Optic Flow Based Reactive Collision Prevention for MAVs Using the Fictitious Obstacle Hypothesis

Feng Xiao¹, Peter Zheng¹,², Julien di Tria¹, Basaran Bahadir Kocer¹ and Mirko Kovac¹,³

Abstract—Optical flow sensors and optical flow divergence (OFD) have offered partial solutions for obstacle avoidance, landing, and perching with micro aerial vehicles. Theoretically, OFD can indicate the risk of collision, providing that the sensors’ field of view is bounded within a single flat surface on the obstacle. However, in the real world, directly measuring the risk of collision with OFD generates false alarms due to rapidly changing speeds and irregular surroundings. In this letter, we present a new obstacle detection strategy based on an extended Kalman filter (EKF) combining the OFD with inertial sensing. The introduction of a fictitious obstacle hypothesis and the use of the EKF estimates enable us to differentiate the surrounding-generated OFD from the OFD caused by the actual obstacle. An embedded constant zero-OFD controller is then used for post-detection emergency deceleration. The ultra-light OFD estimation and control system, with a mass of 20 g, estimates OFD at 60 Hz. The system was validated on a 1.58 g mini quadrotor in both laboratory and field tests. Experimental results illustrate that the presented system can achieve accurate obstacle detection, near-obstacle distance estimation, and controlled deceleration to prevent collisions [Video attachment: https://youtu.be/yIyHYN0jOyw].

Index Terms—Aerial Systems: Applications; Biologically-Inspired Robots; Collision Avoidance.

I. INTRODUCTION

Obstacle detection and collision prevention during autonomous missions has been an ongoing area of research for micro aerial vehicles (MAVs) with limited payload, computation, and communication capabilities. While state estimation and path planning mitigate the risks, there is a need for an embedded low-level system for sudden reactions. We envision a primary collision prevention system that interrupts the high-level controller and performs control actions fully onboard when danger is detected. Our concept is developed to ensure the survivability of the platform, upon which secondary systems such as vision-based navigation can be added to ensure the continuation of the mission.

Commonly used state estimation and obstacle detection equipment, such as RADAR/LIDAR [1], [2], cameras [3], [4], and event-based cameras [5], require a combination of significant payload capacity and onboard computation. Time of flight (ToF) sensors provide single direction distance sensing. Thus, a single sensor cannot detect clusters of sparse obstacles such as fences and bushes. The weight of these ToF sensors increases with their accuracy and sampling rate. Lightweight options such as the VL53L0x weigh less than 1 g but may have low sampling rates (10 Hz). Therefore, lightweight ToF sensors are neither reliable nor fast enough for real world applications.

Small flying insects neither measure the absolute distances to objects nor their own speed [6]. Instead, they use optical flow (OF), which is the 2-dimensional visual movement patterns on their retina due to the 3-dimensional (3D) motion of flight. This intrinsic information is sufficient to obtain the visual cues containing the relative velocity without a length scale [7], [8]. McGuire et al. designed a 40 g drone with a specialized stereo camera that could estimate distance and optical flow, and derive its own velocity, with which obstacle avoidance was demonstrated in a room at low speed [9]. Due to the sensor’s low sampling rate of 30 Hz, the maximum safe airspeed is limited.

The reciprocal of the time-to-contact can be obtained from the optical flow divergence (OFD) and be used for obstacle avoidance [10]–[12]. One can set two OFD thresholds to detect front and side obstacles in complex 3D environments [13]. OFD has also been used as the observation update in an extended Kalman filter (EKF) to estimate the distance and velocity of a MAV during landing [14]. The constant OFD strategy has been used for smooth landing control [12], [15], [16]. Overall, using OFD for obstacle detection is computationally efficient and lightweight, making it suitable for the primary collision prevention role described above.

While OFD can be calculated with a single camera using computer vision libraries such as OpenCV, it can also be calculated with two cameras facing ±45° about the vehicle’s yaw axis [17], [19]. This method has been implemented on both ground vehicles [11] and fixed-wing aerial vehicles [20]. When using OF sensors which can directly output integrated OF data across the image plane, image processing and onboard computers are not required. In this letter, the pair of OF sensors are named divergent optical flow pair (DOFP). In this

This document is the accepted manuscript version of the following article:

Digital Object Identifier (DOI): see top of this page.

1Feng Xiao, Peter Zheng, Julien di Tria, Basaran Bahadir Kocer and Mirko Kovac are with the Aerial Robotics Lab (ARL), Department of Aeronautics, Imperial College London, South Kensington Campus, London SW7 2AZ United Kingdom (Email: feng.xiao16@imperial.ac.uk, peter.zheng13@imperial.ac.uk, j.ditiia20@imperial.ac.uk, b.kocer@imperial.ac.uk, m.kovac@imperial.ac.uk).

2Peter Zheng is also with the Grantham Institute, Imperial College London, South Kensington Campus, London, SW7 2AZ United Kingdom.

3Mirko Kovac is also with the Swiss Federal Laboratories for Materials Science and Technology (EMPA), Ueberlandstrasse 129, 8600 Dibendorf, Switzerland (Email: robotics.empa.ch).
context, the testing environments in previous implementations are highly idealized. For the use of DOFP and OFD for primary collision prevention to be fully realized, we must systematically characterize the performance and limitations of DOFP in the real world and gain further insights into how to best optimize its use.

The use of DOFP for obstacle detection presents the following challenges: a) The estimation algorithm is based on a flat surface that is large enough to cover the sensors’ field of view (FoV). This limits the usage of the OFD. b) Using an OFD constant as the obstacle detection criterion is simple but this only works when the flight velocity is relatively constant. For aggressive maneuvers, this criterion can easily generate a false positive alarm and interrupt the mission.

In this work, the real-world implications of using DOFP are investigated for OFD estimation, obstacle detection, and collision prevention (Section II). We characterize the effectiveness of the OFD estimation method when the obstacle does not fully cover the DOFP’s FoV and introduce the concept of a fictitious wall to dispense with the flat surface assumption (Section IV). This is further developed into an obstacle detection strategy based on the EKF estimates (Section V). The OFD estimation is then used in a constant zero-OFD controller [21] to control the emergency deceleration when triggered by the obstacle detection system. To validate our framework, we designed a MAV and DOFP prototype (Section II). The results from laboratory and outdoor tests and discussions are presented (Section VI).

II. MODELING AND PROTOTYPE DESIGN

A. Coordinate Systems

While an aerial collision can occur from all directions, it is most likely to occur in the direction of travel. Hence, we define the geometry of the problem with a quadrotor that flies forward, and a static wall as the obstacle (Fig. 2). The body frame of the MAV is fixed at \( O^b \), the MAV’s center of mass. Following the right-hand rule, \( X^b \) points in the forward direction of the MAV, and \( Z^b \) downward. \( X^b \) and \( Y^b \) are fixed on the MAV’s airframe. The frame \( O^b X^b Y^b Z^b \) shares the same center as \( O^b \). The \( X^{b'} \) and \( Y^{b'} \) axes are \( X^b \) and \( Y^b \) projected on the horizontal plane; \( Z^{b'} \) axis points downward. The frame \( O^O X^O Y^O Z^O \) is located on the surface of the flat vertical wall. \( (X^O - Y^O) \) is parallel to the horizontal surface. Each of the two OF camera lenses has a FoV of \( \beta \). Their axes, \( Z^{C1} \) and \( Z^{C2} \), have offsets \( \alpha_1 \) and \( \alpha_2 \) from \( X^b \) respectively. \( V_M \) is the MAV velocity along \( X^{b'} \) axis and is positive when the MAV flies forward.

The MAV may tilt in numerous directions. Thus, the flight direction may not coincide with \( X^{b'} \). However, the flight direction can be obtained by the velocities along \( X^{b'} \) and \( Y^{b'} \) axis. With a conceptual extended design (Fig. 1D), we can activate the two sensors closest to the flight direction. In our approach, direction \( X^{b'} \) is considered as the flight direction for simplicity. Therefore, the roll angle is negligible.
B. Electronic System

The DOFP features two PMW3901 OF sensors, mounted on top of the electronics stack to ensure a clear line of sight (Fig. 1), and near O to match our theoretical model (Fig. 2). These sensors can output the integrated pixel movements across the image plane. The microcontroller computes the OFD and the autopilot runs a modified PX4 firmware with the obstacle detection framework and constant zero-OFD controller. The downward-facing optical flow and distance sensor provide the data to maintain altitude and minimize horizontal drift.

III. OFD ESTIMATION AND CONSTANT ZERO-OFD CONTROL

A. Estimation on an Infinitely Long Wall

OFD is defined as:

\[ \text{OFD} = \frac{V_M}{D_w} \quad (1) \]

where \( D_w \) is the distance to the wall from \( O \) in the \( X^b \) axis (Fig. 2). \( \gamma \) is the incidence angle between the MAV flight path and the axis normal to the wall, \( X^O \).

The OF sensor outputs pixel movement counts \( \Delta x_1 \) and \( \Delta y_1 \) in \( X^c_1 \) and \( Y^c_1 \) axes of the image plane. They represent the relative movement detected by the sensor during one time step. From \( t_0 \) to \( t_1 \), point \( O \) on the wall seen by the left OF sensor moves by \( \Delta x_1 \) on the image plane. The related velocity vector is represented as \( \Delta \mathbf{v}_1 \), which is projected on the image plane by \( V_{m1} \) on the wall or \( V_1 \) on the virtual plane parallel to the image plane crossing \( O \).

\[ V_1 = V_{m1} \cos(\gamma - \alpha_1) \quad (2) \]

As the time step is small, we treat these velocities as velocities at \( t_0 \).

The angular velocity of the pixel motion with respect to the focal length is called optical flow rate \( \Lambda_{x1} \). \( \Lambda_{x1} = \frac{V_1}{d} \), where \( f \) is a scaling factor related to the pixel size and the focal length of the OF sensor that transforms the unit “pixel/second” to “radian/second”. The OF sensor is treated as a black box. \( f \) was determined by comparing OF sensor data with motion capture (mocap) ground truth.

The angular velocity related to \( V_1 \) with respect to the OF sensor origin is \( \omega_1 \), which equals to its measured flow rate \( \Lambda_{x1} \):

\[ \omega_1 = \frac{V_1}{d} = \Lambda_{x1} \quad (3) \]

Based on the geometric relations and the sine rule:

\[ d = \frac{D_w \cos \gamma}{\cos(\gamma - \alpha_1)} \quad (4) \]

\[ \frac{V_{m1}}{V_M} = \frac{|O_1O_M|}{D_w} = \frac{\sin \alpha_1}{\sin(\pi/2 + \gamma - \alpha_1)} \quad (5) \]

From above equations:

\[ \Lambda_{x1} = \text{OFD} \frac{\sin \alpha_1}{\cos \gamma} \cos(\gamma - \alpha_1) \quad (6) \]

where \( \Lambda_{x1} \) is estimated by the OF sensor, and \( \alpha_1 \) is specified in the platform design. With the two OF sensors mounted at \( \alpha_1 = \frac{\pi}{4} \) and \( \alpha_2 = -\frac{\pi}{4} \), OFD can be calculated by

\[ \text{OFD} = \Lambda_{x1} - \Lambda_{x2} \quad (7) \]

B. Adjustment for Quadrotor Platform

The underactuated MAV must pitch to fly forward (Fig. 2B). This induces an error in the OFD estimation. The OFD estimated by the sensor, \( \text{OFD}^s \), is corrected by the MAV pitch angle \( \theta \) such that

\[ \text{OFD} = \frac{V_M}{D_w} = \frac{V_M s / \cos \theta}{D_w s \cos \theta} = \frac{\text{OFD}^s}{\cos^2 \theta} \quad (8) \]

We used a mocap system to obtain the ground truth of the OFD for comparison with the DOFP estimated OFD. A complementary low-pass filter was added to reduce the signal noise. \( \gamma \) implies that the OFD estimation does not depend on the incidence angle \( \gamma \). This was further verified experimentally (Fig. 3). The estimated OFD has a small root mean square error of 0.3274 s\(^{-1}\) compared with the ground truth data ranging from \(-3.5\) s\(^{-1}\) to 3.75 s\(^{-1}\).

C. Single OF Sensor Estimation

As incidence angle \( \gamma \) increases, the wall gradually disappears in one of the OF sensors’ FoV. When \( \gamma > \alpha_{(2)} + \beta/2 \), one OF sensor does not see the wall. In the real world, where the wall is not infinitely long, this critical angle will be lower. In such cases, the OFD estimation with DOFP becomes invalid. However, if the surrounding environment is clear, i.e. the OF sensor looking out of the wall gives near-zero flow rate, \( \gamma \) will become \( OFD \approx \Lambda_{x1} (\Lambda_{x2} \approx 0) \). Thus, with (6), we have:

\[ \frac{OFD}{\Lambda_{x1}} \approx \frac{\sin \alpha_1}{\cos \gamma} \cos(\gamma - \alpha_1) \quad (9) \]

which shows that the approximated OFD and real OFD have a ratio which varies with \( \gamma \) (Fig. 3C). Although the estimation
is not accurate, a single OF sensor can generate a scaled estimation of the OFD, and the ratio is near 1 in the range of 30° to 60°. However, an accurate OFD estimation depends on the γ, which is unknown to a single OF sensor system.

D. Constant Zero OFD Control

The constant OFD strategy has been widely used for docking and landing. By keeping the OFD constant, \( \frac{V_M}{V_w} = \lambda \):

\[
D_w = D_{w0}e^{-\lambda t}, V_M = -\lambda D_{w0}e^{-\lambda t}
\]  

(10)

Therefore, if \( \lambda > 0 \), \( D_w \) and \( V_M \) will converge to zero. This is ideal for scenarios where the velocity needs to decrease gradually when approaching the surface. However, constant zero OFD would be more beneficial for obstacle avoidance. If \( \lambda = 0 \), (10) reduces to \( D_w = D_{w0} \) and \( V_M = 0 \), which means the MAV will hold a constant distance to the obstacle.

The forward position along the \( X^b \) axis is controlled by a proportional controller to maintain \( \text{OFD} = 0 \). The altitude and lateral motion are controlled by proportional-integral-derivative (PID) controllers to keep the MAV flying straight at a constant height.

IV. System Characteristics and Fictitious Wall Hypothesis

A. Close-field and Far-field Estimation

Infinitely long walls do not exist in the real world. However, this is not strictly required for the OFD estimation algorithm to generate useful data. The whole flow field changes when the MAV moves, thus providing sufficient features in the image plane. When objects within the FoV move and the MAV stays static, only a part of the flow field changes. Depending on the percentage of the FoV covered by the changing flow field, the reliability of the OFD estimation may be adversely affected.

An object of width \( L \) at distance \( D \) in front of the MAV (\( \gamma \approx 0^\circ \), and MAV centered) covers a percentage \( c \) of the DOFP FoV where

\[
c = \begin{cases} 
0 & \text{if } \phi < \phi_1 \\
(\phi - \phi_1)/\beta, & \text{if } \phi_1 \leq \phi \leq \phi_2 \\
1, & \text{if } \phi > \phi_2 
\end{cases} 
\]  

(11)

\[
\phi_{1,2} = \alpha \mp \beta/2 
\]  

(12)

\[
\phi = \arctan \left( L/(2D) \right) 
\]  

(13)

The effects of a moving MAV with a static wall and a static MAV with a moving wall were studied against a 2 m wide, 1.2 m high vertical wall. The MAV followed a ±0.25 m square wave position set-point along the \( X^b \) axis with ten different starting points, ranging from 0.5 to 5 m. The Pearson correlation coefficients at different distances indicate that within 1.5 m of the wall, the OFD estimation is always valid (Fig. 4).

As \( |\alpha_1 - \alpha_2| = 90^\circ, \beta = 42^\circ \), the wall covers 23% of the DOFP FoV at 1.5 m according to (11). The effectiveness of the moving wall situation drops sharply if the relevant distance is further than 2 m, when \( c \leq 5\% \).

Beyond 4.5 m (\( c = 0 \)), the moving wall and moving MAV scenarios exhibit different behaviors (Fig. 4B/C). When the wall moves, the sensor OFD stays constant at 0 \( \text{s}^{-1} \) as no motion is captured. When the MAV moves, although the DOFP does not see the wall, surrounding features are observed. This generates noisy but representative data that follows the MAV’s oscillations as if there was a wall in front. Thus, the correlation is higher in the moving MAV scenario. This behavior shows that far-field surroundings can be approximated by a flat wall, relaxing the restriction of the physical flat wall obstacle assumption.

B. Fictitious Wall

The far-field surroundings can resemble a flat wall. However, the “wall” and its location are immaterial. Thus, we introduce the concept of the fictitious wall. The fictitious wall (Fig. 4C) is defined as a virtual wall located in front of the quadrotor with a \( D_F \) distance at time \( t \).

\[
D_F|_t = \frac{V_M|_t}{\text{OFD}|_t} 
\]  

(14)

At each \( t \), the OFD estimation will be equal to observing a static wall located at \( D_F|_t \) in front of the MAV. The fictitious wall is static at each \( t \), and the velocity of the fictitious wall is 0 m s\(^{-1}\) (Section V-E).

C. OFD Threshold as Obstacle Detection Criterion

When the flight speed is relatively constant, an OFD threshold can be used as the obstacle detection criterion. However, during dynamic flights with aggressive maneuvers, a simple constant threshold may generate false positives. Furthermore, there are cases where DOFP-estimated OFD does not indicate the risk of collision. For example, when MAV flies along a clear path with objects on both sides, neither a small nor a large value of OFD necessarily indicates an obstacle ahead.

We propose the fictitious obstacle hypothesis to differentiate between real frontal obstacles and fictitious obstacles: 1) the
fictitious wall should move forward along with the MAV until the obstacle covers most of the DOFP’s FoV. Then the fictitious wall should coincide with the actual obstacle and stop moving. 2) OFD is a relative value affected by both the MAV’s motion and the environment. Acceleration from the autopilot IMU represents MAV’s motion and can be used to decouple the motion and the environment.

With the acceleration and OFD, we designed a 1D EKF to estimate the fictitious wall location, the distance between the fictitious wall and the MAV, and the MAV’s velocity.

V. STATIC OBSTACLE DETECTION WITH FICTITIOUS WALL THEORY

A. Extended Kalman Filter

EKF has been used for multirotor landing control [14], with the control acceleration command being the model input and the OFD being the observation update. The state vector includes just the velocity and the height. As the OFD measurement is in the height direction and the floor is a large static surface, the flat surface assumption is valid.

However, for forward flight, as we are considering a fictitious wall that is always changing in location until the obstacle becomes observable, we constructed an EKF using acceleration from the IMU as model input and divided the distance into two variables: the location of the MAV \( X_M \) and the location of the fictitious wall \( X_F \). The 1D continuous model dynamics can be written as

\[
\dot{x} = \begin{bmatrix} X_M \\ V_M \end{bmatrix} , \quad y = h(x) = OFD = \frac{V_M}{D_F} = \frac{V_M}{X_F - X_M}
\]

where \( a \) is the acceleration along \( X^V \), calculated by compensating the IMU value with the pitch angle. The discrete-time system model and observation model can be written as:

\[
x_{k+1} = \Phi_k x_k + \Gamma_k u_k + w_k \\
y_k = h(x_k) + v_k
\]

The EKF follows the steps below:

\[
\hat{x}_{k+1|k} = \Phi_k \hat{x}_{k|k} + \Gamma_k u_k \\
P_{k+1|k} = \Phi_k P_{k|k} \Phi_k^T + Q
\]

\[
H_{k+1} = \partial h \bigg| \hat{x}_{k+1|k} = \begin{bmatrix} (X_{k+1|k} - X_{M_{k+1|k}})^2 \\ \frac{X_{k+1|k} - X_{M_{k+1|k}}}{V_{M_{k+1|k}}} \\ \frac{-V_{M_{k+1|k}}}{X_{k+1|k} - X_{M_{k+1|k}}} \end{bmatrix}
\]

\[
K_{k+1} = \frac{P_{k+1|k} H_{k+1}^T}{H_{k+1} P_{k+1|k} H_{k+1}^T + R} \\
\hat{x}_{k+1|k+1} = \hat{x}_{k+1|k} + K_{k+1}(OFD_{k+1} - h(\hat{x}_{k+1|k}))
\]

\[
P_{k+1|k+1} = (I - K_{k+1} H_{k+1}) P_{k+1|k}
\]

where \( P \) is the state error covariance matrix, \( H \) is the Jacobian matrix to linearize the observation model, and \( K \) is the Kalman gain.

B. Nonlinear Observability of the EKF

As the observation model is nonlinear, we use the Lie derivatives of \( \mathcal{L}_x h(x) \) with respect to the system model dynamics in [15] to construct the observability matrix \( \mathcal{O} \).

\[
\mathcal{O} = \begin{bmatrix} \mathcal{L}_x^0 h(x) & \mathcal{L}_x^1 h(x) & \mathcal{L}_x^2 h(x) \end{bmatrix}^T
\]

\[
= \begin{bmatrix} V_M/(X_F - X_M) \\ V_M^2/(X_F - X_M)^2 \cdot a/(X_F - X_M) \\ 2V_M^3/(X_F - X_M)^3 + 3V_M a/(X_F - X_M)^2 \end{bmatrix}
\]

Observability of the system is determined by the rank of the Jacobian of matrix \( \mathcal{O} \). As \( X_F \) and \( X_M \) always appear in a pair with opposite signs in the denominator in (27), the Jacobian will not be full rank. Thus, \( X_F \) and \( X_M \) are not observable. The OFD measurement only provides information on the relative distance but not on the absolute location of both. The model input updates \( X_M \) from an arbitrary initial state and does not update \( X_F \). However, our method is still valid as the distance \( X_F - X_M \) and \( V_M \) are still observable under the condition that \( a \neq 0, V_M \neq 0 \), and \( X_F - X_M \neq 0 \).

C. Numerical Investigations

The EKF was validated by numerical simulations in MATLAB (Fig. 5). We generate a time series of acceleration, the corresponding velocity, and MAV position \( X_{M,F} \). Knowing the velocity of the MAV and the geometry of the corridor...
The product of gradients (PoG) of the MAV position and distance is a more obvious critical condition for detection (Fig. 7B). When the MAV flies forward and the fictitious distance decreases, PoG becomes negative, which indicates an obstacle. We can set a negative PoG threshold value as the detection criterion.

However, the PoG method is not applicable in some circumstances. An example of this is a flight through increasingly narrow corridors (Fig. 6). $D_F$ would decrease while the MAV position moves forward. The PoG is negative despite no obstacle in front. Although PoG gave a false signal, the negative value still accurately indicated the increased risk of collision. Other than the narrowing corridor case, we also found that PoG could be negative if we halt the MAV during a forward flight. This is mitigated by reinitializing the EKF when the MAV hovers and adding the condition: $V_M > 0.1 \text{ m s}^{-1}$.

An obstacle becoming observable does not mean that a collision is imminent. A distance threshold is added to trigger the emergency action once the obstacle detected (Fig. 5).

**E. Limitations of the Proposed Approach**

The definition of the fictitious wall has limitations in certain scenarios. OFD should be the ratio of the relative velocity to the relative distance. As the fictitious wall is static, we define the observation model of the EKF using the ratio of MAV velocity over $D_F$. However, if the real obstacle is moving, the EKF becomes invalid. For example, when the MAV flies closely behind an obstacle moving at the same speed, there is no relative motion between the two. Therefore, the DOFP will generate a near-zero OFD. However, based on (16), the OFD should not be zero when MAV velocity is not zero. The observation model and the measurement are in conflict. This is a model-plant mismatch problem.

If we set the time derivative of the fictitious wall position as velocity $V_F$, the observation model in EKF becomes $OFD = \frac{V_F - V_M}{X_F - X_M}$. As discussed, the fictitious wall moves along with the MAV when only the surroundings are observed, $V_M \approx V_F$, which means the OFD by observation model would be around 0. However, the real OFD updated from DOFP will not be zero. Another model-plant mismatch problem occurred. This explains why the fictitious wall has zero velocity.

**VI. RESULTS AND DISCUSSIONS**

**A. System Validation Tests**

Flight tests were conducted with a mocap system for position control before the emergency action and ground truth data collection. As these tests were intended to validate the EKF and the obstacle detection criterion, an idealized test environment was constructed; a 2 m wide textured vertical wall was used as the obstacle. The wall comes within the MAV’s FoV at around 1.5 m away.

The fictitious distance was estimated accurately, and the fictitious wall position stayed relatively constant after the obstacle was detected (Fig. 5A). However, the $D_F$ and $X_F$ drift when the MAV is static. This is due to the EKF being unobservable when the acceleration, velocity, or OFD are zero. Nonetheless, as we only need the gradient of the EKF output,
and the near-obstacle distance is estimated accurately, the EKF is competent for obstacle detection and emergency triggering.

The system is also validated against different approaching velocities (Fig. 7E). The results showed consistent detection and trigger distances at velocities ranging from 0.8 m s\(^{-1}\) to 3 m s\(^{-1}\). The detection and the trigger distances were smaller when flying at 0.8 m s\(^{-1}\) and 1.2 m s\(^{-1}\), and were around 1.5 m and 1 m respectively when the velocity was larger than 1.6 m s\(^{-1}\). The EKF is more accurate with a greater observed motion by the OF sensor; low flight speed increases estimation errors. Nevertheless, the detection, triggering, and deceleration were successful in all thirty flight tests without re-tuning which shows the adaptability and resilience of the proposed method. At the trigger distance of 1 m, the maximum successful approaching velocity achieved is around 3 m s\(^{-1}\).

The ground truth OFD when the emergency action was triggered was not consistent and it varied with the velocity (Fig. 7E). This affirms that the single OFD threshold obstacle detection criterion can only be used for constant velocity flight. We also conducted flights inside a blocked cylindrical tunnel (Fig. 7D), similar to the simulation settings in Section V-C. The trigger OFD is smaller than the maximum OFD before the triggering. These tests validate that our method can prevent false alarms as compared to the single OFD threshold method.

### B. Robustness in Off-design Conditions

In order to test the robustness of the system, flights of incidence angles \(\gamma\) from 0° to 90° in 15° intervals were conducted. The obstacle is a 3.5 m wide, 1.2 m high vertical wall and the approach speed is approximately 2.5 m s\(^{-1}\).

Ten tests were conducted at each \(\gamma\). At \(\gamma \geq 66^\circ\), one of the OF sensor will not see the wall. This should invalidate the OFD estimation by DOFP. However, the system achieved 100% successful rate at 75°, and the maximum achievable angle is 80°, at which the MAV flew almost parallel to the obstacle. At 92.5°, the MAV flew nearby the obstacle without triggering emergency action.

As explained in Section III-C, the estimated and the real OFDs differ by a constant ratio. Although the EKF estimation is inaccurate, the PoG can still become negative when the MAV is near the obstacle. The estimated distances were smaller than 1 m when the obstacle was detected, and the collision prevention was triggered immediately post-detection.
Multiple obstacle avoidance events on a single mission were tested by an onboard forward-trigger-turn loop. The MAV flew continuously inside a room with two different-patterned walls, a cylindrical structure, and nets (Fig. 7F); the command velocity was 1.5 m s⁻¹; the test lasted approximately 150 s. At times the MAV triggered earlier than expected, these were labeled as false positive triggers. In total, there were 42 triggers, 13 of which were false positives, achieving a 69% true positive rate. Based on where the false positives occurred, the possible reasons include the increasingly narrow corridor (corners) cases mentioned in Section V-C and the inaccurate OFD estimation when DOFP facing the cylinder structure and nets. The collision occurred when MAV was too close to the surface after turning and the EKF did not have sufficient time to converge.

C. Natural Environment Tests and Statistical Evaluations

Field tests in challenging environments showed varying degrees of success (Fig. 7J). To test the practicability of the system, the MAV was manually piloted in windy conditions, and flown toward sparse woodland hedgerows and tree trunks. The prevention success rate varied with the sparseness and the texture of the obstacle. At times, the MAV was able to fly through the hedgerows without collisions or triggering avoidance actions. Thus, the system is potentially capable of operating in cluttered environment.

For comparison, a front facing distance sensor in the same weight range as the OF sensors was installed on the MAV and flown toward sparse woodland hedgerows and tree trunks. The prevention success rate varied with the sparseness and the texture of the obstacle. At times, the MAV was able to fly through the hedgerows without collisions or triggering avoidance actions. Thus, the system is potentially capable of operating in cluttered environment.

For comparison, a front facing distance sensor in the same weight range as the OF sensors was installed on the MAV and flown toward sparse woodland hedgerows and tree trunks. The prevention success rate varied with the sparseness and the texture of the obstacle. At times, the MAV was able to fly through the hedgerows without collisions or triggering avoidance actions. Thus, the system is potentially capable of operating in cluttered environment.

For comparison, a front facing distance sensor in the same weight range as the OF sensors was installed on the MAV and flown toward sparse woodland hedgerows and tree trunks. The prevention success rate varied with the sparseness and the texture of the obstacle. At times, the MAV was able to fly through the hedgerows without collisions or triggering avoidance actions. Thus, the system is potentially capable of operating in cluttered environment.

VII. CONCLUSION

An onboard lightweight obstacle detection solution for MAVs was presented. The OFD, combined with inertial measurements in an EKF, enabled a 158 g quadrotor to detect and maintain a safe distance from frontal obstacles. Improving upon the use of OFD, a relative value, as a stopping metric, the EKF allows the estimation of the distance to the obstacle. Using our fictitious wall model, we can differentiate between far-field and imminent obstacles. This detection method allows MAV to fly safely in a broader velocity range. Simulations, idealized indoor tests, and field tests were conducted to benchmark the capabilities of the 20 g sensor suite. The system’s mass makes it attractive to be combined with tactile sensors to form holistic solutions for sensing, impact protection, and surface interaction for MAVs [22], [23].

For future work, a 360° OF sensor suite will increase the fidelity and robustness of detection in all planar directions (Fig. 1D). Two OF sensors facing the flight direction will estimate the obstacle position, while the others, measuring larger OF, would help to provide better OFD estimations. In addition, the model-plant mismatch will be studied to mitigate the false positive rate.

ACKNOWLEDGMENT

The authors would like to thank Dr. Sophie Armanini, Dr. Salua Hamaza and Mr. Hussain Noor for proof-reading this paper, and Miss Nan Zhang for assisting on the fieldwork. We thank Prof. Holger Krapp and Dr. Franck Ruffier for their guidance and inspiration.

REFERENCES


