Experimental Validation of Load Attitude Estimation Using Computer Vision and IMU-Based Approaches for Slung-Load Aerial Robots

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Abstract: With the rise of the drone industry, there has been a surge in demand for its applications. One such critical application is using drones to transport suspended cargo, which requires minimal swing of the load. To achieve this, designing a robust control strategy plays a vital role. Such systems while in operation have critical issue of maintaining stability due to the interacting multi-body dynamics. Furthermore, a quadrotor with a slung load showcases coupled underactuated dynamics that complicates the control design problem. To effectively execute control implementation for such systems accurate feedback of load attitude becomes essential. For that matter, this study proposes two different approaches to determine the load attitude, namely, the computer vision (CV) based method using ArUco markers and the inertial measurement unit (IMU) based approach. The study investigates the real-time feasibility of these approaches through their response frequencies and tracking accuracies by comparing the experimental plots with their simulation counterpart, considering that as an ideal scenario. We also provide the implementation algorithms for both the methods proposed here. Finally, we conclude the findings by throwing light on their suitability to various slung load scenarios with variable swing angle ranges, also dwelling into the steady state behaviour comparisons in both the cases.

1 INTRODUCTION

Unmanned Aerial Vehicles (UAVs) are autonomously operating aircrafts, which has found numerous applications over the years. Amongst those, the load transportation using UAVs have increasingly attracted the attention of the researchers over the last decades. For aerial load transfer, from their initial application in the military, the usages have expanded to serve various purposes, for instance, as a last mile delivery solution (Garg et al., 2023) enabling socio-economic growth and for the humanitarian purposes as in (Mugala et al., 2020), etc. Drones come in various configurations and geometry, among which one is the quadrotor, which is widely used due to its simple geometry. It is a rigid body with six degrees of freedom (DOF), three translational and three rotational but having only four independent inputs (Palunko et al., 2012). This makes it an underactuated system with complex coupled dynamics. With the inclusion of a suspended load on a taut string underneath the quadrotor, there is an increase in the number of uncontrolled degrees of freedom due to the load swing (Zúniga et al., 2018). These include two angles in the 3-D space of the load on a taut string, which define the load attitude. To control the swing of the suspended load, there is a need for an effective feedback mechanism measuring the load attitude, which can be used to control its behavior. An effective feedback mechanism consists of one that can provide accurate data points in real-time or at a very high frequency. These points become important benchmarks of testing before a mechanism is deemed appropriate for the application.

There is a close connection between the motion of the UAV and the swing of the load because the slung

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weight naturally alters the quadrotor's center of mass and applies time-varying torques. As a result, the load swing causes oscillatory forces that might destabilize the UAV and significantly disrupt its flight. Numerous studies quantify the adverse effects of payload swing, which researchers constantly find has a severe impact on stability. For instance, to demonstrate that only the feedback-aware law can actively attenuate swing, (de Angelis and Giulietti, 2023) contrasts two distinct control laws: one that explicitly accounts for swing-angle feedback and another that does not. Uncontrolled swinging can result in significant transients and even crashes. The payload may experience severe degradation by collisions or induced vibrations, which may result in an unstable application with delicate contents (e.g., liquids) if uncontrolled, as in (Guerrero-Sánchez et al., 2017). Consequently, stability and payload safety are severely compromised if swing is disregarded. Thus, for safe, steady, and effective quadrotor operations, the swing angle feedback of a suspended load is essential.

In the literature, a few studies ((Palunko et al., 2012), (Prajapati et al., 2022)) are report that calculate the swing angle for control design in a slung load scenario. However, the emphasis on accurate load attitude feedback during implementation was not addressed. In (Lee and Kim, 2017), the authors have calculated the swing angle from the estimated force components and IMU. A method for estimating angle using visual algorithms and the difference in sky-infrared emissivity, the ability of a surface to emit infrared radiation, through an infrared camera has been proposed in (Deng et al., 2024). In (Huang et al., 2022), the authors proposed a method to measure swing angle using the minimum area circular method along with the Mean Shift (MS) algorithm. In (Tang et al., 2018), the authors suggested payload state estimation with a downward-facing camera and an Extended Kalman Filter (EKF). For the quadrotor with a slung load system, in order to estimate cable attitude, a Cable Attitude Measurement (CAM) device that functions similarly to a joystick was created in (Prajapati et al., 2022). Despite these advancements, there remains a gap of the study of load attitude feedback mechanisms, particularly from the perspective of a quadrotor with slung load systems.

1.1 Contributions

In this paper, a comparative study is presented to evaluate the load attitude feedback performance of two mechanisms, one CV-based and the other IMU-based, tested under identical experimental conditions for slung-load systems with simplified planar assumptions. The CV-based approach makes use of monocular vision and geometric principles, while the IMU-based approach relies on accelerometer readings. The performance, advantages, and limitations of both mechanisms are analyzed to aid in the experimental validation of slung load dynamics control. Both systems consist of components that are straightforward to integrate with the experimental platform, allowing them to be deployed easily in either indoor or outdoor scenarios. Owing to their computational simplicity and minimal hardware requirements, they do not interfere with the primary drone operations during experimentation. As such, they are well-suited as feedback mechanisms for use in an already complex experimental setup. The proposed CV algorithm was implemented on a single-board computer paired with a webcam, with an ArUco marker employed to estimate the pose of the load. Experimental validation involved plotting the measured angles and comparing them with those obtained from real-time video processing. For inertial sensing, an IMU sensor was used to capture the load's attitude. The validation was carried out on a planar setup as described in Section 3.

2 PROBLEM SETUP

The quadrotor with a slung load is an underactuated system (Thakar et al., 2014), characterized by having fewer control inputs than degrees of freedom, which introduces significant challenges in stabilizing the load's swing. In the context of a quadrotor with suspended loads, the underactuated nature arises from the complex coupling between the quadrotor motion and the load's dynamics, leading to oscillatory behavior that complicates control. To validate the proposed methods, we use a simple planar setup explained in detail in Section 3. The planar assumption simplifies the system to a 2D model, focusing on the swing angle α only in a vertical plane.

2.1 CV-Based Method

In this approach, we use a standard artificial geometric pattern fiducial marker, namely ArUco, to accurately and efficiently measure the load attitude. ArUco markers (Garrido-Jurado et al., 2014) are 2D square fiducial markers. Each marker encodes a unique ID using the white and black square pattern. At the detection end, a dictionary of unique identification numbers, which are encoded into the markers, is stored. As a marker is detected in the camera frame, its unique ID is decoded, and the marker is identified. Based on the dimensions of the square patterns, orientation, and position of the marker in the field of view of a calibrated camera, we can derive the exact orientation and position of the marker in the image frame. This information can be utilized to calculate load attitude. To get accurate results from this method, the camera needs to be calibrated properly. The detailed load attitude estimation algorithm using this method is articulated in Section 3.

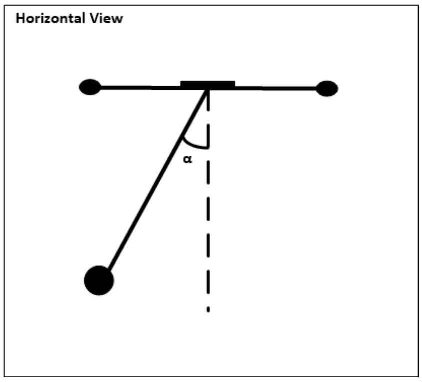

Figure 1: In-plane (vertical) swing angle, α.

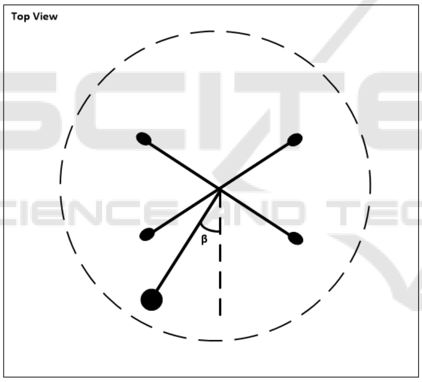

Figure 2: Out-of-the-plane swing angle, β.

Figures 1 and 2 illustrate the in-plane angle, α seen in the vertical plane in 2D motion of the drone and β-represents the out-of-the-plane swing angle.

2.2 IMU-Based Method

In this approach, we use a Micro-Electro-Mechanical System (MEMS) based IMU to determine the load attitude, specifically the planar angle α in 2D. While many control systems estimate load attitude indirectly using the carrier platform's IMU and dynamic models (Nguyen and Caverly, 2021), recent studies have explored the direct measurement of suspended load attitude using dedicated IMUs mounted on the payload. For instance, (Gao et al., 2014) developed a wireless dual-IMU system to monitor swing angles in crane operations with 0.6° (max 2°) accuracy. Thus, these approaches demonstrate that compact, low-power IMUs can reliably capture the 3-DOF orientation of suspended loads in dynamic environments. Following this, we propose the IMU-based load attitude determination method for the suspended load on a quadrotor system.

3 LOAD ATTITUDE ESTIMATION AND EXPERIMENTAL VALIDATION

The methods in this study are experimentally validated based on a simple pendulum apparatus, which emulates the behavior of the suspended load on the quadrotor using a fixed-length, rigid string.

The experiment has been conducted for two methods, namely, the CV-based method and IMU-based method for the simple pendulum-like test setup as displayed in Figure 3.

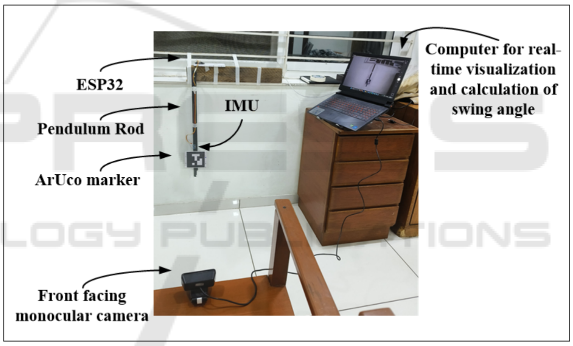

Figure 3: Experimental setup for load attitude measurement combining both - CV-based and IMU-based methods.

3.1 CV-Based Load Attitude Estimation and Setup

The experimental setup of this method consists of a Fingers $1080p$ webcam. It was connected to a computer to capture the real-time video feed. For the image processing OpenCV in Python was used. Initially, the camera was calibrated using the checkered board calibration technique, and the respective camera matrix and distortion coefficients were derived (Bradski and Kaehler, 2000). An ArUco marker of UID 7 of the 5×5 ArUco Dictionary was used as a load marker. The frame rate was set at 60 fps along with an image resolution of $1280 \times 720p$. The distance between the camera and the marker is set to 80 cm. The marker is positioned at various points, and the angles resulting from the algorithm developed are retrieved. The step-by-step method articulating the CV-based load attitude estimation is shown in the form of Algorithm 1.

The CV-based method uses a monocular camera to capture images of the ArUco marker attached to the load. The marker's corners are detected, and their 2D image coordinates are mapped to 3D world coordinates using the camera's intrinsic and extrinsic parameters, obtained through calibration. The pose estimation is performed, which computes the marker's rotation and translation vectors relative to the camera. These vectors are then used to calculate the pitch, roll and yaw angles of the load, as well as the distance of the ArUco marker from the camera. The algorithm is computationally efficient and suitable for real-time applications, provided the marker remains in the camera's field of view and under adequate lighting conditions.

```
Data: Camera frame, ArUco dictionary,
      Camera calibration parameters
Result: Pitch, Roll, Yaw, Load Distance
Initialization: Load ArUco dictionary and
  camera parameters;
while camera is active do
    Capture frame;
    Detect ArUco markers in frame;
    if marker detected then
        Decode marker ID;
        Estimate marker corners;
        Compute pose;
        Extract rotation and translation
          vectors;
        Calculate pitch, roll, yaw, and load
          distance;
        Output attitude parameters;
    else
        Output no detection;
    end
end
```

Algorithm 1: CV-based Load Attitude Estimation.

3.2 IMU-Based Load Attitude Estimation and Setup

The experimental setup of this approach consists primarily of an IMU MPU6050 fitted at the load position and an ESP32-WROOM-DA microcontroller to interpret IMU data and calculate the load attitude angles. The IMU and ESP32 are connected through the I^2C communication protocol. The MPU6050 transmits a 14-byte raw integer string containing accelerometer (a_x, a_y, and a_z) and gyroscope (w_x, w_y, and w_z) values to the ESP32. The code developed in C++ is then deployed on ESP32 which then processes the raw data provided by MPU6050 and converts it into physical units. These physical units are then converted to roll and pitch angles using trigonometric functions by the library MPU6050-light. The final outputs are then timestamped and sent forward to the flight controller over I^2C or laptop (Arduino IDE Serial Monitor) over serial communication.

For the experimental validation of the proposed system, an off-the-shelf available 6-axis IMU MPU6050 is used to determine the load attitude, α, and β. An ESP32 is used to read and interpret the raw data incoming from the IMU to produce the required attitude parameters for quadrotor control. The step-by-step method articulating the IMU-based load attitude estimation is shown in the form of Algorithm 2.

```
Data: IMU sensor data (accelerometer:
      a_x, a_y, a_z; gyroscope: w_x, w_y, w_z)
Result: Pitch, Roll, Yaw
Initialization: Initialize IMU sensor and
  calibrate accelerometer and gyroscope;
while IMU is active do
    Read raw accelerometer data (a_x, a_y, a_z);
    Read raw gyroscope data (w_x, w_y, w_z);
    Convert raw data to physical units (m/s^2
      for accelerometer, rad/s for gyroscope);
    Calculate pitch, roll and yaw angles;
    Output attitude parameters (pitch, roll,
      yaw);
end
```

Algorithm 2: IMU-based Load Attitude Estimation.

4 EXPERIMENTAL AND SIMULATION RESULTS

This section presents the results of experimental setups as proposed in previous sections and provides a comparative analysis of the salient features of both ArUco marker-based and IMU-based methods with the simulation of the pendulum-based suspended-load setup.

Table 1 presents the summary of variables taken under consideration for the experiment.

The following Tables 2 and 3 summarize the data collected during aggressive maneuvers using both sensing methods. The measurements demonstrate each method's responsiveness and coverage across relevant dynamic states.

The pendulum serves as a common platform for comparison of feedback using an ArUco marker and

Table 1: Summary of variables obtained using both methods.

ArUco Based	IMU-based
1. Pitch	1. Pitch
2. Roll	2. Roll
3. Yaw	3. Yaw
4. Load Distance	

Table 2: Feedback from IMU-based method during an aggressive maneuver.

Observation No.	Pitch (Deg.)	Roll (Deg.)
1	32.52	14.82
2	32.49	14.92
3	31.98	15.03
4	31.70	15.09

Table 3: Feedback from ArUco-based method during an aggressive maneuver.

Observation No.	Pitch (Deg.)	Roll (Deg.)
1	-146.8	46.3
2	-138.5	53.0
3	-133.4	56.9
4	-124.5	59.6

Table 4: Summary of frequency of feedback attained.

ArUco Based Frequency	IMU-based Frequency
31.21 Hz	370.48 Hz

IMU. The pendulum swing angle here is α representing the load attitude.

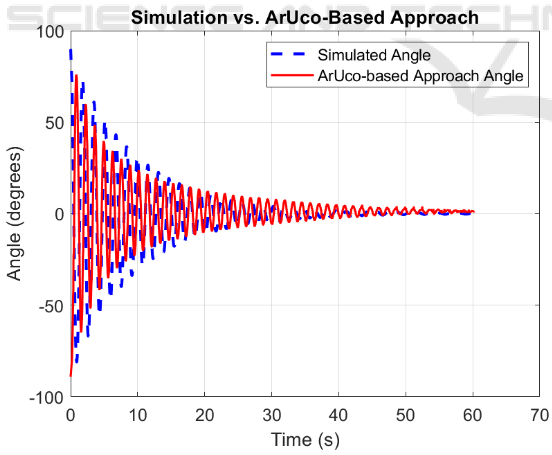

Figure 4: Pendulum load swing angle (α) vs Time plot for CV-based method compared with pendulum simulation.

Figure 4 demonstrates the performance of the CV-based feedback system. The plot shows the simulated response of a pendulum governed by the non-linear dynamic equation:

$$\ddot{\alpha} = -b\dot{\alpha} - \frac{g}{L}\sin(\alpha)$$

where damping coefficient $b = 0.016\frac{Ns}{m}$, length of string $L = 0.6m$, α represents the angular displacement of the pendulum load. These experimental data points obtained from the physical pendulum are compared with the simulated trajectory, with α corresponding to the pitch angle measured using the CV-based method.

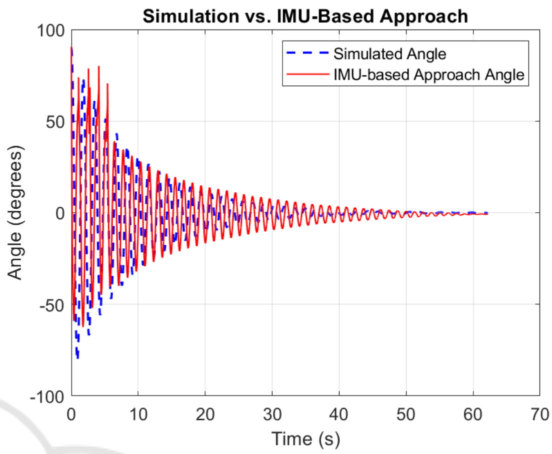

Figure 5: Pendulum load swing angle (α) vs Time plot for IMU-based method compared with pendulum simulation.

Figure 5 displays the performance of the IMU-based feedback system in contrast with the simulation of the system.

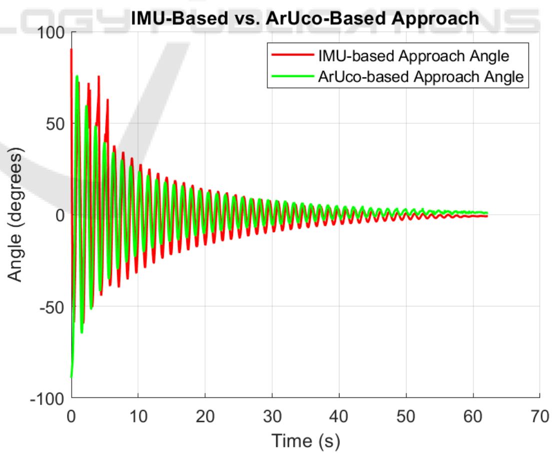

Figure 6: Pendulum load swing angle (α) vs Time plot for both proposed methods.

The Figure 6 demonstrates the comparison of the IMU-based and CV-based feedback system for pitch angle, α, of the pendulum.

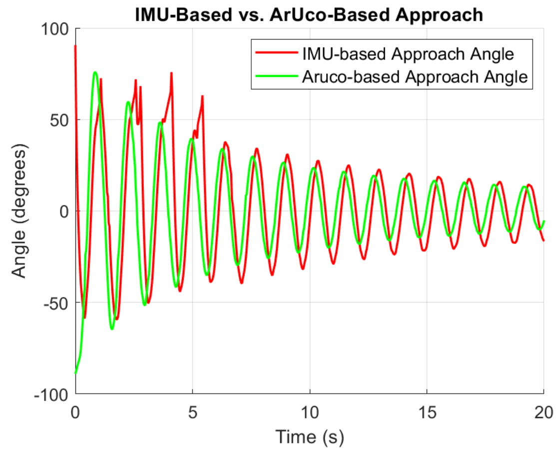

Figure 7: Anomaly in peaks of IMU-based load swing angle during large swing angle variation (greater than $\pm 25^{\circ}$).

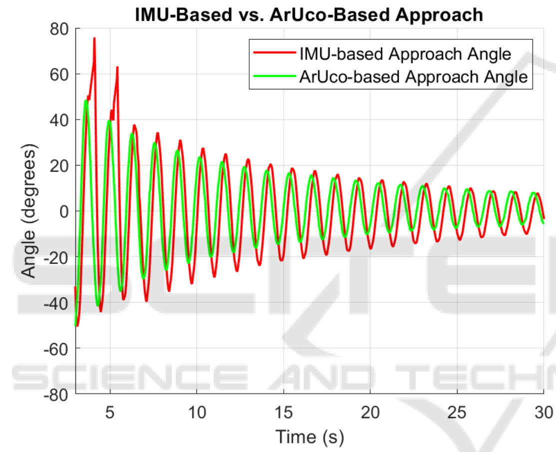

Figure 8: Another set of experimental values recorded for IMU-based method vs. CV-based method for pendulum swing angle.

In Figures 7 and 8, when there are greater variations in the pendulum swing angle, the IMU performs poorly and is unable to accurately determine the pendulum load swing angle. However, the CV-based method outperforms the IMU-based method by providing a consistent and accurate determination of the pendulum load swing angle.

When an almost steady state condition is achieved, the α angle obtained from the IMU-based method exhibits better results compared to the CV-based method, as projected in Figure 9.

As demonstrated in Figure 10, the pendulum system tends towards the neighborhood of equilibrium zero, i.e., near 0°, the CV-based method displays very distorted behavior, while the IMU-based method provides relatively better angle feedback α, which is very useful in the case of quadrotor suspended load when the swing angle of load is usually smaller in value.

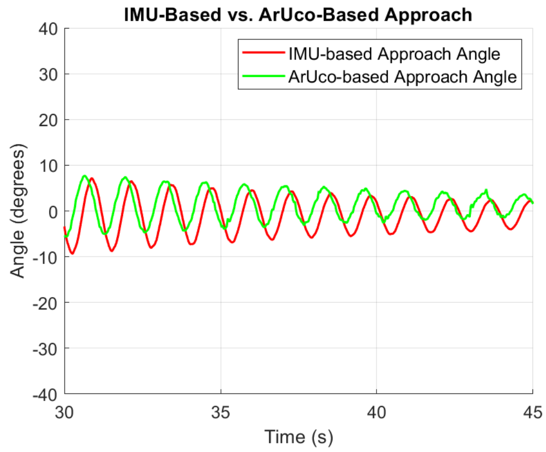

Figure 9: Anomaly in peaks of swing angle (α) using CV-based approach and IMU based approach during smaller angle variations ($< \pm 10^{\circ}$).

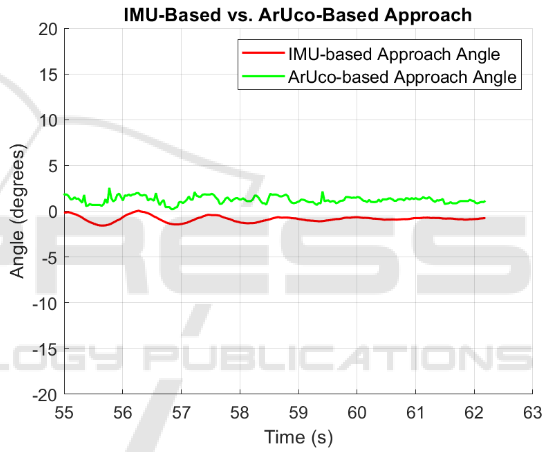

Figure 10: Smaller variation of pendulum swing angle ($\pm 5^{\circ}$) experimental output values for both methods.

5 CONCLUSION AND FUTURE PROSPECTS

This paper presents a comparative analysis of two load attitude measurement methods for drones carrying suspended loads- a CV based system using fiducial markers and a sensor-based system employing an IMU. Each method yields an easy to implement solution offering unique advantages in different scenarios. The IMU-based method performs well when the load deviation is less ($\pm 10^{\circ}$), and results in faster response (approximately 370 Hz), making it easily integrable with flight controllers, making it suitable for real-time precision maneuvering requirements when faster control feedback is essential. Future work will focus on integrating this system into actual flight control loops in quadrotor with slung load. The CV based method, although relatively more computationally intensive but provides rather accurate load attitude measurements. The CV based method performs even well for extreme maneuvers when the load deviation is greater than $\pm 25^{\circ}$. However, further improvements would be required to effectively tackle the robustness issues that accommodate illumination variations and camera calibration errors. In our future works, along with the addresal of these robustness issues, we intend to test the proposed algorithms under real-world conditions, including non-rigid cables to hang the load under the environmental disturbances for the actual drone having suspended cargo in 3D space.

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