Disturbance Observer-based Robust Control of a Quadrotor Subject to Parametric Uncertainties and Wind Disturbance

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ABSTRACT We propose a disturbance observer-based controller to deal with the trajectory tracking problem of a quadrotor subject to parametric uncertainties and wind disturbance. The design is based on the combination of a recursive robust linear-quadratic regulator and a Kalman filter. Robust regulation deals with uncertainties of state and input matrices of the quadrotor in order to minimize, mainly, its trajectory tracking error. Filtering aims to estimate wind disturbance based on an augmented state-space model of the quadrotor. We finish the approach with a compensation controller whose task is to perform disturbance attenuation.

We develop indoor experiments where a wind disturbance source provides a measurable speed pattern. We provide a comparative study among the robust control approach proposed with a feedback linearization controller, a proportional-integral-derivative controller, and a nominal linear-quadratic regulator.

INDEX TERMS Disturbance attenuation, estimation, filtering, quadrotor, robust control, uncertainty.

Nomenclature

Sets and Indices

\( N \) Amount of iterations
\( K \) Set of experiments

Variables

\( \nu \) Velocity input vector of the quadrotor
\( q \) Pose vector
\( q_p \) Position vector
\( q_\psi \) Yaw orientation
\( q^d \) Reference trajectory vector
\( d \) External disturbance
\( \dot{d} \) Disturbance estimation
\( u \) Virtual control signal
\( u^\text{pd} \) Feedforward compensator signal
\( u^\text{com} \) Composite control signal
\( x \) State-error vector of the system
\( d_x \) Disturbance variable
\( d_b \) Disturbance variable derivative

Parameters

\( \Theta / \Gamma \) Quadrotor model matrices
\( \gamma \) Parameter vector of the quadrotor model
\( A / B \) State-space error nominal matrices
\( B_d \) Matrix that maps external disturbances
\( m \) Quadrotor mass
\( I_z \) Inertia moment with respect to the Z-axis

Augmented state vector of the Kalman filter
State-transition matrix of the Kalman filter
Control-input matrix of the Kalman filter
Observation vector of the Kalman filter
Kalman filter observation matrix
Observation noise for the Kalman filter
Optimal R-LQR control signal
Recursive optimal R-LQR gain
Feedforward control signal
Disturbance controller closed-loop matrix
Disturbance compensating gain
Disturbance estimation error
Angular velocity
However, both the contributions in [9], [10] are validated and a sliding mode is designed for the tracking task. More-ness and improves the control performance in the trajectory disturbances by adding an observer, which introduces robust-

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combined with sensors can be implemented when the distur-

difficulties, advanced control techniques should be imple-

[2], precision agriculture [3], and military purposes [4].

 Nonetheless, the use of this type of aircraft, especially in outdoor applications, is often subject to external wind disturbances and parametric uncertainties. To overcome these difficulties, advanced control techniques should be implemented with disturbance attenuation [5]. In general, to attenuate external disturbances, feedforward control techniques combined with sensors can be implemented when the disturbance is measurable. However, most of the time it is very hard to measure external disturbances directly, or even impossible [6], [7].

In that sense, a useful approach is related to disturbance observer-based control (DOBC) when the task of adding sensors to measure disturbances in the quadrotor is prohibitive [8]. The estimated disturbance is compensated by a calculated gain and combined with the control signal from the main controller to design a composed control law that can attenuate external disturbances [6]. Several DOBC architectures have been proposed to deal with different types of disturbance in MAVs, where the main contribution is to provide an approach for both endogenous and exogenous disturbances by adding an observer, which introduces robustness and improves the control performance in the trajectory tracking problem. The work in [9] tackles both the translation and attitude control problem, while a combination of a virtual and a sliding mode is designed for the tracking task. Moreover, a disturbance observer architecture combined with a sliding mode strategy is adopted in [10]. The approach stands out for considering the presence of high-order disturbances. However, both the contributions in [9], [10] are validated with numerical simulations. On the other hand, parametric uncertainties and bounded disturbances are treated with an adaptive sliding controller design in [11]. The proposal provides experimental results restricted to a self-made testbed, where only the attitude control performance is analyzed. No trajectory tracking control experiment with wind disturbance was evaluated.

Based on this scenario, in order to address the trajectory tracking problem of a MAV subject to wind disturbance and parametric uncertainties, the main contribution of this paper is the development of a new DOBC architecture based on a recursive robust linear-quadratic regulator (R-LQR) and a standard Kalman filter (KF). The R-LQR considered was developed based on penalty function and robust regularized least squares methods, see [12] and references therein. The main characteristic of the optimal robust controller is that it depends on only one auxiliary parameter to be tuned where the stability region of the controller is always known. It is useful for online applications. Preliminary results showing the effectiveness of using the R-LQR in quadrotors were presented in [13]. A combination of a Vicon motion tracking system (MTS) and embedded sensors was used for evaluating the trajectory tracking performance of quadrotors.

The architecture we propose in this paper is implemented in a second version of the Parrot® Bebop quadrotor through the robot operating system (ROS) framework using a simplified dynamic model of the MAV, subject to parametric uncertainties in the model. Furthermore, three other controllers are also implemented for the sake of comparison with the R-LQR. The first controller is the standard linear-quadratic regulator (LQR) for nominal systems. The second one is the standard computed torque, which is based on feedback linearization (FL). The third one is the classic proportional-integral-derivative (PID) controller. In order to analyze the performance of the Kalman filter as a disturbance estimator, a standard disturbance observer (DO) is also applied along with the implemented controllers. Indoor experiments are performed in order to evaluate different controller strategies when the MAV is subject to wind gusts. In the following, we summarize the major contributions of this paper:

- A combination of an online robust controller and a disturbance observer is proposed for the problem of trajectory tracking subject to parametric uncertainties and wind disturbance.
- We perform flight tests and analyze the proposed framework with a comparative study based on experimental results among three other standard controllers. They are combined with two different disturbance observer-based control approaches.

The rest of this paper is organized as follows. In Section II, the DOBC technique based on R-LQR and Kalman filter is presented. It is also provided a pre-disturbance compensation to improve the performance of the R-LQR. In Section III, the experimental framework and results of the robust approach proposed to deal with the trajectory tracking problem subject
to wind disturbance is presented. Finally, Section IV presents the conclusions of the paper.

II. DISTURBANCE OBSERVER-BASED CONTROL WITH R-LQR AND KALMAN FILTER

The DOBC has received extensive attention in the fields of theory and engineering applications. Exploring the techniques to estimate disturbances, commonly referred to as soft disturbance measurements, is especially interesting in cases that require rejection or attenuation of disturbances. The DOBC has advantages over attenuation techniques that directly measure disturbances based on sensors (active anti-disturbance control - AADC). Disturbance measurement involves high costs and instrumental difficulties in various industrial processes where many disturbances are not measurable [6].

According to [6], the method consists of a two-part controller, the main feedback control, and the direct (open loop) control used as a disturbance compensator. The main control is generally employed through conventional nominal plant-based techniques in which disturbances (mainly external) and uncertainties are not necessarily considered. In order to be able to reject the action of the disturbance in the plant, an observer can be used for its estimation and a compensator is designed based on the system dynamics. In this way, in order to obtain an optimal estimate of the states and the external disturbance, the Kalman filter can be designed as a disturbance estimator using the state augmentation technique, allowing the disturbance estimation problem to fall into the standard form of the discrete-time Kalman filter [14].

Within this context, we propose a DOBC architecture to deal with position tracking problems of a MAV when it is subject to parametric uncertainties and external wind disturbance, see Fig. 1. A R-LQR is used to solve the trajectory tracking problem when the quadrotor is subject to parametric uncertainties. They may include unmodeled dynamics, changes in the MAV structure, or even extra payload for delivering. Then, a Kalman filter estimates external disturbance defined as wind gusts; and a compensator computes additional control signals to attenuate external disturbance influence on the MAV. Furthermore, we introduce a pose estimation unit for the MAV. More specifically, it is based on the measurements of an optical motion capture system (OMCS), since it provides an accurate localization system. Notice that we can replace the pose estimation system with other localization schemes based on GNSS (Global Navigation Satellite System) or vision-based odometry for an actual outdoor application.

Therefore, the architecture we are proposing is shown in Fig. 1, where the velocity input vector is defined as $q(t) = [q_x(t), q_y(t), q_z(t), q_\phi(t), q_\theta(t), q_\psi(t)]$. It corresponds to values that control linear velocities in the quadrotor coordinate frame relative to $x$, $y$, $z$ axes and the angular velocity around the $z$-axis, respectively. The acceptable range for all inputs of $q(t)$ are in the interval of $[-1, 1]$. Moreover, we define the global frame of the navigation system using the pose vector as $q(t) = [q_x(t), q_y(t)]$, which encompasses the position $q_p(t) = [q_x(t), q_y(t), q_z(t)]$ and yaw orientation $q_\psi(t)$. It is worth mentioning that we also have access to standard roll $q_\phi$ and pitch $q_\theta$ angle values, but they are neglected for this project purposes, since they provide small angles due to embedded stabilization in low speeds. The reference trajectory is defined by $q^d(t)$, $d(t)$ is the external disturbance and $\dot{d}(t)$ its estimation, $u(t)$ is the virtual control signal, $\nu(t)$ is the disturbance measurement, and $\nu_{com}(t)$ is the composite control signal. The detailed steps on how the proposed architecture works are summarized in Algorithm 1.

Algorithm 1 DOBC Operation with R-LQR and KF

Input: Desired trajectory $q^d$

Output: Velocity input vector for the MAV $\nu$

1: Initialize R-LQR: consider (5), (6), and (8) with $F_i$, $G_i$, $E_{F_i}$, $E_{G_i}$, $Q_i > 0$, and $R_i > 0$ to be known for all $i$.

2: while Setpoint is not achieved do

3: Receive $q^d$

4: Compute $\dot{q}^d$ and $\ddot{q}^d$

5: Calculate the R-LQR gain $K_{rlqr,i}$

6: $u_{rlqr,i} = K_{rlqr,i}x_i$

7: Estimates $d$ and $\dot{d}$ with (9)

8: $u_{ff,i} = \alpha K_{com,i}d_i + \beta \dot{d}_i + 1$

9: $u_{com,i} = u_{rlqr,i} + u_{ff,i}$

10: $u_{rlqr,i} = u_{ff,i} + u_{com,i}$

11: Uses $u_{rlqr,i}$ in (3) to generate $\nu$

12: end while

![FIGURE 1](image1.png)

FIGURE 1. Block diagram of the Disturbance Observer-Based Control with R-LQR and Kalman Filter.

The MAV simplified model is given by

$$\dot{q}(t) = \Theta(\gamma, t)q(t) + \Gamma(\gamma, t)\nu(t),$$

(1)

where $\gamma \in \mathbb{R}^8$ is a parameter vector to be identified, $\Theta(\gamma, t)$ and $\Gamma(\gamma, t)$ are full-rank square matrices. A methodology...
describing the identification of the unknown elements in \( \gamma \) is detailed in [15], and the state-error is defined as

\[
x(t) = \left[ \dot{q}(t) - \dot{q}^d(t) \right].
\]

Then, the state-space of the system error is considered with external disturbance as

\[
\dot{x}(t) = A(t)x(t) + Bu(t) + B_d d(t),
\]

where

\[
A = \begin{bmatrix} \Theta(\gamma, t) & 0 \\ I & 0 \end{bmatrix}, \quad B = \begin{bmatrix} I \\ 0 \end{bmatrix}, \quad B_d = \begin{bmatrix} \frac{1}{m} & 0 & 0 & 0 \\ 0 & \frac{1}{m} & 0 & 0 \\ 0 & 0 & \frac{1}{m} & 0 \\ 0 & 0 & 0 & \frac{1}{2I} \end{bmatrix},
\]

where \( m \) is the aircraft mass, \( I_z \) its inertia moment with respect to the Z-axis of the body frame, and

\[
\nu(t) = \Gamma(\gamma, t)^{-1}(u(t) - \Theta(\gamma, t)\dot{q}^d(t) + \dot{q}^d(t)).
\]

Hence, (2) can be discretized using Euler’s method and we can obtain

\[
x_{i+1} = F_ix_i + Gx_i + G_d d_i,
\]

where \( F_i = I + TA(t), G = TB, G_d = TB_d, \) and \( T \) is the sampling time.

In the following, we present the R-LQR, the Kalman filter as a disturbance estimator, and the control compensation design.

A. ROBUST LINEAR QUADRATIC REGULATOR - R-LQR

The R-LQR for time-varying linear systems subject to parametric uncertainties were considered in this paper was presented in [12]. This regulator was developed based on penalty parameter and robust regularized least squares. Consider the following discrete-time linear system subject to parametric uncertainties

\[
x_{i+1} = (F_i + \delta F_i)x_i + (G_i + \delta G_i)u_i; \quad i = 0, ..., N,
\]

where \( F_i \in \mathbb{R}^{n \times n} \) and \( G_i \in \mathbb{R}^{n \times m} \) are the nominal parameter matrices, \( x_i \in \mathbb{R}^n \) is the state vector, \( u_i \in \mathbb{R}^m \) is the control input and \( N \) is the integer number that defines the amount of iterations. We assume the initial state \( x_0 \) to be known and uncertainty matrices \( \delta F_i \in \mathbb{R}^{n \times n} \) and \( \delta G_i \in \mathbb{R}^{n \times m} \) to be modeled as

\[
[\delta F_i \quad \delta G_i] = O_i \Delta_i \begin{bmatrix} E_{F_i} & E_{G_i} \end{bmatrix}; \quad i = 0, ..., N,
\]

where \( O_i \in \mathbb{R}^{n \times p} \) (non-zero matrix for all \( i \)), \( E_{F_i} \in \mathbb{R}^{n \times n} \), \( E_{G_i} \in \mathbb{R}^{n \times m} \) are known matrices, that can be treated as project parameters, and \( \Delta_i \in \mathbb{R}^{p \times 1} \) is a contraction matrix (i.e., \( \| \Delta_i \| \leq 1 \)). According to [12], in order to obtain a R-LQR, the following optimization problem must be solved:

\[
\min_{x_{i+1}, u_i} \max_{\delta F_i, \delta G_i} \bar{J}_i^\mu(x_{i+1}, u_i, \delta F_i, \delta G_i),
\]

where \( \bar{J}_i^\mu \) is the regularized quadratic cost function, also known as performance index and defined by (8)

\[
\bar{J}_i^\mu(x_{i+1}, u_i, \delta F_i, \delta G_i) = \begin{bmatrix} x_{i+1}^T & \delta F_i & \delta G_i \end{bmatrix} \begin{bmatrix} P_{i+1} & 0 & 0 \\ 0 & R_i & 0 \\ 0 & 0 & \mu I \end{bmatrix} \begin{bmatrix} x_{i+1} \\ u_i \\ \delta F_i \\ \delta G_i \end{bmatrix} + \begin{bmatrix} \begin{bmatrix} 0 & 0 \\ 0 & -\delta G_i \end{bmatrix} + \begin{bmatrix} 0 & 0 \\ 0 & -\delta G_i \end{bmatrix} & \begin{bmatrix} 0 & 0 \\ 0 & -\delta G_i \end{bmatrix} \\ \begin{bmatrix} 0 & 0 \\ 0 & -\delta G_i \end{bmatrix} & \begin{bmatrix} 0 & 0 \\ 0 & -\delta G_i \end{bmatrix} \end{bmatrix} \begin{bmatrix} x_{i+1} \\ u_i \\ \delta F_i \\ \delta G_i \end{bmatrix},
\]

where \( P_{i+1} > 0, Q_i > 0 \) and \( R_i > 0 \) are weighting matrices and \( \mu > 0 \) is a penalty parameter that is responsible for holding the equality in (5).

Moreover, for each penalty parameter \( \mu > 0 \), the R-LQR is based on the solution \( (x_{i+1}^\ast(\mu), u_i^\ast(\mu)) \) of the \( \min \)-max optimization problem, where we seek the lower state and control magnitudes for the worst parametric uncertainty scenario. The optimal recursive solution is given by \( u_i^\ast = K_{i,i}x_i^\ast \), where further details are presented in [12].

This controller was applied to the discrete state-space error model described by (4). Thus, by minimizing the error computed by the difference between reference and current pose, it is possible to perform a trajectory tracking control. Furthermore, when the system is not subject to uncertainties, the R-LQR reduces to the standard LQR used in the comparative study in Section III.

B. DISTURBANCE ESTIMATION - KALMAN FILTER

As shown in [14], [16], and [17], the KF can be used to estimate also external disturbances. In most cases, the disturbance \( d \) is modeled in such a way that \( \dot{d} \approx 0 \). Considering \( d_a \equiv d, d_b = \dot{d} \) and \( \dot{d} = 0 \) and using Euler’s method to provide the discrete equation, we obtain

\[
d_{a,i+1} = d_a + Td_{b,i+1} + w_{a,i},
\]

\[
d_{b,i+1} = \dot{d}_b + w_{b,i},
\]

where \( T \) is the sampling time, \( w_{a,i} \) and \( w_{b,i} \) are white noise. In this case, we modify the state-space model so that the disturbance is added to an augmented state vector, according to:

\[
s_{i+1} = \Phi_i s_i + \Xi_i u_i + w_i,
\]

where

\[
\begin{align*}
s_i &= \begin{bmatrix} x_i \\ d_{a,i} \\ d_{b,i} \end{bmatrix}, \\
\Phi_i &= \begin{bmatrix} \Psi_i & G_{d,i} & 0 \\ 0 & I & T \end{bmatrix}, \\
\Xi_i &= \begin{bmatrix} \Psi_i \Xi_i & 0 \\ 0 & 0 & \Xi_i \end{bmatrix},
\end{align*}
\]

\[
w_i = \begin{bmatrix} w_{a,i} \\ w_{b,i} \end{bmatrix}, \quad H = \begin{bmatrix} I & 0 \\ 0 & 0 \end{bmatrix},
\]

where \( \Psi_i = I + T\Theta(t) \) and \( \Psi_i = T\Gamma(t) \) are obtained through the discretization of (1) using the Euler’s method.

Therefore, it is possible to apply the KF algorithm [18] in order to estimate the augmented state vector. This allows one to estimate not only the state but also the plant disturbance \( \dot{d}_a \equiv d \).
C. CONTROL COMPENSATION DESIGN

Once the disturbance signal $\hat{d}$ is estimated on a plant, the compensator shall be designed so that the disturbance is attenuated by a compensation control signal added to the main controller signal, as illustrated in Fig. 1.

The R-LQR provides a control law $u_{rlqr,i} = -K_{rlqr,i}x_i$, where $K_{rlqr}$ is the optimal gain and $x$ is the state vector. According to the method, the following composite control signal is obtained:

$$u_{com,i} = u_{rlqr,i} + u_{ff,i},$$

where $u_{ff,i}$ is the feedforward control signal. Defining the closed-loop matrix $\Lambda_i := F_i - G_iK_{rlqr,i}$, and using the compound control law $u_{com}$, along with the system (4), we get

$$x_{i+1} = \Lambda_i x_i + G_iK_{com,i}\hat{d}_i + G_d,i\hat{d}_i,$$

isolating the state vector $x$ and considering $y_i = Cx_i$, then

$$y_i = C\Lambda_i^{-1}x_{i+1} - G_iK_{com,i}\hat{d}_i - G_d,i\hat{d}_i.$$

Therefore, considering that the estimated disturbance will converge to the actual disturbance value ($\hat{d} \rightarrow d$), the compensator gain must be designed such that the actual disturbance will be suppressed at the output $y$, hence

$$K_{com,i} = -\left[CA_i^{-1}G_i\right]^{-1}CA_i^{-1}G_d,i.$$

For other controllers, the disturbance compensating gain can be obtained in the same way.

1) The Proposed Compensation Control

We propose the design of a compensator to deal with unmodeled uncertainties like the network-induced delay due to the underlying network wireless communication. Therefore, we reduce the proportional gain $K_{com}$ and include an estimation derivative. This proportional-derivative control based on the disturbance estimation itself has the form

$$u_{pd,i} = \alpha K_{com,i}\hat{d}_i + \beta \hat{d}_{i+1},$$

where scalar variables $|\alpha| < 1$ and $\beta$ are design parameters. Therefore, the control law (10) is rewritten as

$$u_{com,i} = u_{rlqr,i} + u_{pd,i}.$$

III. COMPARATIVE STUDY: EXPERIMENTAL RESULTS

In this section, we present the experiments to evaluate the performance of the proposed controllers for the trajectory tracking problem of a MAV in the presence of wind disturbance.

The MAV chosen for the experiments is the Parrot® Bebop 2.0. We implement the controllers in a Samsung Expert X40 laptop running the ROS Kinetic Kame distribution on Ubuntu 16.04 LTS. A Vicon® system with four motion capture cameras is used for the localization of the quadrotor. An electric...
ducted fan E-Flite® Delta-V E15 69mm generated the wind disturbance.

The LQR and the R-LQR were designed based on systems (4) and (5) described in the green box of Fig. 2. Recall that when we cancel the uncertainties of the R-LQR, it reduces to the LQR. We compare both controllers with the standard FL controller presented in Section III-A and the PID controller presented in Section III-B (both illustrated in the blue and red boxes of Fig. 2, respectively), along with the disturbance estimation and compensation.

The results are available through performance indices, which are shown in figures and tables of Section III-H.

A. FEEDBACK LINEARIZATION - FL

In this paper, we are interested in control applications of autonomous quadrotors, high-performance aircraft, and industrial robots whose control law is given by

\[ u_{fl}(t) = \Gamma^{-1}(\gamma, t)(u_{fl}(t) - \Theta(\gamma, t)\dot{q}(t)), \]

where \( u_{fl}(t) = \ddot{q}(t) - K_f \dot{q}(t) - K_d \dot{q}(t) + K_i \int q(t)dt, \)

B. PID CONTROL

The popularity of PID controllers may be partially assigned to the satisfactory performance these controllers present in a wide range of operating conditions and their project simplicity. Furthermore, these advantages allow rapid implementation and analysis. The control law is based on error information between the expected and current response of a plant. The control vector \( \nu(t) \) is built by weighting the current error vector \( \ddot{q}(t) = q(t) - \ddot{q}(t) \), its current rate of change, and the sum of the past error values

\[ \nu_{pid}(t) = K_p q(t) + K_d \dot{q}(t) + K_i \int q(t)dt, \]

where \( K_p \) is the proportional gain, \( K_d \) is the derivative gain and \( K_i \) is the integral gain. In order to adjust all these PID gains, we use the standard Ziegler-Nichols technique.

C. DISTURBANCE ESTIMATION - STANDARD DISTURBANCE OBSERVER

Disturbance observer (DO) aims to estimate external disturbances and model discrepancies. In this work, we use a basic structure of a linear system disturbance observer proposed in [6] which is adapted to a class of discrete-time linear systems in a similar way as proposed in [19]. This disturbance observer structure has been used in several works such as [20], [21], and with some variations for delayed, discrete and nonlinear systems in [22]–[24].

Consider the discrete-time state-space system (4). For this case, the discrete-time DO is represented by

\[ \begin{align*}
  z_{i+1} &= -L G_d (z_i + L x_i) - L (F_i x_i + G u_i), \\
  \hat{d}_i &= z_i + L x_i,
\end{align*} \]

where \( \hat{d} \) is the disturbance estimation, \( z \) is an internal auxiliary vector and \( L \) is the gain of the observer. Define the estimation error \( \hat{e}_{d,i} = \hat{d}_i - d_i \). Then, combining (4) and (16), we obtain

\[ \hat{e}_{d,i+1} = \hat{d}_{i+1} - d_{i+1} = z_{i+1} + L x_{i+1} - d_{i+1}, \]

\[ = -LG_d (\hat{d}_i - d_i) - d_{i+1} = -LG_d \hat{e}_{d,i} - d_{i+1}. \]

The dynamics of the estimation error \( \hat{e}_d \) is stable if the term \(-LG_d \) is Schur stable, i.e., if its poles lie inside the open unit circle. Thus, the \( L \) matrix is designed to guarantee this condition. This approach is used with the R-LQR and LQR controllers. For the FL and PID controllers, we perform the following equivalences \( F \rightarrow \Theta \) and \( G \rightarrow \Gamma \) in order to use these controllers in discrete forms. More details on the DO implementation can be seen in [6].

D. ROS SYSTEM

The Vicon cameras provide the position and orientation of the quadrotor through image processing of optical markers positioned on them. Position information is transmitted from the Vicon console® with a frequency of 100 Hz via Wi-Fi connection. The Parrot® Bebop 2.0 receives control commands at a frequency of 10 Hz; this frequency is used for the design of discrete-time controllers and observers. With the ROS packages vicon_bridge 1 and bebop_autonomy 2, it is possible to receive the pose signals of the quadrotor and send control commands to the MAV.

In this way, we developed our control architecture as a ROS (Robot Operating System) package called drone_dev using C++ language with the aid of Eigen library. This package communicates with Vicon camera through the package vicon_bridge to obtain the MAV pose and with the Parrot® Bebop 2.0 to send control commands computed by the controllers and observers through the package bebop_autonomy.

E. REFERENCE TRAJECTORY

The reference trajectory we consider in the experiments has the shape of an ellipse in a plane in the three-dimensional Euclidean space. Position and velocity desired trajectories \( q^d = [q_x^d, q_y^d, q_z^d, q_w^d]^T \) and \( \dot{q}^d \), are given by:

\[ q^d = \begin{bmatrix} a \cos \omega t & a \sin \omega t & \frac{a}{2} \sin \omega t & 0 \end{bmatrix}^T, \]

\[ \dot{q}^d = \begin{bmatrix} -\omega a \sin \omega t & \omega a \cos \omega t & \frac{\omega a}{2} \cos \omega t & 0 \end{bmatrix}^T, \]

where \( a = 0.3 \) m and \( \omega = 1 \) rad/s. The average flight time to follow the trajectory obtained is 12.6 s.

F. WIND DISTURBANCE SOURCE

The wind disturbance source is composed by an E-Flite® engine fan mounted on a tripod with adjustable height and orientation. The maximum wind velocity provided from the brushless motor fan is 27 m/s, measured by a portable anemometer (Incoterms TAN100).

1http://wiki.ros.org/vicon_bridge - 2015.
2http://wiki.ros.org/bebop_autonomy - 2015.
To illustrate the wind speed pattern emitted by the disturbance source, we constructed an experimental point map. It was built based on anemometer readings combined with its global position, measured by the Vicon camera system. The wind velocity pattern and the representation of the reference trajectory used in the experiments (Section III-E) are illustrated in Fig. 3.

![Wind Sampling Points (m/s)](image)

FIGURE 3. Wind speed (m/s) measure in the experimental space whose intensities are proportional to the circle size.

G. CONTROLLER PARAMETERS

In this section, parameters and gains we use to tune controllers and estimators are presented. An important issue to be highlighted is the choice of parameters $\alpha$ and $\beta$ in (12). In order to allow fair comparison, we opted to use different values in each strategy, so that parameters were tuned to achieve the best tracking performance in each scenario.

1) R-LQR parameters

The quadrotor uncertainties considered to design the R-LQR were heuristically obtained based on experimental flights. Furthermore, according to [12], it should satisfy the following condition $\text{rank}([E_F \ E_q]) = \text{rank}(E_F)$. We define the design parameters of the R-LQR according to: weighting matrices $Q = \text{diag}(1, 1, 1, 1, 1, 1, 10, 5)$, $R = 1.5 \cdot 10^{-1} I_{4 \times 4}$, and uncertainties matrices $E_F = [E_{f1} \ E_{f2}]$, where $E_{f1} = 2.95 \cdot 10^{-1} I_{4 \times 4}$, $E_{f2} = \text{diag}(0.285, 0.285, 2.85, 1.425)$, $E_q = 1.875 \cdot 10^{-2} I_{4 \times 4}$, $\mu \rightarrow \infty$. For the disturbance controller defined in (12) and designed with DO, the following parameters were used: $\alpha_{rlqr}^{do} = 1 \cdot 10^{-1}$ and $\beta_{rlqr}^{do} = 7 \cdot 10^{-1}$. Moreover, for the compensator with KF as a disturbance estimator, we use $\alpha_{rlqr}^{kf} = 4 \cdot 10^{-2}$ and $\beta_{rlqr}^{kf} = 2.5 \cdot 10^{-3}$.

2) LQR parameters

The LQR parameters are heuristically tuned with the aid of experimental flights, based on the Bryson rule. We define the weighting matrices as $Q = \text{diag}(1, 1, 1, 1, 1, 1, 10, 5)\text{ and } R = 1.5 \cdot 10^{-1} I_{4 \times 4}$.

For the disturbance compensator design via DO, we adopt the following gains: $\alpha_{rlqr}^{do} = 7 \cdot 10^{-1}$ and $\beta_{rlqr}^{do} = 9.5 \cdot 10^{-1}$. Additionally, for the compensator with the KF as a disturbance observer, we use $\alpha_{rlqr}^{kf} = 2 \cdot 10^{-1}$ and $\beta_{rlqr}^{kf} = 1 \cdot 10^{-4}$.

3) FL parameters

The FL controller is heuristically tuned based on experimental flights, using the parameters $K_1 = \text{diag}(1.33, 1.40, 4.50, 1.75)$ and $K_2 = \text{diag}(1.50, 1.50, 2.00, 2.00)$. For the disturbance compensator design using DO, we consider the following gains: $\alpha_{pid}^{do} = \beta_{pid}^{do} = 5 \cdot 10^{-3}$. Moreover, for the compensator with the KF as a disturbance observer, we use $\alpha_{klqr}^{kf} = 1 \cdot 10^{-3}$ and $\beta_{klqr}^{kf} = 1 \cdot 10^{-4}$.

4) PID parameters

The PID controller is experimentally tuned based on the Ziegler-Nichols critical gain method. We obtain the gains $K_p = \text{diag}(0.70, 0.70, 2.75, 1.20)$, $K_i = 1 \cdot 10^{-2} I_{4 \times 4}$ and $K_d = \text{diag}(0.75, 0.75, 0.75, 3.35)$. For the disturbance compensator design using DO, we use the following gains: $\alpha_{pid}^{do} = 7 \cdot 10^{-2}$ and $\beta_{pid}^{do} = 2 \cdot 10^{-1}$. Finally, for the compensator with the KF as a disturbance observer, we consider $\alpha_{klqr}^{kf} = 8 \cdot 10^{-2}$ and $\beta_{klqr}^{kf} = 1 \cdot 10^{-5}$.

5) Disturbance observers parameters

For the standard observer design with LQR and R-LQR controllers, we use the gain $L_{regulators} = \text{diag}(0.25 I_{4 \times 4}, 0)_{4 \times 4}$ and when it is designed with the PID and FL controllers, we have $L_{pid-kl} = 2.5 \cdot 10^{-1} I_{4 \times 4}$. For the KF as disturbance estimator, we use the following weighting matrices: $Q = \text{diag}(0.1 I_{4 \times 4}, I_{4 \times 4}, 10 I_{4 \times 4})$ and $R = 3.5 \cdot 10^{-4} I_{4 \times 4}$.

H. PERFORMANCE INDICES

To evaluate the performance of each controller in the trajectory tracking experiments, we use the Euclidean norm to measure the controlled variable errors and control inputs, at each instant of time, according to:

$$E_{q_{p}}(i) = \frac{1}{K} \sum_{j=1}^{K} ||q_{p}^{(j)} - q_{p}^{d}||$$

for position errors ($q_x$, $q_y$ and $q_z$),

$$E_{q_{\psi}}(i) = \frac{1}{K} \sum_{j=1}^{K} ||q_{\psi}^{(j)} - q_{\psi}^{d}||$$

for orientation errors ($q_{\psi}$) and

$$V(i) = \frac{1}{K} \sum_{j=1}^{K} ||\nu^{(j)}||$$

for control inputs. Recalling that $q_{p}$ represents the vector of three controlled variables containing $q_x$, $q_y$ and $q_z$; $\nu$ represents the control input vector; $j$ the experiment index for.
$K$ experiments performed and $i$ defines each iteration. The total errors of the trajectory tracking are computed according to

$$E_{q_p} = \sum_{i}^{N} E_{q_p}(i) \quad \text{and} \quad \bar{E}_{q_p} = \sum_{i}^{N} \bar{E}_{q_p}(i),$$

where $N$ is the number of iterations in each experiment. Regarding the control inputs, the sum of the absolute mean values of all control inputs is

$$\bar{V} = \sum_{i}^{N} \frac{1}{K} \sum_{j=1}^{K} \|u_{i}^{(j)}\|_1,$$

where $\| \cdot \|_1$ stands for the $\ell^1$ vector norm.

In order to compare the performance indices $\bar{E}_{q_p}$, $\bar{E}_{q_\psi}$ and $\bar{V}$, of the RLQR, FL and LQR taking into account the PID controller as reference, we compute the relative improvement $P^\%$ between the indices of the respective controllers ($I$) and PID controller ($I_{ref}$) as

$$P^\% = \left( 1 - \frac{I}{I_{ref}} \right) \times 100.$$

To measure the stationary state behavior of the quadrotor, the performance indices are computed 2.5s after each experimental flight starts.

### I. STATISTICAL RESULTS

In this section we present trajectory tracking results based on two sets of experiments where four flights are performed for each set. They show the performance of the FL, PID, LQR and R-LQR with and without disturbance observer-based controller (DOBC), which is based on Kalman filter and standard disturbance observer. We consider the wind disturbance obtained from the wind source described in (Section III-F). Finally, we compare the execution time of the different sets of controller and estimation to analyze their performance and evaluate hardware requirements during implementation.

1) Without DOBC

Here, we present experimental results for a trajectory tracking task under wind disturbance (Section III-F) without using DOBC.

In the performance indices presented in Table 1, we can see the disturbance effects when it is applied in the Parrot$^8$ Bebop 2.0. Regarding the position and orientation errors, the R-LQR outperforms the other control approaches. Additionally, the input control signals are also presented.

In this case, we can see that the LQR presents the lowest energy consumption when compared to other controllers.

There is also a noticeable equivalence between the control signals spent by the R-LQR and the FL controller in this case.

2) With DOBC

The external wind disturbance shown in Section III-F is applied on the quadrotor considering a fixed waypoint in space. The wind flux is directed against the quadrotor following the X-axis, with the source within a minimum distance of 1.5 m from the quadrotor. In Fig. 4, we show disturbance estimations along the X-axis with respect to the quadrotor coordinate frame using all controllers and estimators mentioned earlier. In the following, we present experimental results based on DOBC (Section II) with the respective estimators, see Figs. 5(a) and 5(b). In addition, we showed in Fig. 6 the input $\nu_x(t), \nu_y(t)$ and $\nu_z(t)$, and in Figs. 7 and 8 the position $q_x, q_y$ and $q_z$ of the MAV along the time to illustrate the input and tracking behavior concerning time during all the experiments.

The position tracking errors shown in Fig. 9(a) and the respective performance indices presented in Table 2 are obtained based on the design of DOBC with DO. Notice the R-LQR controller presents the best performance for these errors. Moreover, it outperforms the PID controller in all considered performance indices. Furthermore, the FL controller presents the worst performance for this index.

Regarding the orientation tracking errors (Fig. 9(b)), the performance indices $\bar{E}_{q_\psi}$ (see Table 2) show the worst performance is obtained with the PID controller. For this case, the best result was presented by the standard LQR controller.

Analyzing control efforts (Fig. 9(c)), and performance indices $\bar{V}$, we observe an equivalent performance between the standard LQR and the R-LQR. The combination of the FL controller with the DOBC, using standard DO, provides the best approach to save control input energy.

The position tracking errors presented in Fig. 10(a) and performance indices presented in Table 3 consider controllers that combine the DOBC with the KF as disturbance observer. Notice the FL controller presents the worst performance regarding the $E_{q_p}$ index, which is very close to the standard LQR. Conversely, the PID controller presents the best time response according to Fig. 10(a). Furthermore, in the trajectory tracking error of Table 3, the R-LQR outperforms the other controllers. Regarding the orientation tracking error (Fig. 10(b) and $E_{q_\psi}$ index), the PID outperforms all other

### Table 1. Performance indices in flights under wind disturbances: without disturbance observer-based controller. Percentage improvement ($P^\%$) considering PID controller as reference.

| Index    | R-LQR | LQR | FL | PID | R-LQR | LQR | FL |
|----------|-------|-----|----|-----|-------|-----|----|
| $E_{q_p}$ [m] | 3.8189 | 4.5709 | 7.2340 | 4.5430 | 14.24% | -2.65% | -62.45% |
| $E_{q_\psi}$ [rad] | 0.4659 | 0.5053 | 0.5034 | 0.6599 | 29.40% | 23.43% | 23.72% |
| $\bar{V}$ | 301.9437 | 234.2222 | 309.2040 | 510.7635 | 40.88% | 54.14% | 39.46% |

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By evaluating the control efforts (Fig. 10(c) and performance index $\bar{V}$), the best result is obtained by the FL controller, followed by the standard LQR and the R-LQR, which provide similar results.

Based on the results presented in Table 4, we notice the effectiveness of controlling quadrotors based on R-LQR and DOBC with KF, mainly to minimize position tracking errors. However, considering orientation tracking errors ($q_\psi$), the DOBC approach does not provide the best performance for all control strategies. In fact, the combination of the R-LQR plus DOBC does not improve the robust performance of the system to deal with orientation tracking errors. The FL plus DOBC provides, in these experiments, the worst performance in terms of flight orientation errors. Notice also that LQR and PID controllers plus DOBC (with standard DO or Kalman

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**TABLE 2.** Performance indices in flights under wind disturbances: disturbance observer-based controller with standard disturbance observer. Percentage improvement ($P^\%$) considering the PID controller as reference.

| Index  | R-LQR (DO) | LQR (DO) | FL (DO) | PID (DO) | R-LQR | LQR | FL |
|--------|------------|----------|---------|----------|-------|-----|-----|
| $E_{qp}[m]$ | 2.8612 | 3.2079 | 4.7891 | 2.9749 | 3.82% | -7.83% | -66.98% |
| $E_{q\psi}[rad]$ | 0.6299 | 0.4854 | 0.6677 | 0.6997 | 9.98% | 30.63% | 4.57% |
| $\bar{V}$ | 325.1448 | 320.7945 | 246.1958 | 462.5749 | 29.71% | 30.65% | 46.78% |

**TABLE 3.** Flights under wind disturbances: disturbance observer-based controller with Kalman filtering.

| Index  | R-LQR (KF) | LQR (KF) | FL (KF) | PID (KF) | R-LQR | LQR | FL |
|--------|------------|----------|---------|----------|-------|-----|-----|
| $E_{qp}[m]$ | 1.9351 | 4.4555 | 4.5092 | 2.7071 | 28.52% | -64.58% | -66.98% |
| $E_{q\psi}[rad]$ | 0.5081 | 0.4229 | 0.8173 | 0.3641 | -39.55% | -16.15% | -124.47% |
| $\bar{V}$ | 295.4157 | 246.9343 | 226.8608 | 480.0604 | 29.71% | 30.65% | 46.78% |
TABLE 4. Percentage relative improvement considering reference flights under external disturbances without using disturbance observer-based controller.

| Controller | Percentage Improvement - P% | DOBC (Standard DO) | DOBC (Kalman filter) |
|------------|-----------------------------|--------------------|----------------------|
|            |                             | $E_{q_p}$ | $E_{q_o}$ | $\bar{V}$ | $E_{q_p}$ | $E_{q_o}$ | $\bar{V}$ |
| R-LQR      |                             | 25.08%    | -35.20%   | -7.68% | 49.33%    | -9.06%   | 2.16%   |
| LQR        |                             | 29.82%    | 3.94%     | -36.96% | 2.52%     | 16.31%   | -5.43%  |
| FL         |                             | 33.80%    | -32.64%   | 20.38% | 37.67%    | -62.36%  | 26.63%  |
| PID        |                             | 33.19%    | -6.03%    | 9.43%  | 39.21%    | 44.82%   | 6.01%   |

FIGURE 6. Control input ($v_x$, $v_y$, $v_z$) with respect to time under wind disturbance based on disturbance observer-based controller. (a) Standard disturbance observer. (b) Kalman filter.

filter) result in effective approaches to provide a certain robustness level for the whole control system. Comparing the results of Tables 1 and 4, we can observe that the R-LQR outperforms other controllers. However, the combination of LQR, FL and PID controllers with DOBC approach provide a relative effectiveness in terms of robustness for this class of non-robust controllers. Notice that the non-robustness of the LQR combined with the non-robustness of both KF and DO, may result in poor, less predictable performance.

Furthermore, Table 5 gathers the average computation time required for performing a single loop in the combined task of control and estimation. We obtained these results by running each combination 100 times. Moreover, in order to alleviate the computational power required to run the R-LQR and LQR algorithms, we also present the case where the control gains are previously computed offline and remain fixed. We present those results as fixed in the given table. Finally, for the tested hardware, we obtained average loop times as low as 58µs in the case of a PID computed running without an estimation and as high as 0.0039s in an R-LQR combined with the KF estimation. Notice that, for the worst-case scenario, the algorithm can still keep an update rate of 250Hz for the task of trajectory tracking.

IV. CONCLUSION

A new framework was proposed to deal with position tracking problems of a quadrotor subject to parametric uncertainties and wind disturbance. It was developed based on the robust recursive linear quadratic regulator and Kalman filter combined with a disturbance observer-based controller architecture. We developed the entire control architecture using the C++ language with the aid of the Eigen library, which promotes high efficiency in online tasks. The developed control architecture is encapsulated as a ROS package which allows easy integration with different localization and aircraft packages.

Experimental results were provided with a comparative study among the proposed architecture and standard LQR, FL, and PID controllers. They are combined first with the KF as a disturbance observer and then with a standard disturbance observer. In the statistical results presented, we can see the effectiveness of the R-LQR to the trajectory tracking errors when the quadrotor is subject to disturbance for both scenarios, with and without the use of a disturbance observer-based controller (DOBC). It outperforms the other control approaches considered. We can also observe that the combination of the DOBC with the standard controllers used in this comparative study provides a certain robustness level. It is also useful for this class of applications. It is effective in the orientation regulation and control efforts. Even computed torque, with feedback linearization, can save energy better.
than other approaches. In general, the design of the model uncertainties of the quadrotor can be obtained by applying artificial intelligence, genetic algorithms, or reinforcement learning. Combined with the recursiveness of the R-LQR, which is useful for online applications, the robustness of this approach will be exploited for different and critical scenarios in future work.

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TABLE 5. Comparison of average loop time (in seconds) for different sets of controller and estimator.

| Estimation          | R-LQR     | R-LQR (Fixed) | LQR        | LQR (Fixed) | FL          | PID          |
|---------------------|-----------|---------------|------------|-------------|-------------|--------------|
| Kalman filter       | 0.0039    | 0.0015        | 0.0032     | 6.392e-5    | 6.6330e-4   | 6.4012e-4    |
| Standard DO         | 0.0033    | 0.0013        | 0.0029     | 7.2198e-5   | 1.2135e-4   | 1.2511e-4    |
| No Estimation       | 0.0031    | 0.0013        | 0.0028     | 8.8808e-5   | 6.2785e-5   | 5.8994e-5    |

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