

UAV Prototype Aerial-Underwater Surveillance System

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Abstract

The use of unmanned aerial vehicles (UAVs) has increased significantly in the field of surveillance, environmental monitoring, and disaster management. Conventional UAVs are able to operate in the sky only and lack the ability to conduct inspections underwater. The aim of this paper is to present the development of a hybrid aerial-underwater UAV surveillance system that can work both in the air and water.

The designed system consists of the following elements: a quadcopter platform, Raspberry Pi Zero 2W board, ESP32 communication module, camera module, and several environmental sensors. Along with the video surveillance function, a light-weight Convolutional Neural Network (CNN) based image classifier is added to enable object recognition and scene analysis. The images captured during flight and diving processes are preprocessed by applying the OpenCV and CNN based feature extraction algorithms to classify the surrounding environment. The conducted experiments have shown a stable flight performance, successful underwater operations, proper functioning of the embedded sensors, successful mode switching, and adequate image processing capacity.

Keywords- Education, Computer Graphics, Visual Depiction, Virtual Reality, Animation, Visual Effects

1. Introduction

Monitoring has become increasingly essential in many areas such as environmental protection, emergency management, and security. Traditional UAVs offer aerial monitoring while underwater vehicles offer submerged monitoring, but do not offer the capability of rapid deployment and broad coverage. The novel Hybrid Aerial and Underwater UAV offers all these capabilities in one device. It is capable of aerial monitoring, landing on water, submerged monitoring, and intelligent image analysis via CNNs.

The next few sections cover background information, system architecture, methodology, CNNs, and experimental results.

2. Related Work

Research in recent years has focused on developing hybrid UAV systems that can work in several environments.

Hassanalian and Abdelkefi addressed the classification of drones and their design issues [1]. Siddall and Kovac considered aerial-aquatic locomotion systems [2]. Chen et al. looked at underwater communication architecture [3].

In recent years, developments in the fields of deep learning and computer vision have resulted in smart surveillance using convolutional neural networks (CNNs). LeCun et al.

[4] Suggested CNN-based methods for extracting features, and Krizhevsky et al. [5] showed how to use deep neural networks for large-scale image recognition. Hybrid UAVs designed to perform tasks in both the air and under water in conjunction with an intelligent vision system have been recently

studied. Surveillance systems for such hybrid drones were considered by Wang et al.

[6]. Kumar and Patel proposed a lightweight CNN-based system for environmental monitoring

[7]. Zhang and Liu described recent developments in aerial-aquatic UAV technologies [8].

3. System Architecture and Methodology

A. System Block Diagram

The overall architecture of the proposed UAV system is shown in Fig. 1.

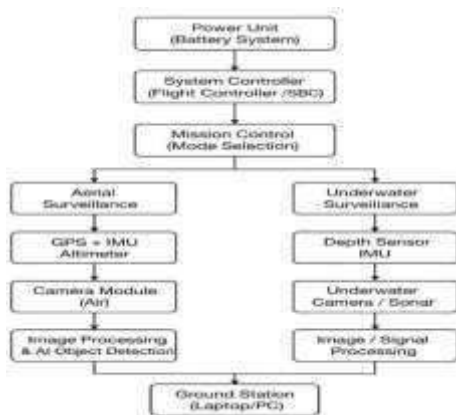


Fig. 1. Hybrid UAV System Block Diagram

The architecture consists of the flight controller layer, sensing layer, processing layer, and communication modules.

B. Hardware Integration

The UAV integrates BLDC motors, ESCs, KK2.1.5 flight controller, Raspberry Pi Zero 2W, ESP32 module, camera module, and environmental sensors.

The Raspberry Pi and ESP32 pin configurations used for system interfacing are shown in Fig. 2 and Fig. 3.

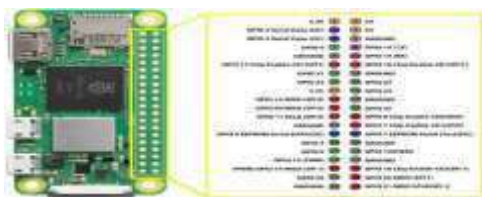


Fig. 2. Raspberry Pi Zero 2W Pin Configuration

4. Implementation

The complete hardware integration and wiring structure of the UAV system is shown in Fig. 4.

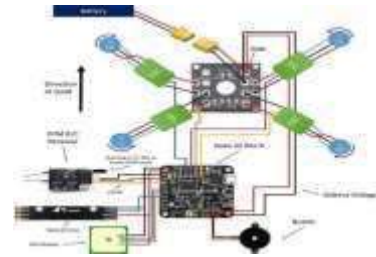


Fig. 4. Circuit Diagram of UAV System

The UAV conducts surveillance activities in the air and underwater using both flight control and underwater navigation systems. Minor vibrations occurred during high-speed movements, but flight stability was adequate for surveillance purposes.

A. CNN-Based Image Classification

In order to improve the surveillance system, the lightweight model of Convolutional Neural Network (CNN) was used together with the Raspberry Pi Zero 2W for image classification and analysis.

The camera on board takes aerial and underwater images at all times while working. These images are preprocessed using OpenCV functions to perform actions such as image resizing, converting into grayscale, normalizing images, and reducing noise in images before inputting into the CNN model.

The CNN model comprises of convolutional layer, ReLU activation, max-pooling layer, flattening layer, and fully connected layers.

The CNN workflow is shown in Fig. 5.

The implemented CNN workflow includes:

- Image acquisition using Raspberry Pi Camera Module
- Image preprocessing using OpenCV
- Feature extraction using convolutional layers

- Object classification using fully connected layers
- Real-time output transmission to the ground station

This allows the UAV to detect the environmental characteristics present around it, such as water bodies, obstacles, vegetation, floating debris, and submerged objects.

Preliminary tests have been done using sample data from aerial and underwater images. While the current model is optimized for lightweight classification because of the constraints imposed by Raspberry Pi Zero 2W, there is scope for further development using more complex deep learning algorithms in the future.

5.Results and Discussion

After successful integration of all hardware and software modules, multiple experimental tests were conducted to evaluate aerial stability, underwater operation, and intelligent image processing performance.

A. Prototype UAV

The developed hybrid UAV prototype is shown in Fig. 6. Stable hovering was achieved during multiple flight tests, and controlled maneuverability was maintained throughout operation.

B. PID Calibration and Flight Stability

PID tuning was performed for yaw, pitch, and roll axes to improve flight stability.

Results from experiments indicated better stability and less oscillation with PID parameter optimization. Figure 7 below depicts yaw-axis stabilization response indicating better yaw control capability with minimized oscillations with proper tuning of PID parameters. The correct yaw axis calibration allowed the UAV to retain its heading stability in hover mode and in other maneuvers. Figure 8 below depicts optimized pitch-axis stability response achieved by tuning of the proportional, integral, and differential parameters. The PID optimized pitch stability allowed the UAV to have more stability when moving forwards.

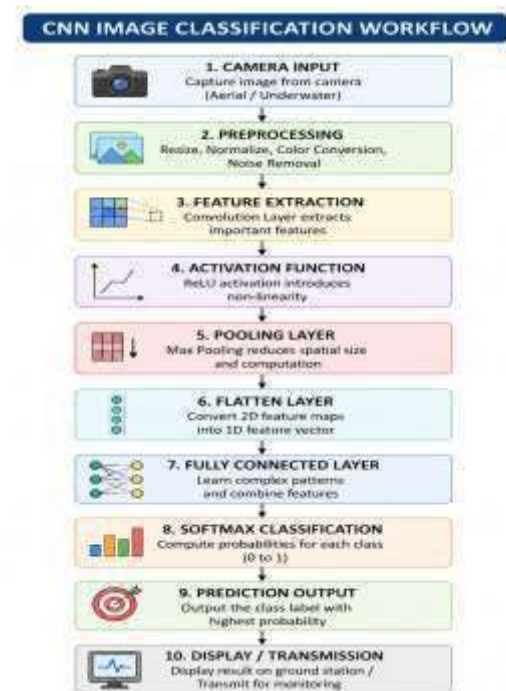


Fig 5:CNN Based image classification work flow



Fig 6: Developed quadrotor prototype used for aerial and shallow-water surveillance testing



Fig. 7. PID tuning response for yaw-axis stabilization

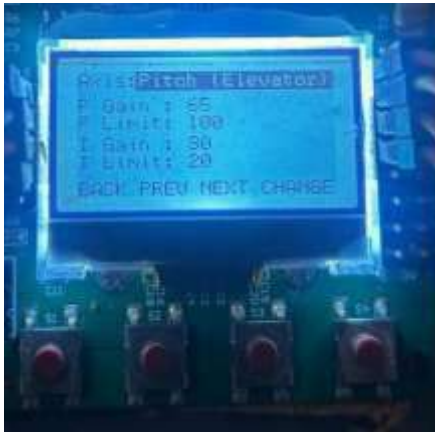


Fig. 8. PID tuning response for pitch-axis stabilization

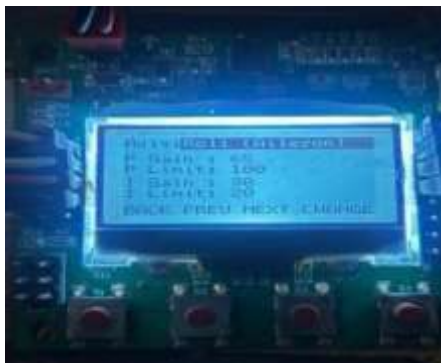


Fig. 9. PID tuning response for roll-axis stabilization



Fig. 10. Flight controller accelerometer calibration

Roll-axis PID response is depicted in Figure 9 below. Tuning of the PID parameters minimized unnecessary roll oscillations which improved the overall stability and maneuvering capabilities of the quadrotor.

The figure below depicts the flight controller calibration process before flying the UAV in midair. Calibration of the flight controller was important in ensuring stable flying capability through sensors' initialization.

C. Control Interface

The FlySky FS-i6 transmitter used for UAV control is shown in Fig. 11.

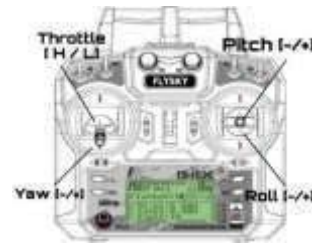


Fig. 11. FS-i6 controller interface used for manual flight operation

The controller provided reliable communication for throttle, pitch, roll, and yaw control throughout experimental testing.

TABLE :I

System Performance Metrics -D .Performance Evaluation

Parameter	Measured Value
Flight Duration	12–15 minutes
Underwater Speed	0.5–1.0 m/s
Camera Depth	1.5–2 m
Video Latency	200–300 ms

The CNN-based image classifier was able to process images taken from the air and under water during experimental testing. It was able to reliably classify water surface, obstacles, vegetation areas, and underwater objects in controlled lighting conditions. In terms of real-time performance, it was still adequate for surveillance applications, although its inference speed had been somewhat lower while continuously processing video streams.

Experimentally, it has been found out that visibility and lighting conditions greatly affected the accuracy of classification. However, the designed CNN-based image classifier shows that intelligent vision-based analysis can be effectively incorporated into inexpensive hybrid UAVs.

5. Conclusion

This paper explored the design and realization of a Hybrid Aerial and Underwater UAV Surveillance System for operating in both aerial and underwater domains. The system proved to perform satisfactorily, showing stability of flight, underwater movement, surveillance, sensor fusion, wireless

communication, and rudimentary CNN based image classification ability. The tests proved that it was possible to have aerial and underwater capabilities on the same UAV system. In future, improvements will be made in the areas of deep learning, navigation, underwater communication, GPS-based missions, and AI-based target detection.

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