

THE DESIGN AND DEVELOPMENT OF AN OBJECT DETECTION DRONE

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BENIN CITY, NIGERIA**

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A PROJECT REPORT SUBMITTED TO THE DEPARTMENT OF MECHANICAL ENGINEERING, FACULTY OF ENGINEERING, UNIVERSITY OF BENIN, BENIN CITY. IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE AWARD OF BACHELOR DEGREE (B.Eng) DEPARTMENT OF MECHANICAL ENGINEERING, FACULTY OF ENGINEERING, UNIVERSITY OF BENIN, BENIN CITY.

SEPTEMBER, 2023

CERTIFICATION

I hereby certify that this project work DEVELOPMENT OF AN OBJECTION DETCTION DRONE was carried out by:

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in the department of Mechanical Engineering, University of Benin, Benin City, Edo State, Nigeria in partial fulfillment of the requirement for the award of bachelor of engineering, (B.Eng.) in Mechanical Engineering

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Engr. Dr. E.G Sadjere
Project Supervisor

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Date

.....
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.....
Date

DEDICATION

This project endeavor is devoted to the Divine Creator who bestowed upon us the fortitude and endurance to execute and complete this project, without whose assistance we would not have attained our current accomplishments.

Additionally, this endeavor is dedicated to our guardians for their immense backing, direction, selflessness, and supplications throughout our educational journey.

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In conclusion, we extend our heartfelt gratitude to our parents, who have stood by us since our earliest moments and aided us in surmounting all challenges and adversities. Their support, affection, and our resolve to bring them joy have undoubtedly served as paramount drivers of our determination. We express profound appreciation for their unwavering assistance, both monetarily and in other aspects.

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ABSTRACT

A drone is defined as any airborne vehicle that receives remote instructions from a controller or relies on software for autonomous flight. Drones, also known as unmanned aerial vehicles (UAVs), perform tasks ranging from routine to highly hazardous. Initially designed for military and aerospace purposes, drones have gained widespread acceptance due to their heightened safety and efficiency benefits. Operating without an onboard pilot, drones eliminate the risk to human life in combat zones and can sustain flight without the need for rest as long as there is fuel available.

Presently, advanced drones find applications across a diverse spectrum, including delivery services, law enforcement, surveillance of flood-prone areas, and numerous others highlighted in this report. The technology outlined in this report caters to various fields falling under the umbrella of Mechatronics, encompassing mechanical, electrical, and digital components.

This project focuses on coming up with and developing a general-purpose drone that can be modified to serve a particular purpose.

CHAPTER ONE

INTRODUCTION

1.1 BACKGROUND TO THE STUDY

Drones have emerged over the years as an innovative technology with vast potential across numerous industries. Drones have become a technology that is interwoven with various fields, thus, improving the efficiency of performance of these industries. For example, they are employed in the survey of construction sites, mining operations and cartography. They are used in monitoring environmental hazards such as wildfire and pollution. Drones are also employed in emergency response systems, assessing hazardous situations without risking human lives. And in logistics and delivery systems.

The demand for an efficient and intelligent aerial system continues to increase, thus, engineers strive to solve the problems that emerges from designing an efficient aerial system. These problems include; flight stability, control mechanisms, and object detection capabilities. Where flight stability refers to the ability of a drone to maintain a steady position and trajectory during flight, even in the presence of external disturbances, while, Control mechanisms involve the regulation and adjustment of various flight parameters, such as altitude, pitch...etc.

However, to achieve flight stability and control, engineers have focused on developing cost-effective and modular solutions. Traditional methods, which rely on complex mechanical designs and components, often lead to high cost in production, thus, limited scalability. Therefore, recent advancements in sensor technology, embedded systems, and control algorithms has made for the possibility of a cost effective and scale able production. This was achieved by utilizing affordable and easily replaceable components, along with slightly complex control algorithms.

Moreover, mankind began their demands for an aerial unmanned system since the 1900s, especially during World War one. This demand has led engineers and researchers to develop and refine the drone system. The course of this project demands the study these past projects, the mechanisms employed and their results. For example, the predator Drone in 2001 became widely recognized for its role in military operations. It was designed for long-endurance surveillance and reconnaissance missions, featuring advanced sensors and communication systems, in 2006, the Micro Air Vehicle (MAV) Project was capable of operating in complex urban environments and support military operations. More drone projects have been carried out such as the; Project wing in 2014, the Wing copter in 2017, the DJI Matrice Series in 2019...etc.

1.2 STATEMENT OF THE PROBLEM

With advances in UAV technology, world growth rate and increasing demand for services delivering around the world, drones have become very popular in the military and civil sector. Global commercial drone market was valued at 27.4 billion U.S. dollars, and it is projected to reach the size of around 58.4 billion U.S. dollars in 2026 (Statista, June 2021). Considering their types, operational and environmental pollution laws and their extensive applications, local design of drones has become pertinent to ease logistics, aid civil and military services, reduce fossil fuel usage and pollution by logistics vehicles especially in urban cities. The local design and deployment of such drones in Nigeria will reduce our dependence on importation of drones from foreign nations, ensure national safety and secrecy as well as create jobs and technological knowhow for Nigerian indigenous manufacturing sector. It is in this regard that the present project is aimed at producing a quadcopter drone using locally sourced materials.

1.3 AIM AND OBJECTIVES OF THE RESEARCH

1.3.1 Aim of the Research

The aim of the project is to design and fabricate a 3D printed drone capable of Flight, being stable while airborne and controllable along with a basic object detection system.

1.3.2 Objectives of the Research

- i. Design and analysis of a 3D Drone air-frame and components; using aerodynamic principles ensuring structural integrity, light weight
- ii. 3D printing of the Drone via a 3D printer using carbon fiber filament
- iii. Analysis and integration of the Propulsion system; the motors, propellers and battery
- iv. Design and integration of the control circuits and flight controller; allowing for precise control and maneuverability of the drone
- v. Integration of the basic object detection system (OPENMV CAM H7); allowing for computer vision and real time relay of captured data; enabling the drone to detect and track object in its vicinity
- vi. Testing the finished drone and evaluating flight, control responsiveness and object detection capabilities.

1.4 SCOPE AND LIMITATIONS:

In this project, we are required to fabricate an unmanned aerial vehicle **UAV** capable of achieving flight while maintaining subsequent stability, control and data transmission in real-time. It would possess a motion detection feature which could be applicable in carrying out surveillance and also in search or rescue operations. This project ought to be completed within the period of two semesters (six months).

This fabrication project would entail these steps/processes listed below:

- Development of frame/structure and control pad with the aid of Auto CAD; a computer-aided design (CAD) software application.
- 3-D printing of developed frame and control pads (physical development) with the application of slicing.
- Drawing of working circuit, wiring outlines and identification of stress points.
- Assembly, wiring and connection of components.
- General function programming and configurations using C++ (programming software) for; flight control, motor control, communication, battery monitoring, data logging and user interface.
- Fitting and fastening of components/parts.

Upon completion, this fabricated **UAV** should be able to perform basic takeoff and landing operations such as; Roll, yaw, ascend, descend and most importantly identify/detect motion within a specific area of coverage. To further perfect this fabrication and the overall functionality of our design, we employed the knowledge of an outsourced programmer for some intricate programming which at this level was unfamiliar to us but we learnt thanks to the programmer guidance

Thus far, we have been able to achieve stability in flight and we are still implementing real-time controls as-well as motion detection. We have taken down some data during our pre-flight and post-flight testing which we believe could further assist our refining and perfection in this project and subsequent ones. Some limitations to this project primarily include; finance, low-availability of required components locally, high exchange rate (NGN to USD), poor/unsteady power supply and limited time period for fabrication.

1.5 SIGNIFICANCE OF THE RESEARCH

Drones or quad-copters, although widely known by many, is not yet adopted and owned by a lot of people around the world, majorly because it is too expensive to acquire, also because it has not yet found a day-to-day use that justifies its cost. People consider it as an unnecessary item to own because its cost is not justified by its function, this has limited the growth of the industry.

The purpose of this project is to design a drone architecture that is cost effective and simple to produce, thus reducing its cost of production.

An object detection system was integrated into the drone which can be paired with a smart phone or computer anywhere in the world to detect objects for surveillance in households, businesses, estates, schools, military, etc.

CHAPTER TWO

LITERATURE REVIEW

2.1 CONCEPTS OF DRONE AND UAVS

The drone technology, formally known as Unmanned Aerial Vehicles (UAVs), is a technology that has an impressive application across a variety of sectors and industry, for example; they are employed in delivery services, rescue operations, surveys in areas that may be too dangerous for human presence...etc.



Figure 2.1

Drones integrated with object detection technology have gained substantial traction across diverse domains due to their ability to identify and locate specific objects or entities. This literature review aims to communicate in detail, the essential components of drones with object detection technology, encompassing definitions, theoretical foundations, general concepts, and notable related projects. Understanding the evolution and applications of this technology is crucial for comprehending its potential and envisioning its future role across various sectors.

Definition

A drone equipped with object detection technology refers to an Unmanned Aerial Vehicle (UAV) or Unmanned Aircraft System (UAS) that incorporates sensors, cameras, computer

algorithms that empower the drone to detect, recognize, and analyze specific objects or patterns within its operational environment.

An object detection drone is an unmanned aerial vehicle (UAV) equipped with advanced sensors and artificial intelligence (AI) algorithms designed to detect, identify, and analyze specified objects from within its environment. This technology has gained significant traction in various industries due to its wide range of applications and potential for automating tasks that traditionally required human intervention.

The core components of an object detection drone include:

- 1. Unmanned Aerial Vehicle (UAV):** The drone serves as the platform for conveying the object detection system. It is typically equipped with propulsion systems for flight, communication devices, and stabilization mechanisms to ensure precise navigation and proper image acquisition.
- 2. Sensors:** Object detection drones are outfitted with an array of sensors such as cameras, infrared sensors, or other specialized devices. These sensors capture images, depth data, or other relevant information about the drone's surroundings.
- 3. Artificial Intelligence Algorithms:** Artificial intelligence algorithms are used to process the data collected by the sensors. These algorithms analyze the imagery and data to identify and classify objects based on predefined characteristics or features.
- 4. Object Detection and Recognition:** The AI algorithms detect objects based on their shapes, colors, textures, or other distinguishing features. Common objects of interest include buildings, vehicles, vegetation, people, and more, depending on the application. Detection may involve identifying the location, size, orientation, and other attributes of the specified objects.

5. Data Processing and Analysis: The data collected by the drone is processed and analyzed in real-time or post-flight to extract valuable insights and actionable information.

Object detection drones are unmanned aerial vehicle equipped with sensors and AI algorithms that enable automated detection, recognition, and analysis of objects, thus, revolutionizing data collection and decision-making processes across diverse industries.

2.2 THEORETICAL FOUNDATIONS

2.2.1 Computer Vision

At the core of object detection in drones lies computer vision, and algorithms for interpreting and comprehending visual data. Drones with object detection capabilities leverage computer vision to process images and videos, enabling them to identify objects and patterns.

2.2.2 Machine Learning

Machine learning, forms a pivotal theoretical foundation for object detection in drones. machine learning algorithms, are extensively utilized for training models to achieve high accuracy and efficiency in identifying objects from images captured by drones.

2.2.3 General Concept

The general concept of drones with object detection technology revolves around the fusion of computer vision algorithms and sensor technology into said drone. This integration empowers drones to autonomously detect, track, and analyze objects, thereby enhancing their applications in sectors such as surveillance, agriculture, search and rescue...etc.

2.2.4 Design Principles

The lift and torque are generated around the rotor's center of rotation, while the drag is generated in the direction perpendicular to flight. Two of a quadcopter's rotors will typically rotate in a clockwise (CW) direction, while the other two will rotate in a counterclockwise (CCW) direction. Every rotor's ability to generate lift and torque independently allows for precise flight control.

However, altering the net center of thrust affects the pitch and roll, whereas adjusting the net torque affects the yaw. Quadcopters often lack cyclic pitch control, which allows the blade angles to change in real time as the rotor hub rotates. This makes them less maneuverable than traditional helicopters. However, the Counter-rotation design in the blades orientation resolves control problems caused by torque. The necessity for a tail rotor, as seen in traditional helicopters, is thus eliminated in a quadcopter when all four rotors are spinning at the same angular velocity, with two rotors rotating clockwise and two counterclockwise. Quadcopters, like other multirotor devices, may use a coaxial rotor arrangement to increase power and stability while decreasing weight. i.e., each arm is powered by a pair of motors working in opposing directions (one facing up and one facing down).

2.3 OBJECT DETECTION DRONES IN NIGERIA

Object detection drones have emerged as a transformative technology with considerable potential for various applications across different sectors in Nigeria.

Introduction

Object detection drones have gained significant attention globally due to their ability to revolutionize data collection, analysis, and decision-making processes across various industries. Nigeria is known for her various landscapes, land mass and a developing economy. This provides

opportunity for technological advancements that stands to benefit from the integration of object detection drones in various sectors.

2.3.1 Applications of Object Detection Drones in Nigeria

Agriculture: In Nigeria, agriculture is a significant sector that can greatly benefit from object detection drones. Drones equipped with object detection capabilities can be developed to monitor crop health, detect soil diseases, assess soil quality, and facilitate precision farming...etc. These applications lead to improved agricultural productivity and better-informed decisions by Nigerian farmers.

Environmental Monitoring: Object detection drones can be employed to monitor and detect illegal activities in protected areas, track wildlife movement, and assess the extent of deforestation. This aids in the conservation efforts and sustainable management of natural resources.

Infrastructure Inspection and Urban Planning: Object detection drones can be developed to inspecting critical infrastructure such as roads, bridges, power lines, and pipelines. They can detect structural faults, identify areas prone to erosion, and assist in urban planning by assessing land use, traffic patterns, and population density.

Disaster Response and Relief: Nigeria is often susceptible to natural disasters such as floods. Object detection drones can play a vital role in disaster response by swiftly assessing the extent of damage, identifying affected areas, and aiding in search and rescue operations. They facilitate rapid and targeted relief efforts, potentially saving lives and minimizing damage.

2.3.2 Benefits of Object Detection Drones in Nigeria

Enhanced Data Collection and Analysis: Object detection drones provide high-resolution imagery and data, enabling more accurate and comprehensive analyses. The AI algorithms on these

drones can process vast amounts of data in real-time, providing valuable insights that support informed decision-making.

Increased Efficiency and Cost Savings: Utilizing drones for object detection significantly reduces the time and resources required for data collection. Drones can cover large areas quickly and efficiently, leading to substantial cost savings compared to traditional data collection methods.

Improved Safety: Drones can be used to reach hazardous or hard-to-reach areas. Thus, eliminating the need for human presence. They can access dangerous terrains, disaster-stricken regions, or remote locations, providing critical information without endangering lives.

2.3.3 Challenges and Considerations

Regulatory Framework: The regulatory framework for drone operations in Nigeria is evolving. Challenges include navigating complex regulatory processes, obtaining appropriate permits, and ensuring compliance with evolving legislation governing drone usage.

Technological Infrastructure: Availability of advanced technological infrastructure and trained personnel to operate and maintain the drones is a significant challenge. Adequate investment in training and infrastructure development is essential to maximize the potential of object detection drones.

Public Awareness and Acceptance: Increasing public awareness about the benefits and potential applications of object detection drones is vital. Community engagement and education campaigns can address misconceptions and concerns, fostering acceptance and support for drone technologies.

2.4 APPLICATION OF DRONES WITH OBJECT DETECTION TECHNOLOGY

Project: Drone-Based Wildlife Monitoring (Wild Watch, 2021): This project exemplifies the application of drones with object detection technology in wildlife monitoring. The drones are employed to monitor and track wildlife in their natural habitats. Utilizing object detection algorithms, the drones can detect and identify specific species, enabling researchers to collect valuable data on population dynamics, migration patterns, and conservation efforts.

Project: Precision Agriculture for Crop Health Assessment (Agri Sense, 2020): In this project, drones equipped with object detection technology are utilized for crop health assessment in precision agriculture. The drones can detect early signs of diseases, nutrient deficiencies, or pest infestations in crops. By identifying these issues early, farmers can take timely corrective actions to optimize their agricultural practices and improve crop yields.

Project: Urban Surveillance and Anomaly Detection (Secure City, 2019): In urban surveillance, drones equipped with object detection capabilities are utilized for enhanced public safety. The drones can detect anomalies or suspicious activities in crowded urban areas, providing real-time alerts to law enforcement agencies. This proactive monitoring allows for rapid response and intervention, contributing to improved public safety and security.

Project: Agricultural Drone for Crop Monitoring:

Date: initiated in 2015

Description: The project utilizes drones equipped with object detection technology to monitor crop health, detect diseases, and optimize pesticide use for improved agricultural productivity.

Project: Wildlife Monitoring and Anti-Poaching Drones

Date: initiated in 2017

Description: Drones are deployed in wildlife reserves to monitor and detect poaching activities, protect endangered species, and collect data for wildlife conservation efforts.

Project: Disaster Response and Search Operations

Date: initiated in 2018

Description: Drones with object detection capabilities are utilized in disaster-stricken areas to assist in search and rescue operations, providing real-time situational awareness and aiding in locating survivors.

Project: Traffic Management with Drone Surveillance

Date: initiated in 2016

Description: Drones are employed to monitor traffic flow, detect accidents, and analyze traffic patterns to improve traffic management and reduce congestion.

Project: Environmental Monitoring of Water Bodies

Date: initiated in 2019

Description: Drones equipped with object detection technology monitor water bodies to detect pollution, track water quality, and identify potential environmental hazards like oil spills.

Project: Infrastructure Inspection for Railways

Date: initiated in 2017

Description: Drones are utilized to inspect railway tracks and infrastructure, detecting faults and ensuring safety, efficiency, and proper maintenance of the railway system.

Project: Disaster Damage Assessment and Mapping

Date: initiated in 2020

Description: Drones are deployed post-disaster to assess damage, identify hazards, and create detailed 3D maps for disaster response and recovery planning.

Project: Law Enforcement and Public Safety Monitoring

Date: initiated in 2019

Description: Drones equipped with object detection technology aid law enforcement agencies in monitoring public events, detecting criminal activities, and ensuring public safety.

Project: Maritime Surveillance for Illegal Fishing

Date: initiated in 2018

Description: Drones are employed for maritime surveillance to detect and deter illegal fishing activities, ensuring sustainable fishing practices and marine conservation.

Project: Mining Site Monitoring and Assessment

Date: initiated in 2016

Description: Drones equipped with object detection technology are used to monitor mining sites, assess mining activities, and ensure compliance with safety regulations.

Project: Real Estate Property Assessment and Marketing

Date: initiated in 2017

Description: Drones capture aerial imagery for real estate properties, utilizing object detection to assess property conditions, provide virtual tours, and enhance marketing efforts.

Project: Insurance Claims Assessment and Processing

Date: initiated in 2019

Description: Insurance companies use drones with object detection technology to assess insurance claims quickly and accurately, providing efficient claims processing for their clients.

These projects showcase the diverse applications and the continuous evolution of object detection drone technology in various domains, contributing to efficiency, safety,

2.5 ADVANCEMENTS AND FUTURE PROSPECTS

Edge AI for Onboard Processing: EdgeAI refers to the combination of edge computing and AI technology to enhance the capabilities of an autonomous object detection drone. The integration of edge computing and artificial intelligence on drones involves deploying AI models on the drones themselves, enabling real-time object detection and decision-making without heavy reliance on ground-based processing. Processing data on board will enhance efficiency, reduce latency, and enable said drone to operate autonomously in changing environments.

5G Connectivity and Low Latency: The advent of 5G networks represents a significant leap in enhancing the capabilities of drones with object detection technology. 5G networks offer low-latency, high-bandwidth communication, enabling drones to transmit data rapidly and receive instructions in real time. The advancement of 5G technology will enhance the speed and accuracy of object detection by providing faster data transmission and response time.

2.6 PREVIOUS PROJECTS

The Unified Foreground Packing (UFPMP-Det).

In order to address the challenge of dealing with numerous instances at very small scales, a novel approach divergent from the conventional method of dividing high-resolution input images into multiple low foreground ratio chips for detection is proposed. This approach introduces the Unified Foreground Packing (UFP) module, which merges sub-regions identified by a coarse detector through clustering to suppress background. The resulting regions are then compactly packed into a mosaic for single inference, significantly reducing overall processing time.

Moreover, to tackle the issue of confusion between inter-class similarities and intra-class variations, which often compromises detection performance but receives minimal attention, the Multi-Proxy Detection Network (MP-Det) is introduced. MP-Det finely models object

distributions by employing multiple proxy learning, ensuring diversity among proxies through the minimization of a Bag-of-Instance-Words (BoIW) guided optimal transport loss. Through these innovations, UFPMP-Det substantially enhances both detection accuracy and efficiency.

Extensive experiments conducted on widely-used datasets such as VisDrone and UAVDT demonstrate that UFPMP-Det achieves new state-of-the-art performance scores at significantly faster speeds, underscoring its advantages. The code for implementation is available at <https://github.com/PuAnysh/UFPMP-Det>.

Introduction

In recent times, unmanned aerial vehicles (UAVs), commonly referred to as drones, have gained significant popularity due to their balance between maneuverability and steadiness in various fields. These include security surveillance, aerial photography, express delivery, and agricultural production, where the primary concern lies in object detection using drone-captured images. Despite substantial advancements in object detection on conventional images facilitated by Convolutional Neural Networks (CNNs) over the past few years, the performance of detection on drone imagery remains constrained in terms of both accuracy and efficiency.

A significant obstacle in detecting objects using drone imagery is the prevalence of numerous instances of very small sizes. In comparison to benchmarks such as PASCAL VOC and MS COCO, the proportion of these small instances is notably high, as illustrated in Fig. 1 (a). Additionally, drones typically have limited computing resources, rendering conventional time-consuming solutions like the image pyramid ineffective. Instead, a common approach involves a coarse-to-fine pipeline, where a coarse detector is initially deployed to locate large-scale instances and sub-regions containing densely packed small ones. A fine detector is then applied to these regions to identify small-sized instances. While these methods yield promising results, the sub-

regions identified by coarse detectors tend to be rough, encompassing a significant portion of background information, resulting in inefficient computations. Moreover, as they partition the input image into multiple chips, each sub-region must undergo individual processing, necessitating multiple inferences for a final decision. These two drawbacks highlight the need for efficiency enhancements.



(b) Semantically similar categories on Vis Drone

Figure 2.2: Challenges in object detection on drone imagery.

Another significant hurdle arises from the semantic closeness between certain object categories within drone datasets, such as VisDrone. Examples include pedestrian versus person, tricycle versus awning-tricycle, where the appearances of instances from these categories are notably perplexing, as illustrated in Fig. 1 (b). Moreover, due to heightened disturbances stemming from factors like flying altitude, viewing angle, and weather conditions, the differences between features of instances within the same category tend to be magnified. Consequently, inter-class similarities and intra-class variations become intricately intertwined, posing a greater challenge compared to general object detection. Regrettably, previous literature has largely overlooked this issue, leaving ample room for enhancement in accuracy.

In order to tackle the aforementioned challenges—namely, the prevalence of small instances and the lack of distinctiveness among similar categories—in this study, we introduce an innovative method for object detection in drone images, referred to as the Multi-Proxy Detection Network with Unified Foreground Packing (UFPMPDet). This approach significantly expands upon the coarse-to-fine framework through the incorporation of two specifically devised modules.

Firstly, we propose the Unified Foreground Packing (UFP) module to address the former challenge. UFP operates in a two-stage manner, where foreground subregions identified by the coarse detector are initially merged using a clustering algorithm to eliminate background interference. Subsequently, the resulting regions are compactly packed into a mosaic with adaptively enlarged scales. This process effectively increases the foreground ratio of small objects, enabling the subsequent fine detector to perform inference in a single pass. Consequently, both detection accuracy and speed are enhanced.

Secondly, we introduce the Multi-Proxy Detection Network (MP-Det) module to tackle the latter challenge. In MP-Det, we adapt the multi-proxy learning scheme, originally developed for image retrieval tasks, to object detection. This scheme aims to improve the performance of the classification head by creating versatile decision boundaries. To mitigate the issue of collapsing during the training of multiple proxies, we introduce Bag-of-Instance Words (BoIW) guided Optimal Transport. This approach effectively models the distribution of each category, considering the confusion arising from both inter-class similarities and intra-class variations. This facilitates feature-proxy matching through Sinkhorn optimization.

We extensively evaluate our proposed approach on two publicly available databases, namely VisDrone and UAVDT, and report state-of-the-art scores alongside significantly improved efficiency, underscoring its effectiveness.

2.7 RELATED WORKS

Generic Object Detection

With the rise of Convolutional Neural Networks (CNNs), Generic Object Detection has witnessed significant advancements in recent years, particularly within the field of artificial intelligence, notably in computer vision. Existing methodologies are typically categorized into two primary approaches: anchor-based and anchor-free, regardless of whether they utilize pre-defined sliding windows or proposals.

Anchor-based detectors partition the box space into discrete bins and subsequently refine object boxes based on these anchors, which serve as regression references and classification candidates. These anchors are employed to infer proposals in multi-stage detectors such as R-CNN, Faster-RCNN, and Cascade-RCNN, or as final bounding boxes in single-stage detectors like SSD, YOLO, and Retina Net. In contrast, anchor-free detectors offer a promising alternative by eliminating the need for complex computations associated with anchor boxes and circumventing corresponding prior hyper-parameter settings. Examples of anchor-free methods include FCOS, FSAF, and GFL v1/v2.

(2020b, 2021) are representatives.

Object Detection on Drone Imagery

Despite advancements in object detection on natural images, such as those in PASCAL VOC and COCO datasets, performance on drone images remains unsatisfactory. The presence of a high proportion of small instances and the lack of distinctiveness among similar categories exacerbate this challenge. Drawing inspiration from region search strategies utilized in general object detection to expedite training and inference, current studies primarily focus on addressing the issue of small instances. They do so by adopting a coarse-to-fine framework, sequentially

employing a basic strategy or coarse detector to roughly identify regions containing densely packed small instances, followed by a fine detector to precisely localize these objects. For instance, in the method proposed by Unel, Ozkalayci, and Cigla, the tiling-based approach divides the image into evenly sized sub-regions, but this can result in instance breakage when truncating images. ClutDet, developed by Yang et al., utilizes a sub-network to extract sub-regions from the raw input, while DMNet, proposed by Li et al., estimates object density in the original image and subsequently separates sub-regions into minimal areas of connected possible blocks.

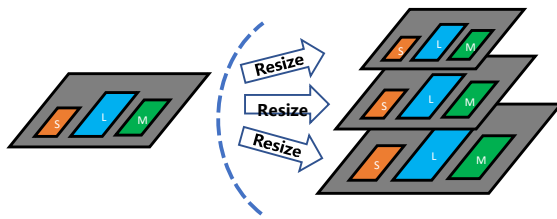
While these techniques do propel the field of object detection in drone imagery forward, the generated sub-regions often contain substantial background noise, and determining an accurate inference for the entire image necessitates multiple assessments of its sub-regions. Both of these aspects leave significant potential for efficiency improvements. Additionally, the lack of differentiation between similar categories has been largely overlooked, imposing constraints on achieving enhanced accuracies.

Small Object Detection

Since the release of MS COCO by Lin et al. in 2014, the detection of small objects has emerged as a crucial area garnering increasing attention. FPN, introduced by Lin et al. in 2017, stands out as a prominent solution for addressing scale variations via a feature pyramid. This concept has been extended into several variants, including EFF-FPN by Gong et al. in 2021 and AugFPN by Guo et al. in 2020, among others. Perceptual GAN, as proposed by Li et al. in 2017, leverages an adversarial network to enhance detection performance by minimizing the representation gap between small and large objects. Additionally, a super-resolution feature generator is trained using appropriate high-resolution target features for supervision. A similar approach is adopted in the work by Noh et al. in 2019, which also considers the influence of

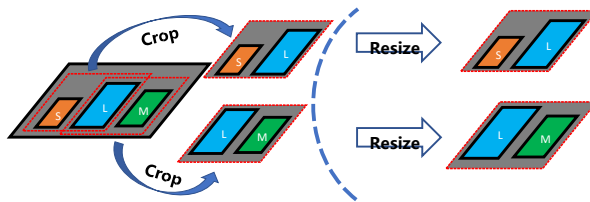
receptive fields of varying sizes. In a different vein, Yu et al. in 2020 introduced the concept of "Tiny Person," asserting that scale discrepancies between data used for network pre-training and detector learning lead to performance degradation. To mitigate this issue, they developed Scale Match, aiming to harmonize object scales across different datasets.

The aforementioned methodologies have been verified using either MS COCO for generic object detection or other detection tasks focusing on specific objects, such as individuals or traffic signs. As previously discussed, object detection using drone imagery presents distinct challenges.



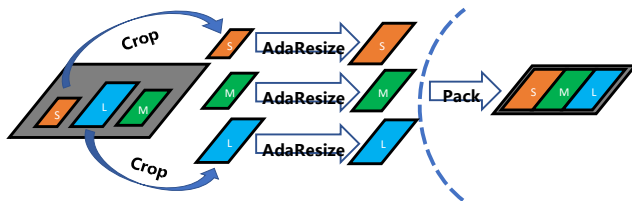
Inference

(a) Image Pyramid



Inference

(b) Cluster Region



Inference

(c) Our UFP

Figure 2.3: illustrates the comparison of various pipelines in managing scale variations. In drone images, the distribution of instance scales differs significantly, and the object categories exhibit semantic similarities, as depicted in Fig. 1 (a) and (b). This characteristic exacerbates the challenge at hand.

The Proposed UFPMP-Det Approach

In response to the dual challenges posed by the prevalence of small instances and the lack of distinctiveness among similar categories, a pioneering approach titled Multi-Proxy Detection Network with Unified Foreground Packing (UFPMP-Det) is introduced. This approach comprises two key stages: firstly, the Unified Foreground Packing (UFP) module, which transforms raw drone images into mosaics with elevated foreground ratios, and secondly, the Multi-Proxy Detection Network (MP-Det) module, which conducts inference on the mosaic images. MP-Det utilizes a multiproxy learning scheme alongside Bag-of-Instance-Words (BoIW) guided Optimal Transport to effectively model intricate object distributions. Further elaboration on these modules is provided below.

Unified Foreground Packing

The objective of the UFP module is to transform initial drone images into cohesive mosaic representations characterized by substantially augmented foreground ratios and enlarged dimensions of small objects. As illustrated in Fig. 3, Algorithm 1 outlines the process for generating foreground regions.

Input: Bounding boxes B_c Output: Merged regions B_r

- 1: Initialize $B_r = \emptyset$.
- 2: while $B_c \neq \emptyset$ do
- 3: $A = \operatorname{argmin}_{A_0 \in B_c} |A_0|$

```

4:  $B_c := B_c - \{A\}$ 
5: for all  $B \in B_c$  do
6:   For  $A$  and  $B$ , find the smallest enclosing
       convex bounding box  $C$ .
7:   if  $(|A| + |B|) \geq |C|$  then
8:      $A = C$ 
9:      $B_c := B_c - \{B\}$ 
10:  end if
11: end for
12:  $B_r := B_r \cup \{A\}$ 
13: end while
14: return  $B_r$ 

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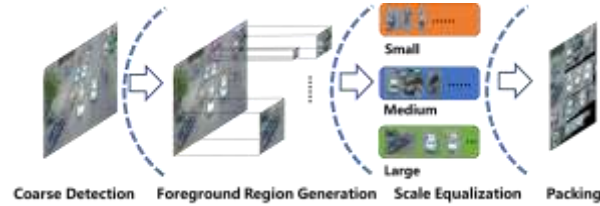


Figure 2.4: Pipeline of Unified Foreground Packing (UFP).

When isolating foreground sub-regions from the drone image using a coarse detector, UFP employs three consecutive procedures: (1) merging foreground sub-regions into several clustered units; (2) dynamically enlarging small-scale clustered regions; and (3) compactly assembling adjusted clustered regions into a unified mosaic.

Foreground Region Generation: To alleviate pronounced biases and substantial overlaps among foreground sub-regions detected in coarse detection, we increase both the width and height of every identified bounding box from its center using an expansion ratio β to encompass its ground

truth approximately. Subsequently, we introduce a greedy Foreground Region Generation (FRG) algorithm to consolidate the expanded outcomes, as outlined in Algorithm 1.

In detail, FRG receives the expanded results of coarse detection, denoted as B_c , as input and identifies the box A with the smallest size as the initial generation point. For each box B within $B_c - \{A\}$, FRG identifies the smallest convex box, denoted as C , that encompasses both A and B . If the combined area of A and B , represented as $|A| + |B|$, exceeds that of C , A is updated to C , and B is eliminated from B_c . This iterative process continues until no box B meets the condition $|A| + |B| \geq |C|$. At this point, A is included as a cluster region in B_r . The procedure is reiterated until B_c becomes an empty set, yielding the final merged region set B_r .

Following FRG, each image is depicted as several cluster regions with varied scales. To standardize their scales, particularly focusing on the smaller ones,

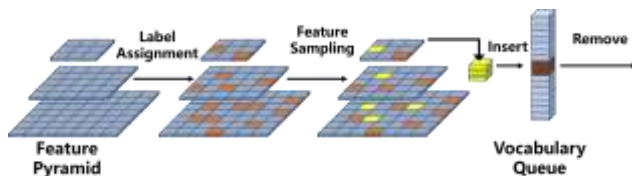


Figure 2.5: depicts the process of updating the vocabulary queue. The orange cells represent positive samples following label assignments, while the yellow cells indicate the oldest elements in the vocabulary queue that are randomly selected for updating.

Initially, we compute the mean scale of the regions from B_r and then expand regions smaller than a predetermined size (e.g., 96×96 in our study) by adjusting their average scale to match the fixed size.

Foreground Region Packing: Existing methods execute fine-grained detection on each cluster region separately, which proves highly inefficient. To circumvent this issue, we amalgamate all the regions into a cohesive mosaic using the PHSPPOG technique (Zhang et al.,

2016). This approach ensures that fine-grained detection is performed just once, resulting in significant time savings.

Multi-Proxy Detection Network

The MP-Det module focuses on alleviating the conflation between inter-class resemblances and intra-class discrepancies within intricate object distributions during classification. It comprises two primary elements: (1) the Multi-Proxy Classification Head and (2) the Bag-of-Instance-Words (BoIW) model.

Multi-Proxy Classification Head: In contrast to the traditional classification head, which assigns a singular weight vector w_i to each category i , the Multi-Proxy Classification Head introduces multiple weight vectors to capture diverse aspects of each category. Assuming x represents the feature extracted by the backbone network, the conditional probability associated with the i -th category is expressed as:

The expression $Pr(Y = y_i|x) = \text{Sigmoid}(w_iTx)$ (equation 1) utilizes the sigmoid function $\text{Sigmoid}(\bullet)$. Equation 1 essentially represents a single proxy classifier, assuming implicitly that each category possesses only one class center at w_i/k .

In contrast, when dealing with drone images, intra-class variance tends to be significant due to considerable changes in size and perspective of instances. Consequently, data pertaining to a single class may span across multiple centers. Hence, we employ a multi-proxy classification head, positing that the i -th category comprises K (where $K > 1$) proxies represented by \cdot . Drawing inspiration from Soft Triple (Qian et al., 2019), the formulation for the multi-proxy conditional probability is as follows:

$$Pr(Y = y_i|x) = \text{Sigmoid}\left(\gamma \sum_k \frac{\exp(s_i^k)s_i^k}{\sum_{l=1}^K \exp(s_i^l)}\right), \quad (2)$$

kT

where $b_i^k = \frac{w_i \cdot x}{\|w_i^k\| \|x\|}$ and γ is a scaling factor. Accordingly, the weights $[w_i^1, w_i^2, \dots, w_i^K]$ can be optimized by minimizing the cross-entropy or the focal loss *w.r.t.* $Pr(Y = y_i|x)$.

As in Eq. (2), the decision boundary for the i -th class is represented by multiple centers (proxies), thus being more flexible and accurate than that by a single one.

Bag-of-Instance-Words guided Optimal Transport The multiple proxies tend to collapse into a similar one during training, caused by extremely imbalanced cluster assignments. To overcome this dilemma, an optimal transport based procedure is adopted as in (Liu et al. 2021a).

Specifically, given the feature vectors $\{f_i^j\}_{j=1}^{N_i}$ of N_i positive instances and K proxies $\{w_i^k\}_{k=1}^K$ for the i -th class, the cost matrix is computed as $C_i = \frac{1-S}{2}$, where $S \in \mathbb{R}^{N_i \times K}$ refers to the cosine similarity matrix between $\{f_i^j\}_{j=1}^{N_i}$ and $\{w_i^k\}_{k=1}^K$ and $\mathbf{1}$ is an all-ones matrix. The transportation

plan $P_i^* \in \mathbb{R}^{N_i \times K}$ is computed as below:

$$\begin{aligned}
 P_i^* &= \operatorname{argmin}_P \operatorname{tr}(C_i^T P) \\
 N_i & \quad K \\
 \times & \quad \times \quad (3) \\
 s.t. \quad & P(j,k) = p_i(k), \quad P(j,k) = q_i(j), \\
 & j=1 \quad k=1
 \end{aligned}$$

where $\operatorname{tr}(\cdot)$ is the matrix trace. $p_i = [p_i(1), \dots, p_i(K)]$ and $q_i = [q_i(1), \dots, q_i(N_i)]$ indicate the marginal probability distributions of $\{w_i^k\}_{k=1}^K$ and $\{f_i^j\}_{j=1}^{N_i}$, respectively. Based on Eq. (3), the instance-proxy matching loss *w.r.t.* $\{f_i^j\}_{j=1}^{N_i}$ and $\{w_i^k\}_{k=1}^K$ is defined as

$$\mathcal{L}_{ot} = \frac{1}{N_c} \sum_{i=1}^{N_c} \operatorname{tr}(C_i^T P_i^*), \quad (4)$$

where N_c is the number of classes.

In Eq. (3), the uniform distributions, *i.e.* $p_i(k) = \frac{1}{K}$ and

$q_i(j) = \frac{1}{N_i}$, are usually used as priors, but this may be different from the ones of real data, thus leading to performance drop. To address this issue, we develop the BoIW model to estimate the intra-class distribution of $\{w_i^k\}_{k=1}^K$.

In specific terms, the Bag-of-Instance-Words (BoIW) initially creates a queue-based vocabulary V_i comprising N representative features for the i -th class. Illustrated in Figure 4, V_i undergoes updating in every minibatch iteration. During this process, m positive instances are chosen, and their features are incorporated into V_i while simultaneously removing the m oldest features. In the case of a two-stage detector, we extract the flattened instance-level features following the RoI layer. For a one-stage detector, we additionally utilize a convolutional layer to extract C -dimensional instance features.

Following this, K-means clustering is employed on V_i to yield K clusters $\{c_{ki}\}$. Subsequently, the marginal distribution π_i is estimated as $\pi_i(k) = \frac{\#|c_{ki}|}{\#|V_i|}$, where $\#|\cdot|$ indicates the count of elements. Given that the clusters $\{c_{ki}\}$ evolve across different stages, we arrange π_i in descending order to ensure that w_{ik} consistently corresponds to the cluster with the k th highest probability. Upon reintroducing $\pi_i(k)$ into Equations (3) and (4), we derive the Bag-of-Instance-Words induced optimal transport loss.

It's important to highlight that the vocabulary V_i serves as the representative feature set for the i -th class. To augment their representativeness further, we incorporate an additional contrastive learning loss concerning V_i and the feature of the positive instance x_i :

$$L_{cl} = -N_i \log \frac{\sum_{v \in V_i} \exp(v^T x_i)}{\sum_{u \in V} \exp(u^T x_i)}, \quad (5)$$

Table 2.1: Comparison of different approaches in AP/AP50/AP75 (%) on the validation set of VisDrone. MS refers to the multiscale trick during inference and ‘-’ indicates that the result is not reported.

Method	References	<u>ResNet-50</u>			<u>ResNet-101</u>			<u>ResNeXt-101</u>		
		AP	AP50	AP75	AP	AP50	AP75	AP	AP50	AP75
Faster-RCNN	(Ren et al. 2017)	21.4	40.7	19.9	21.4	40.7	20.3	21.8	41.8	20.1
ClusDet	(Yang et al. 2019)	26.7	50.6	24.4	26.7	50.4	25.2	32.4	56.2	31.6
DMNet	(Li et al. 2020a)	28.2	47.6	28.9	28.5	48.1	29.4	29.4	49.3	30.6
GLSAN	(Deng et al. 2021)	30.7	55.4	30.0	30.7	55.6	29.9	-	-	-
SAIC-FPN	(Zhou et al. 2019)	-	-	-	-	-	-	35.7	62.3	35.1
AMRNet	(Wei et al. 2020)	31.7	52.7	33.1	31.7	52.6	33.0	32.1	53.0	33.2
HRDNet	(Liu et al. 2021b)	-	-	-	31.4	53.3	31.6	35.5	62.0	35.1
UFPMP-Det	Ours	36.6	62.4	36.7	37.5	63.2	38.3	39.2	65.3	40.2
UFPMP-Det+MS	Ours	37.4	63.7	37.7	38.7	65.1	39.4	40.1	66.8	41.3

where $V = \cup_{i=1}^N V_i$.

By minimizing L_{cl} in Eq. (5), the correlations between the intra-class/inter-class features are increased/decreased.

Dynamic K-Proxy Estimation: The quantity of proxies within each class, denoted as K , holds significance for MP-Det. Instead of relying on a simplistic manual setting, we introduce an adaptive approach for estimation. Specifically, we employ vanilla GFL v1 (Li et al., 2020b) to extract instance features and utilize DBSCAN (Ester et al., 1996) for clustering to ascertain the optimal value of K .

Overall Optimization: The comprehensive training loss of MP-Det encompasses the traditional detection loss L_{det} , the Bag-of-Instance-Words induced optimal transportation loss L_{ot} in Equation (3), and the contrastive learning loss L_{cl} in Equation (5), expressed as:

$$L = L_{det} + L_{ot} + L_{cl}. \quad (6)$$

Throughout the training process, we conduct Bag-of-Instance-Words (BoIW) to periodically assess π (in our instance, every 2,000 iterations). When optimizing L_{ot} , we utilize Sinkhorn-Knopp (Cuturi, 2013) to calculate the transportation plan π^* , resulting in a marginal increase in training time (27.5 hours compared to 33 hours) with no additional expense during testing.

Experimental Results and Analysis

UFPMP-Det undergoes evaluation on the extensively utilized VisDrone (Zhu et al., 2018) and UAVDT (Du et al., 2018) datasets through comprehensive experimentation.

VisDrone encompasses 10,209 high-resolution images (2000×1500) containing 10 object categories, captured by diverse drone-mounted cameras across various areas (urban and rural) and scenarios (sparse and congested). For training, 6,471 images are utilized, with 548 allocated for validation and 3,190 for testing. As the test set isn't publicly accessible, we adhere to the approach

of ClutDet (Yang et al., 2019) and DMNet (Li et al., 2020a) by reporting scores on the validation set.

UAVDT comprises 23,258 training images and 15,069 test images, all captured from urban settings by a UAV at low altitudes, with a resolution of 1080×540 . Three vehicle types (car, bus, and truck) are manually annotated. Consistent with standard protocols for general object detection (Lin et al., 2014), we utilize Average Precision (AP) and APs at IoU thresholds of 0.5 (AP50) and 0.75 (AP75) as evaluation metrics for both datasets.

Table 2.2: Comparison of different approaches with ResNet50 in AP/AP50/AP75 (%) on UAVDT.

‘-’ indicates that the result is not reported.

Method	Reference	AP	AP50	AP75
Faster-RCNN	(Ren et al. 2017)	11.0	23.4	8.4
ClusDet	(Yang et al. 2019)	13.7	26.5	12.5
DMNet	(Li et al. 2020a)	14.7	24.6	16.3
GLSAN	(Deng et al. 2021)	17.0	28.1	18.8
DREN	(Zhang et al. 2019)	15.1	-	-
ARMNet	(Wei et al. 2020)	18.2	30.4	19.8

UFPMP-	Ours	24.6	38.7	28.0
Det				

Table 2.3: Comparison of different methods in efficiency *w.r.t.* the number of packed images (#img) and the inference time cost (in seconds) on VisDrone.

Method	Reference	#img	Inference Time
ClusDet	(Yang et al. 2019)	2716	0.273
DMNet	(Li et al. 2020a)	2736	0.290
UFPMP-	Ours	1096	0.152
Det			

Implementation Details

We implement the proposed methodology utilizing the publicly available MMDetection toolbox. GFL (Li et al., 2020b) serves as the baseline detector, pretrained on ImageNet. UFPMP-Det undergoes training for a total of 60 epochs using the SGD optimizer. The momentum and weight decay remain constant at 0.9 and 0.0001, respectively. Initially, the learning rate is established at 0.01 with a linear warm-up, subsequently decreasing by a factor of 10 after 40 and 55 epochs. Regarding Bag-of-Instance-Words (BoIW), it receives individual updates within the first 10 epochs without engaging in optimal transport and contrastive learning. Subsequently, it is jointly optimized alongside all components, a configuration that has proven empirically stable

during training in our experiments. The input image sizes for our detector are defined as 1333×800 for VisDrone and 1000×600 for UAVDT, respectively.

Comparison with the State-of-the-arts

We compare UFPMP-Det with the state-of-the-art counterparts, including Faster-RCNN (Ren et al. 2017), ClusDet

Table 2.4: Comparison of packing methods in AP/AP50/AP75 (%) and number of packed images (#img) based on FasterRCNN with ResNet-50

Method	Reference	#img	AP	AP50	AP75
EIP	(Yang et al. 2019)	3288	21.1	44.0	18.1
ClusDet	(Yang et al. 2019)	2716	26.7	50.6	24.7
DMNet	(Li et al. 2020a)	2736	28.2	47.6	28.9
UFP	Ours	1096	30.6	52.5	31.0

Table 2.5: Ablation study on UPF *w.r.t.* Foreground Ratio (FR) (%) and proportion (%) of object instances in small, medium and large sizes (using the COCO metric) on VisDrone and UAVDT.

Dataset	UPF	FR	Small	Medium	Large
VisDrone		10.2	68.56	28.68	2.76
VisDrone	X	24.5	6.96	63.35	29.69
UAVDT		5.11	74.87	23.01	2.12
UAVDT	X	22.98	0.64	71.60	27.76

(Yang et al. 2019), DMNet (Li et al. 2020a), GLSAN (Deng et al. 2021), and DREN (Zhang et al. 2019).

Results on VisDrone: Various existing methodologies apply different base networks on the VisDrone dataset. Consequently, we present the performance of UFPMP-Det using various typical backbones, namely ResNet-50, ResNet-101, and ResNeXt-101, to ensure a comprehensive validation. As outlined in Table 1, these methods generally achieve heightened accuracies with more robust networks. Notably, when employing the same backbone, UFPMP-Det consistently outperforms its counterparts by substantial margins, enhancing APs by 4.9%, 5.8%, and 3.5% with ResNet-50, ResNet-101, and ResNeXt-101, respectively. It is noteworthy that UFPMP-Det's performance with ResNet-50 even surpasses that with much deeper networks like ResNeXt-101, establishing a new state-of-the-art. Additionally, employing a multi-scale technique during inference further enhances accuracy.

Results on UAVDT: The majority of detectors utilize the ResNet-50 backbone for assessment on the UAVDT dataset, and we adhere to this configuration for fair comparison. As depicted in Table 2, UFPMP-Det significantly enhances the performance compared to other

detectors, improving the AP, AP50, and AP75 of the second-best ARMNet by 6.4%, 8.3%, and 8.2%, respectively.

Overall Efficiency: To evaluate the efficiency of UFPMPDet, we present the count of packed images along with the inference time cost, juxtaposed with ClusDet (Yang et al., 2019) and DMNet (Li et al., 2020a). All experiments are conducted on a single GTX 1080TI GPU. As demonstrated in Table 3, UFPMP-Det generates less than half of the packed images compared to ClusDet and DMNet, resulting in notably faster inference times, underscoring its superiority.

Ablation Study

We detailedly validate the major components, *i.e.*, UFP and MP-Det, as well as several hyper-parameters on UFPMPDet.



Figure 2.6: Visualization of UFP. Top: input images; middle: clustered regions highlighted by green bounding boxes; and bottom: packed mosaics.

Table 2.6: Validation of different components in MP-Det with ResNet-101 on VisDrone in terms of AP/AP50/AP75 (%).

Method	AP	AP50	AP75
Baseline	29.6	49.8	30.3
Baseline+UFP	36.6	62.3	36.8
Baseline+UFP+MP-	37.0	62.5	37.6
Head			
Baseline+UFP+MP-	37.5	63.2	38.3
Head+BoIW			

Regarding UFP Evaluation: We assess the performance of UFP and juxtapose it with three alternative methods: evenly image partition (EIP) (Yang et al., 2019), ClusDet (Yang et al., 2019), and DMNet (Li et al., 2020a). For equitable comparison, all methods employ Faster-RCNN with FPN as the base detector and ResNet-50 as the backbone. As presented in Table 4, UFP yields fewer packed images through unified adaptive packing, while concurrently achieving superior accuracy by augmenting the Foreground Ratio (FR). To illustrate the advantage of UFP in enhancing FR and reducing the number of small objects, we summarize the FR alongside the percentages of small/medium/large objects on both VisDrone and UAVDT datasets in Table 5. It's important to note that we employ the same metric used in MS COCO to categorize objects as small, medium, or large. As depicted, UFP notably enhances FR and significantly diminishes the percentage of small objects, thereby facilitating subsequent detection.

We provide a visual representation of the intermediate and final outputs of UFP in Fig. 5. The first row showcases the input images, the second row illustrates the FRG clusters derived from

the densely extracted object regions by the foreground detector, and the final row exhibits the packed unified mosaics.

Table 2.7: Comparison of AP/AP50/AP75 (%) on VisDrone by using different methods to set the number of proxies K : Manual vs. MP-Det (Ours).

Method	AP	AP50	AP75
$K = 10$ (Manual)	37.1	62.8	37.8
$K = 20$ (Manual)	37.1	62.6	37.7
MP-Det	37.5	63.2	38.3

Table 2.8: The impact of the size of BoIW (N) on the performance of MP-Det *w.r.t.* AP/AP50/AP75 (%) on UAVDT.

Size of BoIW (N)	AP	AP50	AP75
50	22.3	36.1	25.2
100	24.0	37.6	27.1
200	24.6	38.7	28.0

Table 2.9: The impact of β on UFP *w.r.t.* Foreground Ratio (FR) and AP/AP50/AP75 (%) on VisDrone.

β	FR	AP	AP50	AP75
1.3	32.46	33.9	61.7	33.5
1.5	24.53	36.6	62.4	36.7
1.7	21.07	35.6	61.3	35.8

Concerning MP-Det: MP-Det comprises two key components, namely MPHead and BoIW, which we validate on a more robust baseline using ResNet-101. As illustrated in Table 6, MP-Head initially enhances the baseline accuracy (AP) by 0.4%, with BoIW further augmenting it by 0.5%, underscoring their efficacy.

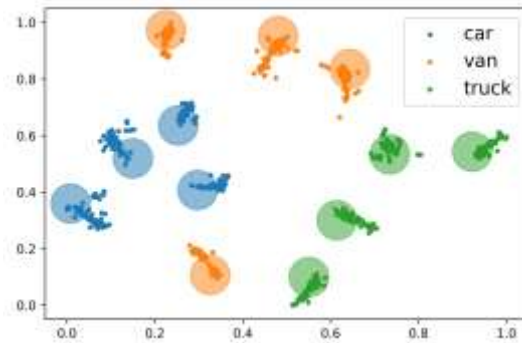
We additionally examine the impact of adaptive K-proxy estimation and the size of BoIW on MPDet's performance. As mentioned earlier, MP-Det dynamically estimates the number of proxies for each class by employing DBSCAN on the instance features extracted from pretrained models. For comparison, we designate manual setting as the baseline approach. As depicted in Table 7, adaptive setting outperforms manual setting when integrated into MP-Det.

Regarding the size of BoIW, we present the results of MP-Det using varying values, such as $N = 50/100/200$ on UAVDT in Table 8. As summarized, MP-Det achieves the highest score with $N = 200$, thus this value is adopted in our research.

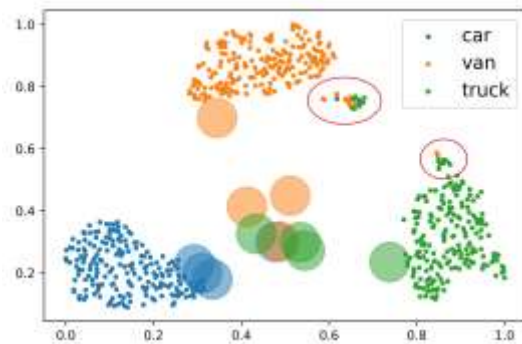
Regarding the size of BoIW, we present the results of MP-Det using varying values, such as $N = 50/100/200$ on UAVDT in Table 8. As summarized, MP-Det achieves the highest score with $N = 200$, thus this value is adopted in our research.

We provide a qualitative demonstration of the influence of optimal transport (OT)-based feature-proxy matching by visualizing the features of object instances and proxies on UAVDT through t-SNE. As depicted in Fig. 6, in the absence of OT, instance features tend to cluster away from proxy points and exhibit considerable distance from the proxies, while proxies from distinct classes lack sufficient discriminative qualities. Conversely, when OT is utilized, the learned features are positioned in small neighborhoods surrounding multiple proxies in a more evenly distributed manner. Additionally, the inter-class distances between proxies are notably widened, facilitating object classification.

Regarding the Hyper-parameter β : As previously mentioned, β impacts both the number of clustered regions and the average recall of raw images. In Table 9, we present the detection accuracies corresponding to various values of β . The findings reveal that FR decreases as



(a) with OT



(b) w/o OT

Figure 2.7: Representation of multi-proxies acquired on UAVDT using t-SNE. Solid dots represent the features of object instances, while translucent circles represent the proxies. Unique colors signify different classes.

As β increases, FR decreases. UFP achieves optimal performance when β is set to 1.5, which is hence adopted in our experiments.

2.7 CONCLUSION

Drones integrated with object detection technology represent a pivotal advancement in aerial technology, promising autonomy and intelligence across various applications. The theoretical foundations rooted in computer vision and machine learning, coupled with notable projects and ongoing advancements is proof of the vast potential of this technology to shape the future of many industries. Further research, innovation, and integration of advanced technologies are expected to augment the capabilities and applications of drones with object detection technology, making them valuable aspects of technological advancement.

CHAPTER THREE

MATERIALS AND METHOD

3.1 INTRODUCTION

The materials used for the drone development were purchased from a vendor. However, the body work (HUB) was developed with the use of 3D printing technology. The materials used in the course of this project are shown in the table below;

Table 3.1: Materials table

SN	Components	Function	Source
1	Electronic speed controller (ESC)	Provides feedback to the motor about how quickly the motor should be turning at any particular moment,	Purchased
2	Battery	The drone's motors and electronic components would be unable to function without this source of energy. Drones often use lithium polymer batteries (Li-Po) owing to their portability, long shelf life, and high energy density.	Purchased
3	DC brushless Motors	The drone's propellers are spun by these motors. Thus, creating lift.	Purchased
4	Transmitter	A Transmitter is an electrical device that utilizes radio signals to communicate orders wirelessly over a predetermined radio frequency to a Radio Receiver, which may be linked to a remote-controlled aircraft.	Purchased
5	Arduino UNO	This is the main board of the system on which other basic electronic components are embedded.	Purchased

6	Propellers	The propellers originate the air draft required for lift, push and directing of the quadcopter.	Purchased
7	Frame	This is the structure on which every other component of the drone is housed.	3D printed.
8	Receiver	The receiver translates radio signals received from the transmitter into control signals (i.e. yaw, throttle, roll & pitch).	Purchased
9	MPU 6040	This serves as the systems gyroscope. It provides information as regards the tilt and spatial alignment of the drone.	Purchased

3.2 HARDWARE COMPONENTS

The design and development of the drone has integrated some hardware component which come together to produce proper flight and object detection capabilities in the drone. These hardware components each have specific functions such that when put together give the drone its features. These components include;

Battery

The serves as the power source for the drone components. This capacity is able to power all essential component of the drone system.



Figure 3.1:

Camera

The camera used for object detection in this project is the OPENMV CAMERA H7plus. The OPENMV H7plus is an embedded vision technology that is designed for computer vision application. This camera is renowned for its ability to perform object detection efficiently and accurately.



Figure 3.2

Key Features

1. **Processing Power and Speed:** The OpenMV Camera H7 Plus is equipped with a powerful microcontroller that facilitates high-speed image processing. The H7 Plus boasts a 480 MHz ARM processor, enabling quick execution of complex algorithms required for real-time object detection.

2. **Onboard Memory and Storage:** With ample RAM and flash memory, the device can store large datasets and handle extensive computational tasks. This is crucial for object detection, as it allows the camera to process substantial amounts of image data efficiently.
3. **Built-in Camera and Image Sensor:** The integrated camera and image sensor provide crisp and clear image captures essential for accurate object detection. The camera is capable of capturing high-resolution images, ensuring that the object detection algorithms have quality input for robust analysis.
4. **Wide Range of Supported Protocols:** The OpenMV Camera H7 Plus supports various communication protocols, facilitating seamless integration with other devices and systems. This enhances its versatility and adaptability in different applications.
5. **OpenMV IDE and Libraries:** The OpenMV IDE, along with a multitude of libraries, simplifies the development process for object detection applications. The IDE offers an intuitive interface for configuring the camera and testing different object detection algorithms.



Figure 3.3

Mpu6050

This is a 6axis IMU device that measures acceleration and orientation. It consists of 3-axis accelerometers and 3-axis gyroscope in a single compact module. This integration provides vital data for estimating the drone's orientation, tilt and movement.

Importance in Drone Applications

1. **Stability and Control:** The MPU6050 plays a fundamental role in stabilizing the drone during flight. The gyroscope measures the drone's angular velocity, enabling the flight controller to adjust motor speeds and control the orientation of the drone. This contributes to stable flight, essential for capturing precise aerial imagery and executing complex maneuvers.
2. **Altitude and Position Estimation:** By analyzing the accelerometer data, the MPU6050 assists in estimating the drone's altitude and position concerning the Earth's surface. This information is vital for altitude hold features and maintaining a consistent flight level, especially during hovering or altitude-specific flight patterns.
3. **In-flight Corrections**The real-time data provided by the MPU6050 enables the flight controller to make immediate corrections to the drone's flight path. This includes adjustments to pitch, roll, and yaw, allowing the drone to respond swiftly to changes in environmental conditions or user commands.

ESC



Figure 3.4:

ESCs are electronic circuits that control the speed of brushless DC motors, commonly used in drones. They regulate the rotation speed of the motors by adjusting the frequency and duration of

the electrical signals provided to them. Their pivotal role lies in translating electrical signals from the flight controller into precise motor speed adjustments, influencing the drone's stability, maneuverability, and overall performance.

Applications

1. **Motor Speed Control:** ESCs play a critical role in adjusting the rotational speed of the motors, enabling precise control over the drone's movements. This control is vital for achieving stable flight, executing maneuvers, and responding to changing flight conditions.
2. **Throttle Response and Efficiency:** ESC performance directly impacts the drone's throttle response. Efficient ESCs ensure rapid and accurate throttle adjustments, providing a smooth and responsive flight experience. Well-calibrated ESCs also contribute to optimizing the drone's power usage and improving flight efficiency.
3. **Motor Synchronization and Balancing:** ESCs facilitate synchronous motor operation, ensuring all motors work in harmony and maintain balance during flight. Proper synchronization prevents imbalances that could affect the drone's stability and flight trajectory.
4. **Dynamic Braking and Directional Control:** Advanced ESCs offer dynamic braking capabilities, allowing for rapid deceleration and directional control. This feature enhances the drone's agility and maneuverability, making it capable of quick stops and direction changes.

ARDUINO UNO



Figure 3.5:

The Arduino Uno features a microcontroller, digital and analog input/output pins, and a USB interface. The Arduino IDE (Integrated Development Environment) provides a simple and intuitive platform for programming and uploading code to the board.

Key Features

1. **Microcontroller:** Arduino Uno is powered by the ATmega328P microcontroller, offering 32KB of flash memory for storing the code, 2KB of SRAM, and 1KB of EEPROM. This microcontroller forms the brain of the board, executing the instructions provided through the programmed code.
2. **Versatile Input/Output Pins:** With 14 digital input/output pins and 6 analog input pins, Arduino Uno can interface with a wide range of sensors, actuators, and other electronic components. These pins enable communication and control, making it suitable for a multitude of applications.

Applications in Drone Technology

1. **Flight Control Systems:** Arduino Uno can serve as the flight controller. By interfacing with the MPU6050, it processes flight data and adjust motor speeds through the Electronic Speed Controllers (ESCs) to maintain stable flight.
2. **Remote Control function:** Arduino Uno is employed in the drone's remote-control system. Thus, it processes inputs from the transmitter and conveys the corresponding signals to the flight controller.
3. **Payload Control (OpenMV camera):** Arduino Uno is used to manage the drone's payload. (i.e., OpenMV camera).

3.3 WIRING DIAGRAM

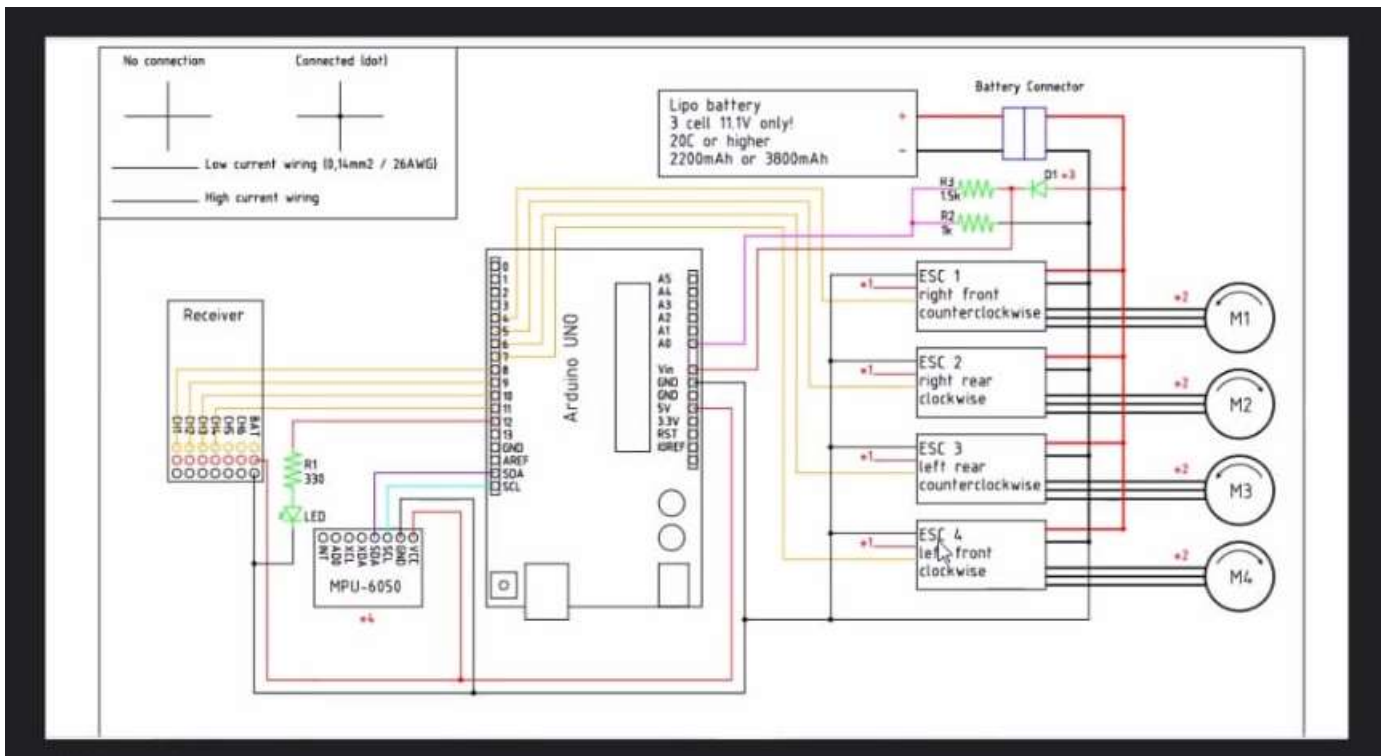


Figure 3.6:

3.4 3D PRINTING TECHNOLOGY

Introduction

3D printing technology has emerged to be a revolutionizing technology in manufacturing and design. 3D printing is also known as additive manufacturing, allows the creation of three-dimensional objects by layering selected materials based on described digital models. This innovative approach has impacted various industries, from healthcare and aerospace to automotive and consumer goods, showcasing its versatility and potential.

The fundamental principle of 3D printing involves the arrangement of material layer by layer, typically from a digital model created using computer-aided design (CAD) software. The material, often in the form of polymers, metals, ceramics, or composites, is carefully deposited or fused, gradually building up the desired object. This additive process provides exceptional precision and customization compared to traditional subtractive manufacturing techniques.

One of the significant advantages of 3D printing is its ability to easily reproduce complex geometries that would prove challenging with the use of traditional methods. This technology has made it easier to reproduce intricate internal structures, lattices, and hollow designs while optimizing materials usage and structural integrity of the reproduced structure. As a result, 3D printing is ideal in the production of lightweight, high-strength components with enhanced performance characteristics.

Furthermore, 3D printing significantly reduces waste by utilizing only the necessary amount of material for the desired object, thus, minimizing the environmental footprint of the manufacturing processes. It also offers a cost-effective solution for low-volume production, rapid prototyping, and custom manufacturing, enabling businesses to respond quickly to market demands and iterate designs efficiently.

The application spectrum of 3D printing is vast and continuously expanding. In the medical field, it has enabled the production of custom prosthetics, implants, and surgical models, revolutionizing patient care and surgical planning. Aerospace and automotive industries leverage 3D printing to create lightweight and durable components, enhancing fuel efficiency and overall performance.

3D printing technology is at the forefront of the manufacturing revolution, offering a novel approach to create intricate and customized objects with unprecedented efficiency and precision. Its potential to disrupt traditional manufacturing paradigms, drive innovation across various sectors, and empower individuals makes it a technology of immense promise and excitement for the future.

3.4.1 Overview of 3D Printing Technology

History and Evolution of 3D Printing Technology

3D printing technology, also known as additive manufacturing, has a fascinating history that traces back to the 1980s. The origins can be attributed to a patent filed by Dr. Charles W. Hull in 1986, who invented a process called stereolithography. This process used a focused UV light beam to polymerize a liquid photopolymer layer by layer, creating a solid 3D object. This invention marked the beginning of the 3D printing era.

Throughout the 1990s, various additive manufacturing technologies emerged, including selective laser sintering (SLS) and fused deposition modeling (FDM). In the early 2000s, the RepRap project, an open-source 3D printer initiative, significantly contributed to the popularization of 3D printing by making it more accessible to a wider audience.

As the technology evolved, so did its applications. Initially used for rapid prototyping, 3D printing expanded into aerospace, automotive, healthcare, consumer goods, and even food

industries. The ability to produce complex geometries and customize designs according to specific needs propelled its adoption across various sectors.

In recent years, significant advancements have been made in the speed, precision, and material diversity of 3D printing. Industrial-grade 3D printers now have the capability to produce high-quality components at a faster rate, enabling large-scale manufacturing and production of end-use parts. Additionally, innovations like bioprinting have paved the way for printing living cells and tissues, holding immense promise in the field of regenerative medicine.

Key Components and Processes of 3D Printing Technology Components:

1. **3D Printer:** The primary device that carries out the additive manufacturing process, guided by digital models and instructions.
2. **Material:** Various materials such as polymers, metals, ceramics, composites, and even biological materials are used based on the desired end-product and application.
3. **Computer-Aided Design (CAD) Software:** Essential for creating the digital model or blueprint of the object to be printed, serving as the foundation for the 3D printing process.
4. **Slicing Software:** Converts the digital model into a series of thin horizontal cross-sections (slices) that guide the printer on how to build the object layer by layer.

Processes:

1. **Layering/Additive Manufacturing:** The 3D printer reads the sliced design and adds material layer by layer to form the final 3D object. This process is additive, as opposed to traditional subtractive manufacturing methods.

2. **Heating and Fusion:** Depending on the technology, the material is heated and fused together. In processes like FDM, thermoplastic materials are melted and extruded through a nozzle onto the build platform.
3. **Cooling and Solidification:** After deposition, the material rapidly cools and solidifies, ensuring the layers bond together and maintain the desired shape and structure.
4. **Support Structure Creation and Removal:** Some 3D printing processes require temporary support structures to prevent sagging or instability during printing. These supports are removed once printing is complete.

3.5 MATERIALS USED IN 3D PRINTING

The materials used in 3D printing are diverse and constantly expanding to meet various application needs. They can be broadly categorized into several types:

1. **Polymers (Plastics):** PLA (Polylactic Acid), ABS (Acrylonitrile Butadiene Styrene), PETG (Polyethylene Terephthalate Glycol), and PVA (Polyvinyl Alcohol) are commonly used for their ease of use, versatility, and cost-effectiveness.
2. **Metals:** Aluminum, titanium, stainless steel, and cobalt-chrome alloys are utilized in metal 3D printing, often for aerospace, automotive, and medical applications due to their high strength and durability.
3. **Ceramics:** Ceramic materials like zirconia and alumina are used for applications requiring high temperature resistance, electrical insulation, and wear resistance.
4. **Composites:** Mixtures of polymers and reinforcing materials like carbon fibers, glass fibers, or Kevlar are used to enhance strength, stiffness, and other properties of the final product.

5. **Biological Materials:** In bioprinting, biological materials such as living cells, hydrogels, and bioinks are used to create tissues, organs, and other biological structures for medical research and regenerative medicine.

PLA (Polylactic Acid) as a 3D Printing Material

Polylactic Acid (PLA) used in the development of the firmware in this drone project, is a prominent and widely used thermoplastic polymer within the realm of 3D printing technology.

Characteristics of PLA

1. **Biodegradability and Sustainability:** PLA is derived from renewable resources such as corn starch or sugarcane, making it a bio-based and biodegradable thermoplastic. Its production has a lower environmental impact compared to traditional petroleum-based plastics, aligning with sustainability goals.
2. **Ease of Printing:** PLA is known for its ease of use and printability. It has a low printing temperature, typically ranging from 180°C to 220°C, which suits a wide variety of 3D printers. It exhibits minimal warping and has good adhesion to build platforms, further enhancing its ease of use.
3. **Low Odor and Minimal Toxicity:** PLA emits a sweet, sugary smell during printing, making it a more pleasant choice for users concerned about odors and potential toxic fumes. It is considered safe for home and educational environments due to its low toxicity.
4. **Wide Range of Colors and Finishes:** PLA is available in a vast array of colors and finishes, including glossy, matte, transparent, and metallic. This variety allows for creative and aesthetically appealing 3D printed models.

5. **High Detail Resolution:** PLA can achieve high levels of detail in 3D prints due to its ability to produce smooth and fine surfaces. This characteristic is particularly advantageous for intricate and detailed projects.
6. **Rigidity and Strength:** While PLA is generally stiffer and more brittle compared to some other 3D printing materials like ABS, it still offers sufficient strength for a wide range of applications. It is suitable for prototyping, display models, and functional parts that do not undergo heavy stress or load.

Benefits of PLA in 3D Printing

1. **Beginner-Friendly:** PLA is often recommended for beginners due to its ease of use, forgiving nature, and minimal printing challenges. It does not require a heated bed (though it can benefit from one) and has a low likelihood of warping during printing.
2. **Fast Printing Speeds:** PLA can be printed at faster speeds compared to some other materials, which reduces overall printing time, making it an efficient choice for quick prototyping and iterative design processes.
3. **Post-Processing Versatility:** PLA is easily post-processed, allowing for sanding, painting, or other finishing techniques to achieve desired aesthetics and surface quality for the final print.
4. **Low Environmental Impact:** The use of PLA supports sustainability efforts due to its biodegradable nature and renewable source. It contributes to a reduced carbon footprint in the 3D printing industry.

Applications of PLA

1. **Prototyping and Models:** PLA is extensively used for rapid prototyping, creating functional prototypes, and producing intricate models for visualization purposes. Its high detail resolution makes it ideal for this application.
2. **Educational Purposes:** Due to its safety, ease of use, and availability in various colors, PLA is commonly used in educational settings to introduce students to 3D printing technology and concepts.
3. **Consumer Products:** PLA is employed in the production of a wide range of consumer goods, including phone cases, toys, home décor, and kitchenware due to its versatility, aesthetic appeal, and safety.
4. **Artistic and Creative Projects:** Artists and creators utilize PLA to bring their artistic designs to life, leveraging the variety of colors and finishes to enhance the visual appeal of their projects.

Considerations and Limitations

1. **Low Heat Resistance:** PLA has a lower heat resistance compared to some other 3D printing materials, limiting its usability in applications exposed to high temperatures.
2. **Brittleness:** Its brittleness can be a limitation in applications that require parts to be highly impact-resistant or flexible.
3. **Hygroscopic Nature:** PLA has a tendency to absorb moisture from the air, affecting its print quality. Proper storage in a dry environment is crucial to maintain its optimal properties.

Polylactic Acid (PLA) is a versatile and popular 3D printing material renowned for its ease of use, environmental sustainability, and wide range of applications. Its attributes make it an excellent choice for both beginners and experienced users, supporting various creative and

functional endeavors within the 3D printing community. Understanding the characteristics, benefits, applications, and considerations associated with PLA empowers users to utilize this material effectively in their projects, contributing to the advancement of additive manufacturing technologies.

Applications of 3D Printing in Drone Manufacturing

3D printing, also known as additive manufacturing, has emerged as a transformative technology with a profound impact on various industries. One industry that has significantly benefited from 3D printing is drone manufacturing. Drones, or unmanned aerial vehicles (UAVs), have rapidly evolved in terms of design, functionality, and application, and 3D printing has played a pivotal role in this evolution. This note explores the diverse applications of 3D printing in drone manufacturing, ranging from design and prototyping to custom components and advanced materials.

1. **Rapid Prototyping and Iterative Design:** 3D printing enables rapid prototyping, allowing drone manufacturers to quickly iterate designs and test various configurations. Traditional prototyping methods can be time-consuming and costly, but with 3D printing, designers can swiftly produce scaled-down drone models to validate designs, make necessary adjustments, and optimize performance.
2. **Customization and Complexity:** One of the most significant advantages of 3D printing in drone manufacturing is the ability to create highly customized and complex components. Drones can be tailored for specific applications, whether it's for surveying, agriculture, search and rescue, or surveillance. 3D printing facilitates the production of intricate geometries, lightweight structures, and unique designs that would be challenging or impossible to achieve with traditional manufacturing techniques.

3. **Reduced Weight and Improved Efficiency:** By utilizing 3D printing, drone manufacturers can design and produce components with optimized geometries, reducing unnecessary material and, consequently, the overall weight of the drone. Lightweight drones achieve improved efficiency, longer flight times, and enhanced maneuverability, crucial factors in the performance and success of UAVs across various applications.
4. **Integration of Functional Features:** 3D printing allows for the integration of functional features directly into the drone components during the manufacturing process. This includes features such as mounting brackets, enclosures, and channels for wiring and cooling systems. Such integration streamlines the assembly process and enhances the structural integrity of the drone.
5. **Aerodynamic Design Optimization:** Designing for aerodynamic efficiency is paramount in drone manufacturing, and 3D printing aids in achieving optimal aerodynamic designs. Manufacturers can rapidly test and modify prototypes to minimize drag, optimize lift, and improve overall flight performance. This iterative process helps in fine-tuning the drone's design for maximum efficiency.
6. **Material Variety and Specialty Polymers:** 3D printing offers a wide range of materials suitable for drone manufacturing, including lightweight polymers, composites, and even metals. Advanced polymers like carbon fiber-reinforced plastics provide high strength-to-weight ratios, enhancing the structural integrity of critical components such as frames and propellers. This variety of materials allows for material selection based on specific application needs.
7. **On-Demand Spare Parts and Repairs:** 3D printing facilitates the on-demand production of spare parts for drones. In case of damage or component failure, manufacturers and operators

can quickly print replacements, reducing downtime and maintenance costs. This capability is particularly valuable for remote operations or critical missions where swift repairs are essential.

8. **Education and Research:** 3D printing in drone manufacturing plays a significant role in education and research. It provides students and researchers with hands-on experience in designing, prototyping, and testing drone components. Additionally, it supports experimentation and innovation, contributing to the advancement of drone technology.

The applications of 3D printing in drone manufacturing are extensive and transformative. This innovative technology enables rapid prototyping, customization, lightweight design, aerodynamic optimization, material diversity, and efficient spare part production. The integration of 3D printing in drone manufacturing not only accelerates the development process but also drives innovation, leading to drones that are more efficient, versatile, and tailored to specific applications. As 3D printing continues to advance, its role in revolutionizing drone technology is expected to expand, further enhancing the capabilities and applications of drones across various industries.

Printing a Drone's Framework with PLA

Unmanned aerial vehicles (UAVs), commonly known as drones, have gained immense popularity due to their versatility and wide-ranging applications. The advent of 3D printing technology has significantly impacted drone manufacturing, enabling the creation of custom drone frameworks with materials like Polylactic Acid (PLA). This note explores the design considerations, benefits, and challenges associated with using PLA for printing a drone's framework.

Design Considerations for Drone Framework

- 1. Weight Optimization:** Designing the drone's framework with PLA requires careful consideration of weight distribution and overall weight. PLA is relatively lightweight, making it suitable for drone applications where weight plays a crucial role in flight efficiency and stability.
- 2. Structural Integrity:** The design should ensure structural integrity to withstand the stresses and forces experienced during flight. Reinforced sections and appropriate ribbing can enhance the framework's strength and durability.
- 3. Aerodynamics:** Streamlined and aerodynamic designs are essential to reduce air resistance and improve the drone's efficiency in flight. The framework should be designed to minimize drag and optimize lift for enhanced performance.
- 4. Component Integration:** The design should facilitate seamless integration of electronic components, motors, propellers, and other necessary hardware within the framework. Mounting points and secure housing should be incorporated into the design for a neat and efficient arrangement.
- 5. Assembly and Disassembly:** Designs that allow for easy assembly and disassembly are beneficial for maintenance and upgrades. Using PLA with appropriate design features can enable snap-fit connections or modular components for straightforward assembly.
- 6. Balance and Center of Gravity:** Balancing the drone and placing the center of gravity in the appropriate location is crucial for stable flight. Designing the framework to accommodate batteries, cameras, and other components while maintaining balance is essential.

Benefits and Challenges of Using PLA for Drone Framework

Benefits:

- 1. Lightweight:** PLA is known for its lightweight nature, making it an ideal material for the drone framework. Reduced weight contributes to increased flight duration and better maneuverability.
- 2. Ease of Printing:** PLA's low printing temperature and minimal warping make it easy to print on a wide range of 3D printers. Its forgiving nature is advantageous, especially for those new to 3D printing.
- 3. Cost-Effective:** PLA is a cost-effective material, making it accessible for hobbyists, enthusiasts, and small-scale drone manufacturers. It allows for experimenting with designs without incurring substantial costs.
- 4. Customization and Iteration:** 3D printing with PLA allows for easy customization and rapid iteration of designs. Design modifications can be quickly implemented and tested, accelerating the development and optimization of the drone's framework.
- 5. Aesthetic Appeal:** PLA comes in a wide variety of colors, providing opportunities for aesthetically pleasing drone designs. The finished framework can have a polished and professional appearance.

Challenges:

- 1. Limited Heat Resistance:** One of the primary challenges of using PLA for drone frameworks is its limited heat resistance. PLA can soften and deform at relatively low temperatures, making it unsuitable for drones operating in high-temperature environments.

2. **Brittleness:** PLA is relatively brittle compared to some other 3D printing materials. This brittleness may pose a challenge in applications where the framework is subject to high impact or stress.
3. **Material Strength:** While PLA has adequate strength for many drone applications, it may not be as strong as materials like ABS or nylon. Design modifications and reinforcement may be necessary to enhance strength in critical areas.
4. **Moisture Absorption:** PLA has a tendency to absorb moisture from the environment, affecting its properties and print quality. Proper storage and handling to mitigate moisture absorption are important considerations.

Using PLA for 3D printing a drone's framework offers several benefits, including lightweight construction, ease of printing, cost-effectiveness, customization, and aesthetic appeal. However, considerations regarding its limited heat resistance, brittleness, and moisture absorption are essential during the design and implementation process. By carefully addressing these design considerations and challenges, PLA can be an excellent choice for creating efficient and customized drone frameworks, contributing to the advancement of drone technology.

3.6 Conceptual Design

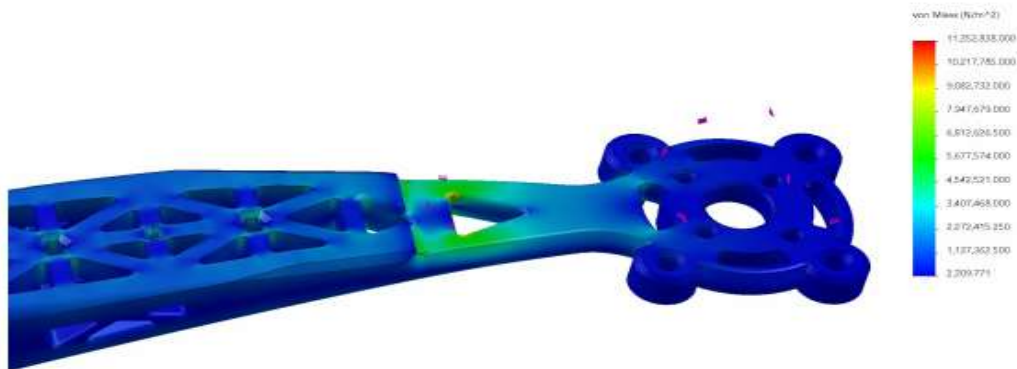
Structural analysis of firmware component

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Study name: Static 1(-Default-)
Plot type: Static strain Strain1
Deformation scale: 13,148.9



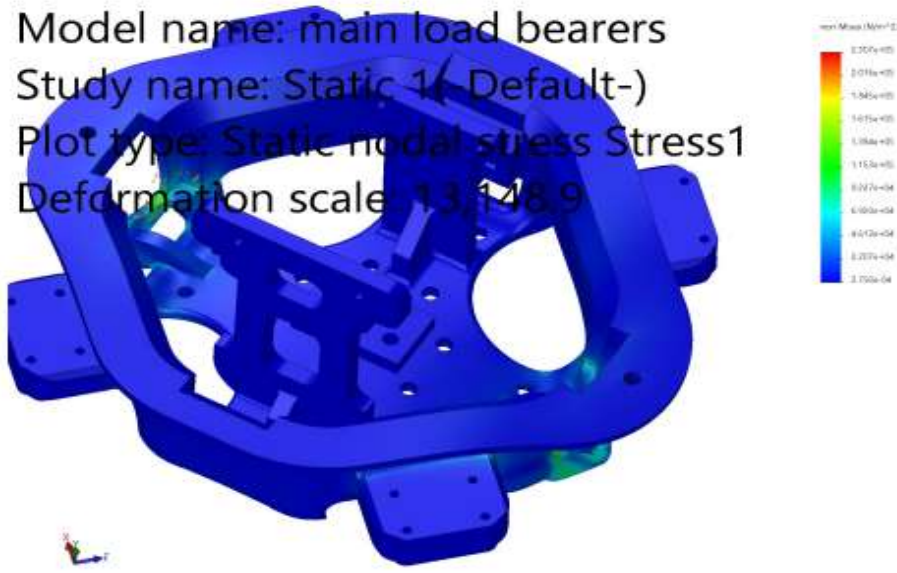
Figure 1 strain analysis of drone arm

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Plot type: Static nodal stress Stress1
Deformation scale: 11.5075



stress analysis of drone arm 1

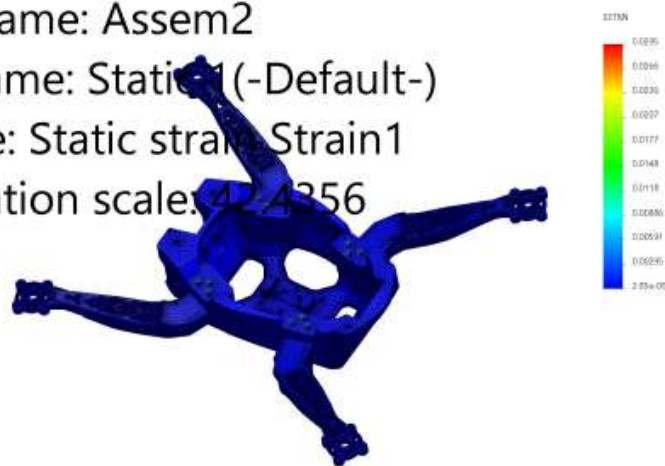
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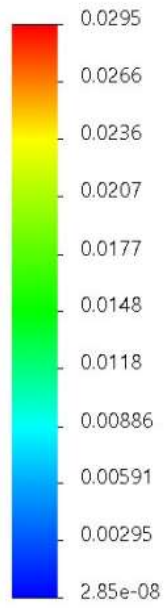
stress analysis of drone hub 1

*strain analysis of drone **hub** 1*

Model name: Assem2
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ESTRN

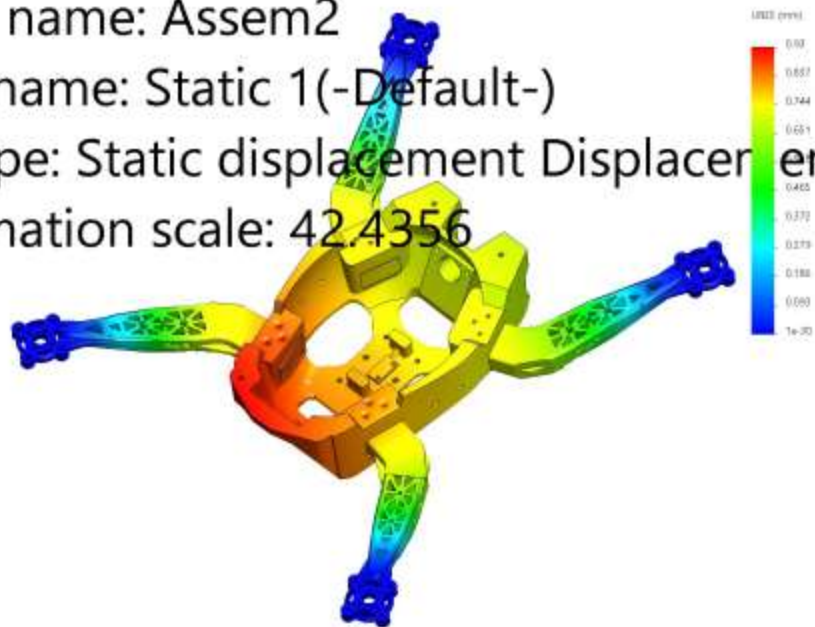


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Study name: Static 1(-Default-)

Plot type: Static displacement Displacement1

Deformation scale: 42.4356

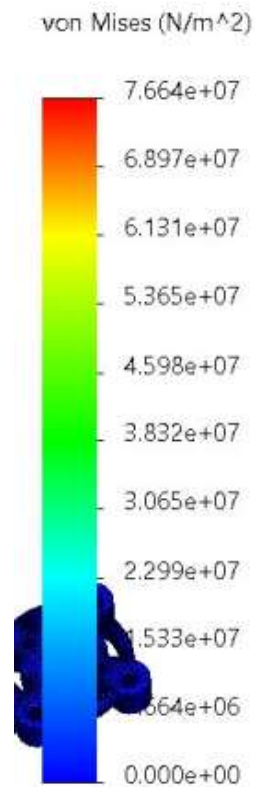
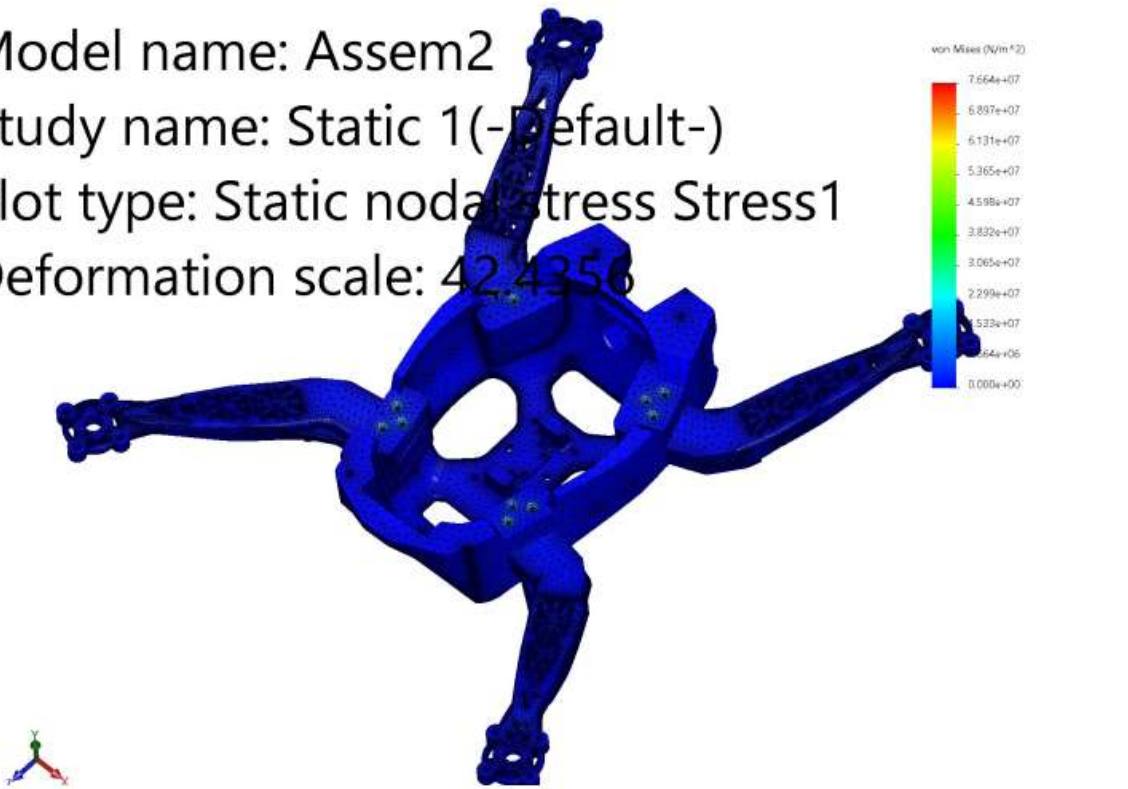


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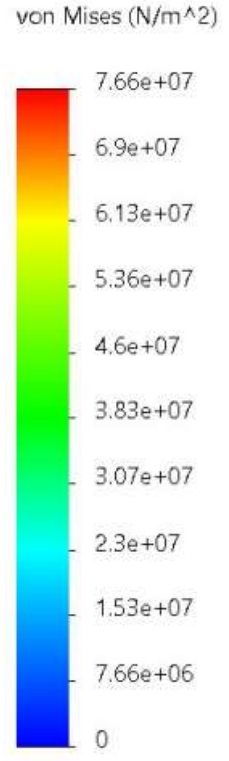
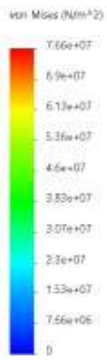
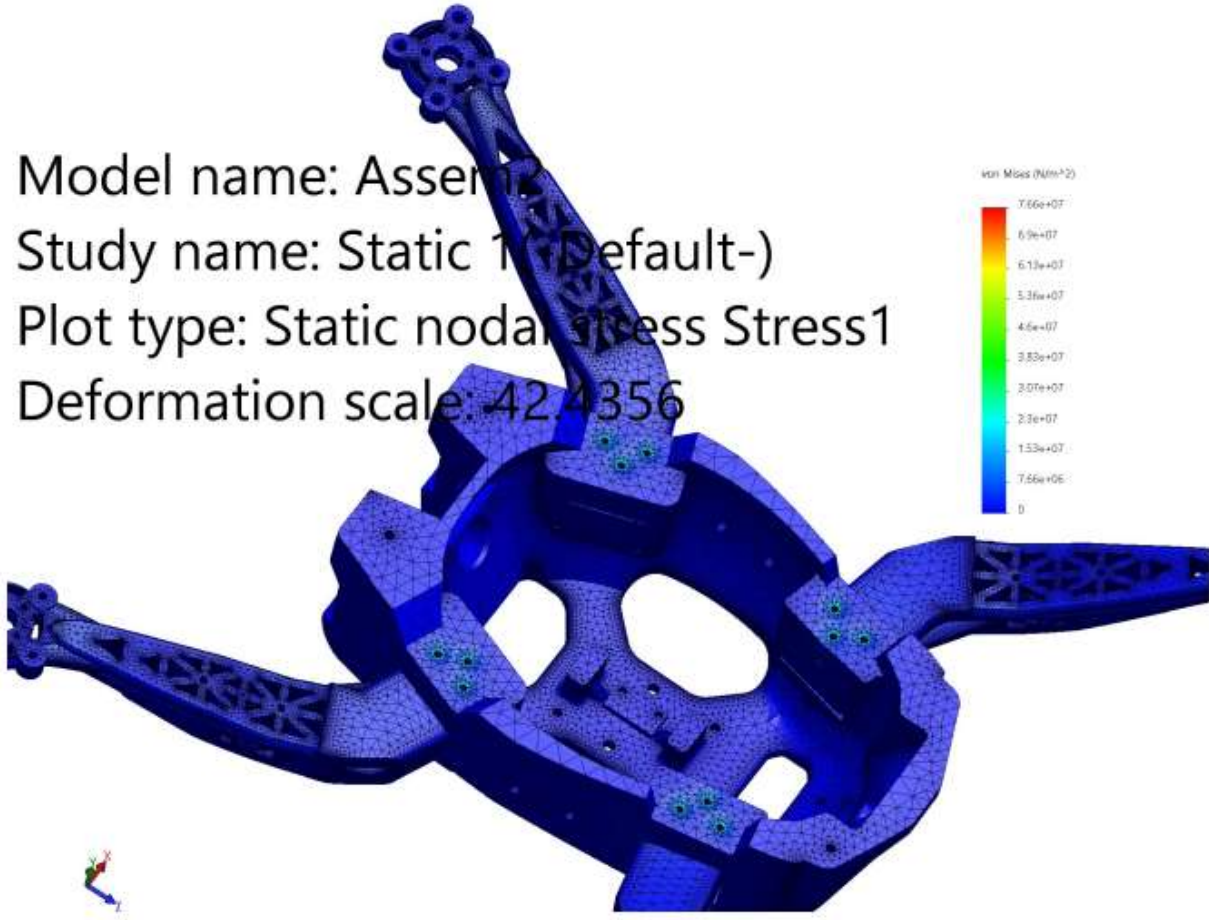


en

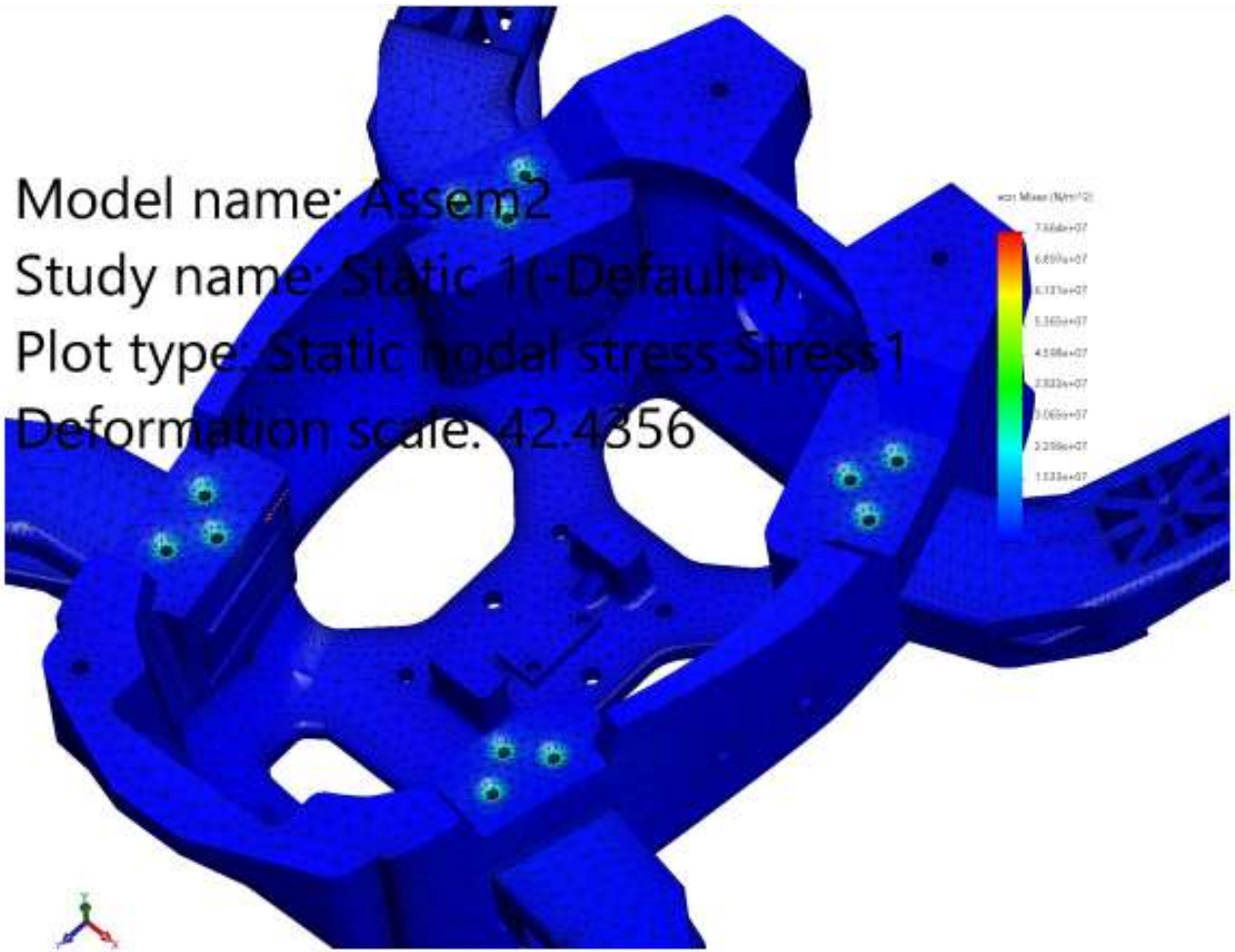
Model name: Assem2
Study name: Static 1(-Default-)
Plot type: Static nodal stress Stress1
Deformation scale: 42.4356



Model name: Assen12
Study name: Static 1 (Default-)
Plot type: Static nodal stress Stress1
Deformation scale: 42.4356



Model name: Assem2
Study name: Static 1(-Default-)
Plot type: Static nodal stress Stress1
Deformation scale: 42.4356

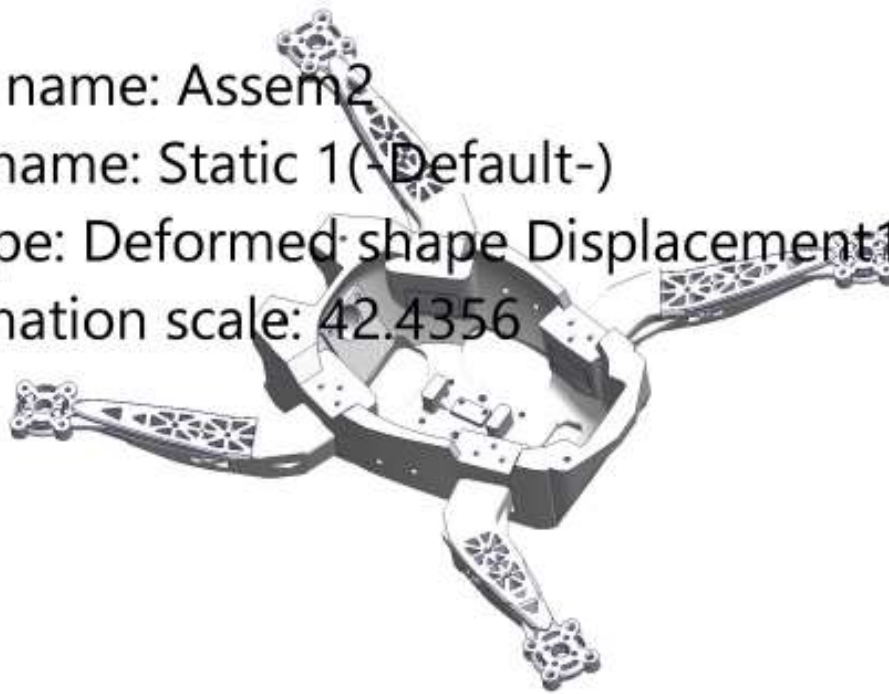


Model name: Assem2

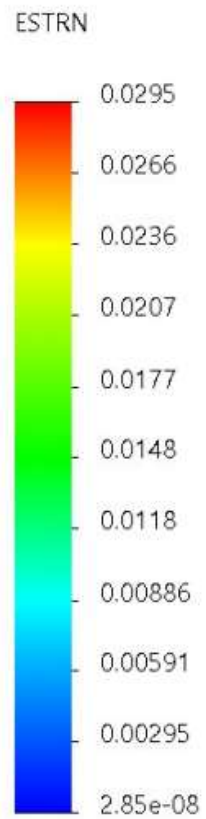
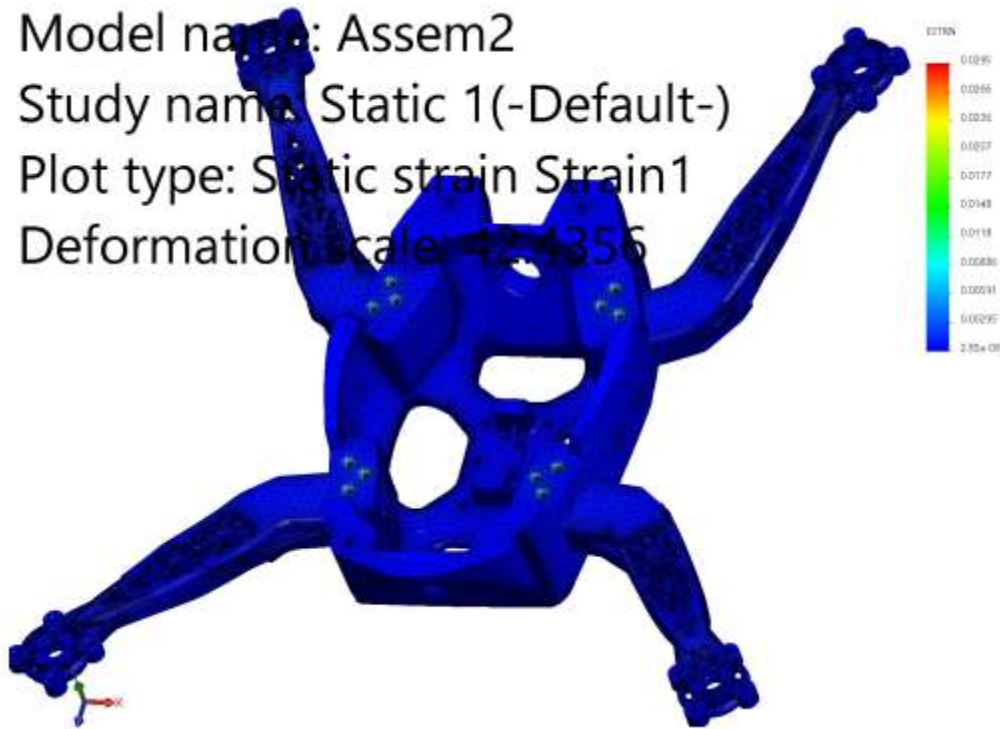
Study name: Static 1 (-Default-)

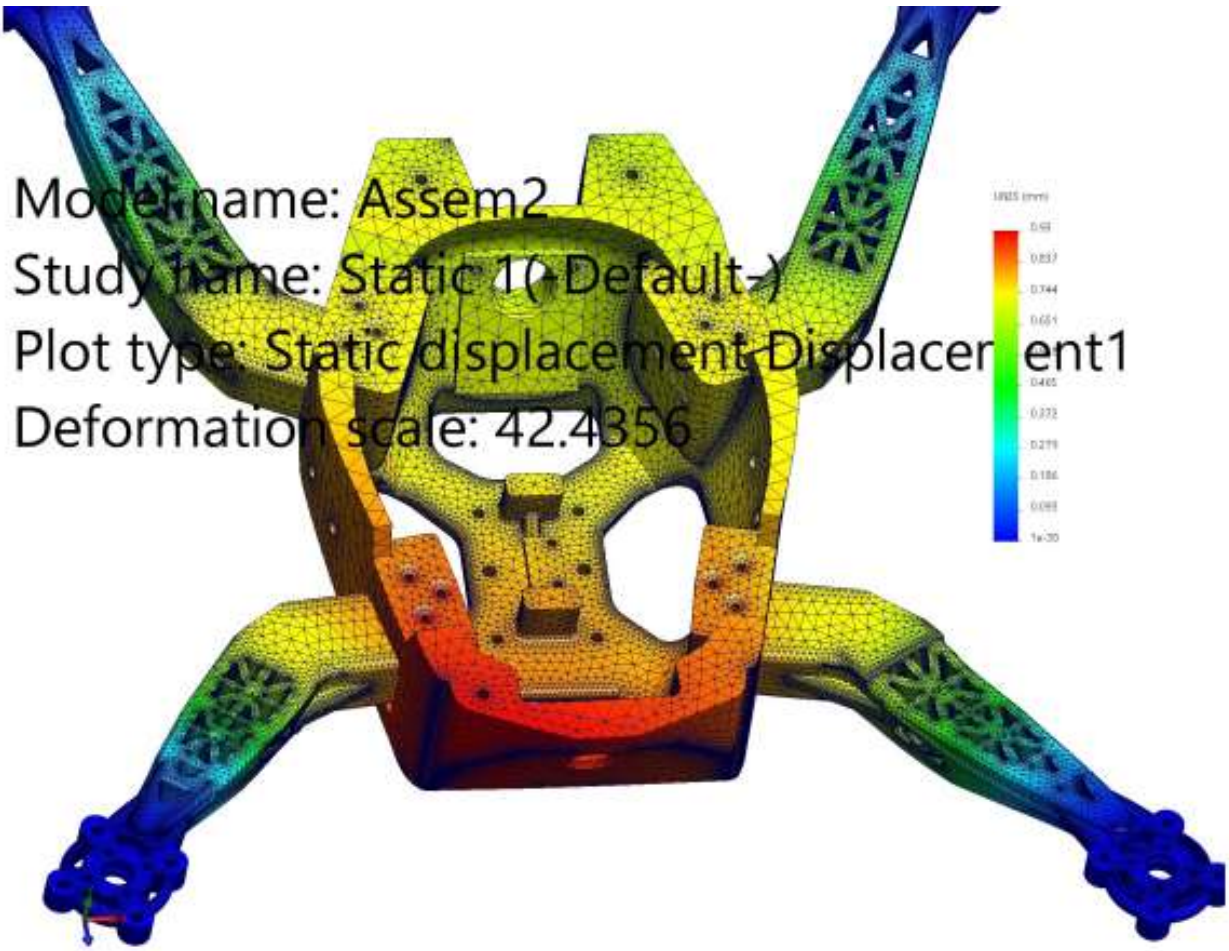
Plot type: Deformed shape Displacement1{1}

Deformation scale: 42.4356



Model name: Assem2
Study name: Static 1(-Default-)
Plot type: Static strain Strain1
Deformation scale: 42.4356



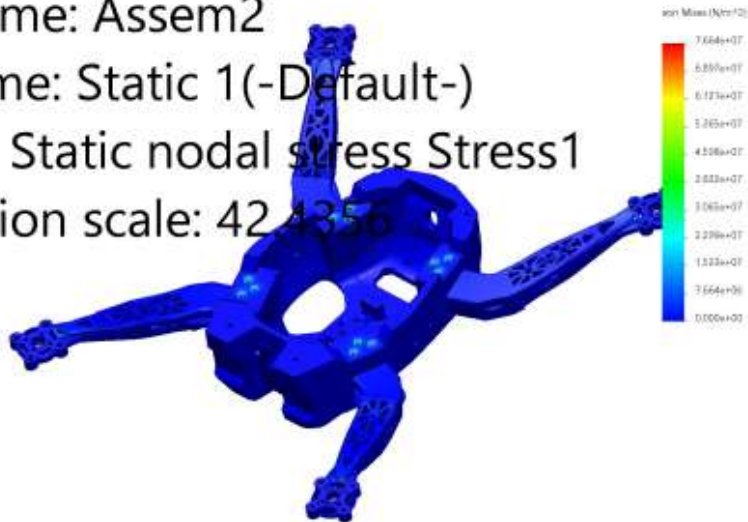


Model name: Assem2

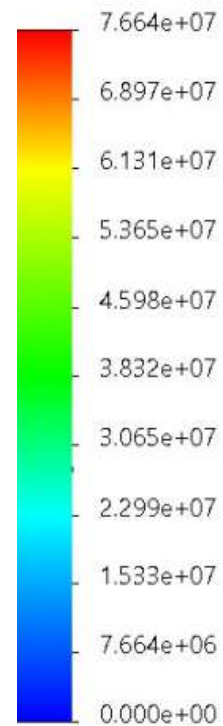
Study name: Static 1(-Default-)

Plot type: Static nodal stress Stress1

Deformation scale: 42.4356



von Mises (N/m²)



3.7 OBJECT DETECTION METHODOLOGY

The concept of objection detection refers to the ability of the drone to identify already specified parameters present in the algorithm. With the use of the OpenMV camera which has an inbuilt microcontroller, we were able to define these identifiable parameters using PHYTON programming language on the OpenMV IDE.

The algorithm that gives this drone its object detection capacity is displayed below. However, it remains important to explain what is expected of this algorithm; the HQVGA and GRAYSCALE libraries are the best for the purpose of face detection. When the conditions on the HQVGA and GRAYSCALE are met this triggers a signal voltage which powers up a beacon and alarm system. This is observed by the audible beep sound accompanied with the physical LED signal on the drone.

Object Detection Code On The Openmv Camera

```
Import sensor, time, image

Import pyb

From pyb import Pin

# Reset sensor

Sensor.reset()

# Sensor settings

Sensor.set_contrast(3)

Sensor.set_gainceiling(16)

# HQVGA and GRAYSCALE are the best for face tracking.

Sensor.set_framesize(sensor.HQVGA)

Sensor.set_pixformat(sensor.GRAYSCALE)
```

```

# Load Haar Cascade

# By default, this will use all stages. Lower stages are faster but less accurate.

Face_cascade = image.HaarCascade("frontalface", stages=25)

Print(face_cascade)

# LED pin

Led = pyb.Pin('P1', Pin.OUT_PP) # Assuming LED is connected to GPIO pin 1

# FPS clock

Clock = time.clock()

While (True):

    Clock.tick()

    # Capture snapshot

    Img = sensor.snapshot()

    # Find objects.

    # Note: Lower scale factor scales-down the image more and detects smaller objects.

    # Higher threshold results in a higher detection rate, with more false positives.

    Objects = img.find_features(face_cascade, threshold=1.75, scale_factor=1.25)

    # Draw objects

    For r in objects:

        Img.draw_rectangle®

    # Check if a face is detected

    If objects:

```

Led.high() # Turn on the LED

Else:

Led.low() # Turn off the LED

Print FPS.

Note: Actual FPS is higher. Streaming the FB makes it slower.

Print(clock.fps())

3.8 BEME (BILL OF MATERIALS)

Table 3.2: BEME (Bill of Materials)

S/N	Component	Materials	Specifications	Quantity	Unit	Total
					cost	cost
					(₦)	(₦)
1	FRAME WORK	PLA (polylactic acid)				150,000
2	brushless motors	dc copper	2200 Kv	4	6,000	24,000
3	Openmv camera					
4	Mpu6040	Semi-conductor		1	15,000	15,000
5	Electronic speed	Semi-conductor	4 amps	4	9,600	38,400

	controllers (ESC)					
6	lipol battery		11.1V	1	36,000	36,000
7	Power distribution board			1	2,000	2,000
8	Epoxy And hardener			1	20,000	20,000
9	Jumper cables connectors			6 pairs	1,000	6,000
10	Battery for receiver			1	4,000	4,000
11	flysky i6x			1	50,000	50,000
12	Propeller 9450			9	4,000	36,000
13	extra BLDC motor			1	7,500	7,500
14	Battery charger			2	4,800	9,300
15	Extra Arduino			1	12,000	12,000

Total 3.3: Cost of Quadcopter

Serial	Description	Amount (₺)
1.	Materials	409,900
2.	Miscellaneous expenses	21,000
3.	Total	430,900

CHAPTER FOUR

RESULTS AND DISCUSION

In the evet of this drone's development, we were able to achieve flight after a series of tests with which we documented and labelled flight test 1-3.

4.1 FLIGHT TEST

Stability Test (Flight Test 1)

The stability test was the very first flight test that was carried out on this project. the aim of this test was to check the ability of this drone to maintain a steady posture during fight and while landing. the success of this test meant the MPU6050(gyroscope) was functioning effectively and programmed correctly.



Figure 4.1

Flight Test 2

During the second flight test, we were able to fly the drone about 70m high. However, we lost directional control of the drone as we were unable to indicate the forward and backward facing directions of the drone while it was in midair.



Figure 4.2

This led to the very first crash of the drone. We sustained a damaged arm, damaged propellers and ESC. We then began brainstorming on the cause of our failed flight test from which we discovered the need for an obvious indication of the forward and backward direction of the drone even while in midair.

Solution; we began building a new arm and gave different colorations to the forward-facing arms and the backward facing arms. This served as the obvious indication which would be needed to successfully navigate the drone in midair.

Flight Test 3

During the third flight test we achieved a positive response from the drone. The drone displayed proper stability and proper flight. However, the drone crashed due to inadequacy of

navigation skills. This led to a crash-land. We sustained damage of vital hardware and bodywork. This raised a new challenge as navigation skills have to be built upon series of trial and error.

Solution; we began building a new body that will be able to sustain multiple crashes. We designed the new frame ware and made modifications that will prevent damage of vital hardware and frame ware. In flight control (particularly unmanned vehicles), knowing the orientation of the drone is important for correct navigation. This difficulty in telling the direction of the drone resulted in the crash of the X-shaped design in flight test(ii). What we referred to as the Blue-Bettle(B-B). This new design took into consideration the need for easy identification of flight direction at any time during flight.



Figure 4.3

CHAPTER FIVE

CONCLUSION AND RECOMMENDATION

5.1 CONCLUSION

This project incorporates the development of an object detection drone. During the course of this project, we faced challenges such as design, material sourcing and code development. The HUB (Bodywork) of the drone was developed with the use of 3D printing technology and the material used to build the framework was PLA (Poly Lactic Acid). The flight controller used to link the different components of this drone together was the Arduino-Uno.

An unmanned object detection system plays an essential role in the advancement of technology, as it can be applied in various sectors and in diverse situations. For example, in agriculture the object detection drone can be designed to identify specific parameters as data which can be processed to give information about the soil, parasites...etc. without the need for human intervention. In public safety, object detection drones can be developed to identify threats such as alien military infiltration, natural disasters...etc. moreover, these drones can have access to hazardous places and situations, thus, preventing the need for human presence in these environments.

The object detection drone is a technology that will revolutionize data collection as this technology will be more efficient and cost less. Furthermore, this technology can report observed data in real time and can provide real time information without the need for human presence.

During the course of this project, we changed our model's design after the third flight test. This was to provide better strength to the protective framework. After series of research, we were able to develop an algorithm that gives the drone a basic object detection capability. The essential Hardware components were purchased and the framework was 3D printed. Proper flight was

achieved after a series of failure, one of which stemmed from our inability to properly pilot the UAV system. The propellers were purchased rather than built with 3D printing technology. This is because, it is critical to have equivalent weight on all four arms of the quadcopter.

The gyroscope present in this system is the MPU6040. This is a subsystem that prevents tilt and enables proper balance in mid-air. The MPU6040 is a 6axis IMU device that measures acceleration and orientation. It consists of 3-axis accelerometers and 3-axis gyroscope in a single compact module. This integration provides vital data for estimating the drone's orientation, tilt and movement.

5.2 RECOMENDATION

With respect to the present research and exposure to this technology, we present the following recommendations:

1. The present research is a promising one which can be extended with the use of more sophisticated and refined system.
2. Extended research can be carried out on varieties of materials beyond what is considered in this research with the aim to achieve durability and versatility of use.
3. Extended research should be carried out on the algorithm which gives the drone object detection capabilities with the aim of refining it for various applications
4. Sectors such as agriculture, urban planning, research facilities, military...etc. should invest in/ employ the use of this technology
5. more research should be done on detection and recognition software as this could be helpful in other aspects of life, not restricted to aviation alone. Identification software could be integrated to; ATMs for identification of currency denomination and counterfeits, Farm drones for detection of malnutrition or disease spread etc.

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