NAVIGATION FOR AUTONOMOUS ROBOTS WITH ADAPTIVE INFORMATION-SEEKING

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ABSTRACT

Accurate location information is essential for autonomous robots since inaccurate localization can impede many robotic tasks or even lead to collisions. We investigate Fisher information theory as tool for assessing the quality of location information and making robots self-aware about their own location uncertainty. We further propose a navigation framework that exploits this location uncertainty for the motion control of the robot and aims for improving the mission performance while reducing location uncertainty. The framework enhances an artificial potential field (APF) controller by an adaptive information-seeking (IS) force towards areas with low spatial uncertainty.

***Index Terms*—** Cramér–Rao bound (CRB); localization uncertainty; artificial potential fields; navigation; robotic systems.

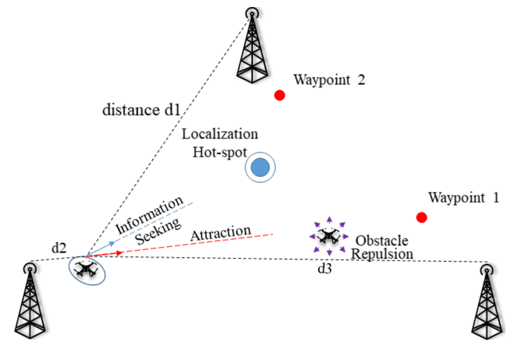

Fig. 1. Adaptive IS for robot localization and navigation. The robot can estimate its own location with some degree of uncertainty and moves towards mission waypoints by superimposing attractive, repulsive and IS forces.

1. INTRODUCTION

The availability of accurate location information is essential for many robotic applications, including autonomous navigation [1, 2], exploration [3] search and rescue [4]. Ubiquitous positioning persists as a research topic because robots are often called to operate in environments without Global Positioning System (GPS) coverage, have limited resources, and must deal with unreliable sensor data. A robot navigates in the environment according to various mission objectives (e.g., navigate to an area of interest, avoid collisions, cover unexplored areas). If not considered, localization estimation and mission objectives can become antagonists while simultaneously being interdependent, which can result in severe degradation of the system's performance. This gave rise to self-aware navigation [5], where mobile robots move towards mission waypoints while exploiting their gained knowledge about themselves and their environment.

Designing an online controller that is able to satisfy mission objectives and consider localization uncertainty is essential for robots [6]. The optimization of localization uncertainty has been approached previously in [7] by means of optimizing the rigidity of a network and in [8], where a distributed framework for Bayesian estimation and control with IS suitable for self-localization and target tracking has been introduced. Zhang et al. [3] developed a framework for multi-robot swarm planetary exploration where the robots of the swarm adjust their positions in such a way to optimize their self- and source- (i.e., subject of interest like a gas source) localization. While the benefit of utilizing a localization-aware controller is evident in multiple works, little or no mention at all has been made about the resource demands (e.g., additional travel distance) arising from such controllers. Furthermore, what transpires when addressing conflicts related to localization in the context of mission goals execution, and what measures can be taken to offset this effect?

In our previous work [9], we presented a localization-aware controller (IS-APF) based on the well-known artificial potential field (APF) path planner [10]. This controller works by superimposing three forces: the attractive force, which drives the robot toward mission waypoints, the repulsive force, which helps to avoid collisions along the paths, and the IS force, which accounts for moving towards areas with high localization accuracy. The relative orientation between the attractive and the IS force change during the mission resulting in settings where they counteract each other and hence significantly prolong the mission execution.

In this work, we introduce adaptive IS, where the weight for IS depends on the relative orientation between the two forces. More specifically, we (1) formulate three adaptive weighting schemes and show that they optimize location uncertainty corresponding to a fixed approach, (2) we show that the adaptive scheme is more resource-efficient as it requires far less computational steps per mission and consequently fewer range measurements to be performed, and (3) we empirically show that IS can increase the likelihood of mission completion as it can motivate robots to move within areas with sufficient coverage.

Figure 1 depicts location-aware navigation with adaptive IS. The robot moves towards mission waypoints along paths considering fast mission completion and high localization accuracy.

2. PROBLEM FORMULATION

Let us consider the navigation problem of N_a mobile robots that operate within a two-dimensional world $\mathbb{R}^2$ and whose positions are denoted by $p = [p_1^T, p_2^T, \ldots, p_{N_a}^T]^T \in \mathbb{R}^{2N_a}$ that we want to localize and control. The robots are part of a navigation system along with N_b so-called anchors $A = [p_1^T, p_2^T, \ldots, p_{N_b}^T]^T \in \mathbb{R}^{2N_b}$. We assume that the anchors know their accurate positions and that all nodes (robots or anchors) are perfectly synchronized and can receive distance information within the sensing range of an anchor.

Each robot i adheres to a simple motion model where it moves according to a control command u_i^k in a step-wise fashion

$$p_i^{k+1} = p_i^k + \mu \cdot u_i^k + \nu_i^k \tag{1}$$

with $k \in [1, \ldots, \kappa]$ being the time step, μ the step size and $\nu^k \sim N(0, \sigma_{tr}^2)$ the transition noise at time step k.

2.1. Localization

A robot aggregates range measurements between itself and the anchor nodes that are within the sensing range (i.e., $d_{ij} <= s_r$). Although various distance measurement techniques can be used, we estimate distances based on the time of arrival (TOA) of an RF signal from a transmitter to a receiver node. A range measurement $\hat{d}_{ij} = d_{ij} + n_{TOA_{ij}}$ is a result of additive white Gaussian noise (AWGN) $n_{TOA} \sim (0, \sigma_{TOA}^2)$ up to a distance d_0 after which we assume that the noise increases in a polynomial fashion [11] according to $\sigma_{TOA}^2 \cdot ((d_{ij}/d_0)^2 + 1)$ to approximate propagation effects. Given the anchor nodes within the sensing range of the robot (i.e., $\hat{d}_{ij} <= s_r$), a robot can estimate its location according to a weighted least squares localizer.

2.2. Localization-aware Navigation

Path planning is concerned with finding a collision-free and, according to the robot dynamics, a feasible path from its current location to a goal location. It is an essential capability of an autonomous navigation system and a thoroughly investigated topic [12]. Path planning algorithms typically aim for different objectives such as minimizing the path length, reducing the energy consumption, and increasing safety wrt. collisions. In this work, we investigate path planning from the perspective of minimizing location uncertainty since we assume that the robot can only estimate its own location with noisy distance measurements.

The Cramér–Rao bound (CRB) [13] is a well-known tool for assessing the performance of an unbiased estimator by identifying the theoretical lower bounds of the estimation with $CRB = F_p^{-1}$, where the Fisher information matrix (FIM) $F_p \in \mathbb{R}^{2N_a \times 2N_a}$ in non-collaborative localization is a block diagonal matrix composed of N_a two-by-two sub-matrices. The following inequality holds on the root mean square error (RMSE) of an estimation, also referred to as position error bound (PEB) [14] $RMSE(p) = \sqrt{\frac{1}{N_a}\mathbb{E}_{\hat{\boldsymbol{d}}}\{(\|\hat{p} - p\|^2\}} \geq \sqrt{\frac{1}{N_a} tr(F_p^{-1})}$, where $\hat{\boldsymbol{d}}$ is the vector representation of all ranging observations $\hat{d}_{ij}$ and $tr()$ represents the trace operator. Hence, the CRB allows a robot to be aware of the fundamental limits of its localization uncertainty at every time step k. The overall objective of our self-aware navigation framework is therefore to reduce this localization uncertainty by moving towards locations minimizing the CRB while improving the navigation performance. The objective of optimizing the localization uncertainty can be formulated as $\min_p tr(F_p^{-1})$. The navigation performance is measured by the steps required to complete the mission and the traveled path length.

3. ADAPTIVE IS-APF

We utilize the well-known online APF path planner, which is known for its simplicity and remarkable real-time performance, for controlling the robot. In APF control, the environment is modelled by attractive and repulsive potentials and the robot moves towards a mission waypoint following the superposition of the attractive force f_a and cumulative repulsive force f_{Tr} trying to minimize the potentials. We enhance the traditional APF control by IS as the third force f_{is} that accounts for optimizing the location uncertainty [9] which we calculate in the same manner for TOA range measurements.

3.1. Adaptation Heuristic

The inclusion of f_{is} in the controller of a robot results in increased mission steps (due to the counter-action with f_a). To compensate this effect, we propose three adaptive weighting schemes for the utilization of the IS force based on the angle ω between f_a and f_{is}.

In order to design a simple and effective weighting scheme we can focus on two parameters: the magnitude of the weight z_{is} and the adaptation threshold ω_t. For absolute angles below the threshold ($|\omega| \leq \omega_t$) IS should be weighted with a (constant) magnitude $z_{isa}(\omega) = z_{is}$. For larger absolute angles (i.e., $|\omega| > \omega_t$) the weight should decline such that IS does not interfere too strongly with navigation, i.e., moving along the attractive force. We propose three decaying schemes: (1) the cutoff, where f_{is} can be weighted with a percentage of z_{is} or completely disabled; (2) the linear decaying function and (3) the sinusoidal decaying function which was selected, as $sin()$ lessens naturally for angles that the forces counteract each other. The weighting functions defined for $|\omega| > \omega_t$:

$$z_{isa}(\omega) = \begin{cases} 0.0 & \text{if cutoff} \\ z_{is} \cdot (180 - |\omega|)/(180 - \omega_t) & \text{if linear} \\ z_{is} \cdot \sin(|\omega|) & \text{if sinusoidal} \end{cases} \tag{2}$$

The control command u_i of robot i is equal to the weighted sum of the effects of the individual forces

$$u_i = z_a f_{a,i} + z_r f_{Tr,i} + z_{isa}(\omega) f_{is,i} \tag{3}$$

with z_a, z_r being scaling factors.

4. SIMULATION STUDY

To assess the controller with the different weighting schemes we created three experimental scenarios (ES) consisting of fixed anchor constellations with a single or multiple robots acting. In the first ES we see a benefit of applying IS compared to a traditional APF controller. The second ES demonstrates the evolution of resources needed in terms of traveled distance and mission steps to complete a mission as we increase the effect of IS. In the third ES, we generalize our metrics over multiple randomly generated missions in a two-robot scenario.

We evaluate the controller and the proposed adaptive weighting schemes with the help of a simulation environment developed in Python. A simulation is initialized by setting the robot, anchor and waypoint locations in a manual or random fashion. We use the following simulation parameters, $z_a = 1.0$, $z_r = 20.0$, the influence range of the repulsive potential $\eta_{thres} = 3.0\,\text{m}$, $\mu = 0.2$, $g_{thres} = 0.10\,\text{m}$ which is the minimum required distance to consider the agent has reached a waypoint/goal, and $\sigma_{tr} = \pm 0.01\,\text{m}$. The sensing range of the agent is set to 30 m, with range measurement standard deviation $\sigma_{TOA} = \pm 0.10\,\text{m}$, $d_0 = 15\,\text{m}$, and $K = 2$. The simulation terminates when all robots have completed their mission successfully or the maximum number of simulation steps has exceeded ($max_{steps} > 10.000$).

We evaluate the controller on the different ES for fixed z_{is} and adaptive z_{isa} IS weights and compare the proposed weighting IS approaches with traditional APF and each another. We measure the performance of the controllers in terms of (1) the traveled distance for solving the navigation problem (path length among the waypoints), (2) the aggregated spatial uncertainty (average RMSE of localization over the duration of the mission), and (3) the steps required to complete the mission (MS). The RMSE for a robot at step k is given by $RMSE^k = \sqrt{\frac{\sum_{i=1}^{100} \|\hat{p}_i{}^k - p^k\|^2}{100}}$.

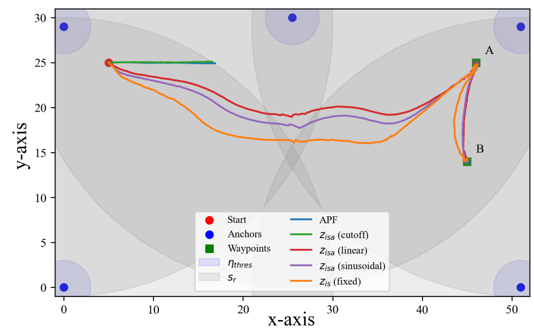

Fig. 2. Example mission scenario where a robot has to operate in an environment with sparse sensing coverage.

Fig. 2 depicts a constellation composed of five anchor nodes resulting in a sparse sensing coverage. In this ES we highlight the effectiveness of self-aware navigation, i.e., that IS aims to reduce the spatial uncertainty of the robot and navigates the robot through well covered areas (within the sensing range of at least 3 anchors) to the goal waypoint B. We set $z_{is} = 0.8$ and run the mission for every weighting scheme 100 times evaluating the controller on position estimates (one-shot approach). The robot with a traditional APF controller and the robot running the adaptive cutoff weighting scheme due to its setup (i.e., $\omega = 90°$ and cutoff weight for angles $\omega_t > 90°$ equal to 0.0) navigates to an area with insufficient sensing coverage and cannot complete their mission successfully as the first one is completely unaware of its localization uncertainty and the latter one does not make use of the IS force field. On the other hand, the robots running the remaining weighting schemes (i.e., linear, sinusoidal and fixed), all finalize their missions successfully with the one running the fixed weighting scheme (Fig. 2 orange) achieving the best mission RMSE (0.21 m) and the robot with the linear weighting scheme (red) achieving the smallest required distance (59.56 m) and computational steps (296). The implemented weighting schemes overcome the competing forces problem successfully which is evident by the decrease in the necessary steps to complete the mission between the linear and sinusoidal (318 steps) against the fixed (799 steps) scheme in the cost of aggregated localization accuracy. The requirement for fine tuning potential based controllers persists since the robot running the cutoff scheme could have finalized the mission if we increase ω_t and/or the cutoff weight.

In the second ES (see Fig. 3), we analyse the effect of applying IS on the mission steps, distance and localization, while varying weights $z_{is} \in \{0.0, \ldots, 0.9\}$ and evaluate the controller performance in nominal conditions (i.e., true robot locations). Starting from waypoint A, the robot has to move along the waypoints B, C, D and return to waypoint A to finalize its mission. Fig. 3 (left) shows the trajectories generated

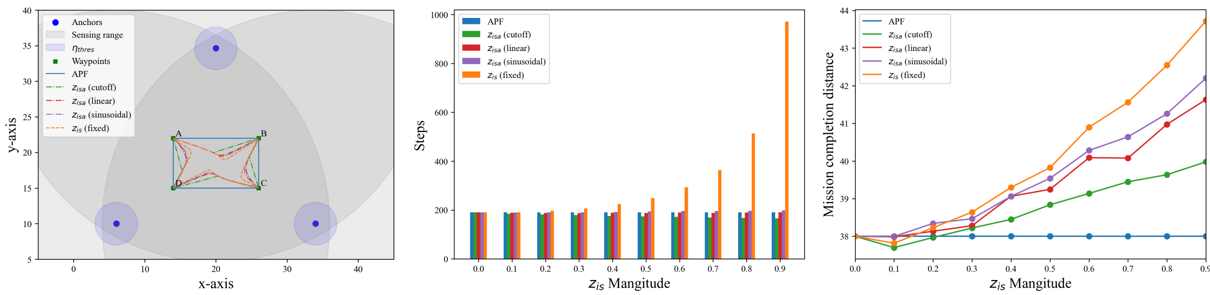

Fig. 3. ES 2 comparison of the generated trajectories (left) for $z_{is} = 0.9$. Steps (middle) and mission distance increment (right) by varying z_{is} for all weighting schemes.

by the different controller settings. As we can see in Fig. 3 (middle), the required computation steps for the mission drastically increase with increasing weight of fixed IS (orange color). On the one hand, this is caused by the increased path length of the missions due to the induced curvatures in the trajectories (see Fig. 3 (right)). On the other hand, the two forces f_a and f_{is} oppose each other for comparable weights and large angles. We can clearly see that the adaptive weighting schemes succeed in mitigating this counteraction of the forces, especially for larger values of z_{is}. Furthermore, since the robot has to perform pair-wise range measurements with the anchors at every time step, the adaptive schemes prove to be more resource-efficient than the fixed scheme. We observe that effect of IS is stronger in cases where the agent has to move close to the "edge" of the coverage area like in the sparse coverage mission scenario. Finally, the best overall mission RMSE was achieved for $z_{is} = .9$ by the linear and sinusoidal controllers with approx. 4.4% improvement against traditional APF, whereas the cutoff and fixed weighting schemes achieved 3% and 3.8%.

In the third ES, we generalize the performance of the controller over multiple randomly generated missions. We assessed their behavior in a setup consisting of two robots in a larger fully covered area (approx. $2800\,\mathrm{m}^2$) created by placing an anchor in the middle and six more anchors on the perimeter of its sensing range. The resulting sensing constellation is mainly composed of areas covered by three or four anchor nodes which change drastically the IS field. We evaluated the controller performance with ten randomly generated missions performed 100 times. In every mission, each of the robots starts on the left and right side of the coverage area and has to pass from three randomly placed waypoints. A mission is terminated when both of the robots have completed their individual assignment. The controllers are evaluated on position estimates with $z_{is} = 0.9$ for all the IS weighting schemes.

In order to generalize the metrics for the performance of the controllers we normalize the recorded metrics with respect to traditional APF and calculate the average percentages over the missions. In particular, IS with the sinusoidal weighting scheme achieves the best improvement on mission average RMSE by 3.13% in comparison to traditional APF. While the the cutoff weighting scheme reduces by 11.44% the required MS as the robot "accelerates" towards the waypoint locations when $\angle(f_a, f_{is})$ for angles $|\omega| \leq \omega_t$ and moves according to traditional APF for larger angles. Out of all the weighting schemes the cutoff shows the least average mission distance increment with 7.97%. The combination of inaccurate range measurements and interaction of the two forces produce oscillations around the mission waypoints which can be clearly seen by the increased average computational steps (388.9%) and mission distance (68.4%) metrics of the fixed weighting scheme. Moreover, we observed that the inclusion of IS in multi-robot scenarios can lead to the robots being trapped at local minima as irrespectively of the missions the localization hot-spots are the same.

5. CONCLUSION

In this work, we have considered the path planning problem for autonomous robotic systems from the perspective of optimizing spatial uncertainty. We have introduced three adaptive weight schemes for IS and demonstrated that they optimize the spatial uncertainty for robots comparably to a fixed approach and can significantly reduce the required steps and hence the required resources for mission completion. IS makes the controller suitable for scenarios with limited sensing coverage of the anchor nodes where the robots have to rely on relative distance measurements and information exchange to determine their positions accurately [15].

Our experimental study investigated static anchor constellations. A natural extension is to assess dynamic multi-robot navigation scenarios where distance information to other robots can be additionally exploited for navigation. Finally, we plan to assess the effectiveness of the controller on different estimation technologies with more realistic world assumptions and implement the controller on a real robotic system, to evaluate its effectiveness and validate the obtained simulation results.

6. REFERENCES

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