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Firefly: Localizing Drones with Visible Light Communication and Sensor Fusion

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***Abstract*—In this paper, we propose a new approach where drones attain accurate localization by fusing information from artificial lighting and their embedded inertial and barometer sensors. Our system is able to provide accurate drone localization without the use of radios, GPS or cameras. We evaluate our framework, dubbed Firefly, with a testbed consisting of four light beacons and a mini-drone. Our results show that Firefly allows locating the drone within a few decimeters of the actual position; and compared to two state-of-the-art positioning methods that rely solely on lighting information, Firefly can reduce the localization error by 50% and 80%, respectively.**

***Index Terms*—Visible Light Communication, Drone localization, Sensor fusion.**

I. Introduction

Autonomous drones are envisioned for a wide variety of applications, both indoors [1] and outdoors [2]. However, making this future a reality faces many challenges in terms of range, safety and infrastructure support.

Drone operation depends on three key components: GPS, RF wireless links and cameras [3]. But what if one of these components fails or its use is prohibited in certain areas? For example, GPS is known to face limitations indoors and in urban canyons [4]; RF signals face ever-increasing spectrum saturation and are prone to interference; and cameras raise privacy concerns (making them undesirable in various areas [5]).

Vision. Similar to the way old lighthouses provided navigational aid to maritime pilots, standard light bulbs –such as those present in our buildings, warehouses, roads and streets – could be transformed into a modern version of those lighthouses. Light bulbs will play the role of air traffic control towers, exploiting advances in *visible light communication* (VLC) [6] to provide accurate positioning services for drones.

Contributions. The use of VLC for *drones* is largely unexplored. There are only a handful of studies investigating the intersection of those two areas. While various methods have been proposed to use visible light for localization, our study is the first to show accurate 3D positioning in scenarios with *six degrees of freedom* and *without requiring a training phase*. Overall, Firefly provides two main contributions.

Contribution 1: Analytical Framework [Sections III & IV]. We analyze the state-of-the-art contributions on visible light positioning (VLP) [7], [8], and show that decomposing the 3D problem into a 2D+H problem (where H stands for height) is the best alternative [9], [10]. After that, we address the limitations of this approach with sensor fusion, using barometer and IMU sensors to obtain an accurate height estimation, and VLP to further obtain the 2D position. Our novel 3D localization method is simple in terms of hardware (making it scalable), and does not require any type of training phase.

Contribution 2: Experimental Evaluation [Section V]. We build a testbed consisting of four light beacons and attach a single photodiode to a drone. We perform our evaluations in a realistic mobile scenario with six degrees of freedom where the drone is exposed to frequent tilting and even ambient light. Our main result shows that we can achieve location accuracy of a few decimeters, an improvement of 50% and 80% compared to two available methods in the state-of-the-art.

II. Background

In this section, we present the background information on the Lambertian patterns of LED lights and the basic localization principles behind this work.

Two types of localization techniques are often used in visible light positioning. The first type makes use of the received signal strength (RSS), and the second type makes use of the angle of arrival (AOA). In this work, we focus on RSS methods because they are more suitable for drones, as detailed in Section III.

In VLP with RSS, LED lights are used as anchor points with known locations, as shown in Fig. 1a. Each LED light (TX1 to TX3) broadcasts a beacon and the receiver measures the RSS of each signal. The receiver uses the received power to estimate its distance to the different light sources and obtains its location through a trilateration or optimization method. Starting at the transmitter, the propagation of light follows a Lambertian pattern which is depicted in Fig. 1b.

The main variables affecting the radiation pattern of light are the irradiance angle ψ at the transmitter, the incidence angle θ at the receiver, and the Lambertian order m. The Lambertian order determines the width of the beam from the transmitter.

The Lambertian pattern defines the optical channel between the transmitter and the receiver, and it is described by the following equation:

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$$H(0) = \begin{cases} A_{\mathrm{r}} \cdot \frac{m+1}{2\pi d^2} \cos^m(\psi) \cdot \cos\theta & \text{for} \quad \theta \in [0, \Theta_c] \\ 0 & \text{for} \quad \theta > \Theta_c \end{cases} \quad (1)$$

where d is the distance between the transmitter and the receiver; A_r is the effective sensing area of the receiver; and Θ_c represents the field-of-view (FoV) of the receiver. Combining the propagation pattern of the transmitter and the effect of the channel, the received power P_r at the photodiode (PD) can be written as:

$$P_r = P_t \cdot H(0) \quad (2)$$

where P_t is the transmitted power.

In VLP for drones, the mobile receiver has 6 degrees of freedom (DoF), as it can move along 3 axes (front/back, up/down and left/right) and perform rotations about each one (roll, pitch and yaw). Compared to the setups of state-of-the-art (SoA) studies, which typically consider static receivers, the movements of drones introduce important dynamics (tilting) that affect the irradiance angle ψ and incidence angle θ.

The above effects can have a significant impact on the RSS (P_r), making the location problem more challenging.

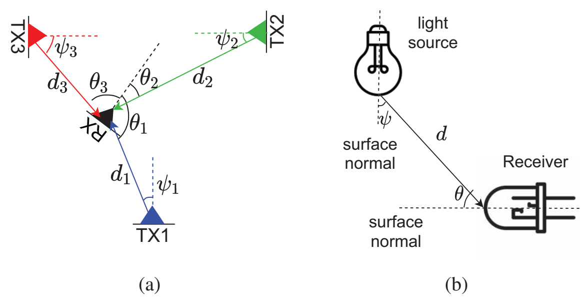


Fig. 1: (a) Basic trilateration; (b) LED propagation properties.

Key takeaway from the Lambertian model for drone operation. The above equations show that, due to the exponent m affecting $\cos(\psi)$, angular errors at the light source (ψ) are significantly more detrimental for localization than errors at the drone's photodiode (θ). Considering that $\cos(\psi) = h/d$, where h is the height of the drone, an accurate measurement of h would improve the estimation of ψ, and as a consequence, enhance the accuracy of the localization system.

In this study we show that the key limitation of RSS VLP methods is the adverse effect that tilting has on height estimation. To overcome this limitation, we exploit the sensors present in drones to provide an accurate estimation of height.

III. Analysis of the State of the Art

In this section, we analyze various VLP techniques and identify the ones that have the most potential for drones.

1) A taxonomy of VLP techniques: We introduce the available VLP techniques in four categories: AOA-based 3D, RSS-based 3D, RSS-based 2D+H and IMU-enhanced 3D; and we analyze the feasibility of each category for drone localization using the following criteria:

- The complexity of the transmitter design, which is critical to easily transform lighting infrastructure.
- The complexity of the receiver design considering the limited weight capacity and power budget of drones.
- The complexity of the algorithm, which constraints the limited processing and memory resources of the drone.
- Whether tilting is considered, since tilting is a fundamental part of drone mobility, as discussed in Section II.

2) 3D VLP with AOA: In previous studies, AOA-based methods have shown to be more accurate than RSS-based methods for 3D VLP. However, AOA-based methods have considerably higher complexity in terms of the required infrastructure, mathematical framework and the computational requirements. It is common to encounter designs for the receiver that include multiple PDs arranged at different angles [11], convoluted frameworks that result in long computation times [12], and complex transmitter arrangements consisting of multiple tilted LEDs [13].

While AOA-based methods can achieve a high accuracy, they require either complex receiver designs and algorithms, which are infeasible for small drones; or elaborated and costly transmitters, which do not scale well.

3) 3D VLP with RSS: Compared to AOA-based methods, RSS-based methods require considerably less infrastructure but impose some stringent constraints on the evaluation setup. A popular assumption in RSS-based methods is that the receiver and transmitter are parallel to each other [14]–[16]. While effective to simplify the problem, this is not a valid supposition for scenarios with drones flying.

RSS-based methods have potential for 3D VLP for drones, as the hardware required is less complex compared to AOA-based methods. However, its main shortcomings is that the methods are accurate only with *static* receivers maintaining a *parallel orientation* with the transmitters.

4) 2D+H VLP with RSS (Indirect-H): A promising approach in using RSS-based methods for 3D VLP is to decompose the problem space into *2D+H*, where the height (H) and the 2D position of the receiver are independently estimated. The studies of [9] and [10] have achieved 3D VLP with modest infrastructure and algorithmic complexities, and report favorable results for *static* receivers that are parallel to the transmitters. In the study of [10], however, *when tilting is introduced, the positioning error of their method increases more than 30 times when it is just 5°*. A key problem of 2D+H methods is that they use an *indirect* approach to estimate height (solely through RSS measurements). This approach works well with parallel and static receivers, but is severely affected by tilting.

5) 3D VLP with IMUs: To the best of the authors' knowledge, only one recent study explores the use of visible light for drone localization [17]. Similar to Firefly, that study combines information coming from photo sensors and inertial sensors, but the mechanisms differ significantly. The main advantage of our approach is that it does *not* require a training phase. In [17], the system requires an expensive training phase to obtain fingerprints, but it has two key limitations. First,

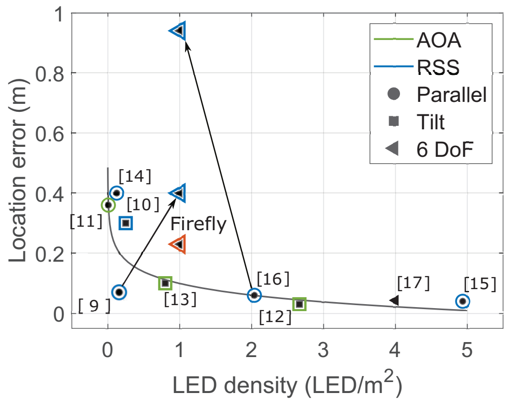


Fig. 2: Accuracy vs LED density for different SoA studies. The curve represents the trend for static scenarios in the SoA.

the complexity increases exponentially as a function of the evaluation area and the accuracy requirements. Second, the system is not resilient to changes in ambient light because the fingerprints become stale.

6) Summary of the taxonomy analysis: To conclude this section, we show the performance of the discussed SoA methods in terms of accuracy (reported positioning error) and the LED density in Fig. 2. The density of sources is a major indicator of how well a VLP system will perform and provides a good basis for comparison [8].

Except for [17], all the studies in the SoA, including the ones evaluating tilting, consider only *static* receivers in their experimental evaluations. While good results have been demonstrated for those *static* receivers, localization for *mobile* receivers remains a challenge. In order to have a high localization accuracy while keeping the complexity low, we propose Firefly and compare it against two SoA approaches in Section V. To capture the improvement brought by Firefly, in Fig. 2 we use two arrows to show the dramatic decrease in performance that the two SoA methods experience when we test them with mobile (6 DoF) drones.

IV. Proposed Method: Firefly

Due to the limitations of the Indirect-H approaches, we hypothesize that an accurate measurement of height is central to improve the localization accuracy. In Firefly we design a *direct* height estimation method that combines inertial (IMUs) and barometric (pressure) sensors. Most drones are already equipped with IMUs and barometers, hence, no additional hardware is needed beyond the photodiode used for VLP.

A. Reliable height estimation with sensor fusion

To obtain a reliable measurement of the height of a drone we combine inertial and barometric sensors. IMUs are good at measuring instantaneous changes in position and orientation, but their outputs are prone to noise and drift errors, even over a short period of time. On the other hand, barometers can provide a stable measurement of height over time, but their output is sensitive to rapid variations in the air pressure uncorrelated with altitude changes. Considering the *complementary* strengths of both kinds of sensors they can be *fused* to obtain an improved measurement. When combined with inertial sensors, barometers can provide accurate height estimation for drones, for example, with errors less than $15\,\mathrm{cm}$ after $3\,\mathrm{min}$ [18]. In Firefly, we adopt the complementary filter from [19] which is simple to implement and specially suitable for resource-limited UAVs.

Next, we describe how we combine the height estimation and the photosensor data to provide an accurate location.

B. Drone localization with height & light

Building upon the reliable height estimation, we design the VLP method for drone localization, named *Firefly*. As the goal is to keep the hardware complexity as low as possible, we consider an infrastructure where each LED transmitter has a single off-the-shelf light. This maintains the simplicity of the transmitters, making them easily scalable. Similarly, on the receiver's side, the drone is equipped with a single photodiode. In Fig. 3, we show the reference system for clarity.

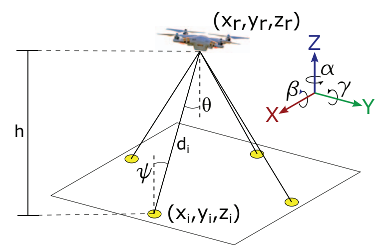


Fig. 3: System reference and parameters. Without loss of generality, we place the LEDs (transmitters) on the ground.

General framework. A main advantage of Firefly is that the parameters required by our method are available in the data sheets of LEDs and PDs. Therefore, with the received power ($P_{r,i}$) from each transmitter i, the distance d_i between a transmitter and the drone can be derived from Eq. 2 as:

$$d_i^2 = \frac{P_t}{P_{r,i}} \cdot \cos^m(\psi_i) \cdot \cos(\theta_i) \cdot c \tag{3}$$

where $c = \frac{(m+1)A_r}{2\pi}$ is a constant.

Note that, except for the irradiance angle ψ_i and incidence angle θ_i, all the other parameters and variables are known.

Irradiance angle. Given that the LEDs are on the same plane, and that the irradiance angle ψ_i is not affected by the receiver's tilt, the following equality holds: $\cos\psi_i = \frac{h}{d_i}$.

Incidence angle. The 3D orientation of the receiver determines the incidence angles θ_i. We can obtain this information using rotation matrices. Denoting (x_r, y_r, z_r) as the unknown location of the drone, (x_i, y_i, z_i) as the known locations of the LEDs, and (α, β, γ) as the yaw, pitch and roll of the drone (provided by the IMU), the incidence angle θ_i is determined in the following steps:

Step 1: We start with a vector normal to the surface of the PD: $\vec{n}_{pd} = \begin{bmatrix}0 & 0 & -1\end{bmatrix}^T$, with zero roll and pitch angles.

Step 2: We insert the orientation of the drone applying the following rotation matrices to $\vec{n}_{pd}$:

$$\vec{n}_{pd,rot} = R_z \times (R_y \times (R_x \times \vec{n}_{pd})) \tag{4}$$

where R_x, R_y and R_z are the rotation matrices according to the reference system defined in Fig. 3.

Step 3: We calculate the incident angle θ_i between $\vec{n}_{pd,rot}$ and $\vec{d_i}$, where $\vec{d_i}$ is the vector from the estimated location of the drone to the location of each transmitter: $\vec{d_i} = [x_r - x_i, y_r - y_i, z_r - z_i]$. Given that the height is already estimated ($h = z_r - z_i$), the only unknowns left are (x_r, y_r).

Numerical optimization. Replacing the irradiance angle ψ_i and the incidence angle θ_i in Eq. 3, all the transmitter-receiver distances can be combined into the cost equation below:

$$C(x_r, y_r) = \frac{1}{n}\sum_{i=1}^{n}\left| d_i^{3+m} - \frac{(\theta_{x,i} + \theta_{y,i} + \theta_{z,i}) \cdot h^m \cdot P_t \cdot c}{P_{r,i}} \right| \quad (5)$$

where based on the rotation matrix:

$$\theta_x = (x_r - x_i)cos(\alpha)sin(\gamma)(sin(\beta) + (cos(\beta))$$
$$\theta_y = (y_r - y_i)sin(\alpha)sin(\gamma)(sin(\beta) + (cos(\beta))$$
$$\theta_z = (z_r - z_i)cos(\gamma)(sin(\beta) + (cos(\beta))$$

Minimizing this cost function, we can obtain the 2D position of the receiver (x_r, y_r) that minimizes the mean error to each transmitter. This optimization problem can be solved via nonlinear programming methods.

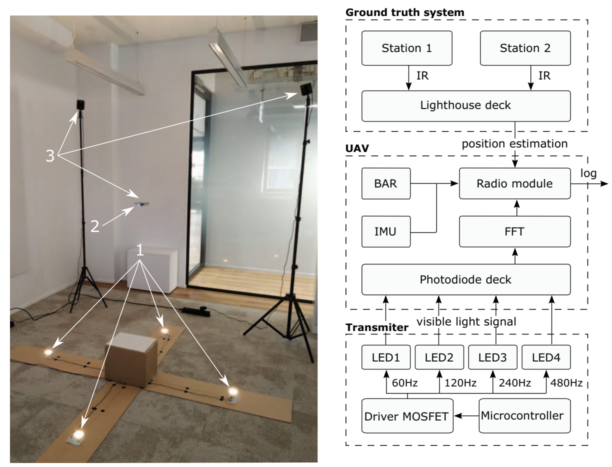
V. Experimental Validation

To evaluate *Firefly* against SoA methods in an indoor testbed, we select two methods as reference: the *3D VLP with RSS* method in [16] and the *2D+H VLP with RSS* method in [9] which have reported favorable results, with errors below 10 cm, as previously shown in Fig. 2.

A. Overview of the testbed

We build a testbed in a 2 x 2 x 2 m indoor environment as shown in Fig. 4a. The testbed has three main components: 1) 4 transmitting LED sources located at fixed positions, 2) the drone, and 3) a ground truth system to determine and control the drone's position during flight. The connection between these components and the schematic overview of their functionalities are shown in Fig. 4b. All the optical parameters (P_t, m, A_r) are obtained directly from data sheets. In our testbed: $P_t = 2.7\,\mathrm{W}$ (50% duty cycle), $m = 14$ and $A_r = 5.2\,\mathrm{mm}^2$.

It is important to note that the lights can be placed at any point (floor or ceiling) since Firefly can infer its location based on the position broadcasted by the LEDs. To transmit the information, we use the frequency division multiple access (FDMA) scheme from [20]. In our setup, the LEDs transmit data simultaneously in their unique frequency IDs, and the combined signal is sampled by the PD in the receiver. In the drone, the signal is decomposed with a Fast Fourier Transform (FFT) to obtain the RSS (P_r) of each light source. With this scheme, Firefly is resilient to high frequency noise as well as the constant DC component of ambient light. This allows Firefly to work in dark and illuminated environments with a simple implementation (i.e. no synchronization and no additional protocol is required by FDMA). To showcase its robustness, our experiments were carried under the presence (interference) of externals sources of artificial and natural light.



(a) (b)

Fig. 4: System overview. (a) Testbed with 1) 4 transmitters; 2) UAV; and 3) the ground truth system. (b) Schematic overview.

Transmitter. CorePro LEDspot LV lamps are used as transmitters.

Receiver. We select the Bitcraze Crazyflie 2.1 as the receiver and attached an OPT101 PD with a custom PCB.

Ground truth system. We use the Lighthouse positioning system from Bitcraze to control and retrieve the ground truth location of the UAV. The system can achieve centimeter level accuracy, but consists of expensive hardware that requires careful setup and calibration (making it impractical to scale).

B. Evaluation results

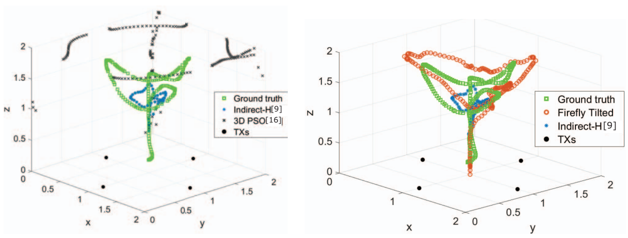
We carry out eight automated flight tests where the drone follows a pre-programmed route with curves and direction changes. As a result, we are constantly inducing tilting on the drone to test the VLP methods in a real scenario.

Although Firefly can run in real time in the drone, executing the three algorithms simultaneously is too demanding. Therefore, we send the sensor data log to a remote server as shown in Fig. 4b and use Matlab to compare them.

Location estimation We compare the performance of Firefly against two SoA methods across eight different flight tests. We label as *Indirect-H* the method from [9] and as *3D PSO* (from Particle Swarm Optimization) the method from [16]. *The mean error across all tests is* $98.53\,\mathrm{cm}$ *for 3D PSO,* $41.04\,\mathrm{cm}$ *for Indirect-H, and* $20.60\,\mathrm{cm}$ *for Firefly*.

In Fig. 5a we support the previous results qualitatively by looking into the flight trajectories of both SoA methods used for comparison. The trajectory plot of 3D PSO displays the expected circular motion in the x-y plane, but the altitude estimation is far from the ground truth, resulting in a wide trajectory. The inaccuracy of 3D PSO can be explained due to the *parallel assumption* between transmitters and receiver in its model. In our mobile setup we see that small angle variations can have a significant effect on the measured intensity.

Comparing the flight trajectories of Indirect-H and Firefly in Fig. 5b, we see that Indirect-H does not capture the full amplitude of motion of the trajectory. Given that the same RSS information is used for both Indirect-H and Firefly, the improvement is mainly due to the accurate height estimation and the consideration of the receiver's tilting. In comparison, Firefly follows the ground truth much closer and improves the mean error accuracy by 50% against Indirect-H, and 80% against 3D PSO.



(a) (b)

Fig. 5: 3D trajectory comparison between (a) Indirect-H and 3D PSO; (b) Firefly and Indirect-H.

Height Estimation. To highlight the importance of our height estimator, let us take a close look at the results of Firefly and Indirect-H in Fig. 6a. During the lift-off (timestep 0 to 60) and landing (after timestep 200), Indirect-H is able to detect the monotonic changes in altitude, but with far less accuracy compared to Firefly. During the route (timestep 60 to 200), Indirect-H cannot track the variation in height. Firefly, on the other hand, closely follows the ground truth even when tilting occurs (Fig. 6b). Considering the height measurements of all (eight) tests, the mean error for Firefly is less than $14\,\mathrm{cm}$ compared to a mean error of $30\,\mathrm{cm}$ for the Indirect-H.

Overall, the significance of our height estimator is that it translates into an accurate and robust estimation of the drone location, as hypothesized in Section II.

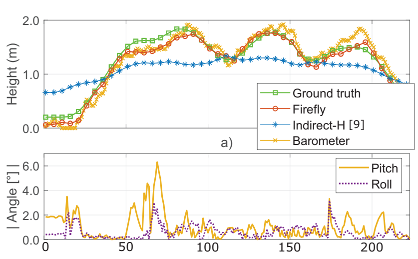


Fig. 6: a) Height estimation and b) Tilt in Test 5.

VI. Conclusion

This work demonstrates that VLC can be used for accurate 3D positioning of drones in a realistic setup without any training phase, which is distinguished from the SoA that only considers *static* receivers. Our localization method decomposes a 3D positioning problem into 2D+H, but provides two novel contributions. By utilising the on-board sensors on the drone, we accurately estimate height and account for tilting of the receiver. As demonstrated by the experimental results, Firefly achieves a mean position accuracy of $20.60\,\mathrm{cm}$ using off-the-shelf LED lights and low-cost sensors. Under the same experimental setup, Firefly reduces the localization error compared to two other SoA methods by around 50% and 80%.

This work serves as a starting point in the design of a visible light communication platform for drones.

Acknowledgments

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