

TrackerBots: Software in the Loop Study of Quad-Copter Robots for Locating Radio-tags in a 3D Space

Hoa Van Nguyen¹, S. Hamid Rezatofighi¹, David Taggart²,
Bertram Ostendorf² and Damith C. Ranasinghe¹

¹School of Computer Science, The University of Adelaide, SA 5005, Australia

²School of Ecology and Environmental Science, The University of Adelaide, SA 5005, Australia
{hoavan.nguyen;hamid.rezatofighi;david.taggart;bertram.ostendorf;damith.ranasinghe}@adelaide.edu.au

Abstract

We investigate the problem of tracking and planning for a UAV in a task to locate multiple radio-tagged wildlife in a three-dimensional (3D) setting in the context of our **TrackerBots** research project. In particular, we investigate the implementation of a 3D tracking and planning problem formulation with a focus on wildlife habitats in hilly terrains. We use the simplicity of Received Signal Strength Indicator (RSSI) measurements of VHF (Very High Frequency) radio tags, commonly used to tag and track animals for both wildlife conservation and management in our approach. We demonstrate and evaluate our planning for tracking multiple mobile radio tags under real-world digital terrain models and radio signal measurement models in a simulated software-in-the-loop environment of a Quad-Copter.

1 Introduction

Civilian Aerial Robots or so-called Unmanned Aerial Vehicles (UAVs) have rapidly evolved to enable Autonomous systems on UAVs are expected to make them more flexible and scalable [Chung *et al.*, 2018]. Achieving autonomy in the wild and in a 3D space is challenging [Robin and Lacroix, 2016].

In this paper, we focus on investigating tracking Very High Frequency (VHF) radio-tagged targets in unknown terrain environments using an autonomous UAV. Radio-tagged tracking is an established field over 50 years [Cochran and Lord Jr, 1963; Kenward, 2000]. According to [Kays *et al.*, 2011; Tremblay *et al.*, 2017; Webber *et al.*, 2017], radio-tagged tracking methods are still the most important and low-cost technique to study individual wildlife species or different size over long periods. Recently, we have seen developments in tracking wildlife using vision-based sensors [Selby *et al.*, 2011; Olivares-Mendez *et al.*, 2015] or infrared-based sensors

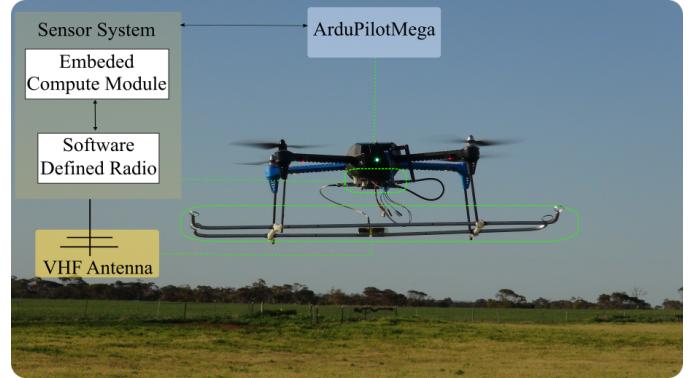


Figure 1: **TrackerBot**: Our autonomous UAV platform prototype under development. Currently capable of autonomous tracking and localization tasks in mostly flat terrains using a 2D implementation of tracking and planning.

[Gonzalez *et al.*, 2016; Ward *et al.*, 2016]. However, radio tagging avoids the data association problems [Bar-Shalom, 1987; Stone *et al.*, 2013] and other vision-related issues such as target occlusions [Gonzalez *et al.*, 2016] can make monitoring wildlife in the wild difficult.

Initial proposals to use commercial UAVs to track radio-tagged targets can be traced back to [Posch and Sukkarieh, 2009; Körner *et al.*, 2010] or more recently in [Dos Santos *et al.*, 2014; Jensen *et al.*, 2014; Cliff *et al.*, 2015; VonEhr *et al.*, 2016; Bayram *et al.*, 2017; Nguyen *et al.*, 2017; Nguyen *et al.*, 2018]. All of these methods assumed that the terrains are flat and implemented tracking and planning algorithms to localize radio-tagged targets in two dimensions (latitudes and longitudes only) on the ground plane. The elevations (the ground surfaces) have been ignored in the previous work. In this paper, we investigate our tracking and planning formulation in [Nguyen *et al.*, 2017] in three-dimensions to account for the unknown terrains, especially in hilly areas. Although [Nguyen *et al.*, 2017] has demonstrated an aerial robot system, for the first

time, capable of planning trajectories to track and localize multiple mobile VHF wildlife radio tag targets, the validation of the method in a 3D environment remains. In this paper, we use received signal strength indicator (RSSI) measurements, which exploits the simplicity of antenna and receiver designs to build a lightweight payload system, to validate our approach in a 3D environment. We take the *first* step towards autonomous tracking and localizing under unknown terrains in 3D environments using a UAV with RSSI-based measurements.

In summary, our main contributions are:

- We implement a 3D tracking and planning formulation using RSSI-based methods in software in the loop simulation of a Quad-Copter.
- We simulate tracking and localizing multiple mobile radio-tagged targets in hills or valleys where the terrain information is unknown.
- We compare our 3D tracking method to tracking and localize radio-tags in the unknown terrains with one where the terrain information is known.
- Our investigations are based on the real-world Digital Elevation Model (DEM) data published by [Australia-Geoscience, 2018] for the simulated software-in-the-loop (SITL) Quad-Copter.

2 Background

In this paper, we study the problem of tracking and localizing multiple radio-tagged targets using a UAV autonomously. Given that we do not have to address a data association problem, the tracking problem can be formulated by running multiple Particle Filters simultaneously, while the control algorithm is calculated using the Partially Observable Markov Decision Process (POMDP) framework. Our formulation is based on [Nguyen *et al.*, 2017], where a system was only implemented in a 2D environment. In the following sections, we provide an overview of our problem and the background of Particle Filters and POMDP before providing a formulation for the 3D problem.

2.1 Problem Statement

We consider the problem of tracking and localizing multiple mobile radio-tagged targets in the hilly terrains using a UAV. The proposed platform is discussed in [Nguyen *et al.*, 2017], with the following elements, as shown in Fig. 1:

- A civilian, commercial and low-cost UAV with an accurate Global Positioning System (GPS) measurements in latitude and longitude, but using an unreliable barometer sensor in altitude measurements. The UAV maneuverability is determined by that of a Quad-Copter.

- A sensor system—the main payload—includes a directional VHF antenna to receive the transmitted signals, an embedded computer module connected to a software-defined radio device to detect and measure the received signal strength indicator (RSSI) through VHF antenna.

Further, we assume that each radio-tag transmits an on-off-keying signal with known transmission power P_0 in every T_0 seconds. The target is located in a hilly area where its altitude can vary in $[z_{\min}, z_{\max}]$ m. We did not consider the exploration problems in this work where the reward functions can be formulated in both exploration and localization parameters [Charrow *et al.*, 2015]. Instead, we assume that the UAV can detect all of the targets, which is reasonable in a moderate size search area; we concentrate on improving the tracking performance for detected targets.

2.2 Particle Filters

The Particle filters belong to a class of approximation methods to nonlinear systems in the Bayesian filter family. The basic method of the particle filters is to use a random sampling process (Monte Carlo) to approximate the probability distributions of interest [Vo *et al.*, 2015].

Formally, suppose \mathbf{x}_k is the state of a target at time k , which generates an observation \mathbf{z}_k based on the observation model:

$$\mathbf{z}_k = g_k(\mathbf{x}_k, \mathbf{w}_k), \quad (1)$$

where \mathbf{w}_k denotes the observation noise. In general, the observation can be characterized as a likelihood function $g_k(\mathbf{z}_k|\mathbf{x}_k)$, which is the probability of observing the measurement \mathbf{z}_k given the state \mathbf{x}_k . Further, the target state \mathbf{x}_k evolves over time based on the transition model:

$$\mathbf{x}_k = f_{k|k-1}(\mathbf{x}_{k-1}, \mathbf{v}_{k-1}), \quad (2)$$

where \mathbf{v}_{k-1} denotes the process noise. Generally, the target state can also be characterized by the transition kernel $f_{k|k-1}(\mathbf{x}_k|\mathbf{x}_{k-1})$, which is the probability of transitioning to the target state \mathbf{x}_k , given its previous state \mathbf{x}_{k-1} .

The objective of the filtering problem is to estimate the belief density $\pi_k(\mathbf{x}_k|\mathbf{z}_{1:k})$ based on the history of observation data $\mathbf{z}_{1:k}$ from time 1 to time k . Using the Bayes recursion roles, from the initial density π_0 , the belief density can be calculated sequentially using the prediction and update steps as followed:

$$\begin{aligned} \pi_{k|k-1}(\mathbf{x}_k|\mathbf{z}_{1:k-1}) &= \int f_{k|k-1}(\mathbf{x}_k|\mathbf{x}_{k-1}) \pi_{k-1}(\mathbf{x}_{k-1}|\mathbf{z}_{1:k-1}) d\mathbf{x}, \\ \pi_k(\mathbf{x}_k|\mathbf{z}_{1:k}) &= \frac{g_k(\mathbf{z}_k|\mathbf{x}_k) \pi_{k|k-1}(\mathbf{x}_k|\mathbf{z}_{1:k-1})}{\int g_k(\mathbf{z}_k|\mathbf{x}) \pi_{k|k-1}(\mathbf{x}|\mathbf{z}_{1:k-1})} d\mathbf{x}. \end{aligned} \quad (3)$$

The Particle Filters implements the random sampling process called Monte Carlo (MC) method [Gordon *et al.*, 1993] to approximate the belief density by a weighted set of independently and identically distributed (i.i.d) particles $\{(w_k^i, \tilde{\mathbf{x}}_k^i)\}_{i=1}^N$, *i.e.*:

$$\pi_k(\mathbf{x}_k | \mathbf{z}_{1:k}) \approx \sum_{i=1}^N w_k^i \delta(\mathbf{x}_k - \tilde{\mathbf{x}}_k^i), \quad (4)$$

where $\delta(\cdot)$ denotes the Kronecker delta, and $\sum_{i=1}^N w_k^i = 1$.

2.3 POMDP

We propose to formulate the UAV path planning problem under the Partially Observable Markov Decision Process (POMDP) framework. The POMDP framework has demonstrated its effectiveness in controlling the robots to achieve predefined tasks based on reward functions in uncertain observations [Kaelbling *et al.*, 1998; Hsu *et al.*, 2008; Ragi and Chong, 2013; Baek *et al.*, 2013; Gostar *et al.*, 2016].

A POMDP can be described by the 6-tuple $\langle \mathcal{S}, \mathcal{A}, \mathcal{T}, \mathcal{R}, \mathcal{O}, \mathcal{Z} \rangle$, where \mathcal{S} denotes set of states, including the target state \mathbf{x} and the UAV state \mathbf{u} , *i.e.*, $\mathbf{s} = \{\mathbf{x}, \mathbf{u}\} \in \mathcal{S}$; \mathcal{A} denotes the set of UAV control actions; \mathcal{T} denotes the state transition kernel, *i.e.*, $\mathcal{T}(\mathbf{s}, \mathbf{a}, \mathbf{s}') = \pi(\mathbf{s}' | \mathbf{s}, \mathbf{a})$, which is the probability of transitioning to the state \mathbf{s}' from the state \mathbf{s} if the action \mathbf{a} is taken; $\mathcal{R}(\mathbf{a})$ denotes the reward function if the action \mathbf{a} is applied; \mathcal{O} denotes a set of observations \mathbf{o} , and \mathcal{Z} denotes the observation likelihood, *i.e.*, $\mathcal{Z}(\mathbf{o}, \mathbf{s}, \mathbf{a}) = \pi(\mathbf{o} | \mathbf{s}, \mathbf{a})$, which is the probability of an observation \mathbf{o} given the state \mathbf{s} and the taken action \mathbf{a} .

The purpose of the UAV path planning is to find the optimal control action $\hat{\mathbf{a}}$ that maximizes the reward function over a look-ahead horizon H [Beard *et al.*, 2017], *i.e.*,

$$\hat{\mathbf{a}} = \arg \max_{\mathbf{a} \in \mathcal{A}_k} \mathbb{E}[\mathcal{R}_{k+H}(\mathbf{a})], \quad (5)$$

where $\gamma \in (0, 1]$ denotes the discount factor, which modulates the effects of future rewards over the current rewards, and \mathbb{E} denotes the expectation operator.

The reward function can be calculated using task-based or information-based methods [Beard *et al.*, 2017]. When the uncertainty is high, the information-based methods are preferable since it helps to reduce uncertainty by increasing the information gain. For information-based methods, there are several approaches to measure the information divergence, including Kullback-Leibler (KL) divergence [Hero *et al.*, 2008], Rényi divergence [Ristic and Vo, 2010; Ristic, 2013] or Shannon entropy [Cliff *et al.*, 2015; Charrow *et al.*, 2015]. According to [Cliff *et al.*, 2015], the information gain measures the change in Shannon entropy between the

prior belief density $\pi_1 = \pi_{k+H}(\cdot | \mathbf{z}_{1:k})$ and the posterior belief density $\pi_2 = \pi_{k+H}(\cdot | \mathbf{z}_{1:k}, \mathbf{z}_{k+1:k+H}(\mathbf{a}))$, *i.e.*,

$$\mathcal{R}_{k+H}(\mathbf{a}) = \mathcal{H}(\pi_1) - \mathcal{H}(\pi_2), \quad (6)$$

where $\mathcal{H}(\pi(\mathbf{x})) = -\int \pi(\mathbf{x}) \log \pi(\mathbf{x}) d\mathbf{x}$ is the Shannon entropy.

3 Problem Formulation

In this work, we focus on formulating the problem of tracking and localizing radio-tagged targets in unknown terrains and follow our previous work in [Nguyen *et al.*, 2017]. The state of a single target is $\mathbf{x} = [x, l] \in \mathbb{R}^3 \times \mathbb{L}$, where $x = [p_x^{(\mathbf{x})}, p_y^{(\mathbf{x})}, p_z^{(\mathbf{x})}] \in \mathbb{R}^3$ is the target 3D position in x, y and z axes of the Cartesian coordinate system; $l \in \mathbb{L} \subset \mathbb{N}$ is the unique natural number represents the frequency of the target transmitted signal, which is used as the target unique ID. The state of a UAV is $\mathbf{u} = [u, \theta^{(\mathbf{u})}] \in \mathbb{R}^3 \times [0, 2\pi)$, where $u = [p_x^{(\mathbf{u})}, p_y^{(\mathbf{u})}, p_z^{(\mathbf{u})}] \in \mathbb{R}^3$ is the UAV position in 3D coordinate; $\theta^{(\mathbf{u})}$ is the UAV heading. Further, we assume that the number of targets $|\mathbb{L}|$ in the search area is known, and the search operation terminates when all of the searching targets are tracked and localized.

3.1 Multi-target tracking

We propose using a particle filter to implement as our tracking algorithm to account for the nonlinear system dynamics and noisy measurement data from signal strength measurements interfered by radio-wave scattering and attenuation or thermal noise of the receiver [Nguyen *et al.*, 2017]. Since each target is uniquely identified by its frequency index l , the RSSI-based measurements provide a known data association. Further, we assume that there is no false-alarm or misdetection for our RSSI-based measurements as in [Cliff *et al.*, 2015; Nguyen *et al.*, 2018; Nguyen *et al.*, 2017]. Therefore, we can track and localize multiple radio-tagged targets by running multiple particle filters simultaneously, one particle filer for each target, as proposed in [Charrow *et al.*, 2015; Nguyen *et al.*, 2017]. The particle filter requires correctly modeling for both target transition and observation models to achieve good performance.

Target transition model: For wildlife targets, their dynamic behaviors are usually unpredictable. Thus we model their behaviors as a random walk model, *i.e.*,

$$f_{k|k-1}(\mathbf{x}_k | \mathbf{x}_{k-1}) = \mathcal{N}(x_k; x_{k-1}, Q^{(\mathbf{x})}) \delta(l_k - l_{k-1}) \quad (7)$$

where $\mathcal{N}(\cdot; \mu, Q)$ denotes a Gaussian density with mean μ and covariance Q ; $Q^{(\mathbf{x})} = [\sigma_x^2, \sigma_y^2, \sigma_z^2] \mathbf{I}_3$ is the 3×3 covariance matrix of the process noise, and \mathbf{I}_n denotes the $n \times n$ identity matrix.

Observation model: We consider the *LogPath* measurement model experimentally validated with VHF frequencies in [Nguyen *et al.*, 2017]. Here, the received power $h(\mathbf{x}_k, \mathbf{u}_k)$ [dBm] at the UAV with state \mathbf{u}_k transmitted from target with state \mathbf{x}_k comprises only the LOS component, *i.e.*,

$$h(\mathbf{x}_k, \mathbf{u}_k) = P_0 - 10n \log(d(\mathbf{x}_k, \mathbf{u}_k)) + G_r(\mathbf{x}_k, \mathbf{u}_k). \quad (8)$$

Here, P_0 is the reference power [dBm]; n is the unitless path loss constant, which characterizes how signal attenuates over the distance with a typical range from 2 to 4; $d(\mathbf{x}_k, \mathbf{u}_k) = \|\mathbf{x}_k - \mathbf{u}_k\|$ is the distance between the target and the UAV; $G_r(\mathbf{x}_k, \mathbf{u}_k)$ is the directional antenna gain, which depends on the UAV heading $\theta^{(\mathbf{u}_k)}$ and its relative position to the target \mathbf{x}_k .

The measured power or the received signal strength indicator (RSSI) \mathbf{z}_k [dBm] is corrupted with noise, *e.g.*, thermal noise or signal interference from other sources. We assume the noise is white. Thus, the measurement likelihood model is

$$g_k(\mathbf{z}_k | \mathbf{x}_k) = \mathcal{N}(\mathbf{z}_k; h(\mathbf{x}_k, \mathbf{u}_k), Q^{(\mathbf{z})}), \quad (9)$$

where $Q^{(\mathbf{z})}$ is the 1×1 covariance matrix of the measurement noise.

3.2 Path Planning using the Shannon entropy information gain

In this section, we present our approach to calculating an optimal control action for the UAV. At time k , the UAV needs to plan how it will navigate over the time interval $\tau = k+1 : k+H$ with the look-ahead horizon H . Since there are multiple targets in the search area, we select the target with the strongest RSSI-based measurement as the one to be tracked and localized first [Nguyen *et al.*, 2017]. Formally, suppose $\mathbf{Z}_k(\mathbf{X}_k) = \bigcup_{l \in \mathbb{L}} \mathbf{z}_k(\mathbf{x}_k)$ be a set of measurements at time k generated from the respective set of targets $\mathbf{X}_k = \bigcup_{l \in \mathbb{L}} \mathbf{x}_k$, and \mathbf{F}_k be of the set of localized targets (a target is considered localized if its estimation uncertainty is smaller than a predefined bound), the selected target $\mathbf{\tilde{x}}^*$ for the path planning at time k is

$$\mathbf{\tilde{x}}^* = \arg \max_{\mathbf{x} \in \mathbf{X}_k \setminus \mathbf{F}_k} \mathbf{Z}_k(\mathbf{X}_k). \quad (10)$$

Let \mathcal{A}_k be a discrete set of control actions for the UAV at time k . We define \mathcal{A}_k contains $|\mathcal{A}_k|$ number of actions, that control the UAV to change its heading to one of the following $\{0, 2\pi/|\mathcal{A}_k|, \dots, 2\pi(1 - 1/|\mathcal{A}_k|)\}$ angles, then moves forward according to the selected angle until another control action applies. For each control action $\mathbf{a} \in \mathcal{A}_k$ applies to the UAV, it generates a discrete sequence of the UAV poses $\mathbf{u}_\tau(\mathbf{a}) = [\mathbf{u}_{k+1}, \dots, \mathbf{u}_{k+H}]$ with corresponding measurements $\mathbf{z}_\tau(\mathbf{a}) = [\mathbf{z}_{k+1}, \dots, \mathbf{z}_{k+H}]$.

The goal in path planning is to find an optimal control action $\mathbf{a}^* \in \mathcal{A}_k$ that maximizes the expected reward, *i.e.*,

$$\mathbf{a}^* = \arg \max_{\mathbf{a} \in \mathcal{A}_k} \mathbb{E}[\mathcal{R}_{k+H}(\mathbf{a})]. \quad (11)$$

Since the expected reward requires an integration, which does have an analytic formula, we implement the Monte Carlo integration [Ristic and Vo, 2010; Beard *et al.*, 2017; Nguyen *et al.*, 2017] by drawing multiple sampled measurements $\mathbf{z}_\tau^{(m)}(\mathbf{a})$ for $m = 1, \dots, M$, then calculate the sampled reward $\mathcal{R}_{k+H}^{(m)}(\mathbf{a})$. Thus, the expected reward can be approximated by the mean of all the sampled rewards, *i.e.*,

$$\mathbb{E}[\mathcal{R}_{k+H}(\mathbf{a})] \approx \frac{1}{M} \sum_{m=1}^M \mathcal{R}_{k+H}^{(m)}(\mathbf{a}). \quad (12)$$

In this work, we implement the change in Shannon entropy as the reward function¹ as in [Cliff *et al.*, 2015; Charrow *et al.*, 2015]:

$$\mathcal{R}_{k+H}^{(m)}(\mathbf{a}) = \mathcal{H}(\pi_{k+H}(\mathbf{\tilde{x}}^* | \mathbf{z}_{1:k})) - \mathcal{H}(\pi_{k+H}(\mathbf{\tilde{x}}^* | \mathbf{z}_{1:k}), \mathbf{z}_\tau^{(m)}(\mathbf{a})) \quad (13)$$

For notational simplicity, let $\pi_1 \triangleq \pi_{k+H}(\mathbf{\tilde{x}}^* | \mathbf{z}_{1:k})$ and $\pi_2 \triangleq \pi_{k+H}(\mathbf{\tilde{x}}^* | \mathbf{z}_{1:k}, \mathbf{z}_\tau^{(m)}(\mathbf{a}))$. Since we use the particle filter as our tracking filter, each density can be approximated by the same set of particles with different weights:

$$\pi_1 = \{(w_1^i, \tilde{\mathbf{x}}^i)\}_{i=1}^N; \pi_2 = \{(w_2^i, \tilde{\mathbf{x}}^i)\}_{i=1}^N. \quad (14)$$

Thus, the reward function in (13) can be approximated as followed:

$$\mathcal{R}_{k+H}^{(m)}(\mathbf{a}) \approx \sum_{i=1}^N [w_2^i \log(w_2^i) - w_1^i \log(w_1^i)]. \quad (15)$$

4 Software In The Loop Experiments

In this section, we validate and demonstrate our approach by tracking and localizing multiple radio-tagged targets in two different unknown terrains. Further, we compare our 3D tracking algorithm with a tracking method where the terrain information is already known. The terrain information is based on the real-world DEM data published by [Australia-Geoscience, 2018] with 5 m in latitude and longitude resolutions, and ± 0.3 m in altitude errors.

¹Notably, multiple other information gain measures can be employed. In [Nguyen *et al.*, 2017], we investigated several reward functions. We selected Shannon entropy here due to its simplicity and because our goal is to take the first steps to demonstrate that RSSI based measurements from an aerial robot can be used to realize tracking in realistic 3D settings.

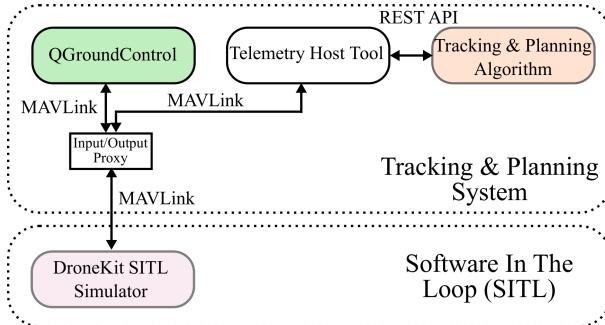


Figure 2: Block diagram of our proposed SITL settings for emulated experiments. The *Tracking and Planning System* communicates with the *DroneKit SITL* simulator through the MAVLink protocol.

4.1 Simulation Experimental Setup

We evaluate our algorithm using the real-time emulated SITL environments, as shown in Fig.2. The tracking and planning algorithm is written in MATLAB, which sends control actions in way-points through the *Telemetry Host Tool* and the Input/output proxy—*IO proxy*, both are written in Rust-lang, to the *DroneKit-SITL* simulator [Ryan *et al.*, 2015] using the MAVLink protocol. For the *DroneKit-SITL*, we use the *copter-3.3* library to emulate a quad-copter. Further, the *QGroundControl* (a popular and cross-platform ground station control software) can also communicate to the *DroneKit-SITL* simulator to facilitate and control the emulated copter in arming, taking off, and changing its altitude to a defined altitude above ground level (AGL). The tools and software developed for the **TrackerBot** project will be publicly available at our project repository²

We conduct several software-in-the-loop (SITL) trials under two different terrain settings: i) South Australia (SA) - Lower Glenelg National Park; ii) New South Wales (NSW) - Dorrigo National Park as shown in Fig.3 to verify and demonstrate the capability of planning to track multiple mobile targets with RSSI based measurements from an aerial robot.

Algorithm Evaluations: To evaluate our proposed algorithm, we measure the Root Mean Square (RMS) error—the average error distance between the targets’ estimated locations versus its ground truths— $\text{RMS} = \sum_{l \in \mathbb{L}} \|x_{\text{truth}} - x_{\text{est}}\| / |\mathbb{L}|$ [m], and the flight time [s]—the

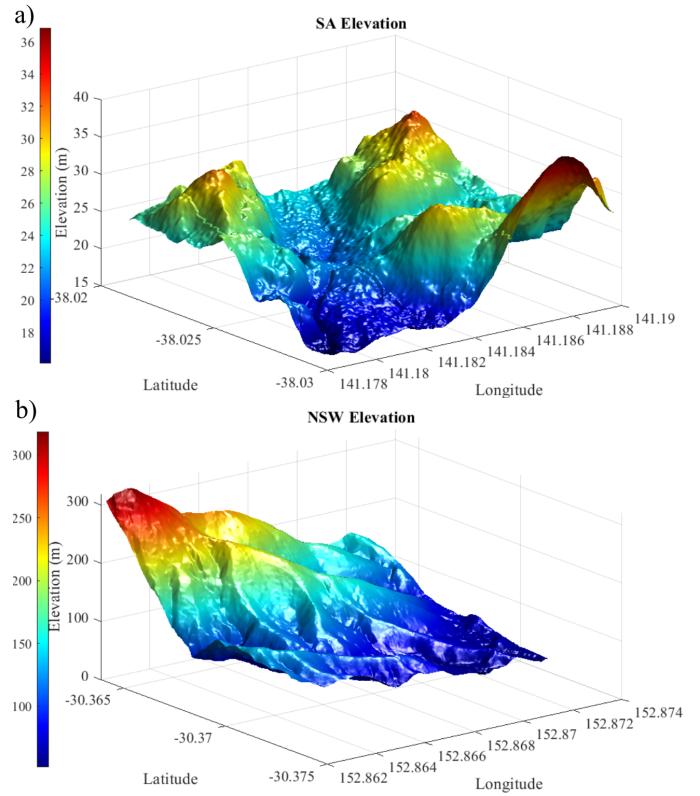


Figure 3: The terrain information for two site settings: a) Lower Glenelg National Park terrain, South Australia (SA); b) Dorrigo National Park terrain, New South Wales (NSW).

time a UAV takes to localize all of the targets, including planning time. As in our previous work [Nguyen *et al.*, 2018; Nguyen *et al.*, 2017], a target is considered tracked and localized if its estimation uncertainty is smaller than the predefined bound: 15 m for the x-axis and y-axis, and 25 m for the z-axis. The reason z-axis has a higher bound that the directional antenna does not provide an accurate antenna gain in z-axis causing higher uncertainty in the estimation (see the antenna pattern modeled and evaluated in [Nguyen *et al.*, 2017] where the measurements validated the pattern in the xy plane due to the difficulty of accurately controlling the UAV position to measure the field pattern in the xz plane).

Scenario 1: The first scenario considers tracking and localizing three mobile radio-tagged wildlife in Lower Glenelg National Park, South Australia. We selected a search area of $1000 \text{ m} \times 1000 \text{ m}$ (100 hectares) where the elevation changes from 16 m to 36 m based on the real-world Digital Elevation Model (DEM) from [Australia-Geoscience, 2018], as shown in Fig. 3a. Its initial position in latitude, longitude, eleva-

²The TrackerBots project repository <https://github.com/AdelaideAuto-IDLab/TrackerBots>

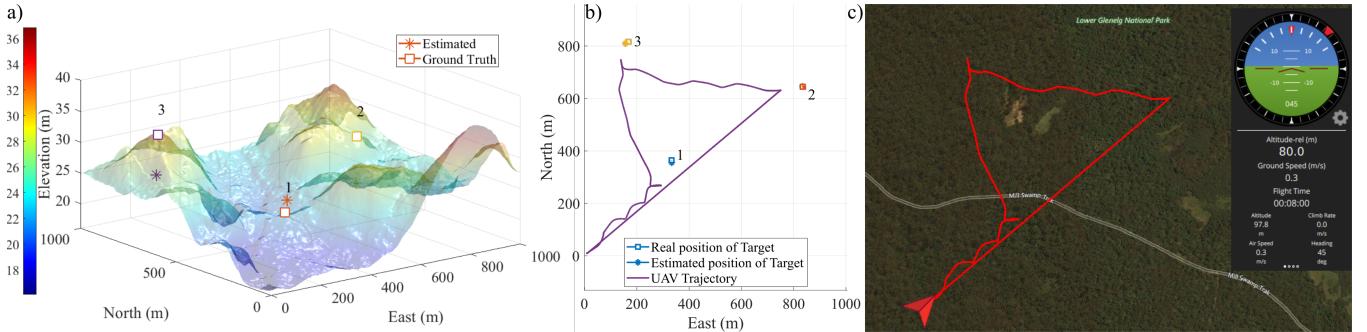


Figure 4: The tracking and localization results *without terrain awareness* to track and localize three radio-tagged targets in the Lower Glenelg National Park - SA: a) the ground truth vs. the estimated positions in three dimensions (North-East-Elevation); b) the UAV trajectory using the Shannon entropy and its estimated locations in two dimensions (North-East); c) the screen-shot of the QGroundControl with the UAV trajectory.

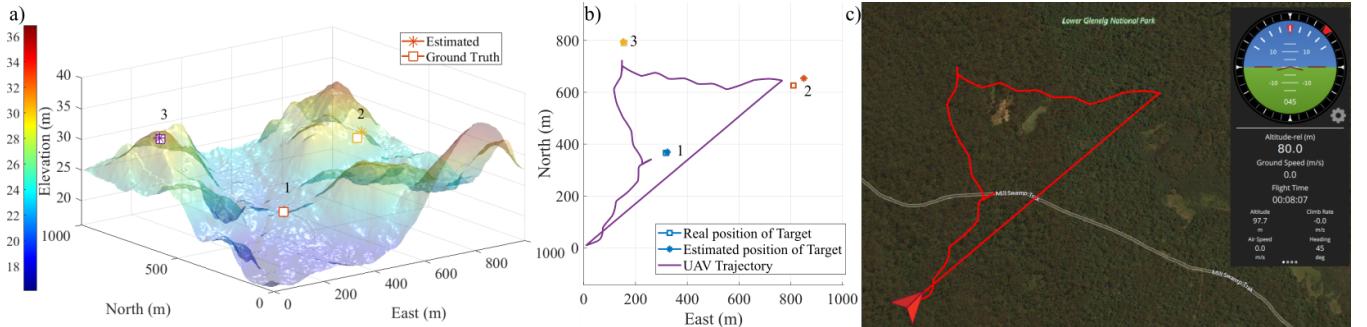


Figure 5: The tracking and localization results *with terrain awareness* to track and localize three radio-tagged targets in the Lower Glenelg National Park, SA: a) the ground truth vs. the estimated positions in three dimensions (North-East-Elevation); b) the UAV trajectory using the Shannon entropy-based reward function and the estimated locations of the radio tags in two dimensions (North-East); c) A screen capture of software in the loop simulation with QGroundControl showing the UAV trajectory. Here the straight-line path shows the UAV returning to its home location after the tracking task is complete.

tion is $[-38.0300, 141.1783, 17.7]^T$, which is converted to $[0, 0, 17.7]^T$ m in the xyz-axes.

For generating the ground truth, the initial positions of three mobile targets are $[320, 361, 21.5]^T$ m, $[826, 640, 26.7]^T$ m, and $[166, 796, 30.3]^T$ m. Targets are assumed to follow the random walk model with standard deviations in x-axis and y-axis as $\sigma_x^{(x)} = \sigma_y^{(x)} = 1$ (m/s), while its elevation in z-axis is derived from the DEM data based on its x and y positions.

For tracking and planning algorithm *without terrain awareness*, the target location is unknown, and its initial distribution is sampled from a uniform distribution over the predefined ranges with the number of particles $N = 40,000$, *i.e.*,

$$\pi_0(x_0) = \mathcal{U}[0, 1000] \times \mathcal{U}[0, 1000] \times \mathcal{U}[12.7, 37.7],$$

where $\mathcal{U}[a, b]$ denotes the uniform distribution on the interval $[a, b]$ (m). The covariance matrix of the process noise is $Q^{(x)} = [1, 1, 0.1]^T \mathbf{I}_3$ (m/s)². We set the measurement duration $T_0 = 1$ s, the measurement noise

$Q^{(z)} = 5^2$ (dBm)², the reference power $P_0 = -35.4$ dBm, the path loss constant $n = 2$, and the look-ahead horizon time step $H = 10$. The UAV is armed, taken off, and its altitude is set to 80 m AGL using QGroundControl, *i.e.*, its initial state is set at $\mathbf{u}_0 = [10 \text{ m}, 10 \text{ m}, 97.7 \text{ m}, \pi/4 \text{ rad}]^T$ and its maximum ground speed at 10 m/s. We consider the number of control actions is $|\mathcal{A}| = 30$, *i.e.*, the allowable heading changes are $\{0, \pi/15, \dots, 29\pi/15\}$ (rad).

For tracking and planning algorithm *with the terrain awareness*, since the elevation data (z-axis) are already available, we only need to estimate the target position in two dimensions of the xy-axes, then deriving the elevation in z-axis from the DEM data based on its x and y estimated positions. For parameter settings, we implement the same settings as in the case *without terrain awareness*, except the particles of the initial distribution is only sampled from $\mathcal{U}[0, 1000] \times \mathcal{U}[0, 1000]$ for xy-axes, while z-axis particles are calculated from DEM data based on the particles of the xy-axes. Further, given

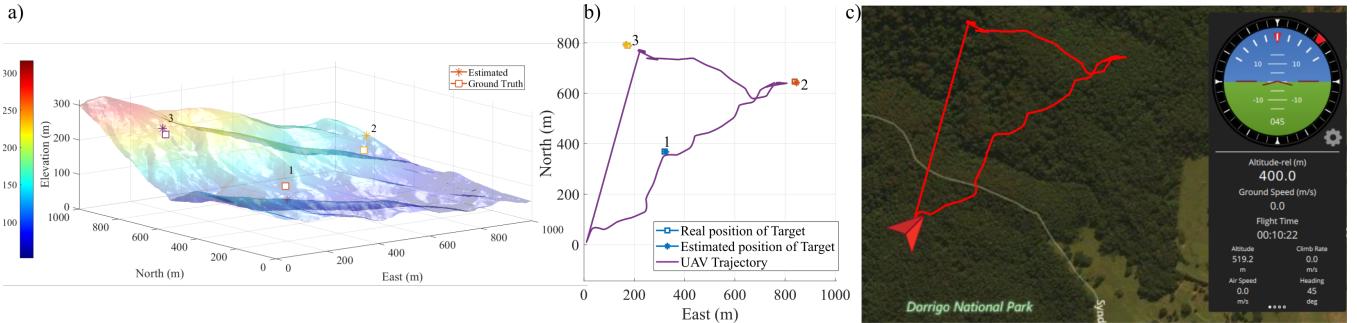


Figure 6: The tracking and localization results *without terrain awareness* to track and localize three mobile radio-tagged targets in the Dorrig National Park, NSW: a) the ground truth vs. the estimated positions in three dimensions (North-East-Elevation); b) the UAV trajectory using the Shannon entropy-based reward function and the estimated locations of the radio tags in two dimensions (North-East); c) the screen capture of the software in the loop simulation with QGroundControl showing the UAV trajectory. Here, the straight-line trajectory shows the UAV returning home after completing the tracking task.

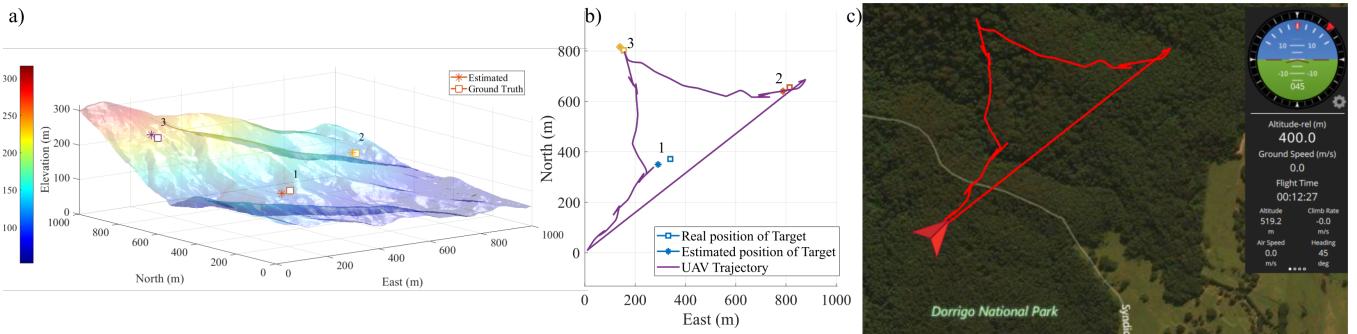


Figure 7: The tracking and localization results *with terrain awareness* to track and localize three radio-tagged targets in the Dorrig National Park, NSW: a) the ground truth vs. the estimated positions in three dimensions (North-East-Elevation); b) the UAV trajectory using the Shannon entropy and its estimated locations in two dimensions (North-East); c) the screen capture of the software in the loop simulation with QGroundControl showing the UAV trajectory. Again, the straight-line path shows the UAV returning to its home location after completing the task.

Table 1: Tracking and localizing performance over 10 Monte-Carlo runs for tracking radio-tagged targets in the Lower Glenelg National Park, SA

Terrain Aware	Error (m)			RMS (m)	Flight Time (s)
	x-axis	y-axis	z-axis		
No	12.6	13.4	4.2	20.78	414.4
Yes	14.4	13.5	0.3	21.53	379.1

known terrain information, the covariance matrix of process noise is $Q^{(x)} = [1, 1, 0]^T \mathbf{I}_3$ (m/s)².

Fig. 4 and Fig. 5 depict the tracking and localization results *with terrain awareness* and *without terrain awareness* algorithms, respectively. Table 1 provides detailed comparisons between these two approaches over 10 Monte-Carlo trials in SITL emulated environments. We can see that the tracking error in terms of RMS is similar for both algorithms with or without terrain data. It is expected that the algorithm using terrain infor-

mation has a smaller z-axis error, which is due to the errors in estimating positions in xy-axes. Further, we notice that the flight time for terrain awareness is significantly shorter because it only needs to estimate two unknown variables compared to the algorithm *without terrain awareness*. Thus, when the terrain information is readily available, we should implement the tracking algorithm with *terrain awareness* to improve flight times. However, most areas in Australia still do not have a Digital Elevation Model, thus implementing our algorithm—tracking *without terrain awareness*—can play an important role in tracking wildlife targets in unknown terrains. Notably, flight times of approximately 400 seconds for environments without terrain information are easily achievable with modern small size battery-powered UAVs.

Scenario 2: The second scenario considers the problem of tracking and localizing three mobile radio-tagged targets in Dorrig National Park, NSW. This

terrain is more challenging than *Scenario 1* since the Dorrigo National Park site has larger elevation variations ranging from 51.7 m to 318.7 m. Its initial positions in latitude, longitude, and elevation are $[-30.3730, 152.8622, 119.1]^T$, which is converted to $[0, 0, 119.1]^T$ m in the xyz-axes.

For parameters, we apply the same settings as in *Scenario 1* for the algorithm *with terrain awareness*. For the algorithm *without terrain awareness*, all settings are kept as the same as in *Scenario 1*, except for the elevation settings. The initial particles for the elevation are sampled from $\mathcal{U}[49.1, 319.1]$ m. Since the variation in the elevation in this site is higher, we set the covariance matrix of the process noise as $Q^{(x)} = [1, 1, 1]^T$ (m/s)². Further, the UAV is armed, taken off, and changed to an altitude of 400 m AGL³ using the QGroundControl, *i.e.*, its initial state is set at $\mathbf{u}_0 = [10 \text{ m}, 10 \text{ m}, 519.1 \text{ m}, \pi/4 \text{ rad}]^T$.

Fig. 6 and Fig. 7 present the tracking and localization results *with terrain awareness* and *without terrain awareness* algorithms, respectively, for tracking radio-tagged wildlife at Dorrigo National Park, NSW. Here, the elevations change significantly. We can see that our algorithm can still perform well and accurately localize three mobile radio-tagged targets in this challenging survey area. In this particular mission, the RMS and flight time are (31.8 m, 705.1 s) and (28.2 m, 603.3 s) for algorithms *without terrain awareness* and *with terrain awareness*, respectively. Although the RMS values are higher compared with those in Table 1 due to the challenging environment, the results demonstrate the robustness of our proposed algorithm. Our RSSI based measurements based planning for tracking can localize the mobile radio-tagged targets under very challenging terrain variations. Notably, the flight times are longer than with *Scenario 1*; however, flight times of approximately 700 seconds are still achievable with modern battery-powered medium size UAVs in the 2 kg to 4 kg range. For instance, our **TrackerBot** demonstrated in [Nguyen *et al.*, 2018] has a flight time of approximately 6-10 minutes whilst carrying a sensor system payload of mass 260 g.

5 Conclusions and Future work

We have validated our approach for planning to track multiple mobile VHF radio-tagged targets in realistic 3D environments using a measurement model validated in field experiments using the software in the loop simulations. Therefore, we have taken the first steps towards three-dimensional tracking and planning for a UAV using

³We understand that it is legally not possible to fly a UAV at an altitude higher than 120 m AGL [Civil Aviation Safety Authority, 2017]. However, as a proof of concept and in an emulated environment, we set the relative altitude to 400 m AGL to remove the obstacle avoidance problem from our formulation. We leave this for future work.

an RSSI-based method with or without terrain awareness.

The results confirm the validity of our formulation and software in the loop simulations confirm that we can expect the system to be successful with a Quad-Copter UAV in field experiments. However, we also observe in our results in Table.1, when terrain information is widely available, we can rely on this information to reduce flight times. Although our study has validated our approach in a 3D environment, there are a number of tasks that formulate our future work in **TrackerBots** to demonstrate our approach in field experiments. We briefly outline these below.

- We implemented Shannon entropy used in [Cliff *et al.*, 2015; Charrow *et al.*, 2015]. However, we recognize that other information-theoretic reward functions such as Rényi divergence can improve planning decisions. Better control decisions can lead to shorter flight times and conservation of battery life. Therefore, other information gain measures should be formulated and evaluated with Shannon entropy.
- We have considered a measurement model that does not consider multi-path propagation effects possible from ground reflections and potential scattering losses of signal strength information from, for example, tree canopies. Therefore, future research should consider a more complex measurement model to understand the potential performance improvements such a model can provide in more complex signal propagation environments.
- Although we have conducted several experiments in realistic environments, the next step is to validate our method in field experiments.
- We recognize that Pixhawk firmware has the capability to follow terrain maps. We should also evaluate tracking and planning under terrain-following when the terrain information is available.
- Recent research in the field suggests that wildlife may be disturbed and flee at the sounds of a UAV [Hodgson and Koh, 2016; Mulero-Pázmány *et al.*, 2017]. This can make the tracking task more complicated. Therefore, future planning formulations should consider planning with situational awareness of VHF radio tags to avoid approaching the targets.
- We have not considered the detection problems, such as false-alarms and misdetections. Future planning for tracking formulations should consider detection problems as well as the formulation of a potential track-before-detect method based on measurements from the SDR based receiver architecture of a **TrackerBot** [Nguyen *et al.*, 2018].

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