Perception Model for Mobile Robots Assisting Humans in Decision-Making during Complex Situations

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Abstract

Perception, the process of comprehending and deriving meaning from one's surroundings, is fundamental to human decision-making. In this context, we explore the development of a robust perception model designed for mobile robots to facilitate effective human-robot communication and decision-making in dynamic and intricate scenarios. Achieving localization without GPS in a network of roads using stratified sequential importance sampling where the stratification levels are based on semantic object spaces in the map and on the running time, we articulate and describe the proposed development and experimentation environment, demonstrating the potential of our perception model.

Introduction

A multi-modal interactive service and rescue robot capable of communicating with humans in complex environments is our aim where localization and perception in a complex situation is an essential step. Robotics perception is the making sense of an unstructured real world, where incomplete knowledge of objects and scenes may lead to imperfect actions and ultimate failures. Making contact with the physical world through multi-modal senses (Lafuente-Arroyo et al. 2024) and completing desired tasks in a human-robot teaming is our ultimate goal.

We present a novel semantic localization (Martínez-Gómez et al. 2016) framework for robots without GPS in a multi-road map. Particle filtering is the common approach for many types of localization, but tuning parameters for achieving high quality results can be complex in certain applications. The new framework is supported with a benchmark generator including an environmental feature generator and stratified sequential importance sampling (SIS) based particle filter localizer where the stratification levels are based on semantic object spaces on the map and on the running time.

Benchmark Generator

An experiment was designed based on a dedicated simulator and a set of randomly generated benchmarks in a symbolic space. As such, first a space of symbolic semantic maps (Chen, Li, and Zhang 2023; Dube et al. 2020) was selected for the experiment. Each semantic map consists of a road graph from which one path is selected as the planned trajectory of the robot. The spatial size associated with the observability of each map object ω is denoted $|\omega|$, and is generated from a uniform distribution $X \sim U(\omega_{min}, \omega_{max})$, and the object types come from a symbolic space Ω. A set of such benchmark maps is created using a contiguous sequence of seeds for the Knuth's linear congruential pseudo-random number generator (Knuth 2014).

Observation Histories Under the assumption that the robots will use standardized sensors, and also assuming a fixed trajectory history up to the point of decision, the benchmarks also contain logs of observation histories. A bounded space Γ of symbolic observations is selected allowing for a controlled amount of confusion between the map objects. Confusion is parameterized by a coefficient γ. Observations are assumed to be drawn from a known mixture distribution obtained by combining three uniform distributions with standard deviation correlated to γ. The obtained confusion amount is related to the boundness of the feature space.

$$U(\mu-\gamma, \mu+\gamma)P_1 + U(\mu-2\gamma, \mu+2\gamma)P_2 + U(\Gamma)(1-P_1-P_2)$$

where in tests, $P_1 = 0.75$ and $P_2 = 0.175$, and μ is randomly associated with the objects at the current location in the semantic map space Ω, uniformly distributed in Γ.

For each benchmark, the generator produces a prefix of the selected path with potential deviations into the rest of the road graph, and a history $\mathcal{H}$ of observations produced based on the aforementioned generative model, to an intermediary point obtained according to a specification λ, point which may or may not be on the selected path in the map.

The localization in each benchmark map is performed with our dedicated simulator that uses a particle filter fed with the observations $\mathcal{H}$ in the benchmark, and hypothesising into the states $\mathcal{S}$ defined by the map. $\mathcal{S}$ is discrete, where $|\mathcal{S}|$ is variable but bounded by the size of the Cartesian product of semantic objects and past running time steps.

Particle Filter Parameters

The Particle Filter simulator assumes that the observation emission probability distribution function is as described above, and uses it to weight samples. The transition probability from state ω to adjacent state ω' on the map is based on state proximity on the map and on the duration of travel, according to a bounded linear distribution $X \sim L(0, \sigma|\omega|)$, with inflection point at $|\omega|$, scaled with parameters σ, tuned as described in subsequent test graphs. The transition probability distribution is one of the most sensitive factors in the stability of the results.

Resampling is based on stratified sequential importance sampling where the stratification levels are based on semantic object spaces in the map and on the running time. Also, a probability mass redistribution to unpopulated states is performed, accounting for 0.0001% of the total probability mass and including at least one particle per state.

Objects	Target	Particles	Error	Seeds
50	25	1000	0	89
			1	9
			2	1
			offroad	1
	35	1000	0	92
			1	6
			2	1
			offroad	1
	45	1000	0	90
			1	7
			2,3	2
			offroad	1
50	25	100	0	89
			1	9
			2	1
			offroad	1
	35	100	0	88
			1	9
			2	1
			offroad	1
	45	100	0	89
			1	8
			2,10,34	3
1000	700	100	0	75
			1	8
			7	2
			67-292	6
			offroad	9
	900	100	0	74
			1	11
			7	2
			2-704	5
			offroad	10

Table 1: Results on benchmarks by history duration. For each seed, a separate benchmark was generated. The last column specifies the number of seeds (benchmarks) with the same results. The column Error shows the displacement from target in state space.

Results As shown by the preliminary results in the tables 2 and 3, the performance is very sensitive to transition probabilities. The observation probability model is also important but when the transition model is good, the sensitivity to the observation model is reduced. The behavior was also tested with millions of particles where the performance was not significantly modified but the execution of our simulation implementation took several seconds per benchmark. The performance only slowly decreases with the increase in the number of objects in the semantic map.

When the localization algorithm decided that it arrived at a point in the map that was not on the actual trajectory, the situation is described in tables as *offroad*. With much bigger maps, the outliers can be far away from the actual trajectory.

Objects	Target	Particles	σ	Error	Seeds
1000	900	100	1	0	74
				1	11
				7	2
				2-704	5
				offroad	10
	900	100	1.5	0	73
				1	17
				201-863	5
				offroad	6
	900	100	2	0	53
				1	16
				48-712	12
				offroad	19

Table 2: Results by transition distribution.

Objects	Target	Particles	Features	Error	Seeds
50	35	100	4	0	88
				1	9
				2	1
				offroad	1
	35	100	10	0	87
				1	10
				9,11	2
				offroad	1
	35	100	20	0	69
				1	28
				2,4,11	3

Table 3: Results by standard deviation of acuity distributions.

Conclusion

A motivating problem is introduced including perception by sensor fusion for localization in networks of roads without GPS. An abstract framework is developed for formalizing this problem enabling the construction of benchmarks and objectively comparable algorithms. Benchmark generators and a baseline solution are provided to open the way for a principled and scientific approach of the problem by the community. Results evaluated according to a proposed performance metric for the baseline solution are provided and shown to launch a competitive area where significant quantifiable improvements are possible in future research.

References

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