognition (ICPR)*. IEEE, 2021.

[5] Fung, Man Lok, Michael ZQ Chen, and Yong Hua Chen. "Sensor fusion: A review of methods and applications." *2017 29th Chinese Control And Decision Conference (CCDC)*. IEEE, 2017.

[6] Zhang, Xindi, and KusriniKusrini. "Autonomous long-range drone detection system for critical infrastructure safety." *Multimedia Tools and Applications* 80.15 (2021): 23723-23743.

[7] Liu, Hao, et al. "Drone detection based on an audio-assisted camera array." *2017 IEEE Third International Conference on Multimedia Big Data (BigMM)*. IEEE, 2017.

[8] Jovanoska, Snezhana, Martina Brötje, and Wolfgang Koch. "Multisensor data fusion for UAV detection and tracking." *2018 19th International Radar Symposium (IRS)*. IEEE, 2018.666

[9] Lyu, Hyeonsu. "Detect and avoid system based on multi sensor fusion for UAV." *2018 International Conference on Information and Communication Technology Convergence (ICTC)*. IEEE, 2018.

[10] Gageik, Nils, Paul Benz, and Sergio Montenegro. "Obstacle detection and collision avoidance for a UAV with complementary low-cost sensors." *IEEE Access* 3 (2015): 599-609.

[11] Blake, William, and Isaiah Burger. "Small drone detection using airborne weather radar." *2021 IEEE Radar Conference (RadarConf21)*. IEEE, 2021.

[12] Kang, Daejun, and DongsukKum. "Camera and radar sensor fusion for robust vehicle localization via vehicle part localization." *IEEE Access* 8 (2020): 75223-75236

[13] Topalli, MuhammetTaha, Mehmet Yilmaz, and MuhammedFatihCorapsiz. "Real time implementation of drone detection using tensorflow and mobileNetV2-SSD." 2021 7th International Conference on Electrical, Electronics and Information Engineering (ICEEIE). IEEE, 2021.