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AUTONOMOUS DRONE WITH LiDAR-CAMERA FUSION BASED CALIBRATION AND GNSS FOR SMART NAVIGATION APPLICATIONS

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Abstract

Drones have emerged as transformative tools for executing aerial tasks that were once challenging for manned aircraft, offering substantial safety benefits, economic advantages, and environmental gains. This paper introduces an innovative approach to the design and analysis of autonomous drones tailored for smart navigation applications, underpinned by the fusion of LiDAR-Camera technology and GNSS (Global Navigation Satellite System) integration. The drone featured in this research is a Quadcopter, equipped with DYS D2836-6 1500KV motors and 30A BLDC ESCs for control. Its power source is an Orange 5200mAh 4S LiPo battery, providing both efficiency and longevity. The heart of the drone lies in the ARM Cortex M4-based controller, which orchestrates its autonomous flight. It exhibits a wide operational altitude range, maintaining a constant height between 5 to 20 meters above ground level, while achieving a top velocity of 2 meters per second. The core innovation of this research resides in the integration of LiDAR-Camera fusion technology. Leveraging RPLiDAR with a 180-meter range and a remarkable point cloud density of 1000 points per square meter, the drone is equipped to perceive its surroundings with unprecedented accuracy. The accompanying camera boasts a high-resolution 1920 x 1080 pixel sensor with a 360-degree horizontal and 180-degree vertical field of view, facilitating comprehensive visual data acquisition. For object recognition and tracking, the drone employs the YOLOv4 algorithm for real-time identification and utilizes the Kalman filter for precise object tracking. These advancements in computer vision contribute significantly to the drone's autonomous navigation capabilities. The drone's navigational prowess is complemented by the APM2.5 NEO-M8N GNSS receiver, ensuring precise geospatial positioning.

Keywords: Autonomous drones, Computer vision, Obstacle recognition and ranging, Navigation, Robot operating system.

1. Introduction

Unmanned Aerial Vehicles (UAVs), commonly referred to as drones, have proliferated across various industries, as illustrated in Fig. 1. They have found widespread application in diverse fields, encompassing routine tasks such as delivery, surveillance, construction, agriculture, and military operations [1, 2]. The utilization of drones not only streamlines operational processes but also offers notable advantages, both from environmental and financial perspectives, while concurrently reducing risks to human life [3].

The soaring sales figures of drones, reaching millions, are indicative of their growing significance, particularly in the recreational market [4]. This surge is propelled by advancements in technology, adherence to regulatory frameworks, and the increasing acceptance of drones by the public [5]. Despite the substantial progress in drone technology, several challenges persist in the domain of drone-based applications.

These challenges encompass multiple facets, including the optimal placement of drones, efficient path planning, enhancing payload capacity, effective drone management, maximizing flight time, and ensuring secure communication among flying drones. Addressing these multifaceted concerns necessitates the development of minimal cryptographic primitives and protocols tailored to the unique requirements of drone-based systems [6, 7].

Fig. 1. Autonomous drone applications.

A LiDAR(Light Detection and Ranging) and Camera oriented 3D object detector creates trajectory, object recognition, and ranging using data from the LiDAR sensor and information from the camera [8, 9]. The quality of the data collected by the LiDAR sensor directly affects effectiveness. Utilising point cloud stitching to reduce the sparsely of a picture at locations far from the sensor makes the challenge more difficult to solve [10].

The trade-offs include the size and physical characteristics of objects that require object detection or classification. A UAV with a LiDAR sensor obtained the data set utilised to examine these trade-offs [11, 12]. The analytical method being investigated uses convolutional neural networks, which were trained on various objects to be classified in the LiDAR dataset.

Recently, several innovative techniques have been used to overcome the issues with object recognition on point clouds [13, 14]. As illustrated in Fig. 2, the point-cloud representation splits these methods into point-based, graph-based, and voxel-based strategies. The point-based techniques have poor perceptual skills and take too long to sample data compared to a CNN [15].

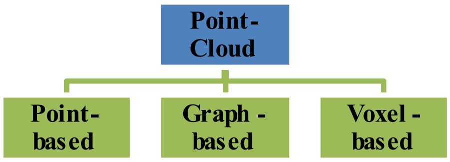

Fig. 2. Types in point-cloud.

Graph-based techniques create a more obvious structure when the property is considered. Sparse and erratic point clouds are converted into consistently sized voxels by voxel-based techniques, which CNNs may be able to comprehend better [16, 17]. Voxel-based algorithms frequently have high speeds and decent accuracy, but they are extremely susceptible to hyperparameters.

Voxel-based approaches also inevitably lead to information loss, especially regarding the precision of fine-grained localisation [18]. For a car to be self-driving, high-precision GNSS technology must provide the accuracy, and reliability needed. A fully autonomous vehicle requires a reliable localization system and the assurance that it is accurate [19].

This paper is prepared as follows: Section 2 discusses the LiDAR-Camera and GNSS based autonomous drone's related work. With a preceding literature survey, a clear problem statement and detailed methodology is discussed in Section 3. An implementation aspects of autonomous drone with LiDAR-Camera, voxel-based based point cloud, Deep learning approaches and GNSS are discussed in Section 4. Results and discussions are described in Section 5. Finally, the paper was concluded in Section 6.

2. Related Work

Autonomous drones are increasingly vital for various applications, including search and rescue, precision agriculture, environmental monitoring, and infrastructure inspection. The fusion of LiDAR and camera data in drone design plays a pivotal role by enabling these aircraft to navigate and interact with their surroundings with exceptional precision and safety [20]. LiDAR technology provides accurate distance measurements, while cameras capture high-resolution visual data, and when combined, they enhance the drone's ability to perceive its environment, identify objects, and ensure obstacle avoidance, making autonomous drones indispensable in critical tasks and enhancing their overall operational effectiveness.

The autonomous drones with LiDAR-camera fusion and GNSS as per state-of-art are listed in Table 1. And few commercially available LiDAR with specifications is listed in Table 2. To examine the detection accuracy of LiDAR system, the system SNRE is:

$$SNR_E = 20\log\frac{V_p}{\sqrt{V^2{}_b + V^2{}_d + V^2{}_h}} \quad (1)$$

where V_d is indeed the RMS noise of the photoelectric detector, V_h is the RMS noise of the high-speed digitizer, and V_p is just the peak voltage.

Table 1. Autonomous drones for smart applications state-of-art.

Ref.	Description	Board	Calibration	Point-Cloud	GPS	Dataset	Limitations
[21]	Modelling for a drone's components has been demonstrated. The 3DEXPERIENCE programme, which offers modelling, simulation, and optimization tools, was used to simulate.	SP Racing F3	Neato LiDAR	Point-based	GPS NEO-6M	KITTI	Only fly, no navigation.
[22]	Showed the advantages of swarms of heterogeneous vehicles. The algorithms are adaptable, reconfigurable.	DJI	---	Graph-based	Ublox NEO-7M	nuScenes	Fly with navigation but no stability.
[23]	Tensor Processing Unit (TPU) devices for edge computing were suggested as hardware support due to their computational capability.	RC Flight Controller KK 2.1.5	Slamtec RPLiDAR A1M8	---	APM2.5 NEO-M8N GPS Module GYGPSV1-8M	KITTI	Only fly, no navigation.
[24]	Compared to ground truth reference data, measurements taken along a vertical flight route showed potential.	Pixhawk PX4 Autopilot 2.4ss.8	MakerFocus TFmins Micro	Graph-based	--	ONCE	Fly with navigation but moderate stability.
[25]	UAV systems can efficiently collect the regular collection of high-quality data needed for emerging precision agriculture approaches.	APM 2.8 Flight Controller with Built-in Compass	---	Voxel-based	---	nuScenes	Fly with navigation but moderate stability.
[26]	Utilizing the distributed swarm control algorithm, a multi-UAV system for agriculture was developed, and the system's performance was assessed.	Pixhawk PX4 Autopilot 2.4ss.8	---	Voxel-based	GPS NEO-6M	ONCE	Fly with navigation but moderate stability.
[27]	Demonstrates how to perform vertical and horizontal near-ground operations on a moving target without knowing the vehicle's height or the target's speed.	APM 2.8 Flight Controller with Built-in Compass	Slamtec RPLiDAR A1M8	Graph-based	APM2.5 NEO-M8N GPS Module GYGPSV1-8M	KITTI	Only fly, no navigation.

Table 2. LiDAR's for autonomous drone's state-of-art [28-30].

LiDAR	Feature	Range	TOF	Frame rate(Hz)
TF-LC02	UART module for single-point ranging Supported by Raspberry Pi and Pixhawk for drone obstacle avoidance.	3cm-200cm	180	--
Youyeetoo TFmini-S	Single-Point Ranging Module for Drones that works with Pixhawk and Raspberry Pi.	0.1-12m	180	1~1000
Yahboom LiDAR EAI YDLIDAR X3	Robot Obstacle Avoidance and Navigation with 5Hz–10Hz Adjustable 8m Radius Ranging Scanning Supporting ROS1.	8m	360	3000
Youyeetoo Slamtec RPLiDAR A3	Outdoor AGV Drones' Scanning Radius & Mute Brushless Motor LiDAR Sensor for Obstacle Avoidance and Navigation.	25 m	360	16000
VP300-30	Industrial-Grade Laser Radar Scanner for Robotic Obstacle Avoidance Indoor and Outdoor Waterproof Dust-Proof IP65 LiDAR.	30 m	300	20000
Velodyne HDL-64	The HDL-64E offers substantially more environmental data than was possible with its full 360 HFOV by 26.8 VFOV. With a user-selectable frame rate of 5–15 Hz and an output rate of more than 1. 3 million points per second.	120 m	360	---
RIEGL VUX-1HA	The RIEGL VUX-1HA is a very portable and small laser scanner that can handle the system integration and measure airborne laser scanning performance requirements by helicopter, gyrocopter, and other small aircraft.	420 m	360	2 MHz

The high-speed digitizer's datasheet contains information on V_h. The space between the i^{th} item and LiDAR system is denoted as d_i and determined after Gaussian fitting.

$$d_i = \frac{1}{2}(\mu_i - \mu_T)T_s C \quad 1 \leq i \leq N \tag{2}$$

where c is the laser broadcast speed, and T_s is the high-speed digitizer's sample period. The Gaussian fitting approach involves fitting a typical laser pulse, *t(n)*, to

$$t(n) = A_T e^{-\frac{(n-\mu_T)^2}{F_T^2/(4in2)}} + K_T + \varepsilon_T(n) \tag{3}$$

where, n is the sampling time, A_T, μ_T and F_T are the amplitude, mean and FWHM respectively, ε_T is the residual error. The received laser echo, *s(n)*, is fitted using-

$$s(n) = \sum_{i=1}^{N} A_i e^{-\frac{(n-\mu_i)^2}{F_i^2/(4in2)}} + K_R + \varepsilon_R(n) \tag{4}$$

where, N is the number of the Gaussian functions in s(n), KR is the DC offset of s(n), and εR is the residual error [31].

Object detection and classification techniques that take advantage of Convolutional Neural Network (CNN) architecture have recently been researched, as shown in Table 3 [32, 33]. The ImageNet classification competition was won by AlexNet, which utilized CNN for better performance.

Table 3. Different modules and algorithms for object detection and ranging.

Module	Algorithms
Fusion	Kalman filter, Extended Kalman filter, Unscented Kalman filter, Particle filter, Bayesian filter
Object Detection	YOLO, SSD, RCNN, Faster R-CNN, Mask R-CNN
Ranging	Time-of-flight, Phase-shift, FMCW, Triangulation, Stereovision

Additionally, several works, including the PASCAL Visual Object Classed and the ImageNet Big Scale Visual Recognition Challenge, have demonstrated good classification performance on large datasets. While some earlier efforts concentrated on their performance, architecture designs that reduced computing expenses are available in the literature. The classification performance, however, could be impacted if a model emphasises execution durations more than performance.

3. Problem Statement and Detailed Methodology

Achieving stability in autonomous aerial vehicles is a significant research challenge, and the integration of a compass-equipped controller can be a valuable solution to enhance drone stability. Furthermore, improving the accuracy of object recognition and ranging, a crucial element in obstacle avoidance, is addressed through the utilization of trained Deep Neural Networks in combination with LiDAR-Camera fusion technology, resulting in enhanced precision and reliability, as shown in Table 4.

By, ensuring high connectivity in autonomous vehicle navigation is vital, and the implementation of advanced GNSS modules like the APM2.5 NEO-M8N offers improved connectivity with reduced error, contributing to the efficiency and reliability of navigation systems in autonomous drones. Aim to locate and detect things in 3D space using a point cloud and picture data as inputs. 3D SLAM techniques like Cartographer and LOAM to create 3D maps and predict high-precision trajectories. The autonomous drones are become vital because of more scalability and mobility the abilities help these drones to address many research challenges in potential applications like agriculture, military, video surveillance and delivery. These major requirements of the autonomous drones are navigation, object recognition and ranging.

Table 4. Problem statement.

Parameter	Research Challenge	Description	Possible Solution
Drone	Stability	Design of drone with more stability is really a potential research challenge in autonomous aerial vehicles.	The controller with compass helps to improve stability.
Object Recognition and Ranging	Improving Accuracy	Obstacle avoidance with ranging is one of the primary requirements in drones.	Trained Deep Neural Network with LiDAR-Camera fusion addressed the so many issues related to Object Recognition and Ranging with more accuracy.
Navigation	Connectivity	Autonomous vehicles demand high connectivity GNSS modules with less error.	The high end GNSS modules like APM2.5 NEO-M8N offer more connectivity with less error.

This paper presents a sturdy autonomous drone with navigation, object recognition and ranging capabilities. The detailed methodology of this work is as shown in Fig. 3. KITTI Dataset (5.1) The Toyota Technological Institute in Chicago and the Karlsruhe Institute of Technology generated one of the earliest datasets.

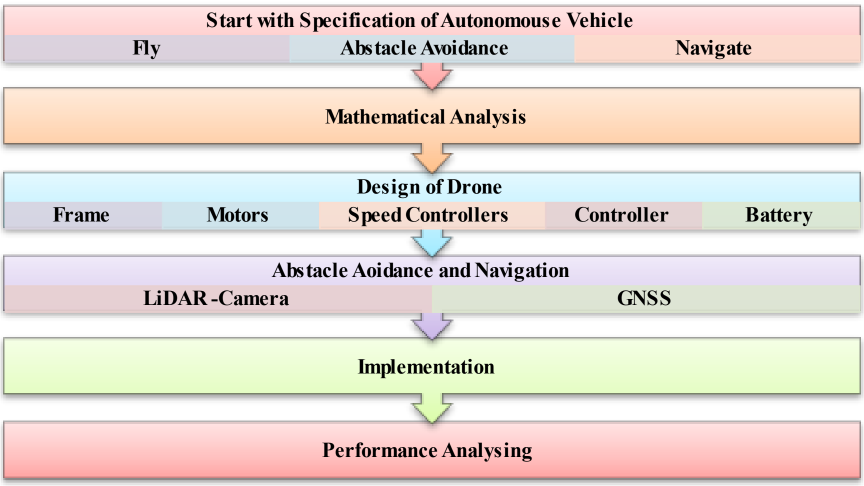

Fig. 3. Detailed methodology.

Localization data, a 360-degree point cloud derived from a Velodyne HDL-64E LiDAR sensor mounted on top of the vehicle, and colour and grayscale photos captured by two high-definition stereo camera systems looking ahead are all included. The present work aims to address the need for a transformative and innovative drone design that leverages LiDAR-Camera fusion technology and GNSS integration. The specific challenges include achieving accurate environmental perception, real-time object recognition and tracking, and precise geospatial positioning, while maintaining a constant altitude between 5 to 20 meters above ground level and a top velocity of 2 meters per second. The research seeks to integrate these technologies to enhance the drone's autonomous navigation capabilities, thus addressing the need for safer, more efficient, and environmentally friendly aerial tasks compared to traditional manned aircraft.

4. Implementation

The Quadcopter was implemented with DYS D2836-6 1500KV motors and 30A BLDC ESCs. Its power source is an Orange 5200mAh 4S LiPo battery, providing both efficiency and longevity as shown in Fig. 4. The heart of the drone lies in the ARM Cortex M4-based controller, which orchestrates its autonomous flight. The LiDAR-Camera calibration helps to estimation relative position and orientation between a LiDAR and a camera in a system. Cameras provides colour information, while a LiDAR sensor provides an accurate 3D structural and locational information of the objects. When fuse together we can enhance the performance of perception and mapping algorithms for autonomous driving and robotic applications.

LiDAR and camera fusion is a technology that combines the capabilities of a LiDAR sensor and a camera to provide more accurate and comprehensive object detection and ranging. LiDAR is a remote sensing technology that uses laser light to measure distances, while a camera captures images using visible light. By combining the data from both sensors, LiDAR and camera fusion can provide a more detailed understanding of the environment and objects.

Fig. 4. Autonomous drone with object detection-ranging and navigation.

The drone should be able to carry a camera and LiDAR sensor, have a flight time of at least 30 minutes, fly up to 400 feet, and have a maximum speed of 50 mph. Once the requirements are gathered, the next step is to design the frame of the drone. The frame should be lightweight, durable, and able to accommodate all the necessary components. It should also be aerodynamic to improve the drone's flight performance. The next step is to choose the necessary components, including the motors, Pixhawk flight controller, ECS, battery, and camera and LiDAR sensors (Table 5).

Table 5. Autonomous navigation drone specifications.

Parameters		Details
Drone	Type	Quadcopter
	Motors	DYS D2836-6 1500KV
	Electronic Speed Controllers	30A BLDC ESC
	Battery	Orange 5200mAh 4S 40C/80C
	Processor	ARM cortex M4
	Maximum Constant Height (Altitude)	20 m
	Minimum Constant Height (Altitude)	5 m
	Velocity	2 m/s
Object Recognition and ranging	LiDAR	RPLiDAR
	Dataset	KITTI
	Camera resolution	1920 x 1080 pixels
	Camera field of view	360 degrees horizontal, 180 degrees vertical
	LiDAR range	180 meters
	LiDAR point cloud density	1000 points per square meter
	Object detection algorithm	YOLOv4
	Object tracking algorithm	Kalman filter
Navigation	GPS	APM2.5 NEO-M8N
	Monitoring	Ardupilot Mission Planar

The motors should be chosen based on the drone's weight and flight requirements. The Pixhawk flight controller is responsible for controlling the drone's flight, while the ECS controls the speed of the motors. The battery should provide enough power to allow the drone to fly for the required amount of time, and the camera and LiDAR sensors should be chosen based on the required resolution and range. Once all the components are chosen, the next step is to integrate them into the drone and test their functionality.

This includes testing the motor speed control, the Pixhawk flight controller, and the camera and LiDAR sensors. The GNSS system should also be integrated and tested for navigation. With the drone's components working, the object detection and ranging system can be developed using camera and LiDAR fusion. The system should be able to detect objects in real-time and provide the drone with the necessary data to avoid obstacles.

To estimate an object 3D bounding box size, range, and angle using a 360-degree camera and LiDAR fusion with the following specifications. Acquire the KITTI dataset, which consists of labelled images and corresponding LiDAR point cloud data. Train an object detection model using the KITTI dataset. There are various approaches you can take, such as using deep learning frameworks like TensorFlow. The model training and optimize completed it is deployed on a resource-constrained device like Raspberry Pi. This may involve model compression techniques or quantization to reduce the model's size and computational requirements.

Algorithm

```
Pre-requisites:
Object detection and Ranging.
{Train Network with KITTI dataset and deploy it in raspberry pi;
Connect LiDAR and Camera with Raspberry Pi;
LiDAR-Camera fusion image is given as input to Trained Network for Object Detection and
Ranging.
Connect Rapberry Pi to Pixhawk drone controller;}
Position Monitoring.
{Connect GNSS to Pixhawk drone controller;}
Start.
Define input variable i.e., GNSS (Longitude (Lo), Latitude(La)), and LiDAR-Camera (Object
detection(O), Ranging (R));
Define output variables i.e., Fly(F), Speed (S), Throttle (T), Rudder (Ru), Right (Ri), Left(Le) and
Land (L).
Input Variable Initialization Lo=0, La=0,O=0,R=0;
Output Variable Initialization  F=0,S=0,T=0,Ru=0,Ri=0,Le=0,L=0;
Read Input (Lo & La);
If (O==0)
{F=1;}
Elseif(O==1)
{F=0;}
```

The software module on the Raspberry Pi that receives input from both the LiDAR and camera. Develop an algorithm that fuses the LiDAR and camera data to generate a combined image. Feed the fused image as input to the trained object detection model to perform object detection and ranging. Identify the communication interfaces available on both the Raspberry Pi and Pixhawk drone controllers.

Ensure compatibility between the interfaces of the Raspberry Pi and Pixhawk. Establish the connection between the Raspberry Pi and Pixhawk using appropriate cables or connectors. Set up the necessary software communication protocols between the Raspberry Pi and Pixhawk, such as MAVLink, to enable data exchange between the two devices.

The GNSS module connected to the Pixhawk using the appropriate interface. The Pixhawk was configured to receive and process the GNSS data. The GNSS connection was verified by checking the position information reported by the Pixhawk.

5. Results and Discussions

The presented drone flying in autonomous mode as shown in Fig. 5. The camera and LiDAR fusion details are as listed in Table 6. The camera has a resolution of 1920 x 1080 pixels, which means it captures images with 1920 pixels in width and 1080 pixels in height.

Table 6. Camera and LiDAR fusion details.

Parameter	Description
Camera resolution	1920×1080 pixels
Camera field of view	360 degrees horizontal, 180 degrees vertical
LiDAR range	180 meters
LiDAR point cloud density	1000 points per square meter
Object detection algorithm	YOLOv4
Object tracking algorithm	Kalman filter

The camera has a wide field of view, covering 360 degrees horizontally and 180 degrees vertically. This means it capture a full panoramic view horizontally and half of a sphere vertically. The LiDAR system has a range of 180 meters, meaning it detect objects up to a maximum distance of 180 meters from the sensor. LiDAR system generates a point cloud representing the 3D environment. The specified density of 1000 points per square meter means that for every square meter of the scene, the LiDAR system captures 1000 individual points. The YOLOv4 algorithm is used for object detection. YOLO stands for "You Only Look Once," and it is a popular algorithm for real-time object detection in images and videos.

Fig. 5. Presented autonomous drone in fly mode.

YOLOv4 is an improved version of the YOLO algorithm, known for its accuracy and speed in detecting objects. The Kalman filter is used for object tracking. The Kalman filter is a recursive algorithm that estimates the state of a system over time, incorporating new measurements while considering the system's dynamics and uncertainty. The framework was tested within a collapsed building through simulation and actual flight tests. False positive readings from particular object visualisations were the reason for the varied distribution of victim GNSS locations in mission mode.

Drone location monitoring using Ardupilot Mission Planner involves using a GCS to view and monitor the drone's location in real-time. Ardupilot is an open-source autopilot system that is widely used in UAVs and drones, and Mission Planner is a GCS software that enables users to plan missions, monitor telemetry data, and control the drone's flight. By using the Mission Planner software and connect to the drone by selecting the appropriate communication port and baud rate. The GCS will display various telemetry data such as the drone's altitude, speed, and location as shown in Fig. 6.

Fig. 6. Drone location monitoring using Ardupilot mission planner.

The map will display the drone's current location as well as its flight path. Users can also view other useful information such as the battery level, GPS signal strength, and altitude. In addition to monitoring the drone's location, users can also use Mission Planner to plan and execute autonomous missions, set waypoints, and perform various other flight operations. The drone leverages a high-resolution camera with a capability of 1920 x 1080 pixels and an expansive field of view encompassing 360 degrees horizontally and 180 degrees vertically.

Utilizing the YOLOv4 object detection algorithm, the camera processes each frame and identifies the presence and position of an aeroplane within the 2D image. The algorithm locates the aeroplane in the frame, specifying its coordinates in a bounding box. Simultaneously, a LiDAR system with a range of 180 meters and a point cloud density of 1000 points per square meter is engaged to generate 3D point cloud data. By analysing the LiDAR point cloud, the system accurately computes the aeroplanes distance from the sensor.

The integrated Kalman Filter then ensures that the aeroplanes trajectory is precisely tracked over time by predicting its future position and enhancing the overall accuracy of the system in detecting and determining the range of aeroplane within the captured environment. LiDAR and Camera Data Fusion to Detect and Range the Object in Different Positions as shown in Fig. 7. The system's comprehensive approach combines data from the camera image, which identifies the 2D position of an aeroplane, and information from the LiDAR point cloud, which provides the 3D position and distance of the aeroplane.

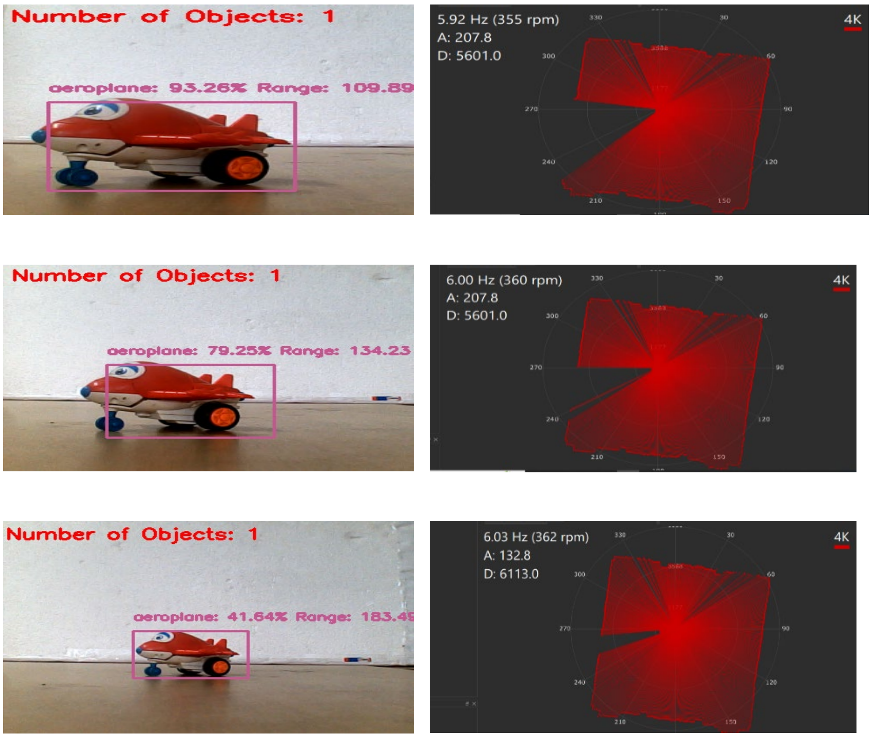

Fig. 7. LiDAR and camera data fusion to detect and range the object in different positions.

Through the coordinated use of the YOLOv4 object detection algorithm and the Kalman Filter for tracking, the system offers a robust solution for aeroplane detection and range estimation. If the camera image, with a resolution of 1920 x 1080, captures the scene. Let's say it identifies an aeroplane and its 2D position in the image with bounding box coordinates *(x1, y1)* and *(x2, y2)*. The centre of the aeroplane in the image is *(x_center, y_center, z_center)*.

The LiDAR, with a range of 100 meters and a point cloud density of 1000 points per square meter, scans the environment. It identifies a cluster of points corresponding to the detected pedestrian. LiDAR point cloud indicates the pedestrian's 3D position as *(x_LiDAR, y_LiDAR, z_LiDAR)*. Calculate the distance from the LiDAR sensor to the pedestrian,

$$Range = \sqrt{\begin{array}{l}(x\_LiDAR - x\_Center)^2 + \\ (y\_LiDAR - y\_Center)^2 + \\ (z\_LiDAR - z\_center)^2\end{array}} \quad (5)$$

By fusing data from the camera and LiDAR, the system effectively combines 2D position information from the camera with 3D range information from the LiDAR. The integrated information enables accurate detection and precise range as listed in Table 7. The Presented work was compared with the state of art as listed in Table 8.

Table 7. Object range in different positions.

Position	Camera (x_center, y_center, z_center)	LiDAR (x_LiDAR, y_LiDAR, z_LiDAR)	Range in Meters
Position 1	(700, 550, 0.0)	(10, 5, 0.5)	11.18
Position 2	(600, 600, 0.0)	(15, 10, 0.6)	11.07
Position 3	(800, 700, 0.0)	(30, 20, 0.7)	10.88

Table 8. Present work comprehensive analysis with state-of-art.

Parameter	[34]	[35]	[36]	Present Work
Drone Type	Quadcopter	Quadcopter	Quadcopter	Quadcopter
GPS	GPS NEO-6M	APM2.5 NEO-M8N	GPS NEO-6M	APM2.5 NEO-M8N
LiDAR	Youyeetoo TFmini-S	Yahboom Lidar EAI YDLIDAR X3	RP LiDAR	RP LiDAR
Dataset	KITTI	ONCE	ONCE	KITTI
DL Approach	CNN	GoogleNet	Res NET101	CNN
Application	Agriculture	Monitoring	Industry	Smart monitoring and Navigation

6. Conclusion

This paper presents a comprehensive design and analysis of an autonomous drone equipped with LiDAR, camera, and GPS technologies for smart navigation applications. The Quadcopter drone, driven by an ARM Cortex M4-based controller, integrates LiDAR for obstacle detection and ranging, and GPS for precise localization. The utilization of a high-resolution camera with a wide field of view enables detailed visual data acquisition essential for navigation tasks. The LiDAR boasts a remarkable range of 180 meters and a dense point cloud density of 1000 points per square meter, ensuring accurate obstacle detection and environmental perception.

One of the key findings of this study is the successful deployment of the YOLOv4 object detection algorithm coupled with the Kalman filter for robust object tracking. This combination enhances the drone's ability to identify and track objects in real-time, contributing to safer and more efficient navigation in dynamic environments. Additionally, the integration of LiDAR, camera, and GPS technologies provides a holistic solution for autonomous navigation, enabling the drone to navigate with precision and reliability.

Nomenclatures

A_T	Amplitude of the Gaussian function
C	Laser transmission speed
d_i	Distance between the i^{th} item and LiDAR system
F_T	FWHM of the Gaussian function
K_T	DC offset of the emitted laser pulse
N	Sampling time
$s(n)$	Received laser echo
T_s	High-Speed Digitizer's Sample Period.

Greek Symbols

ε_T	Residual error

μ_T	Mean of the Gaussian function
Abbreviations	
CNN	Convolutional Neural Network
GCS	Ground Control Station
GNSS	Global Navigation Satellite System
GPS	Global Position System
SSD	Single Shot MultiBox Detector
UAV	Unmanned Arial Vehicle
YOLO	You Only Look Once

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