Survey of Robotics Using Artificial Intelligence

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Abstract**-** *Despite a very strong synergy between Robotics and Artificial Intelligence at their starting phase, the two fields progressed apart in the following decades., We are witnessing interest in the fertile domain of embodied machine intelligence(Robotics using AI), which is due in particular to the dissemination of more mature techniques from both areas and more accessible robot platforms with advanced sensory motor capabilities, and to a better understanding of scientific challenges of the Robotics using AI intersections. The aim and vision of the paper is to contribute to this revitalization of the Robotics Process. It proposes overview of problems and approaches to autonomous deliberate action in robotics using AI. The paper supports for a wide understanding of considerable functions. It represents a synthetic planning prospective, acting, perceiving, monitoring, goal reasoning and their integrative architectures, which is shown and evaluated through several contributions that addressed deliberation from the Robotics using AI point of view.*

Keywords**-** Robotics , AI , Mobile information robots, industries , military , Medicine, Explorations.

I. INTRODUCTION

Robotics is an integrative field, at the confluence of several areas, ranging from mechanical and electrical engineering to control theory and computer science, with extensions toward material physics, bioengineering or cognitive sciences. The Robotics using AIcoming together is very strong techniques for perfection in robotics. It covers issues such as:

- Action, planning, acting, monitoring and goal reasoning,
- Perceiving, modeling and understanding environments,
- Interacting with humans and other robots,
- Learning models required by the above mentioned functions,
- Integrating these functions.

Robotics has always fertile inspiration for AI research, frequently referred to in its literature, in particular in the above topics. The early days of AI are rich in pioneering projects fostering AI research agenda on robotics platforms. Typical examples are Shakey at SRI and the Stanford Cart in the sixties, or Hilare at LAAS and the CMU Rover in the seventies. But, in the following decades the two fields developed in diverging directions; robotics expanded widely outside of AI laboratories. Hopefully, a revival of the synergy between the two fields is currently being witnessed. This revival is due to more mature techniques in robotics using AI, to the development of inexpensive robot platforms with more advanced sensing and control capabilities, to a number of popular competitions, and to a better understanding of the scientific challenges of machine intelligence, to which we would like to contribute here. This revival is strong in Europe where a large number of groups is actively contributing to the Robotics using AI. For example, out of the 260 members of the Euron network,

1. About a third investigate robotics decision and cognitivefunctions. Many other European groups not within Euron and projects outside of EU programs are relevant to the Robotics using AI. This focused deliberative capabilities in robotics cannot pay a fair tribute to all European actors of this synergy.
2. Its motive is not to cover a comprehensive survey of deliberation, and even less of the Robotics using AI intersection. In the limited scope of this special issue, we propose a synthetic view of deliberation functions. We discuss the main problems involved in their development and exemplify a few approaches that addressed these problems.

This “tour d’horizon” allow us to advocate for a broad and integrative view of deliberation, where problems are beyond search in planning, and beyond the open-loop triggering of commands in acting. We hope through this perspective to strengthen the Robotics using AI synergies. The outline of the paper is the following: five deliberation functions are introduced in the next section; these are successively addressed through illustrative contributions; section 8 is devoted to architecture problems, followed by a conclusion.

II. DELIBERATION FUNCTIONS IN ROBOTICS

Deliberation refers to purposeful, chosen or planned actions, carried out in order to achieve some objectives.e.g. robots in manufacturing and other well-modeled systems; vacuum cleaning and other devices limited to a single task; surgical robots. Deliberation is a crucial and critical functionality for an autonomous robot facing a variety of environments and a variety of tasks.

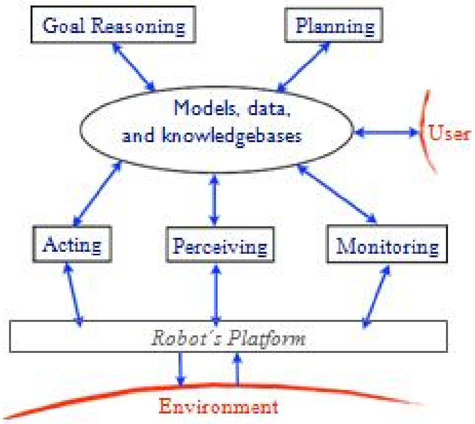

Fig. 1. Schematic view of deliberation functions

Several functions can be required for acting deliberately. The frontiers between these functions may depend on specific implementations and architectures, but it is clarifying to distinguish the following five deliberation functions, schematically depicted in figure 1:

- Planning: It Joins prediction and search to synthesize a trajectory in an abstract action space, using calculated models of feasible actions and of environment.
- Acting: It executes on-line close-loop feedback system that process streams of sensors to actuators commands in order to refine and control achievement of planned actions.
- Perceiving: It extracts features to identify states, events, and situations relevant for the task. It collects and combines bottom-up sensing, from sensors to meaningful retrieved data, with top-down focus mechanisms to sensing actions and planning for information collecting.
- Monitoring: compares and detects discrepancies between predictions and observations, performs diagnosis and triggers recovery actions.
- Goal reasoning: keeps current commitments and goals into perspective, assessing their relevance given observed evolutions, opportunities, constraints or failures, deciding about commitments to be abandoned, and goals to be updated.

These deliberation functions communicate within a complex architecture (not depicted in Fig. 1) that will be discussed later. i.e., devices offering sensing and actuating capabilities, including signal processing and low-level function control. The frontier between the sensory-motor functions and deliberation functions depends on how variable environments and the tasks actually are.

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. Learning capabilities change this frontier, e.g., in a familiar environment a navigation skill is compiled down into a low-level control with preached parameters. A met reasoning function is also needed for trading off deliberation time for action time: critical tasks require careful deliberation, while less important or more urgent ones may not need.

III. PLANNING

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. Robotic mechanism stresses some issues in automated planning, eg, handling time, 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.

The Asymov planner combines a state-space planner with a search in the motion configuration space. It defines places which are both states, as well as sets of free configurations. Places define bridges between the two search spaces. The state space search prunes a state whose corresponding set of free configurations does not meet current reachability conditions. Asymov has been extended to manipulation planning and to multirobot planning of collaborative tasks, such as two robots assembling a table. The integration of motion and task planning is also explored in with AHP Angelic Hierarchical Planning. AHP plans over sets of states with the notion of accessible set of states. These sets are not computed exactly, but bounded, e.g., by a subset and a superset, or by an upper and a lower bound cost function. A plan is acceptable if it has at least one feasible decomposition. The bounds used to characterize reachable sets of states are obtained by simulation of the primitives, including through motion and manipulation planning, for random values of the state variables. A different coupling of a hierarchical task planner to fast geometric suggester’s is developed.

These suggesters are triggered when the search in the decomposition tree requires geometric information. They do not solve completely the geometric problem, but they provide information that allows the search to continue down to leaves of the tree. The system alternates between planning and execution of primitives, including motion and manipulation actions. Online planning allows to run motion or manipulation planners (not suggesters) in fully known states. The approach considers that the geometric conditions of the actions can be computed quickly and efficiently by the songsters, and that the sub-goals resulting from actions decomposition are executed in sequence (no parallelism). The resulting system is not complete. Failed actions should be reversible at a reasonable cost. For problems where these assumptions are met, the system is able to quickly produce correct plans.

IV. ACTING

In contrast to planning that can easily be specified as an offline predictive function, decoupled from the intricacies of the executing platform, acting is more difficult to define as a deliberation function. The frequent reference to execution control is often reductive: there is more to it than just triggering actions prescribed by a plan. Acting components has to handle noisy sensors and imperfect models over the time. It requires non-deterministic, partially observable and dynamic environment models, dealt with through closed-loop commands. To integrate these requirements with predictive planning models, different forms of hierarchization are explored:

- Planning deals with abstract preconditions-effects actions;

- Acting refines opportunistically each action into skills and a skill further down into commands. This refinement mechanism may also use some planning techniques but with distinct state space and action space than those of the planner.

V. MONITORING

The monitoring function is in charge of (i) detecting discrepancies between predictions and observations, (ii) classifying these discrepancies, and (iii) recovering from them. Monitoring has at least to monitor the planner’s predictions supporting the current plan. It may have also to monitor predictions made when refining plan steps into skills and commands, as well as to monitor conditions relevant for the current mission that are left implicit in planning and refinement steps. Although monitoring functions are clearly distinct from action refinement and control functions, in many cases the two are implemented by the same process with a single representation. For example, the early Planex performs a very simple monitoring through the iterated computation of the current active kernel of a triangle table. In most procedure-based systems there are PRS, RAP, ACT or TCA constructs that handle some monitoring functions.

However, diagnosis and recovery functions in such systems are usually limited and ad hoc. The spacecraft is modeled as a fine grained collection of components, e.g., a thrust valve. Each component is described by a graph where nodes are the normal functioning states or failure states of that component. Edges are either commands or exogenous transition failures. The dynamics of each component is constrained such that at any time exactly one nominal transition is enabled but zero or more failure transitions are possible. Models of all components are compositionally assembled into a system allowing for concurrent transitions compatible with constraints and preconditions. Two query modes are used: (i) diagnosis, i.e., find most likely transitions consistent with the observations, and (ii) recovery, i.e., find minimal cost commands that restore the system into a nominal state.. This classification of almost 90 different contributions to Monitoring in robotics is inspired from the field of industrial control, where Monitoring is a well-studied issue.

Several authors have synthesized state-reachability conditions, called invariants, from the usual planning domain specifications. Going further, proposes extended planning problems, where the specifications of planning operators are augmented by logical formula stating invariant conditions that have to hold during the execution of a plan. Indeed, planning operators and extended invariants are two distinct knowledge sources that have to be modeled and specified distinctly. These extended invariants are used to monitor the execution of a plan. Furthermore, extended invariants allow to monitor effects of exogenous events and other conditions not influenced by the robot. This approach assumes complete sensing and perfect observation function.

VI. PERCEIVING

Situated deliberation relies on data reflecting the current state of the world. It may involve deliberation and can be quite effective. But of the above areas, methods for designing perceiving functions remain today a limiting factor in autonomous robotics, a hard and challenging issue to which surprisingly not enough efforts have been devoted. The building blocks for such a function can to be taken from the fields of signal processing, pattern recognition and image analysis, which offer a long history of rich developments. However, the integration of these techniques within the requirements of autonomy and deliberation remains a bottleneck.

As defined in, anchoring is the problem of creating and maintaining over time a correspondence between symbols and sensor data that refer to the same physical object. Anchoring concerns specific physical objects. It can be seen as a particular case of the symbol grounding problem, which deals with broad categories, e.g., any “chair”, as opposed to that particular chair-2. Anchoring an object of interest can be achieved by establishing and keeping an internal link, called an anchor, between the perceptual system and the symbol system, together with a signature that gives estimate of some of the attributes of the object it refers to. The anchor is based on a model that relates relations and attributes to perceptual features and their possible values. 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. There is also the issue of which anchors to establish, when and how, in a bottom-up or a top-down process. These objects can only be defined by intension (not extensively), in a context-dependent way. There is also the issue of tracking anchors, i.e., taking into account objects properties that persist across time or evolve in a predictable way. Predictions are used to check that new observations are consistent with the anchor and that the updated anchor still satisfies the object properties. Finally, reacquiring ananchor when an object is re-observed after some time is a mixture of finding and tracking; if the object moves it can be quite complex to account consistently of its behavior.

VI. GOAL REASONING

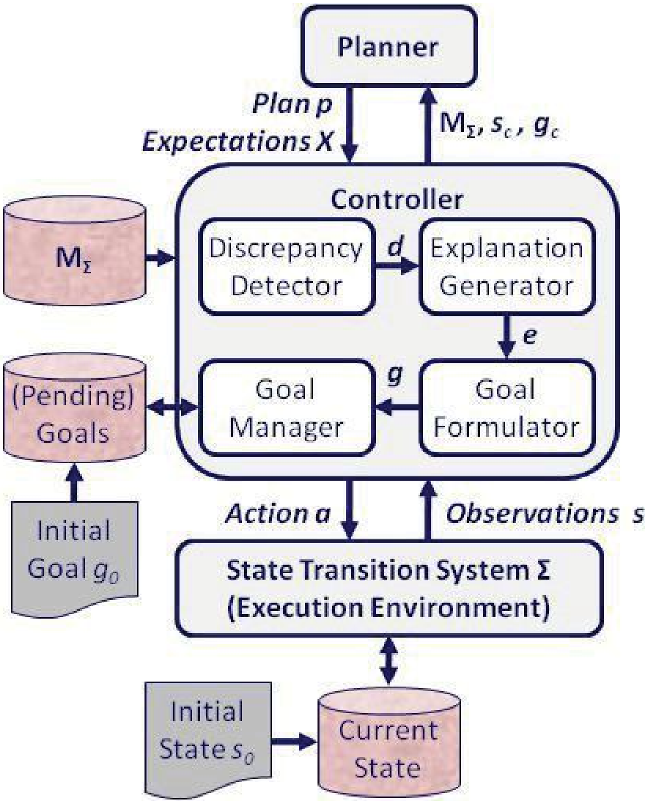

Fig. 2 Goal Reasoning Model

Goal reasoning is mostly concerned with the management of high-level goals and the 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. It clearly shares similarities with the monitoring function. Still, Goal Reasoning is not akin to planning as it does not really produce plan, but merely establish new goals and manage existing one which are then passed to the planner. Similarly to monitoring, it continuously checks unexpected events or situations. These are analyzed to assess current goals and possibly establish new goals. As shown on figure 5, their system includes a classical planner; when it executes a plan, it detects discrepancy (Discrepancy Detector), generates an explanation, may produce a new goal (Goal Formulator) and finally manages the goals currently under consideration by the system.

The Goal Manager can use different approaches to decide which goal to keep (e.g., using decision theory to balance conflicting goals). Similarly, in the authors point out that planning should be considered from a broader point of view and not limited to the sole activity of generating an abstract The resulting PMA system heavily relies on temporal and causal reasoning, and is able to plan with partial commitments, allowing to further refine a plan when needed. It is nevertheless needed for complex and large systems managing various long term objectives while aking dynamically into account new events which may trigger new goals.

VII. INTEGERATION AND ARCHITECTURE

Beyond the integration of various devices (mechanical, electrical, electronical, etc), robots are complex systems including multiple sensors, actuators and information processing modules. Various system architectures have been proposed to tackle this task, among which the following:

- Reactive architectures, e.g. the subsumption architecture, are composed of modules which close the loop between inputs (e.g. sensors) and outputs (e.g. effectors) with an internal automata. They do not rely on any particular model of the world or plans to achieve and do not support any explicit deliberative activities. Nevertheless, there are a number of work.

- Teleo-reactive architectures are more recent. They propose an integrated planning– acting paradigm which is implemented at different levels, from deliberation down to reactive functions, using different planning–acting horizons and time quantum. Each planner–actor is responsible for ensuring the consistency of a constraint network (temporal and atemporal) whose state variables can be shared with other planners–actors to provide a communication mechanism.

VIII. 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 tele operator. 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. We have referred to the reasoning capabilities as deliberation functions, interconnected closely 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.

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