

Intelligent Robotics

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Abstract— Robotics has always been a fertile inspiration paradigm for AI research, frequently referred to in its literature, in particular in the above topics. The ambition of this paper is to review revival. It proposes an overview of problems and approaches to autonomous deliberate action in robotics. The paper advocates for a broad understanding of deliberation functions. It presents a synthetic perspective on *planning, acting, perceiving, monitoring, goal reasoning* and their *integrative architectures*, which is illustrated through several contributions that addressed deliberation from the AI–Robotics point of view.

Keywords— Robotics, Kino Dynamic, Tommy Model, Deliberation, Reasoning.

I. INTRODUCTION

In this paper we review the information requirements for robot tasks. Our work takes as its inspiration the *information invariants* that Erdmann ' introduced to the robotics community in 1989 [241, although rigorous examples of information invariants can be found in the theoretical literature from as far back as 1978.

Robotics is an interdisciplinary integrative field, at the confluence of several areas, ranging from mechanical and electrical engineering to control theory and computer science, with recent extensions toward material physics, bio engineering or cognitive science s.

The AI–Robotics intersection is very rich.

It covers issues such as:

- deliberate action, planning, acting, monitoring and goal reasoning,
- perceiving, modeling and understanding open environments,
- interacting with human and other robots,

- learning models required by the above functions,
- integrating these functions in an adaptable and resilient architecture.

• Deliberation functions in robotics

Deliberation refers to purposeful, chosen or planned actions, carried out in order to achieve some objectives. Many robotics applications do not require deliberation capabilities, e.g., fixed robots in manufacturing and other well-modeled environments; vacuum cleaning and other devices limited to a single task; surgical and other operated robots. Deliberation is a critical functionality for an *autonomous* robot facing a *variety of environments* and a *diversity of tasks*.

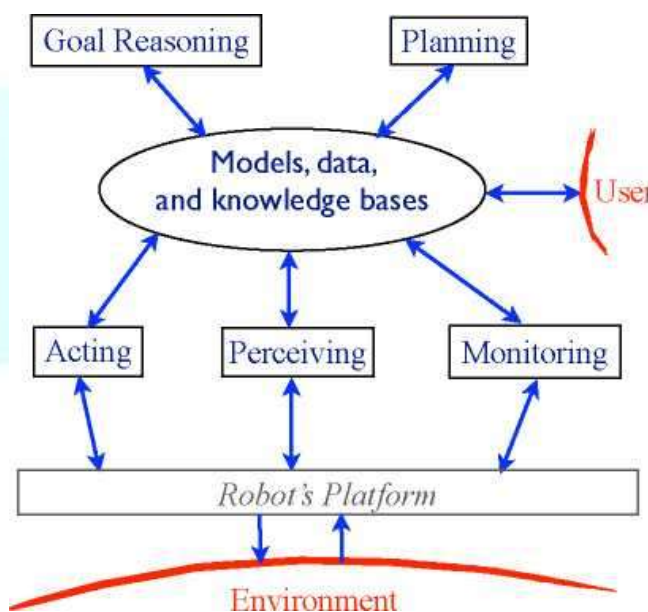


Fig. 1. Schematic view of *deliberation functions*.

These deliberation functions interact within a complex architecture (not depicted in Fig. 1) that will be discussed later. They are interfaced with the environment through the robot's *platform functions*, i.e., devices offering sensing and actuating capabilities, including signal processing and low-level control functions. The frontier between sensory-motor functions and deliberation functions depends on how variable are the environments and the tasks. For example, motion control

along a predefined path is usually a platform function, but navigation to some destination requires one or several deliberation skills, integrating path planning, localization, collision avoidance, etc.

The goals outlined here are ambitious and we have only taken a small step towards them. The questions above provide the setting for our inquiry, but we are far from answering them. This paper is intended to raise issues concerning information invariants, survey some relevant literature and tools, and take a first stab at a theory. Part I of this paper (Sections 1-3) provides some practical and theoretical motivations for our approach. In part II (Sections 4-9) we describe one particular and very operational theory. This theory contains a notion of *sensor equivalence*, together with a notion of *reductions* that may be performed between sensors. Part II contains an example which is intended to illustrate the potential of a such a theory. We make an analogy between our “reductions” and the reductions used in complexity theory. Readers interested especially in the four questions above will find a discussion of “installation complexity” and the role of calibration in comparing sensors in Section 5 below. Section 8 discusses the semantics of sensor systems precisely; as such this section is mathematically formal, and contains a number of claims. This formalism is used to explore some properties of what we call situated *sensor systems*. We also examine the semantics of our “reductions”. The results of Section 8 are then used in Section 9 to derive algebraic algorithms for reducing one sensor to another.

Over the past decades, the field of automated planning achieved tremendous progress such as a speed up of few orders of magnitude in the performance of Strips-like classical planning, as well as numerous extensions in representations and improvements in algorithms for probabilistic and other non-classical planning [35]. Robotics stresses particular issues in automated planning, such as handling time and resources, or dealing with uncertainty, partial knowledge and open domains. Robots facing a variety of tasks need domain specific as well as domain

independent task planners, whose correct integration remains a challenging problem.

- *Details of the following task*

We now review the task of following in some more detail. Consider two autonomous mobile robots. The robots we have in mind are the Cornell mobile robots, but the details of their construction are not important.

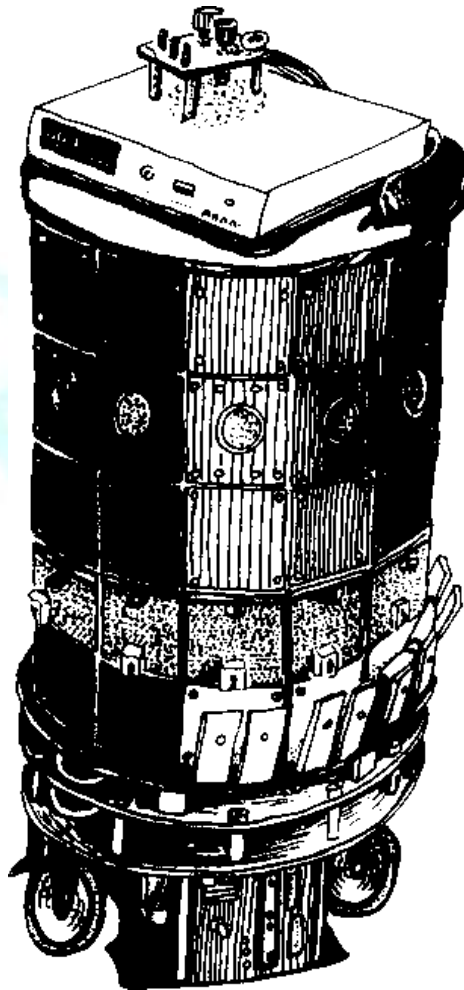


Fig. 2. Figure above showing Cornell mobile robot 'TOMMY'.

Note :- mounted top to bottom on the cylindrical enclosure, the ring of sonars, the IR Modems, and the bump sensors. **LILY** is very similar.

The robots can move about by controlling motors attached to wheels. The robots are autonomous and equipped with a ring of 12 simple Polaroid ultrasonic sonar sensors. Each robot has an onboard processor for control and programming. We pause for a moment to note that this simple, experimentally-determined quantity is our first example of an information invariant. Now, modem i is mounted so as to be at a fixed angle from the front of the robot base, and hence it is at a fixed angle δ_i from the direction of forward motion, which is defined to be 0. Now, suppose that TOMMY is traveling at a commanded speed of U . For the task of following, each modem panel i on TOMMY transmits a unique identifier (e.g., 'Tommy'), the angle δ_i , and the speed U . That is, he transmits the following triple: 4.

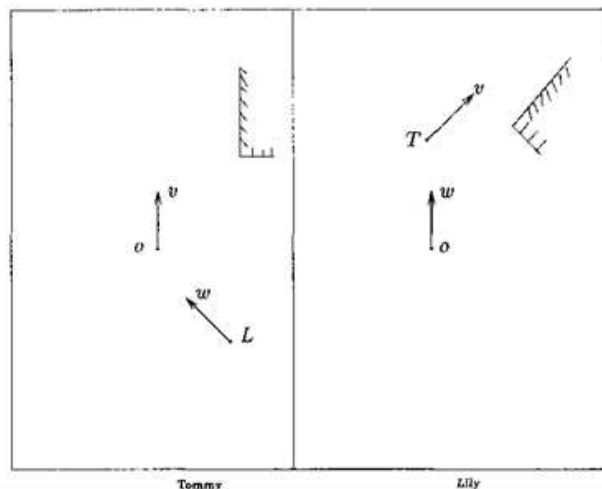


Fig. 3. The “radar screens” of TOMMY and LILY. TOMMY (T) is approaching a wall (on his right) at speed U , while LILY (L) follows at speed W .

In this task, LILY transmits the same information, with a different id of course. This means that when the robots are in communication each can “detect” the position (using sonars and IRS), the heading, and the name of the other robot.⁵ In effect each robot can construct a virtual “radar screen” like those used by air traffic controllers, on which it notes other robots, their position and heading, as well as obstacles and features of the environment. The screen (see Fig. 3) is in local coordinates for each robot. It is important to realize that although Fig. 2 “looks” like a pair of maps, in fact, each is simply a local reconstruction of sensor data.

Moreover, these “local maps” are updated at iteration through the servo loop, and so little retained state is necessary.

- **Perceiving**

Situated deliberation relies on data reflecting the current state of the world. Beyond sensing, perceiving combines bottom-up processes from sensors to interpreted data, with top-down focus of attention, search and planning for information gathering actions.

Perceiving is performed at:

- The *signal level*, e.g., signals needed in control loops.
 - The *state level*: features of the environment and the robot and their link to facts and relations characterizing the state of the world.
 - The *history level*, i.e., sequences or trajectories of events, actions and situations relevant for the robot’s mission.
- The signal level is usually dealt with through models and techniques of control theory. Visual serving approaches for tracking or handling objects and moving targets offer a good example of mature techniques that can be considered as tightly integrated into the basic robot functions. Similarly for simultaneous localization and mapping techniques, a very active and well advanced field in robotics, to which numerous publications have been devoted. These geometric and probabilistic techniques, enriched with topological and semantic data.

Establishing an anchor corresponds to a pattern recognition problem, with the challenges of handling uncertainty in sensor data and ambiguity in models, dealt with for example through maintaining multiple hypotheses. Ambiguous anchors are handled in as a planning problem in a space of belief states, where actions have causal effects that change object properties, and observation effects that partition a belief state into several new hypotheses.

- **Goal reasoning**

Goal reasoning is mostly concerned with the high level of reasoning and global mission. Its main role is to manage the set of objectives the system wants to achieve, maintain or supervise. It may react to new goals given by the user or to goal failure reported acting and monitoring. In several implementations, this function is embedded in the planning or acting functions.

Goal reasoning has been deployed in a number of real experiments. Notably in the DS1 New Millennium Remote Agent experiment and in the CPEF framework. Yet, overall, the goal reasoning function is not often developed. It is nevertheless needed for complex and large systems managing various long term objectives while taking dynamically into account new events which may trigger new goals.

- **Conclusion**

Autonomous robots facing a variety of open environments and a diversity of tasks cannot rely on the decision making capabilities of a human designer or teleoperator. To achieve their missions, they have to exhibit complex reasoning capabilities required to understand their environment and current context, and to act deliberately, in a purposeful, intentional manner. In this paper, we have referred to these reasoning capabilities as deliberation functions, closely interconnected within a complex architecture. We have presented an overview of the state of the art for some of them. For the purpose of this overview, we found it clarifying to distinguish these functions with respect to their main role and computational requirements: the perceiving, goal reasoning, planning, acting and monitoring functions. But let us insist again: the border line between them is not crisp; the rational for their implementation within an operational architecture has to take into account numerous requirements, in particular a hierarchy of closed loops, from the most dynamic inner loop, closest to the sensory-motor signals and commands, to

the most “offline” outer loop. The reviewed theory allows us to compare members of a certain class of sensor systems, and, moreover, to transform one system into another. However, it does not permit one to judge which system is “simpler” or “better” or “cheaper”. In particular, for a given measurement problem, it does not permit a “simplest” sensor system to be identified. There are several reasons for this. The first is that there are inherent limitations on comparing absolute sensor complexity-and these problems represent structural barriers to obtaining good notions of “better” or “simpler”. The theory is designed, in part, to get around some of these limitations. We discuss these problems-which are quite deep-in Appendix B at some length. Second, such comparisons would require an explicit performance measure. We discussed such measures as speed (or execution time), reviewed paper argue that such performance measures allow us to apply *Kino dynamic* analysis tools. There is no doubt that external performance measures such as “simpler” and “better” and “cheaper” could be used with our framework-but we don’t know what exactly these measures are. It appears that efficient algorithms for exploiting these measures will have to take advantage of their structure.

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• References

- [1] M. Blum and D. Kozen On the power of the compass (or, why mazes are easier to search than graphs), in: *Proceedings 19th Symposium on Foundations of Computer Science*, Ann Arbor, MI (1978) 132- 142.
- [2] M. Ben-Or, D. Kozen and J. Reif, The complexity of elementary algebra and geometry, *J. Camp. Syst. Sci.* 32 (1986) 251-264.
- [3] M. Blum and W. Sakoda On the capability of finite automata in 2 and 3 dimensional space, in: *Proceedings 17th Symposium on Foundations of Computer Science* (1977) 147-161.
- [4] A. Briggs, An efficient algorithm for one-step compliant motion planning with uncertainty, *Algorithmic* (2) (1992) 195-208.
- [5] R.G. Brown, Forthcoming Ph.D. Thesis, Computer Science Department, Cornell University, Ithaca, NY, USA.
- [6]J. Canny, On computability of fine motion plans, in: *IEEE International Conference on Robotics and Automation*, Scottsdale, AZ (1989).
- [7] B. Argal 1, S. Chernova, M. Veloso, and B. Browning. A survey of robot learning from demonstration. *Robotics and Autonomous Systems*, 57(5):469–483, 2009.

- [8] T. Bailey and H. Durrant-Whyte. Simultaneous localization and mapping (SLAM): part II. *IEEE Robotics and Automation Magazine*, 13(3):108–117, 2006.
- [9] M. Beetz. Structured reactive controllers: controlling robots that perform everyday activity. In *Proceedings of the annual conference on Autonomous Agents*, pages 228–235. ACM, 1999.
- [10] M. Beetz and D. McDermott. Improving Robot Plans During Their Execution. In *Proc. AIPS*, 1994.
- [11] S. Bernardini and D. Smith. Finding mutual exclusion invariants in temporal planning domains. In *Seventh International Workshop on Planning and Scheduling for Space (IWSPSS)*, 2011.
- [12] J. Bohren, R. Rusu, E. Jones, E. Marder-Eppstein, C. Pantofaru, M. Wise, L. Mosenlechner, W. Meeussen, and S. Holzer. Towards autonomous robotic butlers: Lessons learned with the PR2. In *Proc. ICRA*, pages 5568–5575, 2011.
- [13] D. Chapman, Planning for conjunctive goals, *Artif Intell.* 32 (3) (1987) 333-378.
- [14] J. Canny, B. Donald, J. Reif and P. Xavier, On the complexity of kinodynamic planning, in: *29th Symposium on the Foundations of Computer Science*, White Plains, NY (1988) 306-316.
- [15] J. Canny and J. Reif, New lower bound techniques for robot motion planning problems, *28th Annual IEEE Symposium on Foundations in Computer Science*, Los Angeles, CA (1987).
- [16] D. Cox, J. Little and D. O’Shea, *Ideals, Varieties, and Algorithms*, Undergraduate Texts in Mathematics (Springer-Verlag, New York, 1991).