Bio-inspired Obstacle Avoidance for Flying Robots with Active Sensing

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Abstract—This paper presents a novel vision-based obstacle avoidance system for flying robots working in dynamic environments. Instead of fusing multiple sensors to enlarge the view field, we introduce a bio-inspired solution that utilizes a stereo camera with independent rotational DOF to sense the obstacles actively. In particular, the rotation is planned heuristically by multiple objectives that can benefit flight safety, including tracking dynamic obstacles, observing the heading direction, and exploring the previously unseen area. With this sensing result, a flight path is planned based on real-time sampling and collision checking in state space, which constitutes an active sense and avoid (ASAA) system. Experiments demonstrate that this system is capable of handling environments with dynamic obstacles and abrupt changes in goal direction. Since only one stereo camera is utilized, this system provides a low-cost but effective approach to overcome the view field limitation in visual navigation.

Index Terms—Collision Avoidance, Active Vision, Motion and Path Planning, Visual Navigation

I. INTRODUCTION

Obstacle avoidance is one of the fundamental abilities of flying robots. Fast and precise sensing towards obstacles is required in the first place to achieve this ability in unknown environments. When potential dynamic obstacles, such as pedestrians and other robots, exist, the situation becomes more complex, and the sensing is of more significance.

Multiple types of sensors can be used in the sensing process, among which the stereo camera is a cheap and light-weight sensor that can provide both depth information and color information in high resolution, and thus is widely utilized on flying robots. However, a nonnegligible limitation of this sensor is that the field of view (FOV) is usually narrow. To ensure safety, an intuitive approach is to generate path candidates only inside of FOV [1], [2], while the outside area is considered to be invalid, which leads to a heavily constrained planning effectiveness. In contrast, building an obstacle map could enlarge the valid area for path planning [3], [4]. However, the free space in the map that is not covered by FOV currently could still be insecure because of the existence of dynamic obstacles.

To better adapt to the dynamic environment, one solution is to mount multiple stereo cameras that could cover 360 degrees [5], which enables real-time detection of obstacles from an arbitrary direction. Nevertheless, an obvious disadvantage is that the weight of the sensors and the required computing resource would be multiplied. Another straightforward solution is to control the fuselage’s yaw angle to make the camera heading direction follow flight velocity direction [6], [7], which ensures the timely update of the area along the planned path. However, for many flying robots, such as quadrotors, yaw rotation is coupled with linear motion [8], and thus this approach would sacrifice flight performance. Furthermore, dynamic obstacles could still come from the blind area and cause a severe crash.

Inspired by owl, we propose a new solution to tackle with obstacle avoidance in dynamic environment with active stereo vision. Although owls are unable to move their eyes in any direction (similar to stereo cameras), they have a very flexible neck that can swivel up to 270°, which enables them to rapidly observe even behind without relocating the torso [9]. Following this paradigm, a servo motor and a stereo camera are mounted on a quadrotor to play the roles of “neck” and “head”, as is illustrated in Fig. 1(a). The head is only a light stereo camera. Hence it can swivel much faster than the body while bringing very little influence to flight performance. We estimate the sense update degree (SUD) of each direction and plan the head rotation angle to realize an active sense of the neighborhood area. Tracking and predicting the trajectories of dynamic obstacles is concerned to adapt to dynamic environments. Based on the sensing result, a collision-free path for the flying robot is planned in real-time through sampling in state space. Altogether, this system is called an ASAA system. As far as we know, this is the first system that applies active stereo vision to realize obstacle avoidance for flying robots.

The main contributions of this paper are as follows:

1) Proposed a biomimetic active stereo vision structure with a corresponding sensor planning algorithm.
2) Improved a sampling-based path planner to handle challenging situations with dynamic obstacles and abrupt
changes in goal position.
3) Established a complete sense and avoid system for flying robots in dynamic environments.

II. RELATED WORK

Obstacle avoidance is a vital capability for flying robots. Sensing and path planning are two essential components of obstacle avoidance. Multiple types of sensors can be used for sensing, such as lidar, radar, monocular camera, and stereo camera. Among these sensors, lidar and stereo camera can provide high resolution position information of obstacles and thus are widely used \[10, 11, 5, 12\]. Lidar could have a detection range up to 360 degrees but is often heavy and expensive, and is unable to provide color information. In comparison, the stereo camera is lighter and can output both position and color information. Nevertheless, the limitation of the narrow FOV is nonnegligible. Obstacles outside of the FOV could be dangerous to the flight, especially in dynamic environments. Although some researchers have studied special stereo cameras that have omnidirectional vision \[13, 14\], these cameras are not popularized because of limitations like low precision and large size.

The fusion of multiple stereo cameras \[5\] or multiple types of sensors \[15\] are usually adopted to enlarge the FOV. This approach is practical but significantly increases the weight and computation cost of the system. An alternative approach is to adopt active vision \[16\] to change the FOV to the direction that benefits the flight safety. One way to realize this kind of FOV changing on a flying robot is to use a fixed camera mounted in the front and rotate the fuselage yaw direction. Usually, the yaw direction follows currently planned velocity direction to align the FOV along the flight path \[6, 7\]. In accordance with the dynamic property of flying robots like multirotors \[8\], yaw rotation is strongly coupled with the linear movement, and thus obvious control error on the linear movement can be caused by rotating the yaw angle, especially when large curvature occurs on the flight path and the yaw angle has to be rotated fast. To reduce this control error, \[7\] applies additional constraints in the flight path planning phase to make the curvature of the flight path smaller. In static environments, the way of aligning the FOV along the flight path is sufficient. However, when dynamic obstacles exist, after more observation towards dynamic obstacles, which could come from any direction, is required to predict their future trajectories for collision avoidance. The FOV direction is supposed to change frequently and rapidly to achieve observation towards more directions. A more effective approach is still required.

With the observation data from sensors, a collision-free path can be planned to realize obstacle avoidance. Some works directly use point cloud \[1\] or depth image \[17, 18\] in the FOV to plan the path, which reacts fast but the planning range is constrained in the FOV. Others prefer building a map to store the previously observed result and then plan in the map through search-based method \[19, 20\], optimization-based \[3\] method, or the combination of both \[21\]. Compared to the method that only use the sensing result in FOV, map-based methods could enlarge the valid area to search for safe paths. The most popular map is the voxel map, such as Octomap \[4\] and circular map \[3\]. These voxel maps are built upon the probability accumulation of occupancy status at discrete positions in the 3D space and hence are suitable for static environments. Regarding the dynamic obstacles, the response of this accumulation paradigm is not fast enough, and lots of noise would occur on the map. The work in \[6\] tries to decrease the response time and reduce noise by removing and re-adding the voxels inside of FOV.

To better fit the dynamic environment, a sense and avoid (SAA) system \[22\] that can predict the future trajectories of dynamic obstacles and plan a flight path to avoid potential collisions is required. In a relatively high flight space for large unmanned aerial vehicles, the environment is usually open, and dynamic obstacles are other aerial vehicles. The SAA system mainly concerns avoiding collision towards other aerial vehicles \[23\]. In a near-ground environment for the flying robot like ours, the situation is more complicated. Various kinds of dynamic obstacles could appear, while the optional paths are also constrained by static obstacles. Only a few works have tackled this issue. \[24\] considers moving obstacles like pedestrians in the front depth view and use a chance-constrained model predictive controller to realize fast and collision-free flight. The work in \[25\] applies a Bin-Occupancy filter to track dynamic obstacles in a voxel map. The path of the quadrotor is planned by optimizing the real-time control commands that have a low probability of collision in the next N steps. Due to the complexity caused by dynamic obstacles, there is still a huge room for improvements in these works.

III. METHODS

We first present the design basis and the overview of our system. Then the sensor planning algorithms to realize active stereo vision are stressed. Finally, the dynamic obstacles modeling and the flight path planning approaches are described.

A. System Design

The system aims to enhance the observation performance of a single stereo camera to realize safe and rapid flight in dynamic environments. Consider the attitude control model of a regular quadrotor \[8\]. Let \(\phi, \theta, \psi\) denote roll, pitch, and yaw angle. The state vector of attitude is

\[
x = \begin{bmatrix} \phi & \dot{\phi} & \theta & \dot{\theta} & \psi & \dot{\psi} \end{bmatrix}^T
\]

Then the simplified state space equations are usually expressed as:

\[
x = \begin{bmatrix} \phi \\ \dot{\phi} \\ \theta \\ \dot{\theta} \\ \psi \\ \dot{\psi} \end{bmatrix} = \begin{bmatrix} \dot{\phi} \\ \theta + \dot{\psi} a_1 + \dot{\theta} a_2 \Omega_r + b_1 U_2 \\ \dot{\theta} \\ \psi + \dot{\phi} a_3 - \dot{\psi} a_4 \Omega_r + b_2 U_3 \\ \dot{\psi} \\ \theta + \dot{\phi} a_5 + b_3 U_4 \end{bmatrix}
\]

where \(\Omega_r\) is the roll rate of the quadrotor, and \(a_1, a_2, a_3, a_4, a_5, b_1, b_2, b_3\) are the parameters of the system.
plan to better control performance.

Therefore, we prefer adding a “head” with additional DOF to realize active vision rather than swivel the yaw angle $\psi$ of the quadrotor. Define the angle of the head as $\xi$. It is worth noting that changes on $\xi$ would cause variations on $I_{xx}$ and $I_{yy}$, which makes the system time-varying and hard to be controlled. Thus we prefer a head that is very light and small compared to the whole quadrotor so that the variations on $I_{xx}$ and $I_{yy}$ are neglected. More advantage of a light and small head is that its moment of inertia $I^h_{zz}$ is small. Thus when the head is rotating, it requires less $U_4$ to provide reactive torque, which can be derived from:

$$\ddot{\xi}I_{zz}^h = \dot{\psi}I_{zz} = U_4 + \dot{\theta}\dot{\psi}(I_{xx} - I_{yy}) \approx U_4$$

(3)

Hence a stereo camera that takes only 3.3% weight of the whole flying robot is applied to act as the rotatable head, and the other hardware components are fixed. Through numerical estimation in CAE software, $I_{zz}^h$ takes only 0.1% of $I_{zz}$ in our flying robot while the variations on $I_{xx}$ and $I_{yy}$ are less than 2%. A regular flight controller running PID algorithms is enough for proper performance in this case. A servo motor with a high-precision encoder is connected under the stereo camera to form an active vision device with one rotational DOF. Then the device is placed on the top center of the quadrotor to have a clear view field, as is illustrated in Fig. 1(a).

With this rotatable camera as the head, we designed a complete ASAA system, as Fig. 2 shows. The main system could be divided into two subsystems: the active sense subsystem and the avoid subsystem. The former subsystem is composed of two detectors designed respectively for dynamic obstacles and static obstacles, and particularly, planner and controller for the sensor rotation. The latter subsystem consists of the path planner and the controller of the quadrotor. Both controllers for the sensor rotation and the quadrotor flight are simple PID controllers. The rest components are specified in the following subsections.

B. Sensor Planning

Sensor planning in our system is to plan the rotation angle of the stereo camera for a FOV that benefits flight safety. Since the environment is unknown and potential dynamic obstacles exist, this planning is a complex high-dimension problem of which a complete or optimal solution can hardly be found. In this work, we plan the rotation angle heuristically based on five objectives that try to imitate biological behavior and ensure flight safety.

Let $\xi_t$ denote camera rotation angle to be planned. The first objective is that direction of the goal $D_g$ should be included in the FOV. The second objective is that the real current flight direction $D_v$ should be inside of the FOV. $D_g$ and $D_v$ can be very different if an abrupt change in the goal direction occurs. The third objective is to observe the state of dynamic obstacles frequently. Avoiding a collision with dynamic obstacles requires state estimation and prediction of their trajectories, which demands more observation than static obstacles. The fourth objective is to observe the direction. $G(\psi)$ is the function to get the SUD of a specific direction. $G(\psi)$ describes penalty when a direction is not in the camera view field. Suppose the angle of a direction is $\theta$.

$$G(\psi) = \begin{cases} 0, & \text{if } \psi \in [-\frac{\theta_1}{2}, \frac{\theta_2}{2}] \\ \psi^2 - \frac{\theta_1^2}{4}, & \text{otherwise} \end{cases}$$

(6)

Let $v_t$ denote the current horizontal velocity of the flying robot. While the velocity increases, more attention should be given to $d_v$. Since the attention towards $d_v$ is quite crucial when $v_t$ is large, we define this tendency as quadratic growth.

$$f_2(\xi_t) = v_t^2 \cdot G(\xi_t - d_v) \cdot (1 - U(d_v))$$

(5)

$$f_3(\xi_t)$$

(7)

$$f_3(\xi_t)$$

is related to the state estimation result of the dynamic obstacles. If the currently estimated relative position and relative velocity of the $j_{th}$ dynamic obstacle are $p^j_0$ and $v^j_0$ respectively, and $p^j_0$ lies in the direction $d^j_o$, then $f_3(\xi_t)$ can be described as:
where $N$ is the number of dynamic obstacles in tracking. The obstacle with smaller $|p^0_d|$ and larger $|v^0_d|$ should be valued more. $\beta$ is a coefficient defined to adjust the relative importance of $|v^0_d|$ towards $|d^0_d|$.

The forth cost function concerning exploring the less-updated area is simply given by

$$f_4(\xi_t) = U(\xi_t).$$

The last cost function is to resist large direction changes. Let $\xi_{t-1}$ denote the rotation angle planned last time. $f_5(\xi_t)$ is calculated by:

$$f_5(\xi_t) = (\xi_t - \xi_{t-1})^2$$

Then an overall cost function can be given to simplify the problem.

$$F(\xi_t) = \sum_{i=1}^{5} \lambda_i f_i(\xi_t)$$

where $\lambda_i$ are the weighting coefficients.

To find the optimal solution with the simplest approach, the direction angle is discretized with resolution $\delta$ and the optimal solution $\xi^*_t$ is searched by enumeration. If the camera can rotate freely, the searching domain of $\xi$ (to avoid unnecessary large rotation), the searching domain is $S = \{\xi_0 - \pi, \xi_0 - \pi + \delta, \xi_0 - \pi + 2\delta, ..., \xi_0 + \pi - \delta\}$, where $\xi_0$ is the real current angle. If there is a limited rotation range $[\xi_{min}, \xi_{max}]$ that satisfies $\xi_{min} < -\pi - \delta$ and $\xi_{max} > \pi + \delta$ (a margin larger than $\delta$ is required to avoid unnecessary large rotation), the searching domain is $S = \{\xi_0 - \delta, \xi_0 - \pi - \delta, ..., \pi + \delta\}$. In our case, the rotation range is limited by the cable on the camera thus the latter domain is adopted.

The behavior of the result camera rotation is comprehensive. Different states of the flying robot and the environment could lead to different behaviors. When the flying robot is hovering with no goal position received, $f_1$ and $f_2$ are zero for any angles. If no dynamic obstacle is detected, the camera rotates in a range of 360 degrees to scan the whole neighborhood area due to the effect of $f_4$ and $f_5$. When a goal position is received, but the flying robot is still hovering because the flight is not allowed or the robot is trapped in a very dense area, $f_1$, $f_4$ and $f_5$ take effect, and the camera rotates in a relatively small area around the goal direction to search for a valid flight path. If dynamic obstacles appear, the camera will pay more attention to them due to $f_3$. When the flying robot is moving, $f_2$ takes effect, and the behavior of the camera is a comprehensive result of all the five optimization components.

C. SUD Estimation

Our SUD is used to assess the fully updated probability of each direction in $S$. A fully updated direction suggests all the obstacles along this direction are observed recently. The SUD of each direction is stored in a one-dimension buffer. Suppose the probability of one direction $d_i$ to be fully updated at a discrete time $t$ in log-odds notation $L(d_i|y_{1:t})$, given the previously measurement $y_{1:t}$. The update formula regarding current measurement $y_t$ can be expressed as:

$$L(d_i|y_{1:t}) = \max(\min(L(d_i|y_{1:t-1}) + L(d_i|y_t), l_{max}), l_{min})$$

where $l_{min} = 0$ and $l_{max} = 1$ describe the lower and upper bound. $y_t$ is related to the rotation of the camera and the movement of the flying robot. Let $\Delta p$ denote the position displacement of the flying robot during one calculation period. The logarithmic form $L(d_i|y_t)$ is calculated by:

$$L(d_i|y_t) = -\varepsilon_1 \Delta p \cdot \tilde{d}_i L^{-1}_h \varepsilon_2 |\Delta p \cdot k| + l(d_i)$$

where $\tilde{d}_i$ represents the unit direction vector of angle $d_i$, $L_h$ describes the valid depth measurement distance of the stereo camera and $k$ represents a unit vector along z axis. $\varepsilon_1$ and $\varepsilon_2$ are two weighting coefficients. The first item and the second item in Eq. (15) give the probability decrease or increase caused by horizontal movement and vertical movement, respectively, via an exponential model. For the reason that the camera swivels in the $xy$ plane in body frame, we take $\varepsilon_2 > \varepsilon_1 = 1$ in practice. $l(d_i)$ describes the log-odds increase of the probability when direction $d_i$ is in the camera view and is given by:

$$l(d_i) = \begin{cases} l_{hit}, & \text{if } |d_i - \xi_0| \leq \frac{\theta_2}{2} \\ l_{miss}, & \text{otherwise} \end{cases}$$

with $l_{hit} > 0$ and $l_{miss} < 0$. Function $U(\ast)$ in Eq. (5) and Eq. (7) is to query the buffer to get the SUD of one direction.

D. Dynamic Obstacle Modeling

To model and predict the trajectories of dynamic obstacles, a multiple object tracker (MOT) is adopted. Since all our computation is conducted in an onboard computer with quite limited computing power, a very efficient MOT is required. In addition, multiple dynamic obstacles could be around the flying robot in different directions, and some could only be seen occasionally due to the limited FOV. This leads to a difficult occlusion problem [26]. Here we modified SORT [27] to adjust our requirements. SORT is a very light algorithm that first detects objects and then uses Kalman Filter (KF) and Hungarian algorithm for tracking and data association. The features estimated in KF are the pixel position and pixel velocity of the pedestrians. In our MOT algorithm, we use the tiny version of YOLO V3 [28] as the detector considering the limited onboard computing power. Dynamic obstacles like pedestrians and other robots are trained to be detected. To tackle with the occlusion problem, we add color histogram and label as additional features for the data association. In addition, the real position and velocity of the obstacles in global coordinate are estimated in KF because the pixel position would easy to lose due to the camera rotation.

The motion model of each dynamic obstacle in KF is defined as a linear constant velocity model with independent motion on each axis. Take the motion on $x$ axis as example. The acceleration of an obstacle $o^j$ is $a^j_x = N(0, \sigma^j_x^2)$, where $\sigma^j_x^2$ is the variance and is initialized according to the label of the obstacle. Suppose the time interval from $t - 1$ to $t$ is $\Delta t$.

The state vector $s^j_t = [x^j_t, \dot{x}^j_t]^T$ at $t$ is predicted as:
where \( l \) controls the angle range of \( S_p \) in FOV. Let our flying robot is equipped with active stereo vision, our described in [1] is adopted to generate motion primitives. Since composed of two parts, which are motion primitives generation and collision checking. The state distribution center is \( \hat{s}_t^j = [x_{t-1}^j + \hat{x}_{t-1}^j \Delta t, \hat{x}_{t-1}^j]^T \) while the covariance matrix is calculated by

\[
\text{Var} \left( s_t^j \right) = E \left[ (s_t^j - \hat{s}_t^j)(s_t - \hat{s}_t^j)^T \right] = \sigma^2 \left[ \begin{array}{ccc} 0.25\Delta t^4 & 0.5\Delta t^3 & \Delta t^2 \\ 0.5\Delta t^3 & \Delta t^2 & \end{array} \right] \]

(16)

E. Flight Path Planning

The flight path planning is conducting in real-time and is composed of two parts, which are motion primitives generation and collision checking. The state-space sampling method described in [1] is adopted to generate motion primitives. Since our flying robot is equipped with active stereo vision, our sample region for flight direction candidates is not limited in FOV. Let \( p_{\text{goal}} \) denote goal position and \( p_{\text{rob}} \) denote the current position of the flying robot. Suppose

\[ l_1 = p_{\text{goal}} - p_{\text{rob}}, \quad l_2 = p - p_{\text{rob}} \]

(17)

The sampling region is

\[ S_p = \{ \forall \mathbf{p} \in S_p \mid |l_1, l_2| < \theta_{\text{val}}, |l_2| \leq l_{\text{vis}} \} \]

(18)

where \( l_{\text{vis}} \) is the depth visible distance, and \( \theta_{\text{val}} \in [0, \pi] \) controls the angle range of \( S_p \). If \( \theta_{\text{val}} > \frac{\pi}{2} \), direction candidates that point to the opposite of \( l_1 \) might be sampled. Selecting these candidates would temporarily lead to a path away from the goal but is conducive to flight safety in the environment with dynamic obstacles. For instance, when a dynamic obstacle comes closely in a sudden and no collision-free motion primitive to the goal direction can be found, a decent strategy is to fly to a posterolateral position temporarily to avoid collision and then search for a valid path to the goal. If \( \theta_{\text{val}} = \pi, S_p \) represents a sphere with a radius of \( l_{\text{vis}} \), which suggests a real-time omnidirectional observation can be acquired. For the reason that the rotation speed of our camera is limited, the direction opposites to \( l_1 \) is usually unable to be observed immediately, \( \theta_{\text{val}} = \frac{\pi}{2} \) is taken.

Then the direction candidates are sorted, and motion primitives can be generated by [1]. Let \( p_{\text{gen}}^i(t), t \in [0, T] \) denote the position setpoint on the \( i \)th generated motion primitive at a future time \( t \), where \( T \) is the estimated flight time in motion primitive generation and \( p_{\text{gen}}^i(0) = p_{\text{rob}} \). Our collision checking approach is described as follows.

The collision checking considers both static obstacles and dynamic obstacles. The static obstacles are represented by an egocentric local occupancy map [3]. The voxels in the position of dynamic obstacles are set to be free directly to eliminate the noise caused by dynamic obstacles. Then the Euclidean distance field (EDF), which describes the distance from each free voxel to the nearest obstacle, can be generated based on this map [3].

Distance to a dynamic obstacle is related to the motions of both the flying robot and the dynamic obstacle. \( p_{\text{goal}} \) denote goal position and \( p_{\text{rob}} \) denote the current position of the flying robot. Suppose

\[
\begin{bmatrix} x_t^j \\ \dot{x}_t^j \end{bmatrix} = \begin{bmatrix} 1 & \Delta t \\ 0 & 1 \end{bmatrix} \begin{bmatrix} x_{t-1}^j \\ \dot{x}_{t-1}^j \end{bmatrix} + \begin{bmatrix} \frac{1}{\pi} a_s^2 \Delta t^2 \\ \frac{1}{\pi} \end{bmatrix} \]

(15)

The squared form of the Mahalanobis distance is to calculate this distance. Suppose the predicted position of the \( j \)th dynamic obstacle at time \( t \) is \( \hat{p}_t^j(t) \). Let \( \Delta p_t^j(t) = p_t^j(t) - \hat{p}_t^j(t) \). The squared form of the Mahalanobis distance is:

\[ d_M^2(t) = \Delta p_t^j(t)^T \Sigma_j^{-1}(t) \Delta p_t^j(t) \]

(19)

According to Eq. (16),

\[
\Sigma_j(t) = \frac{1}{4} \left[ \begin{array}{ccc} \sigma_x^2 & 0 & 0 \\ 0 & \sigma_y^2 & 0 \\ 0 & 0 & \sigma_z^2 \end{array} \right] \]

(20)

Assume that the distance of \( p_{\text{gen}}^i(t) \) to its closest obstacle, among static or dynamic obstacles, is \( D(p_{\text{gen}}^i(t)) \). The \( i \)th motion primitive is safe if \( \forall t \in (0, T) \), the following condition is true for both static and dynamic obstacles:

\[ D(p_{\text{gen}}^i(t)) > D_{\text{min}} \lor \tilde{D}(p_{\text{gen}}^i(t)) > 0 \]

(21)

where \( D_{\text{min}} \) is the distance threshold. The former condition describes that the setpoint too close to obstacles is unsafe. The latter condition is considered because the dynamic obstacles might unbidenly come to a very close distance (less than \( D_{\text{min}} \)) to the flying robot, and the flying robot might also intrude to the area close to the obstacles due to control error or external disturbance. In these cases, the former condition can not be satisfied no matter which direction the primitive leads to, making the flying robot stuck. However, if \( \tilde{D}(p_{\text{gen}}^i(t)) > 0 \) is satisfied, it suggests that the primitive is leading to a position far from the obstacles, which should also be treated as a safe path. Take the setpoints discretely with time interval \( \Delta t \) and let \( p_{i,k} \) denote the \( k \)th \((k \in \{1, 2, ..., \frac{T}{\Delta t}\}) \) position setpoint on the \( i \)th motion primitive. Eq. (21) turns to \( \forall k \in \{1, 2, ..., \frac{T}{\Delta t}\} \),

\[ D(p_{i,k}) > D_{\text{min}} \lor D(p_{i,k}) \geq D(p_{i,k-1}) \]

(22)

Equal to is taken in the latter condition because the distance resolution in EDF is limited. Two adjacent voxels in the local map might have the same distance value.

IV. IMPLEMENTATION

Two essential details during the implementation are emphasized in this section. The first is to reduce the depth estimation error of the stereo camera while the second is to synchronize the data from different sources. The following presents our strategies for these details.

A. Depth Estimation

Rotating the camera provides an agile way for observation while motion blur would occur and the depth estimation would be inaccurate. Let \( v_{\text{cam}}^j \) denote the relative velocity of an obstacle \( j \) towards the camera and \( d_{\text{cam}}^j \) denotes the distance between the camera and the obstacle. \( v_{\text{cam}}^j \) is derived by

\[ v_{\text{cam}}^j = \dot{d}_{\text{cam}}^j(\xi + \psi)k_{\text{cam}} + v_{\text{rob}} - v_o \]

(23)

where \( k_{\text{cam}} \) is a unit vector perpendicular to the camera direction in \( xy \) plane. \( \psi = 0 \) is taken in the experiments because the rotation for observation is achieved by \( \xi \). \( |v_{\text{cam}}^j| \) can be very large if \( \xi \) is large, which would result in terrible
the motion blur phenomenon. The measurement for the depth of obstacles would be inaccurate.

Deblurring methods can be used to alleviate motion blur, but this would consume computation resources and cause more latency. Therefore, we instead tune the camera parameters, such as exposure time and brightness, and set a limitation $\xi_{\text{max}}$ for the maximum rotation speed in the camera PID controller. The value of $\xi_{\text{max}}$ is investigated through an experiment. We set different $\xi$ and measure the depth error $d_{\text{error}}$ of an obstacle in the depth image when the obstacle is in front of the camera. The real depth is $d_{\text{cam}}^{\text{real}} = 3.0$ m. Both the flying robot and the obstacle are static during the test thus $|v_{\text{cam}}|=d_{\text{cam}}^{\text{real}}\dot{\xi}$. The experiment result with a Realsense D435 camera is shown by a box plot with average value curve in Fig. 3. In practice, the maximum permissible depth error in $d_{\text{cam}}^{\text{real}} = 3.0$ m is set to be 0.2 m, which means $|v_{\text{cam}}| \leq 4.5$ m/s. Considering the movement of the flying robot and the dynamic obstacles, we set $\xi_{\text{max}} = 1.2 \text{ rad/s}$ in real-world experiments.

B. Time Synchronization

Since the camera could rotate rapidly, images or point clouds collected between two adjacent frames could be quite different. Synchronizing the data from different sources is very important. The data include images and point clouds from the stereo camera, the body pose estimated by the flight controller, and the camera rotation angle from the servo motor, whose updates are fulfilled by individual threads with the rates of 30Hz, 100Hz, and 50Hz respectively. The time delays in the body pose estimation and the camera rotation angle estimation are ignored because these estimations can be fulfilled in a few milliseconds with no distinct variations. However, collecting images or point clouds from the stereo camera have a non-negligible delay. We first measured the average delay time in image collection and then adopted two queues to store the pose data and the rotation angle. The popped-out pose and rotation angle data from the queues are stamped and further synchronized by ROS synchronizer with the data from the stereo camera in the local mapping node. In addition, since the object detection for dynamic object tracking would cause over one hundred milliseconds delay with our limited onboard computing power, we record the synchronized body pose and camera rotation angle when an image arrives at the object detector and use the recorded data to calculate the object’s global position when the detection is finished. The average time difference after the synchronization is below 10 ms. Then the influence of this difference is further alleviated by our KF.

V. Experiments

A. Experimental Settings

Beyond the commonly-used experiment of flying to a goal position and avoiding obstacles along the way, a more challenging experiment is designed to validate the effectiveness of our ASAA system, where the flying robot plays the role of an owl to catch a virtual rat. The rat is so smart and agile that it will escape and show up at a random position on the other side whenever the flying robot approaches it, which models the abrupt changes in goal direction. More difficultly, both static obstacles and dynamic obstacles exist in the testing field, thus excellent sense and avoid ability is required to ensure flight safety.

A quadrotor with the axle base of 400 mm is adopted. Realsense D435 with a horizontal view field of 72° is applied to be the “head”. And a servo motor with an encoder whose resolution is 0.088° is utilized to be the “neck”. A UP Core Plus computing board running ROS is adopted as the onboard computer. The mounted CPU is Intel Atom x7 (4 Cores, 1.8 GHz). A Vision Plus module with three Myriad X neural computing chips is also equipped to run the YOLO V3 (Tiny) detection model. Our flight controller is Pixhawk running PX4 firmware. Pose estimation comes from the Vicon motion capture system during the test. We intend to test the real-time sense and agile obstacle avoidance ability of our system thus the length of the egocentric local map is set to be merely 6.4 m and $l_{\text{vis}}$ is set to be 1.5 m, which means the sensing range is merely about 3.2 m and the avoidance maneuver has to be taken within 1.5 m to the obstacles.

Table I describes the coefficients for camera rotation planning in the test. The maximum velocity of the flying robot is set to be 1 m/s. The dynamic obstacles are several ground vehicles loaded with foam pillars (yellow top with Letter “R” in our figures), which move at a maximum speed of 0.5 m/s.

B. Results

We first measure the time consuming of the utilized algorithms on our onboard computer. The results are presented in Table II. The star on the time consumption of dynamic obstacle detection indicates that the delay caused by this process is different. Unlike other algorithms in our system, detection is
Fig. 4. Episode 1: collision avoidance to a dynamic obstacle. (a) to (e) present bird’s-eye view snapshots, where the violet arrow or sphere indicates the goal position and the red angle marker presents the horizontal FOV. (f) to (j) illustrate the data visualization in RViz. Static obstacles are described as colored point clouds, while the dynamic obstacle is described with a yellow robot model. The FOV is shown by a translucent pyramid, and the trajectory in the last three seconds is presented with a red curve. Arrows on the curve indicate the direction of the camera.

Fig. 5. Episode 2: blocked by an obstacle and choose another way twice. (a) to (e) present bird’s-eye view snapshots. (f) to (j) illustrate the data visualization in RViz. Symbols are the same as Fig. 4.

Fig. 6. Pitch and roll angle tracking curves of Episode 1.

Fig. 7. Pitch and roll angle tracking curves of Episode 2.
Fig. 6 both reached a peak at $t_2$ to decelerate and make a turn. The red curve in Fig. 4(j) presents the flight trajectory of this episode, and the yellow arrows indicate the direction of the stereo camera.

b) Episode 2: starts with a situation when the flying robot received a new goal position and turned to fly to the right side. However, a dynamic obstacle came in a sudden and blocked its way (Fig. 5(a) and 5(f)). Thus an agile maneuver was taken and a motion primitive to the forward (in camera view, which is posterolateral to the goal direction) was chosen temporarily to find another valid path to the goal. Unfortunately, the dynamic obstacle also moved forward and continued to block the way (Fig. 5(b) and 5(g)). A short time later, the motion primitive to the backward was chosen because of the obstruction of the wall. Finally, from $t_2$ to $t_4$, the flying robot successfully avoided collision to the static obstacle and approached the goal. The dynamic obstacle on the right side was also detected and tracked while it moved far from the flight path and caused a little effect. The relative pitch and roll angle curves are shown in Fig. 7.

During the test, the camera in our ASAA system rotates very flexibly according to the planning result of our optimizer to observe the neighborhood area and prevent collision. In Fig. 4(i) and 5(g), the dynamic obstacle is out of the FOV but is still considered in collision checking with the prediction result. When the dynamic obstacle has not been detected for two seconds, the covariance is too large, and thus the prediction no longer utilized, as is illustrated in Fig. 4(i) and Fig. 5(h). More experiment results are presented in the video: [https://youtu.be/nkbnfcaqJ0g](https://youtu.be/nkbnfcaqJ0g)

VI. CONCLUSION

Obstacle avoidance for flying robots in unknown and dynamic environments is a task of great challenge. This paper presents a bio-inspired sense and avoid system using active stereo vision to tackle this task. Unlike many existing flying robots that try to fuse multiple sensors to realize obstacle avoidance in such environments, our ASAA system requires only one stereo camera, which can substantially reduce cost and benefit commercialization. Despite the progress we have made, the completeness and optimality of planning the sensing direction through the proposed objectives can hardly be proved. Future works will study more on biological behaviors and try to integrate reinforcement learning-based methods to improve sensing performance further.

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