

Effect of UAV Size on EKF-Based Position Uncertainties and the Performance of UAV-Mounted RIS

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Abstract

Reconfigurable Intelligent Surfaces (RIS) are able to extend the range of radar applications, allowing coverage of areas that were previously impossible or hard to reach. This is achieved by dynamically manipulating the electromagnetic wave properties with multiple adjustable reflecting elements in real time. This capability proves most effective when the RIS is positioned in line-of-sight (LoS) and proximity to the transmitter and receiver. To meet these criteria in real-world applications, the RIS is mounted on an unmanned aerial vehicle (UAV). However, a UAV is exposed to many disturbances during flight, which compromise the performance of the RIS-enabled link. Our previous work has shown that dynamically adjusting the RIS using the UAV position estimates from an extended Kalman filter (EKF) can effectively counteract disturbances and significantly enhance the channel link quality compared to a static RIS configuration. We quantified the uncertainties regarding the position estimation of the RIS in experiments. Data have so far been collected using a laboratory-scale UAV, i.e. a UAV with a rotor-to-rotor diameter of 500mm.

In this work, we deploy a UAV with a rotor-to-rotor diameter of 1060mm to investigate the position uncertainties of the UAV-mounted RIS and their impact on the channel link quality for a UAV that is capable of more demanding real-world missions. Building on this, we conduct a comprehensive comparison with our laboratory-scale UAV to assess the scalability of the proposed measurement methodology.

Keywords: Unmanned Aerial Vehicle (UAV), Reconfigurable Intelligent Surface (RIS), Uncertainty Propagation, Experimental Measurements, Prototypes

Introduction

Reconfigurable intelligent surfaces (RISs), originally designed for 6G wireless networks [1], have attracted attention for sensing applications due to their ability to control the propagation environment. By adjusting the phase, amplitude, and frequency of the incoming signals at each element, RISs are capable of extending the range of radar applications, allowing coverage of areas that were previously inaccessible [2].

A key performance metric for sensing is the effective end-to-end channel quality between the transmitter (Tx)-RIS-receiver/target (Rx), which directly influences the achievable signal-to-noise ratio. This effective channel and the resulting radar performance depend on proper configuration of the RIS as well as its position, where maintaining a line-of-sight (LoS)-link is particularly important. However, environmental factors such as blockages or changing terrain heights often prevent these conditions from being satisfied. To circumvent this problem, unmanned aerial vehicles (UAVs) have been

proposed to carry the RIS, such that the LoS-link can be guaranteed. Because of its low weight and power efficient design, RISs are excellent alternatives to heavy and power-hungry base stations for use with UAVs.

While mounting the RIS on a UAV enables reposition, the UAV is subject to external disturbances and internal sources of uncertainty. These uncertainties lead to constant changes in the position of the UAV, even during hover flight. Consequently, the RIS-reflected path is subject to these changes, affecting signal transmission. Due to the resulting continuous changes in the channel link, it becomes evident that a constant, predetermined RIS configuration does not suffice [3].

Our previous works have shown that using UAV onboard sensors in combination with an extended Kalman Filter (EKF) for state estimation of the UAV, followed by adjusting the RIS configuration based on the UAV state, can significantly improve the channel link quality compared to a static, time-invariant configuration [4,5]. These performance gains

persist despite the presence of estimation uncertainties. However, prior experiments have been limited to deployment of a laboratory-scale UAV, restricting conclusions regarding real-world performance.

In this work, we extend our analysis by deploying a larger UAV with a rotor-to-rotor diameter of 1060 mm to investigate the effect of UAV size on position uncertainties and their impact on the channel link quality. Similar to previous works, we follow the *Guide to the expression of uncertainty in measurement (GUM)* [6] to analyze the uncertainties. Based on the results obtained, we perform a comprehensive comparison with a laboratory-scale UAV to evaluate the scalability of the proposed measurement methodology.

System and Channel Model

The system model in this paper assumes a single-antenna Tx transmitting signals to a single-antenna Rx on the ground. It is further assumed that the direct Tx-Rx link on the ground is blocked and a UAV-mounted RIS is used to establish a LoS link. Each RIS consists of M elements, capable of altering the phase of the reflected signal. The reflected signals from the RIS are then received by the Rx. The effective Tx-RIS-Rx channel can be expressed as

$$h^{eff} = \sum_{m=1}^M h_m \theta_m g_m,$$

where h_m and g_m represent the channel coefficients between the m -th RIS element and the Tx/Rx, respectively. The reflect coefficient $\theta_m = A_m(\varphi_m)e^{j\varphi_m}$ is defined by the tunable phase $\varphi_m \in [0, 2\pi)$ induced to the reflected signal at each reflecting element m , and the phase-dependent reflect amplitude $A_m \in [0, 1]$. The cascaded channel coefficient between Tx-RIS-Rx over the m -th RIS element can be formulated as $h_m^{casc} = h_m g_m$.

We use pose data obtained from experimental measurements to compute the channel coefficients. We determine the cascaded channel components for each reflecting element m based on the geometry of the LoS path, where d_m^h (d_m^g) is defined as the distance between the Tx (Rx) and the m -th RIS element. The cascaded Tx-RIS-Rx channel through the m -th RIS element is given by [7]

$$h_m^{eff} = \left[\frac{c}{4\pi\nu d_m^h} e^{j\frac{2\pi}{\lambda} d_m^h} \right] \left[\frac{c}{4\pi\nu d_m^g} e^{j\frac{2\pi}{\lambda} d_m^g} \right], \quad (1)$$

where c is the speed of light, $\nu = 5.53\text{GHz}$ the frequency and λ the corresponding wavelength.

Experimental Setup

We mounted RIS prototypes [8] to two UAVs varying in size (see Fig. 1) and recorded their orientation and position both as estimated with the EKF and measured with a high-precision motion capture system (MCS) during outdoor hover flight. By comparing these datasets, we investigate the effect of UAV sizes on the uncertainties in the EKF position estimation. The impact on the channel link quality is subsequently analyzed.

The larger UAV used for the experiments is a PM-X6 hexacopter with a rotor-to-rotor diameter of 1060mm and a net weight of 5kg. The laboratory-scale UAV is a customized Holybro X500 quadcopter with a rotor-to-rotor diameter of 500mm and a net weight of 1.8kg. Both UAVs are controlled by a Pixhawk CubeOrange flight controller powered by a STM32H753 microcontroller to eliminate any influence from processing performance. The flight controller holds three different inertial measurement units (IMU), which are used for redundancy (specifically, the primary IMU is a ICM20602, the second one a ICM20948 and the third one a ICM20649¹). The open-source software ArduPilot² (V4.2.0) is installed on the flight controller, running an individual EKF for every IMU. This enables the UAV to use lane-switching³, a transition between multiple EKFs in case variances exceed a certain threshold. The active EKF is selected in the same order as the IMUs. The primary and secondary IMU are mounted on a separate temperature-controlled, vibration-isolated board, while the third IMU is located directly on the flight controller. Three different IMUs are installed on the flight controller, as they have different frequency responses and will therefore respond differently to vibrations. We tuned filter parameters for better filtering of vibrations by running an in-flight Fast Fourier Transform on the UAV and analyzing spectra for characteristic frequencies. Measurements of the IMU are then fused with other sensors by the EKF. We install a Here3 GNSS antenna on the UAV, for position estimates in the x-y-plane. The Here3 is running a ublox M8P-2 GNSS⁴ module allowing for position measurements with a precision of 2.5m. We use the barometer installed on the CubeOrange flight controller for measuring the

¹ <https://ardupilot.org/copter/docs/common-thecubeorangeoverview.html>

² <https://ardupilot.org/>

³ <https://ardupilot.org/dev/docs/common-ek3-affinity-laneswitching.html>

⁴ <https://docs.cubepilot.org/user-guides/here-3/here-3-manual>

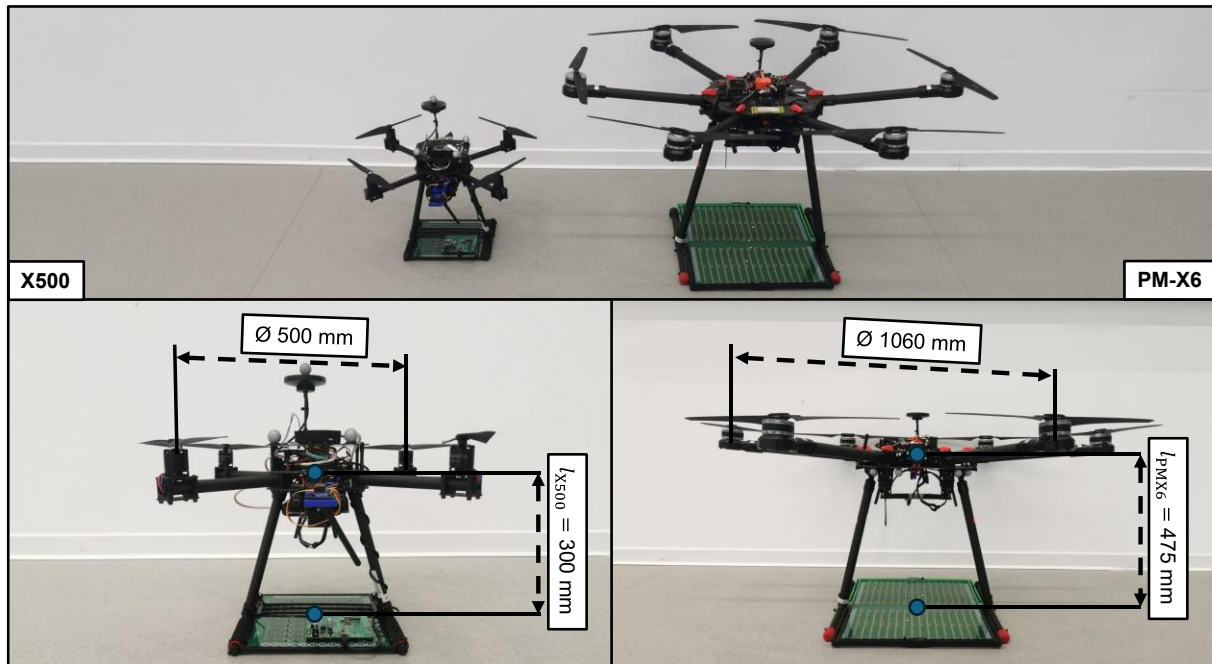


Figure 1: UAV setup for flight experiments. Blue dots represent the origin of the UAV's body frame (top) and the center of the RIS (bottom).

height over ground. Specifically, we use a MS5611 barometer, which is mounted on the same temperature and vibration-isolated board as the first and second IMU. To maintain the heading of the UAV, we fuse the IMU measurements with ICM20948 magnetometer data.

For the larger UAV (PM-X6), the RIS is mounted $l_{\text{PMX6}} = 475\text{mm}$ underneath the origin of the UAV's body frame (see Fig. 1), with no offsets in the x-y-plane. Similarly, the RIS is mounted $l_{\text{X500}} = 300\text{mm}$ underneath the origin of the laboratory scale UAV (X500). A Raspberry Pi, acting as the RIS controller, is installed on the UAVs. Note that the RIS mounted on the larger UAV is scaled to approximately four times the size of the laboratory-scale counterpart. This is possible because the larger UAV can support a larger RIS, which is beneficial for system performance and reflects realistic deployment scenarios. However, due to the RIS shape, it can interact with the rotor airflow, potentially contributing to system uncertainties. Given the larger rotor-to-rotor diameter, the increased RIS size on the larger UAV ensures a fair comparison with the laboratory-scale platform.

All experiments are conducted outdoors on an open field under the same environmental conditions. We perform 10 hover flights, each lasting 30s, with both UAVs. The UAVs are maneuvered to an altitude of approximately 3.5m using the stick inputs of a Hex Herelink 1.1

controller. The position is then maintained autonomously by the flight controller (position hold mode⁵). We restart the UAVs and calibrate the IMUs on the flight controller before every flight to ensure the same initial conditions. The EKF state estimates are recorded on an onboard SD-Card with a frequency of 100Hz. Reference data for the UAV position and orientation is measured and recorded with an MCS. Specifically, 10 Vicon Vantage V5 infrared cameras and the Software Tracker 3 were installed. This system is able to track objects equipped with an asymmetric pattern of reflective markers with a root mean squared error of less than 0.2mm with frequencies of up to 420Hz⁶. We calibrate the motion capture system once, after it has reached its working temperature. The motion capture system sampling frequency is set to 100Hz, i.e., the same logging frequency as the flight Controller.

We synchronize the motion capture system and UAV data prior to evaluation to remove the temporal phase shift between the two sets of data. Subsequently, we discard the first and last 5s of the recorded data, as these intervals correspond to takeoff and landing. Within the remaining 20s, we randomly extract a contiguous interval of 10s of hover flight. The corresponding 1000 data points are then used for investigating the uncertainty in estimating the position in the following section.

⁵ <https://ardupilot.org/copter/docs/poshold-mode.html>

⁶ <https://www.vicon.com/>

Uncertainty in RIS-Position Estimation

We characterize the uncertainties of the RIS position estimation with the EKF for both UAVs to evaluate the effect of UAV size on the estimation accuracy of the EKF, which is crucial for adjusting the RIS configuration. We evaluate the position uncertainties of the attached RIS by propagating the UAV position and orientation uncertainty. Orientations and their uncertainties enter because of the offset between the center of the RIS and the origin of the UAV body frame as described in the previous section.

We characterize the difference of the UAV position and orientation $x_{k,MCS}$, $y_{k,MCS}$, $z_{k,MCS}$, $\Phi_{k,MCS}$ (roll), $\theta_{k,MCS}$ (pitch), $\psi_{k,MCS}$ (yaw) measured with the MCS at time point k to the position and orientation $x_{k,EKF}$, $y_{k,EKF}$, $z_{k,EKF}$, $\Phi_{k,EKF}$, $\theta_{k,EKF}$, $\psi_{k,EKF}$ estimated with the EKF. Because the EKF introduces errors that are not mean free, we need to characterize these means. Let $x_{k,UAV}^e = x_{k,MCS} - x_{k,EKF}$, refer to the absolute error of the x -position of the UAV at time point k and let $y_{k,UAV}^e$, $z_{k,UAV}^e$, $\Phi_{k,UAV}^e$, $\theta_{k,UAV}^e$, and $\psi_{k,UAV}^e$ be defined accordingly. In order to avoid repeating expressions for x , y , z , Φ , θ , and ψ , we use q to refer to any of the six components (e.g., $\bar{q}_{UAV}^e$ in (2) may be replaced by $\bar{x}_{UAV}^e$, $\bar{y}_{UAV}^e$, or any other component). We characterize the absolute position and orientation errors with the arithmetic mean

$$\bar{q}_{UAV}^e = \frac{1}{n} \sum_{k=1}^n q_{k,UAV}^e, \quad (2)$$

the experimental variance of observations

$$s_{q_{UAV}^e}^2 = \frac{1}{n-1} \sum_{j=1}^n (q_{j,UAV}^e - \bar{q}_{UAV}^e)^2, \quad (3)$$

the experimental standard deviation $s_{q_{UAV}^e}$, the variance of the mean

$$s_{\bar{q}_{UAV}^e}^2 = \frac{s_{q_{UAV}^e}^2}{n}, \quad (4)$$

and the experimental standard deviation of the mean $s_{\bar{q}_{UAV}^e}$.

After calculating $\bar{q}_{UAV}^e$ with (2), we can calculate our best estimate for each component, i.e.

$$q_{k,EKF} - \bar{q}_{UAV}^e, \quad (5)$$

which is mean-free by construction and where the two terms have the uncertainties

$$u_{q_{UAV}^e}, \quad (6)$$

and

$$u_{\bar{q}_{UAV}^e} = s_{\bar{q}_{UAV}^e}, \quad (7)$$

respectively, with $s_{\bar{q}_{UAV}^e}$ found with (5), and where $u_{\bar{q}_{UAV}^e}$ is called the standard uncertainty. The uncertainty in (6) represents that of a single

EKF estimate. Unlike (7) and the experimental variance of the mean in (4), it must not be scaled down by the factor $1/n$ that results from n repeated measurements. Consequently, the reduction factor $1/n$ in (4) must be dropped, which implies $u_{q_{UAV}^e}^2 = s_{q_{UAV}^e}^2$.

Assume a quantity of interest $M \in \mathbb{R}^3$ ('the measurand') cannot be measured directly but determined from measurable quantities q_i with a measurement function f , i.e.,

$$M = f(q_1, q_2, \dots, q_n). \quad (8)$$

Then the uncertainty of M can be characterized with the combined standard uncertainty $u_{c,M}$, which is the positive square root of the combined variance [6, Sec. 5]

$$u_{c,M}^2 = \sum_{i=1}^n \left(\frac{\partial f}{\partial q_i} \right)^2 u_{q_i}^2, \quad (9)$$

where the partial derivative is evaluated at the estimates of the input quantities and where u_{q_i} is the standard uncertainty of the input quantity q_i .

For our system, three measurands, the components of the estimated position of the RIS center $p_{RIS} = [x_{RIS}, y_{RIS}, z_{RIS}]^T$ must be treated. The three instances of the measurement function (8) read

$$p_{RIS} = P_{UAV} + R(\Phi, \theta, \psi) l_{RIS}, \quad (10)$$

where $l_{RIS} = [0, 0, -l_m]$ describes the spatial offset between UAV center of mass and the RIS, where $m \in \{\text{PMX6}, \text{X500}\}$. The position of the UAV is given by $p_{UAV} = [x_{k,EKF} - \bar{x}_{UAV}, y_{k,EKF} - \bar{y}_{UAV}, z_{k,EKF} - \bar{z}_{UAV}]^T$ as in (6) with uncertainties (7) and (8), and $R(\Phi, \theta, \psi) \in \mathbb{R}^{3 \times 3}$ is the product of the rotation matrices

$$R(\Phi, \theta, \psi) = R_z(\psi) R_y(\theta) R_x(\Phi).$$

Evaluating (9) for the three measurands $p_{RIS} = [x_{RIS}, y_{RIS}, z_{RIS}]^T$ and their measurement functions (10) yields the combined variances

$$\begin{aligned} u_{c,x_{RIS}}^2 &= u_{x_{UAV}}^2 + u_{\bar{x}_{UAV}}^2 + \sum_{q_i} \left(v_x^T \frac{\partial R}{\partial q_i} \Big|_{\Phi_0, \theta_0, \psi_0} l_{RIS} \right)^2 u_{q_i}^2 \\ u_{c,y_{RIS}}^2 &= u_{y_{UAV}}^2 + u_{\bar{y}_{UAV}}^2 + \sum_{q_i} \left(v_y^T \frac{\partial R}{\partial q_i} \Big|_{\Phi_0, \theta_0, \psi_0} l_{RIS} \right)^2 u_{q_i}^2 \\ u_{c,z_{RIS}}^2 &= u_{z_{UAV}}^2 + u_{\bar{z}_{UAV}}^2 + \sum_{q_i} \left(v_z^T \frac{\partial R}{\partial q_i} \Big|_{\Phi_0, \theta_0, \psi_0} l_{RIS} \right)^2 u_{q_i}^2 \end{aligned} \quad (11)$$

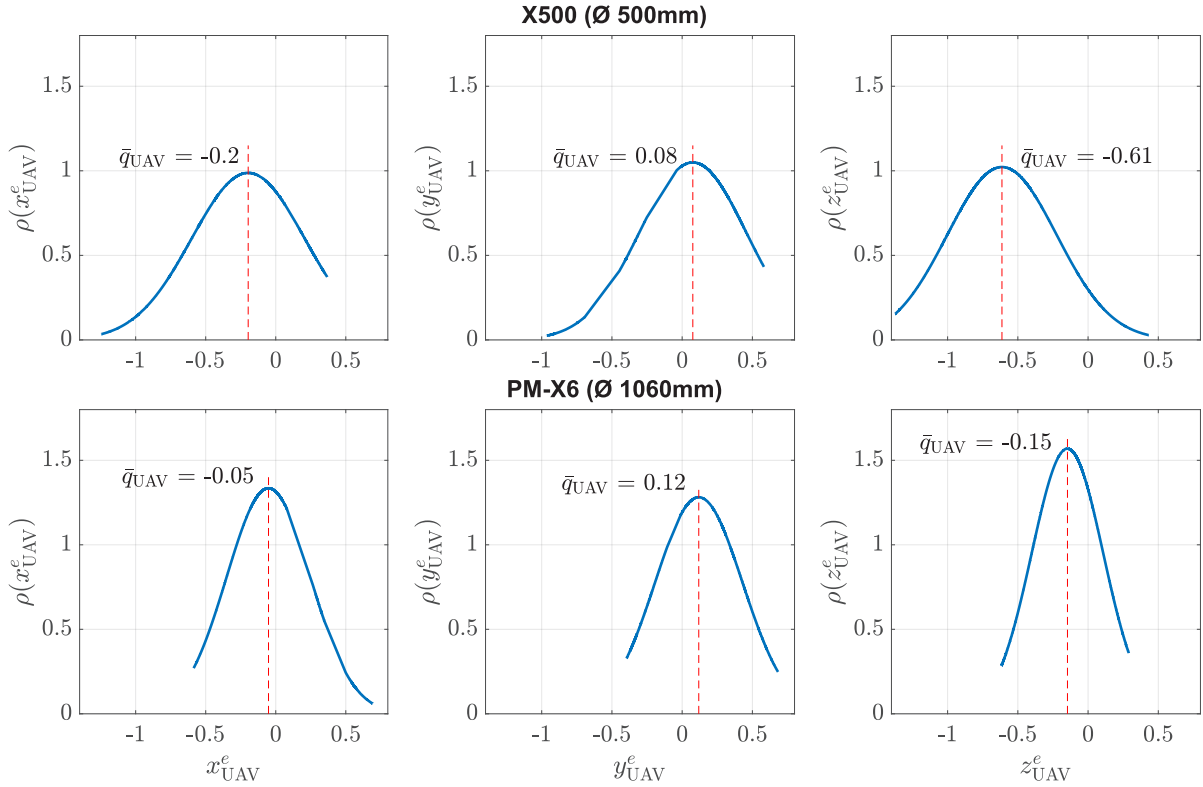


Figure 2: Normal distributions of the position errors for the laboratory-scale UAV X500 (top) and the larger UAV PM-X6 (bottom). Red lines indicate arithmetic means.

where sums are carried out for $q_i \in \{\Phi, \theta, \psi\}$, v_x , v_y , and v_z are the cartesian unit vectors, and $\Phi_0 = \theta_0 = \psi_0 = 0$ because we are treating hover flight. Moreover, $u_{\bar{x}_{\text{UAV}}}$ is as introduced in (7) and $u_{\bar{y}_{\text{UAV}}}$ and $u_{\bar{z}_{\text{UAV}}}$ are defined accordingly. The resulting combined standard uncertainties $u_{c,x_{\text{RIS}}}$, $u_{c,y_{\text{RIS}}}$, and $u_{c,z_{\text{RIS}}}$ are stated in Tab. 1.

Table 1 also lists the expanded combined uncertainty U_c for completeness. The expanded uncertainty is an interval of the form

$$q - U_c \leq q \leq q + U_c, \quad (12)$$

with $U_c = bu_{c,m}$. We choose $b = 2$, which corresponds to U_c defining an interval with an approximate 95% confidence level, commonly used in UAV and networking applications [9, 10].

Given the results in Tab. 1, the influence of orientation uncertainty for the larger UAV is found to be relatively small, similar to the laboratory-scale UAV, making the position uncertainty the predominant source of uncertainty. Although the larger RIS increases the effective surface area exposed to wind disturbances and alters the airflow around the UAV, the increased mass and inertia of the UAV itself appear to counteract these effects, resulting in orientation uncertainties of the same order for both systems. In fact, based on the findings in [4], these orientation uncertainties

are sufficiently small that they do not impact the channel link quality.

Tab. 1: Uncertainties in the UAV and RIS position estimation of the laboratory-scale UAV X500 (first values) and the larger UAV PM-X6 (second values).

	X500 /PM-X6		
GUM params	Φ in °	θ in °	ψ in °
$\bar{q}_{\text{UAV}}^e$	0.23 /-0.001	0.22 /-0.005	-0.06 /0.06
$u_{\bar{q}_{\text{UAV}}^e}$	0.005 /0.002	0.005 /0.002	0.002 /0.004
$u_{q_{\text{UAV}}}$	0.49 /0.20	0.48 /0.18	0.18 /0.43
	x in m	y in m	z in m
$\bar{q}_{\text{UAV}}^e$	-0.20 /-0.05	0.08 /0.12	0.61 /-0.15
$u_{\bar{q}_{\text{UAV}}^e}$	0.004 /0.003	0.004 /0.003	0.004 /0.003
$u_{q_{\text{UAV}}}$	0.40 /0.30	0.40 /0.30	0.38 /0.25
$u_{c,q_{\text{RIS}}}$	0.43 /0.30	0.43 /0.31	0.38 /0.25
$U_{c,q_{\text{RIS}}}$	0.86 /0.60	0.86 /0.62	0.76 /0.50

For the position uncertainty of the UAVs, the differences become more pronounced. For better comparison, Fig. 2 shows the normal distributions of the position uncertainties in each spatial direction for both UAVs. It can be observed that the larger UAV exhibits significantly smaller position uncertainties than the laboratory-scale UAV, with reductions of approximately 25% in the x- and y-directions and about 35% in the z-direction. Since the UAV position uncertainty represents the predominant contribution to the RIS position uncertainty, similar improvements are observed for the RIS position uncertainty. With more than 2.7 times the mass, and thus greater inertia, disturbances like wind result in slower position changes for the larger UAV compared to the laboratory-scale UAV. This behavior facilitates tracking by the EKF, resulting in more accurate position estimates. Based on these results, we expect an improvement in channel link quality compared to the laboratory-scale UAV, even though both UAVs are equipped with the exact same sensor setup. However, the remaining position uncertainties with an expanded uncertainty of about 60cm may still be too significant to achieve optimal channel quality at this frequency.

Comparison of the Inference of the Channel Link Quality

In this section, we assess how different uncertainties affect the channel link quality by comparing one representative flight of each of the UAVs. Furthermore, we show that, although the uncertainties associated with the larger UAV are between 25% and 35% smaller than those of the laboratory-scale UAV, they remain too significant to achieve optimal channel quality.

The Tx antenna is positioned at (0,0,0) below the center of the RIS with the Rx antenna positioned 2m away along the x-axis of the coordinate system from the Tx antenna. We calculate the current RIS position $p_{k,\text{RIS}}$ at time step k according to (10) for both UAVs based on data from an extra flight, which was performed and processed in the same way as the other 10 flights, but was not used for calculating the uncertainties. We assume $\phi = \theta = \psi = 0^\circ$ for the RIS orientation at all times, in order to isolate the effect of position fluctuations. Although the RIS carried by the larger UAV has been scaled from laboratory dimensions to a size suitable for real-world missions in order to capture airflow-related uncertainties, we additionally assume that both RISs have identical dimensions and the same number of elements. Specifically, we set $M =$

120, such that only position uncertainties affect the channel link quality.

Under these assumptions, we can calculate the distances d_m^h and d_m^g , i.e., between each reflecting element m for the Tx-RIS and RIS-Rx link, respectively. Consequently, we can determine the cascaded channel coefficients h_m^{casc} for each time step k with (1), which is prerequisite for the optimization process.

With the above assumptions, it becomes possible to compute the optimal RIS configurations based on the values of h_m^{casc} in the observed interval. Because this optimization must be performed in real-time, i.e. at every time step k , we need to carefully consider the computational cost when designing the optimization algorithm. Furthermore, the RIS is limited to applying only 180° phase shifts, i.e., $\varphi_m \in \{0^\circ, 180^\circ\}$, and suffers from a -3 dB loss in reflection amplitude A_m for $\varphi_m = 180^\circ$, consistent with the behavior of its physical counterpart.

Due to the blocked path between Tx and Rx, the phase of the effective channel h^{eff} can be selected arbitrarily during the optimization process. This can be expressed as

$$\varphi_m^*(C) = C - \varphi'_m, \quad (13)$$

where $C \in \mathbb{R}$ denotes an arbitrary value for the desired phase of h^{eff} and $\varphi'_m = \frac{2\pi}{\lambda}(d_m^h + d_m^g)$. We select C from a finite set of to ensure the optimization to be fast enough for use in real time. In the present paper, we use the values

$$C \in \zeta = \left\{0, \frac{\pi}{4}, \frac{\pi}{2}, \frac{3\pi}{4}, \pi, \frac{5\pi}{4}, \frac{3\pi}{2}, \frac{7\pi}{4}\right\}, \quad (14)$$

which results in a suitable trade-off to identify a good solution within the available time [8]. It will also be evident from the results in the following section that this restriction to $|\zeta| = 8$ values does not constitute any limitation.

After optimizing the phase shift φ_m^* for every patch $m = \{1, \dots, M\}$, we need to determine which of the patch states, $\varphi_m^* = 0^\circ$ or 180° , is the optimal choice. We choose a fast rounding operation in light of the real-time requirements. Note that the same approach would still hold if continuous phase shifts were available. In fact, the problem would become simpler, as removing the hardware-imposed constraint of selecting only discrete phase states allows for more flexible optimization and can potentially improve performance. For the resulting binary RIS configurations, we choose the best performing one by assessing and comparing the simulated channel quality of the resulting RIS-facilitated links. This procedure can mathematically be formulated as maximizing h^{eff} for all $C \in \zeta$

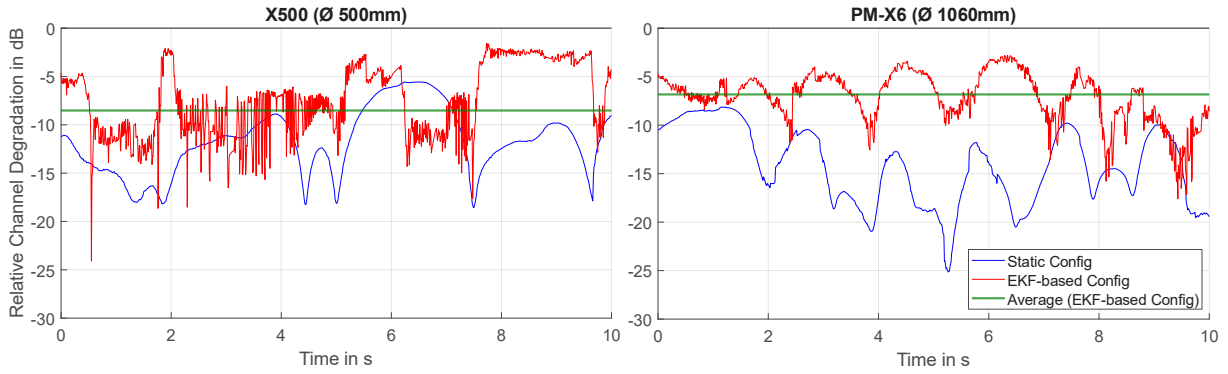


Figure 3: Relative channel degradation of the laboratory-scale UAV (X500 – left) and the larger UAV (PM-X6 – right). The base line (0dB) is the optimal channel quality achieved by using MCS data (i). Red lines indicate relative channel degradation for the EKF-based RIS configuration (ii), where the green lines show the average relative channel degradation for (ii). Blue lines show the average relative channel degradation for the static RIS configuration (iii).

$$h_c^{eff}(C) = \sum_{m=1}^M h_m^{casc} A_m \left(\text{rd}(\varphi_m^*(C)) \right) e^{j \text{rd}(\varphi_m^*(C))}$$

$$\text{with } A_m(\tau) = \begin{cases} 0.5012 \text{ (-3dB)}, & \text{if } \tau = \pi \\ 1, & \text{otherwise} \end{cases}$$

$$\text{rd}(\tau) = \begin{cases} \pi, & \text{if } \frac{\pi}{2} \leq \tau \leq \frac{3\pi}{2} \\ 0, & \text{otherwise} \end{cases}$$

$$C \in \zeta = \left\{ 0, \frac{\pi}{4}, \frac{\pi}{2}, \frac{3\pi}{4}, \pi, \frac{5\pi}{4}, \frac{3\pi}{2}, \frac{7\pi}{4} \right\} \quad (15)$$

in every time step k . This optimization can be carried out efficiently, because the optimal C and $\varphi_m^*(C)$ can be found independently for each patch by comparing the $|\zeta| = 8$ choices and rounding subsequently.

Finally, we can compare how different UAV sizes and their uncertainties affect the channel quality h^{eff} when optimizing the RIS with the respective EKF data. While realistic propagation environments introduce additional effects such as multipath fading and scattering, which may degrade performance, the real-time reconfigurability of the LoS path of the RIS provides performance gains that outweigh these effects, leading to significant observable improvements in practice [3].

We recall that we want to analyze the impact of the different EKF-based RIS position uncertainties and thus assume the RIS orientation to be constant and the UAVs carrying identical RIS. We evaluate the optimal effective channel h^{eff} for three different cases of RIS position information for each UAV: (i) based on the UAV's position and orientation measured with the motion capture system for reference, (ii) based on the UAV's position and orientation estimated with the EKF, (iii) under the assumption that only the target position is available, where (iii) is equivalent to assuming a fixed known x-, y-, z-position for all times. For cases (i) and (ii), the optimal RIS configuration is determined according to (15). For case (iii), we optimize the RIS for $x = y = 0$ and $z = 3.5$

once and maintain the resulting RIS configuration for all k .

Figure 3 shows the optimal effective channel h^{eff} based on the MCS measurements from the flight experiments conducted with the laboratory-scale X500 (left) and the larger PM-X6 (right). The static (iii) and EKF-based (ii) setups are compared against the MCS configuration (i), which acts as a reference. The figure shows that the static and EKF-based RIS configurations deteriorate in performance when compared to the MCS-based configurations for both UAVs, which highlights the impact of the RIS position estimation uncertainties on the channel gain. However, when comparing the impact of the position uncertainties on the channel gain between the larger PM-X6 and the X500, it becomes evident that the PM-X6 significantly outperforms the X500. Specifically, configuring the RIS based on the EKF information from the PM-X6 degrades the channel gain by 6.75dB on average, whereas reconfiguring the RIS based on X500 data degrades the channel by 8.5dB, corresponding to an approximately 21% higher loss in dB. The relative loss is consistent with the uncertainties determined in the previous section, indicating that the reduction in uncertainty is directly impacting the quality of the effective channel. A similar trend is observed for the maximum channel degradation. The estimates from the PM-X6 degrade the channel by up to 17.6dB, while the estimates from the X500 reach a maximum degradation of 24.1dB. This corresponds to a difference of approximately 27%, aligning with the previously determined uncertainties. These results reveal that scaling the proposed measurement technology to larger platforms is not only feasible but also beneficial, as it reduces uncertainty and improves potential measurement accuracy. Note that in practice, differences in the absolute channel gain may be even more pronounced,

since larger UAVs are capable of carrying significantly larger RIS arrays.

Conclusion

We investigated the effect of UAV size on the position uncertainties and the channels of UAV-mounted RIS, by conducting flight experiments with a laboratory-scale UAV and a UAV more than twice its size. For investigation of the position uncertainties, we followed the *Guide to the expression of uncertainty in measurement (GUM)* [6]. Despite the larger surfaces exposed to wind and the increased airflow disturbances caused by the larger RIS mounted on the larger UAV, the higher mass and inertia of the larger UAV mitigate these effects. This results in slower dynamics, which improve the tracking performance of the EKF and lead to reduced position uncertainties compared to the laboratory-scale setup.

We subsequently analyzed the impact of the uncertainties on the channel link quality by adjusting the RIS configuration based on real EKF data from both UAVs through numerical simulations. Consistent with the results from the uncertainty analysis, the deployment of the larger UAV results in reduced channel degradation relative to the optimal RIS configuration compared to the laboratory-scale UAV, indicating that scaling the proposed system to larger platforms is beneficial. However, despite the reduced uncertainties achieved with the larger UAV, they remain too high to match the channel quality when adjusting the RIS configuration based on ground truth data. Consequently, system upgrades are still necessary, where additional sensors like real-time kinematic GNSS could be particularly useful. These upgrades also become essential when considering more dynamic flight maneuvers, as position uncertainty is likely to increase due to more rapid changes in the estimated state.

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