Research Statement

Joydeep Biswas – University of Texas at Austin

Overview

We are approaching the golden era of robotics — we are finally starting to see robots in the real world, at homes, in hospitals, and on sidewalks. It may be tempting to declare victory, but in fact under the veneer of seemingly "solved problems" lies a host of challenges still unsolved by the state of the art. Under nominal circumstances, a home robot may exhibit precise navigation, but moving the couch around, or even dropping a few unfortunately placed backpacks is sufficient to confuse the robot about its location in the world, and waylay its ability to navigate to the kitchen. A delivery robot may be fully capable of robustly traversing a clearly marked sidewalk on a well-lit sunny day, but ask it to deliver a package in the rain while navigating amidst puddles and slick sidewalks, or following a winding and unmarked gravel driveway to a customer's door, and it may get stuck, slide off the sidewalk, or perhaps even trample the customer's precious petunias in its zeal to get straight to the door. Finally, ask anyone with a robot vacuum how often they've wished they could just stop and give a few corrective demonstrations to their robot getting stuck when navigating around that one armchair for the umpteenth time, and we start to see the real limitations of the state of the art in service mobile robots.

Notably, all the aforementioned limitations are of *robot mobility* — understanding enough of the world to plan how to move around and perform tasks robustly and accurately, not just for short one-off deployments, but continually over days, weeks, and years. My research is focussed on addressing the limitations of long-term robot mobility to enable a future of capable, robust, and frustration-free service mobile robots. Specifically, I am interested in investigating four sub-problems of long-term robot mobility:

1. **Long-term localization and mapping**: how can robots reason about the world and estimate their location, despite inevitable changes over time?
2. **Introspective perception for competence-aware mobility**: how can robots identify unanticipated failures of their perception algorithms, and learn to overcome them?
3. **Learning for terrain-aware navigation**: how can robots reason about types of terrain for mobility, and learn to drive accurately no matter what the terrain?
4. **Program synthesis and repair for end-user customizability**: how can end-users provide minimal corrections and demonstrations to correct robot behaviors in a transparent and user-friendly manner?

I also strongly believe that it is essential to deploy fully integrated service mobile robots, even research robots, *in the real world*, to ensure that we are solving the real problems, and to make sure that we are making real progress. To this end, we actually "dogfood" our own robots — we deploy them to escort visitors, deliver mail across campus, and in general support a rich set of applications research among a wide set of users, such as testing campus-scale autonomous robot delivery during the COVID shutdown of 2021 [1].

The rest of this document describes my research while focusing on a few selected works central to the overarching research agenda. Over the course of my research, I have investigated a number of interesting side-problems relevant to specific projects; for a complete listing of my publications please see my CV.

Real-world autonomous deployments of our robots at UT-Austin: The CoBot, Jackal, and Spot.

Long-Term Localization and Mapping

There are two key challenges to long-term localization and mapping: how can we represent maps that are robust to changes, and how can we factorize probabilistic inference to account for unexpected observations?

My early research focussed on vector map representations for 2D [2] and 3D [3]; localization using various sensors including WiFi [4], LIDAR [2, 5, 6] and depth cameras [7, 3]; and reasoning about sensor-specific limitations for localization [8]. To tackle the problem of probabilistic inference in changing environments, I introduced Episodic non-Markov Localization (EnML) [5, 6] to explicitly reason about correlations between unmapped observations while simultaneously exploiting partial observations from a long-term map. At run-time, EnML performs probabilistic inference as to whether observations are of long-term static objects (such as architectural features), short-term static objects (such as chairs and parked cars), or dynamic objects (such as pedestrians and bicyclists). EnML allowed us to extensively deploy the CMU CoBots for more than $1,000$km [9] autonomously, and more recently the UMass Campus Jackal and the UT Jackal, Husky, and Spot at the campus scale, without requiring detailed up-to-date maps of the world.

Localization using probabilistic object maps accurately places observed parked cars (yellow) at parking spots (satellite image for reference).

More recently, we have been re-thinking the localization and mapping problem – what if a robot could reason about the world in terms of semantically meaningful entities instead of the low-level features such as points, or visual descriptors used in the current state of the art? Furthermore, what if instead of reasoning about the world in terms of *static objects*, it only leveraged *probabilistic distributions of movable objects*? As a step in this direction, we introduced probabilistic object maps (POMs) [10], which represent the distributions of movable objects using pose-likelihood sample pairs derived from prior trajectories through the environment. We empirically showed that localization using POMs is indeed effective at producing globally consistent localization estimates in challenging real-world environments such as parking lots without the need for long-term static maps.

Introspective Perception for Competence-Aware Mobility

Long-term deployed robots will inevitably encounter challenging scenarios that result in unmodeled perceptual errors. To detect and overcome completely novel and unmodeled failures, we introduced *introspective perception* — by exploiting sensing redundancy and spatio-temporal consistency constraints naturally present in the data collected by a mobile robot, introspective perception learns an empirical model of the error distribution of perception algorithms in the deployment environment and in an autonomously supervised manner.

With Introspective Vision for Obstacle Avoidance (IVOA) [11], we leveraged occasionally available supervisory sensing to autonomously detect failures in depth estimation. Given a black-box stereo vision algorithm, IVOA is able to predict which parts of sensed images are likely to result in perceptual failures, and the types of distinct failure modes. We further investigated competence-aware planning using the results of IVOA to identify locations in the world where a robot is likely to experience perceptual failures. We introduced competence-aware path planning via introspective perception (CPIP) [12], a Bayesian framework to iteratively learn and exploit task-level competence in novel deployment environments. Experiments in real world settings with perception challenges such as reflections and textureless surfaces show that CPIP is effective at predicting potential causes of failure, and effectively plans to avoid such error-prone regions.

We further introduced Introspective Vision for SLAM (IV-SLAM) [13] to autonomously learn context-aware noise models for features extracted for visual SLAM. IV-SLAM leverages spatio-temporal consistency of 3D landmarks in visual SLAM to autonomously identify when regions in captured images were likely to lead to tracking failures. Using this autonomously supervised data collection, IV-SLAM learns a context-aware noise model to predict feature reprojection errors. We empirically demonstrated on standard datasets and real-world data with the UT Jackal that IV-SLAM 1) is accurately able to predict sources of tracking error, 2) reduces tracking error compared to visual SLAM, and 3) increases the mean distance between tracking failures by more than 70% compared to V-SLAM in challenging real-world settings.

Learning For Terrain-Aware Navigation

Urban environments include a wide variety of types of terrains – robots deployed in such environments will have to reason about *which paths to take*, accounting for terrain preferences and social norms, and when required, be capable of *robustly and accurately driving* over such terrains.

VRL-PAP inferred terrain costs (right) from input image (left) on a park trail, accurately identifying the trail despite lighting variations and imprecise boundaries.

Most existing solutions to preference-aware path planning problem use semantic segmentation to classify terrain types from camera images, and then ascribe costs to each type. Unfortunately, there are three key limitations of such approaches – they 1) require pre-enumeration of the discrete terrain types, 2) are unable to handle hybrid terrain types (*e.g.,* grassy dirt), and 3) require expensive labelled data to train visual semantic segmentation. We introduced Visual Representation Learning for Preference-Aware Path Planning (VRL-PAP) [14] to overcome all three limitations: VRL-PAP leverages unlabeled human demonstrations of navigation to autonomously generate triplets for learning visual representations of terrain that are viewpoint invariant and encode terrain types in a continuous representation space. VRL-PAP empowers our robots to successfully pick paths on the UT Campus that reflect demonstrated preferences, and allows us to adapt to novel terrain types with minimal additional unlabeled demonstrations.

Driving accurately on different terrain types requires accurate understanding of kinodynamic interactions. While such interactions may be modelled analytically on high-traction homogeneous surfaces [15], they are hard to analyze for unstructured surfaces such as dirt, gravel, or grass. However, given a recent sliding window history of inertial measurement unit (IMU) responses to controls, we posited that such kinodynamic interactions could be corrected using a learned inverse kinodynamic (IKD) model. Building on this idea, we introduced an IMU-IKD [16] model to learn inverse kinodynamics for accurate high-speed off-road navigation on unstructured terrain. For environments with frequent and abrupt changes in terrain type (*e.g.,* transitioning between gravel and concrete), a robot needs to *anticipate* the corresponding changes in kinodynamic responses. To tackle this problem, we introduced Visual-Inertial IKD (VI-IKD) [17] — VI-IKD conditions on visual information from a terrain patch ahead of the robot and past inertial information to anticipate kinodynamic interactions in the future. We demonstrated VI-IKD on a scale 1/5 UT-AlphaTruck off-road autonomous vehicle to show that compared to other state-of-the-art approaches, VI-IKD enables more accurate and robust off-road navigation on a variety of different terrains at speeds of up to 3.5 m/s.

Program Synthesis and Repair For End-User Customizability

Having deployed robots extensively across a variety of environments over extended periods of time [18, 9], one of our takeaways was the importance of end-user customizability and repair. In particular, such customization and repair should be 1) learned from a small number of non-expert demonstrations, 2) robust to small environmental variations, and 3) interpretable. Motivated by these key constraints, we have been pursuing *symbolic program synthesis and repair* as a novel approach to end-user customizability and repair for robots — unlike much of the existing work on robot learning using neural networks, we develop algorithms to synthesize decision-making policies as symbolic programs. This approach requires orders of magnitude fewer demonstrations, produces programs that are physically meaningful and hence generalize better, and are readable by humans.

As a first step, we introduced SMT-based robot transition repair (SRTR) [19] to repair parameterized transition functions in decision-making policies — SRTR leverages a small number of corrections from humans, and performs a lightweight analysis of programmatic transition functions to frame the corrections as SMT formulae, the solution to which are new parameters that effect the corrections while minimizing change in behavior at other parts of the state space. We demonstrated SRTR outperforming expert-tuned repairs on real-world robot soccer controllers (including the robot soccer attacker policy that we used to win the lower bracket at RoboCup 2017), and a live demonstration of this work [20] won the **best interactive demo award** at AAMAS 2018.

We introduced layered dimension-informed program synthesis (LDIPS) [21] to synthesize physically meaningful programmatic policies from demonstration. A key feature of LDIPS is that it introduces a type system to reason about physical dimension constraints, thus significantly pruning the search space for program synthesis, and resulting in programmatic policies that generalize significantly better than just type-directed synthesis. We demonstrated that LDIPS can generate action selection policies that perform as well as reference policies, with two orders of magnitude fewer demonstrations than required to train neural network policies. We also showed that LDIPS-generated policies transfer from simulation to real robots with just a small number (< 10) of corrections, a feature that neural network policies struggle with.

Long-Term Research Directions

Perception for long-term autonomous mobility: I am interested in continuing our investigations of high-level perceptual reasoning of the world in terms of entities, and moving away from low-level geometric and feature-based maps. As we we have shown in our recent work on probabilistic object maps [10], we actually don't need long-term static maps for robust localization. I envision extending this work to include richer probabilistic models to infer likely long-term consistent trajectories of different semantic classes of entities. I expect this approach to be particularly instrumental for home robots, where a small number of common semantically meaningful objects are likely to be sufficient for robust long-term spatial reasoning.

Competence-aware planning for safe and robust mobility: While we have made some good initial progress on model-free competence estimation for perception, we have a long way to go before a robot can reason about competence at all levels of its autonomy stack. Our initial work on competence-aware planning via introspective perception [12] is a small step in this direction, but to be more generalizable, we will have to tackle reasoning about the impact of environmental conditions on competence — for example, that a robot's depth cameras are blinded by sunlight near a particular window at particular times of the day.

Label-free learning for robot mobility: I contend that it is impractical to expect end-users of service mobile robots to be able to provide large volumes (or any quantity of) labelled training data to help robots finetune or re-train their perception stacks. However, it is reasonable to occasionally ask users to provide a few unlabeled demonstrations — for example, how to navigate around a tricky piece of furniture, or the path to the door avoiding the petunias. Recently, we have been excited to see the real-world effectiveness of visual representation learning for preference-aware planning [14], building on a small number of unlabeled demonstrations. I am very interested in pursuing this direction further, to develop new approaches to label-free learning for robot mobility.

Neuro-symbolic program synthesis for customization of mobility: We introduced dimension-informed program synthesis [21] for few-shot learning of symbolic action selection policies from human demonstrations. While symbolic policies are effective at high-level reasoning, they are not quite as adept at dealing with high-volume low-level perceptual data such as raw sensor streams. I am thus interested in fusing neural modules along with symbolic synthesis to gain the best of both worlds — in particular, I am interested in exploring the potential to use symbolic policies for high-level discrete decision-making, while leveraging low-level neural modules to infer context-specific rewards. For example, in the context of taking an elevator, while a symbolic policy is more effective at deciding when the robot should enter the elevator, a neural module is more well suited to the task of identifying where in the elevator the robot should stand, as a function of the observations around it. I am also interested in understanding how we can effectively perform lifelong learning with neuro-symbolic program synthesis. We have recently started investigating counter-example guided dataset curation to avoid catastrophic forgetting while minimizing the growth rate of the dataset as a first step towards this direction.

Conclusion

In summary, my current and future work will continue exploring how to enable robust, long-term mobility in real-world settings. I look forward to a future enabled by this research where home robots are not confused by furniture rearrangements, package delivery robots are capable of avoiding driving over flowerbeds without having to be trained on flower detection datasets, and home robot butlers are amenable to frustration-free corrections from end-users to customize them to their own homes.

References

[1] Asha Kailin Jain, Maxwell Svetlik, Nicholas Machak, Kavan Singh Sikand, Cem Karamanli, Kaiyu Zhou, Justin Hart, Joydeep Biswas, Luis Sentis, and Junfeng Jiao. An Open-Source Framework for Last Mile Delivery with Heterogeneous Robots. AAAI Spring Symposium Series, Machine Learning for Mobile Robot Navigation in the Wild, 2021.

[2] Joydeep Biswas, Brian Coltin, and Manuela Veloso. Corrective gradient refinement for mobile robot localization. In *Intelligent Robots and Systems (IROS), IEEE/RSJ International Conference on*, pages 73–78. IEEE, 2011.

[3] Joydeep Biswas and Manuela Veloso. Planar polygon extraction and merging from depth images. In *Intelligent Robots and Systems (IROS), IEEE/RSJ International Conference on*, pages 3859–3864. IEEE, 2012.

[4] Joydeep Biswas and Manuela Veloso. Wifi localization and navigation for autonomous indoor mobile robots. In *Robotics and Automation (ICRA), 2010 IEEE International Conference on*, pages 4379–4384. IEEE, 2010.

[5] Joydeep Biswas and Manuela Veloso. Episodic non-markov localization: reasoning about short-term and long-term features. In *Robotics and Automation (ICRA), 2014 IEEE International Conference on*, pages 3969–3974. IEEE, 2014.

[6] Joydeep Biswas and Manuela M. Veloso. Episodic non-markov localization. *Robotics and Autonomous Systems*, 87:162 – 176, 2017.

[7] Joydeep Biswas and Manuela Veloso. Depth camera based indoor mobile robot localization and navigation. In *Robotics and Automation (ICRA), 2012 IEEE International Conference on*, pages 1697–1702. IEEE, 2012.

[8] Joydeep Biswas and Manuela Veloso. Multi-sensor mobile robot localization for diverse environments. In *RoboCup 2013: Robot World Cup XVII*, pages 468–479. Springer Berlin Heidelberg, 2014.

[9] Joydeep Biswas and Manuela Veloso. The 1,000-km challenge: Insights and quantitative and qualitative results. *IEEE Intelligent Systems*, 31(3):86–96, 2016.

[10] Amanda Adkins and Joydeep Biswas. Probabilistic Object Maps for Long-Term Robot Localization. In *Intelligent Robots and Systems (IROS), IEEE/RSJ International Conference on*, 2021.

[11] Sadegh Rabiee and Joydeep Biswas. IVOA: Introspective Vision for Obstacle Avoidance. In *Intelligent Robots and Systems (IROS), IEEE/RSJ International Conference on*, pages 1230–1235. IEEE, 2019.

[12] Sadegh Rabiee, Connor Basich, Kyle Hollins Wray, Shlomo Zilberstein, and Joydeep Biswas. Competence-Aware Path Planning via Introspective Perception. *IEEE Robotics and Automation Letters*, 2022.

[13] Sadegh Rabiee and Joydeep Biswas. IV-SLAM: Introspective Vision for Simultaneous Localization and Mapping. In *Conference on Robot Learning*, 2020.

[14] Kavan Singh Sikand, Sadegh Rabiee, Adam Uccello, Xuesu Xiao, Garrett Warnell, and Joydeep Biswas. Visual Representation Learning for Preference-Aware Path Planning. In *Robotics and Automation (ICRA), IEEE International Conference on*, 2022.

[15] Sadegh Rabiee and Joydeep Biswas. A friction-based kinematic model for skid-steer wheeled mobile robots. In *Robotics and Automation (ICRA), IEEE International Conference on*, pages 8563–8569. IEEE, 2019.

[16] Xuesu Xiao, Joydeep Biswas, and Peter Stone. Learning Inverse Kinodynamics for Accurate High-Speed Off-Road Navigation on Unstructured Terrain. *IEEE Robotics and Automation Letters (RA-L)*, pages 1–7, 2021.

[17] Haresh Karnan, Kavan Singh Sikand, Pranav Atreya, Sadegh Rabiee, Xuesu Xiao, Garrett Warnell, Peter Stone, and Joydeep Biswas. VI-IKD: High-Speed Accurate Off-Road Navigation using Learned Visual-Inertial Inverse Kinodynamics. In *Intelligent Robots and Systems (IROS), IEEE/RSJ International Conference on*, 2022.

[18] Joydeep Biswas and Manuela M Veloso. Localization and navigation of the CoBots over long-term deployments. *The International Journal of Robotics Research*, 32(14):1679–1694, 2013.

[19] Jarrett Holtz, Arjun Guha, and Joydeep Biswas. Interactive Robot Transition Repair With SMT. In *International Joint Conference on Artificial Intelligence (IJCAI)*, pages 4905–4911, 2018.

[20] Jarrett Holtz, Arjun Guha, and Joydeep Biswas. Demo: Interactive robot transition repair, 2018.

[21] Jarrett Holtz, Arjun Guha, and Joydeep Biswas. Robot action selection learning via layered dimension informed program synthesis. In *Conference on Robot Learning*, 2020.