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DISTURBANCE ESTIMATION OF QUADROTOR USING AUTO-TUNING ADAPTIVE UPDATE LAW

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Abstract. *A quadrotor consists of a body fixed frame and four rotors which can generate four independent thrusts. By varying the rotor speeds, one can control the pitch, roll, and yaw attitude and can be moved to a desired position. The effect of disturbances such as wind or weight on the quadrotor flight control can be quite significant, and can lead to dangerous situations. The estimation and compensation mechanism of the disturbances improves the stability and the positioning accuracy of the vehicle. This paper presents an adaptive estimator of the wind disturbances and the mass of a quadrotor by using accelerometer. An auto-tuning adaptive estimator for the disturbance and the mass in the translational dynamics is derived. The performance of the proposed estimator is verified both in the simulation and the experiment by using the MATLAB/Simulink and a real quadrotor.*
Keywords: Quadrotor, Adaptive estimator, Accelerometer measurement, Crazyflie2.0

1. **Introduction.** In recent years, the researches on control for stabilizing or flying of multicoptor type UAV (UAVs) became one of the attractive areas [1]. A quadrotor consists of a body fixed frame and four rotors which can generate four independent thrusts. By varying the rotor speeds, one can control the pitch, roll, and yaw attitude and move to a desired position [2]. Moreover, the center of mass can be placed to the center of its body easily compared with a helicopter. For these reasons, it has already started using for various industrial scenes such as surveying, guarding and maintenance of architecture.

Since a quadrotor has no mechanical stabilizer for the attitude stabilization besides propellers, it is a serious drawback that slight unbalance of propeller thrust forces or small amount of external disturbance make a quadrotor unstable. Furthermore, in the case of payload delivery a mass of the quadrotor changes with payloads. Consequently, it is one of the important issues that we estimate unknown disturbances or the parameters using limited data obtained by equipped sensors, and guarantee its robustness against the parameter variations by designing controller using estimator [3, 4]. Nowadays, the disturbance observer based control methods are proposed for a quadrotor [5, 6]. The disturbance observer can estimate disturbances as one of the states of the system. Therefore, we are able to compensate these disturbances or can estimate changes of physical parameters directly by using disturbance observer.

We have recently proposed the auto-tuning velocity estimator [7]. In this work, we apply this estimator to an adaptive estimator with an auto-tuning gain in order to estimate the disturbances and the mass based on the output model of the translational dynamics. By focusing the fact that we can obtain accelerations of quadrotor in bodyframe from Inertial Measurement Unit (IMU) basically mounted on quadrotor, we design an estimator which gives the disturbance and the mass estimates with the acceleration signals. The performance of the proposed estimator is verified by using MATLAB simulation. We also verify the performance of the estimator using the measurement data obtained by Bitcraze AB's crazyflie2.0.

2. **Output Model Based on Accelerometer.**

2.1. **Quadrotor equipment.**
An Inertial Measurement Unit (IMU) has been mounted on a quadrotor. In general, the IMU calculates the orientation and the attitude using measured acceleration, angular velocity and angle values of three axes in the sensor fixed frame. Basically, the IMU has the 3-axis rate gyros and accelerometers, so that we can obtain the omni dimensional accelerations and the angular velocities. In this work, we estimate the disturbances and the mass in the translational motion using accelerometers.

2.2. **Output model for translational dynamics.**
The translational motion in the body fixed frame can be written by

$$\begin{bmatrix} \dot{u} \\ \dot{v} \\ \dot{w} \end{bmatrix} = \begin{bmatrix} rv - qw \\ pw - ru \\ qu - pv \end{bmatrix} + \begin{bmatrix} -g\sin\theta \\ g\cos\theta\sin\phi \\ g\cos\theta\cos\phi \end{bmatrix} + \frac{1}{m}\begin{bmatrix} 0 \\ 0 \\ -F \end{bmatrix} + \begin{bmatrix} d_x \\ d_y \\ d_z \end{bmatrix} \tag{1}$$

where $\begin{bmatrix} u & v & w \end{bmatrix}^T$ is the body frame velocity vector, $\begin{bmatrix} p & q & r \end{bmatrix}^T$ is the roll, pitch and yaw rate vector, $\begin{bmatrix} \phi & \theta & \psi \end{bmatrix}^T$ is the roll, pitch and yaw angle vector, m is the mass of the quadrotor, F is the total thrust force, $\begin{bmatrix} d_x & d_y & d_z \end{bmatrix}^T$ is the disturbance vector in the body fixed frame, and g is the gravity constant.

The outputs of the accelerometer of the quadrotor are given as in [2]:

$$\begin{aligned} a_x &= \dot{u} + qw - rv + g\sin\theta \\ a_y &= \dot{v} + ru - pw - g\cos\theta\sin\phi \\ a_z &= \dot{w} + pv - qu - g\cos\theta\cos\phi. \end{aligned}$$

From the translational dynamics (1), we obtain the relationships between the measured accelerations and the disturbance as

$$a_x(t) = d_x(t) \tag{2}$$

$$a_y(t) = d_y(t) \tag{3}$$

$$a_z(t) = -\frac{F(t)}{m} + d_z(t) \tag{4}$$

Therefore, we can use the horizontal acceleration measurements, a_x, a_y, as the estimates of the disturbances directly. In the case of a payload delivery, a mass of the quadrotor changes with payload. Thus, d_z and m must be identified simultaneously using the measured acceleration a_z. Since d_z is time-varying, we approximate it as a basis function expansion such as

$$d_z(t) = \theta^T \xi(t) \tag{5}$$

$$\theta^T = \begin{bmatrix} \theta_0 & \theta_1 & \theta_2 & \theta_3 \end{bmatrix} \tag{6}$$

$$\xi(t)^T = \begin{bmatrix} 1 & \frac{t}{1+\epsilon t} & \frac{t^2}{1+\epsilon^2 t^2} & \frac{t^3}{1+\epsilon^3 t^3} \end{bmatrix} \tag{7}$$

where $\xi(t)$ is a kind of the third order Taylor polynomial when $\epsilon = 0$. We select ϵ as a small positive number considering the boundedness of the basis function for all time.

Equation (4) can be rewritten in the vector form:

$$a_z(t) = \begin{bmatrix} \theta_m & \theta^T \end{bmatrix} \begin{bmatrix} -F(t) \\ \xi(t) \end{bmatrix} \tag{8}$$

where $\theta_m = \frac{1}{m}$.

3. **Design of Adaptive Estimator.** The goal of this work is to estimate d_z and m simultaneously using the measured acceleration a_z from the output model:

$$a_z(t) = \begin{bmatrix} \theta_m & \theta^T \end{bmatrix} \begin{bmatrix} -F(t) \\ \xi(t) \end{bmatrix} \tag{9}$$

To design an adaptive estimator, we assume that we can also measure the control input signal $F(t)$. Using the available signals $\begin{bmatrix} -F(t) & \xi(t) \end{bmatrix}$, we design the adaptive update law for the unknown parameters $\begin{bmatrix} \theta_m & \theta^T \end{bmatrix}$. We apply the auto-tuning adaptive update law proposed in [7].

The output estimator is given by

$$\hat{a}_z(t) = \begin{bmatrix} \hat{\theta}_m & \hat{\theta}^T \end{bmatrix} \begin{bmatrix} -F(t) + n(t) \\ \xi(t) \end{bmatrix} - ke(t) \tag{10}$$

where $e(t) = \hat{a}_z(t) - a_z(t)$, k is a positive number, and $n(t)$ is an additive random noise to satisfy a persistently exciting condition. From [7], the auto-tuning adaptive update laws for the unknown parameters are derived as

$$\dot{\hat{\theta}}_m(t) = -\gamma_0\gamma(t)(n(t) - F(t))e(t) \tag{11}$$

$$\dot{\hat{\theta}}(t) = -\gamma_0\gamma(t)\xi(t)e(t) \tag{12}$$

$$\dot{\gamma}(t) = \delta_1\gamma(t)^2 e(t)^2 - \delta_2\gamma(t)^n \tag{13}$$

where γ_0, δ_1, and δ_2 are positive constants, and n is an odd number. The second term of the right-hand equation in the last equation is a forgetting factor. The estimate of the disturbance d_z is given by

$$\hat{d}_{z1}(t) = \hat{\theta}(t)^T\xi(t) \tag{14}$$

4. **Numerical Simulation.** Consider the following signal:

$$a_z(t) = d_z(t) - \frac{1}{m}(F(t) + n(t)) \tag{15}$$

$$m = 5 \tag{16}$$

$$d_z(t) = 0.5\sin 25t \tag{17}$$

$$F(t) = 1 + p(t) \tag{18}$$

where $p(t)$ is a rectangular pulse function with the amplitude 0.5, the period 2[sec], and the duty cycle 50%, and $n(t)$ is a Gaussian white noise with $N(0, 0.5)$. Equations (15) and (9) are different, because we add an additive noise to the input signal to satisfy the sufficient richness. We choose the parameters of the estimator as $\delta_1 = 500$, $\delta_2 = 0.05$, $k = -50$ and $\gamma_0 = 500$.

Figures 1 and 2 show the output signal $a_z(t)$ and the input signal $F(t)$, respectively. Figures 3 and 4 show the estimates of the mass and the disturbance. The adaptive estimator works out satisfactorily. In this simulation, the additive noise in the input is emitted as a part of the output a_z and plays an important role to satisfy the persistently exciting condition. Figure 5 shows the output estimation error.

5. **Experiment Result.** In this section, we verify the performance of our estimator for the actual environment by using the actual quadrotor. We use Bitcraze AB's crazyfile2.0 for the experiment. The crazyflie2.0 is a small quadrotor equipped with an IMU which consists of a 3-axis accelerometer, a rate gyro and a magnetometer. Furthermore, crazyflie2.0 also equips a high precision pressure sensor: LPS25H. For controlling their flight, the crazyflie2.0 mounts a micro control unit (MCU): STM32F405 as the flight control processor. The duration of flight is 7 minutes by charging battery for 40 minutes. This aircraft is an open-source develop platform, so that we can find or improve the circuit

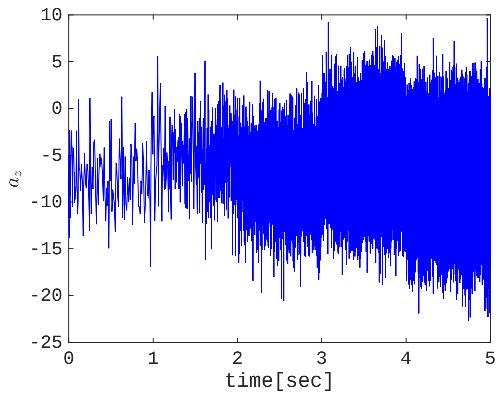

FIGURE 1. Output signal $a_z(t)$

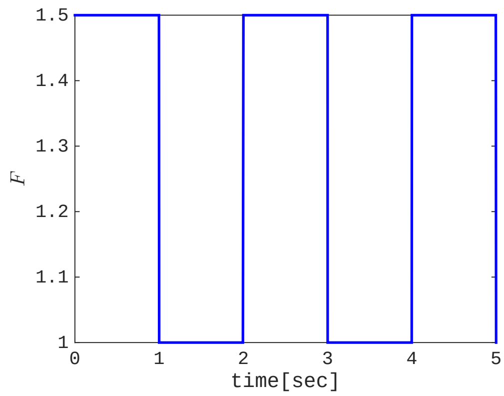

FIGURE 2. Input signal $F(t)$

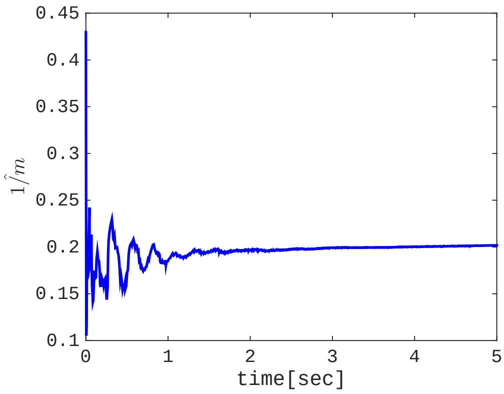

FIGURE 3. Estimate of m^{-1}, $\widehat{m^{-1}}(t)$

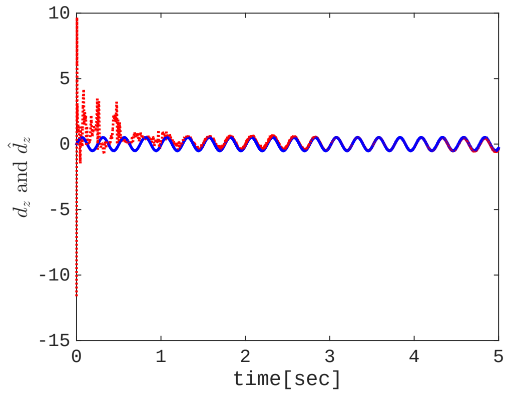

FIGURE 4. Disturbance $d_z(t)$ (solid line) and its estimate $\hat{d}_z(t)$ (dotted line)

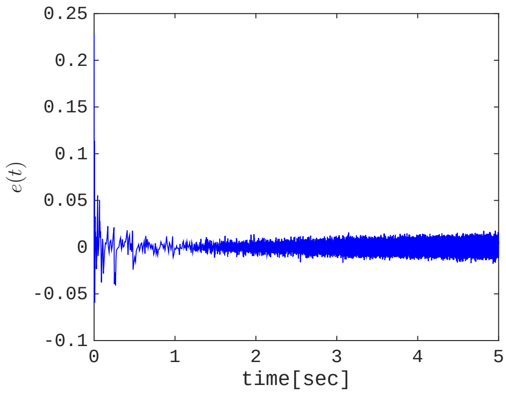

FIGURE 5. Output estimation error $e(t)$

diagrams, the hardware specifications, and the firmware source. In this experiment, we use the Log blocks function which is the pre-installed macro function in order to output measured data, and then we apply these data into the MATLAB/Simulink environment to estimating the unknown parameters of the translational dynamics.

5.1. **Experiment test bed and available data.**

5.1.1. *Requirements for estimation.* To use the proposed estimator, following output signals are needed

- acceleration about vertical axis in bodyframe: $a_z(t)$
- control inputs: $F(t)$.

5.1.2. *Available sensor outputs from crazyflie2.0.* The crazyflie2.0 can output the measured data of the accelerometer and the rate gyro in the IMU. The sampling rate is 1000[Hz]. Then these raw data are applied into a low pass filter with cutoff as 260[Hz] to removing high frequency noises. After attenuating high frequency noises, the sensor outputs are obtained using I2C at the sampling rate 500[Hz], and then the data are subjected to the first order low pass filter processing with the cutoff frequency set to 50[Hz]. At last, the sample values are remapped into acceleration of gravity G [kg·m/s^2]. Since the accelerometer also measures the acceleration occurring by the gravity, we have to remove the influence of the gravity to get only the translational acceleration. Thus, we introduce the Madgwick's filter [8] to substitute the effect of gravity. Since the crazyflie2.0 has already been implemented with the controller with the Madgwick's filter, we obtain the calibrated data from these filters as the output of sensor values.

5.1.3. *Control inputs from crazyflie2.0.* The crazyflie2.0 controls the attitude and the height by using a PID controller. At this process, the control signals are sent to the motor driver as 16bit integer, and the motor driver supplies an appropriate voltage to each motor by using 8bit PWM signals. In other words, since the true control inputs are signals from the motor driver, we can represent the relationship between the motor control signals δ_* and the thrust force of each motor and propeller δ_* generated as

$$F_* = k_* \delta_* \tag{19}$$

where k_* is specific constants of the propellers. However, we have to find the relationship between the propeller-constants k_* and the control signals δ_* experimentally, and it is difficult to measure them accurately during flights. Alternatively, we cite the data certificated by Bitcraze AB, and we introduce the following transfer function about the sum of all thrust forces and 8bit PWM signals pwm:

$$F = \left(0.409 \times 10^{-3} \cdot pwm^2 + 140.5 \times 10^{-3} \cdot pwm - 0.099\right) \times 10^{-3} \tag{20}$$

5.2. **Test condition.** In the experiment, we estimate the mass of the crazyflie2.0 and the external disturbance affected for vertical orientation of bodyframe by using our adaptive estimator. The experimental equipment is shown in Figure 6. We connect the airframe with the anchor by string, and then we handle the crazyflie2.0 as a kite that attaches string. Since the maximum length of the string is set as 0.7[m], it is shorter than the maximum reaching height of the crazyflie2.0. If the crazyflie2.0 flies out of the range of the string, the force of the tension is applied as an external disturbance. Assuming that the vertical component of the tension in the bodyframe is a non-periodic disturbance for the crazyflie's dynamics, we verify the performance of our proposed estimator. The true value of the mass of the crazyflie2.0 is 27×10^{-3}[kg]. For the estimation, we collect two values: the acceleration about the vertical orientation without the gravity and all of the propeller thrust forces. We log these data in the logging interval 20[ms].

5.3. **Estimation result.** In this section, we present the estimation result. To evaluate the estimation performance of the disturbance, we calculate the actual disturbance d_z as

$$d_z = a_z + F / \left(27 \times 10^{-3}\right)$$

assuming the mass is known. We choose the parameters of the estimator as $\delta_1 = 500$, $\delta_2 = 0.05$, $k = -50$ and $\gamma_0 = 500$. The additive noise is selected as a Gaussian white noise with $N(0, 0.5)$.

Figures 7 and 8 show the true acceleration value a_z and the total thrust force F. Figure 9 shows the estimate of the inverse of the mass. The estimated value does not converge to the true value $\frac{1}{27 \times 10^{-3}}$. Figure 10 shows the comparison of the true acceleration value

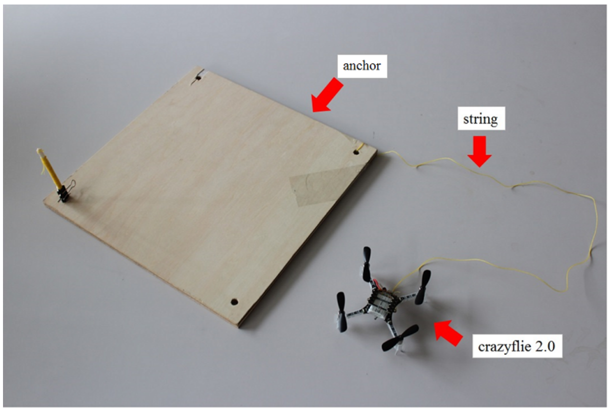

FIGURE 6. Experimental environment of crazyflie2.0. The string is mounted on crazyflie's body and the other side is attached to the anchor.

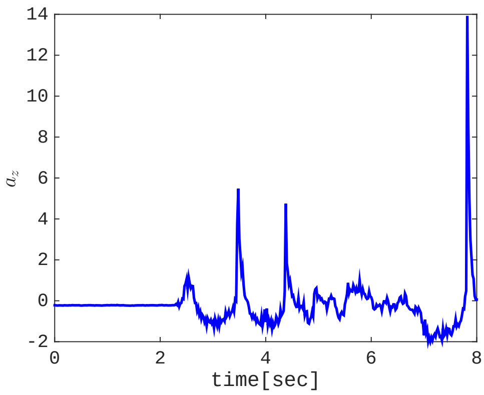

FIGURE 7. Measurement data of acceleration value $a_z(t)$

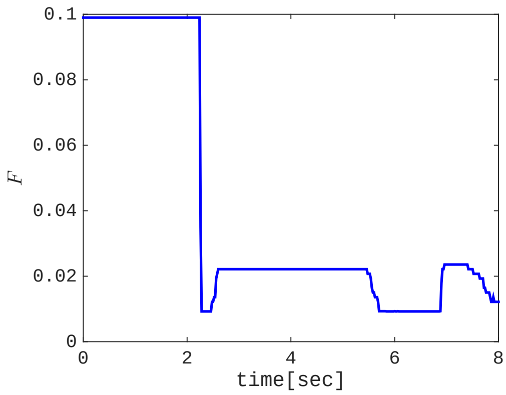

FIGURE 8. Total thrust force $F(t)$

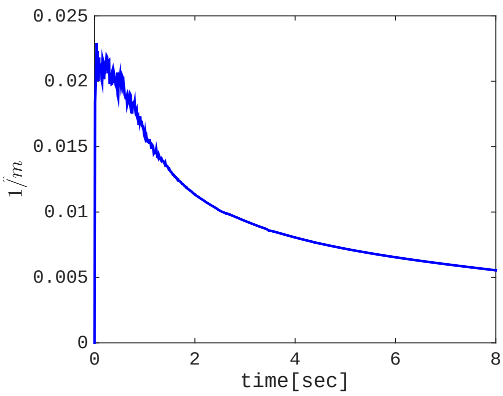

FIGURE 9. Estimate of m^{-1}, $\widehat{m^{-1}}(t)$

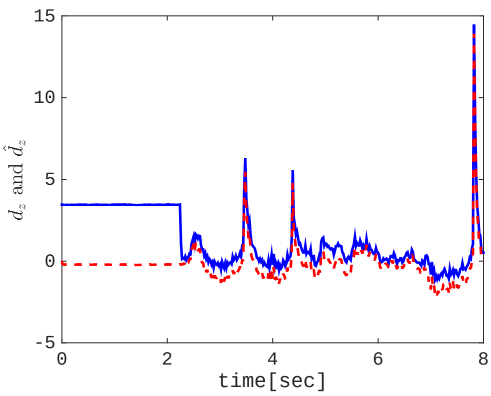

FIGURE 10. True disturbance $d_z(t)$ (solid line) and its estimate $\hat{d}_z(t)$ (dotted line)

d_z and the estimated value $\hat{d}_z$. The estimate is close to the real value since 2[sec]. Figure 11 represents the output estimation error. The gap between the simulation in Chapter 4 and the experiment is that we cannot add a noise to the input signal. The additive noise is used only in the estimator. Thus, the lackness of the sufficient richness condition causes the estimation errors. It should be noted that small variance of the additive noise fails to estimate the disturbance.

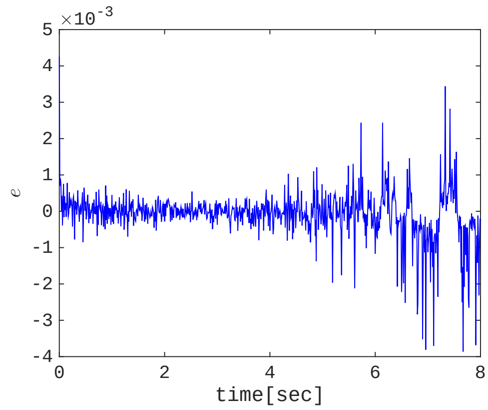

Figure 11. Output estimation error $e(t)$

6. **Conclusion.** In this paper, we presented the adaptive estimator for the disturbance and the mass using the translational dynamics. We show that the estimation performance is dependent on the additive noise to the input signal. It is currently under consideration about the estimation for rotational dynamics because of a problem that we have to establish the method to measure the thrust force for each motor generated respectively. If we can represent the relationship between thrust forces and control signals, we can calculate all control inputs.

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