Towards Optimal Correlational Object Search

Kaiyu Zheng[1], Rohan Chitnis[2], Yoonchang Sung[2], George Konidaris[1], Stefanie Tellex[1]

[1]Brown University *(Department of Computer Science)* [2]MIT (*Computer Science & Artificial Intelligence Laboratory)*

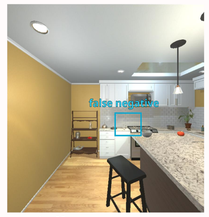
Email correspondence: kaiyu_zheng@brown.edu

International Conference on Robotics and Automation (ICRA) 2022

Motivation

Challenge: Unreliable detection

Target Object



Opportunity: Easier-to-detect, *spatially correlated* objects

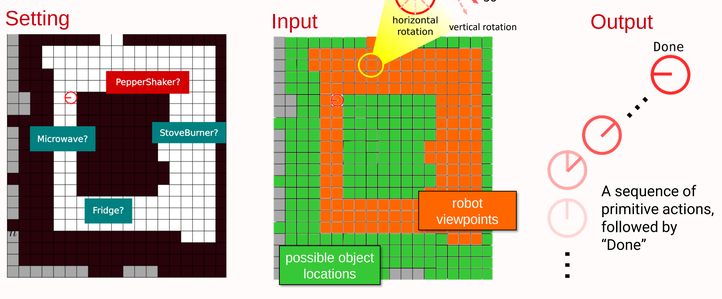
Question: How to leverage **spatial correlation** with **easier-to-detect objects** to *successfully and efficiently* **find hard-to-detect objects** in a **principled manner**?

Contributions

1. Formulate **Correlational object search as a planning problem**
2. Introduce **Correlational Object Search POMDP (COS-POMDP).** It avoids maintaining belief over all objects while **preserving optimal solution**.
3. Propose a **hierarchical planning algorithm** to apply COS-POMDP to practical domains
4. Evaluate in AI2-THOR, a realistic simulator of household environments, with YOLOv5 as the object detector. **Results show that COS-POMDP leads to more robust search perfomance for target objects that are hard-to-detect when the given correlational information is accurate,**

Correlational Object Search

Object locations are ***unknown*** yet follow a **(latent)** ***joint probability distribution***. The robot has access to a set of factored distributions (**correlation models**) and receive noisy observations through on-board object detector (**detection models**)



Objective:

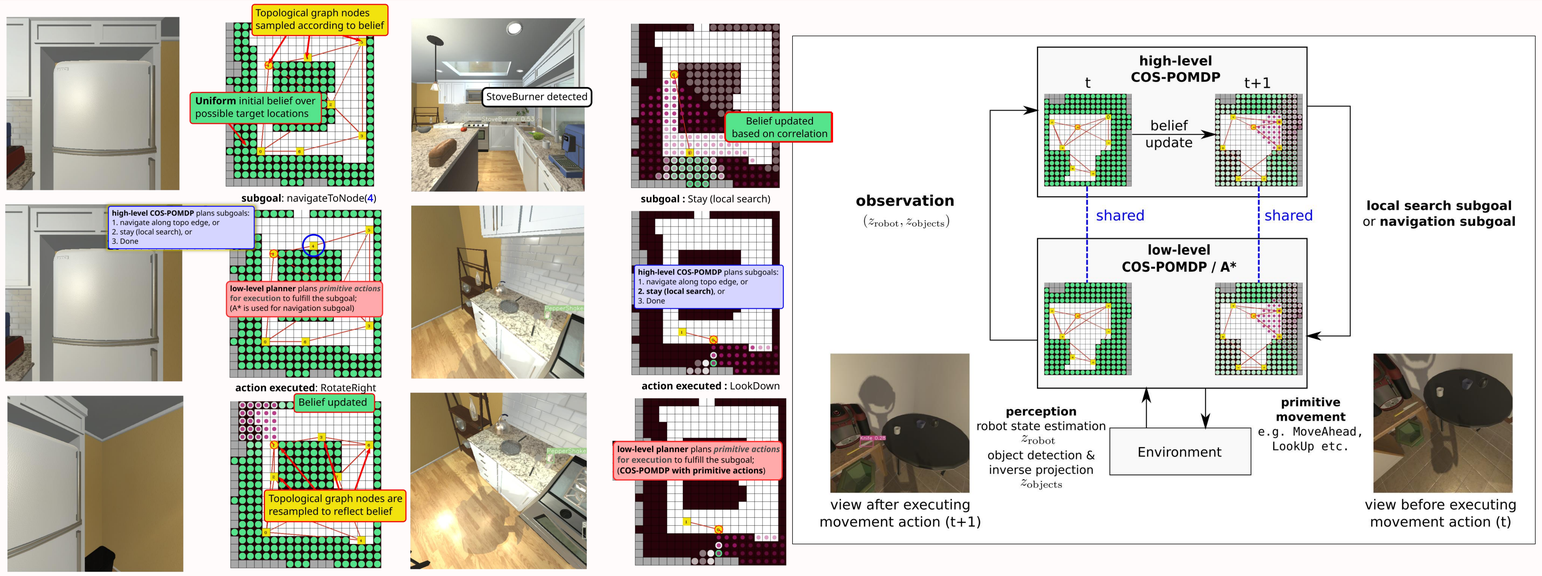
- **Success**: at the time of "Done" the robot is within 1.0m from the target and the target is visible within the camera frame
- **Efficiency:** Minimize the distance traveled to find the target

COS-POMDP

Motivation (Intractable belief state)
Object locations follow joint distribution → Joint state space of all objects → Belief space grows ***exponentially*** as number of objects increases

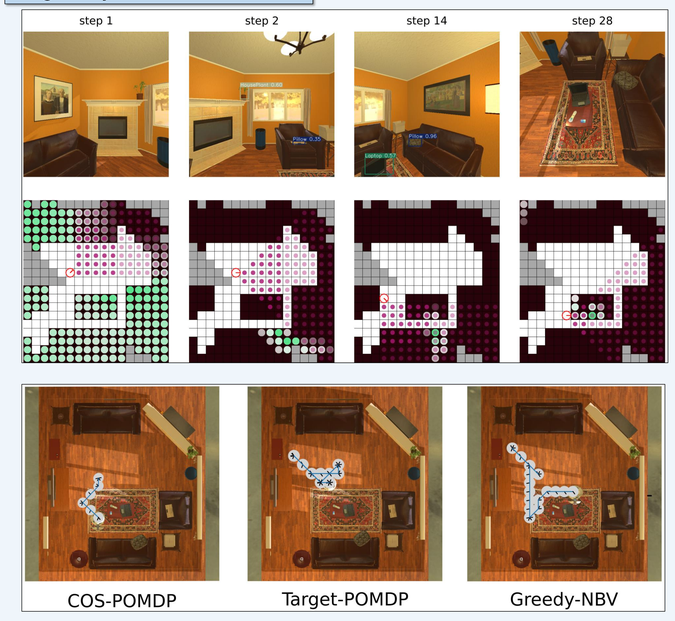
COS-POMDP: State space contains only robot & target states **(cheaper belief state);** Object observations → **correlational observation model**
Theorem (roughly)**:** COS-POMDP preserves the optimal policy compared to a corresponding POMDP that requires modeling the full belief state.

Hierarchical Planning for COS-POMDP



Experiments & Results

Target object: **CreditCard**



Method	Bathroom SPL (%)	Bathroom DR	Bathroom SR (%)	Bedroom SPL (%)	Bedroom DR	Bedroom SR (%)	Kitchen SPL (%)	Kitchen DR	Kitchen SR (%)	Living room SPL (%)	Living room DR	Living room SR (%)
Random	0.00 (0.00)	-82.75 (3.43)	0.00	0.00 (0.00)	-81.51 (3.33)	0.00	6.90 (9.81)	-68.51 (15.61)	6.90	0.00 (0.00)	-82.37 (3.62)	0.00
Greedy-NBV	14.34 (9.12)	-19.86 (11.87)	34.48	16.92 (11.70)	-17.52 (7.32)	26.67	11.61 (8.72)	-17.60 (12.41)	31.03	7.13 (7.11)	-21.41 (8.21)	20.00
Target-POMDP	19.88 (9.47)	**-7.37 (12.42)**	**55.17**	19.79 (12.81)	-20.79 (11.29)	26.67	13.80 (8.67)	-20.17 (12.83)	34.48	24.36 (13.28)	-33.58 (11.88)	40.00
COS-POMDP	**30.64 (12.73)**	-14.48 (11.58)	**55.17**	**24.76 (12.95)**	**-15.57 (9.16)**	**40.00**	**20.45 (12.00)**	**-6.55 (12.73)**	**41.38**	**24.99 (13.95)**	**-14.08 (14.22)**	**43.33**
COS-POMDP (gt)	**31.08 (13.31)**	-13.47 (12.67)	**58.62**	**26.67 (13.13)**	**-11.09 (12.07)**	40.00	**35.58 (13.30)**	**-2.75 (14.37)**	**62.07**	**32.88 (14.25)**	**-13.81 (13.22)**	**56.67**
COS-POMDP (lrn)	17.20 (10.21)	-20.96 (10.75)	41.38	16.78 (11.68)	-31.60 (10.05)	30.00	8.39 (7.94)	-31.36 (13.42)	20.69	14.07 (10.65)	-43.76 (13.30)	26.67
COS-POMDP (wrg)	11.89 (8.14)	-16.55 (10.23)	27.59	14.70 (10.92)	-17.33 (8.38)	23.33	10.51 (8.02)	-20.68 (10.40)	27.59	**31.41 (14.50)**	-15.94 (9.45)	**53.33**

Room Type	Target Class	TP	FP	r (m)	Greedy-NBV SPL (%)	Greedy-NBV DR	Greedy-NBV SR (%)	Target-POMDP SPL (%)	Target-POMDP DR	Target-POMDP SR (%)	COS-POMDP SPL (%)	COS-POMDP DR	COS-POMDP SR (%)
Bathroom	Faucet	56.1	8.0	2.16	28.31 (19.58)	0.73 (22.10)	**70.00**	34.67 (22.86)	**8.00 (24.67)**	**70.00**	28.18 (27.25)	-23.27 (24.36)	50.00
	Candle	29.4	2.4	1.81	12.52 (20.12)	-22.81 (20.80)	22.22	16.56 (13.36)	-7.98 (28.99)	66.67	33.89 (21.83)	**-2.94 (19.08)**	66.67
	ScrubBrush	64.3	9.9	1.71	2.00 (4.52)	-37.79 (17.36)	10.00	8.09 (10.79)	-22.18 (13.51)	30.00	**30.18 (25.78)**	**-16.07 (22.13)**	**50.00**
Bedroom	AlarmClock	79.6	7.4	2.77	**39.49 (31.18)**	**-5.54 (18.07)**	**50.00**	14.31 (22.01)	-23.78 (14.43)	20.00	31.57 (30.85)	-15.85 (21.03)	40.00
	Book	62.6	4.9	2.05	8.42 (12.72)	-20.10 (11.71)	20.00	**29.70 (28.85)**	-13.94 (27.69)	40.00	25.92 (22.50)	**-12.56 (16.69)**	**50.00**
	CellPhone	50.0	3.9	1.69	2.85 (6.44)	-26.91 (5.88)	10.00	15.36 (23.21)	-24.64 (22.20)	20.00	**16.80 (21.48)**	**-18.29 (16.16)**	**30.00**
Kitchen	Bowl	60.6	11.5	1.75	19.88 (26.57)	-15.76 (32.76)	33.33	16.33 (16.00)	-10.06 (27.39)	**55.56**	**20.37 (20.70)**	**-3.33 (27.27)**	44.44
	Knife	37.7	8.7	1.68	7.40 (11.42)	-18.94 (23.71)	30.00	4.62 (10.45)	-36.36 (15.51)	10.00	**23.97 (25.58)**	**-2.59 (25.33)**	**50.00**
	PepperShaker	38.1	9.4	1.43	8.39 (10.53)	-17.90 (17.39)	30.00	**20.69 (21.03)**	**-13.07 (27.64)**	**40.00**	17.01 (24.19)	-13.41 (22.95)	30.00
Living room	Television	85.3	5.2	2.59	8.98 (18.36)	-22.86 (13.31)	20.00	**53.60 (26.06)**	**-8.63 (17.97)**	**80.00**	40.08 (32.14)	-12.22 (28.08)	50.00
	RemoteControl	69.6	4.5	1.93	9.24 (13.99)	-13.21 (20.44)	30.00	18.67 (24.17)	-38.38 (18.29)	30.00	**30.14 (28.99)**	**5.81 (25.29)**	**60.00**
	CreditCard	42.9	4.3	1.48	3.18 (7.19)	-28.15 (11.70)	10.00	0.82 (1.85)	-53.73 (20.32)	10.00	**4.74 (7.19)**	-35.84 (21.62)	**20.00**

TABLE II: **Detection Statistics and Object Search Results Grouped by Target Classes.** TP: true positive rate (%); FP: false positive rate (%); r: average distance to the true positive detections (m). We estimated these values by running the vision detector at 30 random camera poses per validation scene. Target objects are sorted by average detection range. Parentheses contain 95% confidence interval. Metrics are success weighted by inverse path length (SPL) [18], discounted cumulative reward (DR), and success rate (SR). *COS-POMDP* performs more robustly for hard-to-detect objects, such as `ScrubBrush`, `CD`, `Candle`, `Knife`, and `CreditCard`.

For target objects with **a true positive (TP) detection rate below 40%,** COS-POMDP improves the POMDP baseline that ignores correlational information by **42.1%** in terms of the SPL metric *($p = 0.028$)*, and it is more than **2.1 times better** than the greedy baseline *($p = 0.023$)*. Both results are **statistically significant**.