Towards A Generic Framework for Experience-driven Next-best-view Planning

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I. Introduction

Active perception aims at generating motion plans that also attempts to fulfill a perception objective. In this work we would like to answer one basic question which is: with limited field of view (FOV) sensors, how should a robot learn where to look such that it can best perform its objectives?

Initially, Perception and Motion Planning problems were being solved independently. However, recent trends suggest an increased interest in solving the two problems combined with a tighter integration for better performance. Some of the most popular works in active vision are [1]–[7]. However, these approaches are supervised in a sense that they explicitly define the perception objective to be fulfilled in the motion plan. We intend to formulate a generic framework that solves a wide range of active perception problems, without explicitly defining perception goals (features, information gain metrics). For instance, suppose a ground robot needs to perform multiple objectives like localization, obstacle detection and exploration using only a single camera mounted on a gimbal. Our framework would allow the user to append modules for each objective while the framework would attempt to point the camera towards areas which decrease localization uncertainty, look for nearby obstacles or look towards unexplored areas depending upon the confidence required for each objective. The user does not have to specify that looking towards textured regions decrease localization uncertainty, rather the robot would learn this relation from observations. This is particularly helpful when we send robots to remote and diverse areas with multiple perception modules for it to choose the best.

II. Learning Where to Look

Take for instance a single objective Active Perception problem. A robot is required to perform waypoint navigation and the user is using April-tag based localization fused with IMU such that when the April-tag is in view, the uncertainty decreases while it can still perform IMU based dead-reckoning at the expense of location certainty. Fig. 1a shows an example area. Let $\mathbf{x} = [x, y, h]$, $\mathbf{x} \in \mathcal{C}$ denote the robot state in configuration space $\mathcal{C}$, where x, y are its 2D location and h denote heading orientation of the camera sensor. The goal of the framework is to realize that localization uncertainty reduces when it looks towards one of the April-tags and it should actively point the camera towards one of them in upcoming waypoints based on this realization.

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Let $f(\mathbf{x}) : \mathcal{C} \rightarrow [0, 1]$ denote a function that scores a robot configuration based on high-level perception quality; for instance a configuration that leads to less localization uncertainity would have higher score. We model f as a Gaussian Process such that with given observations $D_n = \{(x_1, f_)), (x_2, f_2), \ldots, (x_n, f_n)\}$, we can predict f_* for any robot state x_* by regression using a standard smoothing prior. Employing [8], with fixed-window provies an efficient recursive method to solve this GP.

Now I employ a modified Bayesian Optimization algorithm to determine h_t orientation where the robot should point its camera while at location x_k, y_k at time instance t

$$h_t = \arg\max_h U(h|D_{t-1}, x_k, y_k) \quad (1)$$

where U denotes a utility function for the Bayesian Optimization. We used Expected Improvement EI given as

$$EI(\mathbf{x}) = \begin{cases} (\mu(\mathbf{x}) - \mu^+ - \xi)\Phi(z) + \sigma(\mathbf{x})\phi(z), & \text{if } \sigma(\mathbf{x}) > 0 \\ 0, & \text{if } \sigma(\mathbf{x}) = 0 \end{cases}$$

where $z = \frac{\mu(\mathbf{x}) - \mu^+ - \xi}{\sigma(\mathbf{x})}$, μ^+ is the maximum observed score, ξ is a free parameter, Φ denotes CDF and ϕ denotes PDF.

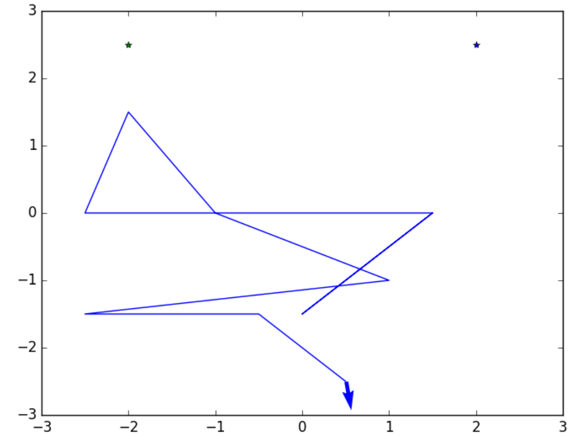
We predict f_* for all the waypoints and for 35 angles ($360°$ range, $10°$ apart) in each waypoint. At the first waypoint the camera samples at three headings: $-180°, 0°$ and $179°$ and then continues with the Bayesian Optimization until convergence for each waypoint. The convergence criteria at location x, y is $\max f(h|x, y) > \epsilon_c$, where ϵ_c determines the quality level for perception and $\arg\max f(h|x, y)$ gives the best orientation for desired perception quality.

III. Experimental Results

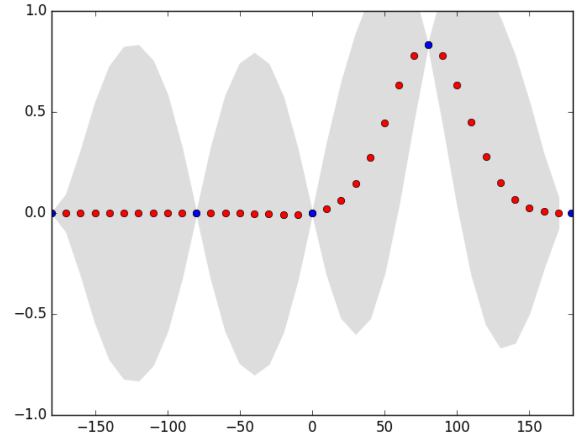
Performed 100 Monte-Carlo simulations in a sample arena Fig. 1a with randomly generated waypoints and April tags at $(2.0, 2.5)$ and $(-2.0, 2.5)$. The robot learned to point the camera towards one of the April-tags and the average Bayesian Inference sampling ratio was 0.8. A ratio less than 1 means that at some waypoints, the framework had already predicted the best orientation angle before reaching it.

IV. Conclusion And Proposed Future Work

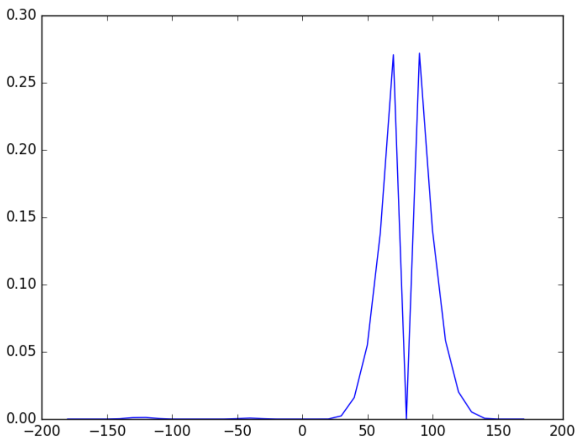
The robot learned that it needs to look towards the April-tags without supervision and just by observing perception quality. The framework provides promising scopes to add multiple objectives while ensuring convergence to the desired quality for each. However, currently, the score function $f(\mathbf{x})$ does not explicitly reason for position of interest point $\mathbf{p}$ (April-tags). Thus, determining the latent function $f(\mathbf{x}, \mathbf{p})$ provides a challenging future prospect.



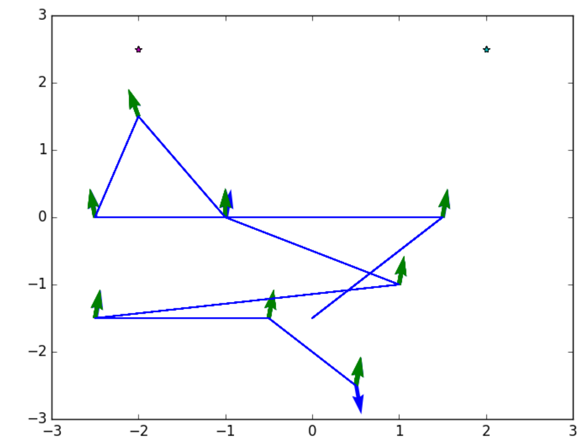
(a)



(b)



(c)



(d)

Fig. 1: (**a**): Sample simulation arena with waypoint path (Blue) and April-Tag locations (Star). (**b**): Example of score function $f(h|x, y)$ at a particular x, y position. Red points denote predicted scores, while Blue points denote sampled scores. Grey region denote 3σ confidence bound. (**c**): Utility function for score function in (b). Notice that since $\max f(h|x, y) < 0.7$ convergence is not reached and Bayesian Optimization suggests sampling in the peaks of the utility function on each side in hopes of reaching convergence. (**d**): After waypoint navigation. Best heading orientation found for the camera at each location (Green arrow). Sampled camera orientations at each location (Blue arrow). Notice that it does not require much samples to learn that the robot needs to point towards one of these april-tags to maximize its score. It is a problem of exploration vs exploitation. At the lowest waypoint in Y-axis, it is evident that the robot sampled away from the april-tags in order to explore other regions. A FOV of 40° was used in the simulations.

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