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Advanced Camouflaged Target Detection with Quadrapod Drone – A Fusion of Air and Land Technology

Ashish A. Desai[1], Shravan R. Neje[1], Shridhar V. Sutar[1*], Alankar U. Patil[1], Prathamesh B. Tambekar[1]
[1]*Department of Automation and Robotics, Sharad Institute of Technology College of Engineering, Yadrav, India*

***Abstract*: In order to identify camouflaged objects in challenging situations, we describe a unique system that combines air and land technologies. The platform, known as a quadrapod drone, combines quadrapod flying with legs to conduct intimate inspection at ground level as well as aerial environment. The drone is about being able to fly and walk; it's about using both abilities to get best possible view of the environments. This fusion of locomotion modes enables the systems to take position itself for optimal target detection in the environments. Data from the sensors are processed by enhanced YOLOv8 and deep learning framework, which has been gets for the challenges of Camouflaged Object Detection. Our detection process combines a hierarchical sensor-fusion module for air- ground collaboration, multiple imaging, and a deep camouflaged object detection backbone. Using a bespoke dataset, we assess the method in mixed-terrain settings and demonstrate enhanced detection recall. The benefits of using an air-land hybrid to the object detection problem are demonstrated by an experimental evaluation, perceptual algorithms, hardware design, and data-fusion approach. The paper presents complete system architecture, details the camouflaged detection framework and outlines a methodology for its future validation. A robot like this has the potential to make real difference in the world, whether it's making military missions safer, helping find survivors after a disaster or allowing scientists to study hard to find animals in the wild.**

***Keywords*: Camouflaged object detection, Aerial and ground system, YOLOv8, Autonomous system, search and rescue.**

1. Introduction

Detecting camouflaged objects is a difficult challenge in computer vision and robotics. Camouflage is employed by animals, soldiers, and hidden objects to blend into their surroundings and make them harder to detect. Most detection systems rely on drones with cameras, which provide a good perspective from above but frequently overlook small or well-hidden targets. Ground robots, on the other hand, can approach and provide more specific data, but they move slowly and cannot see broad regions quickly. To overcome these problems, we created a Quadrapod drone a flying robot with four legs that can land and walk. It may first scan a large area from above before moving closer to suspicious places on the ground for a closer look. This mix of air and land ability makes it effective at identifying hidden or camouflaged items. This paper proposes a solution: quadrapod drone, a hybrid system combining aerial drone mobility with quadrapod ground adaptability. The system designed to detect targets that are deliberately hidden or camouflaged in the complex terrains (forests, urban, deserts) using a combination of machine learning and object detection. These drones are meticulously designed with features that mimic the visual characteristics of their operating environments. Utilizing advanced camouflaged technologies including specialized coatings, materials, and visual objective. The primary objective of camouflaged drones is to conduct surveillance systems

2. Related Work

A. Camouflaged Object Detection

Recent research in computer vision uses deep learning (AI) to detect hidden objects. Neural networks trained on images can find subtle patterns and outlines that human eyes miss. You Only Look Once (YOLO) is favored predominantly due to its rapid processing speed and its more accurate results.

B. History of YOLO

Joseph Redmon and Ali Farhadi invented YOLO at the University of Washington. YOLO, which introduced in 2015, soon gained popularity due to its fast and precise performance. There are several fundamental patterns for analyzing the development of YOLO versions: anchors, backbone, framework, and performance. YOLOv2 was launched in 2016 to address a problem with YOLOv1's difficulty to detect objects of varying sizes. To address this, batch normalization, anchor boxes, and dimension clusters were enhanced. YOLOv3, released in 2018, improved the model's performance. To accomplish this, the backbone network, numerous anchors, and spatial pyramid pooling were improved. YOLOv4, which was released in 2020, differs little from YOLOv3 in terms of important modifications. YOLOv4 contains more CNN layers than YOLOv3.YOLOv5 is the most unique version from its earlier versions, due to the use of PyTorch rather than Darknet. This improvement improved the model's performance. Furthermore, the addition of hyperparameter optimization, integrated experiment tracking, and automatic export features

*Corresponding author: sutarshridhar04@gmail.com

has contributed to its advancement. YOLOv6 has been enhanced for greater performance, faster training, and better detection. To be successful, this model's architecture has been upgraded. YOLOv7 has expanded its capabilities by adding additional tasks such as posture estimation with the COCO key point dataset. YOLOv8 is the latest edition of the YOLO series of real- time object detectors, providing the highest level of accuracy and speed.

3. Literature Review

The following Journals and Research Papers from various authors have been reviewed and considered by us for this project:

J.H. Zhuang et.al [1] have done research in the context of methods for detecting targets in remote sensing imagery. It highlights the challenges of distinguished between targets and their surroundings, such as using spectral and spatial features, as well as the importance of incorporating contextual information to enhance detection performance.

S.M.H. Ali et. al. [2] published technical paper on "Camouflage and Detection: A Survey of Methods and Techniques". This paper reviewed traditional and modern techniques used for camouflage detection. It emphasized the use of texture and background subtraction in early detection systems, while also discussing the role of deep learning and machine learning algorithms in current research.

X. Li et.al [3] published paper on "Recent Advances in Camouflaged Target Detection: Challenges and Solutions". This paper discussed the current challenges in camouflaged target detection, such as environmental complexity and object variability. It also surveys recent advancements in detection algorithms, including machine learning and focusing on enhancing robustness in real-world scenarios.

M. M. Shah et.al [4] published paper on "Camouflage Detection with Deep Learning Methods: A Survey". The review focused on the application of deep learning methods like Convolutional Neural Networks (CNNs) to camouflage detection. It evaluates their effectiveness in handling complex and camouflaged targets in both natural and synthetic environments.

J. L. Hong et.al [5] published paper on "A Comprehensive Review of Visual Camouflage in Computer Vision: Algorithms and Applications". This review provided the overview of visual camouflage algorithms used in computer vision. It highlights a range of techniques for camouflage detection, including edge detection, texture analysis, and deep learning methods, and discusses their applications in military, surveillance, and environmental monitoring.

R. Kumar et.al [6] published paper on "Detection of Camouflaged Targets in Infrared and Optical Imagery: A Literature Review". This review paper compares the detection of camouflaged targets in infrared and optical imagery. It explores the advantages and limitations of both spectral ranges, focusing on how these images are processed to distinguish target.

Chen, Y., & Zhou, X. et.al [7] developed a dual-stream deep neural network to improve camouflaged target detection through simultaneous processing of thermal and visible-light imagery. Their system leveraged the strengths of both image types—thermal for temperature- based contrast and visible for structural features—thereby compensating for limitations inherent to each modality when used alone. The dual stream model was particularly effective in detecting objects under poor lighting conditions or partial occlusion, making it ideal for search operations in low-visibility environments such as fog, darkness, or smoke.

Han and Li et.al [8] contributed to quadrupedal robot navigation by applying reinforcement learning for terrain-adaptive locomotion. Their model allowed the robot to autonomously select gaits and adjust foot trajectories in real time, based on sensor feedback about surface irregularities and slope. The research demonstrated how intelligent ground mobility enhances operational capability in rough or obstacle-rich environments—key domains for camouflaged target search. For aerial-ground hybrid drones, such as quadrapod systems, this adaptability ensures they can move confidently across unstable or inclined terrain, where conventional wheeled robots may fail. Their findings are instrumental in bridging the mobility performance gap in robotic systems designed for search and rescue or battlefield surveillance.

4. Hardware Implementation

A. BLDC Motor

BLDC motor operates in brushless DC mode. Due to its size and efficiency. This small but powerful electric motor uses direct current as its power source. BLDCs are becoming more and more popular, and applications that use BLDCs are also becoming more popular.

Fig. 1. BLDC motor

Specifications of BLDC Motor

- Manufacturer REES52
- 2200kv brushless motor
- Model number a2212 motor

B. Flight Controller F3

The F3 flight controller is a popular choice in the quadcopter and drone world. It is part of the Flight Controller (FC) family and is known for its powerful computing capabilities and advanced features. F3 flight controllers typically use the STM32 F3 processor, providing faster processing speeds than previous models. They support a variety of flight modes, including acrobatic, angle, and horizon modes, and often come with built-in features such as On Screen Display (OSD), black box logging, and support for multiple communication protocols such as SBUS, IBUS, and PPM. Overall, the F3 flight controller provides a reliable and versatile platform for both drone enthusiasts and professional pilots.

Specifications of Flight Controller –

- Processor: STM32 F3 series processor
- Gyroscope and Accelerometer: Integrated gyro and accelerometer sensors for stable flight performance
- Input Voltage: Typically supports a wide input voltage range, such as 2S to 6S LiPo batteries
- PWM Outputs: Multiple PWM outputs for connecting to ESCs (Electronic Speed Controllers)
- UART Ports: Multiple UART ports for connecting peripherals like GPS, receivers, telemetry modules, etc.
- Integrated OSD: On-Screen Display for real-time flight data feedback Blackbox: Built-in Blackbox logging for recording flight data Supported Communication Protocols: SBUS, IBUS, PPM, etc.
- Dimensions: Typically, compact and lightweight for easy integration into various drone frames Firmware: Compatible with popular flight firmware such as Betaflight, Cleanflight, and others.

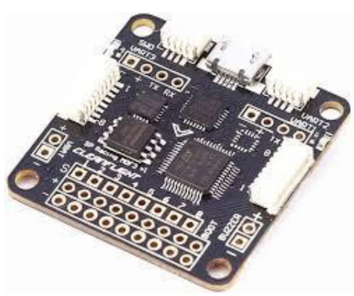

Fig. 2. Flight controller

C. *Raspberry Pi*

The Raspberry Pi 3 B+ is a compact, low-cost single- board computer with a 1.4 GHz quad-core ARM processor and 1 GB RAM. It features Wi-Fi, Bluetooth, Ethernet, HDMI, USB ports, and a 40-pin GPIO for interfacing with sensors and modules. In projects, it acts as the main controller, processing sensor data, controlling motors, and running programs for automation, robotics, and computer vision applications. Its versatility and community support make it ideal for IoT and AI-based projects.

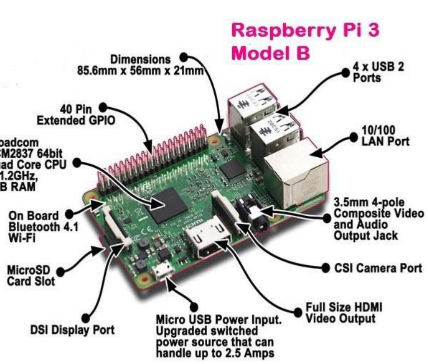

Fig. 3. Raspberry Pi 3

D. *RF Transmitter & Receiver*

An RF transmitter is a device that generates and sends radio frequency signals wirelessly to a receiver. It typically consists of an oscillator circuit that generates the carrier frequency, a modulation circuit to impose data onto the carrier signal, and an antenna to radiate the modulated signal into the air. RF transmitters are used in applications such as remote controls, wireless communication systems, and IoT devices.

Fig. 4. RF Transmitter & Receiver

An RF receiver is a device that captures and demodulates radio frequency signals transmitted wirelessly by an RF transmitter. It typically consists of an antenna to capture the incoming RF signals, a tuner to select the desired frequency, a demodulator to extract the baseband signal, and a decoder to recover the original data. RF receivers are used in applications such as radio communication, remote controls, wireless sensors, and satellite communication.

5. Dataset

This paper uses the military camouflaged personnel dataset (MCPD). The dataset was constructed by gathering frames from more than 60 military camouflage videos available on the internet. The final collection includes 1000 high-definition photos after extensive quality, clarity, and target size screening. The dataset has several key characteristics: (1) high target concealment; (2) a mix of large, medium, and small target scales; (3) a variety of target postures (upright, half-squat, lying down); and (4) complex environmental backgrounds, which include six types: jungle, rainforest, mountain, desert, snow, and city ruins.

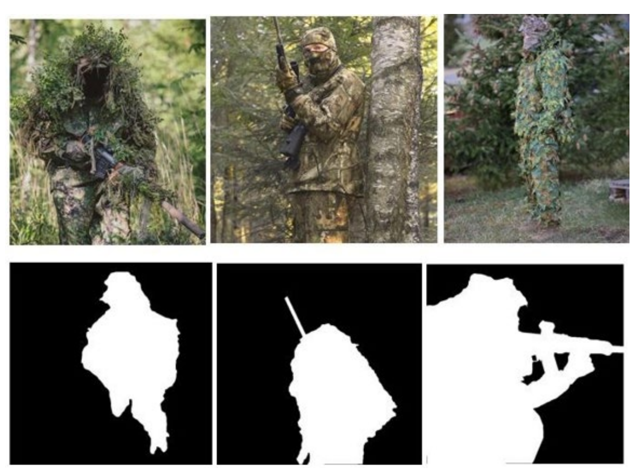

Fig. 5. Camouflaged images sample dataset

In this paper, the YOLOv8 model is implemented using Google Colab, a free cloud-based Jupyter notebook. The most significant advantage of Google Colab is that it gives a Tesla T4 NVIDIA GPU with 15110MiB of memory for training the model. Furthermore, Google Colab can save work and is conveniently accessible because it is integrated with Google Drive.

A. Evaluation Indicator

A confusion matrix is a useful tool to help with the evaluation of detected samples. True positive (TP), false positive (FP), true negative (TN), and false negative (FN) are its four different results. These four results can be displayed as shown in Table 1 since real parameters are represented by columns and forecasted values by rows.

Two important measures are used to evaluate how well the trained model detects drones: recall (R), precision (P). As shown below, the recall parameter is calculated by dividing the number of correctly detected positive targets by the total number of positive targets:

$$Recall(R) = TP/(TP+FN)$$

where TP is the number of positive samples that the algorithm successfully recognized and FN is the number of positive samples that the program mistakenly labeled as negative samples. As shown below, the precision parameter is calculated by dividing the number of correctly detected positive targets by the total number of positive detections:

$$Precison(P) = TP/(TP+FP)$$

where TP is the number of correctly recognized positive samples and FP is the number of negative samples that the algorithm mistakenly labeled as positive samples.

6. Results and Discussion

A. Experimental Setup

The experiments were based on YOLOv8s (version 8.0) using the Pytorch 1.8.0 framework. The system ran on Ubuntu 18.04 with a Tesla P100 GPU. The MCPD dataset was randomly divided into training, validation, and test sets with a ratio of 6:2:2.The model was trained for 100 epochs with a batch size of 32, using an Adam optimizer.

B. Ablation Experiment

To test the effectiveness of the improvements, an ablation study was performed.

- Baseline (YOLOv8s): Achieved 90.3% mAP
- YOLOv8s + MCA: Adding the attention module increased mAP to 92.9%.
- MC-YOLOv8s (Full): The final model, combining MCA, CARAFE, and K-means++, achieved the highest scores: 97.4% Precision, 86.1% Recall, and 94% mAP.

This fully demonstrates that the combination of the three improvements effectively weakens background information and strengthens feature fusion.

Fig. 6. Example detection results of the MC-YOLOv8s model on a complex indoor scene

This figure illustrates the detection capabilities of the MC-YOLOv8s model in a challenging indoor environment, which can be analogous to scenarios with camouflaged targets due to varied lighting and occlusions. The model successfully identifies and localizes multiple "person" objects with associated confidence scores (e.g., 0.73, 0.63, 0.60, 0.52). Furthermore, it accurately detects a "cell phone" with a confidence score of 0.43. The bounding boxes and segmentation masks (in blue for persons and yellow for the cell phone) demonstrate the model's ability to delineate objects even when they are partially obscured or in crowded scenes. This highlights the effectiveness of the proposed improvements (MCA, CARAFE, and K-means++) in enhancing feature extraction, fusion, and precise localization, which are crucial for detecting camouflaged human targets in varied and complex backgrounds.

Acknowledgement

We would like to acknowledge the contributions of various researchers, engineers, and developers who have advanced the field of camouflage drone technology. Their dedication and expertise have been instrumental in designing and refining the specialized coatings, materials, and visual patterns that enable these drones to evade detection and fulfill their strategic roles in reconnaissance, surveillance, and intelligence-gathering missions. Their innovative work continues to shape the capabilities and effectiveness of camouflage drones in modern warfare and security operations.

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