Proceedings of Machine Learning Research 1:1–6, 2010 Workshop Title

Simultaneous Localization and Active Phenomenon Inference (SLAPI)

Olivier L. Georgeon OGEORGEON@UNIV-CATHOLYON.FR
UR Confluence, Sciences et Humanités (EA 1598) - Lyon Catholic University, France
Titouan Knockaert TITOUAN.KNOCKAERT@GMAIL.COM
Université Claude Bernard Lyon 1, LIRIS CNRS UMR5205, F-69622 Villeurbanne, France

Editor: Editor's name

Abstract

This is the abstract for this article.
Keywords: List of keywords

1. Introduction

The problem of getting mobile robots to autonomously learn the position of surrounding objects, recognize them, and keep track of their relative displacements is considered by many to be a key prerequisite of truly autonomous robots. Within this framework, the SLAM problem (Simultaneous Localization and Mapping) has been formalized and studied since the 1990s: constructing and updating a map of an unknown environment while simultaneously keeping track of the robot's position within it (e.g., Taketomi et al., 2017). SLAM algorithms are tailored to the available resources: odometric sensors, sensors of the environment, computational capacities, as well as the landmarks' properties, quantity, and dynamics, and the usage intended for the robot.

When displacements are imprecise and odometric data is not available, when landmarks are not directly identifiable, and below a certain level of scarcity and noise in the sensory data relative to the environment's complexity, it becomes difficult to perform SLAM accurately enough to use the robot for tasks involving complex navigation (Gay et al., 2021). For such robots, we propose the SLAPI problem: Simultaneous Localization and Active Phenomenon Inference. In contrast with SLAM, SLAPI does not aim at constructing a map to use for navigation. Instead, it aims at organizing behavior spatially in the vicinity of objects to design robots that exhibit intrinsic motivation (e.g., Oudeyer et al., 2007) such as playfulness and curiosity as they discover and interact with unknown objects. Possible applications may not include delivery tasks but may include entertainment and games, similar to playing with pets.

SLAPI makes no assumption that landmarks can be directly and passively uniquely identified through sensors. The robot must rather actively interact with objects, possibly from different angles and through different modalities of control loops, to categorize and recognize objects, and possibly use them as landmarks. We call this process *active phenomenon inference*, drawing from the work of Friston et al. (2021) on active inference. Here the term *phenomenon* refers to the knowledge of physical objects actively constructed by the robot from its point of view and "as the robot experiences the object through interaction" (Thórisson, 2021).

We designed a proof-of-concept algorithm to illustrate the SLAPI problem. We demonstrated it in a robot mounted on omnidirectional wheels and endowed with an echo-localization sensor, photosensitive sensors, and an inertial measurement unit, but no camera and lidar. As the robot circles around an object, it constructs the phenomenon corresponding to this object under the form of the set of the spatially-localized control loops that the object affords to the robot. New elements can be subsequently added to this set as the robot improves its knowledge of the object. Results show that the robot drew out a few cries of amusement and endearment from some human observers, which encourages us to keep improving this range of algorithms.

Moreover, we believe that the study of SLAPI problems can shed some light on how animals construct knowledge of objects through sensorimotor interactions, while keeping this knowledge grounded in experience. It can also provide an angle of attack to the more general AI problem of self-motivated open-ended learning in the real world.

2. The representational status of sensory data

An autonomous agent faces the necessity to actively infer the existence and the properties of objects in its environment when the data that it receives through sensors does not already hold a representational correspondence with such objects. The representational status of sensory data has been discussed times and again at the philosophical level (e.g., Williford, 2013). Loosely, two hypotheses collide: the hypothesis that sensory data carry information about features of the world, versus the hypothesis that sensory data carry information about the agent's experience of interaction with the world. We refer to the former as the *representationalist hypothesis*, and to the latter as the *constructivist hypothesis* because it relates to Piaget's theory of construcitivist learning based on sensorimotor schemes (Guillermin and Georgeon, 2022).

SLAPI falls within the constructivist hypothesis because it applies to robots that have coarse sensors that do not provide much descriptive information about the environment. The robot must probe the world a little bit like a blind person who uses a cane to actively construct a mental representation of its surroundings. Probing experiences consist of control loops during which the robot interacts with the environment. They are triggered by an action intended by the robot and result in an outcome that is informative not of the object itself but of the possibility of interaction afforded by the object to the robot. Figure 1 shows this cycle of interaction. The agent selects an action associated with spatial information that specify how the control loop should be enacted in the environment. In return, the agent receives an outcome associated with spatial information that describe how the control loop has been enacted.

Note that this model does not systematically exclude that the outcome carries information about features of the environment. We only avoid baking this assumption in the algorithm *a priori*. As Rudrauf et al. (2017) state about their model based on active inference: "All we need here is the idea that in one way or another the sensory organs provide an independent source of input and correction for the continually updated world model" (p. 19).

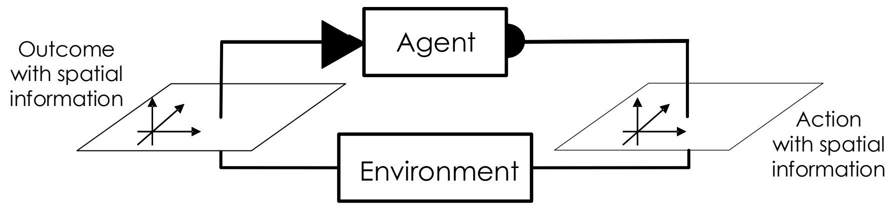

Figure 1: The interaction cycle. Black bullet: the cycle begins with the agent sending an action containing spatial information to enact in the environment (right). Black arrowhead: the cycle ends with the agent receiving the outcome containing spatial information (left).

3. The experimental setup

We use the robot cat made by Osoyoo[1], to which we added an inertial measurement unit. (Figure 2).

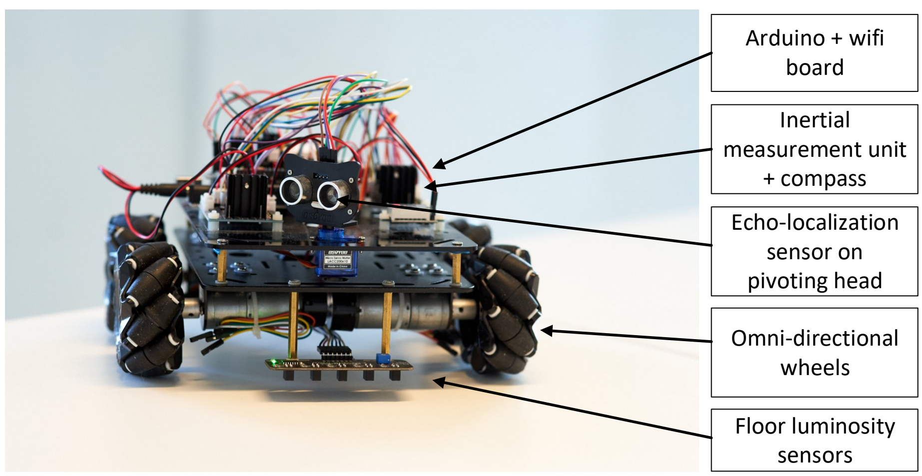

Figure 2: The robot

4. The software architecture and algorithm

The data exchanged between the PC and the robot is as follows:

PC to Robot Action code, focus position (x, y), estimated speed (x, y).

Robot to PC Outcome code, echo distance, head direction, yaw, azimuth, duration.

1. https://osoyoo.com/2019/11/08/omni-direction-mecanum-wheel-robotic-kit-v1/

Table 1: Data exchanged between the PC and the robot through wifi

PC to Robot	Action code, focus position (x, y), estimated speed (x,y)
Robot to PC	Outcome code, echo distance, head direction, yaw, azimuth, duration

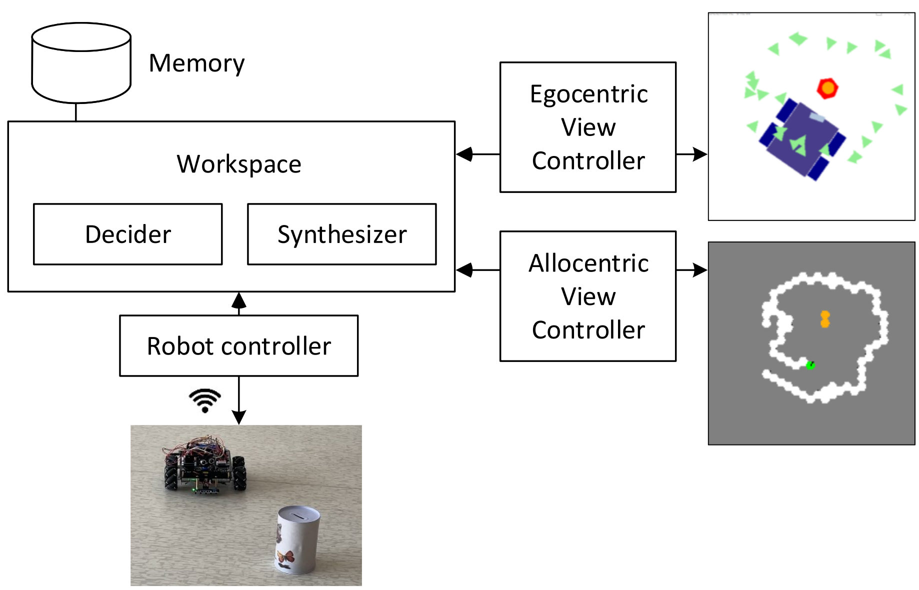

Figure 3: The software architecture. The *Memory* plays the role of the database, and the *Workspace* plays the role of the Model in a regular Model-View-Controller architecture. The *Workspace* contains the *Synthesizer* which infers the phenomena, and the *Decider* which selects the next intended interaction to send to the robot through wifi (bottom). The *Memory* contains the egocentric memory and the allocentric memory which are accessed through the *Workspace* and the *View Controllers* to display on screen (right).

4.1. The actions and outcome

Table 2: Actions available to the robot and their possible outcomes

(a) Actions

Action	Span
Forward Backward Shift left Shift right	During 1 second or until line detection
Turn left	$\pi/4$
Turn right	$-\pi/4$
Head scan	$[-\pi/2, \pi/2]$

(b) Outcomes

Outcome	Description
Line left Line front Line right	Floor sensors cross luminosity threshold
Echo lost focus	No echo where expected
Echo left Echo right Echo far left Echo far right Echo far front Echo close front	Direction and range of the nearest echo
Default	No line, no echo

4.2. The allocentric memory

The allocentric memory is inspired by the hippocampus in the mammalian brain (Grieves and Jeffery, 2017). We implemented hexagonal cells which can have status as follows:

Unknown The cell has not yet been inspected.

Free The cell affords no interaction.

occupied The cell is occupied bu the robot itself.

Line A line interaction was enacted here.

Echo En echo interaction was enacted here.

5. Results

6. Conclusion

This example is meant to illustrate a more profound epistemological assumption that the world *in itself* cannot be accessed through direct representational data. This idea goes back to Kant, relates to Piaget's developmental psychology and constructivist epistemology, and has echos in modern physics. Kark Friston said that addressing this problem may open the door to the third wave of AI (**?**, time code 22:66).

References

Karl Friston, Thomas FitzGerald, Francesco Rigoli, Philipp Schwartenbeck, and Giovanni Pezzulo. Active Inference: A Process Theory. *Neural Computation*, 29(1):1–49, January 2017. ISSN 0899-7667, 1530-888X. doi: 10.1162/NECO_a_00912. URL https://direct.mit.edu/neco/article/29/1/1-49/8207.

Karl Friston, Rosalyn J. Moran, Yukie Nagai, Tadahiro Taniguchi, Hiroaki Gomi, and Josh Tenenbaum. World model learning and inference. *Neural Networks*, 144:573–590, December 2021. ISSN 0893-6080. doi: 10.1016/j.neunet.2021.09.011. URL https://www.sciencedirect.com/science/article/pii/S0893608021003610.

Simon Gay, Kévin Le Run, Edwige Pissaloux, Katerine Romeo, and Christèle Lecomte. Towards a Predictive Bio-Inspired Navigation Model. *Information*, 12(3):100, March 2021. ISSN 2078-2489. doi: 10.3390/info12030100. URL https://www.mdpi.com/2078-2489/12/3/100. Number: 3 Publisher: Multidisciplinary Digital Publishing Institute.

Roddy M. Grieves and Kate J. Jeffery. The representation of space in the brain. *Behavioural Processes*, 135:113–131, 2017. ISSN 0376-6357. doi: https://doi.org/10.1016/j.beproc.2016.12.012. URL https://www.sciencedirect.com/science/article/pii/S0376635716302480.

Mathieu Guillermin and Olivier Georgeon. Artificial Interactionism: Avoiding Isolating Perception From Cognition in AI. *Frontiers in Artificial Intelligence*, 5, 2022. ISSN 2624-8212. doi: 10.3389/frai.2022.806041. URL https://www.frontiersin.org/article/10.3389/frai.2022.806041.

Pierre-Yves Oudeyer, Frdric Kaplan, and Verena V. Hafner. Intrinsic Motivation Systems for Autonomous Mental Development. *IEEE Transactions on Evolutionary Computation*, 11(2):265–286, April 2007. ISSN 1089-778X. doi: 10.1109/TEVC.2006.890271. URL http://ieeexplore.ieee.org/document/4141061/.

David Rudrauf, Daniel Bennequin, Isabela Granic, Gregory Landini, Karl Friston, and Kenneth Williford. A mathematical model of embodied consciousness. *Journal of Theoretical Biology*, 428:106–131, September 2017. ISSN 00225193. doi: 10.1016/j.jtbi.2017.05.032. URL https://linkinghub.elsevier.com/retrieve/pii/S0022519317302540.

Takafumi Taketomi, Hideaki Uchiyama, and Sei Ikeda. *Visual SLAM algorithms: a survey from 2010 to 2016*. 2017. Publication Title: IPSJ Transactions on Computer Vision and Applications.

Kristinn R. Thórisson. *The 'Explanation Hypothesis' in General Self-Supervised Learning*. International Workshop in Self-Supervised Learning, 2021.

Kenneth Williford. Husserl's Hyletic Data and Phenomenal Consciousness. *Phenomenology and the Cognitive Sciences*, 12(3):501–519, 2013. doi: 10.1007/s11097-013-9297-z. Publisher: Springer Verlag.