Active perception for 3D Range-only Simultaneous Localization and Mapping with UAVs

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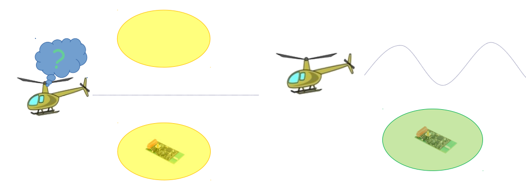
***Abstract*— Most localization approaches do not take into account the possibility of controlling the robot to improve the perception, instead, the robot is just commanded with a predefined path. Active sensing strategies may lead to more efficient exploration and mapping approaches. The robot can adapt its trajectory, avoiding for instance non-observable motions or following those paths which are most informative. In the case of Range-only Simultaneous Localization and Mapping (RO-SLAM), this means selecting the path which is likely to produce the highest reduction in the uncertainty on the landmarks' positions. This paper proposes an active sensing approach able to command the UAV to more informative areas from the RO-SLAM point of view, allowing a faster filter convergence and better mapping accuracy.**

I. INTRODUCTION

Range-only SLAM (or RO-SLAM) is a metric SLAM that aims to create a landmark-based map while at the same time it localizes the mobile robot with respect that map using range-only observations. In this case, landmarks are the position of a set of fixed range-only sensors similar to the visual landmarks used in Visual-SLAM but with less informative observations (only distance between mobile robot and landmark). This rank-deficiency of the observation model associated to range-only observations might lead to a flip ambiguity in RO-SLAM approaches. Thus, in that sense, active perception techniques are able to reduce the amount of uncertainty in the system to select the best hypothesis of the landmark's position.

Active sensing approaches are especially well suited for ill-posed estimators such as RO-SLAM in the early steps of the estimation where perception significantly depends on the robot actions. In this case, there are many possible localization hypotheses that can only be discarded based on the robot trilateration at different positions. This paper solves the problem by using the undelayed RO-SLAM approach described in [1]. This implementation stores in a single Extended Kalman Filter all possible landmark hypotheses and updates their estimation as soon the robot moves to a different position. As the approach is undelayed, the measurements can be integrated into the filter since the very first range data. However, the time required for the filter, no matter the approach, will always depend on the robot trilateration. Actually there is a chance the estimation will never converge to the correct position if the robot trilaterates very poorly or that the filter converges to the wrong hypotheses due to noisy observations.



(a) (b)

Fig. 1: Two examples of range-only localization. The aerial robot receives range data from the beacon at different positions. Ellipses denote estimations over landmark position. (a) Example of vertical flip ambiguity with constant altitude trajectory. (b) Solved ambiguity when using a sinusoidal vertical trajectory.

Figure 1 illustrates the benefit of considering active sensing strategies for RO-SLAM. In this figure, the robot trajectory of Figure 1a converges in two hypotheses with very similar uncertainty (bimodal distribution of the landmark position). On the other hand, Figure 1b shows how adapting the robot trajectory benefits the localization of the landmark.

Active perception techniques requires a metric about the amount of uncertainty reduced when selecting a certain task or action. One of the most common metrics is the gain of information, for Bayesian approaches this gain might be computed as the (expected) variation on the entropy of the beliefs on landmarks' position. An example of this active sensing approach is used in [2], [3] or [4], [5] for exploration and SLAM. In [6], active sensing strategies are applied to the problem of tracking using only range measurements, where the target is represented by a single Gaussian. In [7] it is presented an active perception approach which computes the amount of uncertainty that would result after applying different available robot actions. This amount of uncertainty is measured by analyzing the eigen values of the new estimated covariance matrix at each the expected robot location after each candidate action.

In this paper an active sensing approach is presented in order to maximize the gain of information while the aerial robot moves between waypoints. The paper extends previous work [8] with a full 3D RO-SLAM for aerial robots. The

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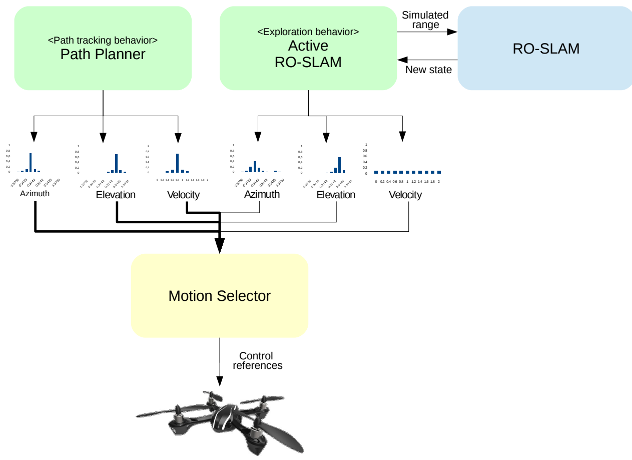

Fig. 2: Combination of behaviors path tracking against exploration behavior using a loose coupling system. The actions of the path planner are weighted with a higher relevance (see thickness of the arrows) with respect active perception actions, making the system follow the initial planned path but with small variations introduced by the exploration behavior used to reduce RO-SLAM uncertainty.

approach is based on the selection of robot actions that allows maximizing the gain of information while the robot is moving. In order to integrate the active perception with a local planner a loose coupling has been selected. The approach has been implemented in C++ under ROS and validated in simulations using a 3D environment simulator.

II. ACTIVE SENSING FOR IMPROVED 3D RO-SLAM

The benefit of using an aerial robot to estimate the position of a set of landmarks is the possibility to control its motion in order to follow the most informative path. On the one hand, from the set of possible motions of the robot, it should take those that allows to estimate the position of the landmarks more accurately. On the other hand, the robot should try to avoid motions that decrease the observability of the landmark position.

When using active perception techniques for a particular aerial robot mission, a common approach is to use a combination of behaviors as shown in Figure 2. These systems are based on a combination of tasks, each of them with an associated cost function and a normalized behavior weight which allows the system to select the action which best fit the requirements of all behaviors according to their priority. In this paper, two major tasks are considered: the most important task is the tracking of a path given by a local motion planner, the second task is the exploration of the environment in order to map the position of a set of radio beacons or landmarks. For the exploration of the environment, the system computes the gain of information when using a particular action. This gain of information is estimated using the expected variation of entropy of the RO-SLAM covariance matrix.

A. Brief summary of 3D RO-SLAM estimator

The RO-SLAM estimator used in this paper is based on a multi-hypotheses fully centralized EKF approach presented in previous work [1]. This method uses Gaussian Mixture models to represent unobserved azimuth and elevation variables of landmarks position.

In order to make feasible the implementation of this centralized multi-hypotheses filter, a reduced parametrization of the state $\mathbf{x}^t$ is proposed for robot $\mathbf{x}_r^t$ and landmark $\mathbf{f}_i^t$ states.

$$\mathbf{x}^t = [\mathbf{x}_r^t, \mathbf{f}_1^t, \mathbf{f}_2^t, \ldots, \mathbf{f}_m^t]^T \tag{1}$$

where $\mathbf{f}_i^t$ is the state of landmark i represented with reduced parameterization:

$$f_i = [x_i, y_i, z_i, \rho_i, \theta_{i1}, ..., \theta_{iN}, \phi_{i1}, ..., \phi_{iM}]^T \tag{2}$$

being ρ_i the initial distance between the robot and landmark i when the first range observation has been received from robot position x_i, y_i and z_i. And θ_{ij} and ϕ_{ij} being the N azimuth and M elevation hypotheses of the landmark respectively.

On the other hand, the RO-SLAM estimator also presents an improvement with respect the Federated Information Sharing approach used in [9], extended to 3D RO-SLAM. The improvement consist on a reduced number of correction equations of the filter as compared to Federated Information Sharing approaches implemented in [10], [9]. This improvement is based on the computation of the expected value of the azimuth and elevation Gaussian Mixtures.

Additionally, to reduce the computational burden of the multi-hypotheses estimator, some of the hypotheses are pruned or merged as the filter converges to the final solution.

B. Entropy-based active sensing strategy

The key idea is to select the action that maximize the reduction in entropy in the centralized EKF covariance matrix. Thus, the robot should be actively moved to gain as much information as possible. In order to do this, it is needed to define a measurement of the information gain obtained when executing a certain exploration action.

A common metric about the information of a probability distribution is its associated entropy. The entropy H of a probability distribution $p(x)$ is defined as the expected value of the information $-\log[p(x)]$:

$$H(p(x)) = E_x[-\log p(x)] = -\int p(x) \log p(x) dx \tag{3}$$

With this entropy definition, the information gain is defined as the variation in the entropy of the distribution after carrying a certain action $\mathbf{u}_t$. After the execution of this action, the new distribution $p(\mathbf{x}_{t+\Delta t}|\mathbf{u}_t, \mathbf{z}_{t+\Delta t})$ is obtained from the future measurement $\mathbf{z}_{t+\Delta t}$ with an associated new entropy value denoted by $H(p(\mathbf{x}_{t+\Delta t}|\mathbf{z}_{t+\Delta t}, \mathbf{u}_t))$.

Then, as the only parameter which can be controlled is $\mathbf{u}_t$, the expected entropy should be computed for all potential measurements $\mathbf{z}_{t+\Delta t}$ obtained from this action. Therefore, the expected information gain associated to action $\mathbf{u}_t$ is defined as:

$$\Delta(\mathbf{u}_t) = H(p(\mathbf{x}_t)) - E_{\mathbf{z}_{t+\Delta t}}[H(p(\mathbf{x}_{t+\Delta t}|\mathbf{z}_{t+\Delta t}, \mathbf{u}_t))] \quad (4)$$

This metric can be used to chose the action that maximizes the value $\Delta(\mathbf{u}_t)$.

C. Entropy of a Gaussian Mixture

The entropy, as defined in equation (3), can be obtained analytically for certain distributions, including the Gaussian distribution. However, there is no analytical solution for the case of Gaussian Mixtures, defined by the following equation:

$$f_X(x) = \sum_{j=1}^{N} \omega_j \mathcal{N}(x; \mu_j, \sigma_j) \quad (5)$$

One option is to numerically integrate (3), for instance using Monte Carlo methods. However, this is computationally demanding, as a high number of samples may be required (the accuracy depends on the number of samples). The proposed approach uses upper bounds of the entropy as an approximation to the actual entropy value. Thus, instead of analyzing the expected variation using the analytical solution for a particular action, the expected variation of the entropy bound will be considered.

In [11], an analytical solution is derived to the Gaussian Mixtures entropy along to an upper and lower bound approximation. For active sensing approaches it is of particular interest the upper bound of the entropy, which might be computed for a Gaussian Mixture in a very cheap way as:

$$H(f(\mathbf{x})) \leq \sum_i \omega_i(-\log \omega_i + \frac{1}{2}\log((2\pi e)^N |\Sigma_i|)) \quad (6)$$

for $\mathbf{x}$ of dimension N.

Moreover, this bound is exact when only one hypothesis remains, or when the hypotheses are separated. Therefore, a possible strategy is to compare actions taking into account how they affect not the entropy itself, but the upper bound. While in theory a decreasing in the bound could not reflect on a decreasing of the actual entropy, in the experiment section it will be seen that the procedure is effective reducing the actual entropy of the distributions.

D. Active sensing architecture

The robot considered here is an aerial vehicle. The variables controlled by the local planner are the linear velocity v of the robot, the azimuth θ and the elevation ϕ angle. As previously introduced, the robot makes use of a loose coupling system able to merge two or more motion behaviors. Each motion behavior send the motion votes that satisfy its objectives to a centralized arbiter (as in [12]) that merges them and take the action that better satisfy all the behaviors in the system. This combination associates a set of weights for all the potential contributions of the different behaviors.

Algorithm 1: Active perception algorithm

Data: $p(\mathbf{x}_t)$, Δt
Result: $(\Delta(\theta_i), \Delta(\phi_j))$
1: $\Theta = \{\theta_1, \cdots, \theta_i, \cdots\}$ A set of M orientations
2: $\Phi = \{\phi_1, \cdots, \phi_j, \cdots\}$ A set of N orientations
3: $H_t \leftarrow$entropy $(p(\mathbf{x}_t))$
4: **for all** $\theta_i \in \Theta$ **do**
5:   **for all** $\phi_j \in \Phi$ **do**
6:     $\mathbf{r}_{t+\Delta t} \leftarrow$ predict_robot $(\mathbf{r}_t, \theta_i, \phi_j, \Delta t)$
7:     **for all** (μ_k, Σ_k) in $f(\mathbf{x}_t)$ **do**
8:       $\mathbf{z}_{t+\Delta t} \leftarrow$ simulate_measurement$(\mathbf{r}_{t+\Delta t}, \mu_k, \Sigma_k)$
9:       $p(\mathbf{x}_{t+\Delta t}|\mathbf{z}_{t+\Delta t}) \leftarrow$ update $(p(\mathbf{x}_t), \mathbf{z}_{t+\Delta t})$
10:       $H_{i,j,k} \leftarrow$ entropy $(p(\mathbf{x}_{t+\Delta t}|\mathbf{z}_{t+\Delta t}))$
11:     **end for**
12:     $\Delta H \leftarrow H_t - \frac{\sum_k H_{i,j,k}}{K}$
13:     $\Delta(\theta_i) \leftarrow \Delta(\theta_i) + \Delta H$
14:     $\Delta(\phi_j) \leftarrow \Delta(\phi_j) + \Delta H$
15:   **end for**
16: **end for**
17: Normalize $\Delta(\theta_i)$
18: Normalize $\Delta(\phi_j)$

Algorithm 1 shows the strategy to compute the votes associated to the active sensing behavior. Only the azimuth θ and the elevation ϕ angles will be considered, which are discretized into a set of M azimuth values $\{\theta_1, \cdots, \theta_L\}$ and N elevation values $\{\phi_1, \cdots, \phi_N\}$. For each potential angle (θ_i, ϕ_j) it is possible to predict the future position of the robot for a certain time horizon Δt. At that future position, the potential range measurements to the known landmarks are considered. The basis of the algorithm is given by lines 8, 9 and 10. Within the for loop, each hypothesis within the Gaussian mixtures about the position of the known landmarks is considered correct, and an artificial measurement $\mathbf{z}_{t+\Delta t}$ is simulated for that hypothesis at line 8. Then, the filter described in [1] is applied by the function `update` to estimate the future belief, and the upper bound of the entropy (6) is computed.

The final expected information gain is computed as the mean of these entropies. That is, taking the expectation with respect to all the potential measurements, which corresponds to the second term of the right hand side of (4).

Although not depicted in Algorithm 1, the final algorithm applies the same operation for all the currently known beacons that are within communication range. Therefore, the final vote $\Delta(\theta_i)$ and $\Delta(\phi_j)$ for a particular action is the sum of the variations of the entropy for each of these beacons.

The final votes for all elevation and azimuth angles are normalized. These votes are then combined with the votes indicated by other behaviors. Figure 3 shows an example of particular interest. It shows how the strategy not only can lead to reductions on the uncertainty, but also to avoid non-observable motions, like straight lines. In this example, it can be seen how there are two symmetric entropy variation maxima.

III. RESULTS

The approach presented in this paper is tested in simulation, where it can be assured that sensor data and UAV actions can be under control. The whole active sensing architecture has been implemented in C++ using ROS. Actually, the same sensors used in other experiments for [13], [1], [14] are used, but with the difference that sensor data are artificially created based on the known position of the UAV and the range sensors. On the other hand, UAV dynamics are emulated based on ROS-GAZEBO 3D models. Range-only sensor data are modeled taking into account outliers, Gaussian noise, bias, etc.

For this particular implementation the prediction interval Δt has been set to $2s$. Small values of Δt are discarded because landmark trilateration is almost not affected (for medium UAV velocities) when UAV traverses short distances. On the other hand, much longer periods result in inaccuracies due to EKF linearizations. Thus, $\Delta t = 2s$ is a compromise between efficiency and accuracy.

The UAV was commanded to follow a given trajectory based on waypoints. As previously presented, the active approach will modify the desired elevation and azimuth angles in order to maximize the gain of information. The trajectory commanded to the UAV and the active actions resulted from the approach are presented in Figure 3. It can be seen how the active perception systems tends to move the UAV around the predefined path in order to gather more information of the range landmarks. From a theoretical point of view, the active perception system should force the UAV to move to positions that increase the trilateration with respect the sensor landmarks.

The improved trajectory resulted in a better trilateration of the sensor landmarks and, hence, better estimation of the map. Figure 4 shows the estimated landmark position error with respect the ground-truth when active perception is considered and compared without it. It can be seen in the figure how the average error in the landmark position is clearly reduced, although the individual errors of some landmark position are larger without active perception. This effect is mainly produced by the approach itself that tries to improve the information gain globally, which might end with worst errors for individual landmarks in favor of a better global map error.

The active perception approach has also impact in the convergence time needed by the SLAM approach to reach single hypothesis representation for each beacon in the map. This is consistent with the theory because a better trilateration helps to remove inconsistent hypotheses and, hence, it should provide faster convergence time. The evolution on the number of beacons hypotheses in the SLAM filter is shown in Figure 5 with and without active perception. It can be seen how the number of hypotheses converges to single faster with active perception, the average convergence time without active perception is 40s (since the landmark is discovered) while with active strategies it is reduced to 26s.

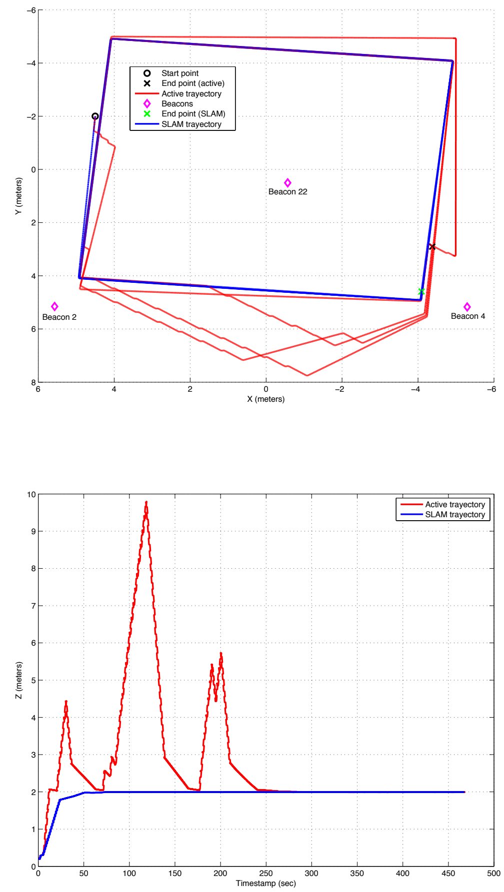

Fig. 3: UAV trajectory with (red) and without (blue) active perception. (Top) XY trajectory. (Bottom) Z trajectory

IV. CONCLUSIONS

Most of localization approaches do not take into account the possibility of controlling the robot to improve the perception, instead, the robot is just commanded with a predefined path. This paper has presented an active perception approach based on a loose coupling system used to fuse different robot behaviors. In this case the system is based on path tracking and exploration behaviors.

The active perception technique proposed in this paper is aimed to reduce the uncertainty of the map belief. The method is based on an action selection technique that uses the entropy of the SLAM belief to compute the estimated gain of information which turns out from each possible action. The set of actions considered in this approach are based on a fixed speed and a set of azimuth and elevation velocity angles between which the system must take a decision to reduce the map uncertainty.

In order to compute the gain of information, the system needs to compute the entropy of landmarks belief. However, this entropy is computationally inefficient for Gaussian Mixture distributions. For this reason, this paper proposes to use a upper bound of the entropy which is sufficient to select the action with a higher gain of information.

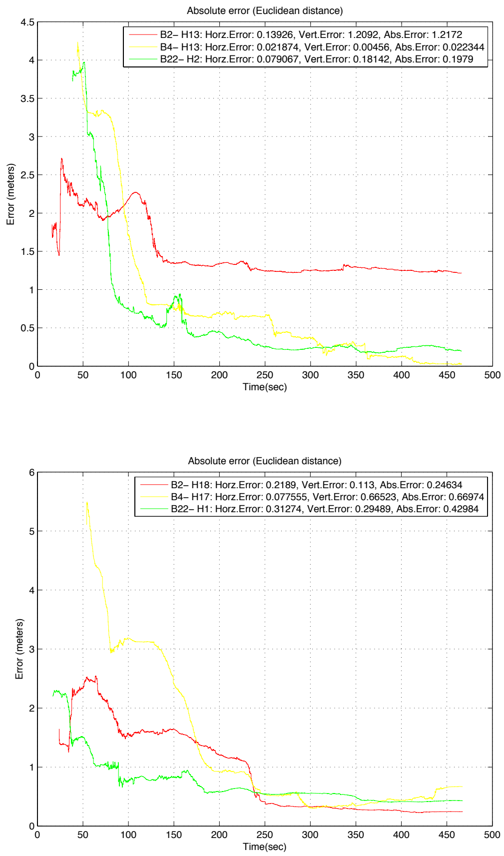

Fig. 4: Evolution of the absolute localization error of every sensor landmark in the experiment. (Top) Estimation without active perception (Bottom) Estimation with active perception.

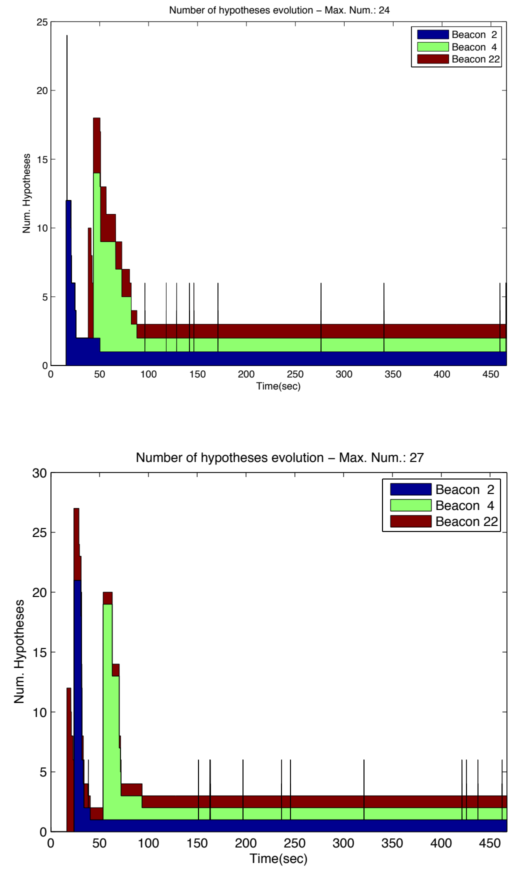

Fig. 5: Evolution of the total number of beacon hypotheses with time. Results converge to 3 (one hypothesis per beacon). (Top) Results without active sensing. (Bottom) Results with active sensing).

The paper ends showing simulation results of the method. These results proves how the system improves the convergence of hypotheses while at the same time allows to get a better accuracy in the mapping results.

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