On-board Communication-based Relative Localization for Collision Avoidance in Micro Air Vehicle teams

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Abstract Micro Air Vehicles (MAVs) will unlock their true potential once they can operate in groups. To this end, it is essential for them to estimate on-board the relative location of their neighbors. The challenge lies in limiting the mass and processing burden needed to enable this. We developed a relative localization method that only requires the MAVs to communicate via their wireless transceiver. Communication allows the exchange of on-board states (velocity, height, and orientation), while the signal-strength provides range data. These quantities are fused to provide a full relative location estimate. We used our method to tackle the problem of collision avoidance in tight areas. The system was tested with a team of AR.Drones flying in a 4m × 4m area and with miniature drones of ≈ 50g in a 2m × 2m area. The MAVs were able to track their relative positions and fly several minutes without collisions. Our implementation used Bluetooth to communicate between the drones. This featured significant noise and disturbances in signal-strength, which worsened as more drones were added. Simulation analysis suggests that results can improve with a more suitable transceiver module.

Keywords Relative Localization · Collision Avoidance · Micro Air Vehicles · Autonomous Flight · Indoor Exploration · Swarm

1 Introduction

The agility and small scale of Micro Air Vehicles (MAVs) make them ideal for indoor exploration (Kumar and Michael, 2012). We imagine several autonomous MAVs navigating through a building/house for mapping or inspection. The swarm could spread out and thus complete the task in a short time. This approach would also bring robustness, scalability, and flexibility to the system, being no longer tied to the success and ability of only one unit (Brambilla et al, 2013). During this scenario, however, it may happen that a few MAVs end up flying together in a small area (e.g. a common bedroom, office, meeting room, hallway), leading to a significant risk of intra-swarm collisions (Szabo, 2015). This is a failure condition to be avoided to ensure mission success without the unwanted loss of units. We have developed and tested a method to tackle this issue which uses only wireless communication between MAVs. Two or more MAVs estimate their relative location via the wireless connection and adjust their path to avoid collisions. In this paper, we describe the details of the algorithm and present real-world results on autonomous drones.

The primary contribution in this article is an on-board relative localization method for MAVs based on intra-swarm wireless communication. The communication channel is used as a method for the exchange of own state measurements and as a measure of relative range (based on signal strength), this provide each MAV sufficient data to estimate the relative location of another. Our implementation uses Bluetooth, which is readily available at a low mass, power, and cost

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penalty even on smaller MAVs (McGuire et al., 2016). The advantages of our solution are: a) it provides direct MAV-to-MAV relative location estimates at all relative bearings; b) it has a low dependence on the lighting and sound conditions of the environment; c) it has low mass, battery, and processing requirements; d) it does not require the use of dedicated sensors. The findings also apply to other indoor localization problems, because it shows that only one access point is sufficient to obtain a localization estimate, as opposed to multiple ones in current state of the art (Malyavej et al., 2013; Choudhry et al., 2017). The secondary contribution is a reactive collision avoidance strategy that is easily tailored to the anticipated performance of the localization estimates. The strategy was inspired by the concept of collision cones (Fiorini and Shiller, 1998), tailored to suit the expected relative localization performance.

The paper is organized as follows. First, we review a set of related literature in Sect. 2, exploring other approaches towards our goal. Then Sect. 3 introduces the communication-based relative localization methodology, and Sect. 4 describes our collision avoidance strategy. To test the system, we developed a representative room exploration task, explained in Sect. 5. We gradually detail the experiments and results that have been performed, starting from simulation (Sect. 6) to real-world fully autonomous drones (Sect. 8), with positive results. All results are further discussed in Sect. 10. Concluding statements and future challenges are laid out in Sect. 11.

2 Related Work and Research Context

MAVs should be designed to be as efficient as possible to decrease mass and maximize flight-time. This means that they are often limited in sensing, computational power, and payload capabilities (Remes et al., 2014; Mulgaonkar et al., 2015). Collision avoidance is important for mission success but it must not exhaust the already limited resources, which should remain free to pursue the real mission. Arguably, the simplest method to avoid collisions is to have the MAVs fly at different heights. However, experiments by Powers et al. (2013) have shown that MAV multi-rotors flying on top of each-other are subject to considerable aerodynamic disturbances. Furthermore, height sensor (e.g. sonar) readings could be disturbed. Based on this limitation, we conclude that lateral evasive maneuvers are needed, and these require relative location estimates between MAVs.

One method to achieve relative localization is to provide a shared reference frame in which each MAV knows its own absolute location. The MAVs can share absolute pose data and infer a relative estimate. In outdoor tasks, Global Positioning System (GPS) receivers can be used to obtain global position data to share. This has enabled formation flying (Min and Nam, 2016) and large-scale flocking (Vásárhelyi et al., 2014). In indoor tasks, where GPS is not available, absolute position data can be measured using external sensors/beacons in a known configuration, such as: motion tracking cameras (Michael et al., 2010), fixed wireless transmitters/receivers (Guo et al., 2016b; Ledergerber et al., 2015), or visual markers (Faigl et al., 2013). However, these solutions are unsuitable for indoor exploration tasks because they rely on a pre-arranged environment. Simultaneous Localization and Mapping (SLAM) methods circumvent this by generating an indoor map on-board during flight, which then provide position information that can be shared (Scaramuzza et al., 2014). However, if on-board map generation is not part of the mission, then this is a resource intensive practice to be discouraged (Ho et al., 2015). Therefore, the more direct strategy is for the MAVs to directly localize each-other.

To this end, vision has received significant attention, where front-facing cameras are used to detect and localize other MAVs. Current implementations generally adopt mounted visual aids in the form of: colored balls (Roelofsen et al., 2015), tags (Conroy et al., 2014), or markers (Nageli et al., 2014). However, experiments during exploratory phases of this study have shown that using vision without such aids, for very small drones, and at low resolution (128×96px, as seen on the Lisa-S Ladybird (McGuire et al., 2016)) is prone to false-positives/false-negatives. Other disadvantages of using vision are: dependence on lighting conditions, the need for a front-facing camera, limited field-of-view, and high processing requirements (Alvarez et al., 2016).

Roberts et al. (2012) proposed Infra-Red (IR) sensors. If arranged in an array, these enables an accurate measure or relative bearing between two MAVs. Unfortunately, because IR is uni-directional, several sensors are needed to each face in a direction. This is not easily exportable to smaller MAVs.

Alternatively, recent work by Basiri (2015) uses on-board sound-based localization. A microphone array and a chirp generator are mounted on-board of the MAVs, and the difference between arrival times of the chirp at the different microphones is used to estimate the relative bearing (Basiri et al., 2014, 2016). This method requires dedicated hardware, which for smaller MAVs can account for an increase in mass of even 10%-20% (Basiri et al., 2016; Remes et al., 2014).

To truly minimize the footprint, we decide to focus on a component that is mounted by necessity on all MAVs: a wireless transceiver. This is typically used for communication with a ground station (Lehnert and Corke, 2013; McGuire et al., 2016), but it may also be used for intra-swarm
communication. The signal strength of a wireless communication decreases with distance from the antenna, and can be used as a measure for range between MAVs. Szabo (2015) first exploited this on-board of real MAVs as a measure for range sensing. However, range-only data, coupled with significant noise and disturbances, were found insufficient to guarantee safe flight of two or more MAVs in a confined area in spite of relying on a complex evolved avoidance behavior. Amrita and Kumaar (2016) recently also explored range-only avoidance on WeBot robots (in simulation only), but range measurements were aided by an array of proximity sensors.

Transceivers can be exploited for both ranging and data-exchange. Based on this, we developed a fusion filter that can determine relative location estimates via communicating on-board states between MAVs. To the best of our knowledge, the only instance of on-board relative localization using a wireless transceiver was recently brought forward by Guo et al (2016a) with Ultra Wide-Band (UWB) technology. However, they make use of one of the MAVs as a static beacon and their method relies on highly accurate distance measurements. Based on this, we developed a fusion filter that communicates the following states to each other: planar velocity in the body frame, orientation with respect to North, and their method relies on highly accurate distance measurements. Instead, we propose a method that complements possibly noisy distance measurements by communicating on-board states between moving MAVs. We then show how it can be used for indoor collision avoidance. We extensively validate this on real platforms as light as 50g that communicate between each other using Bluetooth, which is highly prone to noise and disturbances.

3 Communication-Based Relative Localization

Relative localization is achieved via wireless communication link between the MAVs. The idea is that the MAVs communicate the following states to each other: planar velocity in the body frame, orientation with respect to North, and height from the ground. When communicating, the MAVs can also capture the strength of the signal, which acts as a measure of distance. For Bluetooth Low Energy (BLE), the technology chosen in our implementation, signal-strength measurements are referred to as Received Signal Strength Indication (RSSI). Each MAV fuses the received states, the RSSI, and its own on-board states to estimate the relative pose of another MAV. When multiple MAVs are present, multiple instances of the fusion filter run in parallel so that each MAV may keep track of the others. This section details the design and implementation of the relative localization scheme and presents some preliminary localization results that were obtained in early stages of the research.

3.1 Framework Definition for Relative Localization

Consider two MAVs $\mathcal{R}_i$ and $\mathcal{R}_j$ with body-fixed frames $\mathcal{F}_{B_i}$ and $\mathcal{F}_{B_j}$, respectively. We define the relative pose of $\mathcal{R}_j$ with respect to $\mathcal{R}_i$ as the set $\mathbf{p}_{ji} = [\rho_{ji}, \beta_{ji}, z_{ji}, \psi_{ji}]$, where $ho_{ji}$ represents the range between the origins of $\mathcal{F}_{B_i}$ and $\mathcal{F}_{B_j}$, $\beta_{ji}$ is the horizontal planar bearing of the origin of $\mathcal{F}_{B_j}$ with respect to $\mathcal{F}_{B_i}$, $z_{ji}$ is the height of $\mathcal{R}_j$ with respect to $\mathcal{R}_i$, and $\psi_{ji}$ is the yaw of $\mathcal{F}_j$ with respect to $\mathcal{F}_i$. See Fig. 1 for an illustration. Note that $\rho_{ji}$ and $\beta_{ji}$ are related to their cartesian counterparts via:

\[
\rho_{ji} = \sqrt{x_{ji}^2 + y_{ji}^2 + z_{ji}^2}
\]

\[
\beta_{ji} = \arctan2(y_{ji}, x_{ji})
\]

$x_{ji}$, $y_{ji}$, and $z_{ji}$ are the Cartesian coordinates of the origin of $\mathcal{F}_j$ in $\mathcal{F}_{B_i}$.

3.2 Signal Strength as a Range Measurement

Let $S_{ji}$ be the RSSI measurement in $dB$. It is correlated with $\rho_{ji}$ by a function $\mathcal{L}(\rho_{ji})$. We define this function based on the Log-Distance (LD) model (Seybold, 2005):

\[
S_{ji} = \mathcal{L}(\rho_{ji}) = P_n - 10 \cdot \gamma \cdot \log_{10} (\rho_{ji}).
\]

$P_n$ is the RSSI at a nominal distance of 1m. $\gamma$ is the space-loss parameter, which dictates how much the signal strength decays with distance (for free-space: $\gamma = 2.0$).\footnote{Experimentally, it has been found that office buildings can feature $2 \leq \gamma \leq 6$ (Kusuki et al, 2008). Performing a sensitivity analysis of the LD model shows that an accurate identification of $\gamma$ has a low impact on the distance estimate at small distances.}

In preliminary tests, we analyzed the LD model with Ladybird MAV (Remes et al, 2014) connected via Bluetooth...
to a fixed W1049B omni-directional antenna (Pulse, 2008). The MAV was carried in concentric circles at different distances around the antenna whilst RSSI was being recorded with the antenna. Its orientation with respect to North was kept constant, thus varying the relative bearing to the antenna. Ground-Truth (GT) data was recorded with an Optitrack Motion Capture System (MCS). The results from a representative data-sample are shown in Fig. 2, to which the代表ative data-sample are shown in Fig. 2, to which the MA V was carried in concentric circles at different distances around the antenna whilst RSSI was being recorded.

![Fig. 2](image_url) Results of RSSI measurements during an experiment whereby a Ladybird MAV was carried in circles around a fixed Bluetooth antenna.

The LD model could be expanded with this, but the susceptibility to environmental disturbances would lead to a confounding element between bearing and range which could be detrimental to the convergence of the fusion filter. We also observed a change of the error with the relative bearing. This is shown in Fig. 2b, and accounts for the disturbances that can cause this were found to be: propagation lobes, interference by the reflection of the signal in the environment, the presence of other signals in the 2.4GHz spectrum, or other objects that obstruct the signal (Seybold, 2005; Svečko et al, 2008; Caron et al, 2008).

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\( w_k \) represents the noise in the measurements at time step \( k \). Note that \( \rho_{ji} \) is expanded as per Eq. 1 so as to observe \( x_{ji} \) and \( y_{ji} \).

The EKF cannot be initialized with a correct relative localization estimate, since this is not known; it must converge towards the correct estimate during flight. Appropriate tuning of the EKF noise covariance matrices is key to achieving this. In the EKF, the measurement noise matrix \( R \) is a diagonal matrix with the form shown in Eq. 6.

\[
R = \begin{bmatrix}
\sigma_m^2 \\
\sigma_l^2 \cdot I_{4 \times 4} \\
\sigma_y^2 \cdot I_{2 \times 2} \\
\sigma_z^2 \cdot I_{2 \times 2}
\end{bmatrix}
\]  \(6\)

\( \sigma_m \) is the assumed SD of \( S_{ji} \), \( \sigma_l \) is the assumed SD of \( \rho_i \) and \( \rho_j \), and \( \sigma_y \) is the assumed SD of the magnetic orientation measurements. \( \sigma_z \) is the assumed SD of the height measurements. \( I_{n \times n} \) is an \( n \times n \) identity matrix. Based on our preliminary RSSI noise analysis, \( \sigma_m \) is tuned to 5\( dB \). All other SDs were tuned to 0.2, unless otherwise stated.

The process noise matrix \( Q \) is the diagonal matrix presented in Eq. 7.

\[
Q = \begin{bmatrix}
\sigma_{Q_{\rho}}^2 \cdot I_2 \times \alpha_2 \\
\sigma_{Q_{l}}^2 \cdot I_{4 \times 4} \\
\sigma_{Q_{y}}^2 \cdot I_{2 \times 2} \\
\sigma_{Q_{z}}^2 \cdot I_{2 \times 2}
\end{bmatrix}
\]  \(7\)

\( \sigma_{Q_{\rho}} \) is the SD of the process noise on the relative position update. \( \sigma_{Q_{l}} \), \( \sigma_{Q_{y}} \), and \( \sigma_{Q_{z}} \) are SDs for the expected updates in velocity, orientation, and height respectively. The tuning of \( Q \) defines the validity of the process equations (Malyavej et al, 2013). The tuning is made such that a high-level of trust is put on the relative position update. This approach is key to encouraging convergence and helps to discard the high noise and disturbance in the RSSI measurements. Unless otherwise stated: \( \sigma_{Q_{\rho}} \) = 0.1, while \( \sigma_{Q_{l}} = \sigma_{Q_{y}} = \sigma_{Q_{z}} \) = 0.5.

The filter is limited by flip and rotation ambiguity as defined in (Cornejo and Nagpal, 2015). When the motion of \( R_j \) perfectly matches the motion by \( R_i \), range-only measurements remain constant and are not informative for bearing estimation. If the MAVs do not fly in formation, the probability of this event is low (Cornejo and Nagpal, 2015). The same ambiguity takes place when both \( R_i \) and \( R_j \) are static; motion by at least one MAV is required.

3.4 Implementation Details

We used BLE to enable communication between the MAVs. The data is sent and received by means of advertising messages scheduled using a Self-Organized Time Division Multiple Access (STDMA) algorithm (Gaugel et al, 2013). This way, each MAV’s Bluetooth antenna alternates between advertising and listening. This enables direct communication and circumvents the Master-Slave paradigm otherwise enforced by the Bluetooth standard (Townsend et al, 2014). The message rate is 5\( Hz \), i.e. data is received every 0.2s.

3.5 Preliminary Relative Localization Tests

We performed preliminary localization tests with a Ladybird MAV around a fixed Bluetooth W1049B antenna. The objective was to determine how well the antenna could localize the MAV. An Optitrack MCS was used to guide the MAV in circular flights and record its GT velocity, orientation, and height. The antenna measured the RSSI with the MAV. The recorded GT data was altered with Gaussian noise with \( \sigma_{\rho} = 0.2 m/s \), \( \sigma_{\psi} = 0.2 m \), and \( \sigma_{\gamma} = 0.2 rad \), and then used as measurements for the EKF. In the LD model of the EKF: \( P_n \) = \( -63 dB \) and \( \gamma = 2.0 \). The EKF was initialized with a null guess position of \( x_{ji} = y_{ji} = 1 m \). In these preliminary tests, the localization filter was applied off-board.

Fig. 3 shows the results. Estimates for \( x_{ji} \) and \( y_{ji} \) are shown in Fig. 3a and Fig. 3b, the EKF converges towards GT in the first few seconds, after which it tracks successfully. Fig. 3c shows the estimated range, where we can observe a significant improvement in error with respect to an inverted LD model. Note that the range error increases with distance, this is due to the logarithmic nature of RSSI propagation. Fig. 3d shows the bearing error, which is small throughout most of the flight. The only exceptions are occasional spikes which occur at small distances which cross over \( x_{ji} = 0 m \) and \( y_{ji} = 0 m \). This is because at very small distances, a small error in \( x_{ji} \) or \( y_{ji} \) can translate into a significant error in \( \beta_{ji} \). Thanks to the avoidance algorithm, such small distances should be avoided altogether during flights.

4 Collision Avoidance Behavior

The avoidance algorithm was inspired by the Collision Cone (CC) frame-work as seen in the works by Fiorini and Shiller (1998) and Wilkie et al (2009). A collision cone is a set of all velocities of an agent that are expected to lead to a collision with an obstacle at a given point in time. Its name is derived from the fact that it is geometrically cone-shaped. This section details our implementation of collision cones and how it is used to determine an avoidance trajectory.

4.1 Collision Cones and Avoidance Strategy

Take two MAVs \( R_i \) and \( R_j \). The collision cone \( CC_{ji} \) (depicted in Fig. 4) would include all velocities of \( R_j \) which
could lead to a collision with $R_j$. It is constructed in three steps.

1. A cone $CC_{ji}$ is defined as in Eq. 8. $\alpha$ is an arbitrary angle. $x$ and $y$ are points on $x_B$ and $y_B$, respectively. The cone is characterized by an expansion angle $\alpha_{CC_{ji}}$, subject to $0 < \alpha_{CC_{ji}} < \pi$.

$$CC_{ji} = \{ (x, y) \in \mathbb{R}^2; \alpha \in \mathbb{R}; |\alpha| \leq \frac{|\alpha_{CC_{ji}}|}{2} : \tan(\alpha)x = y \}$$ (8)

2. $CC_{ji}$ is rotated so as to be centered around the estimated bearing to the obstacle $R_j$, as in Eq. 9, where: $\bar{\beta}_{ji}$ is the estimated $\beta_{ji}$ from the EKF, $\leftarrow$ is an update operator, and $R(\cdot)$ is a rotation operator for the set.

$$CC_{ji} \leftarrow (R(\bar{\beta}_{ji}) \cdot CC_{ji})$$ (9)

3. The cone is translated by the estimated velocity of $R_j$ expressed in $F_B$, to account for the fact that the obstacle is moving, as per Eq. 10. \(\overline{p}_{ji}R_i\) is the estimated $p_{ji}R_i$ from the EKF. The operator $\oplus$ denotes the translation of a set by a vector.

$$CC_{ji} \leftarrow CC_{ji} \oplus \overline{p}_{ji}R_i$$ (10)

In a team of $m$ MAVs, each member $R_i$ holds $m-1$ collision cones that it can superimpose into a single set $CC_i$:

$$CC_i = \bigcup_{j=1}^{m-1} CC_{ji}$$ (11)

If, during flight, $\dot{p}_i \in CC_i$, then a clock-wise search about the $z_B$ axis (starting with the current desired velocity) is used to determine the desired escape velocity. If no solution is found, then the search is repeated for a higher escape speed.

The clock-wise search encourages a preference for right-sided maneuvers with respect to the current flight direction. This differentiates it from the Velocity Obstacle (VO) avoidance method, which selects a flight direction that minimizes the required change in velocity. This automatically resolves an issue known as “reciprocal dances”, which are left-right dances when two entities heading towards each other repeatedly select the same escape direction. Other solutions to reciprocal dances assume reciprocity, meaning the assumption that the other member will also take a certain evasive action (Snape et al, 2009, 2011; Van Den Berg et al, 2011). In our case, however, due to the potential for large relative localization errors, MAVs cannot safely assume that the others will participate in a suitable and reciprocal escape maneuver.

4.2 Tuning the Expansion Angle of the Collision Cone

The expansion angle of a collision cone is dependent on the distance between the MAVs (the MAV radii becomes more significant as distance decreases), and the relative estimation errors (Conroy et al, 2014). Based on this knowledge, we formulated (12) to calculate the expansion angle:

$$\alpha_{CC_{ji}} = 2 \cdot \tan^{-1} \left( \frac{2r + \rho_{ji} + \varepsilon_\alpha}{\kappa_\alpha \cdot \rho_{ji}} \right),$$ (12)
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Fig. 4 Depiction of $CC_j$ that $R_i$ holds with respect to the estimated location of $R_j$

Fig. 5 Effect of $\kappa_\alpha$ on $\alpha_{CC_{\text{asymptote}}}$ ($r = 0.1m, \epsilon = 0.5$)

where: $r$ is the radius of a MAV (modeled as a circle); $\hat{\rho}_{ji}$ is the estimated range between $R_i$ and $R_j$; $\epsilon$ is an additional margin, the properties of which are discussed in Sect. 4.3; and $\kappa_\alpha$ is a coefficient describing the quality of the estimate. The expansion has a lower bound $\alpha_{CC_{\text{asymptote}}}$ which is dependent on $\kappa_\alpha$:

$$\alpha_{CC_{\text{asymptote}}} = \lim_{\hat{\rho}_{ji} \to \infty} \alpha_{CC_{ji}} = 2 \cdot \tan^{-1} \left( \frac{1}{\kappa_\alpha} \right).$$  \hspace{1cm} (13)

Its impact may be appreciated in Fig. 5. In this work, unless otherwise stated, we use $\kappa_\alpha = 1$, leading to $\alpha_{CC_{\text{asymptote}}} = \frac{\pi}{2}$. This incorporates the expected bearing errors expected during flight based on our preliminary results.

4.3 Preserving Behavior in Rooms of Different Size

The expansion angle of the collision cone widens towards $\pi$ as the distance between two MAVs decreases. This implies that in smaller rooms, the collision cones will always feature wide expansion angles, leading to most of the environment becoming out of bounds. This restriction in freedom of movement creates oscillations in MAV trajectories. To solve the issue, we propose using the margin $\epsilon_\alpha$ as a tuning parameter. The effect of varying $\epsilon_\alpha$ may be appreciated with Fig. 6: as $\epsilon_\alpha$ decreases, the decay of the expansion angle with distance increases. A faster decay is suitable for smaller rooms so that motion is less restricted.

We devised a method to tune $\epsilon_\alpha$ intuitively. By re-arranging Eq. 12, $\epsilon_\alpha$ is expressed by:

$$\epsilon_\alpha = \kappa_\alpha \cdot \rho_{eq} \cdot \tan \left( \frac{\alpha_{CC_{eq}}}{2} \right) - 2r - \rho_{eq}. \hspace{1cm} (14)$$

This translates tuning $\epsilon_\alpha$ to tuning a pair $\{\rho_{eq}, \alpha_{CC_{eq}}\}$, where $\alpha_{CC_{eq}}$ is the desired angle of expansion at a distance $\rho_{eq}$. Note that $\alpha_{CC_{eq}} > \alpha_{CC_{\text{asymptote}}}$, and $\epsilon_\alpha \geq -(r_i + r_j)$ if $\kappa_\alpha \geq 1$. In all our tests, $\rho_{eq}$ is set to half of the side length of the room. $\alpha_{CC_{eq}}$ is kept at $1.7 \text{rad}$.

5 General Testing Methodology

5.1 Description of Arbitrary Task for Performance Testing

A test exploration task was developed where multiple MAVs fly in a room, at the same altitude, and attempt to pass through the center. This is designed to provoke collision and observe if/how they are resolved. Consider a team of $m$ homogeneous MAVs. Each MAV $R_i$ can control its velocity. Let $\dot{p}_{\text{cmd}, k}$ be the desired velocity for $R_i$ expressed in its body-frame $\mathcal{F}_{Bi}$ at a given time-step $k$. Let $d_{\text{wall}}$ be the distance between $R_i$ and the arena border that is closest to it, with $d_{\text{safe}}$ being a safety distance to the arena’s borders. Remember that each robot $R_i$ features $m-1$ EKF instances to keep track of the other members and uses their outputs to determine its collision cone set $CC_i$, see Eq. 11. At each-time step $k$, the EKF outputs are updated and $CC_i$ is re-calculated. $\dot{p}_{\text{cmd}, k}$ is then chosen as follows: $\dot{p}_{\text{cmd}, k} = \dot{p}_{\text{cmd}, k-1}$ unless conditions M1 and M2 take place.
After this, the technology was also ported ending with autonomously controlled flight with on-board increasing realism and autonomy, starting with simulation and commanded by the collision avoidance algorithm, remain within the arena. At all time-steps, unless other-wise Condition M1 holds priority over M2 to ensure that the MA Vs could lead to a collision with one or more team members. An escape velocity is sought according to the strategy proposed in Sect. 4.

Condition M1 holds priority over M2 to ensure that the MAVs remain within the arena. At all time-steps, unless other-wise commanded by the collision avoidance algorithm, \( |\mathbf{p}_{cmd, k}| = v_{nominal} \), where \( v_{nominal} \) is a fixed speed magnitude.

5.2 Assessment Strategy

Assessment of Relative Localization: During the task, this can be assessed by comparing the estimated relative locations to ground-truth data.

Assessment of Collision Avoidance: This is partially dependent on the performance of the relative localization, yet can be assessed independently by identifying failure cases and observing general behavior properties. It is also interesting to determine the likelihood that the error falls within the expected collision cone bounds.

Assessment of the Full System: The parameter of interest is the mean flight-time between collision. Ideally, a successful system is one that systematically ensures that collision will not take place. This metric is dependent on how crowded the airspace is. By modeling MAVs as circles, airspace density is calculated with:

\[
D_m,c = \frac{m \cdot \pi r_c^2}{s_c^2}
\]  

where \( r_c \) is the radius of a MAV in configuration \( c \), \( s_c \) is the side length of the squared arena at configuration \( c \).

Experiments were performed in separate stages with increasing realism and autonomy, starting with simulation and ending with autonomously controlled flight with on-board measurements. After this, the technology was also ported and tested on miniature drones. The results of all tests are discussed in the next four chapters. Videos of the experiments are available at: https://www.youtube.com/playlist?list=PL_KSX9GOn2P9f0qyWQNBMj7xpe1HARSpc.

6 Simulation Experiments

Simulations allow to assess the collision avoidance algorithm and the full system. We can easily assess the performance of the system for several airspace densities, noise scenarios, etc., and obtain statistically relevant insights.

6.1 Simulation Environment Set-Up

The simulation environment was developed using Robotics Operating System (ROS) (Quigley et al., 2009), the Gazebo physics engine (Koenig and Howard, 2004) and the hector-quadrotor model (Meyer et al., 2012). Multiple quad-rotor MAVs can be simulated simultaneously. A ROS module (or "node") for each MAV simulates the Bluetooth communication and enforces the controller described in Sect. 5.1. A rendered screen-shot of a simulation run is shown in Fig. 8a.

The RSSI is simulated using the LD model \((P_e = -63dB, \gamma = 2.0)\) with added Gaussian noise (SD of 5\(dB\)) and horizontal antenna lobes, unless otherwise stated. The lobes were modeled using a third order Fourier series with unitary weights, see Fig. 8b. The other measurements were altered with the same standard deviations as in the preliminary localization tests of Sect. 3.5. Furthermore: \(v_{nominal} = 0.5m/s\), \(d_{safe} = 0.25m\), and \(\Psi = 0rad\) for all MAVs. The MAVs begin at different corners of the arena. The EKF is initialized such that the initial position guess is towards their initial flight direction (i.e. the center of the arena).

We investigated twelve combinations of arena size and MAV diameter for teams of two MAVs and three MAVs. The combinations will be referred to by the encircled numbers in Fig. 9. Each configuration was simulated 100 times. Each simulations was automatically interrupted if a collision occurred, or after 500s of collision-free flight.

6.2 Results

Mean time-of-flight for each configuration is shown in Fig. 10. Flights with three MAVs consistently show a lower performance than with two MAVs. The performance drop is a result of the team dynamics at play, namely: 1) increased airspace density; 2) decreased freedom of movement due to superposition of collision cones. These two factors are analyzed in the remainder of this section.
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Fig. 8 Figures relating to the development of the simulation environment

Fig. 9 The twelve configurations tested in simulation with configuration numbers shown in the white circles

Fig. 10 Mean flight-time to collision for all simulated configurations. Average results without collision avoidance, not shown in this figure, range between 3.9s and 14.3s.

When the arena side-length remains constant and the MAV diameter increases, a decrease in mean flight-time is observed. This is seen by comparing within the configuration triads 4-7-11, 3-6-10, and 2-5-9, and the pair 8-12. The result is analogous when MAVs of the same diameter are used in arenas of different sizes, see the configuration quartets 1-2-3-4, 5-6-7-8, and 9-10-11-12. This implies that a lower density improves the probability of success, but this is found to not strictly be the case. Fig. 11a shows the flight time to collision as a function of the airspace density. A portion of configurations show low results in spite of the low airspace density, and are outliers in the negative linear trend. These correspond to configurations 1, 2, 5, and 9, which feature smaller arena sizes. The conclusion is that room size affects performance even when airspace density remains constant. This is a remaining limitation of the current status of the system when operating in smaller room sizes. Its causes are discussed in Sect. 10.2.

Fig. 11b shows the impact of airspace density on area coverage for all flights with two MAVs and three MAVs. Area coverage was measured as follows. The total area is divided in sections of 0.20m × 0.20m. A section is marked “covered” when one of the MAVs crosses it during a trial. Area coverage is the percentage of covered sections. With this, two patterns arise.

1. A higher airspace density leads to a lower overall coverage. This is due to: a) lower flight times, providing less overall time to complete the mission, and b) decreased freedom of movement due to larger portions of the arena being covered by collision cones.

2. Three MAVs systematically achieve lower area coverage than only two MAVs in the same configuration. This is explained by analyzing the flight trajectories in more detail, from which an emergent circular behavior is discerned. See, for instance, Fig. 12, which shows two exemplary runs from a simulation with two (Fig. 12a) and three (Fig. 12b) MAVs from configuration 10. When more than one MAV to avoid is present, the superposition of multiple collision cones significantly discourages the pursuit of the desired trajectory. The result is clock-wise
motion along the sides of the arena for all MAVs. Oscillations along the border are observed as conditions M1 and M2 alternate.

6.3 Impact of RSSI Noise on Performance

In simulation, two further case-studies were explored. In the first case, the simulated RSSI noise is reduced from 5\text{dB} to 3\text{dB}, but lobes are still simulated. In the second case, RSSI noise is kept at 5\text{dB} but sensor lobes are removed. All other parameters remain the same as in the primary simulations. The configurations tested are those with the lowest performance: 1, 2, 5, 6, 9, 10. The results are shown in Fig. 13, and show that removing the antenna lobes provides the largest improvement in performance. A lower noise also improves results, yet the impact is generally lower than antenna lobes. The lower error in relative position estimates translates to a more successful collision avoidance system. This implies that performance could be improved further if operating in cleaner environments, if using better antennas, or with a better filtering of noises.

7 Experiments featuring External Own-State Measurements

These experiments use Optitrack to accurately inform MAVs of their velocity, orientation, and altitude. This isolates the impact of using real RSSI measurements and Bluetooth communication on the relative localization system during flight. It also provides system performance data in the case of high-quality on-board estimates.
On-board Communication-based Relative Localization for Collision Avoidance in Micro Air Vehicle teams

7.2 Results

Four flights were performed with two AR.Drones for a cumulative time of 25.3 min. Only one collision took place, which occurred in the second flight after 5.6 min. The other flights lasted 6.1 min, 7.6 min, and 6.0 min without collisions; they were ended manually due to low battery.

Six controlled flights were performed with three AR.Drones for a cumulative time of 15.3 min. Five flights ended in collisions. The flights ending with collisions reached a mean flight time of 160 s (2.7 min). The shortest flight was 33 s, the longest was 5.2 min. The other flights lasted 1.9 min, 2.6 min, and 3.0 min. The flight without a collision was manually ended after 2.0 min due to low battery. Overall, this set-up with three MAVs can expect a collision once every 184 s (≈ 3 min).

All relative localization range errors shown in Fig. 15a and Fig. 15b, and the bearing errors are shown Fig. 15c and Fig. 15d. The Root Mean Squared Error (RMSE) for flights with two MAVs is 0.57 rad for bearing, and 0.86 m for range. With three MAVs, the RMSE rises to 0.70 rad and 1.14 m, respectively. On occasion, we observe that the bearing error temporarily diverges towards ±π. This error does not necessarily lead to collisions due to the non-reciprocal nature of the avoidance behavior. Nevertheless, it introduces a temporary uncertainty in the system. The error is more frequent with three AR.Drones. We also observe that the convergence rate for bearing estimates over flights with three AR.Drones is worse than with two AR.Drones. This may be appreciated in Fig. 16, zooming into the first 30 s of Fig. 15c and Fig. 15d in more detail. Convergence times for flights with three MAVs reach up to 30 s prior to settling (Fig. 16b). By comparison, the convergence in flights with two AR.Drones only (Fig. 16a) is found to be at most within 5 – 10 s.

8 Experiments featuring On-board Own-State Measurements

The experiments from the controlled flights were repeated but with on-board state estimation by the MAVs. Therefore, on-board MAV sensors measured and controlled velocity, orientation, and altitude. This shows real-world relative localization performance for collision avoidance.
8.1 Experimental Set-up

Velocity was estimated using the bottom facing camera and the EdgeFlow (McGuire et al, 2016). Orientation was measured using gyroscope integration (given an initial orientation towards North). Height from the ground was measured using sonar. Optitrack was only used to enforce condition M1 (wall detection), which featured $d_{safe} = 0.5$ This is because wall detection is outside of the purpose of this research. To further stress-test the system, a further change was that the EKFs initial relative position assumption was $x_{ji} = y_{ji} = 1m$ for any MAV $\mathcal{R}_i$ with respect to any other $\mathcal{R}_j$, as opposed to the center of the arena. The AR.Drones communicated with a ground-station using a Wi-Fi link for logging and take-off/land control.

8.2 Results

Four flights were performed with two AR.Drones for a cumulative flight time of 17.3 min. The flights lasted 3.9 min, 4.4 min, 8.0 min, and 1.0 min. Only the first and the last ended due to collisions. The second and third were ended due to low batteries. The third flight suffered from a near-collision in the early stages, but afterwards successfully continued until 8.0 min without collisions. Another four flights were conducted with three AR.Drones, which lasted 8.3 min cumulatively. The flights lasted 1.2 min, 3.2 min, 2.3 min, 1.6 min. The second flight was ended due to low batteries on one MAV. The other flights ended due to collisions between two of the three drones.

The bearing estimation error is shown in Fig. 17. The error has increased with comparison to the previous results. With two AR.Drones, the mean RMSE over the first three flights is 0.85 rad. This is sufficient for a long collision-free flight time. In the last flight, however, the RMSE was 1.3 rad, possibly due to large disturbances in RSSI. This is eventually lead to a relatively early collision after 1.0 min. With three drones, the bearing RMSE over all flights is 1.0 rad. Furthermore, observing Fig. 17 we can note an accumulating error bias in bearing over time due to the accumulating gyroscope bias. This should be corrected for future implementations by using the magnetometer to limit the accumulating bias.

9 Porting the technology to Miniature Drones

To show that the proposed solution scales to smaller MAVs, we ported the technology to Ladybird MAV. One test-ready MAV and its components are shown in Fig. 18. As for the AR.Drones, the Wi-Fi link was used for logging and take-off/land control.

9.1 Experimental Set-Up

A bottom facing camera and a gyroscope measured velocity and orientation, respectively. In the LD model, following a short hand-made calibration $P_n = -55 dB$. Given the smaller size of the drones, the enforced flight arena was reduced to $2m \times 2m$ with $d_{safe} = 0.5m$. This scenario is similar to configuration 2 from Fig. 9. For simplicity, given the lack of a tested height sensor, height was controlled using Optitrack. The drones flew at slightly different heights to limit dam-
ages in case of failure by the collision avoidance system. All other test parameters stayed as for Sect. 8.

9.2 Results

Three flights were performed with this set up, lasting 2.8min, 3.7min, and 3.1min. The first flight saw no collision cases. The second flight saw near collisions at 1.35min and at 3.7min. The latter came in light of low-batteries by one of the drones. As it lowered its height, the two MAVs also collided. The third flight saw a near collisions after ≈ 60s and ≈ 90. Both took place in the corner when condition M1 takes over the drones, and are thus are regarded more as a failure of the behavior than the relative localization. This shows the importance of implementing a method that keeps taking into account other drones while also avoiding the walls, which was not implemented in our controller.

It is noted that a slightly lower performance than previous experiments was expected due to the smaller arena size, an effect which was also observed in simulation and is discussed further in Sect. 10.2. Nevertheless, we also note a decrease in accuracy for relative localization as RMSE per flight ranges from 0.8rad to 1.37rad. Inspecting the data in more detail shows that this is the result of larger errors in both RSSI noise as well as lower quality on-board velocity estimates. The former is explained by the fact that the Bluetooth module was placed right next to the Wi-Fi module, creating disturbances.

10 Discussion

10.1 Performance of Relative Localization

In all AR.Drone tests, a noticeable loss in relative localization performance was measured when introducing a 3rd MAV. The effects were longer convergence times as well as higher relative bearing/range errors. A decrease in performance was also observed when using on-board velocity estimates. This was due to a combination of over-under estimation of velocity or occasional spikes in the measurements.

The relative localization scheme was implemented with an EKF. This may be criticized for its reliance on a Gaussian noise model. Robust (Kallapur et al, 2009) or adaptive (Sasiadek and Wang, 1999) variants of Kalman filters, or a Particle Filters (PFs) (Svečko et al, 2015), might be better suited to this end. However, a mere change in filter could increase computational costs without bringing a higher quality estimate. This is because there are a number of other limitations.

- The logarithmic decrease in RSSI makes it intrinsically insufficient to measure changes in range at larger distances. Without measurable changes in RSSI, bearing is no longer observable.
- RSSI disturbances in the environment cannot be fully modeled unless the environment is known a-priori.
- The proposed process update equation makes the null assumption that all velocities remain constant between time-steps. Improvements may come from including more complex dynamic properties in the process equation, e.g. acceleration and/or jerk.
- As seen throughout our tests, major improvements can come by improving the quality of on-board state estimates.

Further investigations are encouraged to define a filter that lowers the expected worst-case error.

Further improvements could also come from a change in communication hardware. In this work, we have achieved promising results using Bluetooth, which was selected due to its prompt availability on several drones. The noise and disturbances with Bluetooth, however, are large. Other hardware, such as UWB, would offer a significant reduction in noise, leading to better overall relative localization results. Based on our simulations from Sect. 6.3, this should automatically result in an improved overall system performance.

10.2 Performance of Collision Avoidance

In simulation, all twelve configurations have also been tested without active collision avoidance. The obtained mean flight times ranged between 3.9s and 14.3s. A t-test with 95% confidence level (Dekking, 2005) shows a statistically significant improvement in flight time for all configurations when using our method.

Fig. 11a showed that smaller rooms lead to poorer performance than larger rooms despite similar airspace density. The parameter ε_z, as explained in Sect. 4.3, implements room scaling within the collision cones. Reasons for this are:

- The ratio of arena size to \( v_{nominal} \) decreases in smaller rooms.
- The communication rate is constant, which limits the decision rate of the collision avoidance controller.
- In smaller rooms, M1 is called more frequently, in which case collision cones are ignored according to the task in this article.
It was observed, and confirmed in simulation, that collisions for flights with three MAVs likely occur along the edges of the area. In the simulations of configuration 11, which is the one tested with the AR.Drones, 81% of the collided simulated flights with three MAVs ended within 0.5 m of the arena borders. By comparison, only 35% of collisions with two MAVs occurred within this space. An example extracted from an AR.Drone flight recounted by the three events below (shown in Fig. 19).

1. One MAV is at the corner and reluctant to make movements towards the center. At time $t = 180$ s (Fig. 19a), we see this for the bottom right AR.Drone (blue). Its slow speed causes the red MAV to mistake its estimate of the blue drone. In normal conditions, collision avoidance could still be achieved by the blue MAV, but it cannot react as it is trapped in the corner.

2. Another MAV turns towards the same side. In time $t = 182$ s (Fig. 19b), the central AR.Drone (red) avoids the black AR.Drone (on left) but in doing so goes to the right.

3. The second MAV also ends along the border and reluctant to make movements. At time $t = 188$ s (Fig. 19c), the two oscillate along the border until a collision occurs.

This scenario is less likely with two MAVs due to the larger freedom of movement and the higher relative localization accuracy. One method to limit this would be to reduce the angle of the collision cones for further-away MAVs, which increases mobility. Furthermore, it is also necessary to create an avoidance scheme that takes into account the wall and the drones together. This shall be tackled in future work.

11 Conclusion and Future Work

We have shown that it is possible to use wireless communication as a relative localization sensor that can be used on-board of MAVs operating in a team. This leads to a large reduction in collisions without the need of a dedicated sensors. With the solution proposed in this paper, a team of AR.Drones in a $4 \times 4$ m area could fly for several minutes without collisions. The technology was also used with miniature drones, showing its portability. With respect to the scenario in mind (i.e. the exploration of indoor spaces by MAV teams), this is an efficient method to limit collision risks in the event that MAVs end up flying in the same room.

The combined relative localization/collision avoidance system as presented and tested in this paper will be further improved in future work. Importantly, we will investigate UWB modules instead of a Bluetooth module. Bluetooth suffers from high disturbances and noise that is detrimental to the performance, especially as more MAVs are introduced. Using UWB instead is expected to considerably improve the distance measurements used by the filter. Furthermore, the introduction of an avoidance strategy that makes a more informed decision near walls or when multiple MAVs are present is needed. This could resolve the more complex collision scenarios, especially in smaller rooms.

Videos

Videos of experiments are available at: https://www.youtube.com/playlist?list=PL_K8X9G0z2Pf9t0yWNBMj7spe1HARSpc.
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