Perception Aware Quadrotor Control: An Experimental Evaluation

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Abstract. Accurate localization of an Uncrewed Aerial Vehicle (UAV) in GPS-denied environments remains a fundamental and unresolved challenge in robotics. Traditional approaches treat state estimation, trajectory planning, and control as separate modules, often assuming perfect state information. However, when visual sensors are used for localization, this assumption often breaks down under challenging conditions, such as poor lighting or textureless environments, resulting in significant drift and unreliable control decisions. Yet, perception performance can be significantly improved if the UAV's motion is planned with the constraints and capabilities of onboard vision in mind. In this context, Perception-Awareness (PA) emerges as a strategy to adapt a UAV's maneuvers based on the real-time perception of the environment. In this paper, we implement and evaluate a PA quadrotor controller through an extensive experimental campaign, demonstrating a reduction in odometry drift of up to 70% compared to a non-PA control approach.

Introduction

Perception-Awareness (PA) consists in adapting UAV's maneuvers based on the real-time perception of the environment. Previous works in PA control have focused on improving the performance of vision based odometry [1]. These efforts typically incorporate feature-based objectives such as:

1. Enforcing the visibility of a given set of landmarks.
2. Minimizing the reprojection error for certain landmarks.
3. Keeping the centroid of observed features centered in the image [1].
4. Minimizing the projected velocity of features to reduce motion blur.
5. Maximizing co-visibility across consecutive frames [2].

Depending on the formulation, PA strategies may influence only the timing of the trajectory, or they may directly affect the UAV's position [3], yaw angle, or both. A widely used method to incorporate such perception objectives into the control loop is Model Predictive Control (MPC). A notable example is PAMPC [1], which integrates perception objectives directly into the MPC optimization problem. This approach explicitly accounts for feature visibility within the camera's field of view (FOV) and penalizes motion that induces image blur.

The main contributions of the paper are the seamless integration of the PAMPC framework into a PX4-based quadrotor (equipped with a forward-looking stereo camera), and the comprehensive experimental evaluation of the resulting Visual Inertial Odometry (VIO) performance. We systematically compare PAMPC against a conventional, non-perception-aware MPC strategy, demonstrating the benefits of coupling perception and control in real world flight scenarios.

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Methodology

The perception-aware control problem is formulated as an Optimal Control Problem (OCP):

$$\min_{u(\cdot)} \int_0^T \left[L_a\big(x(t),u(t)\big) + L_p\big(z(t)\big)\right] dt \dot{x}(t) = f\big(x(t),u(t)\big), x(0) = x_0, x(t) \in \mathcal{X}, u(t) \in \mathcal{U}, \tag{1}$$

where, $x = [p_{WB}, v_{WB}, q_{WB}]^{\top}$ is the quadrotor state, including position, velocity and orientation of the body frame B with respect to the world frame W, expressed in world frame. The perception state $z = \left[s, \dot{s}\right]$ includes the image coordinates of the centroid of observed features, referred to as Point Of Interest (POI), expressed in pixel coordinates in the image plane, $s = (u, v)$, as well as its velocity on the image plane, $\dot{s}$. The cost L_a penalizes deviations from a reference trajectory, and L_p penalizes deviation from the null perception state $z = 0$, thus introducing perception objectives that keep the centroid of observed features centered in the image and minimize their projected velocity on the frame, a detailed derivation can be found in [1]. The optimized quadrotor control input is $u = [c, \Omega_B]$, where c is the mass-normalized thrust along the vertical axis in the body frame B, and $\Omega_B = \left[\omega_x, \omega_y, \omega_z\right]^{\top}$ is the angular velocity in body frame. The quadrotor state dynamics is described by:

$$\dot{p}_{WB} = v_{WB}, \dot{v}_{WB} = g + q_{WB} \odot c, \dot{q}_{WB} = \frac{1}{2} \Lambda(\Omega_B) \cdot q_{WB}, \tag{2}$$

where $\odot$ denotes the multiplication between a quaternion and a vector, and

$$\Lambda(\Omega_B) = \begin{bmatrix} 0 & -\omega_x & -\omega_y & -\omega_z \\ \omega_x & 0 & \omega_z & -\omega_x \\ \omega_y & -\omega_z & 0 & \omega_x \\ \omega_z & \omega_y & -\omega_x & 0 \end{bmatrix}. \tag{3}$$

The constraints imposed ensure the thrust, angular and linear velocities remain within feasible limits:

$$X = \{v_{WB} s.t. -v_{max} \le v_{WB} \le v_{max}\}, U = \begin{Bmatrix} c_{min} \le c \le c_{max} \\ -\Omega_{max} \le \Omega_B \le \Omega_{max} \end{Bmatrix}. \tag{4}$$

The POI coordinates in world frame are computed as follows: first, grayscale images from left camera are processed using an ORB feature detector to identify relevant landmarks, then, depth

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information is used to map 2D frame coordinates to 3D space in the camera frame using the pinhole model; finally, camera pose information is utilized to transform this information into the 3D world frame. Figure 1(a) shows an example of the POI computed. The resulting OCP is discretized using Direct Multiple Shooting within ACADO and solved in a receding horizon fashion.

Experimental results

The solver runs in real time on the quadrotor companion computer at 50 Hz, the resulting velocity and acceleration commands are tracked by PX4's cascaded P-PID running at 250 Hz. Perception metrics (POI and s) are computed onboard using ORB feature detection and stereo triangulation. The experiments have been conducted inside the Flying Arena for Rotorcraft Technologies (FlyART) of the Aerospace System and Control Lab (ASCL). The FlyART is an indoor facility whose flight volume is $12 \times 6 \times 4$m. The quadrotor used in the experimental campaign is equipped with a forward-facing stereo camera, the ZED 2i and a Jetson Xavier NX. Communication between the various components is performed through Robot Operating System (ROS).

Experiments include straight-line flights at 0.3 m/s under both good and low-light conditions. Figure 2 shows the Experimental setup, while Figure 1(c) and 1(f) show the quadrotor's heading during the experiment. The Motion Capture system (MoCap) is used as the ground truth to evaluate the VIO performance. Figure 3 shows the odometry experimental result, with good illumination conditions PA reduced the in-plane drift rate from 0.49cm/s to 0.1cm/s. With low illumination conditions drift rate with and without PA are 0.20cm/s and 1.14cm/s, respectively.

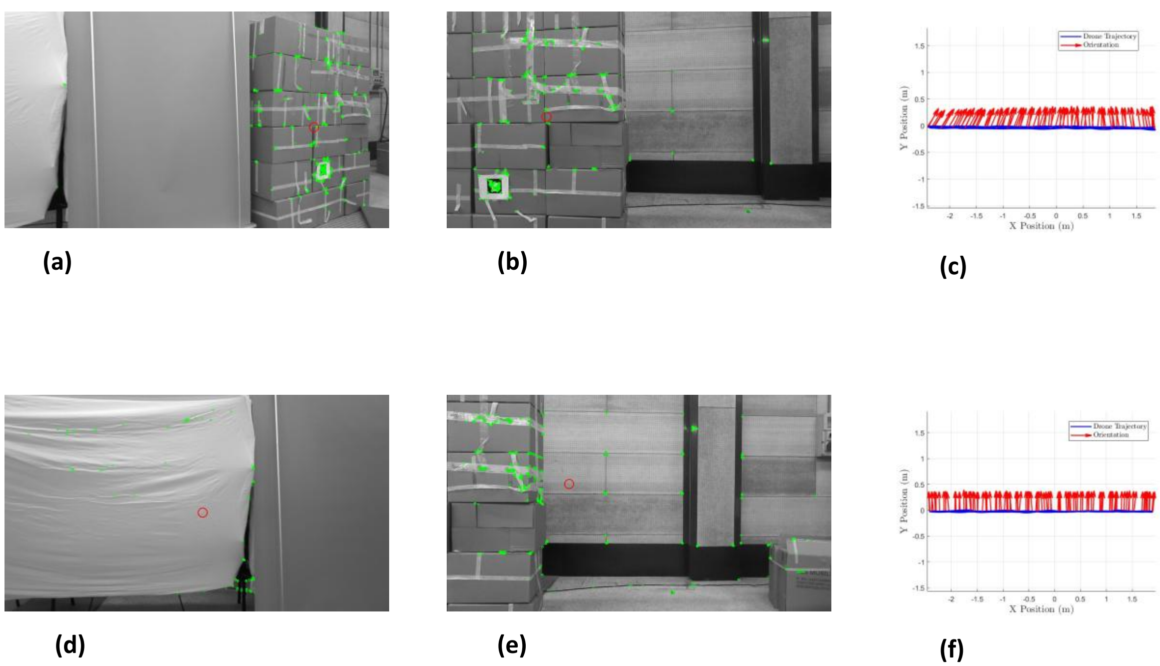

Figure 1. The top and bottom rows illustrate drone orientation with and without PA, respectively, during a linear trajectory. With PA, the quadrotor consistently adjusts yaw to keep the feature-rich region in the FOV. In contrast, without PA, the drone's camera captures mostly blank sheet (left bottom image).

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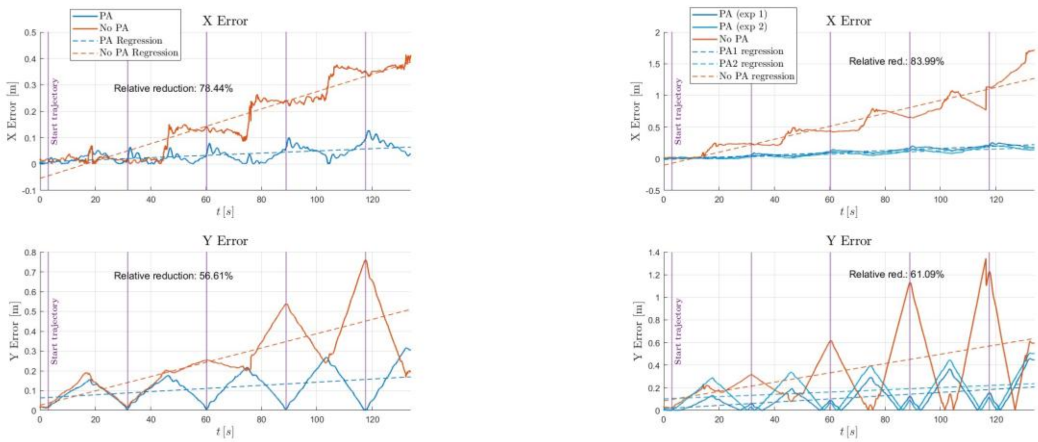
(a) Good illumination **(b) Low illumination**

Figure 2. Experimental setup.



(a) Good illumination **(b) Low illumination**

Figure 3. Absolute x- and y-coordinate odometry error (w.r.t MoCap position estimate) in linear flight.

Conclusion

By integrating perception objectives, maximizing the visibility of the feature centroid and minimizing its projected velocity on the camera plane, into the control strategy, the resulting control actions enhance VIO performance. Experimental results demonstrate that the PA framework enhances overall VIO accuracy, even under challenging low-light conditions, ultimately leading to better decision-making based on visual information.

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