Real-time localization of transmission sources using a formation of micro aerial vehicles

Matouš Vrba*, Jakub Pogran*, Václav Pritzl*, Vojtěch Spurný* and Martin Saska*

Abstract—Techniques designed for using teams of small and therefore safe Micro Aerial Vehicles (MAVs) for realization of antenna-like sensing devices with flexible shape, which may be adaptively changed based on the currently sensed properties of the scanned medium, are presented in this paper. This approach enables using simple and cheap sensors carried onboard of MAVs and cooperatively deploying them in the environment to optimize overall sensitivity of the compound sensory array. Two case studies of a deployment of MAV teams in the application of real-time radio transmitters localization are discussed as an example. The first method relies on Kalman Filter-based fusion of distributed RSSI measurements used to estimate distances between the transmitter and multiple receivers, which results in precise, robust and fast transmitters location in the environment. The second method utilizes onboard rotating directional antennas to estimate angles between transmitters and receivers at different positions and a Weighted Robust Least Squares method to determine transmitters locations. Both algorithms were verified in a realistic simulation system under gazebo simulator in ROS and in real experiments with a fleet of MAVs, with a focus on aspects of real-time information fusion and coordination of MAVs sharing the same workspace with small mutual distances.

I. INTRODUCTION

Micro Aerial Vehicles (MAVs) provide high flexibility of motion in a 3D space and therefore enable the optimization of their states (positions and orientations) based on the sensed properties of the environment. In addition, their small size and possibility to be precisely stabilized in desired positions facilitate deployment of possibly large MAV teams of a compact shape. This can be beneficial in numerous information gathering scenarios, where the measured phenomena is time variant and where measurements provided simultaneously in different locations can increase the overall performance of such a distributed sensor. In fact, the multi-MAV approach is suitable in most of the applications where the gain of the measurement can be increased by enlarging the surface of the sensor/antenna. Using an MAV group flying in small mutual distances, the total mass of the detector can be significantly reduced and comparable results can be achieved by low-size, light-weight and low-cost sensors carried onboard of flying robots due to their high maneuverability as we have shown in [1].

In this paper, we focus on an interesting example of such distributed sensor arrays, used for real-time electromagnetic field (EMF) measurement and localization of EMF transmitters. The ability to change flight altitude using MAVs (in comparison with ground solutions) is crucial in the transmitter localization case, as it enables avoiding occlusions and reflections of the EMF by obstacles. MAVs with available light-weight sensors enable solving the mentioned tasks easily (position and shape of the distributed “antenna” can be altered during the mission as visualized in video[1]). From the multi-MAV research perspective, this is a challenging example of using large groups of self-stabilized MAVs, whose shape is directly determined by the measured properties of the surrounding environment.

The radio transmitters (beacons) localization task itself is a broad problem with many possible applications and can be used as a meaningful example to show possibilities of the distributed deployment of a closely flying MAV team. The transmitter localization applications can be of a civilian character, such as finding working tools, machinery on a construction site, cattle on large grasslands, stocktaking in warehouses, and localization of victims of natural disasters denoted by first-aid doctors, as well as military character, such as locating wounded soldiers or substituting a positioning system in a GPS-denied area [2], [3], [4]. Most of these applications cannot rely on a pre-installed localization infrastructure and need to be solved adaptively following end-user requirements. MAVs can be deployed on-demand, offer high mobility and can process the data on-line, which enables reacting in real-time and potentially increases the localization performance.

Two different approaches of localization of wireless transmitters with a group of relatively stabilized MAVs are discussed in this paper, both relying on received signal strength indication (RSSI) of the underlying wireless platform. The first approach utilizes a model of signal propagation in free space to estimate the distance between the transmitter and receiver from signal strength. The second approach uses a rotating directional antenna to find an
A. Related work and contributions

Many different data collection applications using MAVs are frequently being studied. In this paper, we are focused on measurement of the electromagnetic field and using this information for localization purposes using the RFID (radio frequency identification) technology. A comprehensive comparison of different RFID localization algorithms using RSSI is in [5], where the authors even provide an experimental evaluation of several of the studied algorithms. In [2], the authors used a winged MAV and an algorithm based on Bayesian Optimization to localize a WiFi device in an area of 1000 × 1000 m² with 20 m precision. An alternative approach to localization using a directional antenna is presented in [6], where a particle filter is used for the transmitter location estimation. The authors test the system in a small-scale indoor experiment with an MAV. In [7] and [8], a combination of using RSSI and AoA is suggested to achieve better localization performance, based on simulations. In [9], optimal planning for localization of radio devices was tackled using a gradient descent algorithm with three different criteria, based on the covariance matrix of the current EKF estimate of the radio device location. In [10], the authors also studied the planning problem, but used the Cramér-Rao lower bound as the optimization criterion.

In contrast to most of the related studies, we are focused on an approach using several cooperating MAVs, flying in a close formation, to solve the localization problem in real-time. We also suggest a trajectory planning method, which is less reliant on a correct model of the signal noise, caused by shadowing and multi-path propagation of the radio signal. This noise is usually modeled as a gaussian random variable (see above mentioned related works), but our real-world experiments indicated, that this assumption is too optimistic in some environments. Our proposed trajectory planning algorithm is designed so that it is robust and less sensitive to wrong noise assumptions as it does not rely on the EKF covariance matrix or Cramér-Rao lower bound to plan the MAV trajectory. We rely on real-world experiments to compare viability of our proposed localization methods and to use meaningful data for design of the algorithms and for estimation of parameters of the proposed models, which is in contrast with the cited literature.

Different radio localization methods may use Time Difference of Arrival (TDoA) or Ultra-High Frequency (UHF) radio to estimate distance. TDoA is used for localization with MAVs in [3], where the authors propose using it to substitute GNSS (Global Navigation Satellite System) in battlefield areas. UHF is more suitable for radio localization in small-scale indoor environments, which is studied in [11]. UHF technology can result in extreme accuracy over a small area -- authors of [11] claim a localization error < 3.2 cm over an area of 3.5 × 2.5 m². Fingerprinting is another localization method, which may offer a more precise and robust localization, but depends on extensive preinstalled infrastructure and careful prior measurements in the whole area of localization [12], [13].

To sum up this survey, the proposed approach is unique in sense of applying a team of cooperating MAVs in real world scenarios of localization of static as well RFID transmitters using a low-cost radio technology. The proposed approach allows integration of a feedback from the measurements simultaneously obtained in different locations into formation control to increase the overall gain of the composed sensor in the next step of the measurements.

B. Problem description

We assume a known number of static radio transmitters with unknown positions, but known IDs, in a given area. The area is free from obstacles in the altitude in which the MAVs are supposed to operate. We assume a team of M MAVs, each equipped with an onboard receiver capable of measuring RSSI of each transmitter that has to be localized. A broadcast communication ability is assumed within the group to be able to fuse measurements from multiple sensors in different locations, taken at the same time, and use this information for adaptive formation control. All MAVs are equipped with a system enabling relative localization of neighboring MAVs (such as the one described in [14], [15]), which provides a knowledge of complete state of the group (mutual distances and headings). In addition, inaccurate GNSS information, possibly obtained from multiple MAVs simultaneously, is fused together with the result of mutual localization to get a rough estimate of a global position of the group in the environment (details on the MAV state estimation from multiple sensors and a precise position controller can be found in [16], [17]).

C. Preliminaries

1) Log-Normal model of signal power loss: A generalized form of the Friis transmission equation, called Log-Normal signal transmission model, is used to model the RSSI dependence on the distance d between the transmitter and receiver. In ideal conditions, the received power P_r can be estimated as

\[ P_r = P_0 - 10n\log_{10}(d) + \chi, \]

where \( P_0 \) and \( n \) are model parameters, and \( \chi \) is a random variable representing noise with a presumed normal distribution with zero mean and standard deviation \( \sigma_\chi \). The parameters \( P_0, n \) and \( \sigma_\chi \) are usually determined empirically by analyzing a set of initial measurements.

An example of a measured RSSI over distance characteristic of a wireless transceiver, together with the theoretical curve of the Log-Normal model, is shown in Figure 2. The characteristic was measured using two XBee S2C transceivers, one positioned on the ground in a known location and the second one was mounted on an MAV with precise RTK GNSS positioning (a video record of the experiment is available\(^1\)). Parameter \( P_0 \) for the model was calculated from the measured data and parameter \( n \) was chosen as \( n = 2 \), which corresponds to a free space environment. The anomaly in the measurements under approximately 5 m distance is caused by saturation of the receiver.

The Log-Normal model can be used to estimate distance directly from measured RSSI values as

\[ d = 10^{\frac{P_r - P_0}{10n}}. \]

Direct estimation of the distance is used to initialize the Kalman filter (as described in section II-A).

2) Weighted Robust Least Squares formulation: WRLSQ serves to estimate a parameter vector x of a function \( \varphi(t,x) \) based on a set of samples \( (t_i, y_i) \), which were generated by

\[ y_i = \varphi(t_i, x) + \epsilon_i, \]

\(^1\)https://youtu.be/kDCEO6pXjyk
where $\epsilon_i$ is a measurement error.

As opposed to a regular least squares method, the squared errors $(\phi(t_i, x) - y_i)^2$ are weighted by a weighting function $w(t, y)$ (in order to emphasize more important samples), which depends on the application. Our weighting function is described in section II-B.

To increase precision, the method uses a sublinear loss function $\rho(z)$ to discriminate outliers and prevent overfitting. In this work, the Cauchy loss function has been applied,

$$
\rho(z) = C^2 \log \left( 1 + \frac{z}{C^2} \right),
$$

where $C \in \mathbb{R}_{>0}$ is the scaling parameter, and $z$ is the (weighted) squared error.

The resulting estimate of $x$ is such $\hat{x}$, for which the cost function

$$
\tau(t, y, \hat{x}) = \frac{1}{2} \sum_{i=1}^{n} \rho \left( w(t_i, y_i) (\phi(t_i, \hat{x}) - y_i)^2 \right)
$$

is minimal. This minimization problem can be solved by any solver with boundary restrictions of the variables. We used the Trust Region Reflective algorithm [18] to achieve the presented results.

II. PROPOSED METHODS

A. Localization using an Extended Kalman filter

The first approach to the localization problem relies on a non-linear state-space model of the system and an Extended Kalman filter (EKF) to estimate the location of a transmitter. The MAVs follow given trajectories in the designated area and continuously sample the measured RSSI. One sample is a $2M$-tuple $(p_1[k], ..., p_M[k], s_1[k], ..., s_M[k])$, where $s_i[k]$ is RSSI value measured by the $i$-th receiver (MAV) at time step $k$ and $p_i[k]$ is its position in the common coordinate frame, obtained by fused data from the relative localization and inaccurate GNSS, if a precise external localization is not available.

The Extended Kalman filter requires a model of the system and an initial state estimate in order to estimate the system states. The system model is described in section II-A.1. Initial estimate of the state for EKF is obtained by simple trilateration using the transmitter-receiver distance estimated from the filtered RSSI signal using equation [2].

Note that the description of this localization method considers only one transmitter for simplification, but in case of multiple transmitters (with unique IDs) a separate filter can be easily instantiated for each of them.

1) System model: The system is modeled as a non-linear discrete state-space system in the following form:

$$
x[k + 1] = Ax[k] + Bu[k] + v[k],
$$

$$
z[k] = h(x[k]) + w[k].
$$

The states, measured values, inputs and random noises of the system are defined as

$$
x[k] = \begin{bmatrix} \hat{p}_1[k]^T, \ldots, \hat{p}_M[k]^T, \hat{s}_1[k]^T, \ldots, \hat{s}_M[k]^T \end{bmatrix}^T,
$$

$$
z[k] = \begin{bmatrix} p_1[k]^T, \ldots, p_M[k]^T, s_1[k], \ldots, s_M[k] \end{bmatrix}^T,
$$

$$
u[k] = \begin{bmatrix} \Delta p_1[k]^2, \ldots, \Delta p_M[k]^2 \end{bmatrix}^T,
$$

$$
v[k] \sim \mathcal{N}(0, Q), w[k] \sim \mathcal{N}(0, R),
$$

where $\hat{p}_i[k]$ is EKF estimate of the $i$-th MAV position, $p_i[k]$ is EKF estimate of the beacon position, $\Delta p_i[k]$ is difference between the last and current position of the $i$-th MAV, $Q$ is process noise covariance matrix, and $R$ is measurement noise covariance matrix. The matrices $A$ and $B$ are defined as

$$
A = I_{3(M+1) \times 3(M+1)}, \quad B = \begin{bmatrix} I_{M \times 3M} \\ 0_{3 \times 3M} \end{bmatrix}.
$$

The measurement function $h(x[k])$ is defined as

$$
h(x[k]) = \begin{bmatrix} \hat{p}_1[k] \\ \vdots \\ \hat{p}_M[k] \\ P_{0,1} - 10n_1 \log_{10} \left( d_1 \right) \\ \vdots \\ P_{0,M} - 10n_M \log_{10} \left( d_M \right) \end{bmatrix}.
$$

The last $M$ elements in $[13]$ are estimations of the signal strength from distance $d_i$ between the current MAV positions and the estimated transmitter position, based on the Log-Normal model (as described in section [C-1]). $P_{0,i}$ and $n_i$ are used to indicate parameters of the model, belonging to the $i$-th receiver.

2) Adaptive formation control: Based on observations from numerous simulations we have designed the following strategy of adaptive formation control using onboard processed measurements taken in multiple locations at the same time. The localization precision is maximal when the beacon is inside the formation and scale of the formation is the smallest. If the beacon is outside the formation, the precision is improved when scale of the formation is the smallest. If the beacon is outside the formation, the precision is improved when scale of the formation is the smallest. If the beacon is outside the formation, the precision is improved when scale of the formation is the smallest. If the beacon is outside the formation, the precision is improved when scale of the formation is the smallest. If the beacon is outside the formation, the precision is improved when scale of the formation is the smallest. If the beacon is outside the formation, the precision is improved when scale of the formation is the smallest. If the beacon is outside the formation, the precision is improved when scale of the formation is the smallest. If the beacon is outside the formation, the precision is improved when scale of the formation is the smallest.

The formation center is in the rest of the localization steps. Estimation of transmitter positions in each step is done using the EKF method. The adaptive formation control strategy is described in Algorithm [4].

B. Localization using a directional antenna

The second approach to the localization problem uses a rotating directional antenna to estimate an angle between the transmitter and receiver (MAV) at a certain location. Information from multiple measurements in different locations is combined to calculate the transmitter position. The measurements can be made by one MAV flying through the measurement locations or by multiple MAVs simultaneously, which has the advantage that the localization process is faster and more importantly enables localization of moving targets in real-time, which is almost impossible using state-of-the-art solutions. The antenna directionality is utilized to estimate the
Algorithm 1 The adaptive formation control algorithm

1: Input:
2: c       // starting center of the MAV formation
3: β       // starting scale of the MAV formation
4: ℓt      // estimation difference threshold
5: Δβ      // formation scale change
6: Output:
7: pα      // estimation of beacon position
8: done ← False
9: first_run ← True
10: p0 ← c
11: p0,prev ← c
12: while not done do
13: if ||p0,prev − pi|| > ℓt or first_run then
14:     // the ”rough localization” stage
15:     p0,prev ← p0
16:     p0 ← estimate_transmitter_position()
17:     c ← p0
18:     β ← β − Δβ
19:     // move the formation center to c
20:     move_formation(c)
21:     // change the formation so that the scale is β
22:     change_formation_scale(β)
23:     first_run ← False
24: else
25:     // the ”finalization” stage
26:     p0 ← estimate_while_moving()
27:     done ← True
28: end if
29: end while

angle as the antenna has the strongest gain from one direction. Dependency of gain on the angle of the directional antenna was measured in preliminary experiments. Examples of the measured characteristics are in Figure 4 and a video from these experiments is available [4].

During the localization, RSSI samples are measured at L locations. At each location, the antenna is turned one full rotation in N-steps. This results in a total of LN samples. The i-th sample is represented by a triplet (si, αi, pi), where si is the measured RSSI, αi is the antenna rotation angle, and pi is the location at which the sample was taken.

A simple two-dimensional geometrical model is used in this method to calculate the transmitter location from the measured samples. The i-th sample, taken at location pi, with the antenna rotated by an angle of αi radians from the x-axis, corresponds to an equation in the form

\[ p_i + l_i \cdot 1(\alpha_i) = p_0, \]  

where p0 is the unknown location of the transmitter, 1(αi) is a unit vector, rotated by αi, and li is an unknown variable, representing length of the vector from pi = [xi, yi] to p0 = [xb, yb].

The equation (14) can be rewritten for each coordinate as

\[ x_b - \cos(\alpha_i)l_i = x_i, \]  

\[ y_b - \sin(\alpha_i)l_i = y_i. \]  

By repeating these equations for each measurement from all positions, 2NL equations are obtained, which form an overdetermined set of equations for NL + 2 unknown variables. Only two of the variables are important to solve the given task – the transmitter location coordinates xb and yb.

These equations are weighted based on the measured RSSI. The RSSI values are first normalized so that each value is relative to the maximal RSSI measured from the same location. The weight of each sample is then calculated using the weight function

\[ w(s_i) = \begin{cases} \frac{1}{a}b^{-s_i}, & \text{if } \frac{1}{a}b^{-s_i} \geq w_{\min}, \\ w_{\min}, & \text{otherwise}, \end{cases} \]  

where a ∈ R > 0, b ∈ R and wmin ∈ R > 0 are parameters, obtained empirically from simulations, and ̂si is the relative RSSI value of the sample.

The weighted equations are evaluated using the Weighted Robust Least Squares method (as described in section 3.2) using the Cauchy loss function and with respect to the bounding conditions of variables li ≥ 0.

III. EXPERIMENTS

The localization methods have been implemented using two wireless technologies – Bluetooth 4.0 Low Energy (BLE) and XBee – and were experimentally verified. An MAV platform, developed by the Multi-robot systems group from the Faculty of Technical Engineering at the Czech Technical University, was used in all the experiments with MAVs (for details on the system see [17, 19]).

A. Experiment using the EKF method in an outdoor environment.

Three MAVs were cooperatively localizing two static BLE beacons on a field with an area of 80 × 60 m². The MAVs were moving through a predefined trajectory, while keeping a formation using precise RTK-GNSS localization, and logging measurement data (see movie 8).

Only samples above a threshold, corresponding to an 8m distance between the transmitter and receiver, were used for the EKF to reduce the number of samples with a low SNR. This distance was chosen empirically, based on the measured RSSI over distance.

https://youtu.be/lpT_dYN07Gg

https://youtu.be/P20vZmcoLm8
Fig. 4: Characteristics of the directional antenna (model CW8DPA) used in experiments in different heights \( z \) and different distances to the transmitter.

Fig. 5: Images related to the outdoor experiment using EKF. Photos of the MA V formation (MA Vs are circled in red) during the experiment at times 20 s and 50 s are in the 1. and 2. pictures. MAV trajectories and ground truth positions of transmitters are in the 3. picture. Graph of the localization error (euclidean distance between the ground truth and localized positions of the beacon) over time is in the 4. picture.

Fig. 6: Localization error over time during the experiment with adaptive formation control. Subfigure 6a corresponds to the rough localization and 6b to the finalization stage. Overhead photos from the experiment are shown for different times of the experiment (MAVs are marked as red circles, the beacon as blue circle).

B. Evaluation of the adaptive formation control algorithm performance

The localization planning algorithm was tested in simulations in the Gazebo simulator. A formation of three MAVs was localizing a single transmitter on a field of \( 80 \times 60 \text{ m}^2 \). The localization RMS error was under half meter after 75 s of the simulation, which is significantly less than if using a static formation. Graphs from the experiment and positions and shapes of the MAV formation at different times are shown in Figure 6. A video of the experiment is available.

C. Experiment using the directional antenna method

In this experiment, one MAV was localizing one static beacon on a field with an area of \( 80 \times 60 \text{ m}^2 \). It was taking measurements in designated locations, while carrying a device to rotate the directional antenna, which was designed specifically for this experiment (see Figure 4). Photos from the experiment and the measurement locations together with the true and estimated beacon positions are in Figure 7. A video is available on youtube.
error in the experiment was evaluated using the method, described in section II-B. Localization were taken and averaged into one sample. The measured data were revolution in 64 increments. At each increment, 16 measurements in blue. Measurement positions of the MA V and true and localized positions of the beacon are in the last frame.

At each of the locations, the directional antenna rotated a full revolution in 64 increments. At each increment, 16 measurements were taken and averaged into one sample. The measured data were evaluated using the method, described in section II-B. Localization error in the experiment was 2.14 m.

Reliability of the method was also statistically tested in 100 runs of simulations of the measurement process using the measured antenna characteristics (see Figure 3) and RSSI and angle noise values based on data from real experiments. The 95% accuracy percentile was 3.96 m.

D. Experiments summary

When comparing the experimental results using the two methods, it may be concluded that the approach using the directional antenna offers better precision. However, a major difference between the two approaches aside from the precision is the time needed to execute the localization task. For the EKF-based method the time is dependent on the size of the searched area and the chosen search trajectory, whereas for the directional antenna method the localization time is dependent mostly on the parameters L and N (number of measurement positions and number of rotation steps per position). It may be desirable to increase these parameters in order to improve localization precision, but this increase must respect the maximal flight time of the specific MA V platform used, which can be limited. On the other hand, using an adaptive planning algorithm, such as the one presented in this paper, can significantly reduce localization time and improve precision of the EKF-based localization method, as was demonstrated in the simulations.

IV. Conclusion

In this paper, two methods designed for localization of RFID transmitters by micro aerial vehicles and teams of MAVs have been described and experimentally verified. The proposed approaches take advantage of flexible motion of multi-rotor MAVs and possibility of their stabilization in formations of compact shapes. Thus, even a low-cost radio technology can be used for reliable RFID transmitter localization as the receivers onboard of MAVs can be adaptively relocated towards the currently estimated position of the transmitter aimed at increasing the overall gain of the distributed sensor in consequent measurements. The approach using a directional antenna proved to be more robust and accurate than the EKF-based method using an omnidirectional antenna since the bearing estimate provides additional information for the localization process. On the other hand, using the directional antenna requires a more complicated setup of the MAV platforms and more importantly, this method is significantly affected by a limited flight time of the employed MAVs. Therefore, a combination of both approaches would be beneficial mainly for large groups of heterogeneous MAVs searching in a broad workspace, which is our main interest in future research.

REFERENCES


Fig. 7: Experiment with the directional antenna. The first three frames are photos of the MA V in the three measurement positions. The MA V is circled in red and the beacon being localized is circled in blue. Measurement positions of the MA V and true and localized positions of the beacon are in the last frame.